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Smart Production Planning and Control: Technology Readiness Assessment

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Abstract

There is a clearly identified need to support SMEs to be aligned with technology advances in the context of Industry 4.0 throughout the end-to-end engineering across the entire value chain. Thus, this study aims to adapt and utilize the Smart SME Technology Readiness Assessment (SSTRA) methodology to enable SMEs to gain available information and data to process it in a standardized manner to analyze the technology readiness to implement industry 4.0. The SSTRA framework and methodology is implemented in a real case study with a focus on the smart production planning & control phase. Also, the conceptual model for Smart production planning & control development is proposed and validated. Feedback shows how this method can be effective to implement throughout the worldwide smart SMEs development to support the strategic transition to Industry 4.0 era.

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Keywords: Industry 4.0; Smart production planning & control; Maturity model; SMEs; Assessment methodology

1. Introduction

In the last few decades, many privileges have been brought for the entire value chain by the evolvement of information and communication technologies (ICT) and its integration into manufacturing processes. These have enhanced industrial productivity in one side and on another side, have reduced production costs and provided more effective solutions to serve customers with appropriate quality, speed, and cost [1]. Global manufacturing is currently undergoing a significant transformation driven by the digitalization of its infrastructure and systems. This

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transformation has been termed Industry 4.0 (i.e. the fourth industrial revolution). Industry 4.0 is the newest industrial revolution that was announced in Hannover in 2011 [2]. It highlights the importance of new and innovative technologies being readily available to businesses in the 21st century. The three previous 'industrial revolutions' that have come before the concept of Industry 4.0, relate to the introduction of engine power, mass production with the aid of electrical power and automation using IT [3]. Industry 4.0 represents the next step to significantly increase the efficiency and quality of the products while offering flexibility and customization that is not possible with conventional production systems. It promises to offer huge opportunities for companies regarding modular, efficient, and intelligent systems using software to improve by analyzing data [4]. This allows creating customized products in a batch size of one with the same economic conditions as mass producing them. From the improvements in production and service management point of view, "Industry 4.0 focuses on the establishment of intelligent and communicative systems including machine-to-machine communication and human-machine interaction" [5]. To become Industry 4.0 recognized, a business must enhance its current autonomy, optimization, control, and monitoring [6].

Small and medium-sized enterprises (SMEs) is defined by the European Commission as a company that employs less than 250 employees and has a turnover of less than €50 Million [7]. SMEs make up 90% of businesses across the world in which guarantee the growth and prosperity of every society. The SMEs who are the driving force of many manufacturing economies need to be technologically advanced to optimize their performance with the integration and application in the concept of Industry 4.0 [8]. However, they face various challenges to transform to Industry 4.0 due to limitation on internal resources, specialist workforce, and lack of knowledge and experience to define the appropriate strategy to implement Industry 4.0 from theory to practice [9,10]. Hence, to provide a clear picture of the SMEs strengths and weaknesses to decide in which areas or technologies need to focus more to keep its operation compatible towards the digital era, the main objective of this research work is to adapt SSTRA methodology to support SMEs to examine their current state of technology readiness toward Industry 4.0 from the smart production planning & control point of view. In contrast, with some existed tools/methods, although, the implementation of the SSTRA methodology may require more time and resource (e.g. experts, workshops). Instead, as this is a step-by-step approach to decision making, assist SMEs to reduce the risk of further investment and implementation in their journey towards Industry 4.0 benefits.

2. SSTRA methodology

The SSTRA is a systematic approach which allows practitioners to measure smart SMEs technology capability/readiness for implementing Industry 4.0 throughout the end-to-end engineering across the entire value chain. In this regard, SSTRA helps SMEs to evaluate their current situation concerning Industry 4.0 requirements, provides a clear perspective about their strengths and weaknesses and allows identifying key barriers in their transition to the Industry 4.0. Briefly, the SSTRA can be recognized as an integrated framework based on closely coupling several techniques and methodologies to enabling SMEs to examine their level of technology readiness to implement Industry 4.0. Implementation of the SSTRA process consists of three main phases including Requirements data collection phase, Benchmarking phase and Assessment phase. Fig. 1. shows the SSTRA framework with its three phases and illustrates the flow of activity from beginning to end. In the following, each phase is explained in detail.

