Multi-criteria evaluation of real-time key performance indicators of supply chain with consideration of big data architecture

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Abstract
One of the major issues a designer of Big Data Architecture has to trade with is incorporating real-time predictive analytics capability using offline synergistic approaches like simulation, fuzzy analytic network process, and Technique for Order Preference. Further, under this setting, which involves re-engineering of operational units, the present study proposes a simple, yet practical heuristic to quickly handle the unstructured relational key-performance-indicators (KPIs) data of a supply chain that are obtained from the results of the simulation. Within the big data framework, the proposed model can be used as a decision support tool by the companies to evaluate their KPIs in a real-time dynamic system.

Keywords: Big data; real-time mechanism; key performance indicators; fuzzy-ANP; discrete event simulation; supply chain management

1. Introduction

The development of high values of a performance measure is an important component in supply chain management (SCM) to ascertain the efficiency and/or effectiveness of an existing system. The technological evolution, such as the internet of things (IoT) has resulted in exponential growth of data. However, given the potential application of IoT across various industries, including production, the supply chain of the manufacturing sector, engineering, finance, health sector, the distribution of a number of interconnected devices is expected to be 24 billion by 2020 (O´Donovan, Leahy, Bruton, & O´Sullivan, 2015). Therefore, given the rapidly changing goals of the organizations with stringent time limits, there are shortages of personnel that are capable of making quick decisions for managing this exponential data growth. Managers are short of time to identify the significance of individual key performance indicators (KPIs) when the situation requires an immediate solution. Therefore, it is pertinent to depict the mutually dependent relationships among KPIs of a supply chain under the purview of stochastic operational parameters. Further, the priority of KPIs should be monitored in relation to operational units of SC processes. Thus, there is a need for the tools and frameworks that can simplify the process.

Due to the infusion of big data in various sectors of industry, the application of high-level networking sensors is indeed on the increase and is offering leading edge in supply chain management (Addo-Tenkorang & Helo, 2016). The use of RFID-enabled sensors for the real-time information in the context of production logistics control in the supply chain has been indicated by several researchers, including (Zhong, Lan, Xu, Dai, & Huang, 2016; Tsao, Linh, & Lu, 2016). The supply chain performance can be improved through reliable RFID tracing and tracking systems considering both the hardware and the software integration (e.g., middleware and ERP integration). The operational units concerning manufacturing typology to develop the RFID strategy include supply chain visibility to improve forecasting quality, inventory level monitoring to avoid stockouts, lot size tracking in production and distribution to improve customer service level, and others (Canetta, Salvadè, Schnegg, Müller, & Lanini, 2011). The company like Tesco mines their huge amount of client data to inform decisions from promotions to strategic segmentation of clients. Amazon came early to the frontier of data analytics based on predictive modeling technique called collaborative filtering. Walmart was also an early adopter of data-driven supply chains. They got to the supply-and-demand signal visible between retail stores and suppliers. The company optimizes all its supply chain decisions like inventory tracking, customer fulfillment using point-of-sale (POS) and radio-frequency identification (RFID) sensors (Sanders, 2014).

To manage the large volume and variety of data the methods of data science in the form of predictive analytics have been deployed (Gunasekaran, Tiwari, Dubey, & Wamba, 2016). Simulation models are used for predictive analysis to generate scenarios based on historical data to interpret the future (Power, 2013). From the manufacturing point of view, the inappropriate adoption of various operational units involving (i) forecasting error due to volatile demand, (ii) review period under different collaborative information policies of SC like vendor managed inventory (VMI), collaborative forecasting, planning and replenishment (CPFR) and continuous replenishment (CR), (iii) lead time due to transportation of product within a supply chain under different scenarios (e.g. JIT, push or pull system), (iv) swing in perpetual inventory at various echelons due to varying customer satisfaction and thereby the service levels, result in various characteristics of big data, i.e., volume, velocity, variety, veracity, and value adding. Testing the adaptive strategies in real-world SC networks with enormous data under such a stochastic setting of operational units necessitate for discrete event simulation as a relevant predictive analytics tool, especially in the case of SC re-engineering setting (Waller & Fawcett, 2013).

Predictive analytics through simulation modeling are expanding their scope and commonalities in the era of big data analytics (Miller & Buckley, 2013). Predictive analytics through simulation can also overcome the challenges confronted by traditional statistical analysis relying on *p*-value which may not be efficacious in an environment with large data sets (e.g., false correlations) (George, Haas, & Pentland, 2014). Given the complexities and uncertainties, coordination in SC network, which is at the core of these simulation environments, further appends to robust and flexible supply chains (Ketter & Srour, 2009).

The researchers and practitioners realize that given the enormous data pool related to operational units of the production system, it is a challenge to analyze and filter out the right kind of information relevant to the improvement of KPIs. Zadeh (1979) proposed an information granulation theory to deal with big data naturally. It simply clusters the data to distinguish the relevant information in a structured way (Yao, 2005; Zadeh, 1998). The analytical network process (ANP) enables information granulation (Saaty, 2006) by representing the relationship of the given information in a networking structure (i.e., networking granulation). With the existing knowledge (i.e., a conceptual framework), the authors have recommended the integration of the ANP as a multi-criteria decision making (MCDM) method with fuzzy on the soft handling of big data (Portmann & Kaltenrieder, 2015).

One of the MCDM decision-making tools to solve the problems of performance metrics' trade-off by weighing the importance of different KPIs is the Analytic Hierarchy Process (AHP) by linking the scorecard's KPIs to the overall mission, objective, and strategies (Huang, Sheoran, & Wang, 2004). However, AHP is only to determine the 'weight' or relative importance of individual KPIs; it does not specify the relationships among KPIs and their significance in accomplishment efforts, which is a very important factor for continuous supply chain performance evaluation in a dynamic environment. In order to solve this problem, Saaty (1996) proposed a new MCDM method, the ANP, to overcome the problem of interdependence and of feedback between criteria and alternatives in the real world. The ANP is the extension of the AHP; actually, it is the general form of AHP. Another decision-making technique is grey relational analysis, which has been applied to analyze the financial performance of the business. To decide on significant financial performance measures, Kung and Wen (2007) applied the weighing of the grey relational matrix. Similar to AHP approach, the grey relational analysis does not show accomplishment to prioritize the KPIs within a stochastic supply chain environment. In other words, grey relational analysis has not been considered to make decisions in dynamic situations.

Once the key performance indicators have been identified, another challenge is that it is required for the accomplishment of improvement in key KPIs. One of the methods is the performance optimization. The optimization philosophy assumes that there is an optimal performance point when maximizing or minimizing the identified KPIs. In theory, the performance optimization approach is commonly accepted by researchers. However, it is difficult to apply in practice, in terms of big data acquisition and computing of a high complexity due to stochastic parameters in an SC network. It is also difficult for the decision-maker to understand in real SCM situations. Further, optimization does not bring into account the relationships among KPIs. Therefore, it calls for a methodology that studies the relationships among KPIs related to different SCM processes. Further, the decision to adopt appropriate performance for SC requires a trade-off between ideal and non-ideal solutions involved so as to assess efficient ranking of various organizations. This calls for a very well-known technique TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) TOPSIS was first established by Hwang and Yoon (1981). TOPSIS is widely used to solve many complicated MCDM problems because of its effectiveness in solving MCDM and computational simplicity. When there are few criteria, TOPSIS is proven better method than AHP in addressing the rank reversal issue (Kocaoğlu et al. 2013). TOPSIS has the ability to identify the best alternative quickly (Parkan & Wu, 1997). The basic idea of TOPSIS is that the best decision should be made to be closest to the ideal and the farthest from the non-ideal solution. Furthermore, the transparent construction process of ANP and TOPSIS enables them to understand easily by academicians and practitioners (Wang & Chan, 2013). The present paper proposes a conceptual framework for analyzing the big data on operational factors of the supply chain so as to evaluate its KPIs in a real-time setting. The present study integrates the fuzzy ANP (FANP) and TOPSIS as the MCDM methods for information granulation of big data, with both predictive and prescriptive analytics using discrete event simulation as an output data generator tool.

