Studies in Big Data 64

Srikanta Patnaik *Editor*

New Paradigm of Industry 4.0

Internet of Things, Big Data & Cyber Physical Systems

Springer

Studies in Big Data

Volume 64

Series Editor

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New Paradigm of Industry 4.0

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ISSN 2197-6503 ISSN 2197-6511 (electronic)
Studies in Big Data
ISBN 978-3-030-25777-4 ISBN 978-3-030-25778-1 (eBook)
https://doi.org/10.1007/978-3-030-25778-1

This Springer imprint is published by the registered company Springer Nature Switzerland AG
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

Editorial

The Fourth Industrial Revolution, also known as Industry 4.0, has gained attention from researchers, academicians, and industry personnel across the world over the past few years. The first three revolutions being (i) the invention of steam engine; (ii) the invention of electricity and adoption of mass production by division of labor; and (iii) the combining development of computers with information technology (IT) to automate things have brought a lot of changes to industrial developments. Now, with the advent of Internet of things (IoT) and cyber-physical systems (CPS), both industries and governments have started investing huge amount in related projects to develop Internet of everything in all sectors. During this digital transformation phase, novel industrial technologies have made it easier to gather data from machines and analyze them for enhancing efficiency, flexibility, and speed for producing high-quality goods at optimal cost, thus increasing productivity and growth of companies.

Some of the key technologies forming the building blocks and driving the research of Industry 4.0 include: big data and analytics, cloud computing, vertical and horizontal integration, cyber-physical systems, autonomous robots, Internet of things, cyber-security, additive manufacturing, augmented reality, and simulation of concepts and models. While adoption of big data analytics enables collection and evaluation of data from heterogeneous sources such as various industrial equipments, processes, and systems, these outcomes can be utilized to generate insights for making several real-time decisions. Cloud computing enables data sharing across the globe among different production sites beyond the boundaries, thus opening more doors for data-driven services for various connected systems. Vertical and horizontal integration of data-driven networks and services in Industry 4.0 will lead to evolution of fully automated value chains. Deploying autonomous robots will enhance production capability and efficiency to a great extent at reduced costs. Moreover, these robots are capable of interacting with each other as well as human beings and can learn things eventually. Again industrial IoT enriches field devices with embedded computing that allows devices to interact and communicate with each other as well as centralized and decentralized controllers for real-time response and decision making. Also, the intensified network connectivity and increased use of communication protocols to enhance accessibility in Industry 4.0 make the system quite vulnerable and exposed to several types of threats. This induces adoption of cyber-security processes to provide reliable and secured communication channels and essential authenticity management systems.

Further, additive manufacturing methods help in producing customized products according to requirements. And augmented reality supports providing real-time information through smart phones or devices to make decisions regarding selection of objects in warehouses or other instructions regarding repairing of machines, etc. Finally, simulation of concepts and models or prototypes of machines, products, and processes with different parameter settings will allow fine-tune and optimize the prototypes in the virtual world before implementing them physically and will also improve quality. Although there are so many positive aspects to adopt Industry 4.0, still there are many challenges that companies and firms face at a stretch.

However, being a developing research area, the current literature about Industry 4.0 still lacks systematic coverage of different aspects of this new wave of revolution. Although there are lots of articles and research papers available all over, still the unavailability of the state of the art of the current progresses in the field lacks to provide a complete picture of the current developments as well as to what extent researchers have been progressed. This book attempts to focus on current and future research directions of Industry 4.0. It addresses a wide range of application fields of Industry 4.0 and various issues being faced by the companies while adopting Industry 4.0. It also tries to establish some standard concepts which can further form the base for future models and applications. This book again provides a platform to the authors to study underlying processes and develop tools and solutions for effective management of these processes. Finally with selective chapters, this book aims to systematically address the gap between the academic investigation of different aspects of Industry 4.0 and actual feasibility and challenges being faced by companies while adopting Industry 4.0.

The volume consists of eight selective chapters to fulfill the purpose of the book and provide a broad coverage of the topic. Chapter "Management of V.U.C.A. (Volatility, Uncertainty, Complexity and Ambiguity) Using Machine Learning Techniques in Industry 4.0 Paradigm" provides an introduction to Industry 4.0 and identifies various risk factors involved in the digitization process of machineries as volatility, uncertainty, complexity, and ambiguity (VUCA). The authors define the terms and showcase their systematic relationships associated with Industry 4.0 practices. They also provide some future research directions in the same context.

Chapter "Role of Industry 4.0 in Performance Improvement of Furniture Cluster" investigates critical success factors (CSFs) and studies their impact on channelizing resources and improving performance of furniture clusters by utilizing data effectively for decision making. Chapter "Imparting Hands-on Industry 4.0 Education at Low Cost Using Open Source Tools and Python Eco-system" examines various areas of the Industry 4.0 paradigm and discusses how open-source tools like Python and their supporting libraries can be utilized to provide education through hands-on sessions. Further, chapter "Decision Support Framework for Smart Implementation of Green Supply Chain Management

Practices" focuses on the development of a decision support framework for adopting green supply chain management practices in an attempt to reduce carbon footprints. The authors present a hybrid decision-making approach that adopts multicriteria evaluation approach to process orders dynamically and cope with market variations. Also, chapter "Decision Support System for Supply Chain Performance Measurement: Case of Textile Industry" proposes a decision support framework that identifies the key performance indicators that contribute toward performance measurement of supply chain management systems in textile industry.

Chapter "A Review Study of Condition Monitoring and Maintenance Approaches for Diagnosis Corrosive Sulphur Deposition in Oil-Filled Electrical Transformers" studies corrosive sulfur depositions in oil-filled electrical transformers and establishes an effective plan for maintenance. The authors monitor relevant conditions to reduce transformer failures by diagnosing the corrosion caused inside the transformer. The authors further suggest a dynamic and cost-effective condition-based maintenance plan for detecting failures at early stages, so as to avoid any hazardous effect. Chapter "Principal Components Based Multivariate Statistical Process Monitoring of Machining Process Using Machine Vision Approach" attempts to integrate a machine-vision-based multivariate statistical process monitoring technique with principal component analysis to monitor machining process and provide automated industry-ready solution. Lastly, chapter "Green IS—Exploring Environmental Sensitive IS Through the Lens of Enterprise Architecture" focuses on green information system (green IS) and explores enterprise architecture and several related aspects and challenges in the context of supporting organizations to attain sustainability goals for Industry 4.0.

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Acknowledgements

I am thankful to Editor-in-Chief of the Springer Book series on "**Studies in Big Data**" Prof. Janusz Kacprzyk for his support to bring out this volume. I would like to extend our heartfelt thanks to Dr. Thomas Ditzinger, Executive Editor, and his Springer publishing team for his encouragement and support.

I am personally thankful to all the authors of this volume for their valued contribution in this upcoming research area.

I am sure that the readers shall get immense benefit and knowledge from this volume entitled *New Paradigm of Industry 4.0: Internet of Things, Big Data & Cyber Physical Systems*.

Contents

Management of V.U.C.A. (Volatility, Uncertainty, Complexity and Ambiguity) Using Machine Learning Techniques in Industry 4.0 Paradigm

Bhagyashree Mohanta, Pragyan Nanda and Srikanta Patnaik

Abstract With the fast advancement in technology and induction of information technology and internet into various aspects of organizations, there has been both large scale of both quantitative as well as qualitative changes in industries. These revolutionary changes being done to attain digital transformation for organizational improvements, has been termed as Fourth Industrial Revolution also known as Industry 4.0. However, transforming the traditional processes and machineries for digitization involves lots of risk factors such as volatility, ambiguity, complexity and uncertainty. The amalgamations of all risk factors can be abbreviated as V.U.C.A. where V stands for volatility, U stands for uncertainty, C stands for complexity and A stands for ambiguity. It's just like the cancerous cells that are present in each organization, if ignored at an early stage then it can lead to the deterioration of the organization. Hence for identifying and defining the contingencies, V.U.C.A. can play a highly pioneer role and thereby avoiding catastrophic results and cascaded issues in an organization. One effective way to manage V.U.C.A. is integrating machine learning (ML) techniques into Industry 4.0 applications. ML acts as a guide to identifying, getting prepared for, and responding to events in each category. In this paper, therefore, we have reviewed the V.U.C.A. terminologies and its importance associated with Industry 4.0 practices; the various effects of V.U.C.A. which are presented in a systematic overview about Industry 4.0 along with its peripherals, challenges, and finally identifying some future research directions. It also includes the different ML techniques with their applications towards each factor.

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S. Patnaik (ed.), *New Paradigm of Industry 4.0*, Studies in Big Data 64,
https://doi.org/10.1007/978-3-030-25778-1_1

Keywords Ambiguity · Autonomy · Big data · Complexity · Cyber physical systems · Decentralization · Industry 4.0 · Internet of Things · Machine learning (ML) · Uncertainty · Volatility · V.U.C.A.

1 Introduction

In past, the introduction of advanced technologies like mechanization, computerization, automation, and digitization in industries lead to industrial revolutions. The main objective of the fourth industrial revolution in any sector is to serve risk free, effortless operations and on-time delivery of services as set previously before production. Cyber physical systems and Internet of Thing (IoT) concepts are the basic backbone of industry 4.0. More efficient the technology, there is more the chances of huge data generation. So, big data concept with cloud data storage concept are collaborated into industry 4.0 to effectively handle this issue. The present scenario of industrialization can be considered as fourth industrial revolution or Industry 4.0. It comprises of upgraded trends of technologies by keeping the compatibility intact to integrate interactive intelligent systems with the concept of big data. Now a days, almost every organization is in rush for digitization which has lead them to face different challenges and struggle. Besides it's not about digitization only but it's about different aspects of the risk factors also. With so many challenges, forecasting the future of any organization is really very difficult. Hence, considering today's business world with all the challenges concluding the scenario to be a V.U.C.A. world is highly recommendable (Kinsinger and Walch 2012). Every industry has to tackle with these four factors, which are volatility (rapid rise and fall in market), uncertainty (unpredictable market conditions), complexity (difficulties in problem understanding) and ambiguity (confusion in market situations) (Bennett and Lemoine 2014a). All the aforesaid four factors are inter-related to each other which can definitely affect the growth of the business for industries. Hence the decision-making power of an organization definitely relies on these V.U.C.A. terminologies and concepts (Bennett and Lemoine 2014b). Basically, these are considered by the higher authorities of any organizations to deal with the possible adverse situations arising in future.

1.1 Industry 4.0 Paradigm

Over a period of hundreds of years, the search of innovative solutions for providing competitive advantages in emerging markets has led to various revolutions in industrial developments. In current technological development era, with the advancement in digitization of organizations, Industry 4.0 has evolved as a consequence of fourth industrial revolution. Before this fourth revolution in industries, there are three phases of revolutions.

The phase-I is considered as Industry 1.0 or first industrial revolution, where water and steam machines were developed to facilitate the workers efficiency in the era of 1800s. The true mechanization concept was introduced in this period. With the increase in production capabilities decentralized decision making was needed which was previously handled by the owners of their own.

The phase-II or second industrial revolution or Industry 2.0 concept was introduced in 1910 by Patrick Geddesand was firstly being used in 1951 by the economists Erick Zimmerman. In this phase of electrical machines were the primary contributors in industrial revolution as they are much more efficient as these takes least time to complete the job and easy to operate and to maintain. The assembly line was firstly introduced and mass production using assembly line systems were became an easy practice in this era of revolution.

The phase-III or third industrial revolution or Industry 3.0 was introduced in around 1970. In this era computer aided machines are introduced. Automation is the key concept of this revolution, still it required human intervention.

The term Industry 4.0 was coined in 2011 in Germany, for a high-tech project strategy by the government of Germany to promote digitization of industrial manufacturing system. Industry 4.0 involves automation of data exchange process among manufacturing systems by integrating IoT with cognitive and cloud computing, thus known as Cyber Physical Systems (CPS). Industry 4.0 holds within itself innumerable paradigms and technologies including collaborative product development, cloud computing, Internet of Things (IoT), Enterprise Resource Planning (ERP), Information and Communication Technology (ICT), Radio Frequency Identification (RFID) etc. (Brettel et al. 2014; Gruber 2013; Hermann et al. 2016; Ivanov et al. 2016). In a way Industry 3.0 laid the foundation for Industry 4.0, since the realization of the former focused on automation of individual processes and machines while Industry 3.0 involves digitization of almost all physical systems along with their integration with each other to form a digital ecosystem across the value chain. The four phases of industrial revolution has been shown in Fig. 1.

The rapid growth of industrialization, induction of IoT concepts with the benefits of cyber physical systems lead to huge amount of data flow in the system. For easy maintenance and processing of these data, big data concept came into demand.

1.1.1 Industrial IoT

IoT is a concept that is introduced by British technology pioneer Kevin Ashton in the year 1999. In this smart world almost, everything is connected to each other through highly intelligent interactive systems, so as to form a smart automated world. The concept behind the term “Smart” is, to handle organizational challenges efficiently by effectively utilizing the sensitive information with advance communication and internet technologies. This conceptualizes an ideal concept of smart technologies, termed as “Smart Industries”. The IoT devices interact with other connected devices and act accordingly they get information from one another. This advances the ways of organizational approach that their businesses, industries and markets think and

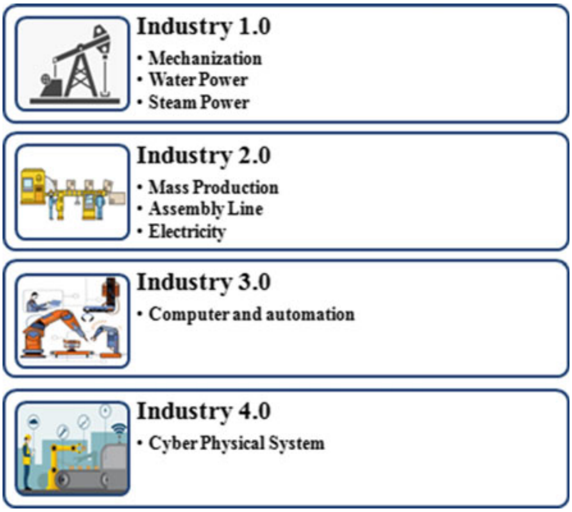


Fig. 1 Four phases of industrial revolution

behave and gives them the tools to improve their business strategies. It enables the devices to monitor their overall business processes flow, improve the customer experience, enhance employee productivity, integrate and adapt business models, integrate and adapt business models save time and money, make better business decisions and generate more revenue.

The four phases of an IoT system eases and advances the process flow of entire system. In the first phase, generated data are sensed through sensors and actuators; then collected and transferred the sensed data to nearest base station for further analysis and processing. In the second phase, data collected through sensors are aggregated and processed; the data conversion such as analog to digital and vice versa is also carried out. The third phase comprises the edge IT processing systems that may be located in remote offices or other edge locations for pre-processing of the data before it is transferred to the data center or cloud platform. In last phase the data generated are stored, maintained and in-depth processing for future analysis is established.

The automated computerized mechanization with highly active sensory devices is the basic building blocks of Industrial IoT (IIoT). IIoT with big data concept jointly known as cyber physical system which led to fourth industrial revolution. It also accelerated the interaction and coordination processes of cyber-physical systems. Here self-governing machines are well equipped with wireless sensors, which can be monitored remotely through any devices like computers, laptops even from mobile phones. The smart machines are operated through smart technology concepts with least human intervention. The increase of smart industries concept will increase the product customization and flexibility in working process which will impact the consumer-supplier dependencies on these smart self-governing processes. In the near future Industry 4.0 is going to set a new standard in manufacturing industries.

The rapid increase in digital market and with the increase in consumer's demand, directly affect the production process. The induction of CPS in manufacturing industries acts as a boon to the production process. In IIoT themed industries all the machineries are automated and interacted through wireless sensor networks. The sensors attached to each machine automatically sense the requirement of the production process and perform its assigned job in time and with higher accuracy without human intervention. Industries with IoT concepts operate more efficiently that understand customers' demand to deliver enhanced customer service, improve decision-making and increase the profitability of the business.

But it's not correct to assume that IIoT devices are the replacements of human beings. Rather it enhances the efficiencies of the workers and upgrading their skills.

1.1.2 Big Data

In today's digital world, there is hardly any aspect of business environment that has not been touched by digitization. The induction of new digital technologies to traditional business world has lead to use of online channels and fast algorithms by large number of organizations. This digitalization in industries leads to huge dataflow in the systems. During this changing time, data keeping, processing and maintenance became a major concern due to large amount of structured and unstructured data generation from different sources. Big data is a concept which can efficiently analyze and process these voluminous and wide verities of data. Literally, Big Data means massive collection of data containing massive information. Although initially Big Data was defined using four dimensions by IBM data scientists (Gartner and Beyer 2011). Now, this concept is mainly defined by 5 dimensions that can be considered as 5Vs of data (Mohanta et al. 2018). 1st one is the Volume: refers to huge amount of data being generated. 2nd one is the Variety: refers to the different kind of structured and unstructured data, generated from different data sources. 3rd one is the Velocity: the rate at which the data are generated and analyzed for further processing. 4th one is the Veracity: refers to data authenticity and the 5th one is the Value: refers to the age of generated data in order to improve the accuracy of the information generated with proper analysis. This resulting information being specific about processes, manpower, sales and marketing, pricing and customer requirements, can be used to make crucial decisions in unfavorable conditions leading to increased returns in different forms. Thus, Big Data is going to fuel the realization of Industry 4.0.

In current scenario, Big Data is laying the foundation for digital transformation of all sorts of businesses ranging from small to large scale businesses, thus playing a major role in the development of Industry 4.0. As discussed previously, realization of smart factories with inter-connected machines and infrastructures communicating with each other via global network is the prime goal of Industry 4.0. These smart factories are supposed to make intelligent products which while being used, collect, analyze and transmit huge amount of real-time data. The information, thus generated provides improved insights to provide smart processes which in-turn provides intelligent interactive services to internet-based end-customers.

Using Big Data in various industrial functions and applications will provide cost-effective and fault-free process execution by reducing, further enhancing the performance and quality levels to meet requirements. Again, proper collection and analysis of Big Data will improve competitive productivity in several sectors such as product fabrication, predictive manufacturing, supply chain management, logistics and risk management etc. (Chen et al. 2012; Reichert 2014).

As the rise of industrialization may arise the issue of proper data management due to huge data flow and decision making process of any organization due to possible occurrences of V.U.C.A. factors. ML techniques are in recent trends that can efficiently handle the above mentioned issues. They can effectively grasp unknown, volatile, uncertain and ambiguous data without prior training.

1.2 V.U.C.A. Factors

V.U.C.A. is a concept which is derived from the military education of US Army War College to manage the volatility, uncertainty, complexity and ambiguity factors of wars. The abbreviation was introduced back in 1991 which changed the nature and condition of wars (U.S. Army Heritage and Education Center 2018). Unlike the war's unpredictable conditions, the nature of business environment is also unpredictable and dynamic. It is a trendy managerial term stands for volatility, uncertainty, complexity and ambiguity which can possibly affect the industrial survival. As Darwin said "Survival of the fittest", same principle applies for the ever-changing business world that is subjected to vary unexpectedly and challenges the smart intelligent machines which can successfully reorganize these factors and beat these challenges, will only survive (Bennett and Lemoine 2014b). These challenges address the expected future conditions and getting ready to tackle these situations to survive in the competitive business world and in highly dynamic industrialization. The volatility refers to highly changeable business environment which lead to uncertainty that refers to the unpredictable business performance followed by complexity in decision making process (Prem et al. 2016). The volatile, uncertain and complex business environment generates ambiguity via changeable, unpredictable market situations (Bennett and Lemoine 2014a).

In Fig. 2, organizational risks are categorized based upon four basic parameters that are, volatility, uncertainty, complexity and ambiguity, which are acronym as V.U.C.A.

a. *Volatility*: It is a term that indicates extreme and rapid fluctuations in business environment. The pace, the volume and the magnitude of change can define as the degree of turbulence it creates, in the business or industrial environments. Volatility is a concept that is created inside an organization; hence, the possible causes of change are known. E.g. price volatility might be an effect of supply-chain risk. Lack of availability of commodity in contrast to its demand flow,

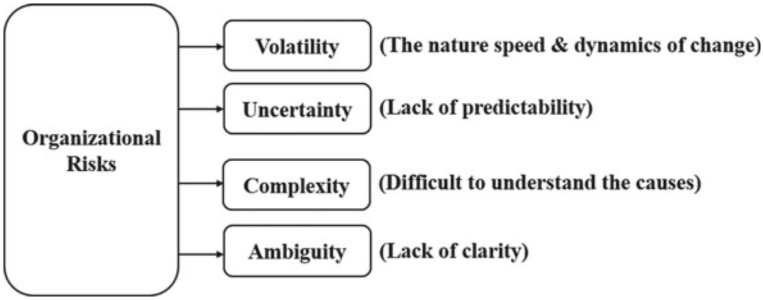


Fig. 2 V.U.C.A. term categorization

can cause price risks. This might result in fall in stock value which directly hit increase in cost.

b. *Uncertainty*: It is a concept that comes from outside the organization; hence, the cause and effect of risks are unknown. The lack of knowledge about the situations causes uncertainty in any field which results an unpredictable future and affects the long-term grown of that organization. Some of the factors that may cause uncertainty in any organization are never-ending customer needs and changes in customer's tastes and preferences; technological changes; introduction of new trade policies and multiple barriers to trade; launching of new product as a substitute of currently used product in market etc.
c. *Complexity*: With the rapid industrialization, complexity arises due to the inter-connected parts, networks and procedures within the organization; the external business environment which might even be unidentifiable and contradicting with each other and lead to complexity in decision-making. More the inter-relatedness in an organization, more difficult to understand the cause of problem statement of risks. The complexity may arise due to outsourcing activities (some of them are human resource management, facilities management, supply chain management, accounting, customer support and service, marketing, computer aided design, research, content writing, engineering, diagnostic services etc.) and induction of new supply chain with the introduction of new product range in production. E.g. a successful consumer goods company that contains different brands, products, efficient network of global distribution may lead to complexity in understanding the cause of future risks.
d. *Ambiguity*: If the problem statement lacks clarity, confidence in probability assessments and the diversity of potential results in which the outcome cannot be clearly described; then it is termed as ambiguity in business environment. E.g. when a new product or plan or technology is introduced in the market, then the diversity in customer's expectations and behaviours may cause ambiguity in decision making to an organization.

By conceptualizing these factors today's industries can be able to outperform in their respective fields. The rapid growth of industrializations and induction of new technologies in business environment has led to high risk factors in every organization. It's not sufficient if an organization only grows, smartness is needed to challenge the possible V.U.C.A. factors. Today's techno park revolution is the possible solution to these challenges as it introduces automation, cyber-physical systems, intelligent interactive systems (IISs) and Internet of Things (IoT) concept that includes big data analysis and cognitive computing in different industries through different machine learning algorithms. Machines are trained with different machine learning techniques in accordance to the V.U.C.A. parameters.

The smart business concept enhances the intelligent interactive interconnections between machines, devices, sensors and people to communicate smartly through IoT systems. The cyber-physical systems provide technical assistance to humans to tackle the adverse conditions of V.U.C.A. factors of business risks. Information transparency and decentralized decision making power are the two major characteristics of cyber-physical systems that automated the process flow in an organization. Today's machines are trained by expert machine learning techniques (rules); that includes software packages so that proper decision can be taken. Markets like ecommerce, stocks which are highly competitive, volatile etc.; and ever changing dynamic learning of machines by using machine learning techniques, post data analysis through V.U.C.A. will be highly profitable.

The continuous attempt to survive in today's competitive era has led to the rise of innovative solutions in the form of technologies and services. In other words, we can say innovative solutions in the form of smart products and services are driving the global competitive markets which lead to the fourth industrial revolution named as Industry 4.0. Big Data fuels the realization of Industry 4.0 and dealing with Big Data poses several crucial challenges due to its inherent complexities.

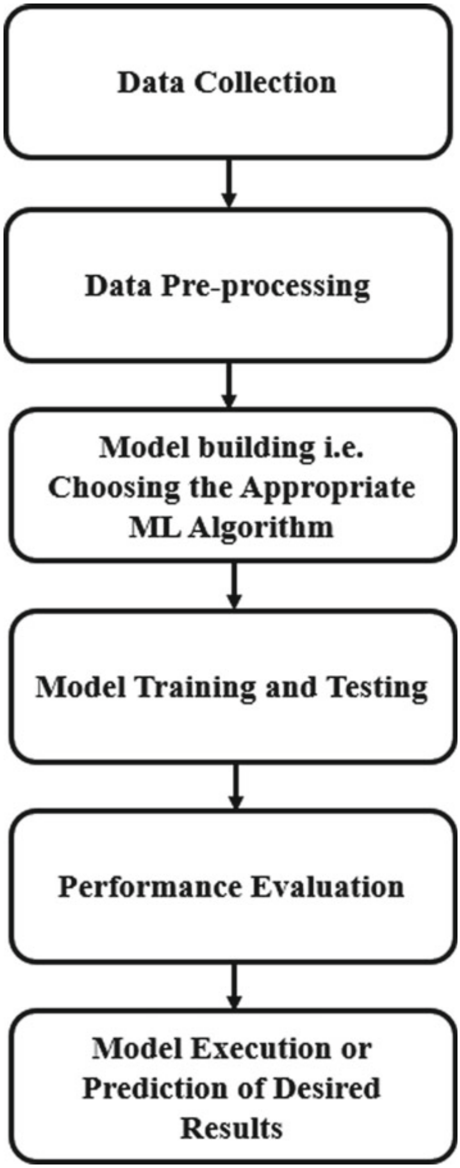
1.3 Applied Machine Learning

ML comes under data science which can be considered as an umbrella term covering all aspect of data processing like data analysis, preparation and useful decision making in an organization. It is a branch of artificial intelligence, gives machines the ability to learn by their own without human intervention. Machines can adapt automation without being explicitly programmed and act according to that. Online shopping's recommender system is a real time live application of ML used by almost everyone.

Figure 3 depicts the generalized machine learning process flow. The process starts from dataset identification and proper analysis of the identified dataset. Based on the V.U.C.A. factors, types of machine learning algorithms are adopted and an analytical model is formed to train the identified test dataset. Lastly the model is executed to get the desired results.

a. *Data collection*: This is the first and most important step of ML work flow. Here, relevant data are collected according to the problem statement. The data collected should be accurate one as per the problem requirement to maintain the integrity

Fig. 3 ML process flow



of entire process of ML model and determine the predictive model's accuracy to solve the problem statement. If irrelevant data are gathered for the process, then further processing of those data is worthless. The gathered data are considered as the training data.

E.g. if the problem statement is to identify an image type, then the data collection needs to be of image type, corresponding to the problem requirement.

b. *Data pre-processing*: In this step, feature extraction engineering is carried out to make the collected incomplete, inconsistent or erroneous data to a feasible one so as to well fit the ML model. After removing the errors like inconsistency, redundancy and missing data from the dataset, features are extracted by feature engineering process and those features are used for model training purpose.

   E.g. If the problem statement is that to identify a person's face, then the features that are extracted for training and evaluation is shape of the image or outline of the image like width and breadth of nose, eyes, ears, mouth and face etc.

c. *Model building*: This is the step where appropriate ML techniques are chosen to evaluate the desired result. Different ML techniques are there like supervised, unsupervised and reinforced learning, which are further categorized to many different techniques such as logistic regression, Support Vector Machine (SVM), Naïve Bayes, Linear regression, k-Means, Dimensionality Reduction process etc. Some of the techniques are well suited for image data for image processing, some are used for signal process like voice, music, text data etc.

d. *Model training and testing*: After model was chosen, the pre-processed dataset is divided into two parts as training and testing dataset. Usually for smaller dataset train/test dataset ratio is 70/30 or 80/20. With the increase in train dataset size, test dataset should decrease in size i.e. the train/test dataset ratio should be 99/1 for large dataset size. In model training, ML algorithm takes training dataset and learned specific features that will minimizes the error during model evaluation. Once the model is trained, it is then tested on the training dataset which are never been used for training purpose to evaluate the efficiency of the model chosen for prediction and how accurately the model behaves in the real world. It only tries to perform on the test dataset by using the knowledge gained from the model training process. It uses some evaluation metrics such as F1 Score, Mean Absolute Error (MAE) and Mean Squared Error (MSE) to evaluate the test dataset.

e. *Performance evaluation*: In this step, the performance of tested model can be improved on both train/test dataset by using various methods such as cross-validation, hyper-parameter tuning or by trying out multiple machine learning algorithms and using the one which performs the best or even better, by using assembling methods which combine the results from multiple algorithms.

f. *Model execution*: This is the step where the value or output of the ML model is predicted or realized. The model is finally used to predict the desired result with higher accuracy.

   E.g. in an image classification, if the problem statement is to predict a person's face, here the model can able to predict or detect the face of the person efficiently with high accuracy.

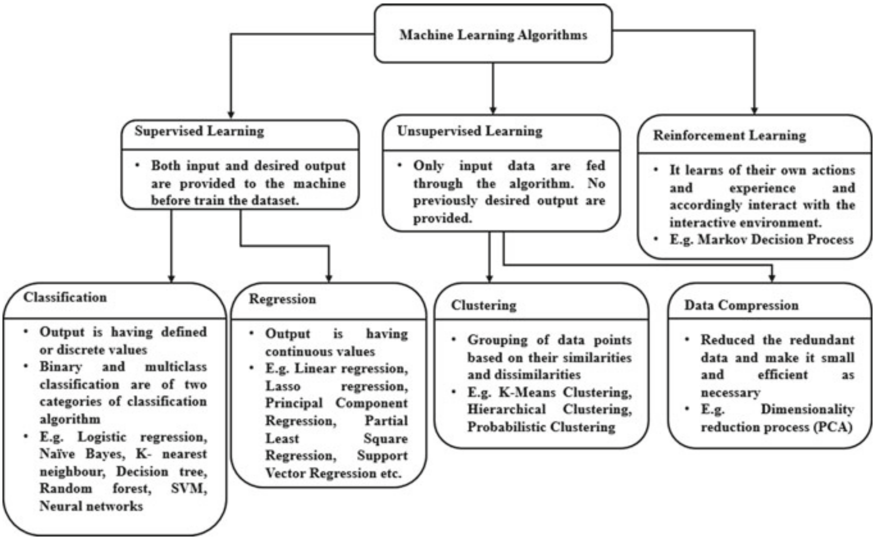


Fig. 4 Categorization of machine learning algorithms

Broadly, there are three machine learning algorithms, such as supervised, unsupervised and reinforcement learning (Fig. 4).

In supervised machine learning both input and desired output are provided to the machine before train the dataset. Then minimize the error calculated by comparing the calculated outputs and the desired output. Some examples of supervised learning algorithms are Logistic regression, Linear regression, K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Naïve Bayes, Neural Network etc. It is categorized by two sub categories, such as classification and regression algorithms. Classification algorithms classify the problem to produce a categorical solution and the output is having defined or discrete values whereas regression algorithms are used to produce continuous values in output.

In unsupervised learning, only input data are fed through the algorithm. No previously desired outputs are provided. Algorithms adopt features of their own to train the dataset. It is categorized by two sub categories, such as clustering and data compression algorithms. In clustering process, the data are grouped based on their similarities and dissimilarities. E.g. K-Means Clustering, Hierarchical Clustering, Probabilistic Clustering etc. where as in data compression process redundant data are minimized and make the minimized data efficient as it's necessity. E.g. Dimensionality reduction process (PCA).

Reinforced learning is a type of machine learning which learns of their own actions and experience and accordingly interact with the interactive environment. It's all about taking suitable action for a particular situation which is resulted in receiving an award. E.g. Markov Decision Process.

2 Role of Some Common ML Techniques Applied in Industry 4.0 Platforms for V.U.C.A. Management

2.1 The Role of Linear Regression

It is a type of supervised machine learning algorithm under the category of regression algorithm. It predicts the dependent variables (predicted value) from given independent variables (continuous variables) and resulting to a linear relationship between dependent and independent variables. If there is a single independent variable, the method is considered as simple linear regression and if there are multiple independent variables, the method is considered as multiple linear regressions. As simple linear regression method has single feature as input variable, the prediction is represented in 2D plan whereas multiple data are used in multiple linear regression, the prediction is represented in n-dimensional plan.

The simple linear regression is represented by a linear equation,

$$Y = w_0 + w_1 * X. \tag{1}$$

where, Y represents dependent variable.

X represents independent variable.

w_0 represents intercept.

w_1 represents slop.

The multiple linear regression is represented by a generalized equation,

$$y(x) = w_0 + w_1x_1 + w_2x_2 + \cdots + w_nx_n \tag{2}$$

where, y(x) represents dependent variables.

$x_1 \ldots x_n$ represent the independent variables.

w_0 represents the intercept.

$w_1 \ldots w_n$ represent the slops.

Application

This can be applied in food production industries as it is highly volatile and uncertain. It is generally used to analyze the risks in different insurance companies; sales forecasting etc. which efficiently deals with the volatility and uncertainty issues that can highly influence the business environment. It is also applied in financial portfolio prediction, salary forecasting, real estate predictions and in traffic in arriving at estimated time of arrivals (ETAs).

For example, Amul industry produces milk only. Due to induction of new brand of milk in market, it starts producing different milk products like ice cream, condensed milk, cheese etc. as customer's expectations and needs are uncertain and the market condition is highly volatile. Similarly, if traffic condition is taken as an example, it is highly volatile due to increase in number of vehicles per household, so its highly unpredictable the traffic condition. But through this method machine can analyze the historic data of particular road and can able to predict the expected condition of traffic which is now already implemented in smart AI devices that take the data from Google map and predict the result.

He and Yau (2007, pp. 1823–1828) built a model of linear regression approach to predict the future stock market volatility with the help of implied volatility series and compare these results with some traditional approaches. The final result showed that this linear regression model outperforms among other historical approaches with the moving average method and with GARCH for predicting volatility that may arise over different perspective of predictions.

2.2 *The Role of Logistic Regression*

It is a supervised machine learning algorithm under the category of classification algorithm. It is used to predict in output in discrete values like 0 or 1, Yes or No, True or False etc. from given independent variable as input values. It is a regression algorithm but performs classification as it classifies the class of dependent variables. The evaluation process is initiated from linear regression i.e. $\mathrm{Y} = \mathrm{w}_0 + \mathrm{w}_1 * \mathrm{X}$ to get the model. Then logistic regression formula is applied to the model to predict the probability of the class to which the data belongs to i.e.

$$P = \frac{1}{1 + \boldsymbol{e}^{-y}} \tag{3}$$

Logistic sigmoid function and

$$ln\left(\frac{\boldsymbol{p}}{1 - \boldsymbol{p}}\right) = \mathrm{w}_0 + \mathrm{w}_1 * \mathrm{X} \tag{4}$$

Log odds

Log odd gives the probability of occurrence of an event with the probability of non-occurrence of an event and resulted to the higher voted of higher probability to classify the event.

Application

It is used to analyze the factors that may increase susceptibility of different diseases and their possible solutions in healthcare system, weather forecasting, voting applications to predict the voters list for a specific candidate, credit card dispatcher company to predict the customer status like defaulter or non-defaulter etc.

Based on some characteristics like annual salary, monthly credit card payments and number of defaults, the credit card companies have to segment the customers in good credit based and bad credit based.

A hospital can apply this test to classify patients into critical and non-critical categories based on selected health attributes.

This method is used by insurance industries to predict the chances that the policy holder will die before the term of policy expires based on characteristics like gender, age and physical examination.

A bank may use this approach to predict the chances that a loan applicant will default on loan or not, based on past debts, past defaults and annual income. Zaghdoudi (2013, pp. 537–543) proposed an early warning predictive model by considering this method to predict the early sign of highly uncertain economic and financial crises of Tunisian bank.

Puagwatana and Gunawardana (2012) developed a model by using logistic regression method to estimate the uncertain and complex business failure in technology industry of Thailand. The author used four variables from Altman's model which are working capital to total assets ratio, retained earnings to total assets ratio, earnings before interest and taxes to total assets ratio, and sale to total assets ratio with the net income (loss) to total assets ratio as indicators on financial status of companies.

Marketers may use this method in estimating whether a customer will respond to a particular ad based on preference of customer and type of web portal customer is active.

Kim and Gu (2010, pp. 17–34) proposed a model using logistic regression analysis to predict possible occurrence of bankruptcy in hospitality industry of about two years in advance. The logit model analyzed the financial data of 16 hospitality firms from U.S. that struggled bankruptcy between 1999 and 2004 and 16 non-bankrupt matching firms and predicted the possible occurrences of bankruptcy with 91 and 85% of accuracy in respective two years.

ul Hassan et al. (2017) studied different machine learning approaches to predict financial distress and made conclusion that logistic regression analysis shows better prediction in financial bankruptcy. Through this method an organization can predict its debtor's financial condition and according to that it can lend money to the debtor organization.

Mraihi (2015) developed a model using logistic regression to predict corporate default and applied to the case of Tunisia by taking 212 healthy and distressed companies in various industries as sample data. The model can successfully predict the failure in financial aspect (e.g. when a home buyer fails to make a mortgage payment, or when a corporation or government fails to pay a bond which has reached maturity).

It is also applied in real estate business platform to predict house values and in the insurance sector to predict customer lifetime value. This algorithm is useful to deal with the uncertainty and complexity risk factors efficiently with high accuracy.

2.3 The Role of Decision Tree

It is a supervised machine learning algorithm under both the categories of classification and regression algorithms. But basically, it is used in classification problems. In this process the dataset is subdivided into smaller parts with homogeneous categories until all the data are categorized and the leaf nodes are the resultant decision nodes. Entropy and information gain are used to construct the decision tree.

Entropy predicts the degree of uncertainty of an event. It evaluates the homogeneity of a dataset. It is denoted as,

$$E(S) = \sum_{\boldsymbol{i}=1}^{\boldsymbol{c}} -\boldsymbol{p}_{\boldsymbol{i}} log_2 \boldsymbol{p}_{\boldsymbol{i}} \tag{5}$$

where,

E(S) = Entropy of the sample dataset.

p_i = The range of data taken for homogeneity classification.

Information gain estimates the high homogeneity without impurities. It evaluates the rate of change of entropy. It is denoted as,

$$Gain(P, I) = Entropy(P) - Entropy(P, I) \tag{6}$$

where,

Gain(P, I) = Information gain.

Entropy(P) = Entropy of the whole dataset.

Entropy(P, I) = Entropy after applying variable I.

The result is analyzed by the highest information gain in each split of the node but the overfitting of nodes should be avoided.

Application

It is used to deal with the ambiguity risk factors in business processes by collecting features and evaluating these features forward and backwardly to derive different results according to the problem. It is generally used in e-commerce marketing to categorize the products based on similar features. Some of the areas of its use are, data analysis, pattern recognition, estimate the pricing in finance in financial marketing and evaluating the risks in diseases in healthcare system. It deals with uncertainty and complexities risk factors possible in any industries.

Wu et al. (2009) proposed a model based on this method and applied it in the agriculture industry to predict and classify the different known and unknown agricultural data. Agriculture is one of the most important sectors of Indian Economy. It accounts for around 18% gross domestic product (GDP) of India. The uncertainty and complexity factors are weather condition, soil fertility, seed quality estimation, effect of pesticides etc., are major concern for agriculture industry. So, the decision tree algorithm efficiently classifies these factors and predicts risks in advance.

Dey (2001) developed a decision support system (DSS) model in analytic hierarchy process (AHP) and decision tree analytics (DTA) framework to deal with the uncertainty and complexity in cross-country petroleum pipeline project in India. The risk associated with the change in project environment increases with the increase in size of the project. The large scale construction projects are highly uncertain due to complexities in planning and design of the project; presence of different working groups like owner of the project and its project group, vendors, contractors, engineers, consultants etc.; availability of resources such as fund, material, equipment etc.; climate condition; political and economical environment; project completion time; project location and its extent of unfamiliarity.

Dey (2012) proposed a decision support system (DSS) model in which risks are identified using cause and effect diagram, the fuzzy analytic hierarchy process (AHP), risk map and decision tree analytics (DTA) framework to deal with the uncertainty and complexity in petroleum oil refinery construction project in the Central part of India. The risk associated with the change in project environment increases with the increase in size of the project. This project concept is risky because of technical complexity, unavailability of resources, involvement of many stakeholders and strict environmental requirements. The proposed risk management framework can be easily adopted, applied and integrated with any project management knowledge areas to tackle with highly uncertain and complex issues in petroleum oil refinery construction project.

Yao and Jaafari (2003) developed a model to predict the risks associated with the project development and investment. The risks associated are such as, complexity in new project realization which can be termed as diversifiable risks or the risks under management's control and uncertainty in associated market environment like profitability and general market return on investment which can be termed as non-diversifiable risks or risks beyond management's control. The non-diversifiable risks which is not predicted by the managerial team, can be efficiently predicted by the proposed model.

