Proceedings in MANUFACTURING SYSTEMS

Proceedings in Manufacturing Systems, Volume 14, Issue 4, 2019, 129-134 ISSN 2067-9238

INDUSTRY 4.0 AND DECISION-MAKING PROCESS

Camelia-Gabriela ARSENE[1,*], George CONSTANTIN[2]

[1)] PhD Student, Eng., Robots and Manufacturing Systems Department, University "Politehnica" of Bucharest, Bucharest, Romania
[2)] Prof., PhD, Robots and Manufacturing Systems Department, University "Politehnica" of Bucharest, Bucharest, Romania

Abstract: *Within the manufacturing environment, data is fundamental when it comes to decisions: even if we think about building a bottom up strategy or if we just adjust the operational levels to meet already traced strategic goals. Data availability, accuracy, relevance and consistency are key drivers in decision-making process, irrespective of the level or the moment when decision happens. The way the data is processed to understand what happens and why it happens and as well to drive decisions is essential– there has never existed a best fit in terms of methodology and reaching a high objectivity level – it has always been a challenge. Both data/information and methodology are main contributors to the decision-making process and today the name of the game is the fast dynamics of manufacturing environment: demand forecast variations, multiple technologies, complex capabilities required, end-to-end supply chain synchronization, etc. Industry 4.0 elements touch both data availability (though Internet of Things, Digitization) and methodology (through Smart Data Analytics and overall Cognitive Technologies). Using a case study – referring to Overall Equipment Effectiveness calculation – from manufacturing environment, then applying and analyzing few traditional models and principles, with the present paper, the authors propose to evaluate how the Industry 4.0 elements may impact the decisional process in terms of data collection and interpretation, how the data may influence the traditional way of performance calculation and how data may be considered as part of performance indicators calculation.*

Key words: *decision-making, decisional model, manufacturing, strategy, operational level.*

1. INTRODUCTION

There are various models and principles proposed for decision- making process: from Neumann & Morgenstern who founded decision models theory in 1944 until today's machine learning and artificial intelligence (AI) based dynamic models [1]. Within the manufacturing environment, the challenge today is the big amount of decisions needed at various management levels and concerning both operational and strategic decisions. The transition from traditional static decision-making process (following classic data collection, analysis, problem identification and solving steps) to the new dynamic fast paced data driven environment is raising opportunities but as well concerns: we have good and fast data to make decisions but we are not ready with analytics capabilities.

Clearly, the Industry 4.0 implementation has a major influence in the way we need to investigate the facts and the way we respond to various situations- with decisions. Adapting the traditional static way before expanding the range of dynamic models is required- we should not forget that an AI is using potential course of actions based on clear identification of the given situation.

AI needs time to develop the baseline of facts and all responses possibilities.

* Corresponding author: Splaiul Independetei 313, sector 6, 060042, Bucharest, Romania,
Tel.: 0040 201 402 9174,
E-mail addresses: *CameliaGabriela.Arsene@garrettmotion.com* (C.G. Arsene).

The study proposes to analyze the influence of digitization – one of the main elements of Industry 4.0 – in making decisions regarding productivity levels, based on a few examples and some traditional decision-making models.

2. TRADITIONAL PRINCIPLES FOR DECISION-MAKING AND OPERATIONAL DECISIONS

2.1. Decision making principles – an overview

As stated in the introduction, literature is providing a rich amount of principles [2] when developing the decisional models, an overview being provided in Fig.1.

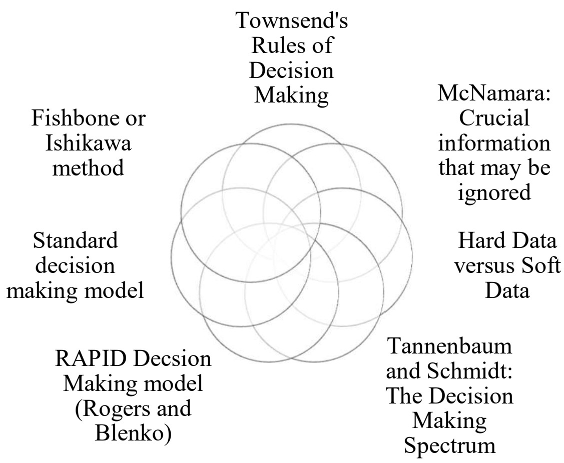

Fig. 1. Decision-making models.