The managers in supply chain usually identify KPIs according to their objective requirements and practical experiences that they receive from the sphere and further examined by experts. However, to get a systematic performance measurement, they often turn to some widely recognized models, such as Balanced Scorecard (BSC) and Supply Chain Operations Reference (SCOR). Considering the complex supply chain characteristics, we resort to process-oriented SCOR-model to identify the basic performance measures. In the present paper, the proposed measurement system focuses the level 1 metric performance attributes of the SCOR-model (Cai, Liu, Xiao, & Liu, 2009) that includes (i) average fill rates, (ii) average order fulfillment lead time (cycle time), (iii) average inventory levels, and (iv) average inventory time (shelf life). These measurements correspond to 'supply chain delivery reliability', 'supply chain responsiveness', and 'supply chain asset management' attributes respectively. The *average fill rates* represent the percentage of orders that can be fulfilled from stock. This shows how quickly the company can respond to customer orders in the uncertain environment. The *average fill rate* (AFR) performance corresponds to the 'supply chain delivery reliability' attribute of the SCOR-model which ascertains: the correct product, to the correct place, at the correct time, in correct condition, in the correct quantity, to correct customer. The average order fulfillment lead time or the *average cycle time* is the average time it takes to actually fill a customer's purchase order. The measure starts when the customer's order is received. The measure ends at the time of delivery to the customer. The *average cycle time* (ACT) corresponds to 'supply chain responsiveness' attribute of the SCOR - model which ascertains the speed with which a supply chain provides products to the customer. The *average inventory level* (AIL) performance represents the number of products in the store. This performance corresponds to 'supply chain asset management' attribute which ascertains the effectiveness as well as the efficiency of an organization in managing assets to support demand satisfaction. This includes the management of all assets: fixed and working capital. The *average inventory time* (AIT) or the shelf life indicates the time it takes to convert the investment in inventory into selling goods. At the upstream level of the supply chain, it indicates the time a raw material remains on the shelf before it is taken in the production. The *average inventory time* also corresponds to 'supply chain asset management'.

There are two complex issues managers face while realizing a well-built performance measurement system.

- Due to constantly varying situations in supply chains, i.e., the dynamic nature of supply chains, some performance measures gets outdated and the others gain priority.
- The companies experience difficulty in identifying the method for prioritizing the performance measures and adapting their continuous changing strategic objectives in the dynamic decision-making environment.

As these problems have received relatively less attention in previous research, the present research attempts to fill these gaps at the conceptual basis of a big data architecture point of view.

The rest of this paper is structured as follows. The paper begins with the literature review survey and the applications of MCDM models in Section 2. Section 3 elucidates the simulation-FANP-TOPSIS based predictive big data architectural (BDA) framework of the extended SCOR

- model of SC network. Section 4 discusses the sensitivity analysis of the model. Finally, Section 5 concludes the paper indicating the limitations and scope for further research.

2. Literature review

Performance measures and measurement systems are used by many organizations to determine their performance (Hudson, Lean, & Smart, 2001; Mettanen, 2005). Some of the research work appeared for the supply chain performance evaluation involves fuzzy logic inference rules (Unahabhokha, Platts, & Tan, 2007; El-Baz 2011; Ganga & Carpinetti, 2011). The MCDM models for understanding the performance of the supply chain has widely been used, including (Seçme, Bayrakdaroğlu, & Kahraman, 2009; Uygun & Dede, 2016; Sari, 2017). Seçme, Bayrakdaroğlu, and Kahraman (2009) applied an integrated approach using fuzzy AHP and fuzzy TOPSIS technique for performance evaluation in the Turkish Banking Sector. Uygun and Dede (2016) proposed a fuzzy MCDM approach involving fuzzy DEMATEL, fuzzy ANP, and fuzzy TOPSIS for evaluating green supply chain management performance. Sari (2017) developed a framework to evaluate the green supply chain management using simulation with MCDM techniques involving AHP and VIKOR.

From the big data analytics point of view, Sushil (2017) explored the manner in which the integrated Total Interpretive Structural Modelling (TISM) and Interpretive Ranking Process (IRP) can be used as the MCDM processes for flexibility in the form of unstructured datasets in the big data framework. Kaltenrieder, D'Onofrio, and Portmann (2015) proposed fuzzy analytical network process (FANP) framework as a potential MCDM process for enhancing the interaction between customer and marketers and thus reducing the challenge of big data. Hofmann (2015) operationalized big data in supply chain decisions in order to mitigate the bullwhip effect. Using the system dynamics, the big data levers 'velocity', 'volume' and 'variety' were transferred into a simulation model. The author found that the data property 'velocity' relatively bears the greatest potential to enhance performance. He, Wang, He, and Xie (2016) proposed an MCDM by integrating Rough Set and fuzzy TOPSIS, which the Rough Set is used for mining the big data of quality, and fuzzy TOPSIS is adopted to model the computational process of product infant failure relation weight. Li, Tao, Cheng, and Zhao (2015) have advocated the integration of ANP and BSC processes for decision making involving outsourcing that requires big data in product lifecycle management. They further pointed out that product manufacturing and quality monitoring generate vast data and simulation has a close relationship with these activities. Groves, Collins, Gini, and Ketter (2014) proposed a set of KPIs in the context of market analysis. They used simulation as the test bed for big data analysis of product life-cycle in the supply chain environment. Shao, Jain, and Shin (2014) proposed a decision support for the smart manufacturing system. They discussed a case to demonstrate one of the uses of simulation to support data analytics in machining operations application. Sun et al. (2014) explore the application of (MCDM) techniques in the area of cloud computing and big data, to find an efficient way of dealing with criterion relations and fuzzy knowledge based on a great deal of information. They combined the interpretive structure modeling (ISM) and ANP-based techniques to model the interactive relations between evaluation criteria, and to handle data uncertainties. However, given the stochastic operational units of a complex SC network, the pairwise comparison within the clusters and among different clusters for ANP through general consensus or Delphi method is extremely difficult. Therefore, in the present research, we proposed integrating ANP with fuzzy logic to address the following issues.

- Integration of fuzzy logic to conventional ANP, thus creating fuzzy analytical network process (FANP), makes it possible to structure the uncertain information in a large data pool (Ahmadi, Yeh, Martin, & Papageorgiou, 2014).
- The utilization of the fuzzy logic helps the decision makers to incorporate incomplete, unquantifiable, and non-obtainable information and partially ignorant facts into decision model (Kulak, Durmusoglu, & Kahraman, 2005). Moreover, the decision maker is normally reluctant to assign crisp values to the comparison matrix of judgment; they prefer interval judgments than to express in just a single numeric value (Chan & Kumar, 2007).

From the IoT perspective, Zhong et al. (2015) and Zhong et al. (2016) proposed RFID-enabled real-time information in the context of the production logistics control framework. However, they confine the usability of RFID-enabled information system within a manufacturing shop floor and warehouse logistics trajectory of the flow of raw material to finished product receiving area. Zhong et al. (2015) specifically pointed out that although RFID-enabled real-time data information is widely accepted by various researchers, there is still a scarcity of application of such data. Zhong et al. (2016) extended the work further by integrating the cloud manufacturing system in an RFID-enabled system of a shop floor. Shao, Jain, and Shin (2014) emphasized in the way simulation tool is used for the data analytics and suggested it as an important issue of research. Xu et al. (2015) suggested that simulation can provide predictions with high reliability for the input information gathered in a vast amount of data. They further, pointed out that multiple runs of large-scale simulation models are easily affordable and viable through the present technology of cloud and grid computing systems.

In view of above, the current paper builds upon the extant literature by filling the existing research gap related to conceptual big data analytics in manufacturing operations. Accordingly, we outline the following research objectives.

(1) A conceptual framework is proposed in which the RFID-enabled dynamic real-time big data information is integrated into the cloud ERP system equipped with modules of inventory system of a supply chain.

