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# Decision Making Process Development for Industry 4.0 Transformation

Ahmad Sajjad<sup>1\*</sup>, Wasim Ahmad<sup>1</sup>, Sulman Hussain<sup>1</sup>

- <sup>1</sup> Faculty of Industrial Engineering, Department of Engineering Management, University of Engineering and Technology Taxila, 47080 Taxila, Pakistan
- \* Corresponding author's e-mail: ahmad.sajjad@uettaxila.edu.pk

### ABSTRACT

Development of design characteristics based dynamic decision support framework is presented in current study, to facilitate the decision makers in transformation of system in the industry 4.0 paradigm. The model development is designed for robust decision making approach to integrate the human and machine knowledge to adopt the smart technologies and system design. The system is based on prioritization of the industry 4.0 design principles and characteristics including flexibility, self-adaptability, slef-reconfigurability, context awareness, decision autonomy and real-time capabilities. It has been revealed from industrial field study, the companies facing difficulty to transform the system, and systematics approach needed to overcome the challenge. A decision support framework has been developed an integrated approach to embed the human and machine knowledge. The machine knowledge feed through connected databases and integrated systems and human inputs the desired information in the developed system. The computation performed in two modules in hybrid mathematical modeling approach; 1) operational flexibility module and 2) prioritization module. The developed system has been validated through industrial case study, the results depicts the operational flexibility, has been measured with improvement using smart manufacturing systems and transformation characteristics prioritized using the Analytical Hierarchical Process. The developed framework has capability to help the system development and estimate the factors involve in transformation. It will also help the decision makers to overcome the challenges of migration from conventional to sustainable smart manufacturing.

**Keywords:** Analytical Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), operational flexibility, Industry 4.0, Multi-criteria decision making (MCDM).

# **INTRODUCTION**

In an era of intense market competition, the manufacturing industry is striving to adopt Industry 4.0 for high quality, cost-effective and customized production. To adapt to the dynamic industrial landscape, major manufacturing economies have formulated government-led smart manufacturing strategies, technologies and applications. These programs are focused at improving firms' capacity to become market leaders in their respective markets [1]. Companies all across the world are gaining the motivation and design to greatly increase digitization in the next five years. As recently reported, Thornton, countries from all continents, has assembled a study. According to a recently published report by Thornton, countries from all regions, including the United States, China, Japan, South Korea, India, the United Kingdom, the United Arab Emirates, the United Kingdom, Sweden, Denmark, Norway, Hungary, Malaysia, and Turkey, aim to improve their current state of digitalization and achieve the desired set goal by their domestic government policy [2]. The design principles of industry 4.0 including modularity, interoperability, decentralization, virtualization, real-time capability, and service orientation are providing a framework for designing or transforming current systems into smart manufacturing. Smart manufacturing (SM) has a set of well-defined design principles that include some features, related technology, and enablers [3].

Operational flexibility, self-adaptability, self-reconfigurability, self-decision and context awareness are all important features of smart manufacturing system design. These qualities serve as the foundation for the transformation of the production system into smart manufacturing. Multiple writers in [4-14] articulated these design elements in sub-features, which are summarized in Figure 1. In a changing world, companies have a significant difficulty in aligning their lean and Industry 4.0 operating strategies. To change lean management in Industry 4.0 technology initiatives, robust methods and ideas are required at the operational level. To lead the company at the operational decision level, suitable decision support models and roadmap frameworks are lacking [15]. To build a decision-based transformation model, it is necessary to quantify the characteristics of smart manufacturing systems.