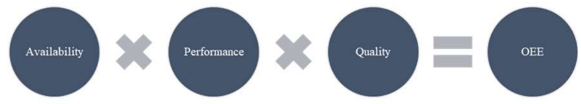

Fig. 2. OEE calculation elements.

All the models and principles are around data: it drives the relevance, the quality of decision and the response time irrespective of the stage: problem identification, analysis or decisions adjustments.

Manufacturing environment involves operational decisions (day by day adjustments that must be applied) and strategic decisions (those who are tracing the main directions to meet the organization's long-term objectives).

2.2. Operational decisions in manufacturing and productivity

The day to day concern in any manufacturing environment is optimizing resources and reducing loss to increase productivity. In the slow-paced growth trend, productivity is crucial for an organization to remain competitive and ensure sustainable business.

One of the usual Key Performance Indicators (KPIs) is OEE (Overall Equipment Effectiveness). It was invented in 1960's by Seiichi Nakajima, one of the founders of TPM (Total Productive Maintenance). Measuring OEE is the best practice in manufacturing and considers three main elements [3] as shown in Fig. 2.

$$OEE = A \cdot P \cdot Q, \tag{1}$$

where A is availability, in %; P – performance, in %; Q – quality, in %; and OEE – overall equipment efficiency, in %.

The difference between actual OEE measured and 100% is considered loss and there are multiple solutions available today to breakdown the loss in subcategories.

The OEE loss classification may go into higher or lower granularity level and it mainly consists of time loss, speed loss, and scrap loss.

Industry 4.0 through its IoT (Internet of Things), Digitization and Cognitive Technologies, enables a more accurate and faster OEE calculation collected in real time, as well a more detailed loss analysis. Today, two concerns are addressed on a large scale:

1. OEE KPI gap after IoT and Digitization implementation driven by more accurate measurement versus the traditional methods;
2. real time data and analytics which need new interpretation and decision-making capabilities.

There are companies put in front of understanding that the old methods to measure the performance presents gaps for both OEE KPI and the losses behind.

2.3. Traditional versus new Industry 4.0 decision-making

Traditional way in monitoring and adjusting the OEE KPI involves several steps displayed by Fig. 3, the analysis being static and the implementation being sequential.

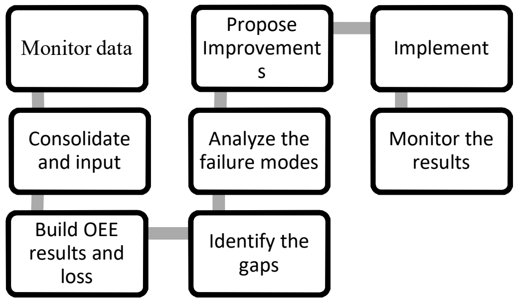

Fig. 3. Traditional steps in measuring and improving OEE.

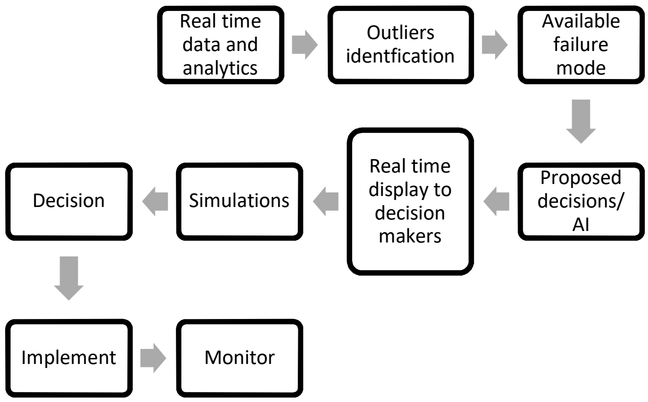

Fig. 4. New steps in measuring and improving OEE.

Actual Industry 4.0 context may involve different steps displayed in Fig. 4.

In terms of decision-making, in the new Industry 4.0 context there are few elements that change and require further focus:

1. understanding the results gaps and adjusting the performance measurement.
2. re-designing decisional layers as data available in real time to all levels.
3. re-shaping the thinking model: static versus dynamic new models.
4. leveraging cognitive technologies to automatically identify the situation and potential decisions.