(2) A prescriptive (real-time) and predictive (simulation of historical data) analytics are proposed.

(3) The present study is based on the realization of the relationship between KPIs and the operational units of SC processes. Specifically, the simulation is used as the output generator of the KPIs of supply chain operating under the stochastic operational units. The results of the simulation are used for the pairwise comparison within the clusters and among different clusters for ANP for which a simple heuristic method is proposed. The vagueness or any imprecision in the heuristic method is captured through fuzzy logic (i.e., FANP).

(4) The ranking of organizations' key performance capabilities is proposed using TOPSIS.

3. A Simulation-FANP-TOPSIS based BDA framework

In the present research, simulation is used offline (Shao, Jain, & Shin, 2014) to generate data for evaluating other analytics applications (FANP and TOPSIS in our case). The main purpose of building simulation model is to use it as a data generator of KPIs which is normally difficult to generate when there are inherent uncertainties that exist in the stochastic supply chain environment. The accuracy of these simulation results can further be enhanced by seamlessly coordinating the SC system and examining the operational units in a real-time environment. However, this entails a high level of coordination within the SC network. We assume this coordination, consistent with Dev, Shankar, Dey, and Gunasekaran (2014a) in which they consider an intelligent arrangement of high intrinsic information sharing capabilities.

The proposed conceptual BDA framework consists of various modules as shown in Figure 1. Firstly, the information related to existing operational units of a supply chain are collected for the ERP system which is assumed to be equipped with modules of inventory related data. To manage the ERP system in a dynamic way, that is, in a real-time information scenario, RFID plays an important role. RFID provides a real-time information of the parameters related to production scheduling including lead time from suppliers, work-in-process inventory levels, setup time, workload, idle time, etc., and also gathers the data associated with the external environment like demand volume, demand volatility, order size, etc. (Canetta, Salvadè, Schnegg, Müller, & Lanini, 2011). One can refer to Zhong et al. (2016) for the technological aspects of gathering data from RFID-enabled cloud manufacturing system.

The information gathered through RFID at the operational level is progressing upward into the ERP system through middleware (e.g. BizTalk RFID, IBM WebSphere RFID, BEA WebLogic RFID, SyBase RFID Anywhere). RFID middleware is used to connect the RFID hardware with the ERP within a company. The functions of RFID middleware include (i) extraction, combination, and filtration of data from the number of RFID readers across the organization, (ii) to direct the data collected to the appropriate enterprise IT system, and (iii) to trigger some events related to certain business rules. For the technological functionalities of integration of middleware with the RFID network at the reader interface, and with the enterprise IT network at the enterprise application adapter interface, one can refer to Hunt, Puglia, and Puglia (2007) and Zhong (2015).

We consider the ERP as a web-based system. Web-based ERP system enables seamless, superior reliability, security, manageability and effective data access to the authenticated users at the right time from everywhere without the need of specific software clients. For the functional features of web-based ERP workflow engine, which could formulate an Application Programmers Interface (API) library, one can refer to Tarantillis, Kiranoudis, and Theodorakopoulos (2008). The API allows the functionalities related to supply chain management, thus, enabling the information to be retrieved from time to time for evaluating the performance of the supply chain.

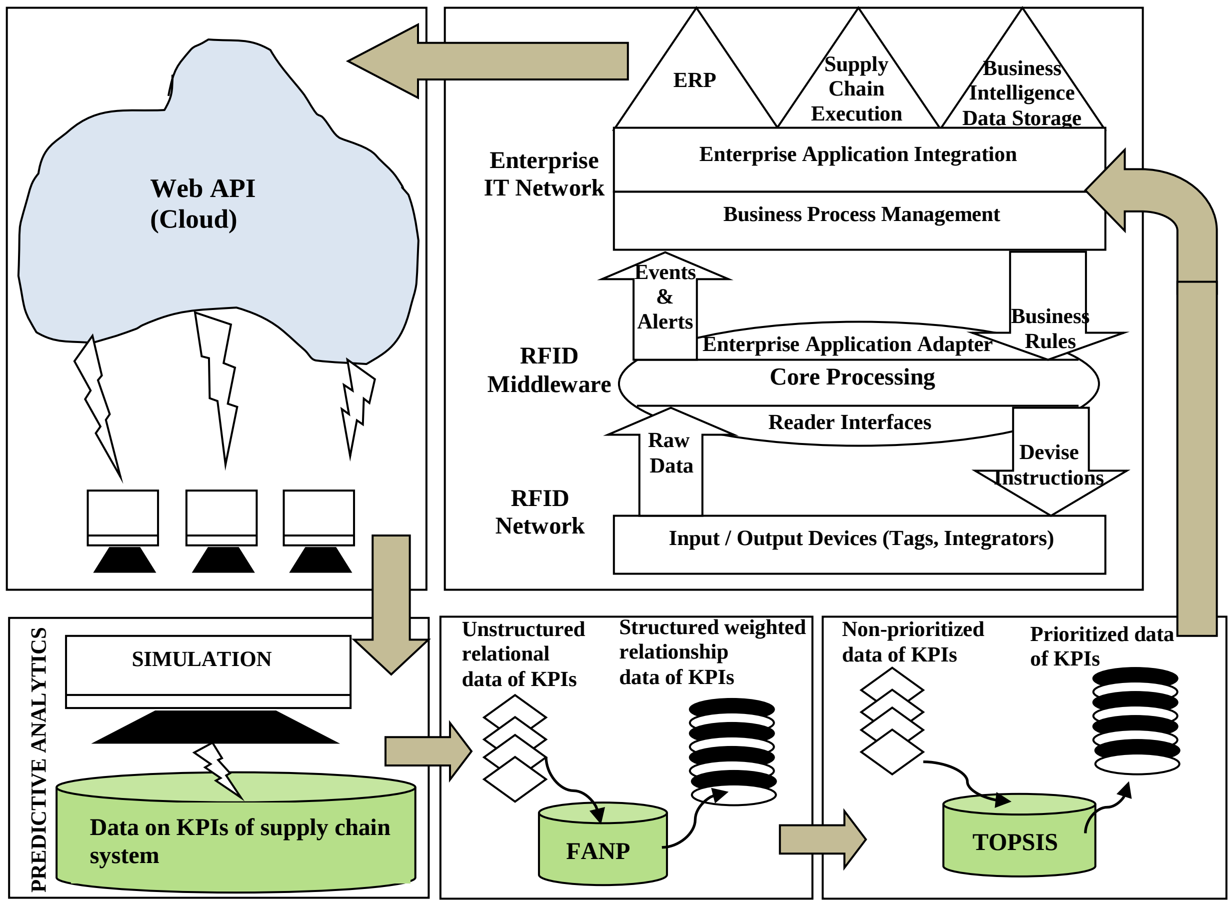

Figure 1: Conceptual BDA framework of evaluating KPIs of SC network (Source: Hunt, Puglia, & Puglia, 2007)

However, Web Service applications are sometimes restricted due to proprietary reasons (Tarantillis, Kiranoudis, & Theodorakopoulos, 2008). Moreover, testing of data analytics application requires large sets of data. Normally, many of the manufacturing companies are not willing to provide access to their factories for the collection of a large set of real factory data, specifically related to operational units (Shao, Jain, & Shin, 2014). In such a case, validated simulation models of real factories can be regarded as virtual factories, which are instrumental in taking on the complexities and generating data for selected KPIs and in formats as they would be in a real factory. The virtual factory offers the advantage of comparing the output of a simulation model to the known input data to evaluate the quality of the analytics (Shao, Jain, & Shin, 2014). Shao, Jain, and Shin (2014) mentioned that advances in technologies for interfacing simulation models, computation, and communication have made the implementation of the virtual factory within reach. Further, in case of time-based performance evaluation (as in our case), simulation offers a much cheaper and faster approach to analyze the dynamicity of KPIs via what-if analysis (Xu et al., 2015).