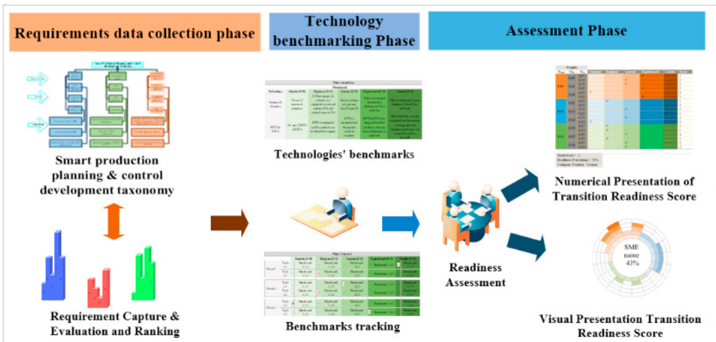

Fig. 1. SSTRA Overall Framework

2.1. Requirements data collection phase

The SSTRA has been shaped to help assessors to collect available information and data to analyze an SME readiness for implementing Industry 4.0 in their enterprise. Mapping of the detailed descriptions and classifications (taxonomy) of the technologies of relevance to SME operation via facilitated workshops is the first step of the data collection phase. This allows SME to identify, selecting, and prioritizing (i.e. weighting) key requirements including Main Criteria (MC), Drivers (D) and Technology (T) to satisfy the market and product needs, enterprise drivers and technology competitiveness position to process it in a standardized manner to analyze an SME readiness for implementing Industry 4.0 in their enterprise. The SMEs are very limited from the resources point of view, so they may need to know by investing in which technology, driver or criterion would help them more to achieve Industry 4.0. SSTRA also utilizes the Analytic hierarchy process (AHP) for supporting SMEs to determine the own relative importance of each main criteria, drivers and technologies which can be decided directly by assigning weight (W) to each criterion. The output of this phase later contributes to the assessment of transition readiness through the assessment phase.

2.2. Technology benchmarking phase

In the second phase of SSTRA, each technology has five benchmarks (*Si*), the value starts from (0-4), corresponding to the Technology Readiness Levels (TRLs) that must be met to complete the level. Each technology is assessed using one of five available benchmarks to indicate progress towards a successful transition to Industry 4.0. This aid SMEs easily compare their technology readiness to identify their current situation concerning a specific technology. The output of this step is used in the assessment phase to measure the SME transition readiness. In the following bullets the TRLs are described:

- ***Si*=0 is Outsider** means SME still follow the conventional methods and technologies to plan & control the production. They are not aware and confident enough to start their journey towards Industry 4.0 or they might assume that Industry 4.0 is irrelevant to them.
- ***Si*=1 is Beginner** who has started to think about changing its strategy to employ Industry 4.0 technologies to design and develop a smart production planning & control. It shows an enthusiasm to implement Industry 4.0. Additionally, a few technologies related to Industry 4.0 are adapted to the production planning & control department, but investment in this area is very limited.
- ***Si*=2 is Learner** refers to a company who defined a clear roadmap towards implementing smart production planning & control and started using some Industry 4.0 technologies but to a limited extent.
- ***Si*=3 is Experienced** refers to a company who employed Industry 4.0 technologies and strategies to a good extent, but it needs to invest more resources in this area to realizes the ultimate potential of Industry 4.0. The company uses Industry 4.0 technologies to a very good extent with the purpose of smart production planning & control.
- ***Si*=4 is Leader** refers to an SME which entirely employed Industry 4.0 related technologies and strategies to design and develop a smart production planning & control. In other words, they satisfy all technology requirements, this is the highest maturity level

2.3. Assessment phase

In the assessment phase, the assessors benefit the outputs from prior phases to evaluate the SME transition readiness. In this phase, the SME is assessed based on the appropriate weighting ($W_{ti}, W_{dj}\ and W_{mcz}$) given to three main key elements: T, D, and MC respectively through prioritizing step in phase one. And the given score to each technology benchmarks (S_i) through the technology benchmarking phase. Thus, the total readiness score of a company toward Industry 4.0 can be evaluated as follows:

- As given in equation (1) the score of each technology (T_i) equals to the achieved score (S_i) multiplied by the weight of that technology (W_{ti}).