2.4. Case Study: OEE before and after Industry 4.0

A manufacturing company (make to stock discrete environment) is transitioning from traditional OEE measurement methods to Industry 4.0 specific solutions. In the past the OEE input data was both manually tracked by the operators and partially automatized; consolidated after the end of reporting period and used as main input in gap analysis and resolution. After IoT and advanced shop floor automated management solutions and Digitization, the same company has a real time data display, generating granulated loss identification, target for OEE being 90%. The company continues to monitor using both traditional and new methods to stabilize new method and understand the gaps and benefit of this new implementation. The new digitized and automated method is already in trusted-mode after some initial fine-tuning period.

In Figs. 5 and 6 the OEE data from the traditional and new processes monitored over the same 5 weeks are shown.

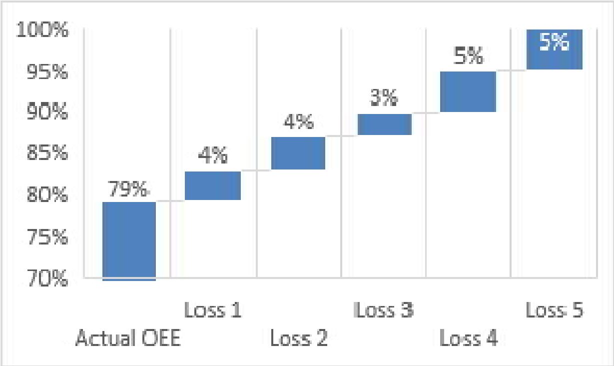

Fig. 5. OEE measurement following traditional method.

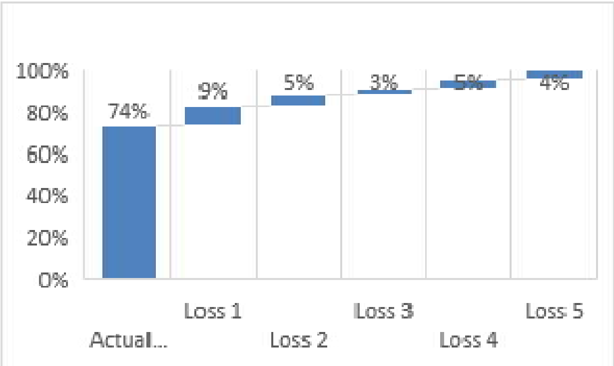

Fig. 6. OEE measurement with IOT and advance shop floor management solution.

For the same 5 weeks period, a 5% OEE difference versus traditional method was noticed after IoT and new advanced automated shop floor management system implemented, as well some different distribution between main types of loss identified.

As a further step, the management team focused on understanding the OEE loss in traditional versus new measurement context to identify which potential opportunities to reduce the loss were missed and to set up corrective actions.

For Loss 1 was noticed a gap of 5% between actual and traditional measurement (Fig. 7).

Decision makers, in. this case the production management layer, discovered that the downtime (loss 1) data gathered with traditional/ manual method was not accurate, consequently the results and decisions must be reconsidered. This pointed out clearly the benefit of the new method where data is automatically retrieved and centralized.

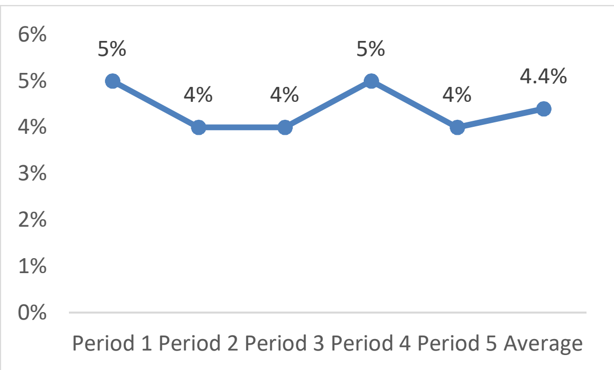

Fig. 7. Loss 1 gap analysis.

But the other observation was that despite data available in real time after automating and digitizing the calculation, the decision-making remained still in the static model.

As a preliminary conclusion, data availability and accuracy is not enough, the companies need as well data dexterity to use the data in the decisional context.

To better understand this behavior and how the new data-driven Industry 4.0 context may influence decisions and traditional decisional process, several models listed earlier will be applied to this particular case study in the following chapters.

3. TRADITIONAL PRINCIPLES FOR DECISION - MAKING INDUSTRY 4.0 INFLUENCE

3.1. Townsend's Rules of Decision- Making applied on current case study

Four main principles are characteristic to this model [1], summarized by Fig. 8.