In the next module of the architecture, we consider an offline simulation execution to generate data for evaluation of other data analytics applications, that is, for FANP and TOPSIS in the present case. However, the resulting KPIs obtained through simulation do not present the relationships among each other in terms of their weights. Therefore, in the next module, we propose FANP model that copes with the uncertainties and convert the unstructured data to a structured data in the form of weighted KPIs. Further, the weighted key performance indicators provide data to the TOPSIS module which prioritizes the KPIs. Consequently, the operational units corresponding to the prioritized KPI could be regulated based on the real-time need of the SC network system. This information can be sent back to the supply chain through enterprise application adapters as explained by (Hunt, Puglia, & Puglia, 2007).

For the sake of completeness of the proposed BDA conceptual framework, we carried out the analysis of a simple extension of the SCOR-model of a supply chain at diminutive level. However, we believe that the proposed framework is instrumental in taking on the complexities involved in analyzing the big data related to the evaluation of KPIs of an SC network in a real-time setting. Thus, the present BDA provides a conceptual response to the issue addressed.

3.1 *Simulation experiment detail*

We consider a simple extension of the SCOR-model of a supply chain that comprises of three suppliers that supply the raw material to the downstream manufacturer with normally distributed supply lead time. A single manufacturer (M) in turn assembles the finished products. The next echelon consists of two distributors (D1 and D2) to which finished product are sent, again with normally distributed lead time. Distributor D1 caters the demand of retailers R1 and R2 while distributor D2 caters the demand of retailers R3 and R4 respectively. Further, each of the four distinct retailers experience different demand patterns, which is exponentially distributed with differing parameters. Importantly, the retailers comprise the only echelon that experiences external demand; accordingly, all customer orders are placed at these retail outlets alone and must be satisfied at the said location only.

3.2 *FANP model development*

As discussed in Section 1.1, in the present paper, we compared four KPIs which are considered as the criteria of ANP: average fill rates, average cycle time, average inventory levels, and average inventory time resulting from the simulation model. Various alternate levels of operational units including forecasting error (FE), review period (RP), lead time (LT), lead time standard deviations (STD), order size (OS), service level (z), and aggregated demand (D) are considered as decision alternatives as shown in Figure 2.

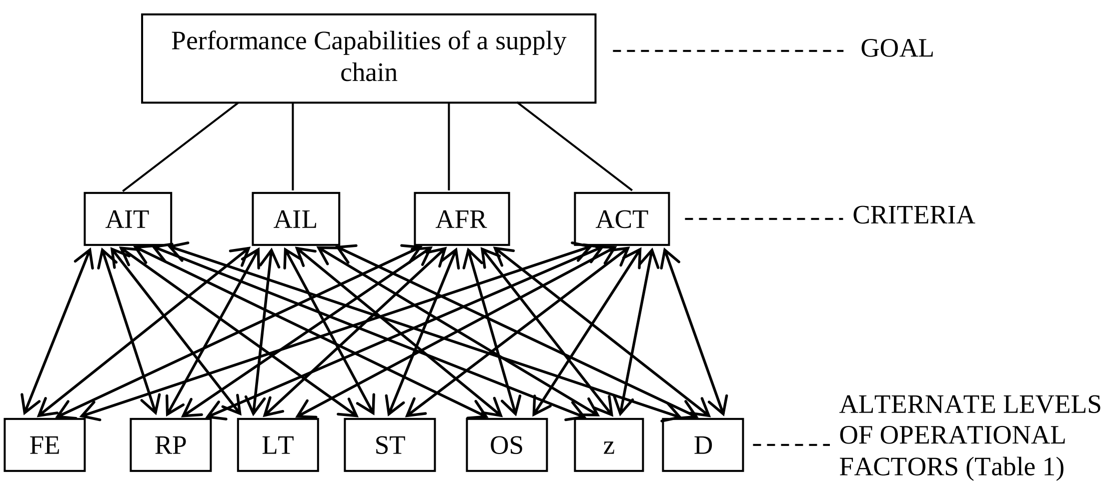

Figure 2: ANP-based framework for overall performance capabilities of a supply chain

Table 1: Levels of operational factors

Factor No.	Factors	Levels		
		I	II	III
1.	Forecasting error (FE) (%)	5	10	15
2.	Review period (RP) (days)	0.75	1.5	3.0
3.	Lead time (LT) (days)	1.5	3.0	4.5
4.	Lead time standard deviation (STD) (days)	0.6	1.2	1.8
5.	Order size (OS) (Nos.)	280	640	900
6.	Service level (z)	0.7	1.4	2.15
7.	Aggregate demand (D) (Nos./day) at four Retailers	25	50	75

Chopra and Meindl (2010) have pointed out the multi-factors related to inventory management which influence supply chain performance including demand, lead time, review period and others. However, in the present research, we consider various decision alternative factors and their values consistent with Dev, Shankar, and Debnath (2014b) as shown in Table 1. The simulation experiments are conducted for three levels of each factor. Thus, there are total 2187 (3^7) simulation experiments performed. The results of simulation experiments were obtained for the four KPIs. A heuristic method is used for determining the pairwise comparison in the judgmental matrix of ANP. The steps are described as follows.

Step 1: The results obtained from simulation experiments for each KPI were divided into five levels; extremely low, low, medium, high and extremely high. We consider these levels on a scale of 0 to 100 percent. The maximum value obtained for a specific KPI is divided into five equal scales, i.e. 20 percent for each of the five levels. Since we are interested in the extremely low and low values for the KPIs; *average cycle time, average inventory levels*, and *average inventory time*, we consider up to 40 percent of the maximum value obtained through simulation results for these KPIs. Whereas for the *average fill rates* we are interested in high and extremely high values, we consider all those values obtained from simulation results which are greater than 60 percent of the maximum value obtained for the KPI.

Step 2: With two factors and three levels of values (low, medium and high), the results of eight combinations (k_i), where i = 1, 2…8, were compared for pairwise comparison in the judgmental matrix. The heuristic algorithm for the KPIs *average cycle time*, *average inventory levels*, and *average inventory time* is as follows.

Let x and y are the two factors for pairwise comparison in the judgmental matrix. If N is the total number of simulation experiments performed (=2187 in our case), then, for each combination k, there would be a $N/k = p$ *number* of experiments (2187/8 = 273) compared for the factors x and y.

Let Max(lk_i) = Maximum number of lower values for combination k_i obtained from simulation results for the KPIs.

For Max(lk_i), there would be $N/2$ number of experiments for two factors (x and y) under comparison (2187/2 = 1093 in our case).

Let lk_ix = number of low values obtained from simulation results for the combination Max(lk_i) of factor x, and

lk_iy = number of low values obtained from simulation results for the combination Max(lk_i) of the factor y.

if ($lk_ix>lk_iy$)

$a_{ij} = lk_ix/ lk_iy$, and $a_{ji} = 1/a_{ij}$;

else

if ($lk_iy>lk_ix$)

$a_{ij} = lk_iy/ lk_ix$, and $a_{ji} = 1/a_{ij}$

where a_{ij} is the element of the judgmental matrix.

Conversely, for the KPI *average fill rates*, the number of high values from the simulation results is considered for two factors under comparison. For the numerical exhibition of the heuristic, we demonstrate the above steps in Appendix A with two factors (one pair) resulted from simulation experiments.

Step 3: The uncertainties and imprecision of heuristics performed in step 2 are handled with linguistic value parameterized by the triangular fuzzy numbers. Fuzzy logic utilizes the linguistic terms to present decision maker's preferences (Zadeh, 1965). The ratios obtained in step 2 are converted into the relative importance factors, which will be used to weigh the significance of each KPI. The maximum value of the ratio (lk_ix / lk_iy or lk_iy / lk_ix) obtained is 1.95 and the minimum value of the ratio is 1.01. Thus, the difference between maximum and minimum values is divided into nine intervals with respective linguistic terms shown in Table 2 (Arshinder, Kanda, & Deshmukh, 2007).