To address the dynamic market issues, the design for dynamic management framework is proposed. The methodology is built on the measurement and ranking of smart system attributes. In this work, a hybrid mathematical modelling and decision-based problem solving technique is used to calculate and prioritize features. It is critical to assess and evaluate the characteristics of smart manufacturing in order to create a transformation decision framework. The evaluation and measurement provides the clear indication that which characteristic is most important to transform the system. In order to maintain low-cost and high-quality products, manufacturing the system should be able to produce a variety of high-volume products, Quality, installation and operating costs are low. It is often difficult to determine whether a design meets all criteria, and management and design engineers are faced with a choice from a set of feasible designs. Furthermore, this choice usually involves a trade-off between product requirements and expected performance [1]. The proposed process, aims to simplify the integration of conflicting requirements in network engineering system (NES) design,



Fig. 1. Industry 4.0 Compass of transformation characteristics

such as flexibility, robustness, resilience, operability, connectivity, and the combination of realtime analytics and intelligence, which is a globally required for manufacturing [2]. The important study related to ranking or prioritization of smart manufacturing is presented by Qu, Y., et al [3]. The author proposes a comprehensive fuzzy Kano model, Fuzzy Analytic Hierarchy Process (FAHP) method for smart features ranking. The results show that the method can provide reliable ranking of SMS requirements for designers' manufacturer. Proposed results the way is the requirements after considering four main characteristics and seventeen sub-characteristics. The scale that is used for comparison in Analytic Hierarchy Process (AHP) enables decision makers to integrate knowledge and experience instinctively and to indicate the number of times one element dominates another, taking into account criteria. The earliest scholars of the process proposed to combine linear programming (LP) with Analytic Hierarchy Process, thus taking into account both intangible and tangible factors [4]. To this end, it is proposed to use the extended concept of Interval Type 2 Fuzzy Sets (IT2FSs) of Analytic Hierarchy Process to weight supplier evaluation criteria. Then, the Complex Proportional Evaluation Method with Grey Interval Numbers (COPRAS-G) method was employed to identify relative importance and rank supplier alternatives [5]. AHP is useful in decision making, it cannot handle ambiguity. Furthermore, artificial neural networks are powerful tools in pattern recognition, but cannot come up with explicit mathematical models. To overcome the above problems, this paper aims to combine AHP with mathematical modeling. The MADM has ease in use, but the decision making relies on the option of experts as the weights assigned to the various criteria. Mathematical programming techniques are an accurate model, but they cannot take into account qualitative criteria. In mathematical models, finding accurate models for decision makers is very difficult. [6] Because of its simplicity, ease of use, and flexibility, AHP can be applied as a stand-alone method or integrated with other techniques. The integrated AHP method proved to be the most commonly used. In addition, the integration of AHP has been widely used in manufacturing and logistics, and the most frequently studied problem is supplier evaluation and selection. The integrative approach of our work is really the AHP-mathematical programming [7]. The systematic literature review has

The third phase pertains to the prioritization of characteristics and alternatives. The Multi-criteria Decision Making (MCDM) is adopted in this research for evaluation and quantitative prioritization of selected characteristics and alternatives.

been conducted to identify the transformation characteristics and sub-characteristics. The shortlisted sub-characteristics are tabulated in Table 1.

# METHODOLOGY

The adopted methodology of research work is elaborated in this section, and brief introduction of techniques used are presented. The overall methodology has been divided in to three phases as presented in Figure 2. The phase 1 comprised on systematic literature review, Industrial expert's feedback and shortlisting of sub- characteristics. Phase 1 is related to the screening and shortlisting of industry 4.0 characteristics. The Industry 4.0 characteristics are more enhanced features of flexibility, self-reconfigurability, self-adaptability, self-decision and context awareness. Initially, these characteristics are identified from the extensive literature review and in next step of phase 1 identify the desirable or undesirable list finalized after feedback from industrial experts. The phase 1 is concluded at the shortlisted characteristics list is finalized by using eligibility criteria and validated from the expert opinion.

The second phase consist of two modules named as qualitative factors weight assignment. In assigning weight module, expert judgment or opinion is used to weight the characteristics and sub-features. The second phase is concluded by providing weighed list of characteristics and alternatives. Total seven brainstorming sessions including personal interviews as well as online interaction with experts from R&D organizations including academia, industrial experts from top management and policymakers have been conducted. The experts have unanimously screened out total 16 critical characteristics under the heading of 5 major features like, flexibility, selfadaptability, self-reconfigurability, self-decision and context-awareness. This phase concluded in the form of questionnaire composed of comprehensively framed comparative questions for AHP. Subsequently, the questionnaire has been disseminated to fill out the comparison table by the all-industrial experts from R&D institutes, top management, and industrial practitioners.