With this case study we have learned already that in the new Industry 4.0 context the data is real-time available at all the levels, which allows applying the 1st principle. To apply the second principle at the lowest level, the Business Analytics capabilities must be developed to ensure that the quick decisions based on data and trends are the proper ones and do not involve expensive corrections.

Admitting that all decisions are lacking data it also emphasizes the need of data. In the case study there is a 5% negative gap between Industry 4.0 data driven diagnosis and the traditional one, as well a constant gap linked to the first loss. One conclusion may be that apart of traditional OEE loss associated to time, speed, quality, an additional loss may be linked to the data and introduced as a standard loss.

3.2. McNamara – crucial information that decision makers may ignore

Although it is not specific to the manufacturing environment, the fallacy model (Fig. 9) summarizes main failures (based on Yankelovitch formulation) when crucial data is ignored- just because is hard to be measured [1].

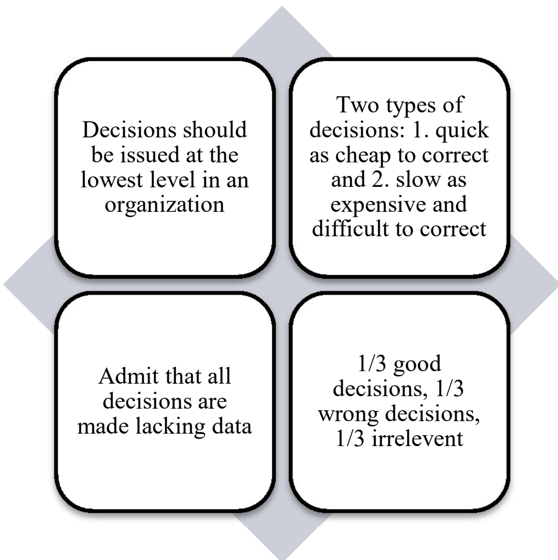

Fig. 8. Townsend's rules in decision-making.

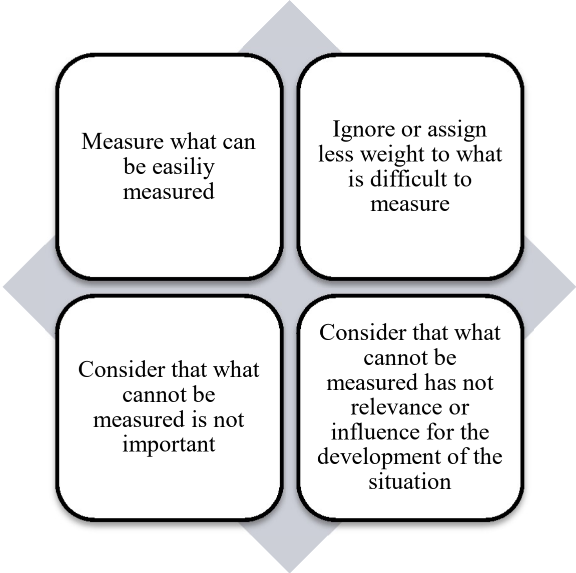

Fig. 9. McNamara fallacy model.

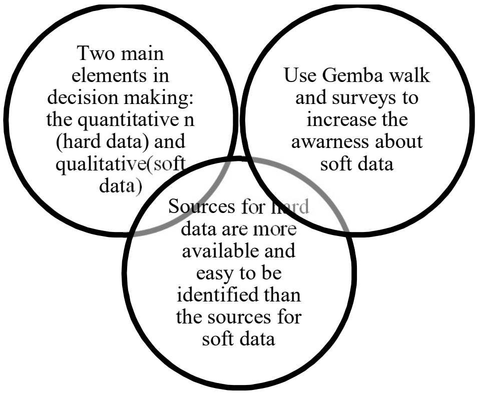

Fig. 10. Hard data-soft data.

In the case study the data availability in the traditional environment is clearly the hidden factor not measured and not considered. Not measuring just because is difficult to do it, may be a trap in the overall decision-making process.

3.3. Hard data versus soft data in decision-making

This model balances hard data with soft data [1] (Fig. 10).

In relation to the case study, there are two elements to be considered mainly to the soft data in the Industry 4.0 context.