Table 2: Linguistic classification of pairwise comparison of KPIs and their corresponding fuzzy numbers and de-fuzzified crisp values

Range of Ratio Max(n_{lk}) / Max(n_{lm})	**Weight**	**Linguistic expression**	**Triangular fuzzy number (m, α, β)**	**De-fuzzified Crisp numbers**
1.0000 – 1.1111	1	Equally significant	(1, 1, 1)	1.00
1.1111 – 1.2222	2	Between	(1, 2, 3)	1.25
1.2222 – 1.3333	3	Low significance	(2, 3, 4)	2.25
1.3333 – 1.4444	4	Between	(3, 4, 5)	3.25
1.4444 – 1.5555	5	More significance	(4, 5, 6)	4.25
1.5555 – 1.6666	6	Between	(5, 6, 7)	5.25
1.6666 – 1.7777	7	Slightly more significance	(6, 7, 8)	6.25
1.7777 – 1.8888	8	Between	(7, 8, 9)	7.25
1.8888 – 2.0000	9	Extremely significant	(8, 9, 10)	8.25

The linguistic terms were then converted into triangular fuzzy numbers. The reason for using a triangular fuzzy number is that it is intuitively easy for the decision-maker to use and calculate (Senthil, Srirangacharyulu, & Ramesh, 2014). For converting the fuzzy values in pairwise comparison to a de-fuzzified definitive number, we used Minkowski formula for the definitive number (Höhle, 1980) given as:

$$x = m + (\beta - \alpha)/4 \tag{1}$$

The crisp values after de-fuzzification are shown in Table 2 for each triangular fuzzy number corresponding to rating levels.

Step 4: The pairwise comparison using de-fuzzified values of rating level results in a judgmental matrix A in which every element $a_{ij}(i, j = 1, 2 \ldots n)$ is the de-fuzzified quotient of the criteria using Equation (1), as shown:

$$A = \begin{bmatrix} a_{11} a_{12} & \cdots & a_{1n} \\ a_{21} a_{22} & \cdots & a_{2n} \\ \vdots \quad \vdots & & \vdots \\ a_{n1} a_{n2} & \cdots & a_{nn} \end{bmatrix} \tag{2}$$

where $a_{ii} = 1$, $a_{ji} = 1/a_{ij}$, $\quad a_{ij} \neq 0$

Further, the mathematical process is commenced to normalize and finding the relative weights of each matrix. The relative weights are given by the right Eigenvector (w) corresponding to the largest Eigenvalue, called the principal Eigenvector (λ_{max}), as

$$A_w = \lambda_{max} w \tag{3}$$

It should be noted that the quality of the output ANP is related to the consistency of the pairwise comparison judgment. The Consistency Index (CI) is

$$\mathrm{CI} = (\lambda_{max} - n)/(n-1) \tag{4}$$

The consistency of the subjective input in the pairwise comparison matrix can be determined by calculating a Consistency Ratio (CR). In general, the CR having a value less than 0.1 implies the pairwise matrix is consistent.

Step 5: The unweighted matrix is obtained using relations consistent to Chen, Shih, Shyur, and Wu (2012). The stable weights are obtained by multiplying the weighted super-matrix by itself until the weights in the super-matrix have converged and stabilized. The concept is similar to the Markov chain process (Saaty, 2005).

3.2.1 *ANP Computation*

In the current study, the relative significance of KPIs criteria with the interaction of supply chain operational units is calculated by the ANP algorithm. The eigenvalues and consequently the value of principal eigenvector λ_{max} were calculated using MATLAB. For the sake of brevity, as shown in Table 3, we report a sample matrix of weights of operational units corresponding to the criteria average inventory time. Table 3 shows the de-fuzzified crisp values using Equation (1) and the weights of each operational unit factor for the KPI average inventory time.

The triangular fuzzy number corresponding to each de-fuzzified value of Table 3 are shown in Table 2. However, in the reverse cell, e.g., in the first column's second row of Table 3, the value is computed as reverse of second column first row's value as:

(2, 3, 4) = (1/4, 1/3, 1/2) = (0.250, 0.333, 0.500)

Using Equation (1), we obtain the de-fuzzified value of reverse cell as 0.2917(0.250 + (0.500-0.333)/4).

Table 3: Weights of operational units for criteria average inventory time

De-fuzzified value matrix								
Average Inventory time	FE	RP	LT	STD	OS	z	D	Weights
FE	1.0000	2.2500	3.2500	1.0000	0.2917	1.0000	0.1512	0.0904
RP	0.2917	1.0000	1.0000	0.4583	0.1792	0.2917	0.1035	0.0372
LT	0.2208	1.0000	1.0000	0.2208	0.1512	0.2917	0.1035	0.0328
STD	1.0000	2.2500	3.2500	1.0000	0.2917	1.0000	0.1512	0.0904
OS	2.2500	4.2500	5.2500	2.2500	1.0000	1.2500	0.1035	0.1570
z	1.0000	2.2500	2.2500	1.0000	0.4583	1.0000	0.1512	0.0867
D	5.2500	8.2500	8.2500	5.2500	8.2500	5.2500	1.0000	0.5056

λmax = 7.0252; consistency index = 0.0042; consistency ratio = 0.0031 (< 0.1)

The consistency ratio values of all the factors were found less than 10%. As shown in Table 3, the consistency ratio turned out to be 0.31%, which is less than 10%. This implies that the ratios obtained through above heuristic method are consistent. The weights of all the factors are then integrated into the super-matrix and obtained the steady state condition of the weights as shown in Table 4. We used Mathematica 9.0 software to obtain the converged and stabilized condition of the weights. The convergence was achieved after 33 iterations. Table 4 shows that the KPI 'average fill rates' followed by 'average cycle time' are the most significant factors that are responsible for achieving the goal – Supply Chain Performance Capability.

Table 4: ANP steady state Super-matrix

	FE	**RP**	**LT**	**STD**	**OS**	**z**	**D**	**AIT**	**AIL**	**AFR**	**ACT**
FE	0	0	0	0	0	0	0	0.1496	0.1496	0.1496	0.1496
RP	0	0	0	0	0	0	0	0.0603	0.0603	0.0603	0.0603
LT	0	0	0	0	0	0	0	0.1369	0.1369	0.1369	0.1369
STD	0	0	0	0	0	0	0	0.1281	0.1281	0.1281	0.1281
OS	0	0	0	0	0	0	0	0.1704	0.1704	0.1704	0.1704
z	0	0	0	0	0	0	0	0.0981	0.0981	0.0981	0.0981
D	0	0	0	0	0	0	0	0.2573	0.2573	0.2573	0.2573
AIT	0.1214	0.1214	0.1214	0.1214	0.1214	0.1214	0.1214	0	0	0	0
AIL	0.2610	0.2610	0.2610	0.2610	0.2610	0.2610	0.2610	0	0	0	0
AFR	0.3130	0.3130	0.3130	0.3130	0.3130	0.3130	0.3130	0	0	0	0
ACT	0.3053	0.3053	0.3053	0.3053	0.3053	0.3053	0.3053	0	0	0	0

From the above results, we can compute the crisp value representing the overall score of the extent of the performance capability of a firm as:

$$EPC = \omega_{AIT}*AIT + \omega_{AIL}*AIL + \omega_{AFR}*AFR + \omega_{ACT}*ACT \quad (5)$$

EPC is the final score for the extent of the performance capability of a firm, whereas, AIT, AIL, AFR and ACT represent the scores for KPIs *average inventory time*, *average inventory levels*, *average fill rates* and *average cycle time* respectively. The performance capabilities are calculated by multiplying the rating value to the weight of the factor as shown in Table 5. In Table 5, we hypothetically assigned the ratings to nine experiments that act as the organizations O1 through O9. The ratings are assigned for all the four KPIs using the scale from 1 (extremely low) to 9 (extremely high). The ratings are based on the 'significance' of a specific KPI in obtaining the overall peformance of an organization. The notions of the varying behavior of KPIs may be due to change in operational units resulting from external and internal uncertainties.