Code	Child criteria	Description of smart sub features				
CC31	Agility	The ability of smart manufacturing system adjust as per external changing requiremen that altering production accordingly. [8-11]				
CC22	Interoperability	The ability of smart manufacturing system to establish communication between the system components/sub-systems through interfaces and these interfaces are also compatible with other components/sub-systems.[12, 13]				
CC54	Reliability	The ability of smart manufacturing system to carry out reliably all production processes and operations to achieve objectives of production system.[14, 15]				
CC21	Modularity	The ability of smart manufacturing system to create the economies of scale. [12]				
CC32	Convertibility	The ability of smart manufacturing system functional adjustment of system to handle the product variety. [16].				
C5	Decision Autonomy	The ability of smart manufacturing system autonomous decision making of production control, planning and operations using smart sensors, actuators, software's and communication technology to enhance the flexibility and productivity of system. [13]				
CC51	Self-controllability	The ability of smart manufacturing system controlling the systems operations and machines autonomously by mean of intelligent computer systems and components. [12, 17]				
CC24	Self-reconfigurability	The ability of smart manufacturing system, planning, decision making, self-controlling capabilities by means of smart system development like cyber physical system (CPS) for parts or assembly.				
CC52	Assets self-awareness	Being able to sense a phenomenon or event within itself (the asset), such as its location, condition or availability within the manufacturing system.[10, 18]				
CC11	Context awareness	Being able to automatically and in real-time collect manufacturing system data via a network of sensors (e.g. IoT), and subsequently conduct real-time processing (event or data driven) to provide the proper information to the right people or system and the right time.[12]				
CC53	Prognostic	Ability to detect or forecast the fault or anomaly in system prior to this happened.[17]				
CC12	Ubiquity	Being able to produce environment of everything at everywhere of manufacturing facilities that are coordinated using information and communication technology.[14, 19]				
CC13	Traceability	Ability to keep record and updates of every activity performed by everything, everywhere in whole system domain [17]				

Table 1. Shortlisted sub-characteristics

The prospective of multiple stakeholders from three diversified domains Research & Development (R&D)/Academia, Policy makers/Top management and industrial experts is scientifically computed by applying Analytical Hierarchal Process. The final outcome in the form of consolidated knowledge-based list of characteristics and alternatives are generated in context of industry 4. 0 for further taking the decision accordingly.

#### **Analytical Hierarchy Process**

The famous MCDM technique to solve the complicated and real decision problems, Analytic Hierarchy Process has been developed by Saaty [20]. The structure of this methodology is used to divide the decision problem in to three levels of hierarchical interconnection of goal/objective, criteria and alternatives. The interconnection of these factors/attributes are represented in the pairwise comparison matrix. Subjective and objective evaluation can be performed by using AHP technique [19]. It is evident from literature, AHP expensively applied in multiple fields of study in academia and industrial research including financial

or investment decision, power/energy policy development, supply chain management, engineering management, industrial policy formulation, education and socio-economic decisions. The detail of computation steps involved in AHP model are cited below. In the first stage, decision problems are formulated in a hierarchy to create a compatibility model that conforms to the AHP method. In addition, pairwise comparisons of the goals/objectives of the study under consideration were performed between predefined criteria using the Saaty-prescribed pairwise comparison scale, as shown in Table 2.