Peterman and Anderson (1999) proposed a method to tackle with the uncertainty in availability and maintenance of natural resource system which arises due to complexity in project planning. With the help of these model any organization can predict the availability of natural resources in the place where that organization is going to plan for a new project.

2.4 The Role of Random Forest

It is a versatile supervised machine learning algorithm under both the categories of classification and regression problems. It creates a forest by randomly collecting decision trees to predict desired outcome. Here, each tree is grown to the largest extent possible but should avoid pruning. Each decision tree classifies new objects and votes for the classes. The highest vote classifies the resultant class of the random forest process.

Application

It is basically used in high risk industrial application to efficiently deal with ambiguity issue. Such as, used by banking industries and financial industries to predict the extent of riskiness of a loan applicant, by automobile industries to predict the chances of failure of mechanical parts. It also helps to estimate the highly volatile business and social media metrics for companies and their performance metrics (Patel et al. 2015).

For example, in banking or any financial industries, it is important to estimate the clients' or customer's financial condition or the extent of riskiness associated to particular client. So, this method is suitable for predicting such risk factors and beneficial to predict the highly profitable customer.

Khalilia et al. (2011) presented a disease prediction methodology using this approach and compared its result to some other approaches and got conclusion with high accuracy. Disease prediction with higher accuracy is very crucial due to its highly uncertain and ambiguous characteristics. They used the National Inpatient Sample (NIS) data to train this approach for disease prediction and efficiently estimated the disease class.

Mori and Umezawa (2007) proposed a method on random forest method to increase profitability and minimization of risk associated with power market. Electricity trading in power market is highly uncertain due to some unpredictable factors such as, abnormal weather condition; uncertainty that may arise due to debit default and may lead to bankruptcy. Here they took JEPX (Japan Electric Power Exchange) as power market and successfully applied to financial data of energy companies.

Random forest approach can also efficiently handle the risk associated with healthcare industries to classify the ambiguity in disease classification. Xu et al. (2017) proposed an efficient predictive modeling using this method to predict and classify the type II diabetes. This method can efficiently classify the risks, early symptoms and highly sensitive ambiguous factors of this disease. The model classifies the sensitive indicators of the disease risks, so that it becomes easy to diagnose the patient having disease with low cost. Pflueger et al. (2015) developed a model using this approach to predict the general risks of reoffending mentally disorder criminals and could give extra attention to high-risk groups for their healing.

Business environment is highly volatile and unpredictable, to tackle the critical factors, Ghatasheh (2014) proposed a business analytics using random forest method. The model successfully predicts the credit risks in any organization mainly the funding organizations like, banking industries. The proposed model efficiently classifies the clients' based on their credit suitability to that organization. Its simplicity and classification accuracy help the decision makers in decision making and easy understanding of problem. Here the authors made comparison through confusion matrix of different machine learning algorithms, where random forest outperforms in prediction of credit risk in business environment.

Natural disaster like flood becomes a social threat which is unavoidable and uncertain. Wang et al. (2015) proposed a flood hazard risk assessment method to predict the possible flood hazard risks by considering the case of Dongjiang River Basin, China. One can't avoid the natural disasters but one can control the rate of damage and losses. By taking the pervious data of flood the model can classifies the risk and can help to minimize the damage and risk associated with it and made a comparison study with other machine learning algorithms to evaluate its performance. Random forest method outperforms than other machine learning approaches.

2.5 The Role of SVM

It is a supervised machine learning algorithm under the category of classification algorithm. It also used for regression problems. It classifies the different classes by generating a hyperplane or decision boundary which separates the samples into different classes. The hyperplane marginalizes the data points by separating the nearest data points of two different classes with maximum possible distance for distinct classification. The sample data points are represented in n-dimensional plane with n features for classification. Each point has different coordinates considered as support vectors.

Application
It is used to handle the volatility, complexity and uncertainty risk factors of business environment. It is used to handle the volatility in stock (Gavrishchaka and Banerjee 2006) market and foreign exchange forecasting from variety and wide range of data (Gavrishchaka and Ganguli 2003).

It is also helpful in predicting the financial return on investments of equity or stock market (Patel et al. 2015; Choudhury et al. 2014) and it normalizes the complexity in hedging exposures of convertible bonds in stock market (Shen et al. 2010).

The scope of SVM covers the demand forecasting of supply chain management system (Carbonneau et al. 2008). SVM algorithm is generally used in feature selection to diagnose the business crisis as it requires more accuracy and efficiency of data. The author used data from SP500 index i.e. an American stock market index based on the market capitalizations of 500 large companies having common stock and suggested that SVM can able to perform efficiently.

Chen and Lin (2010) developed a risk hedging prediction model based on the approach of SVM method for construction material suppliers. The construction material suppliers generally highly exposed to financial risks due to different uncertain, volatile factors such as nature of material import, debt capital structure etc. where SVM method plays efficiently.

The complexity and uncertainty characteristics of natural disaster and their after effects can influence the economy of nation as well as individuals also. Li et al. (2010a) developed a risk prediction methodology to predict the natural disaster in advance and their after effects by using SVM method. The proposed model efficiently predicts the risk possibility of disaster caused by nature with high accuracy like rate of destruction caused by natural disaster, loss of life and asset, mental and physical trauma etc.

2.6 The Role of Naïve Bayes

It is a supervised machine learning algorithm under the category of classification algorithm. It predicts the presence of a feature in a class which is not related to any other feature of that class irrespective of their dependencies among them. It predicts the posterior probability of a class with given predictors or attributes or features.

It is denoted as,

$$P(\text{dependent variable}|\text{independent variable}) = \frac{\boldsymbol{P}(independent\ variable|dependent\ variable) * \boldsymbol{P}(dependent\ variable)}{\boldsymbol{P}(independent\ variable)} \tag{7}$$

where,

P(dependent variable|independent variable) is the posterior probability of class (target dependent variable) according to predictor (independent attribute).

P(dependent variable) is the prior probability of class.

P(independent variable|dependent variable) is the likelihood which is the probability of predictor given class.

P(independent variable) is the prior probability of predictor or given independent variable.

The class which has highest posterior probability is the resultant prediction.

Application

It is used to efficiently deal with complexity risk factors which has no transparency in business dealing like credit scoring in e-lending platform (Vedala and Kumar 2012). It is applicable for real-time predictions, multi-class predictions, text classification, spam filtering, sentiment analysis in social media and smart recommendation system in e-commerce marketing (Patel et al. 2015).

Li et al. (2010b) proposed a catastrophic risk management model for better analysis and prediction of natural disasters. As the natural calamities are uncertain and complex due to other related factors, catastrophic risk management model efficiently predicts and detect the high loss risks and its effects in advance.

Parthiban et al. (2011) developed a model to predict the possibility of occurrences of getting heart disease to the diabetic patients using Naïve Bayes method.

The uncertainty in project cost analysis is a crucial factor for decision makers to deep dive for identifying the parameters which may affect the cost estimation of the project in context. Khodakarami and Abdi (2014) proposed a quantitative assessment model that integrates with the Bayesian networks (BN) for the prediction of traditional probabilistic risk analysis.

In current era, software industry becomes a fastest growing industry but with the growth, possibilities of arising risks are also increasing. Uncertainty and complexity in decision making process of software industries may affect the growth. Hu et al. (2012) developed a risk estimation model in software industry to predict risks in software development projects.

2.7 The Role of kNN (k-Nearest Neighbors)

It is a supervised machine learning algorithm under both the categories of classification and regression problems. It is effectively handling the large and noisy data. It is a simple algorithm which only stores or memorizes different class categories of data to classify a new class. It classifies the new class by considering the majority of voting of its k-neighbors. The class is assigned to the majority voted class category. The voting measurement is done by a distance function. The only con is that as it is not sensitive to outliers in data points, the efficiencies might be affected.

Application
It is basically used in industrial applications as these are dealing with high risk factors like uncertainty, volatility. It is useful for stock market prediction, crypto currency pricing prediction, image classification like handwriting detection and image/video recognition systems.

Crypto currencies like Bitcoin and Ethereum are the future of monetary market. Singh and Agarwal (2018) empirically analyzed the volatility in bitcoin pricing market. They used different supervised learning approaches to predict its volatility in money exchange rates by taking transactional data of last eight years. The result of comparison study depicted that KNN algorithm shows better predictions with higher accuracy and with least error of 0.00021 MSE value.

Imandoust and Bolandraftar (2013) predicted effect of organizational financial distress such as effect on stakeholders using *k*NN. The financial distress model is able to analyze the uncertainty and volatility factors in economic forecasting. It is also suitable for the risk factors prediction of the areas like text categorization; agricultural industries to predict the weather variables; financial industries for stock market forecasting that also includes analysis of market trends, investment planning and strategies for investment, the favorable time for stock purchasing, money laundering analysis, loan management etc.; healthcare industries to diagnose the cause of health issue, to identify the risk factors of prostate cancer and also analyze micro-array gene expression data etc.

2.8 The Role of k-Means

It is an unsupervised machine learning algorithm under the category of clustering analysis. The entire dataset is grouped into k number of clusters. Such as every data members of each cluster are of same class and of different from the data members of other clusters. Clusters are formed by calculating the mean of each cluster and comparing each data points to the mean value and formation of new clusters are performed. This process is continued until convergence occurs i.e. the calculated mean value for each cluster does not change (Hossain 2017).

Application

This can also be applied in manufacturing industries. It is used to handle the volatility, uncertainty, ambiguity in business data processing and decision making process. Some of the areas are customer segmentation by purchase history and classifying them based on their interests in buying and smart recommender (Pondel and Korczak 2018) system to increase the sales, grouping inventories by manufacturing and sales metrics, etc.

For example, uncertainty in rainfall-runoff in urban areas is of great importance considering the consequences and damages of extreme runoff events and floods. K-means method can efficiently predict the consequence of extreme rainfall-runoff. Rainfall-runoff is highly uncertain as uncertainty associated with input data, model parameters. The approach is useful in rainfall forecasting, and future runoff prediction.

3 V.U.C.A. Management in Industry 4.0

The recent trends of automation and data exchange through IoT devices and cyber physical systems; data storage and processing through cloud computing; cognitive computing to assist humans in their decision-making process are the main features of Industry 4.0. The concept is designed to beat the risk parameters that are associated with advancement of digitization. All the risk factors uniquely termed as V.U.C.A. Till date Industry 4.0 is not faced any of the V.U.C.A. terms. Still there is a possibility of occurrence. As the enormous growth in industrialization may directly affect the supply chain demand of product, cost value of the product etc. that may lead to high fluctuation in stock market. Product pricing, introduction of new technologies, launching new product substitute to the current product or induction of new product to compete with some other brand (e.g. When a renowned mobile company named “Oppo” launched a model named “Realme” to give competition to Xiaomi Redmi’s models; in contrast to it Xiaomi Redmi launched “Poco” series) may affect the customer’s demand and expectation on product’s price vs quality, which can’t be predictable. The uncertainty in market situation may lead to unpredictability in organization’s growth. The pace, volume of increase in growth of organization may lead to high inter-relatedness modules in an organization that may increase the complexity in decision making. The volatility, uncertainty and complexity lead to lack of confidence in probability assessments for future growth. The future work is to develop an automated early warning V.U.C.A. model which can analyze and predict the possible V.U.C.A. factors that may arise in rapid digitization and huge data flow in different industries. So, here we discuss different applied machine learning techniques through which volatile, uncertain, complex and ambiguous risk factors can be effectively predicted prior to its affect and ease the work flow of Industry 4.0.

4 Conclusion

Industry 4.0 has impacted almost all sectors thus providing huge benefits such as reduced labor costs, simplified business processes, transparent logistics, improved accuracy in inventory and forecasts, reliable shipping and delivery and many more. All these enhancements and improvisation lead to noticeable increase in productivity and revenue which in turn stimulates economic growth. Moreover, in a corporate world where the nation's economy and revenue are of highest interest, concepts like V.U.C.A. helps drastically in predicting the potential dependencies for achieving the desired results. It's quite easy to predict that the rapid growth and ever-changing digital market in the recent society has led to volatility, uncertainty, complexity and ambiguity in decision making process of an organization. Employing Machine Learning techniques that can be dynamically programmed to make decisions in uncertain situations will induce many benefits like flexibility, customizability, reduced complexity in Industry 4.0 processes. Machine Learning approach would be the best fit to make daily decisions and investments to enhance work practice productivity. Markets like e-commerce, stock exchanges which are highly competitive, volatile etc.; dynamic learning of machines by using machine learning techniques, post data analysis through V.U.C.A. will be highly profitable.

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Role of Industry 4.0 in Performance Improvement of Furniture Cluster

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Abstract In the background of Industry 4.0, cluster can improve its performance by focusing its efforts and spending its resources on some vital factors called critical success factors (CSFs). Identification of these factors is essential for performance improvements of furniture cluster. This paper reviewed the literature on CSFs and various supporting philosophies of industry 4.0. The paper studied the impact of these factors through interaction with various stakeholders. Focused efforts on these CSFs may help in channelizing the resources and efforts of cluster in maximizing the gains through quality and productivity improvements. The researchers can access the impact of these factors by undertaking quantitative analysis. The cluster can improve its performance and gain competitive advantage by concentrating on these factors. It helps clusters in developing the use of effectiveness data in their decision making. This paper contributes to providing a better understanding of CSFs for improving the performance of furniture cluster.

Keywords Critical success factors · CSFs · Cluster · Furniture industry · Performance improvement

1 Introduction

Indian manufacturing sectors which are currently facing challenging market conditions and ever increasing global competition. At the same time global market offers plenty of opportunities for small and medium enterprises (SMEs). So it should learn the strategic thinking of industrial 4.0, and explore the "manufacturing + Internet" actively. CSFs considering the concept of industry 4.0 can be effectively used to overcome these challenges and make the best use of opportunities. India has initiated a range of policy initiatives in the recent years to provide suitable environment for industrial investments. India's market potential, plenty of natural resources

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S. Patnaik (ed.), *New Paradigm of Industry 4.0*, Studies in Big Data 64,
https://doi.org/10.1007/978-3-030-25778-1_2

coupled with big pool of managerial and technical talent offer great opportunities for industries. According to Wali et al. (2003) in spite of its many problems, India has been experiencing high growth rates in industry, higher than that of many developing nations. Foreign investment is gradually increasing and the government is working towards improving international relations and industrial growth.

Literature views cluster as an effective way of overcoming the size limitations of SMEs. It recognizes cluster as an effective mechanism for strengthening the regional and national economies. Andersen and Bollingtoft (2011) stated that Clusters represent a complex form of industrial organization, in which social ties (the community), productive networks of local firms and the web of local institutions and collective agents form a co-operative and competitive density. Cluster represents a new way of thinking about national, state and local economies. It assigns new role for companies, for various levels of government and for other institutions in enhancing competitiveness.

Recently the organisations have realised the importance of CSFs for improving the corporate health and survival in the market place. Initially, manufacturing companies concentrated on some of the key factors hoping that the resulting shop floor efficiencies would solve all existing business problems. Later, these organizations realized significant benefits from CSFs. This has motivated Indian organizations to explore more on CSFs and concentrate on them.

Research has confirmed the strategic benefits of cluster. Morrison and Rabellotti (2009) suggests that clusters are switching to new international strategies such as outsourcing and foreign direct investment to maintain their competitive ability. According to Porter (1998) clustering encourages an enhanced division of labour among firms with physical proximity among numerous competing producers, thereby encouraging innovation. Geographical proximity creates competitive advantages to SMEs which closely cooperate and compete. A host of linkages among cluster members produces synergy effect which results in a whole greater than the sum of its parts. Competitors within the cluster are benefitted from agglomeration effects. They get cost advantage and gain access to resources that are not available to the competitors located outside the cluster (Pouder and St. John 1996). The geographic concentration of industries brings in additional financial benefits and technological externalities (Belleflamme et al. 2000). Technological externalities are defined as those consequences of activity which directly influence the production function in ways other than through the market (Martin and Sunley 1996). In addition, enhanced usage of information technologies enables industry to reduce cost and improve the level of service to the customers (Kumar and Petersen 2006). Geographical proximity decreases the transaction costs (for example, the costs of delivery) as all stakeholders in a value chain and other related institutions are close to each other. The shorter distance reduces transportation costs. It also reduces the risks and the insurance costs (Preissl and Solimene 2003). The concentration of firms in an area leads to a greater emergence of providers of infrastructure, business services and so on. Due to Proximity co-operative linkages between companies are established through enhanced mutual learning and knowledge creation. Knowledge can “spill over” between local firms due to the easier (informal) contact between them (Wolter 2003). Exchange of information between the firms allows for further exploitation of knowledge externalities (Bagella et al. 1998).

The interaction with various stakeholders in the furniture clusters suggests the need of exploratory study of CSFs to gain insight into the performance improvement of cluster. Rockart (1979) described CSFs as those specifically distinguished areas that an organisation needed to “get right” in order for the business to successfully compete. CSFs reflect the activities, which are required to achieve the organizational objectives. These activities must be carried out effectively and efficiently in order to produce the outputs and achieve targets. Furniture industry is relatively more labour intensive as compared to other manufacturing industries. So Indian industries face pressures from low wage economies such as China and Poland. However Indian furniture industries are more resilient and capable of embracing change. This gives them inherent advantages over their overseas counterparts which further fortify their future competitiveness.

2 Literature Review

Daniel (1961) first introduced the concept of key factors. To achieve organisational goals and accomplish its mission the organisation must ensure high performance in these key areas consistently. It was proposed that if certain factors, critical to the success of that organisation are not achieved, the organisation will fail (Huotari and Wilsm 2001). CSFs are those limited areas on which an organisation can spend its resources and focus its efforts to achieve the desired goals (Performance improvement, productivity, quality improvement, and increasing its market share etc.) in most effective and efficient manner.

Many researchers have discussed the importance of the critical success factors. Table 1 gives a list of factors recommended by various authors.

3 Methodology

A research instrument was developed in the form of a questionnaire. Various sources of information like literature review (from national and international journals), formal and informal discussions with practitioners and experts (from industries as well as supporting agencies of government) and field visits formed the basis for this questionnaire. The questionnaire was sent to various stakeholders’ viz. owners, general managers, executives, plant heads, managers from various departments, distributors, retailers, customers and researchers from a wide range of Indian companies in manufacturing sector. They were requested to indicate how they perceived the importance of various input parameters given in the questionnaire. The response was sought on a five-point Likert scale to ensure consistency and ease of data processing (Brah and Lim 2006).

Table 1 List of CSFs as recommended by various authors

Authors factors	Somers and Nelson (2004)	Saravanan and Rao (2007)	Yew Wong (2005)	Cho et al. (2006)	Quesada and Gazo (2007)	Jagannathan (2008)	Bueno and Salmeron (2008)	Antony and Desai (2009)	Talib et al. (2010)	Brun (2011)
Top management involvement	X	X	X	X		X	X	X	X	X
Vision and mission	X	X	X		X	X		X	X	X
Human resource management	X	X	X	X	X	X	X	X	X	X
Quality management						X			X	
Product design				X	X	X			X	
Supplier management	X				X	X	X	X	X	X
Organisational infrastructure	X	X	X				X			X
Organisational culture		X	X	X		X		X	X	X
Information management	X	X	X		X		X			X
Financial management			X		X					
Customer management	X	X			X	X		X	X	

The findings based on the opinion of the respondents, will help in coming out with means and ways to bridge the gaps between the perceptions and expectations of the industries.

The sampling population consisted of micro, small and medium scale furniture industries in and around Nagpur, India. These organisations have been working as clusters. As more than 80% of the respondents are working in the field for more than a decade, their responses were more practical and less influenced by the theoretical concepts. Their experience enriched the value of research. The responses were collected through direct interaction by personally meeting the stakeholders. In all 64 respondents from 38 organisations spread over a wide area covering central India contributed to the survey. Table 2 gives detailed profile of the respondents. A factor analysis was carried out using the SPSS 20.0 software.

Factor Analysis (FA) relies on the use of correlation between data variables. Nunnally (1976) proposed that FA is the most appropriate method for the researcher to apply. It determines the important variables in a given domain. Critical input factors from all 64 responses were analysed using FA.

4 Results and Discussion

1. Cronbach's alpha value was used to find internal consistency (reliability). Kasier-Moyer-Olkin (KMO) value was used to measure sample adequacy. The value of alpha ranged from 0.705 to 0.885 indicating internal consistency. The value of Kaiser-Moyer-Olkin (KMO) varied from 0.668 to 0.841 confirming reasonable adequacy of the sample.
2. The initial factor analysis gave 19 factors by method of extraction and deletion. By further using Principle Component and Varimax rotation with Kaiser Normalization, we got 11 factors. These factors are given in Table 3. The table also shows the reliability coefficient (alpha value) and the KMO value for each factor. Both the tests of reliability and validity for factors are satisfactory. Table also gives the percentage variance explained by these factors.
3. A brief explanation of these factors is given in Annexure. The eleven factors account for about 67% of the variance. The most important factor is Role of Government and Support system.
4. Role of government and support systems, Communication across the clusters, Marketing, Supply chain management are more important in furniture cluster for its performance improvement.

The eleven factors emerged as CSF may be used by Indian organizations in the following manner:

(a) Management of individual industry and cluster association may decide the priority amongst the various initiatives using these critical success factors for improving the performance of the cluster.

Table 2 Contribution of researchers based on literature survey

Year	Ang and Bekaert (2002) (Singapore)	Wali et al. (2003) (India)	Yew Wong (2005) (Malaysia)	Farris et al. (2009) (USA)	Ismail Salaheldin (2009) (Qatar)	Abdoli Bidhandi and Valmohammadi (2017) (Iran)
Construct	Material resources planning (MRP)	TQM	Knowledge Management	Human resource outcomes	TQM for SMEs	Knowledge Management
Item generation	Explorative	Literature review	Literature review	Empirical study	Empirical study	
Questionnaire pre-test	Materials, Planning and Logistics, Production Control, and MIS Departments	General managers, Quality managers, Human resource managers and Production managers	Academics, consultants and practitioners	Mid-level manager	Production Manager, Manager in charge of quality mgt	Academics, consultants and practitioners
Sample size	27	114	18	300	139	37
Random Sample	No	No	Yes	No	No	No
Point on Likert scale	7	5	6	5	5	6
Item placed on questionnaire	Group	Group	Group	Group	Group	Group
Reliability test (Cronbach's alpha)	NA	Yes	NA	Yes	Yes	Yes
Validity Test	Yes	NA	NA	Yes	Yes	Yes
Type of Industry	Manufacturing	Manufacturing and Services	Manufacturing and Services	Manufacturing	Manufacturing	Manufacturing

(continued)

Table 2 (continued)

Year	Ang and Bekaert (2002) (Singapore)	Wali et al. (2003) (India)	Yew Wong (2005) (Malaysia)	Farris et al. (2009) (USA)	Ismail Salaheldin (2009) (Qatar)	Abdoli Bidhandi and Valmohammadi (2017) (Iran)
No. of factors	7	12	11	11	3 (24 sub factors)	12
Major factors	Top managt., Effective project managt., Education and training, Data accuracy, Company -wide support, Suitability of hardware and software, Software vendor support	Leadership, Creativity and Quality Strategy, Worker Manager Interactions, Results and Recognition, Work Culture, Information and Data mgt., Customer Focus, Value, and Ethics, Communication across the organization, Team Working, Congenial Inter-personal Relations, Delegation and Empowerment, Process improvement	Leadership and support, culture, IT, strategy and purpose, measurement, organisational infrastructure, processes & activities, motivational aids, resources, training and education; and HRM	Internal processes, goal clarity, Mgt support, team functional heterogeneity, Team autonomy, goal difficulty, work area routineness, action orientation, tool quality, tool appropriateness, and event planning process	Strategic, tactical, and operational factors	Leadership and support, culture, IT, KM strategy, PM, Organizational infrastructure, Processes and activities, Rewarding and motivation, Removal of Resource constraints, Training and education, HRM, Benchmarking

Table 3 List of critical success factors

Factor no.	Factors based on survey result	Cronbach α	KMO	Percentage of variance explained by these factors
Fac-1	Role of Government and Support system	0.885	0.841	67.205
Fac-2	Communication across the clusters	0.879	0.736	61.79
Fac-3	Marketing	0.848	0.819	55.30
Fac-4	Supply chain management in cluster	0.844	0.779	53.168
Fac-5	Role of Top management	0.798	0.752	51.252
Fac-6	Human resource management	0.783	0.768	54.750
Fac-7	Role of Association	0.777	0.742	53.575
Fac-8	Financial management	0.768	0.707	59.533
Fac-9	Quality	0.732	0.691	54.582
Fac-10	Product Design, Development and Technology management	0.707	0.668	53.254
Fac-11	Work culture	0.705	0.736	47.702

(b) These factors can also be used in a self assessment mode by cluster to access and improve upon these by making concentrated efforts after understanding the gaps.

5 Discussion and Conclusion

With the concept of industry 4.0, cluster is widely used and recognised as way of overcoming the size limitations of industries. However for improving the performance (productivity, innovations and overall competitiveness) of the cluster, it is necessary to align a few CSFs with organisation philosophy. In this paper, an attempt has been made to explore CSFs responsible for improving the performance of the furniture cluster. The CSFs are based on the actual practises followed by organization of the Indian cluster.

The efforts and resources invested in CSFs translate into positive business results. Therefore it is essential to identify, evaluate and implement these factors for performance improvement of the cluster. This paper provides directions for further research.

The industry 4.0 based model and the research method used in this study have several important implications for furniture clusters.

- This method can be very useful to furniture cluster, attempting to identify those characteristics often mentioned in the literature that may provide an opportunities to improve the performance.
- Managers or decision makers in the cluster can use CSFs to obtain a sharper understanding of the existing practices and link them with the performance measures.
- Managers can also bench mark themselves with the identified CSFs and identified the gaps and bridge them.
- The CSFs may provide a realistic way of allotment of resources for improvement.

Annexure: Explanation of Factors

Fact-1	*Role of Government and support system* Government should have a high-profile role in the initial stages, such as guiding the cluster mapping process. In the final stages it can play crucial role in public-private dialogue on policy and institutional bottlenecks that inhibit industry and the business development. It can provide direct access to finance or in less direct ways through the creation of enabling policy frameworks, strategic action plans and trained, motivated service employees
Fac-2	*Communication across the clusters* Effective communication helps in channelizing the efforts of various departments to achieve organisational goals. It avoids duplication of efforts and eliminates conflicts
Fac-3	*Marketing* Marketing in clusters are convergence of distinct activities, with the view to achieve, as a whole, organizational objectives by participating more effectively in the competitive market process and the larger macro environment, ensuring competitive advantage through better efficiencies and innovation
Fac-4	*Supply chain management in cluster* To ensure quality and meet delivery schedule of final product it is necessary to ensure quality of raw materials, bought out items and also their availability in time. Just-in-time (JIT) reduces the inventory level and helps in minimizing the cost of product. For proper JIT functioning supplier relationship and supplier quality management plays an important role. The proponents of TQM have stressed on supplier quality management
Fac-5	*Role of top management* Top management provides leadership to the organisation. Its involvement and commitments plays a crucial role. Prominent researchers have emphasised that role of top management is crucial
Fac-6	*Human resource management* Human resource management has a crucial role in ensuring employee involvement. It is key to workforce development and ensuring their involvement. It ensures high self esteem and instils sense of pride in employees. Committed employees give their best to the organisation

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Fac-7	*Role of association* Association plays a crucial role in marketing. The joint efforts help in reducing cost at the same time synergy effect helps in getting big orders. Association can help reduce inventories and derive benefits of quantity discount. Common facilities of the association help small firms to derive the benefits of R&D and testing. It helps in gaining competitive advantage
Fac-8	*Financial management* Financial performance affects the overall performance of the organisation. Organising long term finance at low interest rate helps in keeping the product cost low. This in turn makes the organisational activities economically viable
Fac-9	*Quality* Quality helps an organisation create niche in the market. It improves the customer satisfaction and creates goodwill in the society. It helps in image building and creates brand loyalty amongst customers
Fac-10	*Product design, development and technology management* Product design determines raw material required, manufacturing methods and machines needed. It influences the cost and performance of the product. The technology management provides data and information to help the managers in knowledge based decision making
Fac-11	*Work culture* Organisational culture influences the behaviour of its people. It is the perception held of the organisation. It motivates the employee and instils the sense of belongingness and pride in them

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Imparting Hands-on Industry 4.0 Education at Low Cost Using Open Source Tools and Python Eco-System

J. Dasgupta

Abstract Industry 4.0 paradigm use methods and techniques that use diverse disciplines including Mathematics, Statistics, Machine Learning, Cloud Computing, Internet of Things, Mobile Computing, Block Chains, Computer Vision, Natural Language Processing, Cyber Security, etc. It is difficult to find software platforms that can be used to teach these at affordable costs, which is an important factor for educational institutes. It was found that open source or free tools such as Anaconda, Python, R, GRETL and others offer good option at low cost. These tools are then compared, and we conclude that Python is the ideal tool for setting up laboratories that can cover most Industry 4.0 areas at affordable cost. To establish this, this chapter examines many of the important Industry 4.0 areas, and explains how core Python, and its many open source libraries can be used to create hands-on sessions to teach students. It is expected that this will help create Industry 4.0 laboratory infrastructure at affordable cost. The approach used is to report findings from experience gained over several years at an institute of higher learning where laboratories were set up to provide hands-on experiments in the newer technology areas.

Keywords Industry 4.0 · Open source software · Anaconda · Python · R · GRETL

1 Introduction

"Industry 4.0 is about the fourth Industrial Revolution, where your shop floor has machines sensing, adjusting processes and communicating with one another every step of manufacturing," says Brad Kinsey, professor and chair of the mechanical engineering department, University of New Hampshire (UNH 2018).

Wikipedia (Wiki 2018) defines Industry 4.0 as "the current trend of automation and data exchange in manufacturing technologies. It includes cyber-physical systems, the Internet of Things, Cloud Computing, and Cognitive Computing. Industry 4.0 is commonly referred to as the fourth industrial revolution. Industry 4.0 creates what has been called a "smart factory". Within the modular structured smart factories,

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S. Patnaik (ed.), *New Paradigm of Industry 4.0*, Studies in Big Data 64,
https://doi.org/10.1007/978-3-030-25778-1_3

cyber-physical systems monitor physical processes, create a virtual copy of the physical world, and make decentralized decisions. Over the Internet of Things, cyber-physical systems communicate and cooperate with each other and with humans in real-time both internally and across organizational services offered and used by participants of the value chain" (Wiki 2018).

Although there is a growing body of evidence reporting adoption of Industry 4.0 paradigm and the attendant technologies and processes, there are many recent reports that talk about the skills gap that is impeding effective implementation of the new paradigm.

Wall Street Journal (Wall Street 2018) reported that "Many senior business executives and government agency leaders from around the world lack confidence in their organizations' readiness to influence and harness the opportunities offered by the Fourth Industrial Revolution, or Industry 4.0—the marriage of physical and digital technologies such as analytics, artificial intelligence, cognitive computing, and the internet of things."

Echoing the skills gap theme, Forbes India (Forbes 2018) also reported that "The top drivers for which the implementation gap was the largest touched on Big Data, Digitalization, Internet of Things and Artificial Intelligence, all pillars of Industry 4.0 along with automation, 3D printing and other digital innovations."

Not surprisingly therefore, we read in Singapore Newspaper Straits Times (Straits Times 2018) about 20,000 public servants, or 14% of the public-sector workforce, will receive data science training over the next five years to speed up efforts to turn Singapore into a Smart Nation. The number has doubled from the original target of 10,000 to reflect the accelerated pace.

Educational institutions preparing young and experienced work force for the new world must find ways to impart relevant skills at an affordable cost. In this chapter, we discuss and propose a way forward using experience gained at an institute of higher education in Mumbai, India.

2 Literature Review

Industry 4.0 concepts and implementations have been researched and reported extensively in the last few years. Lee et al. (2014) report that advances in manufacturing industry have paved way for a systematical deployment of Cyber-Physical Systems (CPS), within which information from all related perspectives are closely monitored and synchronized between the physical factory floor and the cyber computational space. They have proposed a unified 5-level architecture as a guideline for implementation of CPS.

Lasi et al. (2014) describe Industry 4.0 concepts in detail. Blos et al. (2018) report possible problems with data inconsistency in the cyber systems, and ways to deal with it.

Galletta et al. (2018) report that emerging technologies such as Internet of Things (IoT), Big Data Analytics, Artificial Intelligence, Advanced Robotics, and 3D printing are revolutionizing Industry 4.0 enabling a faster smart factory deployment globally. They predict that smart factories will deliver 500 billion dollars in value by 2022. According to them, smart manufacturing involving interactions between humans, machines, and products is becoming a highly competitive area. They describe how the growing global economy and demand for customized products are changing the manufacturing industry, and how as a result manufacturing industry is transforming from a market of sellers to a market of buyers. They feel that smart manufacturing is changing the whole production cycle of industries specialized on different kinds of products. On one hand, the advent of social media makes the customers' experience increasingly inclusive, on the other hand Cyber-Physical System (CPS) technologies help industries to change in real-time the cycle of production according to customers' needs and preferences.

Of particular interest is a paper by Karre et al. (2017) in which they explain in detail how a state of the art laboratory was set up at the Graz University of Technology, Austria. The focus of the lab is more on manufacturing, where as we focus more on the software tools in this chapter.

Gröger (2018) has described the Industry 4.0 analytics platform used internally by Bosch, a global giant multinational. This very impressive platform is again very extensive, good but would require lot of investment to replicate. Very few institutes would be able to afford!

Coskun et al. (2019) have proposed a fine Industry 4.0 ready education structure from Turkish German University. The framework thy have created have three pillars, and is interesting enough to be reproduced here.

Figure 1 aptly and vividly illustrates how expensive an Industry 4.0 laboratory can be to build and operate.

Although these above and many other papers deal extensively with Industry 4.0 topics, there is a gap in literature when it comes to the specific software tools that can be used for teaching Industry 4.0 skills in institutional laboratory environment.

We would take Fig. 1 as an important guideline in creating Industry 4.0 infrastructure. Readers would notice that the framework in this figure rightly includes both software and hardware systems that are useful in Industry 4.0 paradigm. However, in this chapter we focus on the software ecosystem which can act as the glue, or the bridge—between all of these systems.

We examine and report our experience with Python Ecosystem (PyPi 2019), MS Excel (Winston 2014), IBM SPSS (Chawla and Sondhi 2016; Nargundkar 2008), R (R 2018), GRETL (GRETL 2018; Gujarati and Sangeetha 2008) and Python (Python 2018; Bahga and Madisetti 2014, 2015; Narayanan et al. 2016; Zocca et al. 2017) and many more.

3 Methodology

This chapter summarizes about 4 years of experience at an institution of higher learning located in Mumbai, India. Although primarily a management institute, students

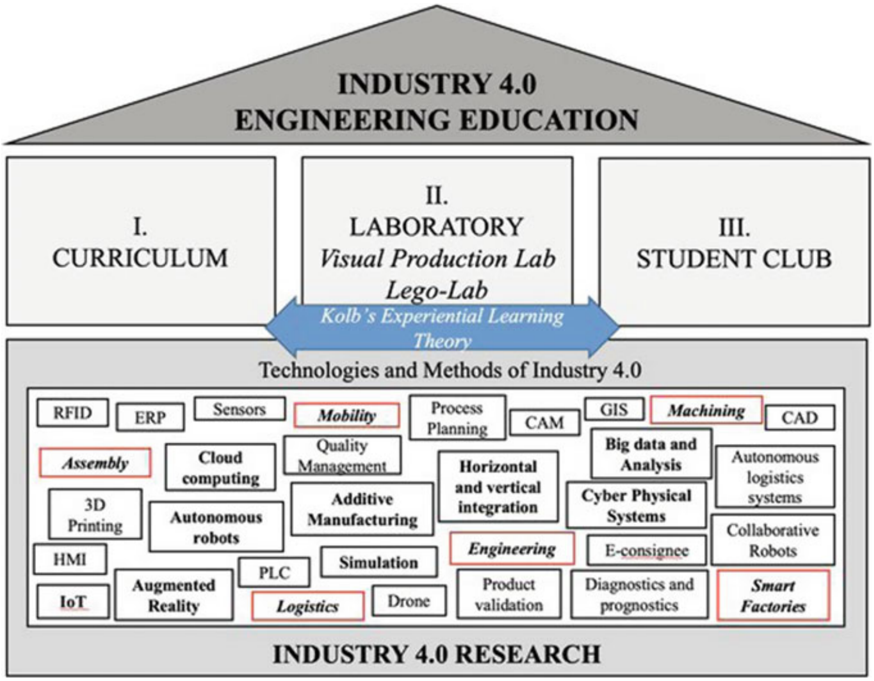

Fig. 1 Industry 4.0 education framework proposed by Coskun et al.

of the institute are employed in diverse sectors. It is therefore important that students should be equipped with knowledge and skills that are critical to succeed in the new paradigm. As discussed earlier, these include Information Technology, Web Computing, Enterprise systems, Analytics, Big Data, Internet of Things (IoT), Cloud Computing, Machine Learning and Artificial Intelligence, among others.

When we had set out on this journey, we did not have a clear roadmap to follow. There were no strict hypotheses to examine and validate. We did have a need to unify the various software systems and tools we were, and in fact—are still using. Each and every tool requires years of training and practice to master. And any one faculty can at best be proficient in only few of these at a time. Therefore, we knew that we need to have fewer tools that can take care of much of the Industry 4.0 topography.

Laboratories in the institute are currently equipped with MS Excel, IBM SPSS, Tableaux, R, GRETL, Python, and other software. We find that each of these software systems are strong in certain areas and therefore are used for skills development for students, faculty, and industry participants.

We started by examining these various software systems. We then zoomed in on the much popular Python eco-system. It was found that Python eco-system is the most inclusive among the many software systems we were using. As it is also free, and has a large community of contributors around the world supporting it—it is an ideal platform to teach Industry 4.0 skills. We report the findings in next sections.

4 Strength Areas

Following sections briefly describe the strength areas of tools that we found are essential for skills building for the new age industries.

4.1 MS Excel

Excel from Microsoft remains a very popular tool for organizations large and small. It is low cost and is found in most computers as an analytics tool. There is an open source version (Open office) and several online avatars such as Office 360 and Google Sheet. It is very user friendly, easy to learn, and has powerful built in mathematical and statistical functions. It comes with VBA programming environment that extends its power further. Excel plotting, charts, pivot tables, solver and goal-seek are hard to match. Excel strength areas are summarized in Table 1.

Table 1 Strength areas of popular Industry 4.0 teaching tools

Feature	MS Excel	IBM SPSS	R	GRETL	Python
Mathematics	Yes	Yes	Yes	Yes	Yes
Statistics	Yes	Yes	Yes	Yes	Yes
Advanced statistics		Yes	Yes	Yes	Yes
Plot/charts	Yes	Yes	Yes	Yes	Yes
Machine learning					Yes
Deep neural nets					Yes
Block chain					Yes
Various AI applications					Yes
Natural language processing					Yes
Programmability	Yes	Yes	Yes	Yes	Yes
Web/cloud computing					Yes
Internet of things					Yes
Mobile apps					Yes
Easy to learn and use	Yes	Yes		Yes	Yes
Industry adoption	Yes	Yes	Yes	Yes	Yes
Open source			Yes	Yes	Yes

4.2 IBM SPSS

IBM's SPSS is a reasonably priced, user friendly and very powerful statistical software package. Popular in both education and industry, it has widespread usage globally. One can extend the capabilities further through a programming interface. SPSS strength areas are summarized in Table 1.

4.3 R

R is considered to be the best and most complete among all statistical packages. An open source tool with a thriving global community of contributors, there are many modules that can practically solve all statistical problems from simple to very complex. It has a strong programming language that can solve complex statistical problems with few lines of code. Please see Table 1 for R strength areas.

4.4 GRETL

GRETL or Gnu Regression, Econometrics and Time-series Library is a very popular and user-friendly package that excels in statistical and time-series computations. First created by Ramu Ramanathan, Professor Emeritus of the University of California, San Diego—it is now open source with a large contributor community. It is easy to use due to a graphical user interface, although HANSL programming language can extend the power further.

4.5 Python

Python is a general purpose, easy to learn, very powerful, open-source, interpreted and modern programming language. It has grown in popularity as an effective educational and professional tool. Part of the power comes from an extensive set of modules that cover virtually all Industry 4.0 areas. To name a few, it can readily solve problems in the areas of mathematics, statistics, machine learning, natural language processing, neural networks, internet of things, cloud computing, computer vision and many more. It is free to use and with an active community of contributors, sees regular upgrades and new modules. Although the Python eco-system is too massive to even cursorily cover in a short chapter, we discuss few Industry 4.0 areas in the following sub-sections. Please note that we have provided links that would allow the reader to explore on their own. Detailed explanation is out of scope of this brief chapter.

4.5.1 Mathematics

Most of the basic mathematical functions are included in core Python package. Additional functions are available in Python packages.

4.5.2 Statistics

Most of the basic statistics functions are included in core Python package. Additional functions are available in Python packages.