Table 5: Values of KPIs capabilities

	AIT	**AIL**	**AFR**	**ACT**		
Organization No.	**0.1214**	**0.2610**	**0.3130**	**0.3053**	**Final weights**	**Normalized weight**
O1	1	2	1	1	1.2617	0.2853
O2	2	1	1	2	1.4274	0.3228
O3	3	5	4	2	3.5318	0.7987
O4	1	2	3	1	1.8877	0.4269
O5	1	2	2	1	1.5747	0.3561
O6	1	2	1	2	1.5670	0.3543
O7	5	4	3	6	4.4218	1.0000
O8	2	2	4	2	2.6274	0.5941
O9	3	1	4	3	2.7931	0.6316

However, the above exercise does not consider the joint effect of ideal and non-ideal solutions among various alternatives of KPIs priorities available. As discussed in Section 1.1, the company is forced to prioritize different KPIs at different time instants according to the required situations. This calls for another exercise in which joint effect of ideal and non-ideal solutions of KPIs is determined. Therefore, to study the effect of a change in KPI priority, we further used TOPSIS.

3.3 *The TOPSIS decision model*

TOPSIS, known as one of the most classical MCDM methods, is based on the concept, that the selected alternative should have the shortest distance from the positive ideal solution and on the other side the farthest distance of the negative ideal solution, proposed by Hwang and Yoon (1981). It is the most classical method of solving MCDM problems. In the TOPSIS process, we consider two ideal solutions: (i) low-is-better (L) (i.e. selecting the least value in ideal solution matrix for the respective KPI) and (ii) more-is-better (M) (i.e. selecting the maximum value from the ideal solution matrix for the respective KPI). The base settings of four KPIs considered for the ideal solution are: AIT = L; AIL = L; AFR = M; and ACT = L.

Table 6 shows the resulting positive and negative ideal solutions (A^* and A') as well as the relative separations (S_i^* and S_i') and closeness values to the ideal solution i.e., C_i^* for the nine organizations. The values of C_i^* were then normalized. We find that for the combined effect of all the KPIs at the base setting, organization 4 is at the frontier capabilities (Normalized value of

Ci^* = 1.0) and acts as the benchmark organization. Since the relative closeness scores of all the nine organizations are between the minimum values of 0.2609 to a maximum value of 0.8275, these can be plotted by taking the normalized Ci^* values on the universe of discourse from 0 to 1 as shown in Figure 3. The universe of discourse can be divided into three linguistic terms as ‘low’, ‘medium’, and ‘high’ KPI capability (Arshinder, Kanda, and Deshmukh, 2007).

Table 6: Results of TOPSIS analysis

	AIT	**AIL**	**AFR**	**ACT**	
$\mathbf{A}^*$	0.0164	0.0329	0.1465	0.0381	
$\mathbf{A}'$	0.0818	0.1644	0.0366	0.2290	
Organization No.	S_i^*	S_i'	Ci^*	**Normalized**	**Rank**
O1	0.1147	0.2246	0.6619	0.7998	5
O2	0.1175	0.2074	0.6384	0.7714	6
O3	0.1408	0.1909	0.5755	0.6955	8
O4	0.0492	0.2362	0.8275	1.0000	1
O5	0.0803	0.2275	0.7391	0.8932	3
O6	0.1209	0.1932	0.6151	0.7433	7
O7	0.2275	0.0803	0.2609	0.3152	9
O8	0.0530	0.2180	0.8045	0.9722	2
O9	0.0831	0.2087	0.7153	0.8644	4

Table 7 shows the linguistic terms and their degree of membership. From Table 7, we find that most of the organizations are either assigned with high (H) or extremely high (EH) KPI capability, of course with varying membership degree.

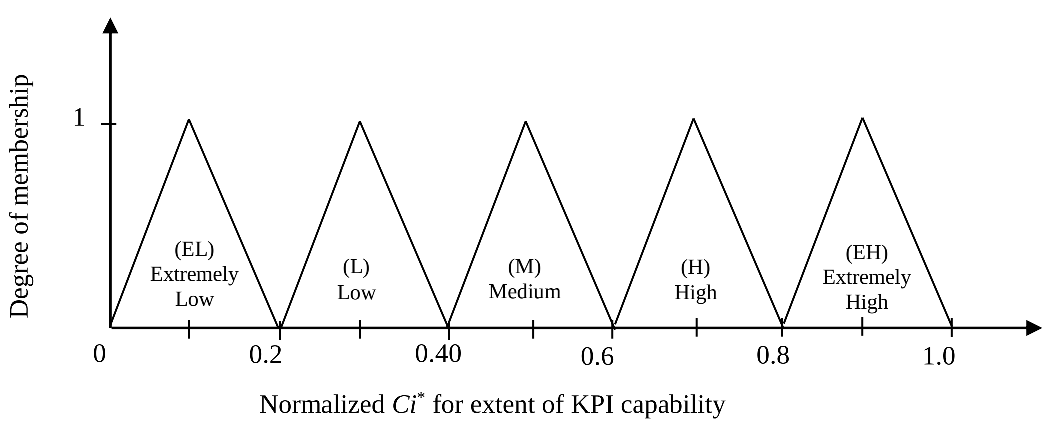

Figure 3: Linguistic terms of the extent of the KPI capability of organizations using TOPSIS

Table 7: Linguistic terms and their degree of membership for relative closeness to ideal solution in TOPSIS

Organization No.	**Normalized Ci^* Value**	**Linguistic term**	**Membership degree**
O1	0.7998	H	0.002
O2	0.7714	H	0.286
O3	0.6955	H	0.955
O4	1.0000	EH	1.000
O5	0.8932	EH	0.932
O6	0.7433	H	0.567
O7	0.3152	L	0.848
O8	0.9722	EH	0.278
O9	0.8644	EH	0.356

4. Sensitivity analysis

The current study proposed an integration of simulation, FANP, and TOPSIS as the predictive analytics in the environment of big data analysis for evaluating an organization's KPI capability. The decision maker might like to perform sensitivity analysis to reveal the effect on the evaluation process and ranking of organizations by changing the ideal solution of the decision attributes, i.e. the criteria factors; AIT, AIL, AFR, and ACT through TOPSIS process. The requirement of carrying out the sensitivity analysis can be explained from an example of a mobile phone industry.

The industry that produces mobile phones faces unique difficulties from the inventory management perspective. Due to the short lifespan of mobile phones, with the introduction of a new phone after every less than two years (Treblin, 2013), there is a sharp decline in the values of mobile phones that are kept in inventory for long periods of time (i.e. the cost of obscelence). Further, it is difficult to foresee how far a given mobile phone model would be accepted. Apple, for example, experienced shortages of the first version of their iPhone. Such situation forces to build an inventory stock to meet the projected peak demand, which could be expensive and risky. The change in the structure of demand during the product lifecycle (introduction, growth, maturity, and decline) causes difficulty in predicting how long each stage will last. Further, uncertainty in demand during lifecycle causes variability in lead time which ultimately affects the cycle time performance. Thus, above situations call for the reconfiguration of operational units as per the suitability of each KPI considered from time to time.

In view of above, we performed the sensitivity analysis by keeping the rating values constant and changing the ideal solution for all the four KPIs in the TOPSIS process. Thus, we performed 16 (2^4) experiments of possible combinations to analyze the effect of (L) and (M) for evaluating four KPI capabilities of various organizations. Table A.3 of Appendix shows that the results are expressed to be sensitive, i.e, the organization with the frontier capabilities changes with the change in the ideal solution, which subsequently depend on the rating of respective KPI. For example, in spite of high rating values of O7 for all the KPIs, we find that O7 outperforms only for those combinations in which (M) is the ideal solution for ACT performance. This is due to the high rating value of O7 corresponding to ACT (=6). Further, it is observed that for some combinations, in spite that the ideal solution of ACT is (M), the frontier capabilities of O7 is offset by the ideal solution (L) of other KPIs (i.e. LLLM, LLMM, LMLM, and MLMM). However, as seen in Table A.3, the values of Ci^* for LLLM, LLMM, LMLM, and MLMM are quite close to the frontier value (=1). Thus, under the fuzzy linguistic term these are considered for extremely high (EH) with varying degree of membership.