1. Data driven decisions in a pure analytics environment may clash with the traditional understanding of problem solving in manufacturing. The employees may not be comfortable to see their method and previous conclusions challenged, therefore an early involvement in new data consumption environment is required. As well through Gemba (leaders go and see in the shop floor) can be noticed how the new methods are absorbed and how comfortable are for the employees from decision making perspective (soft data).
2. In data driven environment, in the case study, some decisions may be taken purely analytical, without evaluating the implications- which is a risk. For instance, if the first loss is most relevant and constantly the top offender, in case it refers to unplanned downtime we may not want to increase preventive maintenance and then speed up and impact the quality.

3.4. The Consequences Model: Kreiner and Christensen

This model [1] perfectly fits the manufacturing decisions requirements for having fast reaction correlated with data and time availability. [4]In the case study- clearly the Industry 4.0 implementation brings more accurate data in real time, as well as increases the concern of not having enough information applying traditional static models.

Figure 11 illustrates main principles summarized by Mc. Grath.

However, encouraging the speed in decision-making may not install a high moral culture in manufacturing environment unless the reliability of data and confidence is strong.

3.5. Tannenbaum and Schmidt: The Decision-Making Spectrum

This model identifies the range of leadership decisions between autocratic and democratic [1].

Implementing data driven real time decision-making in strong connection with reliable solutions, may encourage undebatable prescriptive directions from both lower and higher levels and may drive faster consensus and direct link to objectives. Multi-criteria automated algorithms are now used to deliver objective problem solving and decision-making options [5], removing autocratic versus democratic dilemma.

3.6. RAPID decision-making model (Rogers and Blenko)

This model splits the levels of contribution in decision-making [1] (Fig. 12).

Corelates the time and information available for decision making
Criticize the reluctance and delay in decsion making when some data missing
States that taking or delaying decision are decision themselves which can be good or wrong
Assumes that all decsions are based on incomplete information
Accepts that decisions may require adjustments during development
Uses PDCA model to help improving and refining initial decisions

Fig. 11. The Consequences Model: Kreiner and Christensen.

Five roles in decision-making process:

- R (recommend a course of actiona based on data)
- Agree (validate the course of actions)
- Perform: in charge with decision implementation
- Input: data provider to the Reccomendation role
- Decide: arbitrates and makes final decision

Fig. 12. RAPID Decision-making model – main roles.

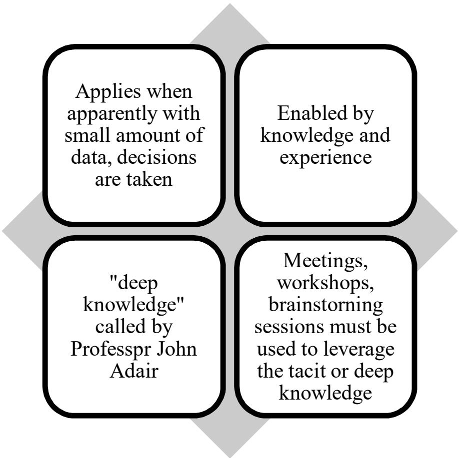

Fig. 13. Tacit knowledge characteristics.

For the case study, the differentiator is the Input: the data being the first element to be considered. The new Industry 4.0 context covers the Input (data), Recommendations and Agree (AI and simulations).

A disadvantage of this model is the big number of employees involved in decision-making, therefore may be too slow in a dynamic data driven dynamic environment.

3.7. Tacit Knowledge in decision-making

This model [1] is stating that decision makers may rely on small amount of data (Fig. 13) to justify and big expertise to anticipate the effects. In Industry 4.0 context which is all data driven and connected, this may be a challenge, unless we associate the machine learning and AI that may follow the same experience-based functionality.

3.8. Standard decision-making model

This model is similar with DMAIC [6] and linked to the case study is more appropriate for traditional static method. Figure 14 illustrates the steps.

In Industry 4.0 context, data collection is empowered by IoT and Digitization and evaluations are made by dynamic simulations.

3.9. Fishbone diagram

In the case study, loss can be disaggregated further based on the categories outlined as well in Ishikawa or Fishbone diagram.

Figure 15 displays the main sources of issues / defects.