4.5.3 Advanced Statistics

Packages like Statsmodels (2019), NUMPY (2019) and Pandas (2019) make handling advanced statistical methods a breeze.

4.5.4 Plots/Charts

PyPlot in Matplotlib, and Matplotlib (2019) offer practically much of the plotting and visualization needs. There are very many more specialized tools too.

4.5.5 Machine Learning

Python really comes into prominence in this field. Too massive to even describe even cursorily, we refer the readers to Zocca et al. (2017) and other excellent references on the web and literature.

4.5.6 Deep Neural Nets

Neural Networks and Multi-layered deep neural networks have come to be recognized as the architecture of choice for many machine learning applications including classifications, regressions and more. Both supervised and unsupervised neural networks of various types are implemented easily using Python. More information may be obtained from Zocca et al. (2017), Python Scikit-learn library (2019), Keras (2019) or TensorFlow (2019).

4.5.7 Block-Chain

There are excellent Python based libraries for Block-chains. Excellent introductions can be found on MOOC platforms like DataCamp (2019) or Udemy (2019) and others. Discourse on block-chains or crypto currencies would be out of scope here.

4.5.8 Various AI Applications

In the burgeoning field of Artificial Intelligence and Machine Learning, often clubbed together and called AI/ML—although a misnomer as AI and ML are similar but mot the same, there are many applications. Too numerous to mention Computer Vision, Computer Games and Robotics stand out. As these are vast field, we will refrain from providing references, except OpenCV (2019) for computer vision. Excellent Python libraries can be found for all these areas.

4.5.9 Natural Language Processing

Python really excels in the exciting field of Natural Language Processing (NLP) which holds the promise of ushering in an era where all language barriers would disappear as computer based devices would make written or spoken conversations a breeze. Some notable examples are led by Natural Language Toolkit (NLTK 2019) and spaCy (2019). There are so many more that it is difficult to mention even a few. Readers are invited to search on the web and find on their own.

4.5.10 Programmability

Although Python has become extremely powerful and popular recently, it grew out of ABC which was developed in the nineteen eighties. Guido Von Rossum, originator of Python, developed the earliest versions in the nineties. Python offers most if not all programming styles including functional programming and Object-Oriented Programming (OOP). This is in stark contrast to many of its competitors. It is a widely used general purpose computing language, adding to its appeal (Budd 2003; Python 2019).

4.5.11 Web/Cloud Computing

Python offers two great frameworks to create dynamic and database driven Web sites. These are Django (2019) and Flask (2019) not to mention countless others. Python based Web frameworks are hosted easily on all major cloud systems including Amazon (2019), Google (2019) or Azure (2019). As it is a very vast field, we leave it to the readers to explore further on their own using these resources.

4.5.12 Internet of Things

Internet of Things (IoT) is an important technological innovation that is driving much of Industry 4.0. As Machine to Machine (M2M) communication get replaced by ubiquitous and dramatically cheaper Internet and get analyzed and acted upon by Big Data Analytics, increasingly dominated by Machine Learning methods residing in the cloud, IoT is expected to dominate Industry 4.0 techniques going forward. Turning to education (Bahga and Madisetti 2014, 2015) we find that systems built around Raspberry Pi Computers (Raspberry 2019) or Arduino (Arduino 2019) are eminently suitable for setting up IoT laboratories. Python can be used in both these easily.

4.5.13 Mobile Apps

In 2019, the Mobile operating systems scenario is dominated by only two—Apple iOS and Android. Windows and others have fallen behind. No software system of repute can be conceived without a mobile based application. The importance of writing native code on these two platforms can not be underestimated. However, Kivy (2019) offers a good alternative using Python.

4.5.14 Easy to Learn and Use

Python eco-system and supporting software is one of the biggest movements or revolutions underway around the globe currently. It can therefore not be claimed that mastery of Python is easy. However, getting started with and attaining reasonable competency in Python is relatively easy. That it is interpreter based and does not require compilation with attendant complications it may bring, helps a lot in making it easier to use for the novice and experienced alike. We will illustrate by citing Bahga and Madisetti (2014, 2015) who introduce Python basics using only a chapter with 24 pages including code snippets!

4.5.15 Industry Adoption

As on 2019, Python is rated as the number one programming language in the world (Tiobe 2018). The interest in the burgeoning field of Artificial Intelligence and Machine Learning, in which it is very hard to ignore Python has made the rate of adoption higher. All major technology companies such as Google, Amazon, Facebook and others have embraced Python as the language of choice.

4.5.16 Open Source

Python and its massive eco-system are completely driven by a world-wide community of developers and contributors. It is completely open source, and therefore free. Open source also means it is extremely reliable, with only very bugs.

Table 1 lists the many advantages of using Python as a learning tool that can support Industry 4.0 well.

5 Conclusion

Table 1 reports the strength areas of these tools as discussed in the preceding section.

We can conclude from Table 1 that while all tools listed have various capabilities that make those popular in educational institutions as well as industry, Python really stands out as it has all desired features, and at no cost being open source. It is not surprising that Python has risen to number 4 in popularity in the widely used Tiobe (Tiobe 2018) index from number 23 in 1998.

Acknowledgements We gratefully acknowledge the help and support from the academic institution where we had an opportunity to offer courses relevant to the Industry 4.0 paradigm as described in this paper. We also thank the organizers of the ICEIND conference, IIIE Odisha Chapter, SoA and ITER for giving us an opportunity to report these findings.

Disclaimer The authors would like to clarify that this chapter is a scholarly work and does not recommend any one product over the other. Also, the context of the research is purely academic, and the sole objective is to help fellow academicians and academic institutes make informed decisions.

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Decision Support Framework for Smart Implementation of Green Supply Chain Management Practices

Arvind Jayant and Neeru

Abstract Sustainability has become a critical issue for both society and businesses globally. With the increase of natural disasters and global issues such as water shortages, acid rain and climate change companies have started focusing on reducing their carbon footprint to ensure that the world's natural resources are sustained for the foreseeable future. Many international and local companies are now looking to incorporate green initiatives into their supply chain management. This has given rise to green supply chain management which is the incorporation of sustainable initiatives into the supply chain of a company. Designing green supply chains (GSCs) requires complex decision support models that can deal with multiple dimensions of sustainability and specific characteristics of products and supply chain. Multi-criteria decision making (MCDM) approaches can be used to quantify trade-offs between economic, social, and environmental criteria i.e. to identify green production options. This study presents a hybrid decision-making approach for group multi-criteria evaluation for green supply chain management (GSCM) implementation criteria, which clubs many green processes with order allocation for dynamic supply chains to cope market variations. More specifically, the developed approach imitates the knowledge acquisition and manipulation in a manner like the decision makers who have gathered considerable knowledge and expertise in this domain. Fuzzy DEMATEL is first applied to find the causal relationship between the criteria and to rank them. Fuzzy SWARA method is used for evaluation of GSCM implementation criteria weights, which are qualitatively meaningful. Thereafter, using fuzzy TOPSIS method, the criteria application is quantitatively evaluated again for order allocation of criteria. To illustrate the applicability of the proposed hybrid framework, a real-life case study is presented in the chapter, and the results are analysed accordingly.

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S. Patnaik (ed.), *New Paradigm of Industry 4.0*, Studies in Big Data 64,
https://doi.org/10.1007/978-3-030-25778-1_4

Keywords Green supply chain management · Fuzzy DEMATEL · Fuzzy TOPSIS · Fuzzy SWARA

1 Introduction

Supply chain management (SCM) is a most extreme critical part of organizations over the world. It is included with basic business procedures, for example, acquirement, logistics, reverse logistics and operational administration and so forth. It distinguishes the SCM as the movement of materials, fund and data as they move from supplier to the producer, then to the distributer, retailer and lastly to the end user. SCM additionally includes the coordination of the flow of material an industry. SCM is the outline and administration of value adding processes over an association's limit to satisfy the requirements of the end buyer. The greening of a SCM alludes to the powerful execution of different practices that makes sustainability within activities of SC. Green supply chain management (GSCM) has numerous definitions and has been an ordinarily utilized term in both the SCM and ecological management literature. GSCM is the mix of natural conduct into SCM. This incorporates the different viewpoints, for example, different material sources and selection, product design, manufacturing processes, the time bound conveyance of the item to the customer and item end-of-life management. Lessening assets and increments in catastrophic events are a portion of the numerous elements that pressurizes organizations to enhance their environmental sustainability. GSCM is additionally a strategy for directing SC activities exercises in an environmentally friendly manner. Inside this unique situation, it is apparent that GSCM has turned out to be more famous among every one of the organizations internationally. It is one of the key aspects to decide the different variables that influence GSCM, keeping in mind the end goal to execute it effectively. Many research papers on GSCM have been published in recent years to ease effective GSCM implementations and recognise the gaps in the previous works. The GSCM practices are chosen to gratify a company's outlooks and objectives, to diminish adverse environmental effects, to enhance economic performance and to increase its green skills. Meanwhile the multi-criteria decision making (MCDM) methods are the helpful tools for enhancing flexibility in decision making, GSCM implements various MCDM methods for solving various GSCM problems (Jayant and Dhillon 2014).

The present work targets to attain the objective, stated as studying the impact of the most substantial GSCM implementation criteria and for while resolving the problem following questions are raised by this research:

(1) What are the criteria that should be adopted by business firms for successful implementation of GSCM practices?
(2) What is the contribution of MCDM methods?
(3) What is the causal relationship between the identified GSCM implementation criteria?
(4) What is the order of preference of various GSCM implementation criteria?

Within the recently used decision-making framework, different ranking results have been obtained by applying various MCDM methods to support the alternative selection process. Thus, it implies that not only the criteria weights, but also the applied MCDM models play an important role in the final selection of an alternative. It is been seen that not much work has been done in ranking the GSCM implementation criteria using various MCDM approach and then comparing the results (Jayant 2014). The present paper uses fuzzy DEMATEL and fuzzy TOPSIS to rank the criteria, while fuzzy SWARA is used to weight them.

The remaining part of this paper is arranged as follows: Sect. 2 presents a brief review of the available literature on GSCM implementation and the application of the described methods. Section 3 introduce the proposed methodology. Section 4 applies the proposed approach to a real case study in an automobile component manufacturing company along with comparative study. Results and discussions are illustrated in Sect. 5. Managerial implications are addressed in Sect. 6, for analysing and discussion of methodology. Finally, the conclusions are provided in Sect. 7.

2 Literature Review

Over the last few years, GSCM has attracted attention of several researchers. A brief detail of the work on GSCM related issues is as follows.

De Oliveira et al. (2018) "presented the Green Supply Chain Management (GSCM) hones from a complete perspective and to break down the subject's conduct over the most recent ten years, through an efficient writing survey/bibliometric investigation in articles published from 2006 to 2016". Luthra et al. (2018) "revealed the Critical Success Factors (CSFs) for powerful reception of sustainability activities in the SC in Indian context. Fifteen CSFs for the fruitful selection of sustainability activities were recognized and concluded right off the bat from the literature and took after by master inputs. A philosophy in view of Grey-Decision Making Trial and Evaluation Laboratory (DEMATEL) was utilized to visualize the association of complex causal relationship between the perceived CSFs". Wang et al. (2017) "built up an integrated MCDM model in view of the cloud model and QUALIFLEX (qualitative flexible multiple criteria method) approach for choosing the ideal green supplier and to evaluate the green performance of companies under economic and environmental criteria". Hamdan and Cheaitou (2017) given "a decision-making tool to illuminate a multi-period green supplier selection and order allocation problem. The tool contains three coordinated segments. Fuzzy TOPSIS and AHP is utilized to appoint the weights and ranking the alternative for both conventional and green criteria. The two combined preference weights got for every supplier are then utilized as a part of expansion to add up to cost to choose the best suppliers and to assign orders utilizing multi-period bi-objective and multi-objective optimization".

Mousakhani et al. (2017) presented "another model in view of collective group decision-making approach under novel compromise ranking method and interval type-2 fuzzy sets (IT2FSs) for the GSS issues and afterwards a contextual investigation is considered to demonstrate the pertinence of the proposed approach. Furthermore, results of the proposed approach are contrasted and the existing method in literature with a specific end goal to represent the approval of proposed model. Besides, a sensitivity analysis is set up to distinguish and decide the impacts of various DMs' weights on ranking results". Sari (2017) studied "proposes a novel decision framework to appraise GSCM practices. The framework is developed by combining Monte Carlo simulation, AHP (Analytical Hierarchy Process) and VIKOR methods under fuzzy environment". Simić et al. (2017) presented "how fuzzy set theory, fuzzy decision-making and hybrid solutions based on fuzzy can be used in the several models for supplier assessment and selection in a 50-year period". Mangla et al. (2017) perceived "30 barriers identified with executing Sustainable Consumption and Production (SCP) inclines in SC. These barriers are gotten from a literature review and from field and industrial experts' inputs. Furthermore, an operational model is recommended utilizing the fuzzy AHP to organize the distinguished barriers with the objective of enhancing general execution. The fuzzy AHP helps determine the priority of concerns of the identified barriers under fuzzy surroundings. Contributions to this work depend on an auxiliary auto manufacturing firm in India". Boutkhoum et al. (2016) presented "the technical and analytical contribution that multi-criteria decision-making analysis (MCDA) can bring to environmental decision-making problems, and specifically to GSCM field. For this reason, a multi-criteria decision-making methodology, combining fuzzy AHP and fuzzy TOPSIS, is suggested to underwrite to a better understanding of new sustainable strategies through the identification and evaluation of the most appropriate GSCM practices to be adopted by industrial organizations". Awasthi and Kannan (2016) tended to the issue of "assessing green supplier development programs and proposed a fuzzy NGT (Nominal Group Technique)- VIKOR based arrangement approach. Sensitivity analysis is performed to decide the impact of modelling parameters on ranking results of alternatives". Nadaban et al. (2016) directed "an overview to offer a general perspective of the advancements of fuzzy TOPSIS strategies and furthermore a literature survey is done to investigate distinctive fuzzy models that have been connected to the decision-making field. At long last, a few utilizations of fuzzy TOPSIS are introduced". Zamani-Sabzi et al. (2016) "examines and measurably thinks about the performances of ten usually utilized MCDM systems: simple additive weights (SAW), weighted product method (WPM), compromise programming (CP), TOPSIS, four of AHP, VIKOR, and ELECTRE. These techniques' performances were looked at utilizing fuzzy criteria and constraints, coordinating the conditions typically found in genuine applications. To direct the correlations, the 10 multi-criteria decision ranking methods were connected to 1250 re-enacted sets of decision matrices with fuzzy triangular values, and 12,500 arrangements of positions were investigated to think about the positioning strategies. SAW and TOPSIS had factually comparative exhibitions. ELECTRE was not ideal in giving full, arranged positions among the options. VIKOR considering its positioning procedure, for particular conditions, relegates indistinguishable positions for a few options; when full, arranged positions are required, VIKOR is ominous, although it is a great system in acquainting the nearest elective with the perfect condition". Galankashi et al. (2016) proposed "an integrated Balanced Scorecard–Fuzzy Analytic Hierarchical Process (BSC–FAHP) model to select suppliers in the automotive industry". Gurel et al. (2015) had done "a literature review for expressing what criteria effect the decision environment to build a better relationship with partners, and a criteria list for green supplier selection for textile industry is proposed in a hierarchical structure which is useful to integrate multi criteria decision analysis". Wu and Chang (2015) used "four dimensions and twenty factors suitable for electrical and electronic industries in Taiwan to identify the critical dimensions and factors and then constructed the digraphs to show causal relationships among dimensions and factors within each dimension in green supply chain management (GSCM). Ten major customers of this case group were invited from international semiconductor packaging plants to evaluate dimensions and factors by decision making trial and evaluation laboratory". Tramarico et al. (2015) presented "a bibliometric study of multi-criteria decision-making methods most applied in publications from 1990 to 2014 and presented relations of papers published in the Web of Science Core Collection, regarding the following keywords: Analytic Hierarchy Process and Supply Chain. The research evidenced that the Analytic Hierarchy Process has been the method most applied in publications from 1993 (Jayant et al. 2011). It also showed the analysis of the predecessor and successor citation network for the selected publications under topics as supplier selection, supply development, performance measurement and value chain through the CitNet Explore software".

Jayant et al. (2014a, b) presented "a methodology to evaluate third party reverse logistics service provider using an integrated approach, in which criteria weights are computed using the AHP method and ranking of the alternatives is computed using the TOPSIS method. In this research nine service providers are evaluated based on ten criteria and a real-life case study of a mobile phone manufacturing company is presented to demonstrate the steps of the decision support system". Kumar and Ray (2014) presented "a methodology to evaluate optimum material for engineering design using an integrated approach, in which criteria weights are computed using the entropy method and ranking of the alternatives is computed using the TOPSIS method. In this research seven number of alternative martial and six criteria for material selection is used for the optimal design". Patil and Kant (2014) proposed "a prediction framework based on the fuzzy DEMATEL and FMCDM for KM adoption in SC. This examination initially recognizing the assessment criteria of KM selection in SC from literature survey and expert conclusion. Further, it utilizes fuzzy DEMATEL to assess weighting of every assessment criteria's, after that FMCDM technique uses to get conceivable rating of achievement of KM selection in SC. The proposed approach is useful to anticipate the accomplishment of KM selection in SC without really received KM in SC. It likewise empowers associations to choose whether to start KM, control selection or embrace healing enhancements to expand the likelihood of fruitful KM reception in SC".

Rouyendegh and Saputro (2014) provided "an overview of the fuzzy TOPSIS and Multi-Choice Goal Programming (MCGP) methods for Multi-Criteria Decision-Making (MCDM) problem under uncertain environments and deals with the optimum decision making for selecting supplier and allocating order by applying the proposed method of integrated fuzzy TOPSIS and MCGP (Multi-Choice Goal Programming). To deal with the uncertain and imprecise judgment of decision makers, a Fuzzy TOPSIS is utilized to express it by triangular fuzzy numbers. The final supplier selection and order allocation are obtained by integrating the closeness coefficients to the MCGP model. A numerical example is given to clarify the main results developed in this paper". Lin (2013) "analysed the influential factors among eight criteria of three fundamental GSCM hones, specifically practices, performances, and outside weights. To manage the unclearness of individual's recognitions, this investigation uses the fuzzy set hypothesis and DEMATEL strategy to shape a basic model to discover the cause and effect relationships among criteria". Zhu et al. (2012) "examines three models used to evaluate the mediation relationships between the external and internal practices of GSCM with respect to environmental, economic, and operational performance. They posit that the strategic stance of manufacturing enterprises in improving their overall performance and competitive position requires a joint coordination of internal and external GSCM practices. Survey data collected from 396 Chinese manufacturing enterprises are used to validate our arguments by testing the mediation effects of two categories of GSCM practices". Irajpour et al. (2012) "studied the influence of the most important factors using fuzzy DEMATEL and to find out the ranking of critical factors in GSCM in automotive corporations and a model with multi-criteria approach and 15 factors in GSCM was presented. Based on our research, we concluded that the top five important critical sub-factors of GSCM in automotive industries in Iran".

3 Methodology

3.1 Fuzzy DEMATEL

Step 1: **Fuzzy pair wise comparison matrix**: "A pair-wise comparison matrix of the evaluation criteria should be presented to the members of the expert group. Then, the experts are asked to make sets of pair-wise comparisons to assign a degree of influence to each cell of matrix. A fuzzy scale with five different degrees of influence is used in this study. The degree of influence is one of five linguistic terms {no influence, very low influence, low influence, high influence, very high influence}. Each linguistic term has its own corresponding positive TFN". The applied fuzzy scale including its linguistic terms and their corresponding positive triangular numbers is shown in Table 1.

"A TFN can be denoted by a triplet (l, m, r) where $l \leq m \leq r$. Suppose $z_{ij}^{k} = (l_{ij}, m_{ij}, r_{ij})$ where $1 \leq k \leq K$, to be the fuzzy assessment that the *k*th expert gives about the degree to which factor i have impact on factor j".

Step 2: **Fuzzy initial direct relation matrix**: "The fuzzy initial direct-relation matrix is the average matrix of k pair-wise comparison matrixes corresponding to the number of k experts. Since the form of fuzzy numbers is not appropriate for matrix operations,

Table 1 Corresponding relationship between linguistic terms and fuzzy numbers

Linguistic terms	Corresponding triangular fuzzy numbers
Very high influence (VH)	(0.75, 1.0, 1.0)
High influence (H)	(0.5, 0.75, 1.0)
Low influence (L)	(0.25, 0.5, 0.75)
Very low influence (VL)	(0, 0.25, 0.5)
No influence (NO)	(0, 0, 0.25)

defuzzication algorithm is needed for additional accumulation. Defuzzication is a method converting fuzzy numbers into a crisp number which is called the best non-fuzzy performance value (BNP). This paper employs CFCS (converting fuzzy data into crisp scores) for defuzzication. The fuzzy aggregation procedure can be applied as follows based on CFCS method".

i. Standardization of the fuzzy numbers

$$Xl_{ij}^{k} = \frac{l_{ij}^{k} - \min\limits_{1 \le k \le K} l_{ij}^{k}}{\triangle \text{ minmax}} \quad (1)$$

$$Xm_{ij}^{k} = \frac{m_{ij}^{k} - \min\limits_{1 \le k \le K} l_{ij}^{k}}{\triangle \text{ minmax}} \quad (2)$$

$$Xr_{ij}^{k} = \frac{r_{ij}^{k} - \min\limits_{1 \le k \le K} l_{ij}^{k}}{\triangle \text{ minmax}} \quad (3)$$

where $\triangle$ minmax $= \max r_{ij}^{k} - \min l_{ij}^{k}$

ii. Calculate the left and right normalized value

$$Xls_{ij}^{k} = \frac{xm_{ij}^{k}}{1 + xm_{ij}^{k} - xl_{ij}^{k}} \quad (4)$$

$$Xrs_{ij}^{k} = \frac{xr_{ij}^{k}}{1 + xr_{ij}^{k} - xm_{ij}^{k}} \quad (5)$$

iii. Compute the total normalized value

$$X_{ij}^{k} = \frac{xls_{ij}^{k}\left(1 - xls_{ij}^{k}\right) + xrs_{ij}^{k} xrs_{ij}^{k}}{1 + xrs_{ij}^{k} - xls_{ij}^{k}} \quad (6)$$

iv. Compute crisp value

$$\mathrm{BNP}_{ij}^{k} = \min \mathrm{l}_{ij}^{k} + \mathrm{x}_{i}^{k} \triangle \mathrm{minmax} \tag{7}$$

v. Integrating crisp value

$$\mathrm{a}_{ij} = \frac{1}{\mathrm{k}} \sum_{\mathrm{k}}^{1 \le \mathrm{k} \le \mathrm{K}} \mathrm{BNP}_{ij}^{k} \tag{8}$$

vi. Thus, obtain the initial direct-relation matrix $A = [a_{ij}]$, where A is a $n \times n$ non-negative matrix, a_{ij} indicates the direct impact of factor i on factor j; and when $i = j$, the diagonal elements $a_{ij} = 0$.

Step 3: **Normalized direct relation matrix**: "Calculate the normalized direct-relation matrix $D = [d_{ij}]$, which can be obtained through Eq. (9). All elements in matrix D are com-plying with $0 \le d_{ij} \le 1$, and all principal diagonal elements are equal to 0".

$$D = \frac{1}{\max \sum_{i=1}^{n} a_{ij}} A$$
$$1 \le i \le n \tag{9}$$

Step 4: **Total relation matrix**: "Calculate the total-relation matrix T using the Eq. (10) in which I is an $n \times n$ identity matrix. The element t_{ij} indicates the indirect effects that factor i have on factor j, so the matrix T can reflect the total relationship between each pair of system factors".

$$T = \left[t_{ij}\right] \sum_{i=1}^{\infty} D^{i} = D(1 - D)^{-1} \quad i, j = 1, 2, 3 \ldots .n \tag{10}$$

Step 5: **Prominence and influence of each criterion**: "To make the outcome more visible, we compute r_i and c_j through Eqs. (11) and (12), respectively. The sum of row i, which is denoted as r_i, represents all direct and indirect influence given by factor i to all other factors, and so r_i can be called the degree of influential impact. Similarly, the sum of column j, which is denoted as c_j can be called as the degree of influenced impact, since c_j summarizes both direct and indirect impact received by factor j from all other factors".

$$r = [r_i]_{n \times 1} = \left(\sum_{j=1}^{\infty} t_{ij}\right)_{n \times 1} \tag{11}$$

$$c = [r_j]_{1\times n} = \left(\sum_{j=1}^{\infty} t_{ij}\right)_{1\times n}^{t} \tag{12}$$

when $i = j$, $r_i + c_i$ "shows all effects given and received by factor i. That is, $r_i + c_i$ indicates both factor i's impact on the whole system and other system factors' impact on factor i. The indicator $r_i + c_i$ can represent the degree of importance that factor i plays in the entire system". The priority weight of each influential factor can then be obtained by Eq. (13).

$$\mathrm{w} = \frac{\sum_{j=1}^{n} ri + ci}{\sum_{i=1}^{n}\sum_{j=1}^{n} ri + ci} \tag{13}$$

Step 6: **Final ranking**: Ranking is done based on weights obtained for each criterion. The criteria with highest weight are ranked first and so on.

3.2 Fuzzy TOPSIS

Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) was "offered by Hwang and Yoon and it is the most recognised technique for solving MCDM problems. This method is centred on the notion that the chosen alternative should have the shortest distance to Positive Ideal Solution (PIS) (the solution which minimizes the cost criteria and maximizes the benefit criteria) and the farthest distance to Negative Ideal Solution (NIS)".

Step 1: **Assignment rating to the criteria and to the alternatives**: "We assume that we have a decision group with K members. The fuzzy rating of the k_{th} decision maker about alternative A_i w.r.t. criterion C_j is denoted $x_{ij}^k = \left(a_{ij}^k, b_{ij}^k, c_{ij}^k\right)$ and the weight of criterion C_j is denoted˜ $w_j^k = \left(w_{j1}^k, w_{j2}^k, w_{j3}^k\right)$".

Step 2: **Compute the aggregated fuzzy ratings for alternatives and the aggregated fuzzy weights for criteria:**

The aggregated fuzzy rating $x_{ij} = (a_{ij}, b_{ij}, c_{ij})$ of *i*th alternative w.r.t. *j*th criterion is obtained as follows:

$$a_{ij} = \min\left\{a_{ij}^k\right\}, \quad b_{ij} = \frac{1}{k}\sum_{k=1}^{K} b_{ij}^k, \quad c_{ij} = \max\left\{c_{ij}^k\right\} \tag{14}$$

The aggregated fuzzy weight $w_j = (w_{j1}, w_{j2}, w_{j3})$ for the criterion C_j are calculated by formulas:

$$w_{j1} = \min\left\{w_{j1}^{k}\right\}, \quad w_{j2} = \frac{1}{k}\sum_{k=1}^{K} w_{j2}^{k} =, \quad w_{j3} = \max\left\{w_{j3}^{k}\right\} \tag{15}$$

Step 3: **Compute the normalized fuzzy decision matrix**: The normalized fuzzy decision matrix is $R = [r_{ij}]$, where

$$r_{ij} = (\frac{a_{ij}}{c_j^+}, \frac{b_{ij}}{c_j^+}, \frac{c_{ij}}{c_j^+}) \quad \text{and} \quad c_i^+ = \max\left\{c_{ij}\right\}(\text{benefit criteria}) \tag{16}$$

$$r_{ij} = (\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}) \quad \text{and} \quad c_i^- = \max\left\{a_{ij}\right\}(\text{cost criteria}) \tag{17}$$

Step 4: **Compute the weighted normalized fuzzy decision matrix**: The weighted normalized fuzzy decision matrix is $V = (v_{ij})$, where $v_{ij} = r_{ij} \times w_j$.

Step 5: Compute the Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS).

The FPIS and FNIS are calculated as follows:

$$A^+ = \left(v_1^+, v_2^+, \ldots.., v_n^+\right), \quad \text{where } v_j^+ = \max\{v_{ij3}\} \tag{18}$$

$$A^- = \left(v_1^-, v_2^-, \ldots.., v_n^-\right), \quad \text{where } v_j^- = \max\{v_{ij1}\} \tag{19}$$

Step 6: **Compute the distance from each alternative to the FPIS and to the FNIS**.

Let

$$d_i^+ = \sum_{j=1}^{n} d\left(v_{ij}, v_j^+\right) \tag{20}$$

$$d_i^- = \sum_{j=1}^{n} d\left(v_{ij}, v_j^-\right) \tag{21}$$

be the distance from each alternative Ai to the FPIS and to the FNIS, respectively.

Step 7: **Compute the closeness coefficient CC_i for each alternative**: For each alternative Ai we calculate the closeness coefficient CC_i as follows:

$$CC_i = \frac{d^-}{d^- + d^+} \tag{22}$$

Step 8: **Rank the alternatives**: The alternative with highest closeness coefficient represents the best alternative.

3.3 Fuzzy SWARA

The step-wise weight assessment ratio analysis (SWARA) "when integrated with fuzzy set theory, it is called fuzzy SWARA. Several factors such as unquantifiable information, incomplete information, unobtainable information, and partial ignorance cause the imprecision in decision making. Since conventional MADM methods cannot effectively handle problems with such imprecise information, therefore, fuzzy multiple attribute decision making methods have been developed owing to the imprecision in assessing the relative importance of attributes and the performance ratings of alternatives with respect to attributes (Jayant et al. 2014c). The process of determining the relative weights of criteria using the fuzzy SWARA method is as same as the SWARA method such as the following steps":

Step 1: **Sort the evaluation factors in descending order of expected significance.**
Step 2: "State the relative importance of the factor j in relation to the previous (j − 1) factor, which has higher importance, and follow to the last factor. After determining all relative importance scores by all experts, to aggregate their judgments, the geometric mean of corresponding scores was obtained. Kersuliene et al. term this ratio as the comparative importance of average value s_j".
Step 3: Obtain the coefficient k_j as (23):

$$k_j = \begin{cases} 1 & j = 1 \\ s_j + 1 & j > 1 \end{cases} \tag{23}$$

Step 4: Calculate the fuzzy weight q_j as (24)

$$\begin{cases} 1 & j = 1 \\ \frac{x_{j-1}}{k_j} & j > 1 \end{cases} \tag{24}$$

Step 5: Calculate the relative weights of the evaluation criteria as (25):

$$w_j = \frac{q_j}{\sum_{k=1}^{n} q_k} \tag{25}$$

where $w_j = \left(w_j^l, w_j^m, w_j^u\right)$ is the relative fuzzy weight of the j_{th} criterion and n shows the number of evaluation criteria.

4 Problem Description

To illustrate the utility of proposed approach, an empirical case of an Indian automobile component manufacturer (namely ABC) was carried out. The case company was established in 1993 in the northern region of India and is serving the escalating market demands for high quality automotive components and is running 8 plant in the country. The company's expertise lies in manufacturing a wide range of plastic components for the automotive sector. "The combined production capacity of its manufacturing units is over 45,000 ton of engineering plastics per annum. The company has installed more than 180 injection molding machines ranging from 150 to 1300 ton across its manufacturing units. To provide a total solution to industry, ABC has set up assembly line in all its unit to assemble parts like Air Cleaner, Fender Rear and Box Battery as well as decoration of painted parts of different models of motorcycles and scooters and Interior and Exterior parts of passenger car". Green supply chain management has become a challenging issue for companies to maintain their competitive positions due to the increased public concern of environmental issues and stricter governmental regulations. After visiting the company, discussing with employees and analysing the company various factors have been considered that helps to implement green practices in traditional supply chain of industries. Considering all the issues discussed above, thirteen important criteria have been selected that will be helpful to improve the performance of the case industry (Table 2).

The selected criteria are manpower involvement (C1), environmental education and training (C2), cooperation with customers including environmental requirements (C3), internal environmental management (C4), investment recovery (C5), green warehousing (C6), green transportation and distribution (C7), reverse logistics (C8), green manufacturing (C9), green purchasing (C10), green design (C11), green process planning (C12), environmental auditing for suppliers (C13). The expert panel including three experts i.e. one of the employees from the case company, my supervisor and me, was established to form initial decision matrix. The experts are considered as decision makers (DM) and named as DM1, DM2 and DM3. All the criteria are analysed and are ranked by fuzzy DEMATEL and fuzzy TOPSIS, fuzzy SWARA is used to weight the criteria that are used while applying fuzzy TOPSIS. Selected criteria and dimensions are shown in Table 3.

D1: Organisational Change

C1: Manpower Involvement

Human components are the key components in lucrative execution of GSCM hones and there is some labor issues associated with the usage of GSCM on the grounds

Table 2 Brief description of company

Business characteristics	Case company
Year of establishment	1993
Turnover (in INR)	11176.80 million
Employees	More than 2000
Products manufactured type/specialisation	Moulded and painted parts, steering wheels, sub-assemblies, safety parts, injection moulds
Type of business	Manufacturer, supplier

Table 3 Dimensions and criteria

Dimensions	Criteria	References
Organisational	Manpower involvement (C1)	Irajpour et al. (2012)
Change (D1)	Environmental education and training (C2)	Irajpour et al. (2012)
Management approach (D2)	Cooperation with customers including environmental requirements (C3)	Zhu et al. (2008)
	Internal environmental management (C4)	Zhu et al. (2008)
	Investment recovery (C5)	Zhu et al. (2008)
Technical aspect (D3)	Green warehousing (C6)	Zhu et al. (2008)
	Green transportation and distribution (C7)	Luthra et al. (2014)
	Reverse logistics (C8)	Dube and Gawand (2011)
	Green manufacturing (C9)	Dube and Gawand (2011)
	Green purchasing (C10)	Dube and Gawand (2011)
	Green design (C11)	Dube and Gawand (2011)
	Green process planning (C12)	Luthra et al. (2014)
External and social aspect (D4)	Environmental auditing for suppliers (C13)	Irajpour et al. (2012)

that the workers of different divisions should assume liability for singular effect and necessity of natural directions and norms as being prescribed time to time.

C2: Environmental Education and Training

Every one of the organizations ought to perceive the requirement for education and training of the employees and furthermore the post effect on quality and item's amount. The training must incorporate: ecological approach and green issues, work specific environmental impacts and points of interest of improved execution. Additionally, workers ought to be made mindful about the environmental impacts from their standard tasks and their exercises. Training and awareness programme to make enhancements in the environmental knowledge, skills and mastery of staff must be a piece of their normal occupation of the workers.

D2: Management Approach

C3: Cooperation with Customers including Environmental Requirements

Any industry's success depends on how they cooperate with their customers and fulfil their demand keeping in mind the ecological aspects. Maintaining customers is the pillar to success and it is a very crucial task. Many industries are implementing it by lowering their prices and also lowering the quality, which leads to the use of sub-standard materials, which is not acceptable. So, it is important to cooperate with customers in a way that the minimum environmental requirement should not get altered.

C4: Internal Environmental Management

IEM includes true commitment of GSCM from top officials to lower ones, cooperation for environmental enhancements, auditing programs for confirming the implementation of green activities, total quality environmental management, ISO 14001 certification, environmental management systems. All these factors help to check the advance and achievement (results) of plans mentioned in reports and internal audits from each facility, and the findings are then reflected when planning for the following year.

C5: Investment Recovery

The term investment recovery, also known as Asset recovery or resource recovery. It is the technique of maximizing the value of end-of-life assets or unused product by doing the effectual reuse. Whenever we referred it in the perspective of a company that is being liquidated, Asset recovery is also described the procedure of liquidating excess inventory, refurbished items, and equipment reimbursed at the end of a lease.

D3: Technical Aspect

C6: Green Warehousing

Green warehouse plays a significant role in the green innovation. The theory of green warehouse is about making warehouse more environment friendly in term of optimum energy efficiency and building design sustainability in warehousing. The concept of energy efficiency can be adopted by reducing operational cost, wastage of energy and energy ingestion and carbon dioxide emissions as well; reuse and recycle warehouse material; or by combining technologies for energy saving, heating and cooling system which emits more than normal warehouse.

C8: Reverse Logistics

Reverse logistics deals with all operations pertaining to the reuse of products. It is also recognised as the course of planning, implementation, and effectual control, economical flow of raw materials, in-process inventory, final products and related information from the consumption point of view to the point of origin, for recapturing value and proper disposal. More precisely, the RL is the method of transporting goods from their distinctive ultimate terminus, for capturing value, or proper disposal. Remanufacturing and refurbishing activities also may be included in the definition of reverse logistics.

C9: Green Manufacturing

The term "green" manufacturing may be explained into two ways: the manufacturing of green products, specifically those utilised in renewable energy systems and clean technology tools of all kinds. Also greening of manufacturing aids in reducing all types of pollution and wastage by minimizing the use of natural resources, recycling and reusing waste material and reducing toxic emissions.

C10: Green Purchasing

By bringing together the green guideline into purchasing, organizations can give design specifications to suppliers that incorporate environmental safety requirements for green acquired things. Green purchasing is a basic action that incorporates diminishment, reuse, and reusing of materials and now a days it is turning into a fundamental and imperative component of GSCM framework.

C11: Green Design

Green product design has been identified as a substantial business exercise in recent years and eco-design or the design which is environment friendly, is critical in GSCM practice to improve company's social responsibility. So, the design of products (and related design of processes) is significant. The most efficient way to reduce environmental impacts is possible by prevention and better design of the product and buildings.

C12: Green Process Planning

Green Process Planning Support System (GPSS) was developed to deal with such problems in optimization of environmental process planning and thus it is the important and vital part of any management system.

D4: External and Social Aspect

C13: Environmental auditing for suppliers

In the era of globalization, it is permissible to work with different suppliers to get raw materials and initial products and GSCM comprises of the introduction and integration of environmental issues as well as concerns into SCM processes by auditing suppliers, by using environmental performance metrics.

5 Proposed Framework to Rank Criteria

The framework proposed consists of three different phases and one sub phase. It is the comparative study, comprising of MCDM techniques, ranking the criteria and comparing it at the end by fuzzy DEMATEL, fuzzy TOPSIS and fuzzy SWARA. Ranking the criteria helps in determining the priority sequence of the criteria and implementing the GSCM practices accordingly. To figure out the entire proposed framework, see the following phases.

5.1 Phase I: Identification Key GSCM Criteria

In this phase, the applicable green and environmental criteria are nominated by seeing the cited literature and the precise structures of the company of the case under scrutiny.

Experts from the company are referring to gather evidence and data to recognise the correct green dimensions and criteria.

5.2 Phase II: Ranking Criteria by Fuzzy DEMATEL

Ranking by fuzzy DEMATEL is carried out by making decision matrix with the decision of three decision makers. According to the weights calculated based on prominence value of the criteria are used to rank the criteria. Also, a causal relationship is developed between the criteria.

5.3 Phase III: Determining Weights by Fuzzy SWARA

Weights of the criteria by fuzzy SWARA are determined by taking mean of the weights by three experts. These weights are used further in fuzzy TOPSIS techniques to rank the criteria.

5.3.1 Phase III: Ranking by Fuzzy TOPSIS

The fuzzy TOPSIS procedure is depends upon an intuitive and simple idea, which is that the optimal ideal solution, having the maximum benefit, is attained by choosing the best alternative which is distant from the most inappropriate alternative which are having minimum benefits. The ideal solution should have a rank of 1, while the worst alternative should have a rank approaching 0. This is done by using weights decided by fuzzy SWARA.

5.4 Phase IV: Comparison of the Results

This is the final phase in which comparison of the results is carried out. Comparison of the results also compare the techniques applied.

6 Implementation of Proposed Framework

6.1 Ranking the Criteria by Fuzzy DEMATEL

The criteria illustrated in Table 4 are evaluated by fuzzy DEMATEL, an ordinary relationship is determined between all the criteria and then ranking is done. Three decision makers namely DM1, DM2 and DM3 helped in making three decision answer matrices and evaluating thirteen criteria. Following are the steps followed under fuzzy DEMATEL.

STEP 1: At first the initial decision answer matrix of pair-wise comparisons by three decision makers namely DM1, DM2 and DM3 is calculated and summarised in Table 4a, b and c. In this step, respondents are asked to indicate the degree of direct influence each factor/element *e*xcerpts on each factor/element *j* (Fig. 1) (Tables 5 and 6).

STEP 2: "Then a fuzzy initial direct matrix is computed, and it is the average matrix of k pair-wise comparison matrices by k experts. As the form of fuzzy numbers is not suitable for matrix operations, de-fuzzication algorithm is required for further aggregation".

(a) Standardization of the fuzzy numbers:-Standardisation of fuzzy numbers given in initial decision matrix by DM1, DM2 and DM3 is done in this step and then using those values the left and right normalised values are calculated. Tables 7, 8 and 9) contain matrices of left and right normalised value
(b) Then total normalised values are calculated and are tabulated in Tables 10, 11 and 12.
(c) Then compute crisp value and integrate. The integrated crisp value is tabulated in Table 13

STEP 3: Calculate the normalized direct-relation matrix $D = [d_{ij}]$. All elements in matrix D are com-plying with $0 \leq d_{ij} \leq 1$, and all principal diagonal elements are equal to 0. Matrix D is summarised in Table 14.