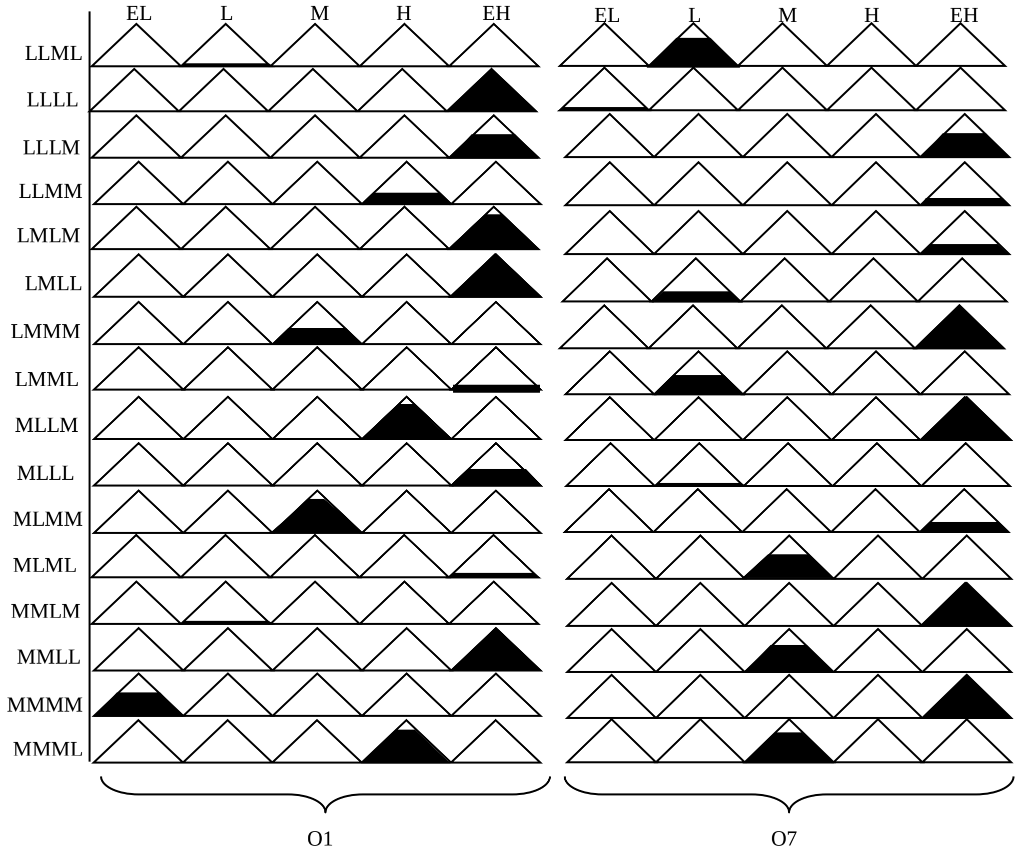

Figure 4: Comparison between organizations O1 and O7 through fuzzy plots for various ideal solution combinations of the four KPIs using TOPSIS

Figure 4 illustrates a sample of comparison between O1 and O7 in which the impact of various ideal solution combinations of KPIs can be visualized. On the basis of this visual comparisonn, the decision maker can quickly suggest adopting the appropriate values of operational units for those organizations which are lagging behind the benchmark organization for a specific ideal solution combination. For example, in Figure 4, it is observed that for the combination LMLM, both the organizations O1 and O7 operate at EH capabilities. However, since the degree of membership of O1 is higher than O7, it is advisable to adopt the operational units under which O1 is operating.

Towards the end, we find that the results obtained through sensitivity analysis suggest that, given the suitability of KPIs (L or M) from time to time during the life cycle of a product, the regulation of levels of value of operational units is required for a specific organization to be at the frontier for performance capabilities.

5. Conclusions

The present paper proposes a “Big Data Architecture” (BDA) conceptual framework that provides an effective approach managing supply chain KPIs under the dynamic environment. It elucidates the performance measure relational problem due to change in business situations by building real-time KPIs evaluation criteria that a company can consider to continuously monitor their performance capabilities. In view of this, the present study proposes an approach to visualize an arrangement of RFID-enabled and cloud ERP system for Big Data of operational units concerning the inventory system of a supply chain. In the process, RFID technology provides real-time information on various parameters related to inventory levels, setup time, idle time, etc., from which the service level of the resources could be estimated.

The present study also responds to the problem that likely happens due to the unwillingness of providing enormous real-time data related to operational units by many companies. In such a case the present research suggests offline predictive applications. This is along the lines of the concept of developing a virtual factory that integrates simulation models for different operational levels supporting data analytics. The ideas of virtual factory integrated with simulation models are also widely being discussed in the principal capabilities of the contemporary paradigm of Industry 4.0 characteristics (Hermann, Pentek, & Otto, 2016) from manufacturing perspectives.

In view of above, the present study proposes a merger of three approaches; discrete event simulation, fuzzy-ANP (FANP), and TOPSIS under the premise of big data analytics environment. The framework and methodology can help companies finding significant KPIs across the entire supply chain in a systematic real-time manner. The conceptual framework and methodologies offer some important contributions to solve interrelated KPI evaluation problem and provide appreciable insights from the big data analytics perspective.

First, this paper attempts to construct a bridge between discrete event simulation and big data analytics to provide decision support for evaluating real-time supply chain KPIs. The role of discrete event simulation includes (i) as a data analytics to perform predictive analysis for big data, (ii) supporting other data analytics offline applications to generate data for supply chain KPIs' analysis. Within the context of the simulation, to cope with the complexity and uncertainties of SC network, the paper also proposed the implementation of high intrinsic information coordination so as to obtain a high degree of accuracy in the results. Although, we have presented a much smaller SC network in the BDA conceptual framework, however, the discrete event simulation provides a generic platform which is instrumental in taking on the complexities of multi-echelon interface interactions under SC uncertainties (Dev, Shankar, Dey, & Gunasekaran, 2014a). Thus, the present SC model can provide a conceptual response to the issue addressed and can be used as a facsimile of any real life industrial SC setup. The simulation of a wider distribution network of the firm can be used as a future work.

Secondly, a significant contribution of the present research highlights the way big data for the pairwise comparison within the clusters and among different clusters for ANP is determined through a simple heuristic method from the output data of the simulation. This provides leverage to the decision maker for evaluating the KPI and quickly regulating the alternate values of operational units of the supply chain in the dynamic real-time environment. This becomes important when the decision maker has to deal with the enormous data or in the case of big data analytics. However, the vagueness of the heuristic method used is taken care of by FANP model. For each KPI, the experiments that act as the organizations were performed with hypothetical ratings through TOPSIS. From the sensitivity analysis we show that under different circumstances of the ideal solution combination for KPIs, the proposed architecture can support the managers to make decisions by adopting the values of appropriate operational units so as to maintain the performance capabilities as close as possible to the frontier organization at different time periods during the life cycle of a product.

Finally, the present paper extends the studies focusing operational units and techniques on evaluating the KPIs in a real-time setting by presenting the role of predictive analytics in Big Data Architecture. The proposed conceptual BDA framework could be extrapolated aiming at the superior architectural models through technological advancement of techniques for big data analytics and could be considered as the future endeavors. Moreover, the proposed architecture can be improvised for the analysis of the contemporary strategies like sustainable supply chain management, green supply chain management, and the circular economy based supply chain structures from the big data analytics perspectives, which can be regarded as a future work.

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Appendix A

For the demonstration of heuristic, we exhibit the simulation results for seven factors, each with two levels that result in 128 (2^7) experiments. For the sake of brevity, we show only a few results from the population of 128 results.

Table A.1: Simulation results for average inventory levels for seven factors with two levels of value.