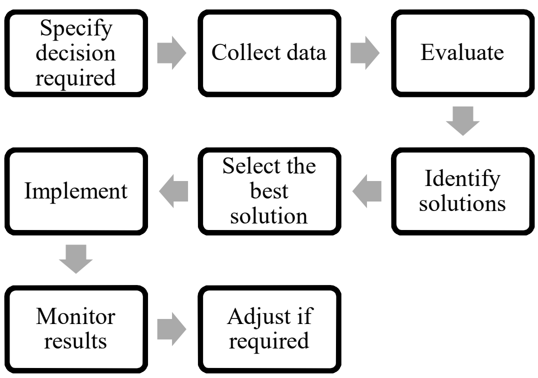

Fig. 14. Standard decision-making process.

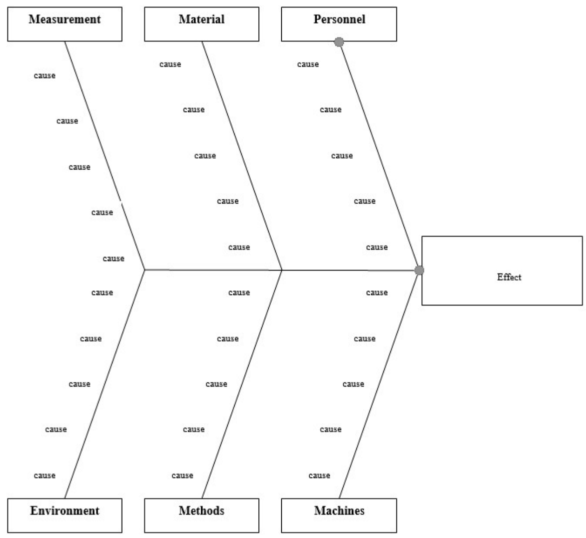

Fig. 15. Fishbone diagram elements.

In the OEE case study, we have learned that Measurement is one major component, therefore linking further this with additional data loss category, may bring the reporting and diagnosis further. Method: the way data is used, is influenced in the new Industry 4.0 context. With Industry 4.0 onboarded, data is used anymore for singular predefined purpose, but is also enabling machine learning / AI to increase the option range.

4. CONCLUSIONS

Using a case study where the data gathering and processing brought different results applying few generic models and principles, the following take-away statements may require further focus while a company is either in a traditional environment or transitioning to Industry 4.0.

Data makes the difference within the old and new context. When it comes to productivity and OEE, data loss may be considered within the type of losses as it influences the decision-making in adjusting the performance. As well data loss may be considered as a leading indicator for OEE. In Fig. 16 it is captured the concept *data loss* in addition to traditional type of losses within the standard calculation.

Specifically, for Industry 4.0 context, the data availability in real time conditions may change the decisional layers when organization desires to speed up the decisional reaction time. To do this, all the levels must be trained on data analytics – which is not very easy especially when the company is facing tacit knowledge phenomenon and intuitive decision-making based on

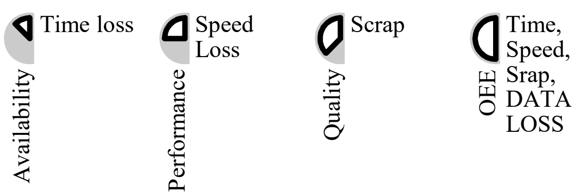

Fig. 16. OEE data proposed approach.

experience. The overall decision-making process must move from static to dynamic.

Data automation as well may fix the way the decisions are acknowledged: more facts and data moving the game into a more objective and documented area. Classifying the data and choosing what is worth to be measured will not be only the decision for strategy development but a normal output from autonomous self-controlled systems.

REFERENCES

[1] L.E. Sucar, E.F. Morales and J. Hoey, *Decision Theory Models for Applications in Artificial Intelligence. Concepts and Solutions*, IGI Global, 2011.

[2] J. McGrath, *The little book of big decision models: The 70 most useful models to help you say Yes or No,* Pearson Education, UK, 2016.

[3] `https://www.oee.com/calculating-oee.html` accessed 27th October 2019.

[4] M. Krogerus, R. Tschäppeler and J. Piening, *The decision boo: fifty models for strategic thinkin*g, W. Norton & Company.

[5] R. Ramanathan, M. Mathirajan and A.R. Ravindran, *Big data analytics using multiple criteria decision-making models,* CRC Press, 2017.

[6] D.M. Levine and H.S. Gitlow, *Six Sigma for Green Belts and Champions Foundations, DMAIC, Tools, Cases, and Certification*, Pearson_Prentice Hall_Pearson Education US, 2010.