STEP 4: Calculate the total-relation matrix T using $T = D^*(I - D)^{-1}$, which I is an $n \times n$ identity matrix. The element t_{ij} indicates the indirect effects that factor i have on factor j, so the matrix T can reflect the total relationship between each pair of system factors (Table 15).

STEP 5: "To make the outcome more visible, we compute ri and cj. The sum of row i, which is denoted as ri, represents all direct and indirect influence given by factor i to all other factors, and so ri can be called the degree of influential impact. Similarly, the sum of column j, which is denoted as cj can be called as the degree of influenced impact, since cj summarizes both direct and indirect impact received by factor j from all other factors" (Table 16).

"When i = j, ri + ci shows all effects given and received by factor i. That is, ri + ci indicates both factor i's impact on the whole system and other system factors' impact

Table 4 Decision matrix by DM1

	C1			C2			C3			C4			C5			C6		
C1	0	0	0.25	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.25	0.5	0.75	0	0.25	0.5
C2	0.75	1	1	0	0	0.25	0.5	0.75	1	0.5	0.75	1	0.25	0.5	0.75	0	0.25	0.5
C3	0.75	1	1	0.75	1	1	0	0	0.25	0.75	1	1	0.75	1	1	0.75	1	1
C4	0.75	1	1	0.75	1	1	0.5	0.75	1	0	0	0.25	0.25	0.5	0.75	0	0.25	0.5
C5	0	0.25	0.5	0.25	0.5	0.75	0.5	0.75	1	0.25	0.5	0.75	0	0	0.25	0.5	0.75	1
C6	0	0.25	0.5	0	0.25	0.5	0.5	0.75	1	0.25	0.5	0.75	0.5	0.75	1	0	0	0.25
C7	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.75	1	1	0.5	0.75	1	0.5	0.75	1
C8	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1
C9	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.75	1	1	0.5	0.75	1
C10	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.75	1	1	0.5	0.75	1
C11	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.25	0.5	0.75
C12	0.75	1	1	0.75	1	1	0.75	1	1	0.75	1	1	0.75	1	1	0.75	1	1
C13	0.75	1	1	0.75	1	1	0.75	1	1	0.75	1	1	0.75	1	1	0.75	1	1

	C7			C8			C9			C10			C11			C12			C13		
C1	0.25	0.5	0.75	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.75	1	1	0.75	1	1	0.75	1	1
C2	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.75	1	1	0.75	1	1	0.75	1	1
C3	0.5	0.75	1	0.75	1	1	0.75	1	1	0.5	0.75	1	0.75	1	1	0.75	1	1	0.75	1	1
C4	0.25	0.5	0.75	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.75	1	1	0.75	1	1	0.75	1	1

(continued)

Table 4 (continued)

	C7			C8			C9			C10			C11			C12			C13		
C5	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.75	1	1	0.75	1	1	0.75	1	1
C6	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.75	1	1	0.75	1	1
C7	0	0	0.25	0.75	1	1	0.75	1	1	0.5	0.75	1	0.75	1	1	0.75	1	1	0.75	1	1
C8	0.75	1	1	0	0	0.25	0.75	1	1	0.5	0.75	1	0.75	1	1	0.75	1	1	0.75	1	1
C9	0.5	0.75	1	0.75	1	1	0	0	0.25	0.5	0.75	1	0.5	0.75	1	0.75	1	1	0.75	1	1
C10	0.25	0.5	0.75	0.5	0.75	1	0.5	0.75	1	0	0	0.25	0.5	0.75	1	0.75	1	1	0.75	1	1
C11	0.25	0.5	0.75	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0	0	0.25	0.75	1	1	0.75	1	1
C12	0.75	1	1	0.75	1	1	0.75	1	1	0.25	0.5	0.75	0.75	1	1	0	0	0.25	0.75	1	1
C13	0.5	0.75	1	0.75	1	1	0.5	0.75	1	0.25	0.5	0.75	0.5	0.75	1	0.75	1	1	0	0	0.25

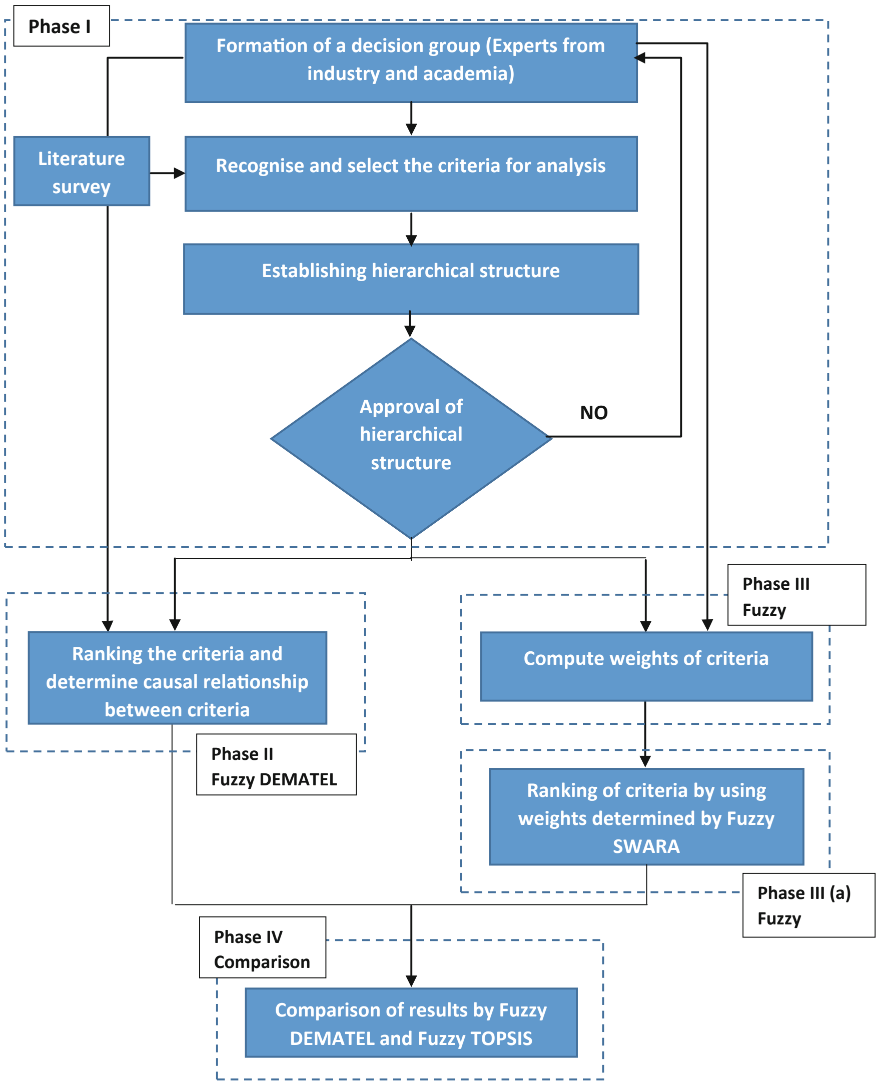

Fig. 1 Proposed framework

on factor i. The indicator ri + ci can represent the degree of importance that factor i plays in the entire system" (Table 17).

STEP 6: The priority weight of each influential factor can then be obtained and then ranking is done on the basis of priority weights. The criteria with highest weight is ranked first and so on (Fig. 2) (Table 18).

STEP 7: "The Cause and Effect Relationship diagram is constructed by mapping all coordinate sets of ($r_i + c_j$, $r_i - c_j$) to visualize the complex interrelationship and

Table 5 Decision matrix by DM2

	C1			C2			C3			C4			C5			C6		
C1	0	0	0.25	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.25	0.5	0.75	0	0.25	0.5
C2	0.75	1	1	0	0	0.25	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.25	0.5	0.75
C3	0.5	0.75	1	0.75	1	1	0	0	0.25	0.75	1	1	0.75	1	1	0.75	1	1
C4	0.75	1	1	0.5	0.75	1	0.5	0.75	1	0	0	0.25	0.25	0.5	0.75	0	0.25	0.5
C5	0.25	0.5	0.75	0.25	0.5	0.75	0.5	0.75	1	0.5	0.75	1	0	0	0.25	0.5	0.75	1
C6	0	0.25	0.5	0	0.25	0.5	0.5	0.75	1	0.25	0.5	0.75	0.5	0.75	1	0	0	0.25
C7	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1
C8	0.5	0.75	1	0.5	0.75	1	0.75	1	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1
C9	0.25	0.5	0.75	0.5	0.75	1	0.75	1	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1
C10	0.25	0.5	0.75	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1
C11	0.5	0.75	1	0.75	1	1	0.5	0.75	1	0.5	0.75	1	0.25	0.5	0.75	0	0.25	0.5
C12	0.75	1	1	0.75	1	1	0.75	1	1	0.5	0.75	1	0.75	1	1	0.75	1	1
C13	0.5	0.75	1	0.75	1	1	0.75	1	1	0.5	0.75	1	0.75	1	1	0.5	0.75	1

	C7			C8			C9			C10			C11			C12			C13		
C1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.75	1	1	0.75	1	1
C2	0.25	0.5	0.75	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.75	1	1	0.5	0.75	1	0.75	1	1
C3	0.5	0.75	1	0.5	0.75	1	0.75	1	1	0.75	1	1	0.75	1	1	0.5	0.75	1	0.75	1	1
C4	0.5	0.75	1	0.5	0.75	1	0.75	1	1	0.75	1	1	0.75	1	1	0.75	1	1	0.75	1	1

(continued)

Table 5 (continued)

	C7			C8			C9			C10			C11			C12			C13		
C5	0.25	0.5	0.75	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1
C6	0.25	0.5	0.75	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.75	1	1
C7	0	0	0.25	0.75	1	1	0.75	1	1	0.5	0.75	1	0.75	1	1	0.5	0.75	1	0.75	1	1
C8	0.75	1	1	0	0	0.25	0.75	1	1	0.5	0.75	1	0.75	1	1	0.75	1	1	0.75	1	1
C9	0.75	1	1	0.75	1	1	0	0	0.25	0.5	0.75	1	0.5	0.75	1	0.75	1	1	0.5	0.75	1
C10	0.25	0.5	0.75	0.5	0.75	1	0.5	0.75	1	0	0	0.25	0.5	0.75	1	0.5	0.75	1	0.75	1	1
C11	0.5	0.75	1	0.75	1	1	0.75	1	1	0.5	0.75	1	0	0	0.25	0.5	0.75	1	0.75	1	1
C12	0.75	1	1	0.75	1	1	0.75	1	1	0.25	0.5	0.75	0.5	0.75	1	0	0	0.25	0.75	1	1
C13	0.75	1	1	0.75	1	1	0.5	0.75	1	0.25	0.5	0.75	0.5	0.75	1	0.75	1	1	0	0	0.25

Table 6 Decision matrix by DM3

	C1			C2			C3			C4			C5			C6		
C1	0	0	0.25	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.25	0.5	0.75	0	0.25	0.5
C2	0.75	1	1	0	0	0.25	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.25	0.5	0.75
C3	0.5	0.75	1	0.75	1	1	0	0	0.25	0.75	1	1	0.75	1	1	0.75	1	1
C4	0.75	1	1	0.5	0.75	1	0.5	0.75	1	0	0	0.25	0.25	0.5	0.75	0	0.25	0.5
C5	0.25	0.5	0.75	0.25	0.5	0.75	0.5	0.75	1	0.25	0.5	0.75	0	0	0.25	0.5	0.75	1
C6	0	0.25	0.5	0	0.25	0.5	0.5	0.75	1	0.25	0.5	0.75	0.5	0.75	1	0	0	0.25
C11	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1
C7	0.5	0.75	1	0.5	0.75	1	0.75	1	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1
C8	0.5	0.75	1	0.5	0.75	1	0.75	1	1	0.5	0.75	1	0.75	1	1	0.5	0.75	1
C9	0.25	0.5	0.75	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1
C10	0.5	0.75	1	0.75	1	1	0.5	0.75	1	0.5	0.75	1	0.25	0.5	0.75	0	0.25	0.5
C12	0.75	1	1	0.75	1	1	0.75	1	1	0.5	0.75	1	0.75	1	1	0.75	1	1
C13	0.5	0.75	1	0.75	1	1	0.75	1	1	0.5	0.75	1	0.75	1	1	0.5	0.75	1

	C7			C8			C9			C10			C11			C12			C13		
C1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.75	1	1	0.5	0.75	1
C2	0.25	0.5	0.75	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.75	1	1	0.5	0.75	1	0.5	0.75	1
C3	0.5	0.75	1	0.5	0.75	1	0.75	1	1	0.75	1	1	0.75	1	1	0.5	0.75	1	0.5	0.75	1
C4	0.5	0.75	1	0.5	0.75	1	0.75	1	1	0.75	1	1	0.75	1	1	0.5	0.75	1	0.75	1	1

(continued)

Table 6 (continued)

	C7			C8			C9			C10			C11			C12			C13		
C5	0.25	0.5	0.75	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.75	1	1
C6	0.25	0.5	0.75	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	0.75	1	1
C7	0	0	0.25	0.75	1	1	0.75	1	1	0.5	0.75	1	0.75	1	1	0.5	0.75	1	0.75	1	1
C8	0.5	0.75	1	0	0	0.25	0.75	1	1	0.5	0.75	1	0.75	1	1	0.5	0.75	1	0.5	0.75	1
C9	0.75	1	1	0.75	1	1	0	0	0.25	0.5	0.75	1	0.5	0.75	1	0.75	1	1	0.75	1	1
C10	0.25	0.5	0.75	0.5	0.75	1	0.5	0.75	1	0	0	0.25	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1
C11	0.5	0.75	1	0.75	1	1	0.75	1	1	0.5	0.75	1	0	0	0.25	0.5	0.75	1	0.75	1	1
C12	0.75	1	1	0.75	1	1	0.75	1	1	0.25	0.5	0.75	0.5	0.75	1	0	0	0.25	0.75	1	1
C13	0.5	0.75	1	0.75	1	1	0.5	0.75	1	0.25	0.5	0.75	0.5	0.75	1	0.75	1	1	0	0	0.25

Table 7 Left and right normalised value matrix 1

	C1		C2		C3		C4		C5		C6	
C1	0	0.2	0.6	0.8	0.6	0.8	0.6	0.8	0.4	0.6	0.2	0.4
C2	0.8	1	0	0.2	0.6	0.8	0.6	0.8	0.4	0.6	0.2	0.4
C3	0.8	1	0.8	1	0	0.2	0.8	1	0.8	1	0.8	1
C4	0.8	1	0.8	1	0.6	0.8	0	0.2	0.4	0.6	0.2	0.4
C5	0.2	0.4	0.4	0.6	0.6	0.8	0.4	0.6	0	0.2	0.6	0.8
C6	0.2	0.4	0.2	0.4	0.6	0.8	0.4	0.6	0.6	0.8	0	0.2
C7	0.6	0.8	0.6	0.8	0.6	0.8	0.8	1	0.6	0.8	0.6	0.8
C8	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8
C9	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8	0.8	1	0.6	0.8
C10	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8	0.8	1	0.6	0.8
C11	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8	0.4	0.6
C12	0.8	1	0.8	1	0.8	1	0.8	1	0.8	1	0.8	1
C13	0.8	1	0.8	1	0.8	1	0.8	1	0.8	1	0.8	1

	C7		C8		C9		C10		C11		C12		C13	
C1	0.6	0.8	0.6	0.8	0.6	0.8	0.8	1	0.8	1	0.8	1	0.8	1
C2	0.6	0.8	0.6	0.8	0.6	0.8	0.8	1	0.8	1	0.8	1	0.8	1
C3	0.8	1	0.8	1	0.6	0.8	0.8	1	0.8	1	0.8	1	0.8	1
C4	0.6	0.8	0.6	0.8	0.6	0.8	0.8	1	0.8	1	0.8	1	0.8	1
C5	0.6	0.8	0.6	0.8	0.6	0.8	0.8	1	0.8	1	0.8	1	0.8	1
C6	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8	0.8	1	0.8	1
C7	0.8	1	0.8	1	0.6	0.8	0.8	1	0.8	1	0.8	1	0.8	1
C8	0	0.2	0.8	1	0.6	0.8	0.8	1	0.8	1	0.8	1	0.8	1
C9	0.8	1	0	0.2	0.6	0.8	0.6	0.8	0.6	0.8	0.8	1	0.8	1
C10	0.6	0.8	0.6	0.8	0	0.2	0.6	0.8	0.6	0.8	0.8	1	0.8	1
C11	0.6	0.8	0.6	0.8	0.6	0.8	0	0.2	0	0.2	0.8	1	0.8	1
C12	0.8	1	0.8	1	0.4	0.6	0.8	1	0.8	1	0	0.2	0.8	1
C13	0.8	1	0.6	0.8	0.4	0.6	0.6	0.8	0.6	0.8	0.8	1	0	0.2

Table 8 Left and right normalised value matrix 2

	C1		C2		C3		C4		C5		C6	
C1	0	0.2	0.6	0.8	0.6	0.8	0.6	0.8	0.4	0.6	0.2	0.4
C2	0.8	1	0	0.2	0.6	0.8	0.6	0.8	0.6	0.8	0.4	0.6
C3	0.6	0.8	0.8	1	0	0.2	0.8	1	0.8	1	0.8	1
C4	0.8	1	0.6	0.8	0.6	0.8	0	0.2	0.4	0.6	0.2	0.4
C5	0.4	0.6	0.4	0.6	0.6	0.8	0.6	0.8	0	0.2	0.6	0.8
C6	0.2	0.4	0.2	0.4	0.6	0.8	0.4	0.6	0.6	0.8	0	0.2
C7	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8
C8	0.6	0.8	0.6	0.8	0.8	1	0.6	0.8	0.6	0.8	0.6	0.8
C9	0.4	0.6	0.6	0.8	0.8	1	0.6	0.8	0.6	0.8	0.6	0.8
C10	0.4	0.6	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8
C11	0.6	0.8	0.8	1	0.6	0.8	0.6	0.8	0.4	0.6	0.2	0.4
C12	0.8	1	0.8	1	0.8	1	0.6	0.8	0.8	1	0.8	1
C13	0.6	0.8	0.8	1	0.8	1	0.6	0.8	0.8	1	0.6	0.8

	C7		C8		C9		C10		C11		C12		C13	
C1	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8	0.8	1	0.8	1
C2	0.6	0.8	0.6	0.8	0.6	0.8	0.8	1	0.8	1	0.6	0.8	0.8	1
C3	0.6	0.8	0.8	1	0.8	1	0.8	1	0.8	1	0.6	0.8	0.8	1
C4	0.6	0.8	0.8	1	0.8	1	0.8	1	0.8	1	0.8	1	0.8	1
C5	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8
C6	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8	0.8	1
C7	0.8	1	0.8	1	0.6	0.8	0.8	1	0.8	1	0.6	0.8	0.8	1
C8	0	0.2	0.8	1	0.6	0.8	0.8	1	0.8	1	0.8	1	0.8	1
C9	0.8	1	0	0.2	0.6	0.8	0.6	0.8	0.6	0.8	0.8	1	0.6	0.8
C10	0.6	0.8	0.6	0.8	0	0.2	0.6	0.8	0.6	0.8	0.6	0.8	0.8	1
C11	0.8	1	0.8	1	0.6	0.8	0	0.2	0	0.2	0.6	0.8	0.8	1
C12	0.8	1	0.8	1	0.4	0.6	0.6	0.8	0.6	0.8	0	0.2	0.8	1
C13	0.8	1	0.6	0.8	0.4	0.6	0.6	0.8	0.6	0.8	0.8	1	0	0.2

Table 9 Standardised fuzzy number matrix 3

	C1		C2		C3		C4		C5		C6	
C1	0	0.2	0.6	0.8	0.6	0.8	0.6	0.8	0.4	0.6	0.2	0.4
C2	0.8	1	0	0.2	0.6	0.8	0.6	0.8	0.6	0.8	0.4	0.6
C3	0.6	0.8	0.8	1	0	0.2	0.8	1	0.8	1	0.8	1
C4	0.8	1	0.6	0.8	0.6	0.8	0	0.2	0.4	0.6	0.2	0.4
C5	0.4	0.6	0.4	0.6	0.6	0.8	0.4	0.6	0	0.2	0.6	0.8
C6	0.2	0.4	0.2	0.4	0.6	0.8	0.4	0.6	0.6	0.8	0	0.2
C7	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8
C8	0.6	0.8	0.6	0.8	0.8	1	0.6	0.8	0.6	0.8	0.6	0.8
C9	0.6	0.8	0.6	0.8	0.8	1	0.6	0.8	0.8	1	0.6	0.8
C10	0.4	0.6	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8
C11	0.6	0.8	0.8	1	0.6	0.8	0.6	0.8	0.4	0.6	0.2	0.4
C12	0.8	1	0.8	1	0.8	1	0.6	0.8	0.8	1	0.8	1
C13	0.6	0.8	0.8	1	0.8	1	0.6	0.8	0.8	1	0.6	0.8

	C7		C8		C9		C10		C11		C12		C13	
C1	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8	0.8	1	0.6	0.8
C2	0.6	0.8	0.6	0.8	0.6	0.8	0.8	1	0.8	1	0.6	0.8	0.6	0.8
C3	0.6	0.8	0.8	1	0.8	1	0.8	1	0.8	1	0.6	0.8	0.6	0.8

(continued)

Table 9 (continued)

	C7		C8		C9		C10		C11		C12		C13	
C4	0.6	0.8	0.8	1	0.8	1	0.8	1	0.8	1	0.6	0.8	0.8	1
C5	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8	0.8	1
C6	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8	0.8	1
C7	0.8	1	0.8	1	0.6	0.8	0.8	1	0.8	1	0.6	0.8	0.8	1
C8	0	0.2	0.8	1	0.6	0.8	0.8	1	0.8	1	0.6	0.8	0.6	0.8
C9	0.8	1	0	0.2	0.6	0.8	0.6	0.8	0.6	0.8	0.8	1	0.8	1
C10	0.6	0.8	0.6	0.8	0	0.2	0.6	0.8	0.6	0.8	0.6	0.8	0.6	0.8
C11	0.8	1	0.8	1	0.6	0.8	0	0.2	0	0.2	0.6	0.8	0.8	1
C12	0.8	1	0.8	1	0.4	0.6	0.6	0.8	0.6	0.8	0	0.2	0.8	1
C13	0.8	1	0.6	0.8	0.4	0.6	0.6	0.8	0.6	0.8	0.8	1	0	0.2

Table 10 Total normalised value matrix 1

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
C1	0	0.6	0.6	0.6	0.4	0.2	0.6	0.6	0.6	0.8	0.8	0.8	0.8
C2	0.8	0	0.6	0.6	0.4	0.2	0.6	0.6	0.6	0.8	0.8	0.8	0.8
C3	0.8	0.8	0	0.8	0.8	0.8	0.8	0.8	0.6	0.8	0.8	0.8	0.8
C4	0.8	0.8	0.6	0	0.4	0.2	0.6	0.6	0.6	0.8	0.8	0.8	0.8
C5	0.2	0.4	0.6	0.4	0	0.6	0.6	0.6	0.6	0.8	0.8	0.8	0.8
C6	0.2	0.2	0.6	0.4	0.6	0	0.6	0.6	0.6	0.6	0.6	0.8	0.8
C7	0.6	0.6	0.6	0.8	0.6	0.6	0.8	0.8	0.6	0.8	0.8	0.8	0.8
C8	0.6	0.6	0.6	0.6	0.6	0.6	0	0.8	0.6	0.8	0.8	0.8	0.8
C9	0.6	0.6	0.6	0.6	0.8	0.6	0.8	0	0.6	0.6	0.6	0.8	0.8
C10	0.6	0.6	0.6	0.6	0.8	0.6	0.6	0.6	0	0.6	0.6	0.8	0.8
C11	0.6	0.6	0.6	0.6	0.6	0.4	0.6	0.6	0.6	0	0	0.8	0.8
C12	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.4	0.8	0.8	0	0.8
C13	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.6	0.4	0.6	0.6	0.8	0

Table 11 Total normalised value matrix 2

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
C1	0	0.6	0.6	0.6	0.4	0.2	0.6	0.6	0.6	0.6	0.6	0.8	0.8
C2	0.8	0	0.6	0.6	0.6	0.4	0.6	0.6	0.6	0.8	0.8	0.6	0.8
C3	0.6	0.8	0	0.8	0.8	0.8	0.6	0.8	0.8	0.8	0.8	0.6	0.8
C4	0.8	0.6	0.6	0	0.4	0.2	0.6	0.8	0.8	0.8	0.8	0.8	0.8
C5	0.4	0.4	0.6	0.6	0	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6
C6	0.2	0.2	0.6	0.4	0.6	0	0.6	0.6	0.6	0.6	0.6	0.6	0.8
C7	0.6	0.6	0.6	0.6	0.6	0.6	0.8	0.8	0.6	0.8	0.8	0.6	0.8
C8	0.6	0.6	0.8	0.6	0.6	0.6	0	0.8	0.6	0.8	0.8	0.8	0.8
C9	0.4	0.6	0.8	0.6	0.6	0.6	0.8	0	0.6	0.6	0.6	0.8	0.6
C10	0.4	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0	0.6	0.6	0.6	0.8
C11	0.6	0.8	0.6	0.6	0.4	0.2	0.8	0.8	0.6	0	0	0.6	0.8
C12	0.8	0.8	0.8	0.6	0.8	0.8	0.8	0.8	0.4	0.6	0.6	0	0.8
C13	0.6	0.8	0.8	0.6	0.8	0.6	0.8	0.6	0.4	0.6	0.6	0.8	0

Table 12 Total normalised value matrix 3

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
C1	0	0.6	0.6	0.6	0.4	0.2	0.6	0.6	0.6	0.6	0.6	0.8	0.6
C2	0.8	0	0.6	0.6	0.6	0.4	0.6	0.6	0.6	0.8	0.8	0.6	0.6
C3	0.6	0.8	0	0.8	0.8	0.8	0.6	0.8	0.8	0.8	0.8	0.6	0.6
C4	0.8	0.6	0.6	0	0.4	0.2	0.6	0.8	0.8	0.8	0.8	0.6	0.8
C5	0.4	0.4	0.6	0.4	0	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.8
C6	0.2	0.2	0.6	0.4	0.6	0	0.6	0.6	0.6	0.6	0.6	0.6	0.8
C7	0.6	0.6	0.6	0.6	0.6	0.6	0.8	0.8	0.6	0.8	0.8	0.6	0.8
C8	0.6	0.6	0.8	0.6	0.6	0.6	0	0.8	0.6	0.8	0.8	0.6	0.6
C9	0.6	0.6	0.8	0.6	0.8	0.6	0.8	0	0.6	0.6	0.6	0.8	0.8
C10	0.4	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0	0.6	0.6	0.6	0.6
C11	0.6	0.8	0.6	0.6	0.4	0.2	0.8	0.8	0.6	0	0	0.6	0.8
C12	0.8	0.8	0.8	0.6	0.8	0.8	0.8	0.8	0.4	0.6	0.6	0	0.8
C13	0.6	0.8	0.8	0.6	0.8	0.6	0.8	0.6	0.4	0.6	0.6	0.8	0

Table 13 Integrated crisp value matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
C1	0	0.6	0.6	0.6	0.4	0.2	0.6	0.6	0.6	0.6667	0.6667	0.8	0.7333
C2	0.8	0	0.6	0.6	0.5333	0.3333	0.6	0.6	0.6	0.8	0.8	0.6667	0.7333
C3	0.6667	0.8	0	0.8	0.8	0.8	0.6667	0.8	0.7333	0.8	0.8	0.6667	0.7333
C4	0.8	0.6667	0.6	0	0.4	0.2	0.6	0.7333	0.7333	0.8	0.8	0.7333	0.8
C5	0.3333	0.4	0.6	0.4667	0	0.6	0.6	0.6	0.6	0.6667	0.6667	0.6667	0.7333
C6	0.2	0.2	0.6	0.4	0.6	0	0.6	0.6	0.6	0.6	0.6	0.6667	0.8
C7	0.6	0.6	0.6	0.6667	0.6	0.6	0.8	0.8	0.6	0.8	0.8	0.6667	0.8
C8	0.6	0.6	0.7333	0.6	0.6	0.6	0	0.8	0.6	0.8	0.8	0.7333	0.7333
C9	0.5333	0.6	0.7333	0.6	0.7333	0.6	0.8	0	0.6	0.6	0.6	0.8	0.7333
C10	0.4667	0.6	0.6	0.6	0.6667	0.6	0.6	0.6	0	0.6	0.6	0.6667	0.7333
C11	0.6	0.7333	0.6	0.6	0.4667	0.2667	0.7333	0.7333	0.6	0	0	0.6667	0.8
C12	0.8	0.8	0.8	0.6667	0.8	0.8	0.8	0.8	0.4	0.6667	0.6667	0	0.8
C13	0.6667	0.8	0.8	0.6667	0.8	0.6667	0.8	0.6	0.4	0.6	0.6	0.8	0

Table 14 Normalized direct-relation matrix D

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
C1	0	0.0662	0.0662	0.0662	0.0441	0.0221	0.0662	0.0662	0.0662	0.0735	0.0735	0.0882	0.0809
C2	0.0882	0	0.0662	0.0662	0.0588	0.0368	0.0662	0.0662	0.0662	0.0882	0.0882	0.0735	0.0809
C3	0.0735	0.0882	0	0.0882	0.0882	0.0882	0.0735	0.0882	0.0809	0.0882	0.0882	0.0735	0.0809
C4	0.0882	0.0735	0.0662	0	0.0441	0.0221	0.0662	0.0809	0.0809	0.0882	0.0882	0.0809	0.0882
C5	0.0368	0.0441	0.0662	0.0515	0	0.0662	0.0662	0.0662	0.0662	0.0735	0.0735	0.0735	0.0809
C6	0.0221	0.0221	0.0662	0.0441	0.0662	0	0.0662	0.0662	0.0662	0.0662	0.0662	0.0735	0.0882
C7	0.0662	0.0662	0.0662	0.0735	0.0662	0.0662	0.0882	0.0882	0.0662	0.0882	0.0882	0.0735	0.0882
C8	0.0662	0.0662	0.0809	0.0662	0.0662	0.0662	0	0.0882	0.0662	0.0882	0.0882	0.0809	0.0809
C9	0.0588	0.0662	0.0809	0.0662	0.0809	0.0662	0.0882	0	0.0662	0.0662	0.0662	0.0882	0.0809
C10	0.0515	0.0662	0.0662	0.0662	0.0735	0.0662	0.0662	0.0662	0	0.0662	0.0662	0.0735	0.0809
C11	0.0662	0.0809	0.0662	0.0662	0.0515	0.0294	0.0809	0.0809	0.0662	0	0	0.0735	0.0882
C12	0.0882	0.0882	0.0882	0.0735	0.0882	0.0882	0.0882	0.0882	0.0441	0.0735	0.0735	0	0.0882
C13	0.0735	0.0882	0.0882	0.0735	0.0882	0.0735	0.0882	0.0662	0.0441	0.0662	0.0662	0.0882	0

Table 15 Total relation matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
C1	0	0.029	0.03	0.0283	0.0182	0.0075	0.031	0.0315	0.0269	0.0355	0.0355	0.0443	0.0422
C2	0.0408	0	0.0318	0.0299	0.0265	0.0138	0.0328	0.0334	0.0284	0.0462	0.0462	0.038	0.0447
C3	0.0375	0.048	0	0.0471	0.0477	0.042	0.0421	0.0526	0.0408	0.0526	0.0526	0.0434	0.051
C4	0.042	0.0354	0.0326	0	0.0199	0.0082	0.0337	0.0429	0.0368	0.0474	0.0474	0.0435	0.0506
C5	0.014	0.0179	0.0294	0.0208	0	0.0247	0.0303	0.0308	0.0263	0.0347	0.0347	0.0351	0.0413
C6	0.0077	0.0081	0.0279	0.0166	0.0267	0	0.0288	0.0292	0.025	0.0292	0.0292	0.0333	0.0433
C7	0.0334	0.0349	0.0363	0.0384	0.0346	0.0303	0.1401	0.0528	0.0325	0.0527	0.0527	0.0434	0.0563
C8	0.0308	0.0321	0.0419	0.0313	0.0318	0.028	0	0.1369	0.0299	0.0485	0.0485	0.0445	0.0469
C9	0.0264	0.0315	0.0411	0.0308	0.0394	0.0275	0.0476	0	0.0956	0.0344	0.0344	0.0482	0.0461
C10	0.0212	0.0293	0.0305	0.0287	0.0328	0.0256	0.0314	0.0323	0	0.0982	0.0321	0.0365	0.0429
C11	0.0272	0.0355	0.0293	0.0275	0.021	0.0099	0.038	0.0387	0.0265	0	0	0.035	0.0454
C12	0.0453	0.0471	0.049	0.0375	0.0468	0.0412	0.0506	0.0517	0.0203	0.042	0.042	0	0.055
C13	0.0349	0.0447	0.0465	0.0356	0.0444	0.0317	0.0481	0.0355	0.0192	0.0354	0.0354	0.0494	0

Table 16 r_i and c_j value

Criteria	r_i	c_i
C1	0.360072	0.361173
C2	0.412599	0.361173
C3	0.557361	0.320326
C4	0.440241	0.282807
C5	0.340079	0.240853
C6	0.305051	0.226805
C7	0.638386	0.219125
C8	0.551123	0.545776
C9	0.503172	0.927619
C10	0.441527	1.458534
C11	0.334119	1.87759
C12	0.528605	2.190518
C13	0.460959	2.450317

Table 17 $r_i + c_j$ and $r_i - c_j$ value

Criteria	$r_i + c_j$	$r_i - c_j$
C1	0.721245	−0.0011
C2	0.773772	0.051426
C3	0.877687	0.237035
C4	0.723048	0.157434
C5	0.580932	0.099225
C6	0.531856	0.078247
C7	0.857511	0.41926
C8	1.096899	0.005346
C9	1.430792	−0.42445
C10	1.900061	−1.01701
C11	2.21171	−1.54347
C12	2.719123	−1.66191
C13	2.911276	−1.98936

provide information to judge which are the significant factors and their influence affect other factors. Interrelation between the criteria is shown by DIGRAPH in Fig. 3”.

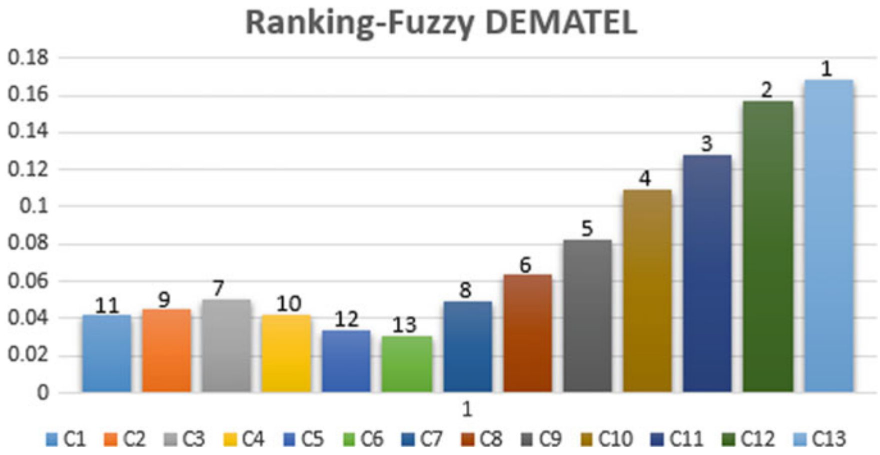

Fig. 2 Ranking by fuzzy DEMATEL

Table 18 Priority weights and ranking

Criteria	w_i	Rank
C1	0.041604	11
C2	0.044634	9
C3	0.050628	7
C4	0.041708	10
C5	0.03351	12
C6	0.030679	13
C7	0.049464	8
C8	0.063273	6
C9	0.082533	5
C10	0.109603	4
C11	0.12758	3
C12	0.156849	2
C13	0.167933	1

6.2 Ranking the Criteria by Fuzzy TOPSIS

Ranking by fuzzy TOPSIS is carried out in two phases. First in which weights are calculated by fuzzy SWARA and second in which ranking is done by fuzzy TOPSIS using weights computed by fuzzy SWARA.

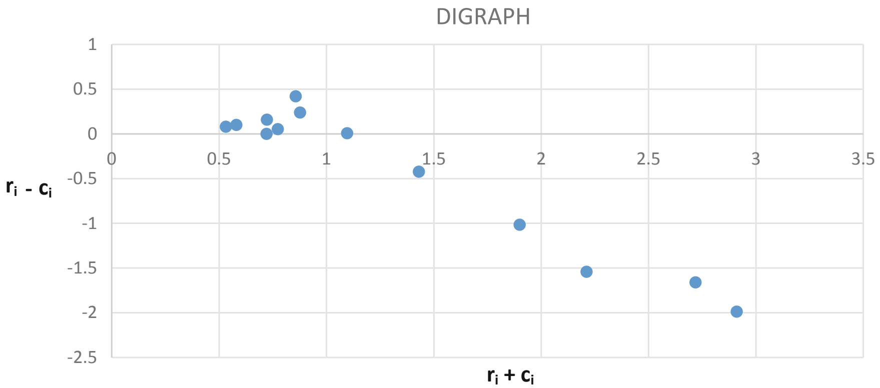

Fig. 3 DIGRAPH

6.3 Computing Weights by Fuzzy SWARA

STEP 1: Decision-makers (DMs) rank alternatives with respect to their estimated priorities and is summarised in Table 19.
STEP 2: Starting from the second criterion, the criterion is compared with its above criterion. That is; criterion j − 1 is compared with criterion j. This comparison gives comparative importance of average value (sj) (Tables 20, 21 and 22).
STEP 3: In final step, the weight of criterion (wj) is determined after determining kj and qj values. Weights are calculated for every decision maker's decision and summarised in Tables 23, 24 and 25.

Table 19 The order of criteria with respect to decision makers

Decision maker	DM1	DM2	DM3
Criteria			
C1	13	12	12
C2	12	13	13
C3	11	11	11
C4	10	10	10
C5	9	9	9
C6	8	8	8
C7	3	3	3
C8	7	7	7
C9	2	2	2
C10	4	4	1
C11	1	5	4
C12	5	1	5
C13	6	6	6

Table 20 s_j value by DM1

Criteria	s_j		
C13			
C12	0.667	1	1.5
C11	0.667	1	1.5
C10	0.667	1	1.5
C9	0.667	1	1.5
C8	0.4	0.5	0.667
C3	0.667	1	1.5
C7	0.4	0.5	0.667
C2	0.4	0.5	0.667
C4	0.667	1	1.5
C1	0.285	0.667	0.4
C5	0.4	0.5	0.667
C6	0.285	0.667	0.4

Table 21 s_j value by DM2

Criteria	sj		
C12			
C13	0.667	1	1.5
C11	0.667	1	1.5
C10	0.4	0.5	0.667
C9	0.667	1	1.5
C8	0.4	0.5	0.667
C3	0.667	1	1.5
C7	0.4	0.5	0.667
C2	0.4	0.5	0.667
C4	0.4	0.5	0.667
C5	0.4	0.5	0.667
C1	0.4	0.5	0.667
C6	0.285	0.667	0.4

STEP 4: Final weights are calculated by taking the arithmetic mean of the weights by three decision makers and are summarised in Table 26.

Table 22 s_j value by DM3

Criteria	sj		
C12			
C13	0.667	1	1.5
C11	0.667	1	1.5
C10	0.4	0.5	0.667
C9	0.667	1	1.5
C8	0.4	0.5	0.667
C3	0.667	1	1.5
C7	0.285	0.667	0.4
C2	0.4	0.5	0.667
C1	0.4	0.5	0.667
C4	0.667	1	1.5
C5	0.4	0.5	0.667
C6	0.285	0.667	0.4

6.4 Fuzzy TOPSIS for Ranking the Criteria

STEP 1: Initially, initial fuzzy decision matrices including preference judgment of supply chain experts (namely DM1, DM2 and DM3) are determined for 13 criteria (Table 27).
Step 2: Aggregated fuzzy decision matrix is then computed in which decision matrices by three decision makers are aggregated in one matrix and is summarised in Table 28.
STEP 3: Compute the normalised fuzzy decision matrix by dividing the values of aggregated decision matrix by 9 (max c_{ij}) (Table 29).
STEP 4: Compute the weighted normalized fuzzy decision matrix by multiplying normalised fuzzy decision matrix with corresponding weights. Weighted normalised fuzzy decision matrix is summarised in Table 30.
STEP 5: "Compute the Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS). They give the reference values for the comparison. Therefore, to achieve an optimal solution and make a compromise ranking, the distances of each alternative from NIS and PIS should be considered. FPIS and FNIS values are summarised in Table 31".
STEP 6: Compute the distance from each alternative to the FPIS and to the FNIS, that is, d^+, d^- and the values are summarised in Table 32.
STEP 7: "Final ranking is given to the supplier based on value of closeness coefficient. It shows the similarity to the worst solution in terms of ratio of distances. The supplier with highest value of relative closeness comes first and the one with lowest closeness coefficient value comes last. Closeness coefficient for each criteria and final ranking is tabulated in Table 33" (Fig. 4).