 $A_{nxn}$  is a square matrix representing the pairwise comparison of criterion i with respect to criterion j, as shown in the equation (1). Relative importance is shown in the elements of a square matrix, eg aij describes the relative importance of criterion i relative to criterion j. In a matrix,  $a_{ij} = 1$  when i = j and  $a_{ji} = 1/a_{ij}$ .

$$A = \begin{pmatrix} 1 & a_{12} & a_{13} & \dots & a_{1n} \\ & 1/a_{12} & 1 & a_{23} & \dots & a_{2n} \\ & \dots & \dots & \dots & \dots & \\ & 1/a_{1n} & 1/a_{2n} & 1/a_{3n} & \dots & 1 \end{pmatrix}$$
(1)



Fig. 2. Framework of research methodology adopted

The step is normalization of score get in result of solving pairwise comparison matrix. To normalize the score equation (2) is used as given below.

$$c_{ij} = \frac{(a_{ij})}{\sum_{j=i}^{n} a_{ij}} \quad \forall i \& j = 1, 2, ..., n$$
 (2)

Post normalization step is related to get the average of rows of comparison matrix using equation (3). This step provides the important values in form of weight or priorities of respective criteria and alternatives.

$$w_{i} = \frac{\sum_{i=j}^{n} c_{ij}}{(n)} \quad \forall i \& j=1, 2, ..., n \quad (3)$$

 
 Table 2. Scale ratio of relative importance of criteria/ alternatives

Scale	Meaning			
1	Equal Importance			
3	Moderate importance/slightly more			
5	Strong/much more importance			
7	Very Strong/very much more importance			
9	Extremely/absolutely more importance			
2,4,6,8	Intermediate values			

Pairwise opinions from experts are needed to check these comparisons for consistency. Consistency analysis is performed in this regard to check for consistency. In this analysis, each value of a column in the pairwise comparison matrix is multiplied by the corresponding priority weight obtained from the equation (3). Then use the equation (4), represents a weighted sum vector by arithmetically summing all values in row order.

$$B = w_{I} \quad \begin{pmatrix} 1 \\ \frac{1}{a_{12}} \\ \vdots \\ \frac{1}{a_{1n}} \end{pmatrix} + w_{2} \begin{pmatrix} a_{12} \\ 1 \\ \vdots \\ \frac{1}{a_{2n}} \end{pmatrix} + w_{3} \begin{pmatrix} a_{13} \\ a_{23} \\ \vdots \\ \frac{1}{a_{3n}} \end{pmatrix} + .$$

$$(1 - 1) = \begin{pmatrix} a_{1n} \\ a_{2n} \\ \vdots \\ 1 \end{pmatrix} = \begin{pmatrix} b_{1} \\ b_{2} \\ \vdots \\ b_{n} \end{pmatrix}$$

$$(4)$$

The weighed sum vector is used to calculate the Eigen vector  $E_n = b_n / w_n$  which leads to find the Eigen value. This Eigen value use in the consistency index (CI) as in Eq. (5). The Eigen value is calculated using  $\lambda$ max expression, it is the maximum value among the average of values of Eigen vector [20].

$$CI = (\lambda_{\max} - n) / (n - 1)$$
(5)

The Consistency Ratio (CR) computation is needed to maintain the consistent recording of expert's opinion using Equation (6);

$$CR = CI/RI$$
 (6)

where: CI= Consistency Index and RI = Value of Random Index which selecting from Table 3.

The decision-making process reliability depends on the value of CR. If the value of CR is less than or equal to 0.1 means MCDM process is meaning full and validate the results. Otherwise, the pair-wise judgments need to record again for desire result [21].

### RESULTS

This section is dedicated to analyze the data and results get using AHP model in responses from the experts of leading manufacturing industry and academia research experts. A software called Expert Choice<sup>®</sup> developed by Thomas

Table 3. Values of Random Index

Saaty [22] and distributed by [23] Expert Choice<sup>®</sup> Inc has been use to manage the computational complexity of AHP model. The initial weights of alternatives and criteria (including sub criteria) aggregated after computation are shown in the computed aggregate initial scores shown in