S.No.	**FE**	**RP**	**LT**	**STD**	**OS**	**z**	**D**	**Average inventory levels**
1	15%	0.75	1.5	0.6	280	0.7	25	229 L
2	15%	3.0	1.5	0.6	280	2.15	25	251 L
3	5%	0.75	4.5	1.8	280	2.15	25	232 L
4	15%	3.0	1.5	0.6	900	2.15	75	438
5	15%	3.0	4.5	1.8	900	0.7	75	570
6	15%	0.75	4.5	1.8	900	0.7	75	523
7	5%	3.0	4.5	1.8	280	0.7	25	188 L
8	5%	0.75	4.5	1.8	280	0.7	25	178 L
9	5%	3.0	1.5	0.6	900	2.15	75	349
10	5%	0.75	1.5	0.6	900	2.15	75	350
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.

128	5%	0.75	4.5	1.8	900	0.7	75	327

Step 1: As shown in Table A.1, in this step, we select low values (L) of "average inventory levels", that is, the values up to 40 percent of the maximum value obtained for the performance average inventory level through simulation experiments.

Step 2: For each pair of the factors with two levels (low and high), there would be four possible combinations shown in Table A.2. For the demonstration, we exhibit only the pairwise comparison of FE and RP. For each combination shown in Table A.2, there would be 32 (=128/4) results that are compared for the best combination that provides a maximum number of low (L) values of average inventory levels. For instance, say, we obtain a maximum 12 (Max(lk_i)) numbers of results which are at low values of average inventory levels. Thus, we get a maximum number of low average inventory level values when FE and RP operate at low-level values, that is, at 5% and 0.75 respectively.

Table A.2: Four combinations for pairwise comparison of two factors (FE and RP)

S.No.	**L-L**	**L-H**	**H-L**	**H-H**
1	232 L	188 L	229 L	244 L
2	178 L	316	251 L	440
3	350	164 L	260 L	246 L
4	167 L	265 L	438	408
5	348	360	467	504
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
32	215 L	345	430	540
Total no. of low values	12	11	6	7

Now, for each factor FE and RP, there would be 64 (=128/2) experiments with low (L) values. For instance, in Table A.1, we find say 21 (lk_ix) number of low values of average inventory levels among 64 low-level values of FE (=5%) and say 17 (lk_iy) number of low values of average inventory levels among 64 low-level values of RP (=0.75). Thus, there is a dominance of the factor FE equal to 1.23 (=21/17) times that of RP. Accordingly, the weight corresponding to the value 1.23 (i.e., equal to 3.0) is inserted in the ANP matrix and consequently the de-fuzzified value (=2.25) in the FANP matrix.

Table A.3: Normalized Ci^*, fuzzy terms, and degree of membership values for various combinations of ideal solution of KPIs for various organizations in TOPSIS process

Ideal Solution Combinations	**O1**			**O2**			**O3**		
	Ci^*	**Linguistic term**	**Membership degree**	**Ci^***	**Linguistic term**	**Membership degree**	**Ci^***	**Linguistic term**	**Membership degree**
LLML	0.7998	H	0.002	0.7714	H	0.286	0.6955	H	0.955
LLLL	1.0000	EH	1.000	0.9684	EH	0.316	0.5300	M	0.700
LLLM	0.8643	EH	0.643	1.0000	EH	1.000	0.3414	L	0.586
LLMM	0.6380	H	0.380	0.7464	H	0.536	0.5892	M	0.108
LMLM	0.8974	EH	0.974	0.8974	EH	0.974	0.6276	H	0.276
LMLL	1.0000	EH	1.000	0.8584	EH	0.584	0.7092	H	0.908
LMMM	0.5535	M	0.465	0.5046	M	0.046	0.8598	EH	0.598
LMML	0.8073	EH	0.073	0.7032	H	0.968	0.9382	EH	0.618
MLLM	0.6972	H	0.972	0.8848	EH	0.848	0.3520	L	0.480
MLLL	0.9580	EH	0.420	1.0000	EH	1.000	0.6237	H	0.237

MLMM	0.4934	M	0.934	0.6654	H	0.654	0.6159	H	0.159
MLML	0.8108	EH	0.108	0.8155	EH	0.155	0.7673	H	0.327
MMLM	0.3908	L	0.092	0.4835	M	0.835	0.4438	M	0.438
MMLL	1.0000	EH	1.000	0.9644	EH	0.356	0.9138	EH	0.862
MMMM	0.0693	EL	0.693	0.2024	L	0.024	0.6437	H	0.437
MMML	0.7090	H	0.910	0.6447	H	0.447	1.0000	EH	1.000
Ideal Solution Combinations	**O4**			**O5**			**O6**		
	C*i**	**Linguistic term**	**Membership degree**	**C*i****	**Linguistic term**	**Membership degree**	**C*i****	**Linguistic term**	**Membership degree**
LLML	1.0000	EH	1.000	0.8932	EH	0.932	0.7433	H	0.567
LLLL	0.8628	EH	0.628	0.9492	EH	0.508	0.9254	EH	0.746
LLLM	0.7635	H	0.365	0.8152	EH	0.152	0.9585	EH	0.415
LLMM	0.7513	H	0.487	0.6893	H	0.893	0.6945	H	0.945
LMLM	0.7864	H	0.136	0.8421	EH	0.421	1.0000	EH	1.000
LMLL	0.8776	EH	0.776	0.9565	EH	0.435	0.9243	EH	0.757
LMMM	0.7300	H	0.700	0.6265	H	0.265	0.6123	H	0.123
LMML	1.0000	EH	1.000	0.8991	EH	0.991	0.7465	H	0.535
MLLM	0.5751	M	0.249	0.6338	H	0.338	0.7641	H	0.359
MLLL	0.8747	EH	0.747	0.9274	EH	0.726	0.8990	EH	0.990
MLMM	0.6317	H	0.317	0.5492	M	0.508	0.5416	M	0.584
MLML	0.9630	EH	0.370	0.8878	EH	0.878	0.7465	H	0.535
MMLM	0.1680	EL	0.320	0.2902	L	0.902	0.4398	M	0.398
MMLL	0.9240	EH	0.760	0.9701	EH	0.299	0.9182	EH	0.818
MMMM	0.3709	L	0.291	0.2138	L	0.138	0.1689	EL	0.311
MMML	0.8428	EH	0.428	0.7759	H	0.241	0.6286	H	0.286
Ideal Solution Combinations	**O7**			**O8**			**O9**		
	C*i**	**Linguistic term**	**Membership degree**	**C*i****	**Linguistic term**	**Membership degree**	**C*i****	**Linguistic term**	**Membership degree**
LLML	0.3152	L	0.848	0.9722	EH	0.278	0.8644	EH	0.365
LLLL	0.1920	EL	0.080	0.7196	H	0.804	0.6703	H	0.703
LLLM	0.8637	EH	0.637	0.7458	H	0.542	0.8945	EH	0.945
LLMM	0.8249	EH	0.249	0.8647	EH	0.647	1.0000	EH	1.000
LMLM	0.9778	EH	0.222	0.6966	H	0.966	0.6652	H	0.652
LMLL	0.2231	L	0.231	0.7122	H	0.878	0.5516	M	0.484
LMMM	1.0000	EH	1.000	0.8686	EH	0.686	0.9044	EH	0.956
LMML	0.3415	L	0.585	0.9504	EH	0.496	0.7528	H	0.472
MLLM	1.0000	EH	1.000	0.6283	H	0.283	0.8624	EH	0.624
MLLL	0.3957	L	0.043	0.7815	H	0.185	0.7683	H	0.317
MLMM	0.9607	EH	0.393	0.8070	EH	0.070	1.0000	EH	1.000
MLML	0.4654	M	0.654	1.0000	EH	1.000	0.9736	EH	0.264
MMLM	1.0000	EH	1.000	0.2594	L	0.594	0.4776	M	0.776
MMLL	0.5236	M	0.764	0.8230	EH	0.230	0.7101	H	0.899
MMMM	1.0000	EH	1.000	0.5694	M	0.306	0.6760	H	0.760
MMML	0.5123	M	0.877	0.8803	EH	0.803	0.7925	H	0.075