Table 23 kJ, q_j and w_j value by DM1

Criteria	kj			qj			wj		
C13	1	1	1	1	1	1	0.389406	0.491759	0.595536
C12	1.667	2	2.5	0.4	0.5	0.59988	0.155762	0.245879	0.35725
C11	1.667	2	2.5	0.16	0.25	0.359856	0.062305	0.12294	0.214307
C10	1.667	2	2.5	0.064	0.125	0.21587	0.024922	0.06147	0.128559
C9	1.667	2	2.5	0.0256	0.0625	0.129496	0.009969	0.030735	0.07712
C8	1.4	1.5	1.667	0.015357	0.041667	0.092497	0.00598	0.02049	0.055086
C3	1.667	2	2.5	0.006143	0.020833	0.055487	0.002392	0.010245	0.033045
C7	1.4	1.5	1.667	0.003685	0.013889	0.039634	0.001435	0.00683	0.023603
C2	1.4	1.5	1.667	0.002211	0.009259	0.02831	0.000861	0.004553	0.01686
C4	1.667	2	2.5	0.000884	0.00463	0.016983	0.000344	0.002277	0.010114
C1	1.285	1.667	1.4	0.000632	0.002777	0.013216	0.000246	0.001366	0.007871
C5	1.4	1.5	1.667	0.000379	0.001851	0.00944	0.000148	0.00091	0.005622
C6	1.285	1.667	1.4	0.000271	0.001111	0.007346	0.00	0.000546	0.004375

Table 24 kJ, q_j and w_j value by DM2

Criteria	kj			qj			wj		
C12	1	1	1	1	1	1	0.371582	0.468655	0.574757
C13	1.667	2	2.5	0.4	0.5	0.59988	0.148633	0.234327	0.344785
C11	1.667	2	2.5	0.16	0.25	0.359856	0.059453	0.117164	0.20683
C10	1.4	1.5	1.667	0.095981	0.166667	0.25704	0.035665	0.078109	0.147736
C9	1.667	2	2.5	0.038392	0.083333	0.154193	0.014266	0.039055	0.088624
C8	1.4	1.5	1.667	0.023031	0.055556	0.110138	0.008558	0.026036	0.063303
C3	1.667	2	2.5	0.009212	0.027778	0.06607	0.003423	0.013018	0.037974
C7	1.4	1.5	1.667	0.005526	0.018519	0.047193	0.002053	0.008679	0.027124
C2	1.4	1.5	1.667	0.003315	0.012346	0.033709	0.001232	0.005786	0.019374
C4	1.4	1.5	1.667	0.001989	0.00823	0.024078	0.000739	0.003857	0.013839
C5	1.4	1.5	1.667	0.001193	0.005487	0.017198	0.000443	0.002571	0.009885
C1	1.4	1.5	1.667	0.000716	0.003658	0.012285	0.000266	0.001714	0.007061
C6	1.285	1.667	1.4	0.000511	0.002194	0.00956	0.00019	0.001028	0.005495

Table 25 kJ, q_j and w_j value by DM3

Criteria	kj			qj			wj		
C12	1	1	1	1	1	1	0.370745	0.470331	0.57424
C13	1.667	2	2.5	0.4	0.5	0.59988	0.148298	0.235165	0.344475
C11	1.667	2	2.5	0.16	0.25	0.359856	0.059319	0.117583	0.206644
C10	1.4	1.5	1.667	0.095981	0.166667	0.25704	0.035584	0.078388	0.147603
C9	1.667	2	2.5	0.038392	0.083333	0.154193	0.014234	0.039194	0.088544
C8	1.4	1.5	1.667	0.023031	0.055556	0.110138	0.008539	0.026129	0.063246
C3	1.667	2	2.5	0.009212	0.027778	0.06607	0.003415	0.013065	0.03794
C7	1.285	1.667	1.4	0.00658	0.016663	0.051416	0.00244	0.007837	0.029525
C2	1.4	1.5	1.667	0.003947	0.011109	0.036726	0.001463	0.005225	0.021089
C1	1.4	1.5	1.667	0.002368	0.007406	0.026233	0.000878	0.003483	0.015064
C4	1.667	2	2.5	0.000947	0.003703	0.015736	0.000351	0.001742	0.009036
C5	1.4	1.5	1.667	0.000568	0.002469	0.01124	0.000211	0.001161	0.006455
C6	1.285	1.667	1.4	0.000406	0.001481	0.008747	0.00	0.000697	0.005023

Table 26 Final weights

Criteria	Final Weights		
C1	0.000463	0.002188	0.009998
C2	0.00098	0.004125	0.016111
C3	0.003077	0.012109	0.036319
C4	0.000478	0.002625	0.010996
C5	0.000267	0.001548	0.00732
C6	0.000149	0.000757	0.004964
C7	0.001976	0.007782	0.026751
C8	0.007692	0.024219	0.060545
C9	0.012823	0.036328	0.084762
C10	0.032057	0.072656	0.141299
C11	0.060359	0.119229	0.20926
C12	0.299363	0.394955	0.502082
C13	0.228779	0.320417	0.428265

Table 27 Initial fuzzy decision matrix

Criteria	DM1			DM2			DM3		
C1	3	5	7	3	5	7	5	7	9
C2	3	5	7	5	7	9	3	5	7
C3	5	7	9	5	7	9	3	5	7
C4	3	5	7	3	5	7	5	7	9
C5	3	5	7	3	5	7	1	3	5
C6	1	3	5	3	5	7	1	3	5
C7	3	5	7	5	7	9	3	5	7
C8	5	7	9	5	7	9	3	5	7
C9	5	7	9	7	9	9	5	7	9
C10	5	7	9	7	9	9	5	7	9
C11	7	9	9	7	9	9	5	7	9
C12	7	9	9	7	9	9	7	9	9
C13	7	9	9	7	9	9	7	9	9

7 Results and Discussions

To further validate the effectiveness and strengths of the hybrid approach proposed in this work, a comparative analysis is conducted between fuzzy DEMATEL and fuzzy TOPSIS. The ranking orders of the thirteen green supply chain criteria produced by both these methods are displayed in one bar chart in Fig. 5.

The study shows that there is no significant change in the results by fuzzy TOPSIS and fuzzy DEMATEL method. According to the comparison carried out between the

Table 28 Aggregated fuzzy decision matrix

Criteria			
C1	3	5.66667	9
C2	3	5.66667	9
C3	3	6.33333	9
C4	3	5.66667	9
C5	1	4.33333	7
C6	1	3.66667	7
C7	3	5.66667	9
C8	3	6.33333	9
C9	5	7.66667	9
C10	5	7.66667	9
C11	5	8.33333	9
C12	7	9	9
C13	7	9	9

Table 29 Normalised fuzzy decision matrix

Criteria			
C1	0.333333	0.629629	1
C2	0.333333	0.629629	1
C3	0.333333	0.703703	1
C4	0.333333	0.629629	1
C5	0.111111	0.481481	0.777778
C6	0.111111	0.407407	0.777778
C7	0.333333	0.629629	1
C8	0.333333	0.703703	1
C9	0.555556	0.851852	1
C10	0.555556	0.851852	1
C11	0.555556	0.925926	1
C12	0.777778	1	1
C13	0.777778	1	1

results of two techniques it is observed that there is change in positions 1, 2, 11 and 12 only while rest are at same position by both methods. According to fuzzy DEMATEL method criteria C13 (environmental auditing of suppliers) is the most important criteria and is ranked first while criteria C6 (warehousing) comes last and the sequence comes out to be C13 > C12 > C11 > C10 > C9 > C8 > C3 > C7 > C2 > C4 > C1 > C5 > C6. But according to fuzzy TOPSIS method criteria C12 (green process planning) comes out to be most important criteria while criteria C6 (warehousing) comes last and the sequence is C12 > C13 > C11 > C10 > C9 > C8 > C3 > C7 > C2 > C4 > C5 > C1 > C6. The reasons of criteria ranking difference

Table 30 Weighted fuzzy normalised decision matrix

Criteria			
C1	0.000154417	0.00137748	0.009998361
C2	0.000326803	0.002597523	0.016111472
C3	0.001025619	0.008521359	0.036319473
C4	0.000159381	0.001652887	0.010996365
C5	0.00	0.000745181	0.0056937
C6	0.00	0.000308418	0.003861076
C7	0.000658664	0.004899788	0.026750907
C8	0.002564048	0.017042718	0.060544562
C9	0.007123779	0.030945989	0.084762386
C10	0.017809447	0.061891978	0.141298898
C11	0.033532791	0.110396922	0.209260169
C12	0.232837711	0.394954897	0.502082204
C13	0.18	0.320417154	0.428265281

Table 31 Fuzzy positive and negative ideal solution

	FPIS			FNIS		
C1	0.009998	0.009998	0.009998	0.000154417	0.000154417	0.000154417
C2	0.016111	0.016111	0.016111	0.000326803	0.000326803	0.000326803
C3	0.036319	0.036319	0.036319	0.001025619	0.001025619	0.001025619
C4	0.010996	0.010996	0.010996	0.000159381	0.000159381	0.000159381
C5	0.005694	0.005694	0.005694	0.00	0.00	0.00
C6	0.003861	0.003861	0.003861	0.00	0.00	0.00
C7	0.026751	0.026751	0.026751	0.000658664	0.000658664	0.000658664
C8	0.060545	0.060545	0.060545	0.002564048	0.002564048	0.002564048
C9	0.084762	0.084762	0.084762	0.007123779	0.007123779	0.007123779
C10	0.141299	0.141299	0.141299	0.017809447	0.017809447	0.017809447
C11	0.20926	0.20926	0.20926	0.033532791	0.033532791	0.033532791
C12	0.502082	0.502082	0.502082	0.232837711	0.232837711	0.232837711
C13	0.428265	0.428265	0.428265	0.177938983	0.177938983	0.177938983

in results may be found because fuzzy TOPSIS considers both distances from the negative and positive ideal solution while in fuzzy DEMATEL strengths of criteria are not included although it considers the interactions between different criteria. The foremost portion of this study was to identify the critical factors of GSCM in automotive company and this identification licenses managers to a better understanding of GSCM practices and follow academic researchers to advance testing theories of green issues. Moreover, the critical factors of GSCM in this study can escort

Table 32 d^+ and d^- values

Criteria	d_i^+	d_i^-
C1	0.007555	0.005727
C2	0.011997	0.009207
C3	0.025938	0.020831
C4	0.008261	0.006316
C5	0.004342	0.0033
C6	0.003022	0.002226
C7	0.019649	0.015262
C8	0.04185	0.034503
C9	0.05454	0.046887
C10	0.084765	0.075703
C11	0.11641	0.110737
C12	0.167301	0.181452
C13	0.157368	0.166296

Table 33 Closeness coefficient and ranking

Criteria	CC_i	Rank
C1	0.431198	12
C2	0.434214	9
C3	0.445404	7
C4	0.433275	10
C5	0.431828	11
C6	0.424146	13
C7	0.437167	8
C8	0.451891	6
C9	0.462273	5
C10	0.471766	4
C11	0.487512	3
C12	0.520288	1
C13	0.513792	2

other researchers to identify those areas of GSCM that need reception and enhancements. Based on present research, top thirteen significant criteria of GSCM are as follows: Manpower Involvement, Environmental Education and Training, Cooperation with Customers including Environmental Requirements, Internal Environmental Management, Investment Recovery, Green Warehousing, Green Transportation and Distribution, Reverse Logistics, Green Manufacturing, Green Purchasing, Green Design, Green Process Planning, Environmental Auditing for Suppliers.

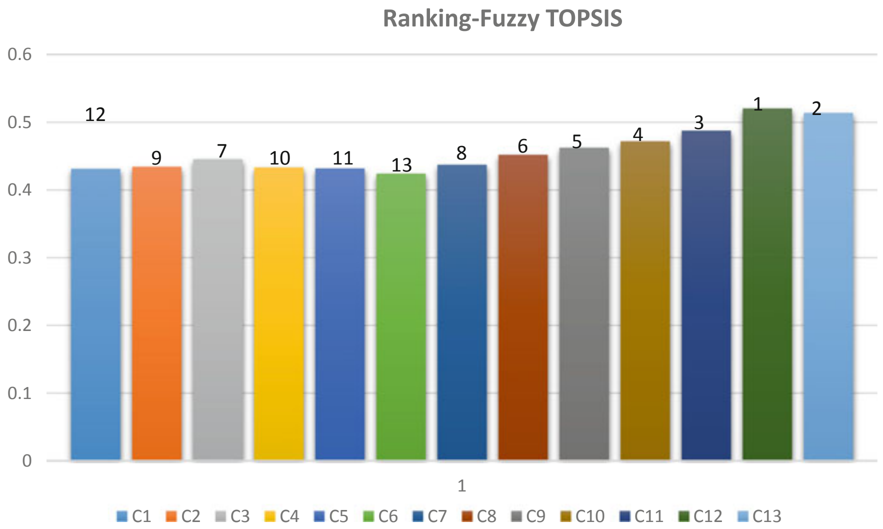

Fig. 4 Ranking by fuzzy TOPSIS

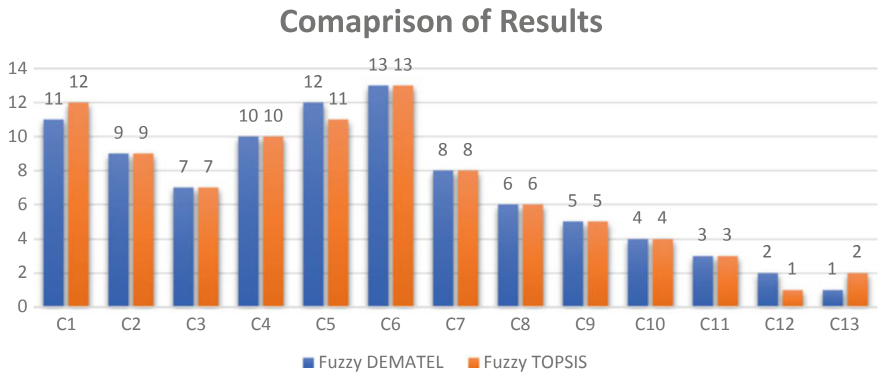

Fig. 5 Comparison of results by fuzzy DEMATEL and fuzzy TOPSIS

8 Managerial Implications

The present study has a few ramifications. Right off the bat, it pays off (in terms of firm performance) to have an outer concentration to environmental issues, by actualizing supplier-related practices such as assess suppliers' performance, conduct environmental audits, provide suppliers with feedback about these audits and/or with training. Also, when working with suppliers, it is expected to go past just checking. Sustainable performance enhances when there is joint-work and cooperation amongst purchasers and service providers. From an approach point of view, this study has critical ramifications. Results recommend that coercive weights (government) might be less proficient than non-coercive weights (e.g. society, clients, contenders, and so on.), as far as invigorating observing and community-oriented activities. As a matter of fact, the effect of coercive weights on joint effort activities might be even negative, as indicated by the aftereffects of this study. The strategy ramifications of this is maybe it would be more proficient to create systems to invigorate the straightforwardness of SC, than to apply coordinate coercive weights. This straightforwardness would offer help to the no coercive weights (e.g. clients, society), through enhanced access to data, and would empower central firms to take part in both checking and cooperative activities. The usage of these activities would enhance natural execution of the central firm, and in a roundabout way the execution of the entire Supply Chain, through enhanced procedures and items. This conceivable connection amongst straightforwardness and non-coercive weights ought to be considered in further studies.

9 Conclusions

Environmental laws, green production and eco products have become substantial matter of worry to many industries and GSCM practices have become gradually substantial for manufacturers and in this competitive market, companies are required to implement GSCM practices in a sustainable manner. Significance of environmental safety has fascinated the governments, customers and companies. Now firms have started paying more devotion to environment and environmental issues, which have become a key factor of performance in the competitive business environment. This study presents application of fuzzy DEMATEL method and fuzzy TOPSIS method, to study the impact of the most vital factors and to find out the ranking of criteria in GSCM implementations and then comparing the results. The insinuations and practicality of the technique are clear, and managers are capable to diagnose what criteria of GSCM within their organization need more consideration and which ones may be given less priority and this method could clearly express the causal relations between criteria. These methods may be used to assistance plan the direction of every organization by determining how one criteria of Green supply chain, influence other ones and if every firm wishes to improve existing green supply chain, this method can provide clear relationships on which criteria of green supply chain should be emphasized to insure greater success of programs. The proposed approach is flexible and applicable to a broad variety of managerial and decision environments. This study highlights that the fuzzy DEMATEL method and fuzzy TOPSIS method can be useful to many researches which must deal with complex criteria problems that need tousle group decision making in the fuzzy environment. This research endeavours to discover and scrutinize the critical factors of GSCM practices in any of the industries.

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Decision Support System for Supply Chain Performance Measurement: Case of Textile Industry

Pranav G. Charkha and Santosh B. Jaju

Abstract The chapter aims to propose decision support framework for identification of key performance indicators for supply chain performance measurement in textile industry. To meet the objective, hierarchical model is developed including criteria, sub-criteria, alternatives. Proposed decision support system (DSS) is developed with objective as textile supply chain performance measurement with 4 stakeholder value creation perspectives (Financial, Customer, Internal business processes, Innovation and learning) suggested by balanced scorecard (BSC) as criteria, having 23 sub-criteria (key performance indicators) and 3 supply chain operations (Procurement-Production-Distribution) as alternatives. Structured Delphi method and Minitab 17.0 software for statistical analysis are used for the development of decision support framework. Whereas, for establishing pair wise comparison and analyzing the relative importance of these criteria, sub-criteria and alternative, analytical hierarchy process (AHP) is used. The paper demonstrates the application of decision support system in identifying key performance indicators and analyzing the importance of KPIs towards overall performance of supply chain in textile. The proposed system is put to test at four textile case industries. Case company wise implication as well general implications on textile supply chain performance is presented. Also, managerial implication and limitations are presented. Proposed study presented novel approach in developing DSS for textile supply chain performance measurement, which is very rare one. This DSS will be used for identifying key performance metrics/indicators and also analyzing their importance towards supply chain performance. Use of BSC perspective has given framework wholesome coverage of all stakeholders' consideration. Also, involvement of supply chain cyclic operation added consideration of supply chain partners.

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S. Patnaik (ed.), *New Paradigm of Industry 4.0*, Studies in Big Data 64,
https://doi.org/10.1007/978-3-030-25778-1_5

Keywords Analytical hierarchy process (AHP) · Decision support system (DSS) · Delphi method · Key performance indicators (KPIs) · Performance measurement · Supply chain management (SCM) · Supply chain performance measurement (SCPM)

1 Introduction

SCM is philosophy of optimizing the usages of resources needed to develop the product or service from its initial stage i.e. from supplier to customer (Cooper et al. 1997). A supply chain mainly has three divisions, namely procurement division, manufacturing/production division and distribution division with link of companies affecting each other's performance as shown in Fig. 1 (Swaminathan 2007). An important issue in SCM is the development of integrated decision support system for performance measurement. Designing performance measurement decision support system in supply chain management is very important activity for the competitive growth among firms in today's era of globalization. With respect to the old saying "you can't improve what you can't measure" and recognizing the importance of strategic organizational changes, the need is felt for developing the performance measures to determine the advancement towards achieving organizational goals, to make available criticism on efforts for continual improvement, and to guide the revolution by adopting progressive steps (Bourne and Neely 2003; Chan 2006). Supply chain performance measurement (SCPM) is related to strategic plan and objectives, and the extensive set of performance measures for supply chain adopted by managers or practitioners is used to examine and guide the business enterprise supply chain to compete within acceptable and desirable parameters (Morgan 2004). Firm's supply chain strategic divisions need to keep on evaluating themselves, for whether firm is meeting customer demands, which helps them understand their functions, identifying the areas of errors, bottlenecking points in supply chain and identifying possible areas of improvement ensuring that decisions are based on fact, not on supposition; and proving the improvement happened. Supply chain performance measurement system development gaining more and more importance in process-based industries, as it enhances output and improves standards (Chan 2006). Following old adages,

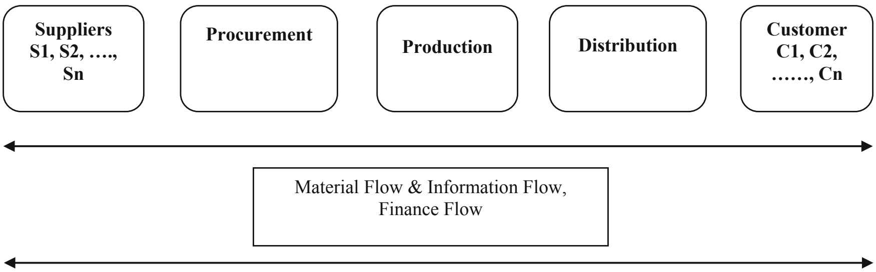

Fig. 1 Generalized supply chain. *Source* Swaminathan (2007)

"Anything Measured Improves", various studies stressed that a key to continuous improvement is to measure, measure and measure (Lapide 2000).

Performance measures have two main effects. First of all, they can be used as a good explanation for the as is condition. Secondly, they can be used to set performance goals (Shah 2005). The competing organization must have comprehensive set of measures to evaluate the progress of company's strategic goal attainment, improving core business processes of supply chain and aligning the firm and needs of the market (Browne et al. 1998). Performance measures and metrics are required to asses and disclose the feasibility of strategies, failing which; a clear understanding would be difficult for initiating improvement and realization of goals (Gunasekaran et al. 2001). Business enterprises are required to ensure the attainment of goals and objectives, therefore, purpose of supply chain performance evaluation is to assess, control and improve efficiency of supply chain strategic divisions (Taghizadeh and Hafez 2012; Digalwar and Sangwan 2011). Performance measurement system supports in developing the set of performance measures by stating clearly measurement criteria, sub-criteria and measuring dimension (Chan 2003). Various studies conducted have developed the frameworks for SCPM, but they often lack in developing suitable and effective performance measures and metrics to achieve integrated supply chain performance measurement system. This is because of lack of balanced approach and consideration of all stakeholder of an enterprise (i.e. firm management, targeted customers, employees involved; Gunasekaran et al. 2001). Various researchers identified performance measures and proposed frameworks, classifying them into financial and non-financial categories. This creates confusion among the practitioners and manager of firm for the selection of suitable performance measures. Also, it lacks in providing the balanced view from different stakeholder's perspective. Stakeholder accountability is considered in the present study for evaluating the corporate performance from strategic point of view using balanced scorecard perspective which are; financial perspective (firm's management), customer perspective (targeted customer), internal business process perspective (firm's management), innovation and learning (employees involved). Based on the above consideration, the study proposes a generic framework using the BSC perspective as criteria to assess the performance of supply chain management, to be tested in textile industry. As already mentioned, selection of performance measures is critical for the firms, hence prioritization of these perspectives and performance measures for the firm's supply chain has emerged as an issue to address for textile supply chain performance. In this paper, we made an attempt to prioritize various supply chain performance measures categorized under four perspectives of BSC. These BSC perspectives as criteria and various sub-criteria under each perspective have been discussed and validated in pilot test with subject matter experts. Further in order to verify accountability of proposed framework, four case companies were identified and respondents were contacted using semi-structured questionnaire. For quantification of subjective judgment obtained during pair wise comparison of criteria, sub-criteria etc., analytical hierarchy process was used.

2 Supply Chain Management and Performance Measurement Systems

SCM is defined as an integrated process that involves the activities starting with the procurement of raw material from supplier to delivery of finished products to target customers; a generalized SC is shown in Fig. 1. It is sophisticated tool to evaluate and optimize an enterprise; it is a complex, controlled business relationship model. It considers all aspects of the processes required to produce your company's product in the most efficient and cost effective manner (Sharma and Bhagwat 2007). It enhances organizational productivity and profitability through a radical philosophy in managing the business with sustained competitiveness (Gunasekaran et al. 2004). It is believed that the evolution of supply chain management has successfully and efficiently provided desired value to end customer in terms of novel and cost centric goods or services and also enhances the profitability of the supply chain (Cao et al. 2008).

In order to enhance productivity, an organization must measure the performance of all its activities and supply chain as whole (Bititci et al. 2005). The main goal of performance measurement and control in the supply chain is to provide management with a set of improvement trial that can be deployed for achieving improved performance and planning the competitiveness enhancing efforts (Beamon 1999; Bourne and Neely 2003). Organizations not only are required to measure effectiveness of the end product/service but also the efficiency of processes involved in reaching the customer's expectation.

Various attempts were made to explore the process of implementation of performance measurement system in small and medium sized enterprises (Agrawal et al. 2016; Singh and Sharma 2015). In recent past, various studies suggested the methods and techniques to evaluate the performance of the firm (Browne et al. 1998). Financial indicators such as return on investment, net present value, and cost and payback period are frequently cited in the literature. Recently, studies in the field of supply chain performance measurement has gained tremendous attention by the researcher, realizing the need to develop integrated PMS and taking account of all the process division or components (i.e. procurement, production and distribution) of supply chain network (Babazadeh et al. 2012; Tabrizi and Razmi 2013). Many studies exhibited the use of financial and non-financial performance measures for SCM as provided by Chan (2003), Gunasekaran et al. (2001, 2004), Bhagwat and Sharma (2007a) and Gopal and Thakkar (2012) at different decision level (i.e. strategic, tactical, operational). They are categorized as quantitative and qualitative factor as shown in Table 12 (as shown in Appendix). Another study suggested framework using resource, output and flexibility as performance measures (Beamon 1999). At the same time, it is agreed that, currently available PMS possess few limitations. First, they mostly utilized financial measures without any process perspective and secondly evaluation is confined to quantitative indicators (Bigliardi and Bottani 2010; Bititci et al. 2005; Browne et al. 1998; Teng and Jaramillo 2005). The answer to these limitations is proposed in our study that modern performance measurement system should support the organization strategies considering balance of quantitative as well qualitative measures and focusing majorly on the features/characteristics of the industry. Industries in developing nations need very specific measurement system and hence it is difficult to develop a generic performance measurement system (Beamon 1999). So in order to recognize the value drivers, practitioners/managers must have performance measurement system designed to capture information on all perspective of business divisions. An attempt has been made to develop mathematical model using AHP and pre-emptive goal programming methods to evaluate the supply chain performance (Bhagwat et al. 2008; Bhagwat and Sharma 2009). Another attempt made, where performance of automated manufacturing system was evaluated and concluded that the most important metric is 'overall equipment effectiveness' (Mathur et al. 2011). Also, the criteria and alternative are prioritized for evaluating flexibility of supply chain (Shah 2005). The need has been felt to select the competitive supply chain using qualitative factor quantified by using fuzzy AHP and extent analysis (Singh and Sharma 2014). Systems using only financial measures are not well suited to recent SCM frameworks (Bhagwat and Sharma 2007a). Reason for failure in using only financial measures was because of their historical orientation, lacking in forward looking perspective, not relating to organization's strategic performance and not considering the operational efficiency and effectiveness (Singh and Sharma 2014). On the contrary, new PMS should take into account a wider perspective (Thakkar et al. 2009). Also good PMS should give an insight to firms about the skills, and systems that your employees needed (*innovation and learning*) to innovate and build the right strategic capabilities and efficiencies (*internal business perspective*) that deliver specific value to the market (*customer perspective*) which eventually lead to higher shareholder value (*financial perspective*). This comprehensive inclusiveness is provided by balanced scorecard (Kaplan 1992). Also, attempt has been made to include the strategic process division in the performance measurement system, and the selection of performance measures should not only be restricted to financial parameters (Hall and Saygin 2011; Charkha and Jaju 2014a, b). Hence, this study proposes the use of balanced scorecard for assessing the performance of supply chain network.

Studies conducted earlier have developed the supply chain performance measurement system are more in area of discrete manufacturing environment. Use of SCPM is rare in process industries in India. In India, process industry also offers major contribution to growth and economy of the nation. Process industry supply chain like textile industry operates with short product life cycle with long lead times with uncertainty in responding to market volatile fashion demands. The textile supply chain comprises of diverse raw material procurement sectors, long production runs which includes ginning facilities, spinning-extrusion process, processing, weaving-knitting, fabric manufacturing/finishing division supplemented with application based textile product production divisions and supported by extensive distribution channels as shown in Fig. 2. SCM in textile industry is more important in improving efficiency and effectiveness of SC. It should also consider SCM to improve sales rate, shareholder value which ultimately boosts competitive advantage (Cao et al. 2008; Lam 2006).

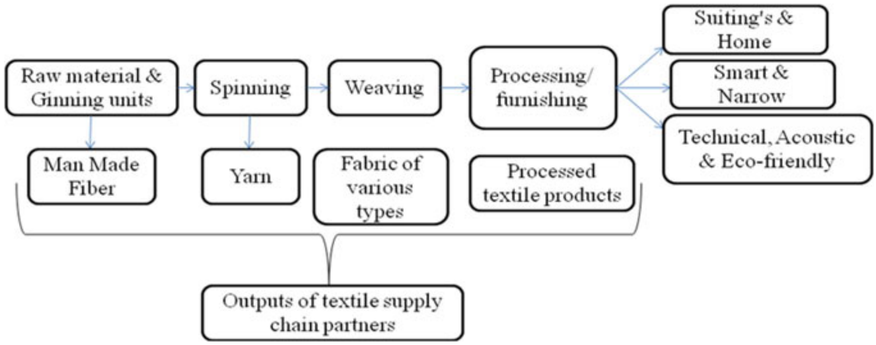

Fig. 2 Textile supply chain

Performance measurement (PM) in SCM facilitates coordination and integration among the supply chain divisions. It addresses the issues which can make firms to know the effectiveness and efficiency of strategies deployed and to identify opportunities to improve (Chan 2006). PM contributes vitally to decision making in SCM, especially in framing/re-designing aims and strategies and also in processes of re-engineering (Chan 2003). Recent research studies congeal the linkage between supply chain practice and its impact not only on company's financial performance, but also other strategic perspectives. The want for improvement in overall supply chain efficiency and effectiveness has additional forced firms/enterprises to appraise, assess and think about the adoption of proper PM for SCM. In addition, authors classified supply chain performers as 'leaders, transformers, decliners and laggards' in an attempt to fragment supply chain cyclic divisions or companies by their SCM performance over two distinct periods. A study identified six measures for measuring supply chain improvement; extent of electronic data interchange (EDI) implementation, supplier's data accuracy, shipping delays by suppliers, improper deliveries by suppliers, production time by original equipment manufacturer (OEM) and delivery time from OEM to end users. Other study suggested performance measurement in terms of inventory investment, service level, throughout efficiency, supplier performance and cost (AriaNezhad et al. 2013). Hence for the effective performance measurement of SCM, most important task is to identify the comprehensive criteria and sub-criteria of tangible/intangible nature (from all the perspective and covering global view with all intermediate supply chain divisions) affecting performance. A comprehensive list of performance measures reviewed from various studies as shown in Table 12 (Appendix) classified as qualitative and quantitative, categorized under four strategic perspectives (Gunasekaran et al. 2001, 2004; Bhagwat and Sharma 2007a). On the other hand, more number of measures creates ambiguity in the system makes it difficult to implement. It is not possible for firms to apply all performance measures in routine business activities/day-to-day operations. Also, this framework does not provide guidelines to prioritize these metrics. An attempt is made to prioritize the metrics and tested them in discrete manufacturing environment (Bhagwat and Sharma 2007b). Existing frameworks can't be readily applied to process industry (textile, petroleum, food processing etc.) owing to its distinguishing features and complex supply chain. Hence, our study focuses on textile industry. The comprehensive performance measurement can be achieved only after considering all stakeholders' perspectives of an industry. Further, SCPM need to envelope the supply chain cyclic divisions/operations (Procurement, Production, and Distribution) in order to figure out which division is contributing at what extent towards overall supply chain performance. It becomes very important with textile industry in developing country like India. As, discussed earlier textile industry is very complex, fragmented and having multiple procurement stages, variety of production shops and various distribution channels. Very few studies used BSC for evaluating supply chain performance of process industry, whereas, textile industry is the rarest in such attempts. The BSC is broadly elaborated through articles (Bhagwat and Sharma 2007a; Bhagwat et al. 2008), books and conferences (e.g. Norton 1997). One study recommended the application of BSC for SCPM (Bhagwat and Sharma 2007a). In this, various performance measures were categorized under different decision level (strategic, tactical and operational) and measured performance for BSC perspective. Our study proposed a framework considering BSC perspectives as the criteria, with sub-criteria under each perspective and supply chain cyclic divisions as the alternatives.

3 Textile Supply Chain

Textiles and clothing sector has been one of the leading process industries of South Asia in terms of its contribution to output, employment and trade. Today the textile industry sector employs 35.0 million people (2nd largest employer), generates 1/5th of total export earnings and contributes 4% to the GDP, thereby making it the largest industrial sector in India (Chandra 2006). Being 2nd largest contributor to the Indian economy, the core textile industry of developing country like India is still very unorganized in managing its resources either in the form of raw material (cotton, jute, silk or wool, etc.), work in process (yarn, rough fabric), finished product (finished fabric) (Chandra 2006) as shown in Fig. 2.

The implementation of SCPM needs to integrate the processes of sourcing (procurement) to manufacturing (production) and to distribution across the supply chain (Beamon 1999; Cao et al. 2008). It is found that one of the common problems encountered in managing a textile supply chain is that of synchronization of activities throughout the life cycle of its products (Chandra and Kumar 2000). Few more issues concerning the textile supply chain are poor procurement planning, operational inefficiencies, huge transportation costs and long distribution channels. Management of various activities at different textile companies needs different strategies, and different processes at different stages need separate solutions. For e.g., demand fluctuations and lead time uncertainty create ruckus in the textile supply chain. In order to respond the quick demand of customers, the considerable stocks at appropriate stages of supply chain is required (Chandra 2006). Quality control problems are the biggest obstruction in achieving balanced supply chain and satisfaction of customers (Lam 2006; Moon et al. 2012).

Textile supply chain as shown in Fig. 2 having unique features that justify a separate supervision of its supply chain (Charkha and Jaju 2016). Some prominent features mentioned below:

1. Process industry
2. Long fragmented and complex supply chain
3. Multiple intermediate procurement stages
4. Complex production processes
5. Long distribution channels.

We conclude that the configuration of textile supply chain involves various complexities. If we try to model and optimize various divisions of textile supply chain at the same time, it will be very difficult to capture every aspect and strategy used at various process divisions. Solution to this is to find the specific problem, execute "what-if analysis" and eliminate bottlenecks considering the impact of that problem on entire textile supply chain. There are various research areas in textile supply chain which need special considerations to solve such bottlenecks. These areas are supply chain integration, supply chain coordination, supply chain performance measurement, waste management etc. The effectiveness of textile supply chain can only be achieved by integrating the supply chain decisions to supply chain strategy. Important building blocks of textile supply chain management are production operations strategy, distribution strategy, procurement strategy, and customer service strategy (Saaty and Keams 1985; Sharma and Bhagwat 2007).

It is very important that, supply chain strategy must be aligned to business strategy (Saaty and Keams 1985). Hence, we propose to relate the textile supply chain strategy to strategic performance measurement tool (i.e. balanced scorecard), and we categorized this relationship as strategic performance measurement of textile supply chain. It is found that most research topic in textile supply chain is supplier selection and evaluation, whereas, topics like supply chain performance measurement, supply chain quality management, supply chain risk management, supply chain flexibility etc. were less focused.

4 Decision Support System Using Balanced Score Card and Analytic Hierarchy Process

The concept of BSC was originated from the research of Kaplan and Nortan (1992). In developing BSC, they put the fact that traditional financial measures are giving very narrow overview of business performance and affecting the future business prospects. With this limitation, they proposed other prospects also to achieve balanced approach (Kumar et al. 2013). The BSC is a tool developed for relating the business activities to the vision and strategy of organizations. BSC meant to monitor organizational performance against strategic goals as it includes four different perspectives. The

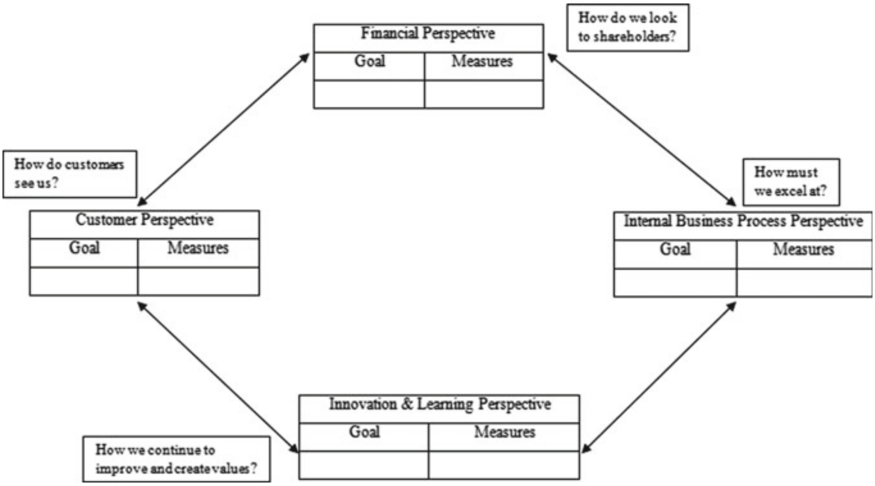

Fig. 3 Balanced scorecard (Kaplan and Nortan 1992)

name of the perspectives reflects the set of measures to envelop all the facets of the organization to maintain a balance of short term and long term goals. The structure of BSC is shown in Fig. 3, it can appropriately be used as an instrument for measuring and analyzing the performance of the supply chain.

It has received enormous attention for application as a multi-dimensional approach to solve organization performance management in various developed countries like USA, UK, Japan, etc. In developing countries like India, few attempts have been observed in the application of the BSC in industries. Varma et al. (2008) used BSC for comparison of multiple petroleum supply chains. Also, Thakkar et al. (2009) applied BSC to small and medium scale enterprises. It identified the importance of implementing the BSC as it would be helpful in understanding the logical weaknesses which is a part of routine work. It facilitates to improve the responsiveness of the supply chain with reduced lead time and enhanced product quality. BSC helps in monitoring the day-to-day activities of procurement, production and distribution of four of its perspectives. Bhagwat and Sharma (2007a) used BSC for supply chain evaluation, where they categorized different metrics under four BSC perspectives. But, still companies in developing countries lack the use of BSC application. The relative importance of different perspective and measures associated in each perspective is a complex task. Hence, in this study, the authors used the BSC perspective and the analytic hierarchy process to evaluate the supply chain performance with the alternative as operation of supply chain network e.g. procurement, production and distribution.

The analytic hierarchy process (AHP) methodology is multi criteria decision making instrument developed by Saaty (1990). The technique presents a procedure for dealing complex problem in a hierarchical manner, where multiple criteria, sub-criteria are involved in making decision. AHP gives a framework to handle with multiple criteria situations, including perceptive, balanced, quantitative and qualitative aspects. The problem represented in a hierarchical way enables the user to describe how changes in priority at upper level have an effect on priority in lower level (Bhagwat et al. 2008; Bhagwat and Sharma 2009; Chan 2003). AHP breaks down a complex problem into smaller parts and facilitates the of various judgment maker using the pair wise comparison for expressing the relative impact and intensity criteria and sub-criteria in the hierarchy (Saaty 1990). These judgments are translated into numbers. Quantification of the subjective judgments were done using pair wise comparison as per Saaty's scale as shown in Table 1. It uses the pair wise comparison among same hierarchy elements in each level. The above stated technique helps managers in the broad area of decision and complex situations. Application of AHP includes supplier selection decisions (Xia et al. 2007, Yadav and Sharma 2015), facility location decisions, and project management decisions. Some of the areas in which AHP is applied performance measurement of supply chain (Turner et al. 2005; Wong and Li 2007), selection of intelligent building system and multi criteria analysis of selection of cranes (Dalalah et al. 2010) etc. AHP has also been used in combination to BSC to align the BSC to the firm's strategy (Bhagwat et al.