The most important factor for the smart manufacturing system implementation is operational flexibility. It is unanimously agreed by the experts of each panel that operational flexibility be the crucial characteristic of industry 4.0 system development and transformation as shown in results. It is also evident from results of panel-1, panel-2 and panel-3, the top priority attribute of smart system is operational flexibility among all other attributes with weight points 0.32, 0.28 and 0.38 units respectively (Figure 3). The second most important attribute is self-decision and self-awareness capability of smart manufacturing system as attributed by panel-1 & 3 and panel-2 respectively. The self-reconfigurability is ranged third by the expert panels. The self-reconfigurability is related to the modularity and interoperability of smart system. So it is attributed as the one of important factor to design and implement the smart manufacturing system. The last but not least is the self-adaptability of system which deal with the agility and convertibility of system. The self-adaptability is ranged at last with minute difference as compared to the features ranked at second and third place in priority list of attributes.

The next step in AHP decision problem is prioritization of alternatives using pair-wise comparison on the basis of weights calculated for criteria in the first step. In this phase the prioritization of alternatives has been carried out by pair-wise comparison of alternatives w.r.t corresponding criteria and its weights. The all expert panels have unanimously ranked the Smart Hybrid Additive and Subtractive Manufacturing (SHA&SM) at the top position, as it is cleared from the Figure 4 (a, b and c). And they recommend it is one of the best choice at present to induct in manufacturing system for better productivity, sustainable and efficient system development in Industry 4.0 paradigm. The important point noted from the results that experts have divided opinion for attribute suitable for second position. The expert panel-1

N	2	3	4	5	6	7	8	9	10
RI	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.51









& 3 considered smart additive manufacturing (SAM) Direct Metal Laser Sintering (DMLS) at second place. Their observation regarding SAM is more appropriate choice for smart manufacturing system at shop-floor level in smart factory

The consideration of expert panel-2 is different from experts of panel-1 & 3, as the autonomous robotic CNC machining (ARCM) is suitable for smart manufacturing and would be placed at second priority. So, the overall results shows, smart additive manufacturing is second best choice for smart manufacturing and autonomous robotic CNC machining is third best choice with little margin. During discussion between experts and other panelists that the role of ARCM and SAM (DMLS) is debatable. But comparatively in current scenario of Industry 4.0, SAM is better option than the ARCM on the basis of attributes or criteria being assessed and evaluated. They feel that in developing countries the manufacturing sector is under performing due many multiple challenges related to economic growth, less human resource development index and inflation The only way to revamp the manufacturing sector is introduction of cutting edge technologies like SAM. The main advantage of SAM is sustainable and efficient systems, dealing with complex product development. The other side of picture is, huge initial investment a biggest challenge to manage the system. The world leading manufacturing countries getting economic and technological benefits from transforming the manufacturing technologies and systems. The return on investment (ROI) period after implementing advance technologies like SAM is less to sustain the business model. For small or medium size product design and manufacturing SAM is an excellent choice. It can facilitate the customized production around the globe no matter where customer has demand. The reason is smart, intelligent and interconnected business model or smart factories in Industry 4.0 paradigm.

The experts in the panel-1 are belongs to academia or research and development background. The panelists suggested the SHA&SM is the future of smart manufacturing. On the other hand panel-2 experts are from industry with SHA&SM experience of mid-level management like operational engineers and managers. They feels the smart system is important for futuristic manufacturing needs, but heavy investment and implementation cost has a disadvantage. The panel-3 representatives are top management, consultants and executives members. The overall aggregation of the results depicted in Table 4, we can conclude that implementation of smart manufacturing is vital to sustain in the Industry 4.0 paradigm. And the Cyber Physical system enabled manufacturing is suitable to enhance the economies of industry. The modern technologies like SAM and

SHA&SM are unanimously recommended to transform the manufacturing infrastructure. In this study also evident that the operational flexibility is the main factor to be consider for smart manufacturing system design, develop and implement.

## Sensitivity analysis performance

The effect of variations in the input of any model reflect the change in the output. It is an important phenomenon that needs to be observed in this decision problem. This phenomenon is attributed as systematic way to check the sensitivity of model called sensitivity analysis. This section is related to the discussion on sensitivity analysis of results get from AHP model.