Table 1 Saaty's 9 point scale (Saaty and Keams 1985)

Intensity of importance rating	Importance definition explanation	Detailed explanation
1	Equal importance	Two activities contribute equally to the objective
3	Weak importance of one over another	Experience and judgment slightly favor one activity over another
5	Essential or strong importance	Experience and judgment strongly favor one activity over another
7	Demonstrated importance	An activity is strongly favored and its dominance demonstrated in practice
9	Absolute importance	The evidence favoring one activity over another is of the highest possible order of affirmation
2, 4, 6, 8	Intermediate values between the two adjacent judgments	When compromise is needed
Above non-zero	If activity i has one of the above nonzero numbers assigned to it when compared with activity j then j has the reciprocal value when compared with i	

2008; Sardar and Lee 2012; Sharma and Bhagwat 2007). The five stages set as steps in using AHP are as follows (Saaty 1990):

1. Define the problem, determine the objective.
2. Develop the hierarchy from the top (objective of problem) to intermediate level (criteria and sub-criteria) to last lowest level of alternatives.
3. Employing the pair wise comparison matrices for each of hierarchy levels.
4. Estimating the consistency test.
5. Estimate the relative weights of the components of each level.

Few advantages associated with AHP are:

1. Ensures consistency of decision judgments.
2. Fragmenting the complex problem into smaller sub-problems.
3. A comparison can be done by teams or a repetitive process till an agreement is achieved.
4. Sensitivity analysis can be done.

The cumbersome algebra of AHP technique now no remained a problem, as user friendly computerized specialized software such as Expert Choice™ exists. Use of AHP does exist in literature, but not predominantly used for SCM evaluation.

5 Research Case Problem

Most of the studies conducted in area of supply chain performance evaluation have concentrated on supply chain of discrete part manufacturing industries. Process industry supply chains have not received the equal weight age as they require (Shah 2005). The textile industry supply chain is one type of process industry differentiating itself from other supply chains due to its distinguishing features. Apart from characteristics mentioned earlier, textile supply chain has design variations, high risks are involved and ruination of product is among some common issues (Moghaddam et al. 2013; Swaminathan 2007). Other issues like less awareness regarding making the technical textiles Research and Development intensive, rationalizing cost at every process division of supply chain, establishing coordination between textile industry and relevant trade firms to make supply chain more efficient. Another important issue in textile supply chain is integration of intermediate division which not only increasing lead time but also adds to cost (Bedi 2009). Hence, it becomes very important to identify specific performance measurement for textile supply chain. Conventional measure for supply chain evaluation such as cost, return on investment etc., may not be adequate to assess the performance. There are other qualitative performance measures which affect the supply chain performance. Balanced approach needs to be adopted while evaluating the supply chain performance focusing the related intermediate process division of supply chain. Our research proposes to evaluate textile supply chain which can help to identify the list of crucial performance measures. For this, we should identify the right combination of procurement strategy, efficient production strategy, and distribution strategy to deliver to potential markets which are more attractive, fruitful, stable, and suitable for the business success. This will help to evaluate the resources and various strategies which will support the long-term goals of a textile business (Saaty and Keams 1985). All these issues are very important in attaining the satisfaction of all stakeholders keeping strategic perspective in mind. In order to evaluate the performance of supply chain, the objectives of the paper are:

i. To validate the framework designed for assessing the supply chain performance in case companies.
ii. To determine the relative weight of all the perspective (i.e. financial, customer, internal business process, innovation and learning), and also determine the relative weight of all criteria under each of the perspective on the basis of the responses of experts from industry for which case study is conducted.

6 Methodology Used in Developing DSS

In current research study, we proposed a generic model to evaluate the performance of textile supply chain with due consideration to its features and characteristics. As there is no model available which identifies the crucial performance measures and quantify them for textile supply chain? Hence, the selection of appropriate performance measure to assess textile supply chain is an important factor; also the importance level of performance measure is an aspect of concentration. This study has categorized the criteria under each of BSC perspective. In such a situation, AHP has proven its benefits to establish pair wise comparison in order to determine relative importance of performance measure with respect to one another. AHP is also used to establish priorities among the criteria and alternative. The study uses the combination of BSC and AHP techniques. The study identified characteristics of textile industry, and since these are generic issues of textile supply chain, they are aligned to four perspective of BSC and treated as strategic objectives of textile supply chain. As stated earlier, right combination of strategies at procurement, production and distribution process division are important, we have selected these three process division as an alternative to estimate their importance towards overall supply chain performance with respect to criteria and sub-criteria. In order to validate the need of the study, list of performance measures identified, criteria, alternative and the relevance of study as a whole. Expert identified are from industry, academia and consultants working in domain area of supply chain management (SCM), textile industry and operation management (OM) etc., with an average experience of more than 15 years. In all, 15 subject matter experts (SMEs) were contacted, out of which, 13 agreed to interact. 13 experts consist of 6 from textile industry (integrated units) located in central India, 4 are academicians teaching to textile engineering with adequate knowledge of SCM and having management qualification, whereas the last three are consultants and working members of state's textile corporation and textile association of India.

In all, total 3 rounds of interaction were undertaken and results were refined. Structure list of questions were used in each round to understand the philosophy of SCM, performance measurement in textile industry. The questions involve subjective and objective responses as well. Very renowned comparison scale developed by Likert was used to estimate the agreement towards the existence of identified BSC perspectives as criteria, sub-criteria in the framework. The mean values and COV values are calculated for the existences of accepted sub-criteria. Also, reliability of responses measured using Cronbach's alpha. Cronbach's alpha also known as coefficient alpha, is a measure of reliability, specifically internal consistency reliability or item interrelatedness, of a scale or test (e.g., questionnaire). Internal consistency refers to the extent that all items on a scale or test contribute positively towards measuring the same construct. As such, internal consistency reliability is relevant to composite scores (i.e., the sum of all items of the scale or test) Also important to note, reliability pertains to the data, not the scale or test measure. Experts were given choice of suggesting any additional criteria/sub-criteria as shown in Tables 2 and 3. Experts were given a choice of suggesting or adding and additional criteria/sub-criteria.

Finally, out of 53 identified measures, 20 were consented to be the part of framework. Along with 20, 2 new performance measures were added as per expert's suggestion namely "Use of Quality Engineering/Quality Management Techniques" and "Employing Information Technology and Knowledge Management Technologies" abbreviated as "Use of QEQM Techniques" and "Employing IT/KM Technology" respectively.

Final list of performance measures under each perspective criteria is mentioned below, whereas final framework is developed as shown in Fig. 4. This final framework and semi-structured questionnaire is used to undertake case studies in four case companies to be discussed in next section.

In order to estimate the relative importance of criteria, sub-criteria with respect to one another and importance of alternatives with respect to each and every sub-criteria, analytical hierarchy process is used to establish pair wise comparison at every level of hierarchy in the framework.

The sub-criteria responsible for performance measurement under financial perspective:

1. Rate of return on investment (A)
2. Supplier's cost saving initiative (B)
3. Information carrying cost (C)

Table 2 First level BSC perspective consensus as criteria

Sr. no.	BSC perspective as performance criteria	Mean	Coefficient of variation
1	Financial perspective	4.6	0.11
2	Customer perspective	4.4	0.124
3	Internal business process perspective	4.8	0.09
4	Innovation and learning perspective	4.2	0.075

Table 3 Coefficient of variation for second level criteria and Cronbach's alpha for performance constructs

Sr. no.	Performance measurement criteria (BSC perspectives)	Performance sub-criteria	Mean	COV	Cronbach's alpha
1	Financial perspective	Net profit versus productivity ratio	3.4	0.36	0.8253
		Rate of return on investment	4.8	0.093	
		Supplier's cost saving initiatives	4.6	0.108	
		Supplier's rejection rate	3	0.408	
		Information carrying cost	4.2	0.106	
		Inventory carrying cost	4.7	0.092	
		Cost per hour of operation	4.6	0.109	
		Manufacturing cost	4.6	0.111	
		Variation against budget	3	0.333	
2	Customer perspective	Quality of goods delivered	4.6	0.109	0.8497
		Customer satisfaction	4.6	0.111	
		Customer query time	4.2	0.106	
		Delivery performance and lead time	4.8	0.093	
		Quality of delivery documentation	2.8	0.298	
		Range of product and services	2.6	0.295	
		Effectiveness of delivery invoice methods	2.8	0.298	
		Effectiveness of distribution planning schedules	4.6	0.111	
		Level of customer perceived value of product	3.2	0.407	

(continued)

Table 3 (continued)

Sr. no.	Performance measurement criteria (BSC perspectives)	Performance sub-criteria	Mean	COV	Cronbach's alpha
3	Internal business process perspective	Frequency of delivery	3.4	0.335	0.8025
		Capacity utilization	4.8	0.093	
		Planned process cycle time	4.6	0.111	
		Total cash flow time	3.6	0.316	
		Total supply chain cycle time	4.6	0.111	
		Product development cycle time	4.4	0.120	
		Flexibility to meet particular customer needs	4.4	0.120	
		Level of supplier's defect free deliveries	3	0.408	
		Extent of cooperation to improve quality	4.8	0.093	
4	Innovation and learning perspective	Order entry method	2.2	0.280	0.7885
		Delivery reliability	2.6	0.319	
		Accuracy of forecasting	4.8	0.093	
		Range of products/services	2	0.5	
		Supplier's booking procedures	2.4	0.475	
		Buyer-supplier partnership level	4.8	0.093	
		Employee satisfaction and skill orientation	4.8	0.093	
		Supplier assistance in solving technical problems	2.8	0.296	
		Supplier ability to respond to quality problems	3	0.408	
		Use of IT/KM technologies	4.4	0.120	
		Use of QE and QM techniques	4.8	0.093	

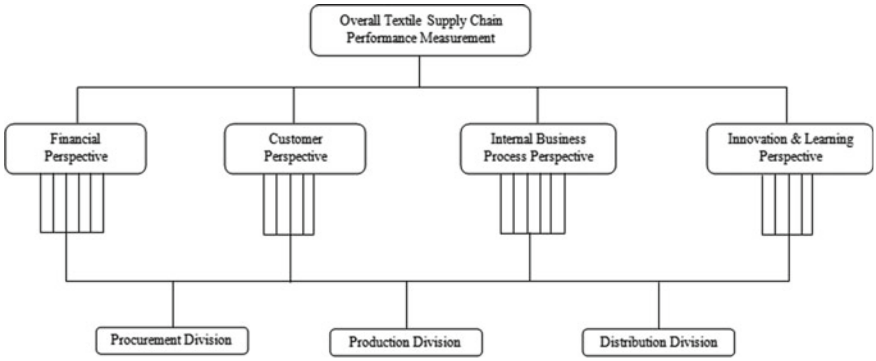

Fig. 4 Hierarchical representation of problem

4. Inventory carrying cost (D)
5. Manufacturing cost (E)
6. Cost per operation hour (F).

The sub-criteria responsible for performance measurement under customer perspective:

1. Quality of goods delivered (G)
2. Delivery performance and lead time (H)
3. Customer satisfaction (I)
4. Effectiveness of distribution planning schedules (J)
5. Customer query time (K).

The sub-criteria responsible for performance measurement under internal business process perspective:

1. Flexibility to meet particular customer needs (L)
2. Total supply chain cycle time (M)
3. Product development cycle time (N)
4. Capacity utilization (O)
5. Planned process cycle time (P)
6. The extent of cooperation to improve the quality (Q).

The sub-criteria responsible for performance measurement under innovation and learning perspective:

1. Buyer-supplier partnership level (R)
2. Accuracy of forecasting (S)
3. Employing IT and KM technologies (T)
4. Use of QE and/or QM concepts (U)
5. Employee skill orientation and satisfaction (V).

7 Case Study

The important objective of the study is to explore the supply chain performance measurement activities/practices in textile industry in India. Few issues that were under consideration during the study are How textile industry operates with SCM?, What functional processes they adopted?, What are the ways they measures the performance of their functions, processes and SCM as whole?, and most important Which performance measures and metrics, they used to evaluate supply chain performance?. These were the number of questions and sub-questions through which nature of the textile industry with respect to supply chain performance measurement studied. The study comprised of interviews with industry respondents using semi-structured- questionnaire. Interviews were considered the most appropriate approach to provide answers to the research question (Chan 2003). Case companies are identified keeping following factors in mind:

1. Standing of more than 25 years
2. Having integrated textile solution in single unit (Ginning-Spinning-Weaving-Processing)
3. Having more than 2000 employees approximately
4. Having implemented technology management concepts such as ISO, TQM and information technology enabled services like ERP etc.

Case companies are based in state located in central India with rich base of cotton suppliers as raw material. The case companies are producing finished fabric (ready to stitch) for garment manufacturing. In all, 10 industries were contacted, out of which, 4 have consented to be the participant for research study. Profile of the case companies are as follows:

1. First company is leading brand manufacturer of textile fabric and fashion garment. Firm is having around 55–60% market share for suiting in India. Firm is having distribution network of approximately 3000 retail outlets in India. Firm exports products to more than 50 countries like US, Canada, Europe, Japan etc. Firm has implemented various process improvement and technology management concepts. The company has more than 3000 employees. Use of computers, IT and IT enabled software systems such as ERP are very predominantly used in the day-to-day processes/operation of company. Innovative ideas, product development and implemented technology management/engineering concept such as SCM, TOC Kaizen and KANBAN are strength of the company.
2. Second company is having an integrated textile solution facility. Industry is ISO 9001:2008 certified. Firm has got numerous awards for its export performance and quality system. Firm produces more than 1 million meter per month of fabric with more 2500 employees working. Exports to more than 30 countries including Italy, Egypt, and Morocco etc.
3. Third company is an ISO certified and among the oldest spinning and weaving company in India. Firm is one of the leading player in fabric development due

to its continuous improvement in technology and research and development philosophy. Exports to more than 20 countries and has popular international and domestic brands as its clients.

4. Fourth company is medium scale company with almost 30 years standing. It is leading exporter of yarn and fabric. Company is first in having 100% viscose open ended plant. Also ISO certified and employing over 2000 employees.

Names of the companies are kept anonymous as per their condition of confidentiality. After this, we identified the industry personnel as respondents with whom we can undergo interview process. The industry respondents have been identified based on the following parameters:

i. Having 20 years of experience in textile industry,
ii. Adequate knowledge of operation management and supply chain management.

Respondents were identified from almost all departments of industry for e.g. procurement/commercial department, production department, quality control and distribution department.

In order to address issues/questions from all three decision making level within the department, two selected one person at manager level, one at Asst. manager level and one from executive officer. Similarly, 3 respondents from each of production shop (spinning-weaving-combing-extrusion-finishing) 3 from distribution department, 1 from quality control and one representative of Top Management level from each company. In all, total 92 person respondents were identified for conducting interview. Out of 92, total 77 interviews were completed. 15 interviews were left incomplete due to exigencies of the official and time constraint involved in interactions.

The medium of interaction with experts was one-to-one interaction with semi-structured questionnaire finalized after conducting pilot interviews with subject matter experts. The respondents from case companies were asked about the process of supply chain management and supply chain performance measurement system in the industry. They were asked about the performance measures in use to evaluate the performance textile supply chain. Finally, they were asked to give the relative priorities to various criteria, sub-criteria and alternative with respect to criteria and sub-criteria as per the Saaty's scale.

8 Data Analysis

The criteria, sub-criteria and alternative chosen to structure a framework as shown in Fig. 4 were assessed for its relative importance at each hierarchical level. In order to arrive at a single figure for relative importance from the respondents of four case companies, geometric mean was taken (Saaty 1990). The response chosen were found to be reliable as the consistency ratio were observed to be less than 0.1 for all of the comparison. Expert choice software was used to check the consistency. Priorities among criteria, sub-criteria and relative importance of alternative are shown from

Table 4 Weights of 4 BSC's perspective after pair wise comparison

Sr. no.	Criteria	Weights
1	Financial perspective	0.229
2	Customer perspective	0.183
3	Internal business process perspective	0.483
4	Innovation and learning perspective	0.105
λmax. = 4.25	CI = 0.0843	CR = 0.0947

Table 5 Pair wise comparison of sub-criteria under financial perspective

Sr. no.	Criteria	Weights
1	Rate of return on investment	0.226
2	Supplier's cost saving initiative	0.113
3	Information carrying cost	0.163
4	Inventory carrying cost	0.126
5	Manufacturing cost	0.254
6	Cost per operation hour	0.119
λmax. = 6.4	CI = 0.08	CR = 0.064

Table 6 Pair wise comparison of sub-criteria under customer perspective

Sr. no.	Criteria	Weights
1	Quality of delivered goods	0.262
2	Delivery performance and lead time	0.191
3	Customer satisfaction	0.204
4	Effectiveness of distribution planning schedule	0.216
5	Customer query time	0.128
λmax. = 5.19	CI = 0.05	CR = 0.05

Tables 4, 5, 6, 7, 8, 9 and 10. While interaction, respondents were asked to give relative ratings to elements at every hierarchical level with respect to its higher level in the framework as objective, for e.g. for first level of criteria respondents were asked to compare the relatively with respect to overall supply chain performance as goal. Similarly relative priorities among second level sub-criteria are established realizing their importance level within their respective criteria and with respect to overall supply chain performance as a goal. At last, third level alternatives were pair wise compared for knowing their contribution level with respect to each and every criteria as well sub-criteria towards overall supply chain performance as objective. There are in all total 22 sub-criteria from A to V as mentioned earlier in Sect. 6.

We also compared the functional processes/cyclic divisions of the supply chain with respect to different perspectives criteria. Their weights are shown in Table 9.

Table 7 Pair wise comparison of sub-criteria under internal business process perspective

Sr. no.	Criteria	Weights
1	Flexibility to meet particular customer needs	0.169
2	Total supply chain cycle time	0.104
3	Product development cycle time	0.14
4	Capacity utilization	0.143
5	Planned process cycle time	0.248
6	Extent of cooperation to improve quality	0.197
λmax. = 6.053	CI = 0.108	CR = 0.009

Table 8 Pair wise comparison of sub-criteria under innovation and learning perspective

Sr. no.	Criteria	Weights
1	Buyer-supplier partnership level	0.28
2	Accuracy of forecasting	0.308
3	Employing IT and KM technologies	0.101
4	Use of QE and QM techniques	0.184
5	Employee satisfaction and skill orientation	0.128
λmax. = 4.25	CI = 0.0843	CR = 0.0947

Table 9 Priorities with respect to performance at 4 BSC's perspectives

Sr. no.	Alternative (functional processes)	Financial perspectives	Customer perspective	Internal business process perspective	Innovation and learning perspective
1	Procurement division	0.279	0.119	0.165	0.285
2	Production division	0.524	0.668	0.522	0.498
3	Distribution division	0.197	0.213	0.313	0.217
Max. eigen value (λmax)		3.064	3.004	3.014	3.0019
Consistency index		0.0035	0.002	0.005	0.009
Consistency ratio		0.068	0.0384	0.096	0.017

Table 10 Priorities with respect to different SCM performance sub-measures at four perspectives of BSC at level 3

Sr. no.	Functional process of SCM	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V
1	Procurement	0.157	0.638	0.405	0.405	0.205	0.197	0.193	0.333	0.263	0.217	0.126	0.203	0.382	0.279	0.173	0.396	0.22	0.626	0.54	0.388	0.22	0.269
2	Production	0.5594	0.105	0.328	0.329	0.618	0.524	0.553	0.354	0.474	0.285	0.425	0.608	0.35	0.524	0.595	0.391	0.578	0.243	0.163	0.444	0.578	0.499
3	Distribution	0.249	0.257	0.267	0.266	0.177	0.279	0.253	0.313	0.29	0.498	0.449	0.189	0.267	0.197	0.228	0.214	0.202	0.131	0.296	0.169	0.202	0.232
Max. eigen value (λmax)		3.35	3.05	3.82	3.84	3.008	3.0053	3.0086	3.078	3.019	3.0199	3.0269	3.0299	3.016	3.04	3.0193	3.047	3.022	3.13	3.044	3.0205	3.0216	3.006
Consistency index		0.05	0.02	0.04	0.04	0.0045	0.0025	0.0043	0.0036	0.0083	0.0099	0.013	0.0149	0.08	0.02	0.00963	0.00235	0.011	0.055	0.022	0.0102	0.011	0.03
Consistency ratio		0.086	0.034	0.068	0.068	0.0076	0.0045	0.0075	0.0062	0.014	0.0172	0.0235	0.0257	0.014	0.03	0.0166	0.0406	0.019	0.094	0.037	0.0176	0.0186	0.05

At last level of hierarchy, the alternatives were pair wise compared for each of supply chain performance sub-criteria. In all there are total 22 sub criteria's combination are aggregated as A to V as shown in Table 10.

During synthesizing the results, overall weights and ranking of PPD network is shown in Table 9.

9 Results and Discussion

While interacting with the industry persons, it was observed that, everyone was very interested in knowing the concept of supply chain performance measurement. As we all know, performance measurement in supply chain is used to improve the efficiency and effectiveness of supply chain functions. It is found in some of literature reviewed that the problems of textile supply chain are excessive lead time, lack of proper production planning, inaccuracy of inventory holding system, ignorance about mass customization, high cost of global sourcing, quick response to fashion variation, forecasting errors and application of feasible ERP system setup. It is clear from Table 2, with reference to overall supply chain performance, internal business process perspective (0.483) is most important which yields value in terms of stakeholder and customer satisfaction. Hence perspectives like financial (0.229) and customer (0.183) follows after internal business perspective; whereas textile supply chain seems to be less aware about using innovative techniques and adopting learning skills as this perspective appeared last.

The pair wise comparison executed at second level of hierarchy among the sub-criteria under BSC perspective as shown from Tables 5, 6, 7 and 8. It is found from Table 5, among financial perspective, manufacturing cost (0.254) is most preferred followed by rate of return on investment (0.226) and information carrying cost (0.163). It indicates that cost incurred on converting raw material to finished product, returns on investment and cost associated with sharing information from department to other are most important criteria chronologically. Table 6 reveals that most important criteria under customer perspective are quality of delivered goods (0.262) with efficiency of distribution planning schedule (0.216) leading to customer satisfaction (0.204). It shows that customer satisfaction is achieved by delivering right quantity of material at right place at right time and in good quality condition, which is the only philosophy of SCM. In next BSC perspective's i.e. among Internal business process perspective, pair wise comparison as shown in Table 7, gives us that planned process cycle time (0.248) followed by extent of cooperation to improve quality (0.197) and flexibility to meet particular customer needs (0.169) are most preferred criteria among the internal business process perspective. It is evident that long lead time and cycle time were problem areas in textile supply chain management (Sanders et al. 2011). Also quality enhancement and flexibility to meet customer needs as mentioned above have been frequently cited in literatures. It is evident from Table 5 that, extent of cooperation to improve quality is also important as cooperation and coordination at every stage of SC is utmost important to deliver effectively and efficiently. Among the Innovation and learning perspective, as shown in Table 8, Accuracy of forecasting (0.308) is most preferred criteria followed by Buyer-supplier partnership level (0.28) and Use of QE/QM techniques (0.184). It is apparent for any successful supply chain, coordination among buyer and supplier or supply chain partners is important and for achieving sustainable growth of firm's supply chain. Use of QE/QM technique also gain importance in responses as it requires commitment from all the section of the industry and this measure is introduced for first time in the study.

Similarly, pair wise comparison is executed for third level alternatives with respect to various sub-criteria at higher level keeping the overall supply chain performance as an objective. Column A to V of Table 10 represents criteria from A to F are under financial perspective, G to K are under customer perspective, L to Q under internal business process perspective and R to V are under innovation and learning perspective.

Table 10, shows that, from rate of return on investment (A) aspect, production division (0.594) is more important followed by distribution (0.249). Further, for manufacturing cost and cost per operation hour, production is preferred to be most important followed by distribution. As all these criteria are associated with operational parameters of the industry, hence results are obvious. Among financial perspective, supplier's cost saving initiative (B) has sought attention of procurement division followed by distribution. Whereas, information carrying cost (C) and inventory carrying cost (D) are perceived to be important at procurement followed by production. The issues of textile industries suffering from excessive inventory are of major concern. Hence, planning for acquisition of raw material/replenishment strategy should be designed considering Just-in-time or push-pull production system and waste must be eliminated at regular intervals using appropriate lean manufacturing philosophies (Jadhav et al. 2015a, b).

The value addition to any product is done during its conversion stage. Also, in time receipt of product/service concept has been driving force for most of the discrete manufacturing system (such as Toyota Production System etc.) and same in case of continuous process manufacturing system of textile industry. Same is revealed as quality of goods delivered (G), customer satisfaction (I) have been preferred for production division (0.553, 0.474) and followed by distribution (0.253, 0.29). Whereas, delivery performance and lead time (H) has been preferred by production (0.354) followed by procurement (0.333), which is obvious, because receipt of raw material at procurement division and transfer of same with specific requirement like design, master production schedule (MPS), material requirement planning, manufacturing resource planning etc. ultimately leads to performance of delivery in optimum lead time. On same note, for efficiency of distribution planning schedule (J) and customer query time (K) criteria, distribution division (0.498, 0.449) are preferred as most important followed by production division (0.285, 0.425).

Variation in fashion demands is one of the most important features in textile supply chain. Hence flexibility to meet particular customer (L) has received production division (0.608) as most important followed by procurement (0.203). As we all know, flexibility in providing customer needs is dependent on the quality of raw material we procured at regular time periods and how to adjust production facilities to produce products in jobs, batch or with mass customization as required by customer. For providing production flexibilities, capacity utilization (O) should be at its optimum level with fullest cooperation to improve quality (Q) and least product development cycle time (N). Hence production division (0.524, 0.578) followed by procurement (0.279, 0.22) for product development cycle time and cooperation to improve quality respectively, whereas, production (0.599) followed by distribution (0.228) were important for capacity utilization. Total supply chain cycle time (M) and Planned process cycle time (P), procurement (0.382, 0.396) followed by production (0.35, 0.391) respectively are important with respect to overall supply chain performance. Strategic coordination among SC partners is very important and also among various SC division. As a result of which, for Buyer- Supplier partnership level (R) procurement division perceived as most important followed by production (0.243). As far as accuracy of forecasting (S) is concerned, procurement (0.54) followed by distribution (0.296) perceived to be important. It is apparent that forecasting affects procurement strategy of SC and also impact on distribution strategy when we consider an extended version of supply chain. In case of criteria metrics of Employing IT/KM technologies (T), Use of QE/QM techniques (U) and Employees satisfaction and skill orientation (V), production division strategy perceived as most important followed by procurement division strategy.

With reference to performance at financial perspective, production (0.524) appeared to be most important followed by procurement (0.279). It means from financial aspect, sub-criteria of supply chain performance measurement which is related to procurement strategy and affecting production strategy should be given attention. It can be explained as, in order to have sustainable growth in globalization, SCM should consider procurement and production division not only quantitatively but also qualitatively. Further, it is needed to evolve new qualitative parameters to deploy strategies continuously to improve functions of production division. With respect to Customer perspective, again, production division (0.668) emerges as most important followed by distribution division strategy (0.213). This reveals, strategies related to production and distribution are most important in order to achieve customer satisfaction. The need is to use the responses/queries or to improve our production and distribution facilities and schedules. Also, customer driven aspect should be incorporated in textile SC. Among internal business process perspective, production and distribution division were most prominent driver of supply chain performance as being the part of internal operation such as proper production planning etc. The performance criteria associated with internal business process should also be explored to include more qualitatively evaluating factors.

Similarly from Innovation and Learning perspective, again production followed by procurement division preferred as most important. It is obvious as performance criteria under innovation and learning perspective such as accuracy of forecasting, buyer-supplier partnership level, employing IT/KM affect more on production and procurement. Industries need to deploy feasible ERP system to share and retrieve information effectively. Also use of QE/QM techniques such as QFD, Kanban, Kaizen, etc. should be adopted to improve overall productivity of firms thereby increasing efficiency and effectiveness of supply chain.

Table 11 Priority weights of PPD network with respect to overall performance

Sr. no.	Alternatives	Weights	Ranking
1	Procurement division	0.291	2
2	Production division	0.46	1
3	Distribution division	0.246	3
λmax. = 3.063	CI = 0.031	CR = 0.0601	

As a whole, with respect to overall performance of textile SC and considering BSC perspective, internal business process perspective is most important followed by financial, customer and innovation and learning as shown in Table 4. Considering different strategic process division of SC, production (0.46) emerged as most important followed by procurement (0.291) and then distribution (0.249) as shown in Table 11. In summary, above results explain prioritization of various measures as sub-criteria for supply chain performance measurement with respect to strategic divisions. It is also used to rank different BSC perspective as supply chain performance measurement criteria.

10 Managerial Implication

1. The hierarchical framework in the study presents very concise approach to supply chain managers to monitor their supply chain performance by estimating the relative importance of various criteria, sub-criteria and relative impact on supply chain cyclic operation in Indian textile industry. This can help them in reviewing their focus on areas/perspectives to concentrate enabling improved supply chain performance.
2. The papers proposed to use BSC perspectives, which will help managers to identify and work upon the grey areas contributing to overall performance of an organization. Also, study has considered supply chain cyclic division. It will help managers to identify the roles and responsibility of leader in order the evaluate supply chain performance.
3. This study opens the useful discussion for supply chain managers and practitioners in area of supply chain performance measurement and become novel approach in developing a framework which involves balanced score card perspective as criteria with 22 sub-criteria measures (quantitative and qualitative) along with supply chain cyclic division.
4. The study can be considered as starting point and can be expanded beyond the traditional concept of supply chain performance measurement to real time performance evaluation of supply chain.

11 Conclusion

Supply chain management has major impact on all industries in today's era of globalization. The consequence of adopting specific supply chain performance practices should offer motivation to practitioner/managers to review the situation of an enterprise. An efficient SC depends on its performance. SC configuration varies industry to industry. Process industry like textile needs specific SC. It should also have definite strategy for its different process divisions (Procurement, Production and Distribution). Effect of various SC performance measures is very important and analyzed in this study. Selection of performance measures is done by analyzing the features/characteristics of textile supply chain and validated with subject matter experts. Supply chain performance is problem of multi-criteria decision making. Various performance measures were utilized in earlier studies, most of them consist of financial parameters only. Though, cost has direct relation with profit and also an easy measurement to decide effectiveness of SC. But misconception about measuring supply chain performance using cost and other financial measures only should be avoided. In recent research studies, quality as a measure was strongly preferred for most industry, especially process ones (Varma et al. 2008). Hence, supply chain performance measures in this study are categorized under different BSC perspectives (Financial, Customer, Internal Business Process, and Innovation and Learning) used to find out relative impact on each other and on supply chain's strategic process division. Quantification of these measures has no definite ground, 22 performance measures under 4 BSC perspectives are categorized based on expert's opinion, with 2 new measures (Employing IT/KM technologies and Use of QE/QM techniques) as contribution of this study. Based on perspective as criteria, sub-criteria and alternative for assessing supply chain performance, a hierarchical framework is designed as mentioned in Fig. 4. Further, AHP method is used to prioritize the elements at each level of hierarchy using pair wise comparison. It is emerged after utilizing AHP for SCM evaluation in textile supply chain that important performance perspectives as criteria are internal business process followed by financial, customer and innovation and learning. Also, as far as strategic divisions of supply chain are concerned, production division emerged as most preferred followed by procurement and distribution. The relative importance of 22 criteria is shown in Tables 5, 6, 7 and 8.

This paper also contributes in ways as below:

- Performance evaluation of SCM practices in Indian textile industry. It figured out the key players in the textile supply chain.
- Study provides an insight to use and prioritize BSC perspective (financial, customer, internal business, innovation and learning) as criteria and associated sub-criteria. This enables firms to focus on more important performance criteria and sub-criteria, affecting the supply chain performance.
- Study provides balanced scorecard for SCM evaluation. It helps organizations not only with faster and efficient process monitoring, but also helps in designing proper strategy for procurement, production and distribution divisions.

- It also figured out strategic process division of supply chain, critical to supply chain performance. The study also investigates relative importance of supply chain cyclic division for various criteria and sub-criteria with respect to overall supply chain performance as an objective.

12 Limitation

Limitation to study is that, not large numbers of industries were contacted for collecting responses in form of perception. Accuracy can be achieved by using survey based approach among textile industries. Further the study was restricted to India and can get different results when applied to other country's textile SC keeping methodology same. The framework proposed for textile SCPM is comprehensive in nature, but still the interactive relationship among various criteria is matter of concern. This is little complicated as criteria involved are dissimilar. These interdependencies will be explored further in our next course of work. Also framework could be helpful in dynamic environment on increasing hierarchical levels but by keeping simplicity of framework.

Appendix

See Table 12.

Table 12 Performance measures identified in literature review and categorized as quantitative and qualitative

Sr. no.		Sub-measures	Qualitative	Quantitative	Authors
1	Financial perspective	Net profit versus productivity ratio		◊	Beamon (1999)
2		Rate of ROI		◊	
3		Variation against budget		◊	Chan (2003)
4		Buyer-supplier partnership level	◊		Bhagwat and Sharma 2007a
5		Delivery performance	◊		Gunasekaran et al. (2004)
6		Supplier's cost saving initiative	◊		Moon et al. 2012

(continued)

Table 12 (continued)

Sr. no.		Sub-measures	Qualitative	Quantitative	Authors
7		Delivery reliability	◊		Gunasekaran et al. (2004)
8		Cost per operation hour		◊	Beamon (1999)
9		Information carrying cost		◊	Gopal and Thakkar (2012)
10		supplier rejection rate		◊	Thakkar et al. (2009)
11	Customer perspective	Customer query time		◊	Gunasekaran et al. (2004)
12		Level of customer perceived value of product	◊		Bhagwat and Sharma 2007a
13		Range of products and services	◊		Gunasekaran et al. (2004)
14		Order lead time		◊	Bititci et al. (2005)
15		Flexibility of services systems to meet particular customer needs	◊		
16		Buyer-supplier partnership level	◊		
17		Delivery lead time		◊	Gunasekaran et al. (2004),
18		Delivery performance	◊		
19		Effectiveness of delivery invoice methods	◊		
20		Delivery reliability	◊		
21		Responsiveness to urgent deliveries	◊		Varma et al. (2008)
22		Effectiveness of distribution planning schedules		◊	Gunasekaran et al. (2004), Beamon (1999)

(continued)

Table 12 (continued)

Sr. no.		Sub-measures	Qualitative	Quantitative	Authors
23		Information carrying cost		◊	
24		Quality of delivery documentation	◊		
25		Driver reliability for performance	◊		
26		Quality of delivered goods	◊		Gunasekaran et al. (2004), Gunasekaran and Kobu (2007)
27		Achievement of defect free deliveries		◊	
28	Internal business process	Total supply chain cycle time		◊	
29		Total cash flow time		◊	
30		Flexibility of service systems to meet particular customer needs	◊		Gunasekaran and Kobu (2007)
31		Supplier lead time against industry norms			Vommi (2016), Turner et al. (2005)
32		Level of supplier's defect free deliveries	◊		
33		Accuracy of forecasting techniques	◊		
34		Product development cycle time		◊	Teng and Jaramillo (2005)
35		Purchase order cycle time		◊	Lam (2006)
36		Planned process cycle time		◊	
37		Effectiveness of master production schedule	◊		Gunasekaran and Kobu (2007)

(continued)

Table 12 (continued)

Sr. no.		Sub-measures	Qualitative	Quantitative	Authors
38		Capacity utilization	◊		
39		Total inventory cost		◊	
40		Supplier rejection rate		◊	
41		Efficiency of purchase order cycle time	◊		
42		Frequency of delivery		◊	
43	Innovation and learning	Supplier's assistance in solving technical problems	◊		Thakkar et al. (2009), Bhagwat and Sharma 2007a
44		Supplier's ability to respond to quality problems	◊		
45		Supplier cost saving initiatives	◊		Shah (2005)
46		Capacity utilization	◊		Shah (2005)
47		Order entry methods	◊		
48		Accuracy of forecasting techniques	◊		Gunasekaran et al. (2001), Gunasekaran and Kobu (2007), Gunasekaran et al. (2004), Chan (2003), Cao et al. (2008)
49		Product development cycle time		◊	
50		Buyer-supplier partnership level	◊		
51		Range of products and services	◊		
52		Level of customer perceived value of product		◊	
		Flexibility of service systems to meet particular customer needs	◊		

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A Review Study of Condition Monitoring and Maintenance Approaches for Diagnosis Corrosive Sulphur Deposition in Oil-Filled Electrical Transformers

Ramsey Jadim, Anders Ingwald and Basim Al-Najjar

Abstract In recent years, many unplanned hazard failures of oil-filled electrical transformers have been reported due to presence of corrosion in form of semi-conductor Copper Sulphide (Cu_2S) which result in formation Corrosive Sulphur Deposition (CSD) on the significant internal components. Formation of CSD leads to a continuous current path lead to overheating fault and deterioration of insulation system which can turn towards transformer failure. The purpose of this study is to establish an efficient maintenance plan of corrosion based on relevant Condition Monitoring (CM) to reduce the transformer failures. In this paper, many investigations have been reviewed to get sufficient data to understand and describe currently applied CM for diagnose the corrosion inside the transformers. The problem addressed is: is the currently applied CM relevant for early and definitely detection of the corrosion to reduce the probability of failures? The major result is the described gaps between the currently applied CM and selection of relevant CM suggested for providing definitely indication of corrosion. The currently CM implies two techniques; oil analysis based only on evaluation the quality of the oil against corrosion and electrical testing based on the variation of electrical properties of the transformer which can be occurred due to corrosion process as well as other faults. Conclusion of this review is a need to develop a relevant CM of corrosion for establishing a dynamic cost-effective Condition Based Maintenance (CBM) to prevent unplanned hazard failures at early stage which can reduce the negative impacts such as industries economic loss and hazard effect on manpower life as well as environment.

Keywords CBM · Corrosive Sulphur · CM · CSD · DBDS · Transformer failure

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S. Patnaik (ed.), *New Paradigm of Industry 4.0*, Studies in Big Data 64,
https://doi.org/10.1007/978-3-030-25778-1_6

1 Introduction

Each electrical transformer is considered as a critical equipment whose protection process is more priority and important for modern societies where continuous electric power is required for the fundamental aspects of social activities (Chiaradonna et al. 2016).

Corrosion fault in oil-filled transformers has been considered as a global problem due to increasing trend of the unplanned hazard failures attributed to corrosion in form of Copper Sulphide (Cu_2S) which result in formation Corrosive Sulphur Deposition (CSD) (Smith and Sen 2010; Holt et al. 2013). The main consequence of formation CSD is reducing the dielectric properties of the insulation system in the transformers due to the semi-conducting nature of Cu_2S (Daisy et al. 2014; Matejkova et al. 2017). Alteration of these dielectric properties can lead to arcing phenomena through the oil (Lewand and Griffin 2006). The failure of oil-filled transformer and relatively incidence of fire and explosion has been increased recently in power substations (Allan 2001).

The reaction mechanisms of corrosion process introduced by Akshatha et al. (2011, 2015), Amaro et al. (2013b), Lewand and Reed (2008), Gao et al. (2019), Ren et al. (2009), Toyama et al. (2009) that the Sulphur compounds which are originally present in the most of insulating oil react with Cu ions of copper conductors and winding to form Copper Sulphide deposits (Cu_2S) companion with hydrocarbon compounds as by-products of the reaction. Study of these mechanisms showed that there is a lack of reaction mechanism which can identified relevant by-products of corrosion rather than the hydrocarbon.

Studies of Akshatha et al. (2012a), Amaro et al. (2013a, b), Smith and Sen (2010), Scatiggio et al. (2009), Ren et al. (2009) introduced two CM techniques oil analysis and electrical testing to diagnose the corrosion process in the transformers. These applied techniques evaluated mainly the quality of the insulating oil against corrosion by determination the quantity of Sulphur compound in the oil whereas the electrical testing measured the variation of electrical properties of the transformers related to corrosion fault. Regardless of using these CM techniques, still a large number of transformer failures are reported because of corrosion problem (Amaro et al. 2013b, p. 144). However, Sulphur compound in the insulating oil is not the only factor can be considered as a source of corrosion, manufacturing components of the transformers such as gaskets and glues may also contain Sulphur in high concentration which can turn the quality of the oil to corrosive during the operation (Smith and Sen 2010).

Because of the lack of relevant CM to detect early the corrosion, the industries turn to use different costly treatment techniques to avoid transformer failure. These techniques are based mainly on process of changing the quality of the oil in-service such as Retro-filling Treatment where corrosive oil is exchanged completely or partially with a new noncorrosive oil or Desulphurization Treatment to remove Sulphur compounds from the oil (Holt et al. 2013; Smith and Sen 2010; Maina et al. 2011). However, removing Sulphur compounds does not necessary mean that corrosion deposits which have already formed on the internal components, will be eradicated (Lewand

and Reed 2008; Wiklund et al. 2007). In addition to these treatment techniques, adding anti-corrosion additive (deactivator or called also passivator) is commonly used to suppress corrosion process where deactivator covers the copper ions in order to prevent corrosion reaction (Haoxi et al. 2018; Smith and Sen 2010; Wiklund et al. 2007; Huang 2012). However, adding the deactivator has undesired impacts due to possibility of gas generation direct after the addition (Maina et al. 2011) and also producing oxidation products when the deactivator amount is exceeded the acceptable limit (Rehman et al. 2016). All these applied treatments can not totally reduce the corrosion process (Cong et al. 2019, p. 4038).

Applying Condition Based Maintenance (CBM) policy based on indication of an upcoming fault early, the failure can be handled cost effectively before its occurrence. Several tasks can be involved in this CBM policy such as identifying failure mechanisms and causes, identifying the deterioration model and determination the costs and effects (Amari et al. 2006). According to Al-Najjar (2007, 2012), the decisions of strategy and policy of cost-effective maintenance can not be accomplished without consideration the relevant CM. These decisions are associated with the failure type and life time of the equipment. Identification of this CM requires conducting an accurate and appropriate technical analysis. The main factor in the setting up benefits strategy in the transformer maintenance policy is the ability to reduce the probability of failures in order to reduce economic loss of expensive breakdowns. Further benefits can be also inferred such as providing better safety for operators and environment (Kwong et al. 2015).

The aim of this study is to describe the currently applied CM techniques of corrosion, their relevance and shortcomings in order to distinguish their applicability and usefulness in the maintenance plan. The problem addressed is: is the currently applied CM relevant for early and definitely detection of the corrosion to reduce the probability of failures? The major result is the described gaps between the currently applied CM and selection of relevant CM suggested for providing definitely indication of corrosion.

2 Literature Survey

Searching in 52 relevant papers results in demonstrating the currently applied of CM techniques, reaction mechanisms and maintenance policy to evaluate the corrosion condition of oil-filled electrical transformers.

2.1 Corrosive Sulphur Problem and Consequence

The semi-conducting nature of Cu_2S deposits is the source of alteration the dielectric properties of the insulating system in the transformers and accordingly thermal fault in the range of 150–300 °C can be generated which is enough to produce saturated

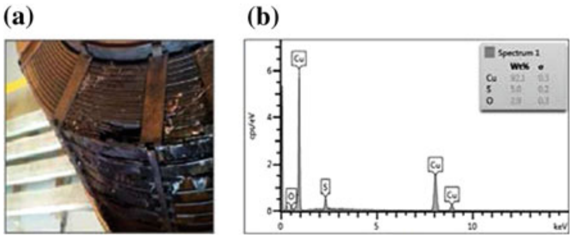

Fig. 1 **a** Melting of transformer HV winding and damage of its insulating paper as a result of arcing fault on the first disk (W phase) due to corrosive deposit. The transformer power rate is 20 MVA and the voltage is 69/13.8 kV. **b** Scanning Electron Microscope (SEM) spectrum of a copper winding sample of the transformer which is exposed to arcing showed presence of corrosive Sulphur. *Source* ARAMCO Company in Saudi Arabia

hydrocarbon gases such hydrogen (H_2) and other fault gases (Papadopoulos and Psomopoulos 2014a). Hydrogen gas is considered as a major fault gas indicator of partial discharge phenomenon and corona between the windings which are usually wrapped with the insulating paper (Akshatha et al. 2012a; Mendler et al. 2011). Overheating due to corrosion problem can lead also to arcing phenomenon where serious damage can be occurred (Lewand and Griffin 2006). Figure 1a is an example of arcing fault due to corrosion problem. Corrosive test (CCD) showed that the oil type Nynas, Nitro 10 GBN, was corrosive. Inspection of the fault site confirmed that the corrosion was visibly located where the arcing fault occurred. Deposits of corrosive Sulphur on copper winding or insulating paper can be tested by using Scanning Electron Microscope (SEM) (Zhao et al. 2016). A sample part of the coper winding was tested by SEM and showed clearly the corrosive Sulphur deposition, see Fig. 1b.

3 Currently Applied CM Techniques

3.1 Oil Analysis Technique

Investigations of Akshatha et al. (2012a), Khan et al. (2012), Matejkova et al. (2017), Rehman et al. (2016), Ren et al. (2009), Minhao et al. (2018) showed that the Sulphur compound Dibenzyl Disuphide “DBDS” is the main culprits of corrosion fault in the transformers. Examples of applied oil analysis technique are:

1. Analysis amount of Dibenzyl Disuphide “DBDS” using gas chromatography technique, method IEC 62697-1. It is the major parameter used in the currently CM for evaluation the corrosion condition (Akshatha et al. 2011; Mitchinson et al. 2011).
2. Analysis amount of Mercaptain “RSH” (R is hydrocarbons) using potentiometric titration method ASTM D3227 (Akshatha et al. 2012b).

3. Analysis amount of Sulphur “S-element” using X-ray fluorescence spectroscopy technique method ISO14596 (Akshatha et al. 2011; Amaro et al. 2015; Holt et al. 2013).
4. Corrosive Sulphur “Covered Conductor Deposit (CCD-test)” is used for evaluation of the oil quality against corrosion according to method IEC 62535 where a copper strip wrapped with paper and immersed in 15 ml of oil sample at 150 °C for 72 h. The result is recorded as noncorrosive or corrosive oil (Amaro et al. 2013b).
5. Dissolved Gas Analysis (DGA) is usually used to evaluate the fault gases in the oil using gas chromatography technique method ASTM D3612-C or IEC 60567 (Akshatha et al. 2012a, b; Papadopoulos and Psomopoulos 2014a, b). Possibility of using DGA test for detection corrosion is stated by Akshatha et al. (2012a, p. 396) that there is an increasing in the concentration of gases carbon monoxide (CO) and Hydrogen (H_2) related to corrosion process.

3.2 Electrical Testing Technique

Electrical testing in general is applied for purpose of detection thermal, mechanical and electrical faults due to overheating operation or electrical short circuit in the winding, core system or other components (Akshatha et al. 2012a, b; Mendler et al. 2011). Examples of applied electrical testing for detection corrosion problem are:

1. Partial Discharge (PD-test) to measure PD phenomenon which is considered as the significant source of the insulation faults as a result of strong electrical stress or overheating (Shuai et al. 2016; Kai-Bo et al. 2013; Rudranna and Rajan 2012; Rajan et al. 2008; Rajan 2009). Studies by Rajan et al. (2008) showed that PD can be occurred more in transformer contains a corrosive insulating oil comparing with noncorrosive.
2. Frequency Domain Spectroscopy (FDS-test) measures the power factor on specific range of frequency. The change in the power factor value can be an indication of presence corrosion due to increase in the conductivity value (Akshatha et al. 2014).
3. Polarization Depolarization Current (PDC-test) measures the differences between polarization and depolarization current using a DC voltage where the variation in the current with time can be an indication of corrosion (Akshatha et al. 2014).
4. Online Corrosive Sulphur Sensor (CSS) is also used for detection the corrosion. CSS provides information about quality of the insulating oil against corrosion during operation using same concept of the laboratory experimental method of corrosive Sulphur CCD-test. The sensor probe is passed in the transformer tank through a valve where the data of corrosion quality of the oil is stored and can be analyzed and evaluated as the oil is corrosive or noncorrosive (Serra et al. 2014).

3.3 Reaction Mechanism of Formation CSD

Reaction mechanism consists of a number of complex steps based on amount of Sulphur compounds in the oil, presence of Cu ions and overheating level (Akshatha et al. 2011, 2015; Amaro et al. 2013b; Lewand and Reed 2008; Ren et al. 2009; Toyama et al. 2009). This mechanism is limited in two concepts: the first concept estimates that the Sulphur compound DBDS, $(C_6H_5)_2CH_2S_2$, undergoes cleavage due to overheating and form Benzyl Mercaptan, C_7H_7SH, which is very active towards Cu ions producing deposition of Copper Sulphide (Cu_2S) companion with the by-product hydrocarbon Ethylbenzene (C_8H_{10}). The second concept uses a different approach for the mechanism that the reaction of DBDS with Cu ions produces a complex DBDS-Cu which is absorbed on the insulating paper first and then decomposes as Cu_2S companion with the by-product hydrocarbon Bibenzyl ($C_{14}H_{14}$).

3.4 Maintenance Approaches

According to the standard EN 13306:2001 Maintenance Terminology, the maintenance is defined as: "*A combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function*".

The modern maintenance policy of transformers takes into account two categories: Condition Based Maintenance (CBM) and Risk Based Maintenance (RBM) (Phadungthin and Haema 2015).

Traditional definition of CBM according to Prajapati et al. (2012) is a maintenance program that recommends actions just when an indication of fluctuating in the asset performances is detected depending on the information collected by CM technique. A study case of CBM of power transformer is introduced by Yadav et al. (2008) where a methodology is adopted for CM and diagnostics of the transformer condition based on factors such as gathering historical records, carrying out oil analysis and electrical testing, evaluating of the data and finding the solutions.

According to Suwnansri (2014), RBM is applied by carrying out an integration of two factors: condition statement and importance assessment of a transformer for an effective maintenance procedure. The condition statement factor is assessed and performed by analysis of suitable oil analysis and electrical testing. Whereas the importance assessment factor is concluded from different data such as transformer load percentage, evaluation of stability and effect of the failure on the transformer, social and environment.

Establishing a relevant CM and development a new diagnostic system which efficiently and early can detect the source and site of the damage, results in fewer components failures (Al-Najjar and Alsyouf 2004). However, using only CM output can not be a cost-effective aspect without applying CBM policy as an organization toolbox to prevent early the failures occurrence (Al-Najjar 2012).

4 Result and Discussion

There are numbers of gaps in the currently applied CM techniques need to discuss for purpose of development a relevant CM technique of corrosion to approach a dynamic cost-effective CBM.

4.1 Gap in Implementation Relevant Oil Analysis

All related studies have focused mainly on importantly of analysis Sulphur compounds amount in the CM technique to evaluate the corrosion based on the currently reaction mechanisms. According to these mechanisms, DBDS in the insulating oil can provide information about corrosion process only when Cu ions presence at high temperature. The experimental work carried out by Smith and Sen (2010), Maina et al. (2011), Mitchinson et al. (2011) indicated that the Sulphur compounds in the oil in-service can be depleted completely though the transformer operation due to overheating. Accordingly, detection traces amount of DBDS in the oil in-service may give incorrect indication that oil quality against corrosion is good whereas actually there is a high possibility of already consumption all Sulphur compounds in the corrosion process. There is a lack in the knowledge of the role of Sulphur compounds in the corrosion problem.

4.2 Gap in Implementation Relevant Electrical Testing

Carrying out electrical testing in general required unit de-energizing which is undesirable process due to economic cost, except PD-test which can be applied online on transformer in-service (Rudranna and Rajan 2012). PD phenomenon can not be considered as a specific symptom of corrosion because it can be attributed also to other factors such as oxidation deposits, electrical stress and thermal fault (Kumar et al. 2014; Stone 2005). The other electrical testing FDS and PDC are also not specific indication of corrosion because the change in the power factor and increasing of polarization and depolarization currents can be attributed also to other aspects than corrosion such as moisture content and ageing condition of the insulation system (Akshatha et al. 2011; Saha and Purkait 2004). Evaluation of online CCS sensor is based on presence of Sulphur compounds in the oil. As the Sulphur compounds can be depleted through operation hence there is possibility that CCS sensor provides false indication of corrosion.

4.3 Gap in Relevant Corrosion Reaction Mechanism

The currently two reaction mechanisms show that the by-products after formation the deposit of corrosive Sulphur are mainly two hydrocarbon compounds “ethylbenzene” and “bibenzye”. However, according to Safarik and Strausz (1997) hydrocarbon compounds can be cracked and decomposed at high temperature. Accordingly, these hydrocarbon compounds can not be considered as an indication of corrosion process. There is a lack of relevant reaction mechanism concerning outcome of specific chemical compounds and corrosive gases through formation of corrosive Sulphur deposition.

4.4 Gap in Detection Relevant Gases By-Products

Concentration of gases in the DGA test is usually used for detection type of transformer fault. Thermal conductivity of copper surface of winding can be changed due to the corrosion and accordingly gases in different level can be generated based on strength of thermal fault. In contrast to the study of Akshatha et al. (2012a) which shows that CO and H_2 gases are an indication of corrosion process, the study by Amaro et al. (2013b) demonstrated that there is no specific correlation between these gases, which can also be generated by thermal fault, and formation of corrosion.

4.5 Outline of Capabilities and Shortcomings

Outline of capabilities and shortcomings of the implemented the currently applied CM techniques of corrosion from maintenance perspective is demonstrated in a matrix schedule, see Table 1.

Table 1 Matrix of capabilities and shortcomings in the implemented the currently applied CM techniques

CM technique	Information provided	Detection of CSD	Risk of incorrect decision
Sulphur compounds	Oil quality against corrosion	No	Yes
Corrosion Sulphur test (CCD)	Oil quality against corrosion	No	Yes
DGA test	Indication of fault type	Yes 50%	Yes
Electrical testing	Indication of fault type	Yes 50%	Yes

The CM techniques in the Table 1 such as Sulphur compounds and corrosion Sulphur test (CCD) are relevant for assessment the quality of the insulating oil against the corrosion but these tests can not provide information about formation of corrosive Sulphur deposition (CSD) due to possibility of depletion of Sulphur compounds through the transformer operation. Using this type of information results in a risk of incorrect decision in the maintenance plan.

DGA test and Electrical testing provide information about the type of the fault in general such as thermal or electrical fault without specification of corrosion problem. It can provide 50% indication about presence of corrosion or oxidation deposits. There is also a risk of incorrect decision in the maintenance plan.

5 Conclusion

The first conclusion that can be drawn from this review is that there is clearly a technical inability of the currently applied CM technique in detecting the corrosion in the transformers at early stage therefore the transformers still experience failures. There are also other significant inabilities can be concluded such as lack in the experimental studies of identification the definitely by-products of corrosion process and lack in the knowledge of the role of Sulphur compounds in the corrosion. These inabilities are attributed to incomplete data of corrosion reaction mechanism. Development a relevant CM technique is very important to establish a dynamic cost-effective CBM.

The recommended future scope based on the results of this study can be summarized in the following steps:

1. Development a new concept of the role of DBDS and other Sulphur compounds in the corrosion process as well as establishing a trend plan of Sulphur compounds consumption which can be used effectively in the cost-effective CBM.
2. Development of relevant electrical testing which can be applied online on transformer for detection definitely the corrosion, can be a useful factor in the making correct decision in the maintenance plan.
3. Development a new corrosion reaction mechanism to approach an accurate concept of corrosion process and identify clearly the relevant by-products for purpose of selecting relevant CM technique.
4. Establishing a dynamic cost-effective Condition Based Maintenance (CBM) based on the relevant CM to prevent unplanned hazard failures at early stage which can reduce the negative impacts such as industries economic loss and hazard effect on manpower life as well as environment.

Acknowledgements The authors wish to acknowledge the support of the ARAMCO, Alkhobar, Saudi Arabia and Center for Engineering Research, King Fahd University of Petroleum and Minerals, Dhahran, Saudi Arabia.

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Principal Components Based Multivariate Statistical Process Monitoring of Machining Process Using Machine Vision Approach

Ketaki N. Joshi, Bhushan T. Patil and Hitendra B. Vaishnav

Abstract Statistical process monitoring using control charts is a well-established quality tool for understanding and improving the performance of manufacturing processes over the time. In view of Industry 4.0, industries are looking forward for innovative, automated solutions to process monitoring and control over the traditional approaches. This chapter presents an innovative approach for monitoring the machining process using integration of three well-established techniques to provide a machine vision based multivariate statistical process monitoring technique (MSPM) with dimensionality reduction using principal component analysis (PCA). The approach is demonstrated using a case study of industrial components manufactured on conventional lathe machines. It involves extraction of critical dimensions and surface characteristics using image processing techniques, data dimensionality reduction using PCA, followed by process monitoring using Hotelling T2 multivariate statistical control chart based on principal component scores. The approach has a potential to provide an industry-ready solution to automated, economic and 100% process monitoring.

Keywords Multivariate statistical process monitoring · Machine vision · Principal component analysis · Hotelling T^2 chart

1 Introduction

Process monitoring using control charts is one of the primary statistical tools for quality control as it helps to understand the variations in the process output over the time, establish control limits for process monitoring and identify out-of-control signals for further interpretation, analysis and control to achieve the expected level of process quality. There are two approaches to statistical process monitoringunivariate and multivariate. In the univariate approach a single quality characteristic is plotted on control charts to monitor the process with respect to time. This approach assumes that only one output defines the quality of the process being monitored. However,

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S. Patnaik (ed.), *New Paradigm of Industry 4.0*, Studies in Big Data 64,
https://doi.org/10.1007/978-3-030-25778-1_7

in actual practice, any process will have a number of parameters defining the final output and hence need to be closely monitored and controlled. This is also true for all the machining processes where the components manufactured must have a number of quality parameters in close tolerances for them to perform their intended function. These parameters relate to dimensional and surface quality of the components. Hence in this scenario, if univariate approach is to be implemented, there will be a large number of univariate control charts which need to be monitored independently. This approach has limitations as it reduces the joint probability of variables being within the control limits simultaneously, which is given by $(1 - \alpha)^p$, where p corresponds to number of variables and α corresponds to probability of type-I error for each variable (Montgomery 2009). Furthermore, the equation is not valid if the quality parameters are interrelated, which is generally the case for components manufactured using different machining operations.

Multivariate approach is more appropriate in this scenario, as it can simultaneously plot all interrelated quality characteristics over the time using a single multivariate control chart. Hotelling T^2 chart by Hotelling (1947), Multivariate Exponentially Weighted Moving Average Chart (MEWMA) by Lowry et al. (1992) and Multivariate Cumulative Sum Charts (M-CUSUM) by Crosier (1988) and Pignatiello and Runger (1990) are the most commonly used multivariate control charts. Hotelling T^2 charts are suitable for detecting sudden large deviations whereas MEWMA and M-CUSUM are more sensitive to small shifts in the process mean. These conventional multivariate control charts are effective in simultaneously monitoring a number of quality parameters. However, their effectiveness in detecting the shift is impacted if the number of parameters increases to a large value. Dimensionality reduction techniques are required in this case to improve the monitoring performance (Montgomery 2009). Principal component analysis is one of the most popular methods used for detecting the prominent directions of unique variance in the data. Principal components based multivariate control charts are more effective in monitoring the machining processes as the approach helps in reducing the dimensionality of the data being monitored which in turn improves interpretability of out-of-control signals.

Furthermore, to monitor a number of quality parameters for the machined components, their dimensional features and surface features need to be measured and plotted simultaneously using multivariate control charts. Measurement of all such quality parameters using traditional metrology instruments can prove to be tedious and time consuming and hence limiting its utility for 100% inspection and monitoring, However, with increasing emphasis on quality in order to stand in global competition and to achieve customer delight, it becomes imperative for companies to ensure the quality of every single product coming out from the manufacturing system. In this case, machine vision has a potential to facilitate 100% process monitoring using imaging techniques.

As stated by Woodall and Montgomery (2014) and Vining et al. (2016), image processing techniques are primarily used in quality engineering for inspection and logical extension would be to use it for process monitoring and control.

Machine Vision Systems (MVS) have proven their potential in inspecting various aspects of dimensional and topographical quality. Multivariate Statistical Process

Monitoring (MSPM) is accepted for its suitability in monitoring the processes with their output defined by a number of quality parameters which are interrelated. Principal Component Analysis (PCA) identifies the factors having unique variance from the data having high dimensionality and represents the data in reduced dimensional space. Integration of PCA and MSPM makes the monitoring process more applicable when a number of interrelated quality parameters define the process output, more sensitive to small shifts in the process mean than MSPM alone and helps in physical interpretation of out-of-control signals. Furthermore, the integration of MVS is more advantageous over traditional metrology instruments in case of 100% inspection and monitoring.

In view of the points discussed above, this chapter presents an innovative and effective approach for monitoring the machining processes using an integration of three well established techniques to carry out PC based MSPM using MVS.

2 Related Research Work

Tong et al. (2005) used machine vision along with Hotelling T^2 chart to monitor wafer (IC) production process based on number of defects and clustering indices. Lin and Chiu (2006) proposed the use of Hotelling T^2 chart to detect the regions of small colour variations (MURA defects). Lin (2007a, b) used wavelet transform with Hotelling T^2 control charts to detect ripple defects in SBL chips of ceramic capacitor. Tunák and Linka (2008) used GLCM features such as energy, correlation, homogeneity, cluster shade and cluster prominence on multivariate T^2 charts to detect the occurrence and position of woven defects.

Lyu and Chen (2009) integrated image processing with multivariate statistical control chart for a component having two concentric circles. The diameters of the two circles were extracted using image processing techniques and plotted on T^2, X^2 and MEWMA chart.

Grieco et al. (2017) used machine vision-based univariate and multivariate control charting for monitoring the leather cutting process using deviation area of the entire profile and deviation area for different segments. Pacella et al. (2017) also demonstrated machine vision-based monitoring of lather cutting process using univariate approach based on deviation area of polygonal curve of real profile from baseline and multivariate approach based on vector of discrepancy measures for multiple segments in the profile. In both the cases, multivariate approach provided better results than univariate.

3 Multivariate Statistical Control Charts

In order to monitor the production from a machining process, it is imperative to measure and monitor different dimensions critical to quality and surface finish of the components manufactured over the time. Analysis of every manufactured component using automated inspection and measurement is one of the situations as stated by Montgomery (2009) where there is no rationale for sub grouping the data before plotting and control charts for individual observations are appropriate. Hotelling T^2 charts for individual observations are proposed for monitoring the production from a machining process and detecting any out-of-control scenarios.

3.1 Hotelling T^2 Charts for Individual Observations

Hotelling T^2 charts developed by Hotelling (1947) are the direct analog of univariate Shewhart $\bar{X}$ control charts.

The statistic to be plotted on the chart is as given in Eq. (1):

$$\mathrm{T}^2 = (\mathrm{x} - \bar{\mathrm{x}})' \mathrm{S}^{-1} (\mathrm{x} - \bar{\mathrm{x}}) \tag{1}$$

where x represents quality characteristics vector for each of the m samples, $\bar{\mathrm{x}}$ is quality characteristic mean vector and S is the sample covariance matrix.

Phase-I control charts are used for retrospective analysis, i.e. to check and ensure that the process is in control. Once the in-control observations are obtained, they are used for establishing the control limits for Phase-II. Phase-II control charts are then used for monitoring the future production. The control limits for phase-I and phase-II of Hotelling T^2 chart are as given below:

Phase-I control limits based on Beta distribution as suggested by Tracy et al. (1992) are given in Eqs. (2) and (3):

$$\mathrm{UCL} = \frac{(m-1)^2}{m} \beta_{\alpha, p/2, (m-p-1)/2} \tag{2}$$

$$\mathrm{LCL} = 0 \tag{3}$$

Phase-II control limits based on F-distribution are given in Eqs. (4) and (5):

$$\mathrm{UCL} = \frac{p(m+1)(m-1)}{m^2 - mp} F_{\alpha, p, (m-p)} \tag{4}$$

$$\mathrm{LCL} = 0 \tag{5}$$

4 Data Dimensionality Reduction Using Principal Components Analysis

Exploratory factor analysis invented by Pearson (1901) is the most suitable technique for analysing the patterns of complex and multidimensional relationships in the data having high dimensionality. It is classified into two types: 'Principal Component Analysis' to derive the factors having unique variance with the objective of data reduction and 'Common Factor Analysis' to find the common variance in the data with the objective of identification of latent structure (Hair 2010).

As already discussed, monitoring the production from a machining process involves a number of parameters critical to dimensional and surface quality of the components being manufactured. Reducing the dimensionality of the data being monitored helps in improving the effectiveness of the monitoring process and physical interpretation of out-of-control situations. In the view of this requirement, PCA is more suitable exploratory factor analysis technique as it can help in identifying the principal components having unique variance from the large data.

Principal components are linear combinations of original variables that represent the information contained by them in the new coordinate system with the new axes providing the directions of maximum unique variability in the data.

Principal components can be represented in general as given in Eq. (6):

$$\mathrm{Z_i = c_{i1}x_1 + c_{i2}x_2 + \cdots + c_{ip}x_p} \tag{6}$$

where the constants c_{ij}'s are to be determined using eigenvectors associated with the eigenvalues as given in Eq. (7).

$$\mathrm{C}'\,\Sigma\mathrm{C} = \Lambda \tag{7}$$

where C is the matrix with its columns representing eigenvectors of p quality parameters, Σ is the covariance matrix and Λ is a $p \times p$ diagonal matrix representing eigenvalues.

In order to reduce the dimensionality of the data, generally first few principal components with eigenvalues greater than 1 are used which satisfactorily describe the variation in the original data.

5 Machine Vision Approach for Extraction of Quality Parameters

Machine vision refers to the use of imaging techniques for inspection and quality control. It is based on extraction of features of interest using image processing techniques. A machine vision system typically consists of an image acquisition device (camera), illumination system to enhance the contrast and quality of the images, image processing hardware and software to extract the features from the images.

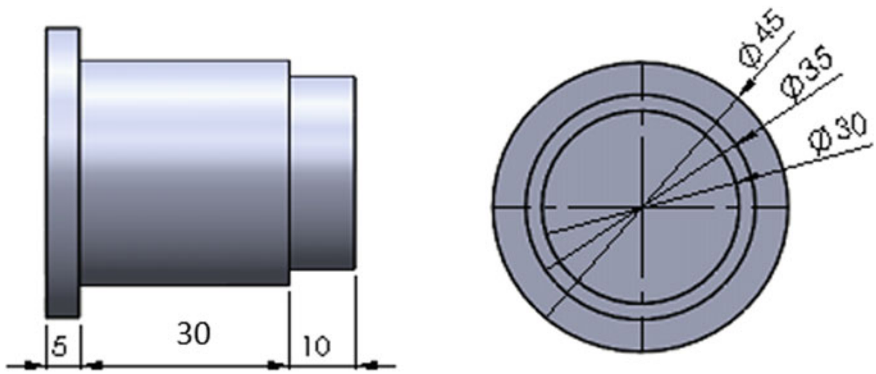
Machine vision is based on various feature extraction techniques, which obtain the relevant information from the original image data by transforming the input data into a set of features. Feature extraction techniques can be broadly classified into three classes: statistical features, transformation and series expansion based features and geometrical and topological features (Kumar and Bhatia 2014).

In order to extract quality parameters of machined components, it is required to capture the images of every component manufactured using camera, acquire and process them using image processing hardware and software to extract different critical dimensions and surface texture features of interest.

6 PC Based MSPM Using MVS: A Case Study

Let us consider the example of components manufactured using step turning operations on lathe machines in order to demonstrate the approach of MVS based process monitoring. The component has three steps as shown in Fig. 1.

The components being manufactured are to be monitored using the approach proposed in this chapter. For extracting features of interest using machine vision, the front view of each component being manufactured is captured using CCD/CMOS camera, the image is then acquired in MATLAB for further processing. Image acquired is pre-processed using conversion from colour to grayscale, adjustment of image intensity, enhancement in contrast followed by conversion into binary image.



All Dimensions in mm

Fig. 1 Details of the components manufactured using step turning operation

6.1 Extraction of Dimensions

Different lengths and diameters of the components are the critical dimensions to be controlled in this case. The important dimensions critical to the quality are different lengths (Len1–5, Len2–30 and Len3–10 mm) and different diameters (Dia1–45, Dia2–35 and Dia3–30 mm). To extract these dimensions from the image, outer edge of the components is extracted using canny edge detection algorithm. This algorithm detects edges by applying Gaussian Filter, calculating intensity gradient using derivative of the filter, applying non-maximum suppression followed by double thresholding, tracking edges by hysteresis to finalize the strong edges in the image (Canny 1987). The straight lines in the image are detected using Hough transform that uses parametric representation of the line given in Eq. (8).

$$\rho = x * \cos(\theta) + y * \sin(\theta) \tag{8}$$

where ρ represents distance of the line from the origin along a vector perpendicular to it, θ represents the angle of the perpendicular projection from origin to the line in degrees measured clockwise from positive x-axis.

Once all the edges are detected from the image of the front view, different lengths and diameters are calculated using their lengths and coordinates of the end points. The values calculated being on the pixel scale are then to be converted into millimetre scale using image calibration.

6.2 Extraction of Surface Texture

Surface texture is also an important quality characteristic to be controlled which can be effectively featured using Grey-level Co-occurrence Matrix (GLCM) based surface texture characteristics. Machine vision can be used to characterize surface texture based on the principal that an image is a two-dimensional image intensity function that characterizes illumination and reflectance for the object under consideration which in turn depends on its surface characteristics (Palani and Natarajan 2011). GLCM is a square matrix with dimensions equal to number of intensity levels in the image and estimates the joint probability $P_{d\theta}(i, j)$ of two pixels a distance d apart along a direction θ having values i and j (Materka and Strzelecki 1998). The distance suggested is 1 and directions can be 0°, 45°, 90° or 135° (Haralick 1979). GLCM features such as contrast, correlation, energy and homogeneity are the most commonly used features for the characterization of surface texture.

To extract surface characteristics of the machined components in the current study, contrast and energy along 0° are calculated from GLCM as given by Eqs. (9) and (10).

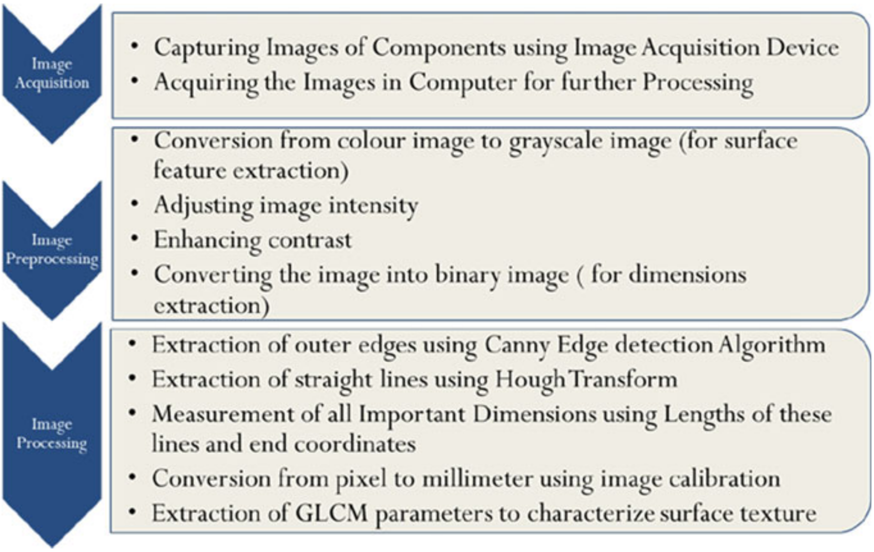


Fig. 2 Methodology for extraction of quality parameters using machine vision

$$\text{Contrast} = \sum_i \sum_j (i-j)^2 P_d(i,j) \tag{9}$$

$$\text{Energy} = \sum_i \sum_j P_d^{\,2}(i,j) \tag{10}$$

In this way, six dimensions and two surface features are to be extracted for every manufactured component.

The methodology discussed above for extracting the dimensions and surface texture values of interest using machine vision approach is as given in Fig. 2.

7 Methodology for PC Based MSPM Using MV

Step 1: Measurement of Quality Parameters using Machine Vision
For every component being manufactured, extract the six quality parameters discussed above using the procedure explained in Fig. 1.

Step 2: Phase-I of Process Monitoring (Retrospective Analysis)

- Select suitable sample size in order to establish control limits for phase-I.
- Carry out principal component analysis using the quality parameter values for the samples examined using step 1.

- Select first few principal components which satisfactorily describe the variation in the data to reduce its dimensionality (generally select eigenvectors having eigenvalues greater than 1).
- Represent original data using principal component scores with reduced dimensionality
- Calculate Hotelling T^2 statistics using this principal components-based data for all the samples.
- Plot the T^2 characteristic on Hotelling T^2 chart along with its control limits for phase-I.
- Remove the outliers and recalculate the control limits when the process is in control, if required.
- Calculate the control limits for phase-II process monitoring.

Step 3: Phase-II Process Monitoring of Future Production

- For every component manufactured thereafter, follow step 1 to extract the quality parameters of interest.
- Represent the parameter values in principal components space using principal component scores.
- Calculate T^2 statistic to be plotted on the control chart and check the value to be within the phase-II control limits.

8 Results and Discussion

For phase-I retrospective analysis, sufficient preliminary sample size is selected for establishing phase-I (say 30). All parameters of interest are extracted using machine vision for these 30 components. Table 1 provides the values of quality parameters extracted using machine vision (Dia1, Dia2, Dia3, Len1, Len2, Len3, Contrast and Energy) for 30 components selected in phase-I analysis.

Principal component analysis is carried out using the data provided in Table 1 and significant principal components are selected for dimensionality reduction. Then the data represented on reduced dimensional space is used to calculate T^2statistic. From the scree plot shown in Fig. 3, it is clear that first three principal components are having Eigen values greater than 1.

Hence first three principal components are selected for reducing the dimensionality of the data which explain 80.397% of the total variance. Table 2 provides the quality parameters data represented on the reduced dimensional scale using three principal components (PC scores: PC1, PC2, PC3) along with T^2 statistic (rounded off up to third digit after the decimal point) for the 30 components selected for phase-I of control chart.

Control limits are calculated for phase-I as follows and the statistic is plotted on Hotelling T^2 chart as shown in Fig. 4.

Table 1 Quality parameter values of components for phase-I analysis

Dia1	Dia2	Dia3	Len1	Len2	Len3	Contr	Energy	Dia1	Dia2	Dia3	Len1	Len2	Len3	Contr	Energy
45.02	35.02	30.02	4.9	30.1	10.1	0.135	0.979	44.98	34.98	29.98	5.1	30	9.9	0.154	0.971
45.01	35.01	30	5	30.1	10	0.155	0.983	45	35	30.01	4.9	30.1	10	0.154	0.971
44.98	34.98	29.99	5.1	30	9.9	0.189	0.978	45.02	35.02	30.02	5	30.1	10	0.154	0.971
44.98	34.98	29.98	5.1	30	9.9	0.155	0.976	45.02	35.02	30.01	4.9	30.1	10	0.119	0.978
45	35	30.01	4.9	30.1	10	0.109	0.987	44.98	34.99	30.02	4.9	30.1	10	0.109	0.987
45.02	35.02	30.02	5.1	30.1	9.9	0.111	0.983	45	35	29.98	5	30.1	10	0.111	0.983
45.01	35.02	30.01	5.1	30	9.9	0.123	0.981	45	35	30.01	4.8	30.1	10.1	0.109	0.987
45	35	30.01	5	30.1	9.9	0.189	0.978	45.02	35.02	30.01	5.1	29.9	10	0.111	0.983
45	35	29.98	4.9	30.1	10	0.189	0.978	45.02	35.02	30.02	4.8	30.1	10.1	0.135	0.979
45	35	30.01	5	30.1	9.9	0.189	0.978	45.01	35.01	30.01	5	30.1	10	0.135	0.979
45.02	35.02	30.01	5.1	29.9	10	0.193	0.977	44.98	34.98	29.99	4.9	30	10.1	0.155	0.983
45	35	30	4.8	30.1	10.2	0.189	0.978	44.98	34.98	29.98	4.8	30.1	10.1	0.189	0.978
45.02	35.02	30.02	4.8	30.1	10.1	0.189	0.978	45	35	30.01	5	30	10	0.155	0.976
45.01	35.01	30.01	4.9	30.1	10	0.194	0.978	45.02	35.02	30.02	4.9	30	10	0.109	0.987
44.98	34.98	29.99	5	30	9.9	0.185	0.979	45.02	35.02	30.01	5	30	10	0.111	0.983

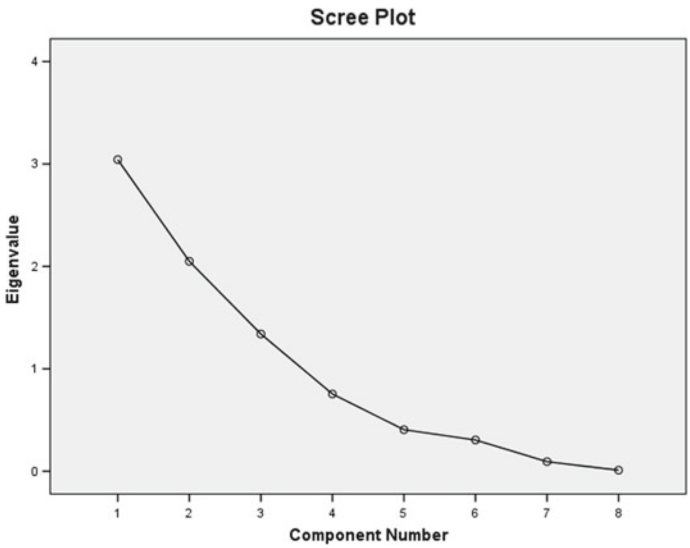


Fig. 3 Scree plot indicating eigen values of extracted principal components

For Phase-I control limits calculations, m stands for number of samples i.e.30, p stands for number of variables which for principal components based Hotelling T^2 chart is the number of significant PC's i.e. 3. Taking 99% confidence interval, the limits are calculated as follows in Eqs. (11) and (12):

$$\begin{aligned}\text{UCL} &= \frac{(m-1)^2}{m}\beta_{\alpha,p/2,(m-p-1)/2} \\ &= \frac{(30-1)^2}{30}\beta_{1-0.01/2,3/2,(30-3-1)/2} = 10.77279\end{aligned} \tag{11}$$

$$\text{LCL} = 0 \tag{12}$$

As it can be seen from the T^2 chart, all the plotted points are well within the control limits. Thus phase-II control limits are then established for monitoring the future production as given in Eqs. (13) and (14):

$$\begin{aligned}\text{UCL} &= \frac{p(m+1)(m-1)}{m^2-mp}F_{\alpha,p,(m-p)} \\ &= \frac{3(30+1)(30-1)}{30^2-30*3}F_{0.01,3,(30-3)} = 15.319\end{aligned} \tag{13}$$

$$\text{LCL} = 0 \tag{14}$$

Table 2 Data reconstructed on reduced dimensional space and T^2 statistics

Comp#	PC1	PC2	PC3	T^2 Statistics	Comp#	PC1	PC2	PC3	T^2 Statistics
1	0.018	0.017	0.015	2.093	16	−0.023	−0.023	−0.022	4.865
2	0.002	0.003	0.002	0.068	17	0.002	0.000	−0.001	1.747
3	−0.022	−0.022	−0.020	3.737	18	0.020	0.019	0.012	4.149
4	−0.024	−0.024	−0.022	4.330	19	0.015	0.014	0.012	1.036
5	−0.003	−0.002	0.002	3.433	20	−0.011	−0.010	−0.003	4.871
6	0.017	0.018	0.013	2.915	21	−0.011	−0.010	−0.006	1.656
7	0.010	0.011	0.007	3.012	22	−0.003	−0.002	0.004	5.217
8	−0.001	−0.002	−0.003	0.772	23	0.014	0.015	0.011	4.449
9	−0.011	−0.012	−0.010	1.539	24	0.017	0.017	0.015	2.929
10	−0.001	−0.002	−0.003	0.772	25	0.007	0.007	0.006	0.225
11	0.014	0.014	0.007	4.146	26	−0.023	−0.023	−0.016	3.358
12	−0.004	−0.005	−0.002	4.697	27	−0.026	−0.027	−0.019	5.893
13	0.017	0.015	0.013	4.368	28	0.000	0.000	−0.002	0.489
14	0.006	0.005	0.003	1.643	29	0.015	0.016	0.015	3.607
15	−0.023	−0.023	−0.020	2.940	30	0.013	0.014	0.012	2.044

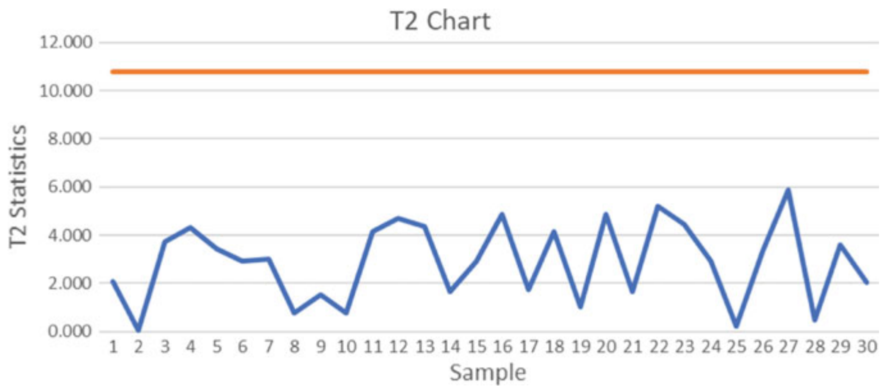


Fig. 4 Hotelling T^2 chart for phase-I

To demonstrate the effectiveness of the proposed method for alarming out-of-control signals, continuing the monitoring process in phase-II, let us consider that 35th component manufactured using the turning operation has its dimensions largely deviated from the mean values. Table 3 provides the values of quality parameters extracted using machine vision for components monitored in phase-II of control chart, along with their representation on reduced dimensional space (PC scores for first three principal components) and T^2 statistic values computed based on PC scores. Then the T^2 statistic is plotted on control chart as shown in Fig. 5.