Figure 5 shows the performance sensitivity graph for the alternative with standard dynamic weights for five different scenarios, including the original one presented in (a). The horizontal line is the corresponding criterion, and its weight is scaled vertically. The performance of each alternative is mapped with all parameters and displayed accordingly. The total score obtained by the alternatives is indicated on the rightmost vertical line in each figure. The results was validated using TOPSIS, the comparison shown in Table 5.

# CONCLUSION

The results obtained from this study show that the goal of developing a decision-making process for Industry 4.0 transformation has been achieved. A design feature-based decision-making method using Analytic Hierarchy Process has been

					-				
Criteria	Sub-criteria	Weight of criteria	Weight of sub- criteria						
ontona	Cub chicha	S	СМ	A	RCM	S	AM	SH.	A&SM
Self-decision	Fault-tolerance	0.016	0.002	0.042	0.005	0.05	0.006	0.087	0.01
	Reliability		0.003		0.007		0.008		0.014
	Prognostic		0.007		0.017		0.019		0.029
	Self-controllability		0.004		0.013		0.017		0.034
Self-reconfigur-	Convertibility	0.013	0.004	0.04	0.012	0.042	0.013	0.09	0.037
ability	Modularity		0.009		0.018		0.029		0.038
Self- adaptability	Agility	0.013	0.008	0.03	0.02	0.032	0.01		0.01
	Interoperability		0.018		0.029		0.02	0.075	0.02
Self-awareness capability	Traceability	0.007	0.003	0.02	0.008	0.029	0.014		0.029
	Ubiquity		0.003		0.009		0.01	0.066	0.028
	Asset self-awareness		0.001		0.003		0.005		0.009

Table 4. Aggregate weights of criteria and sub-criteria with respect to alternatives





developed and validated. The MCDM technology called TOPSIS has been used for the verification process. Validation of the development process validates the transformational decision-making approach. The results obtained from the AHP and the validation obtained from the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method are identical. Operational flexibility is the most important design feature and enabler of Industry 4.0 transformation. Smart Hybrid Additive and Subtractive Manufacturing has been recommended as the most suitable choice for a smart alternative manufacturing technology. The proposed model would be a more suitable option for policymakers and industry experts to adopt a robust systematic decision-making approach for intelligent systems at the planning stage before making high-investment decisions. The developed process will be guideline during decision making process for decision makers, consultants and top executives in manufacturing companies regarding adoption of smart technologies. The consideration of design characteristics in decision making provides the system thinking approach which mostly

Sub abaractoristica	Global ranking			
Sub-characteristics	AHP	TOPSIS		
Fault-tolerance	11	11		
Reliability	10	10		
Prognosis-ability	5	5		
Self-controlability	6	6		
Convertability	7	7		
Modularity	3	3		
Agility	4	4		
Interoperability	2	2		
Traceability	12	12		
Ubiquity	9	9		
Asset self-awareness	8	8		
Operational flexibility	1	1		

 Table 5. Comparison of Ranking using TOPSIS validation

ignore in transformation. From the system designer's point of view, this will help to have a clear understanding of the smart technology, thereby improving operational flexibility to a certain extent.

The current study bridge the research gap as in literature many researcher have worked on the decision making process regarding challenges faced in transformation of industry 4.0. Few authors have only identified the smart system design characteristics only, the design characteristics-based approach for transformation is missing. The developed system provides the systematic method by considering the design characteristics in transformation. The innovative and dynamic approach has been presented for decision makers in industry 4.0 transformation. The current study has few limitation as the scope is confined to considering the only seventeen design characteristics. To avoid the complexity, responses and time constraints in adopted AHP methodology only selected characteristics has been evaluated. The more compressive study may be conducted by considering large number of design characteristics and alternative smart manufacturing technologies for more complex scenarios and requirements. The developed process can been extended for hybrid approach to integrate the machine and human knowledge in real-time.