T^2 statistic for the 35th component shoots up alarming sudden deviation in the parameter values as indicated in the Hotelling T^2 chart in Fig. 5. Hence it is evident that principal components based multivariate control chart plotted using quality parameter values of turned components extracted using machine vision is suitable for monitoring the production effectively and can be used as an efficient tool in statistical quality monitoring and control.

9 Conclusion

Principal components based multivariate statistical process monitoring of industrial components manufactured using step turning operation based on machine vision approach demonstrated in this chapter is advantageous over the use of metrology instruments and univariate control charts. Machine vision provides an effective, automated, non-contact type of measurement system to extract the details of all the parameters defining quality of production. Multivariate statistical process monitoring provides an effective way of simultaneously monitoring the quality parameters of interest using a single Hotelling T^2 control chart. Dimensionality reduction based on PCA allows representation of the data to be plotted on control chart using Principal Components that describe the directions of unique variances in the data. PC

Table 3 Parameter Values, reconstructed data on reduced dimensional space and T^2 statistics for phase-II observations

Comp#	Dia1	Dia2	Dia3	Len1	Len2	Len3	Contrast	Energy	PC1	PC2	PC3	T^2 statistics
31	45.01	35.01	30.01	4.9	30.1	10	0.194	0.978	0.006	0.005	0.003	1.643
32	45.02	35.02	30.02	4.9	30.1	10	0.154	0.971	0.020	0.018	0.013	4.116
33	45.02	35.02	30.01	4.9	30.1	10	0.119	0.978	0.015	0.014	0.012	1.036
34	45.02	35.02	30.02	4.8	30.1	10.1	0.189	0.978	0.017	0.015	0.013	4.368
35	45.04	35.05	30.05	5.1	30.2	10.2	0.194	0.978	0.047	0.045	0.035	13.638

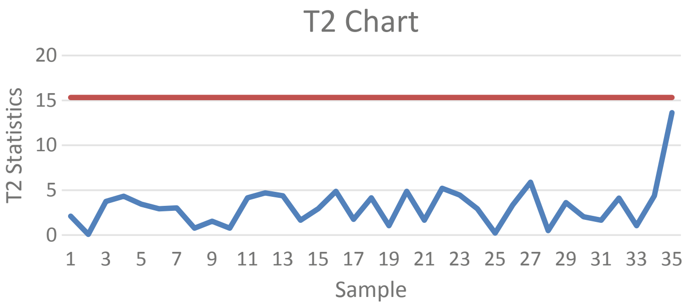


Fig. 5 Hotelling T^2 chart for phase II process monitoring

based Multivariate control charting helps in effective monitoring and analysis of out-of-signals.

The approach of Integration of Machine vision with Principal Component Analysis and Multivariate Statistical Process Monitoring, presented in this chapter has a potential of providing an automated, 100% multivariate statistical process monitoring solution to the manufacturing industry.

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Green IS—Exploring Environmental Sensitive IS Through the Lens of Enterprise Architecture

Somnath Debnath

Abstract For IS domain to support environmental sustainability in firms, it needs to evolve capabilities beyond the traditional IS and respond to the challenges that green*ing* IS (process) would lead to like complexity of integrating environmental sensitivity and plurality of views in designing processes or improving the existing ones, not to mention, the emergent nature of interactions that implementing any form of green IS (outcome) would bring in. Other than fulfilling the automation needs that IS/IT is anyway tasked with, green IS is also expected to seamlessly connect the participating IS/IT elements together in supporting the organizational enactment of sustainability goals. To explore the overlapping issues intertwined with such enactments and to study the environmental *avatar* of IS sub-elements, Zachman Framework from Enterprise Architecture domain has been leveraged in here as the meta-architecture to reflect on how green IS would interact with the organizational information space and shape it. Findings from the chapter are expected to bring coherence to the multiplicity of views associated with green IS in general and in enriching the field of IS scholarship.

Keywords Green IS · Sustainability · Enterprise architecture · Organizational information space · Information field

1 Introduction

Sustainability orientations in firms is about steering organizational strategy and action towards embracing social and environmental considerations, externalized otherwise. This view is challenging, forcing firms to rethink about operations, services, products and processes, and improve these in ways that are environmentally caring and socially inclusive, redefining the role of information systems and technology (IS/IT) as an enabler to the change process beyond traditional paradigm. Advances in IS/IT

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S. Patnaik (ed.), *New Paradigm of Industry 4.0*, Studies in Big Data 64,
https://doi.org/10.1007/978-3-030-25778-1_8

supporting the firms' narratives of sustainability beyond economics have remained fragmented in literature and promoted specific ideas like improving energy efficiency of IS/IT landscape, harnessing IS advances to improve specific business areas like supply chain management (SCM), greening manufacturing and execution system, and in industries like construction, tourism, and aviation, as if the challenges somehow reflect to the uniqueness of the business functions and/or industries. At the same time, changes in firms' behavior due to improved sustainability outlook is an ongoing area of research, including challenges of greening business functions in isolation, or otherwise. Accordingly, for green IS/IT to generate a lasting impact and support firms in meeting stakeholders' demands beyond business-as-usual, it would mean redefining how technology and automation generates meaningful and improved connectivity with the underlying processes and activities (Hack and Berg 2015).

Green IS is an interdisciplinary area of research that needs to address process-technology-information overlaps and its own role in sustaining environmental proactiveness in firms, including for example by deciphering how IS/IT would support firms' sustainability endeavors, how IS components would exchange information and connect with users and subsystems to initiate a positive change (Chasin 2014), or if adoption of a specific framework would support organizational goals better. So, while exploring how green IS/IT would influence business goals, functions, processes, technology, procedures, and the role of employees is natural, the quest needs to shape these relationships and expands to unravel the uncertainties that the interactions between and within the environmental sensitive version of these entities would lead to and how those challenges would influence organizational information space. Further, for the IS/IT elements and emerging information space to be aligned to the organizational goals, scope, relevance, and quality of information are concerns that merit deeper investigations. These challenges expect IS researchers to go beyond greening individual IS components in isolation, in relating these efforts from an overall system perspective—a *big picture* that can transcend divisional views of IS and highlight how individual subsystems can connect, interact and influence others and the organization information space (super structure), within which the green information fields (formal structures) would operate. Accordingly, the objectives of the study covered in this chapter are:

– Uncover challenges of traditional IS in meeting the sustainability needs of businesses,
– Explore greening efforts of business functions and processes and how they challenge the traditional IS in evolving new information fields, and,
– Conceptualize how green IS (as a field of study) influences and redefines different IS elements and information space (as outcomes).

Other than the interconnectivity of information fields (formal IS structures), exploring multi-dimensionality of the subject that characterize green IS needs a meta-architecture through which the individual IS elements and their interactions could be captured. Accordingly, enterprise architecture (EA) framework has been leveraged as a research frame to bring a systemic perspective in Sect. 3 to explore green IS through the EA detailing of different views. Next section reflects on the current literature where exploring interplay of constituent IS subsystems and their interrelationships are covered. Section 4 presents a theoretical view of green IS as a functioning organization of constituents captured through its architectural detailing. Sections 5 and 6 lays path for future research and summarizes some of the key ideas of this exploratory work. Findings from the study can be leveraged in future IS researches and in relating to the information flow with sustainability thinking in firms.

2 Green IS–IS Supporting Environmental Care in Firms

Within contemporary literature, greening of IS/IT has been explored from diverse perspectives that can be synthesized along the four stages of IS lifecycle—the inception, design and implementation, adoption and benefits (Califf et al. 2012). As this chapter is more about uncovering the interdependency IS has with the greening needs of the firms, including envisioning feasible enactment of greening business functions, processes, and the IS side as well, this will need us to review not only *what* changes, but also *how* the changes would interact beyond the conventional boundaries of information fields (traditional IS structures) to (re)shape organizational information space (detailed in Sect. 2.2). Accordingly, the chapter is concentrated within the inception and design areas of green IS. This has led the review of literature to concentrate on the systemic (and *not* the technological) perspectives of green IS/IT and cross-reference the findings to the sustainability efforts in firms. IS researchers and practitioners can leverage the findings and lessons from the chapter to define suitable design, implementation and adoption paths of green IS.

2.1 Green IS—The Need of a "Big Picture"

Thinkers and academicians globally are aligned to the idea that the ecological challenges of this era are of the worst kind, where changes to the natural systems resulting from human endeavors of modern era are unlike the ones from the previous ages where nature had a larger role to play. The ecological challenges post Industrial Revolution are threatening to permanently alter the nature and its life-sustaining capabilities (Jones and Solomon 2013). So, while businesses have started responding towards the challenges by demonstrating (some) care towards environment, and although the role of IS to contribute towards the cause in general is agreed upon, questions regarding the future role of IS are still in the open, as also the micro-view of sustainability or its feasible and acceptable enactment, which leads to question the manner in which IS may support sustainability in firms, or some form it. This includes for example defining the value new IS would bring in and support corporate sustainability (Hack and Berg 2015; Howard and Lubbe 2012; Lee et al. 2014) or benefits that would accrue to the firms by adopting green IS (Esfahani et al. 2015).

Firms are free to ride the populist wave and improve the energy and carbon footprints of technology landscape that are easy to implement although these reflect the utility view of sustainability. In contrast, a wholesome approach towards sustainability (from IS perspective) would be about developing a IS strategy that firms can leverage to promote sustainability through interlocking of people, processes, technologies, and expertise or skill-sets. This approach would be closer to the deep-green view of sustainability.

Extending the findings from the IS literature, we can generalize that the contribution of IS (green or otherwise) is perceived in its ability to be of strategic value to businesses (Fink 2011) (although debated by scholars as well), which if acceptable, translates to viewing green IS as some sort of a tool or solution that encapsulates environment-laden challenges, and in helping firms evolve ecological responsiveness (Butler 2011). This view posits green IS as an enabler in the transformation process in firms and the role it can play within the strategic and operational information needs, while underplaying the emergent nature of sustainability thinking in firms. For example, Seidal et al. (2013) have explored the functional affordance of green IS by examining how the green design aspects, laden with sustainability thinking, can leverage IS flow to lead to the transformation of processes and in product designs. Although an innovative approach, the use of information artifacts to translate the sustainability themes are guided by the changes aimed at achieving it (means to an end). This approach narrows the otherwise under-defined information space within which IS components (technology, hardware, software, networking, processes, knowledge management) and other sub-systems interact, ignoring the semantic barrier of functions and processes, or acknowledge the need to develop a shared interpretation of new ideas and innovations that would share data and information, continually (re)shape the environment within which the IS elements would be functioning (Curry et al. 2011; Dwyer and Hasan 2012), and the uncertainties that would be an undeniable part of the brave new IS world.

To substantiate the arguments further, cases from literature can be referred to in here that have ideated IS related changes in isolation, for example, implementing advanced computing systems, energy efficient hardware and software, environmentally sensitive software like carbon information system, sustainability metrics, knowledge management system within and across supply chains (Meacham et al. 2013), and other stand-alone solutions without examining the impacts of segregated information on business environment, which explains, at least partially, why green IS has been visualized and purposed as incremental to the traditional IS, where the holy grail for the IS is to develop *environmentally-enhanced software and solutions* (Sarkis et al. 2013). Commercial exploitation of this view includes solutions like energy-efficient hardware and infrastructure, stand-alone sustainability solutions proposed by leading software vendors like SAP and Oracle, add-on sustainability reporting applications for firms to participate in standardized GRI reporting, and other social reporting software packages available in the market (KPMG 2012). In here, readiness of the recipient systems within the firms (manual or automated) to deal with new information, specificity of information generation mechanism, and their ability to drive environmental commitments are assumed, leaving the risks associated with the uncertain interactions and the emergent behavior of change agents uncovered. Emergence here relates to the under-defined nature of interactions that IS and organizational constituents would continuously generate by engaging to (re)define an acceptable version of sustainability (outcome or goals) and a form of enactment that the firm can live with. This leads us to examine the information space of firms, explored next.

2.2 *Organization Information Space and IS Information Fields*

Literature has defined organization information space as a set of concepts and relations among them held by an information system. This has been used to relate to the *physical space* that users use to navigate and retrieve information, as well as the *conceptual space* that describes it as a framework to relate to how knowledge and information is captured, codified, abstracted, and diffused (Tsvetkov 2014). I believe this diffuses physical and logical spaces together to create a blob that signifies neither, undermining their individuality. A better way to look at it would be to view *logical space* as an entity separate than the *physical space*. *Physical space* being bounded and structured, represents the information fields holding physical apparatus of generating and disseminating information to be leveraged by users and processes for the purposes they have been created. One the other hand, *logical space* relates to the conceptual space, where organizational knowledge and information exist and include information fields (physical spaces) as well (Fig. 1). To support the argument further, I leverage the concept of common information space (CIS) proposed by Schmidt and Bannon (1992), one that relates to how IS relies on the maturity of

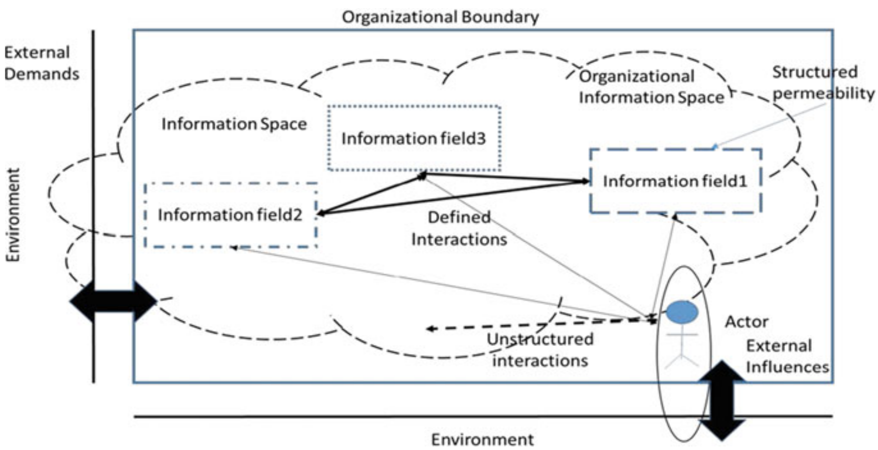

Fig. 1 Organizational information space (conceptualized by author)

processes and uniformity of taxonomy to generate and disseminate information and allow user community to connect with the functional domains, where the usability of information would depend on the maturity of the underlying processes and active involvement of change agents to act based on the contextual background. This view helps to formalize and expand the *logical space*, defined as Organizational Information spaCe (OIC) in here and covers the entire ontological world of semantic activities taking place within the organizational boundary. While this might be a challenge for the traditional IS theories to deal with, OIC allows liberty to define and experiment with evolving nature of knowledge creation and indeterminate state of knowledge objects. Accordingly, OIC relates to the entire knowledge base of the organization and would include (Fig. 1):

– formal (system and process domain based) as well as informal (beliefs and attitudes of employees) knowledge areas,
– structured (knowledge management system) and semi-structured (interaction with external systems) interactions of participating entities,
– characterized by closed (structured and formal) as well as open (adaptable and semi-permeable) information fields (Selvaraj and Fields 2010).

As Fig. 1 relates to, OIC not only holds multiple information fields (information field 1, information field 2, information field 3 …), it allows (structured and unstructured) interactions between entities (within organizational boundary and environment) that would lead to generate new knowledge, improvise old knowledge, and expand boundary of the relevant fields. IS fields constituting a smaller segment of the organizational IS systems (say information field 1), traditionally a formal and closed system, consists of artefacts and objects, interacting in a structured manner (structured permeability) with other entities to produce structured information in a predefined manner for defined purposes.

Upon introducing concepts like 'green' and 'sustainability' within the organizational boundary, organizational systems (like IS, IT, business functions, and goals, to name a few) are expected to generate credible information for the participating entities, processes and change agents, enabling them to consume information produced, and act or react based on the contextual background. Moreover, as the consensus towards micro-view of sustainability and how a firm should be trying to achieve it is far from being settled, differentiated understanding of green objectives and greening processes across domains leads to volatility permeating within the OIC. These complexities hinge on domain-specific characteristics that the participating agencies need to debate on and evolve formal meanings of items under discussion and support formalizing a characterizations beyond what is being communicated. On the other hand, information artefacts supporting and reflecting greening and greenness of processes would carry redundancies, if applied across domains, due to semantic, temporal, and interpretive differences. Accordingly, interactions among the participating entities involving new and under-defined ontologies (subject areas) would introduce dynamism in the formal system of communication, forcing OIC to change, and evolve. The changeovers and interactions in a less formal space are bound to generate new meanings (formal) and interpretations (informal) and would to acquire shape and get formalized within the information fields, challenging status quo of IS fields and expecting legitimacy of new information objects across functions and processes. Moreover, for any organization to develop sustainability capabilities, it would need the support of its human, supply chain, and IT resources to behave in tandem (Dao et al. 2011). Accordingly, in developing environmentally improved capabilities of businesses, and producing non-substitutable, non-imitable, and valuable capabilities, the need for green IS to remain associated with resources and employees is mandatory (Benitez-Amado et al. 2010), including changes needed in the operating IS policies, resources, and skill-sets (Nevo 2010). I however contend that the inherent nature of green IS introduces *concern for environment* as inevitable to the systems thinking, where the changes required within the IS cannot always be separated from the behaviors and interactions of surrounding components and the goals that they contribute to. This contrasts green IS from the traditional IS where the latter deals with static information fields. This contrast leads to a few interesting observations, like:

a. IS in traditional term has covered processes, procedures, hardware, software, and people, and the participating elements (Turban and Volonino 2012), but demand of environmental stewardship in general expands to study the greening of constituting elements as well, like greening of technology, hardware, and networking and other sub-systems (Hedman and Henningsson 2011).
b. We would expect green IS (including IT hereafter, unless referenced specifically) to deal with the challenges that have generally remained outside the purview of the traditional IS, including for example, the ability to work with multiple pro-environment methodologies (like input-output analysis, environmental life cycle analysis, greenhouse gas accounting), environmental aspects (greenhouse gases, wastes, energy sources), and objectives (from undefined goals to numerically defined ones) and so on, although reducing energy needs and carbon footprint of IT infrastructure would only be the first steps in instituting care for environment as a part of IS (Dedrick 2010).
c. Even though IS in general have enabled firms and management to deal with the uncertainties of operating environment effectively (Aral et al. 2012; Mithas et al. 2011), wider impacts of how green IS might adapt to the continuously shifting paradigms of sustainability and its societal enactment are not known which green IS would have to deal with, including its under-defined characteristics and constraints, and systemic pressure of institutional and regulatory frameworks (Gholami et al. 2013). This exclude areas like changing role of employees, internal and external policies of firms, and sphere of information dissemination and the flexibility green IS needs to accommodate changing definitions of information content while remaining open to the feedback, stakeholders' diverse information needs and local norms (for example, emission norms, carbon taxes, and local environmental regulations).

These challenges question not only the greening needs of processes and systems, but also how that might impact organizational IS space, which has remained untangled so far, including finding answers to other W's as well. To appreciate the multidimensionality of green IS beyond the traditional IS and to get a holistic view of participating IS elements, a framework is needed through which the behavior and interaction of all the relevant components can be analyzed, reviewed, and experimented with in a uniform manner. This is where the role of enterprise architecture (EA) and its suitability to examine green IS comes into picture, and is explored next.

3 EA as a Meta-Architecture and Modelling of Green IS

Scholars and experts have supported EA to reflect meanings like structure of the IT systems of an enterprise, or the entire enterprise, or sometimes as an analysis and documentation of this structure rather than the structure itself (Schekkerman 2005; Perks and Beveridge 2007; Bernard 2012). Generalization of EA by Lapalme (2012) details how EA reflects:

(a) the entire enterprise-wide IT platform and components (hardware, software, networking, and so on),
(b) a sociocultural techno-economic system that includes all facets of organizational existence (IT being one of these), and,
(c) to mean enterprise and its environment, which includes not only these two entities but also the bi-directional relationship and the transactions between the two.

Reflecting on sustainability and its impacts for a firm to operate, we have taken the view of EA to mean the enterprise and its environment, including the bi-directional relationship and the transactions that take place, to analyze and document structure (as a process), rather than the structure itself (as a product). This contrasts how EA can be used to understand enterprise integration as an objective of EA architecture and reflects on the interacting space and its dynamics that would undergo changes under different intervention scenarios to co-evolve depending on the manner in which the participating entities would behave and influence the OIC (Lapalme 2012). In here, EA framework and its capabilities are experimented with to theoretically advance the field of green IS and its capability to bring environmental considerations within the OIC. Rest of chapter explores this theme.

To start with: Architecture of a system is defined as consisting of the relationships among its components, the external properties of those components, and the way these create emergent properties with added value for the environment (Zarvić and Wieringa 2014). There can be different views of an architecture (Bass 2007), each of which documents a different aspect of the architecture and which can be brought within a single structure that is the combination of all views. The Federation of Enterprise Architect Professionals (The Federation of Enterprise Architect Professional Organizations 2013) has defined EA as a well-defined practice for conducting enterprise analysis, design, planning, and implementation, using a holistic approach, for the successful development and execution of IS strategy. Here, EA applies to the architectural principles and practices to guide the organizations through business, information, process, and technology changes that might be necessary to execute the relevant strategies. On the other hand, TOGAF 9.1 (TOGAF 2011) defined EA to optimize processes across enterprise in an integrated manner that is responsive to change and supports business strategy, where enterprise "can be used to denote both an entire enterprise—encompassing all of its information and technology services, processes, and infrastructure—and a specific domain within the enterprise (p. 5)".

Zachman framework (ZFIS) is the EA framework leveraged in this chapter through which IS and its greening is explored and covers perspectives of different stakeholders (or participating owners), chosen primarily due to its business-savvy orientation and ability to bring together diverse aspects of business, sustainability, technology, and process related challenges. At the same time, I do not intend to propose the suitability of ZFIS to architect green IS (as end-product) any better as compared to the other EA frameworks (for example, TOGAF, MODAF, DODAF,[1] and others). ZFIS merely serves as a mechanism to position different facets of green IS in relation to each other and the environment within which it operates. I leave it open to the IS research community to experiment with other EA frameworks, including to improve upon the ideas proposed in here.

To gather understanding of how green IS can support organizational sustainability, the interrogative abstractions of ZFIS has been used as the foundation to define and abstract:

– what (material description or structure),
– how (material description or processes),
– where (spatial descriptions or flow),
– who (operation description or people),
– when (timing description or events), and,
– why (motivation) of green IS, through which the architectural patterns are discerned.

4 Green IS as a Functioning Enterprise—EA View

ZFIS is a 6 × 6 two-dimensional grid that uses the primary interrogatives (six W's) as columns and the views of primary owners as rows. Rows include (in serial) views of planner (row 1: architect), owner (row 2: customer), designer (row 3: business process owner), builder (row 4: technology owner) and sub-contractor (row 5: physical architecture components). The last row (row 6) is known as functioning enterprise, which is the end product of this effort. Each row on being intersected by a column

[1]TOGAF—The Open Architecture Framework; MODAF—The British Ministry of Defence Architecture Framework; DODAF—The Department of Defense (US) Architecture Framework.

creates a space to model corresponding perspective of the respective primary stakeholder. Important to note would be the movement from one row to another (along a column) increases the granularity of the model under consideration (Zachman 2003). Readers interested in exploring ZFIS more can refer the book *The Zachman Framework: A Primer for Enterprise Engineering and Manufacturing*. To develop a complete view of green IS, the chapter has relied on enterprise-specific frameworks as rows and introduced models corresponding to the views of the owners. Accordingly, the sub-sections detail row 2 through 4, before returning to planner's view (row 1), which is the architect's view of the system and would depend on other views; and finally develop the big picture. The article has relied on business language to generate corresponding views, instead of technical language generally used in architectural descriptors (AD) in real life. To avoid getting into the actual ADs, the article has refrained from detailing row 5 (subcontractor's view), which is a future project.

In here, I have followed the basic contention of ZFIS that the six interrogatives or abstractions are primitive as well as comprehensive in defining EA of any system. Two interrogatives—when and who—have not been explored beyond reflecting timing (ubiquitous nature of information that values on-demand service) and users (employee privileges and role-matrix) respectively that remains within the realm of a firm's boundary. As the scope of green IS is to develop an IS that enables flow of information reflecting environmental embeddedness of business functions and processes, relevance and meaningfulness of information are the desired attributes to allow space for people and processes to connect and function to optimize environmental sensitivity of processes, functions, services, and decisions, enabling interactions between participating entities to develop a meaningful dialogue and allow it to co-evolve to remediate organizational concerns and stabilize meanings associated with boundary and other IS objects. This would enable formalization of what is relevant for the business to have stakeholders not only 'trust' them, but also enabling firms to 'demonstrate' care for environment.

4.1 Environmentally Sensitive Business Model (Row 2—Owner's Perspective)

Businesses are important economic agents to (re)shape the way human societies interact with nature and has been at the center of controversy due to its unsustainable ways (Chouinard et al. 2011; Frias-Aceituno et al. 2014; Borland and Lindgreen 2013). A business model supporting sustainability outlook is expected to contribute to the social and ecological well-being (beyond economic prosperity) and align business functions to operate effectively within the legal, socio-economic, and political background, caring for the concerns of society, environment, and resources. Although, developing a business model that supports all forms of sustainability is relatively a new concept, the notion of sustainability improving shared values emerges as a guiding force. The need for firms to behave as responsible citizens impact the role of

IS as well, where generating information on how processes within redefined business model are interacting with the environment becomes primary for IS, offering a context to the employees and decision-makers to reflect on the processes and resources, which differs from the conventional paradigm of economic realm. New paradigm would need IS to experiment with new and emerging environment methodologies and generate information on environmental aspects and impacts for internal and external information and reporting needs. The owner's perspectives accordingly would need to have the green IS support environmentally enhanced business model, with components:

- *Green Business Model—What*—a business model that would support businesses to be sensitive about environmental impacts of products, processes, and services. Here *care* is amorphous, ready to be shaped by the intent and actions of the firms.
- *Green Business Model—How*—by having systems and processes in place that would measure and report environmental impacts of process, products, and services through measures defined and calculated using environmentally enhanced tools and techniques like ISO 14000-4, life cycle analysis (LCA) (ISO 14040), greenhouse gases (GHG) accounting (ISO 14064), material flow analysis (MFA) (ISO 14058), and others, where the role of green IS would be to capture data and information while maintaining uniformity of language.
- *Green Business Model—Where*—by building environmental concerns as integral to the business, such that employees, functions, and processes, would be acting, reacting, and performing to achieve the goals of the firms, supported by information flow of green IS.
- *Green Business Model—Why*—Such a model would be crucial to establish the ability of the businesses to handle the priorities of stakeholders (near goals) and develop sustainability as an objective to be pursued as a responsible citizen (ethical approach). Green IS would have to support the businesses with information as well as reporting needs.

Business models also support the enterprise architect (*planner*) to study the behavior of the entity, including the interaction it would have with the environment and the changes needed to enhance and shape it. This is relevant for future advancements and to answer questions like:

a. If green IS can generate information that connect new data and information to the context, supportive of evolving meanings relevant to the context,
b. How to reflect sustainability or environmental behavior of a functions using a common expression, especially when sustainability offers a multi-faceted view of firms impacting the surroundings,
c. What information elements will flow due to the implementation of a specific environmental standard in a firm, for example, if ISO 14001 is implemented as compared to ISO 14004 or any other environmental technique, and measure and quantify a set of environmental aspects (for example, ISO 14064 for calculating GHG exposure, versus ISO 14058 for water and solid waste, ISO 14051 for material flows and waste, and so on),

d. What rules are needed to normalize the environmental impacts against economic ones. For example, environmentally enhanced products and services could behave differently than the conventional products and services in form, fit, and function, and differentiate characteristics and lifecycle of these products from the conventionally produced ones.

4.2 *Environmentally Supportive Systems Model (Row 3—Designer's Perspective)*

Systems model is an abstraction for the designer to define how business processes as an interrelated set of activities contribute to generate (economic) value for a firm (Scheer and Nüttgens 2000), where environmentally sensitive models would promote corresponding environmental and economic values of the firm. Logical or system model depends on the functional decomposition of the business model to replicate the behavior of business processes that are working in tandem to achieve the end objectives of the owning organizations. The designer's perspective is also to develop logical data models that would support data and its interrelationships as a part of new process model and care for environment, connecting new data elements to the business functions and user views (for example, process variations that improve materials reuse), while collaborating by using new business rules that support the user activities in the changed or modified business environment better.

To build a systems model and understand the environmental impacts of a process, a process model decompose it into the constituent elements so that environmental interactions can be modeled for every part of the process, and aspects can be extracted (for example, Fig. 2 details emission due to process: X.0.1.1). Once the environmental interactions are understood through data and information, businesses would have to decide how to fulfil sustainability goals. For example:

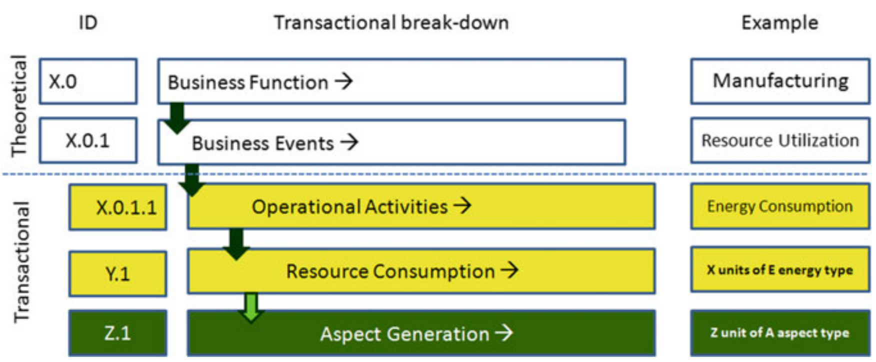

Fig. 2 Functional decomposition of a business function

a. Manufacturing of item ‘A’ is achieved through processing of raw materials that needs ‘Q’ units of energy per batch during the entire conversion process,
Process Change: Clean energy sourced from a wind/solar energy farm would have to be used to run through the conversion process.
b. Dispatch of ‘X’ tons of goods from the warehouse to destination ‘Y’ would need to hire vehicles of a specific capacity.
Process Change: Goods have to be dispatched by rail freight services.

From IS perspective, tool like BPM that aims at modeling, implementing, operating, and monitoring business processes by developing concepts, methods, and tools that translate physical processes into corresponding IS elements by using standardized BPM language like UML and BPMN (Becker et al. 2003) can be extended to design environmentally sensitive IS processes. Accordingly, green BPM (BPM can be enhanced to support environmental sensitivity of business processes) and act as a repository of processes, to be leveraged by green IS to develop the technology view of processes:

- *Green Process Model—What*—Green BPM could be used to model, implement, operate, and monitor business processes using concepts, methods, and tools that would translate environmentally enhanced physical processes into corresponding IS elements.
- *Green Process Model—How*—This would depend on reengineering and designing environmentally improved processes to reduce material and energy intensity of products and services to begin with, for example to design a green supply chain appropriating a feedback loop (any of the 5 R’s) can lead to implement or design new processes as de Paula Alvarenga et al. (de Paula Alveranga et al. 2013) exemplified in case of a furniture manufacturing business.
- *Green Process Model—Where*—The corresponding IS view of green processes is the IS-supported management of activities that would implement business changes including their corresponding environmental impacts and monitor those while applying uniform criteria in modeling the change management (Opitz et al. 2014).
- *Green Process Model—Why*—Expanding these definitions in the context of environmental sustainability would help green IS to model green business processes and support firms in contributing towards environmental care.

While the physical processes in the real world would force data and resulting information to recalibrate environmental enhancement, the new processes would need to achieve the desired goals of reducing environmental load of processes. Accordingly, IS needs to capture process changes as well as interaction of participating elements. Further research will help us to understand:

a. IS view of the business processes (green BPM) would handle the interactions of processes, users, and/or mediating agents as a part of the information generation process and evaluate if these are contributing positively towards the environmental goals of the firms, before letting it flow to the downstream systems (Reiter et al. 2014),

b. Role of green BPM in supporting reengineering of business processes and in improving communication with green IS,
c. Reengineering needed to negate any adverse impact in continuing the support of mature IS applications connecting business and technology models like workflow management system (WfMS), process management system (BPMS), and configuration management (Reiter et al. 2014).
d. In theory, sustainability outlook of business processes can leverage the transformative properties of IS and process-centric view of BPM. However, understanding the interactions of BPM and IS within the sustainability domain in empirical terms, is yet to be explored.

4.3 Environmentally Enhanced Technology Model (Row 4—Builder's Perspective)

Technology model is direct application of advanced technology and hardware (green IT) to generate new solutions that improve the environmental considerations.

- *Green IT—What*—Molla et al. (2009) have defined green IT as the ability of an organization to systematically apply the environmental sustainability criteria to the life cycle of IT infrastructure, encompassing the human and managerial components associated to it.
- *Green IT—Where*—In normative terns, green IT would cover sustainable business practices to improve use of clean energy, product stewardship, and pollution prevention as a part of technology and hardware systems that includes deployment of energy-efficient and cost-effective utilization of IT resources and products as well (Cai et al. 2013).
- *Green IT—Why*—The question of greening IT has assumed importance with growing demands of process automation, improvements in computing power, and expanding pervasiveness of the digital communications (Erek et al. 2009; Jenkin et al. 2011).
- *Green IT—How*—This would include green software designing, green hardware, green networking and technology components, working in unison to exchange and support information, explained hereafter.

As compared to other areas, green IT has been extensively explored and experimented with, where research has advanced to improve first-order environmental efficiency of technology, hardware, computing models, networking, building, and other IS infrastructure through improved materials and energy use.

4.4 Scope of Green IS (Row 1—Scope or Planner's View)

In traditional sense, scope of EA covers overall boundary of things that needs to be covered within the architecture, including interrelationships of things as well. This represents planner's view and to define what all is need to be a part of the architecture, including defining out-of-boundary objects. From IS perspective, this means capturing data elements and their relationships to build a system that support users within/across units with the desired information and outputs. Accordingly, scope of a green IS would define:

- *Green IS—What*—the responsibility of bringing every element from all the models together to develop an information system that has the capability of supporting firms with sustainability needs,
- *Green IS—How*—by adapting environmental-oriented behavior and actions of processes and design system while maintaining uniformity of language across sub-systems,
- *Green IS—Where*—to generate and disseminate information that is in parity with the domain language and carries uniformity in expression,
- *Green IS—Why*—to enable users (employees) and management (decision-makers) to promote, support, encourage, and improve environmental sustainability related goals become a part of the regular affairs of the firm.

Scope of green IS accordingly would be to develop an IS that would enable flow of information reflecting environmental embeddedness of business functions and processes where relevance and meaningfulness of information are expected to support environmentally enhanced business activities of firms, allowing people, systems, and processes to *connect* with each other and *function* to *optimize* environmental sensitivity of processes, functions, services, and decisions. This would need uniformity of language to *interact* and develop a meaningful dialogue that expands information space, co-evolving it to improve boundary and IS objects and remediate ambiguities. This is where structured IS information field expands based on changes within OIC, defining semantic patterns to relate to new field objects and evolving a moving and adaptable framework to incorporate (multiple) user-definable contexts, not to mention, continuously optimize IS environment to meet the organizational goals and in achieving environmental sensitivity.

5 Discussions

5.1 Green IS—Connecting the Views Together

As per ZFIS, a functioning enterprise is the end-product of the efforts where the enterprise functioning is supported by the architected design. In this case, green IS is expected to emerge as an improved version of existing IS, helping firms to behave in environmentally sensitive manner. In this process, uniformity of language in interpreting data and related contexts along the process lifecycle across multiple functional domains is expected to be normalized, removing framework specific bias so as to let it fit within the generic EA framework, evolving the architectural views corresponding to the architectural domains of:

- *Business process architecture* (business functions offering services to each other and to external entities) that would need green IS to connect different functions, including defining contents to be disseminated to the external entities, including for example, explaining how the businesses have started taking care of nature and society along with the details and impacts that these steps would produce (equivalent to business model in ZFIS),
- *Data architecture* (business information and other valuable items to be captured and stored) that would need green IS to expand the existing IS and define and maintain elements that arise due to environmental orientation of new and existing processes, for example, environmental and social impacts and its constituent elements as per any pre-defined standard like ISO 14000 (equivalent to subcontractor model and in ZFIS),
- *Application architecture* (business applications offering information services to each other and to the business functions), that would need green IS to generate information extending beyond the prevailing definition to represent environmental viewpoint, for example, flow of critical resources (water, energy, and materials) (equivalent to systems model in ZFIS), and,
- *Technology architecture* (hardware, network and platform applications offering platform services to each other and to the business applications) that are tuned to improve the environmental impacts through reduced energy usage and improved carbon footprint (equivalent to technology model in ZFIS).

First part of this exercise would be to connect different views of green IS and evolve a conceptual understanding of interconnectivity as a part of enterprise integrator view. Also relevant would be to investigate the systems-in-environment thinking of EA, where enterprise coherency and co-evolution of strategy would contribute, based on the guiding principle that allow systematic design of systems and their relationship with the context within which they are operating (Lapalme 2012). This is a part of ongoing study and relates to understanding how green IS connects with users, processes, software, information through the business, systems, and technology model, and accepts feedback as a part of the information chain to influence physical processes, organizational goals, and external environment.

5.2 OIC and Green IS—Interconnectivity

The overlapping themes from literature and heterogeneity of approaches in developing environmental sensitivity green IS restricts in defining what green IS is or could be, including differentiating it from the traditional IS and how the former supports participating sub-systems if laced with environmental themes any better than the latter. Traditional IS operates within an ordered system where rules of engagements are well-defined, whereas green IS is waiting for the theories to evolve and practices to develop a practicum. Moreover, our inability to view OIC as the conceptual entity providing space for indepedent IS fields to evolve fails to explain how information fields (and physical space of IS artefacts) would evolve and expand to improve the environmental sensitivity of businesses and, in turn, would impact green IS.

My interest in this chapter is to go beyond the the mechanical view of green IS (legacy of traditional IS) to reflect on the interacting space where technology, systems, users, and business process model connect to conceptualize green IS as:

> Green IS supports a green *user* (user interested in getting data or information to act, decide, or contribute to an environmentally conscious task, decision, or action) in using *software*, *hardware*, and *network* (installed or built based on the green themes, or otherwise) to capture *data* and *information* that generate *environmentally relevant information* and *outputs* over and above the information providing capabilities of traditional IS to enable intended outcomes (in pursuance of the organizational goals).

The intent of enabling greening in firms is to develop the enactment process through which the new IS could become the enabler or mediator in greening business process, model, function, and hardware. For example, redesigning a business process to reduce carbon emission might need the firms to have information on the strategic options like relying on clean energy by using captive means or sourcing it from external producers, and any other option (Chou 2013; Corbett et al. 2011; Watson et al. 2012). In this process, IS is expected to co-evolve (from traditional IS to green IS) along with the business needs that it serves, even though the reflexivity of such contributions is yet to be empirically evaluated [as proposed by Lee et al. (2014)].

6 Conclusions

While the practical enactment of social, legal, and ethical boundaries within which firms are expected to perform is still awaiting to define what micro-view of sustainability is or could be, IS related developments cannot wait for it to evolve. This include decision-making and reporting processes, where the usability of information would depend on the maturity of processes and active involvement of change agents to *act* based on the contextuality of information. Using EA framework to connect IS elements and place them in perspective helped us view green IS as a super architecture that houses architectural descriptors and artifacts within its blueprint and connects systems, processes, and technology models with users. Connecting these together would help us view contemporary developments as sub-parts of green IS (as integrator of views), where it offers the value proposition to firms on organizational sustainability, as against capturing few additional data elements, if viewed from the perspectives of the traditional IS. However, important point is the uncertain nature of external contexts from the system-in-environment viewpoint of EA that would keep evolving and would remain a challenge to model green IS within a definitive boundary.

The dependency green IS has in defining and understanding what *green* is and in keeping sync with the changes between business (physical) and information (IS) world by pairing definitions, introduces a certain degree of dynamism which green IS needs to be sensitive to and respond, and allow continuous realignment of IS. This raises questions like how the greening efforts of an organization impact information space as new IS artifacts (from information field) disseminate new information that would lead users, processes, and systems to interact and generate new knowledge on environmental considerations. At the same time, to extract knowledge and search for desirable future state as end objective might require a great deal of sensemaking—a collaborative process through which the collective experiences of people is given meanings, through the shared awareness and understanding of perspectives. Sensemaking is also needed to handle the complexity and subjective nature of human involvement in an IS process. This includes the dynamism that is inherent to any evolving area of reserach and the collaborative efforts needed to develop an effective solution like an IS enterprise strategy or a participative IS design process. While the role of green IS to act as an enabler of organizational goals would depend largely on the ability, maturity and motivation of users to go beyond the specific use of information, it would also depend on the ability of the firms to provide an equally stimulating environment for users and employees willing to be creative enough to evolve imaginative use of information and support firms in becoming increasingly sustainability-savvy, an avid topic of future research.

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