# REFERENCES

1. Milisavljevic-Syed J., et al. Decision-Based Design of Networked Manufacturing Systems (NMS), in Architecting Networked Engineered Systems. 2020, Springer; 41–70.

- 2. Milisavljevic-Syed J., et al. Architecting Networked Engineered Systems: Manufacturing Systems Design for Industry 4.0. 2020: Springer Nature.
- Qu Y., et al. Integrating fuzzy Kano model and fuzzy analytic hierarchy process to evaluate requirements of smart manufacturing systems. Concurrent Engineering. 2019; 27(3): 201–212.
- Mejjaouli S., Albathi R. Fuzzy AHP and Linear Programming Based Decision Support System for Logistics Service Providers Allocation.
- Kaya S.K., Aycin E. An integrated interval type 2 fuzzy AHP and COPRAS-G methodologies for supplier selection in the era of Industry 4.0. Neural Computing and Applications, 2021; 1–21.
- Fallahpour A., Olugu E.U., Musa S.N. A hybrid model for supplier selection: integration of AHP and multi expression programming (MEP). Neural Computing and Applications, 2017; 28(3): 499–504.
- Bruck B.P., et al. A Decision Support System to Evaluate Suppliers in the Context of Global Service Providers. in Proceedings of the 23th International Conference on Enterprise Information Systems (ICEIS 2021). 2021.
- Jung K., et al. Performance challenges identification method for smart manufacturing systems. 2016: US Department of Commerce, National Institute of Standards and Technology.
- Lee Y.T., et al. A classification scheme for smart manufacturing systems' performance metrics. Smart and sustainable manufacturing systems. 2017; 1(1): 52.
- Kibira D., et al. Methods and tools for performance assurance of smart manufacturing systems. 2015: US Department of Commerce, National Institute of Standards and Technology.
- Lu Y., K.C. Morris, and S. Frechette. Standards landscape and directions for smart manufacturing systems. in 2015 IEEE international conference on automation science and engineering (CASE). 2015. IEEE.
- Tao F., et al. Advanced manufacturing systems: socialization characteristics and trends. Journal of Intelligent Manufacturing, 2017; 28(5): 1079–1094.
- Davis J. Cyberinfrastructure in chemical and biological process systems: impact and directions. in Arlington, VA, NSF workshop report; 2006.
- Park H.-S., Tran N.-H. Autonomy for smart manufacturing. Journal of the Korean Society for Precision Engineering. 2014; 31(4): 287–295.
- 15. Cheng K. Keynote presentation 2: Smart tooling, smart machines and smart manufacturing: Working towards the Industry 4.0 and beyond. in 2015 21st International Conference on Automation and Computing (ICAC). 2015. IEEE.

- 16. Lafou M., et al. Convertibility indicator for manual mixed-model assembly lines; 2014.
- Park J., Lee J. Presentation on Korea smart factory program. In: Proceedings of the international conference on advances in production management systems, Tokyo, Japan 2015.
- Davis J., et al. Smart process manufacturing: An operations and technology roadmap. Smart process manufacturing engineering virtual organization steering committee, Los Angeles, CA, Tech. Rep; 2009.
- Papazoglou, M.P., van den Heuvel W.-J., Mascolo J.E. A reference architecture and knowledge-based structures for smart manufacturing networks. IEEE Software. 2015; 32(3): 61–69.
- Karayalcin I.I. The analytic hierarchy process: Planning, priority setting, resource allocation: Thomas
   L. SAATY McGraw-Hill, New York, 1980, xiii+287 pages, £ 15.65. North-Holland; 1982
- Jadoon T.R., et al. Sustaining power production in hydropower stations of developing countries. Sustainable Energy Technologies and Assessments. 2020; 37: 100637.
- French S., Xu D.L. Comparison study of multiattribute decision analytic software. Journal of Multi-Criteria Decision Analysis. 2005; 13(2–3): 65–80.
- 23. Von Winterfeldt D., Edwards W. Decision analysis and behavioral research; 1993.