$$T_i = S_i \times W_{ti} \tag{1}$$

- The score of each driver (D_j) equals to the sum of scores of all its belonged technologies multiplied by the weight of the driver (W_{dj}) (see Equation 2).

$$D_j = W_{dj} \sum_{i=1}^{n} S_i \times W_{ti} \tag{2}$$

- The score of a main criterion (MC_z) equals to the sum of scores of all its related drivers multiplied by the weight of the main criterion (W_{mcz}) (see Equation 3).

$$MC_z = W_{mcz} \sum_{j=1}^{k} W_{dj} \sum_{i=1}^{n} S_i \times W_{ti} \tag{3}$$

Thus, the total score of a company (R) equals the sum of scores of all criteria (MC_z) (see Equation 4).

$$R = \sum_{z=1}^{h} W_{mcz} \sum_{j=1}^{k} W_{dj} \sum_{i=1}^{n} S_i \times W_{ti} \tag{4}$$

Where:
n is the number of technologies,
k is the number of drivers and
h is the number of criteria.

The maximum readiness score that a company can achieve is four which means the company is in the position of a leader. The minimum score is zero which represents an outsider company. It should be mentioned that the total readiness score can be any number between 0 and 4. The obtained total score will show the current situation of the company toward Industry 4.0 readiness. Moreover, it gives a clear picture of the company's current situation with respects to each technology, drivers, and main criterion. The following classification also can be considered in which the boundary between the "*outsider* with *beginner*" and "*experienced* with the *leader*" are logically considered to be narrow:

$$\text{If Readiness Score } (R) \begin{cases} 0 < R \leq 0.5 \rightarrow \textit{Outsider} \\ 0.5 < R \leq 1.5 \rightarrow \textit{Beginner} \\ 1.5 < R \leq 2.5 \rightarrow \textit{Learner} \\ 2.5 < R \leq 3.5 \rightarrow \textit{Experienced} \\ 3.5 < R \leq 4 \rightarrow \textit{Leader} \end{cases}$$

3. The hierarchical requirements model for Smart production planning & control

In this section as shown in Fig. 2, by carefully examining the literature and expert's opinion in this area, the hierarchical requirements model for smart production planning & control is developed. In the following sub-sections, the detail explanation of the proposed model is provided.

3.1 Real-time data management system

A real-time data management system is a "database system" which track, collect, analyze, and protect data from external sources (e.g. customer, supplier, etc.) and internal sources (e.g. inventory movement, shop floor events, etc.) in the real-time which is crucial to provide the SMEs with highly adaptive and responsive planning, scheduling and execution system [11]. As part of the real-time data management system, the use of data acquisition allows SMEs to have the availability of accurate field data in real-time from related databases such as the suppliers, customers, shop floor etc. [12]. In terms of required technologies for data acquisition, Radio Frequency Identification (RFID) has been known as one of the most advanced technologies to capture real-time data across the entire value chain which has a positive effect on improving shop floor productivity and quality [11,13]. Real-time locating systems (RTLS) is another capturing technology which enables continuous detecting and exploring of the location of objects through the entire production in real or near-real-time [14]. Besides, Sensors and Actuators are low-level devices that have a direct responsibility to communicate with the physical world, whether measuring some variables and transferring to higher-level or enabling higher-level devices to affect real-world [15]. The real-time data management system also needs to focus on the management and optimization of production planning & control processes by analyzing historical data, discovering patterns, and taking actions to deal with issues [16]. In this regard, Big Data technology is needed to extract and analyze required data for monitoring the production processes among the large and complex generated data [17]. Cloud computing infrastructures can be utilized to meet both the computational and data storage needs of big data analytics applications [18]. It also supports manufacturing resources optimization by dynamically virtualizing and scaling resources [19, 20]. Due to using cloud computing widely in the real-time data management system, the need of data security is critical to enhancing security in “Data Transfer”, “Data Storage” and “Data lineage” [21]. Block-chain is one of the technologies that can add trust, security, and decentralization to a variety of industries including SMEs [22]. A virtual private network also would extend security for data shared over the public network and including company applications [23].

3.2. Dynamic production Planning

In today’s uncertain and competitive market to address rapid changes in the business environment and customer requirements, the urgency of more responsive production planning is undeniable. By addressing the goal of Industry 4.0, this system is also very agile and can respond quickly to environmental changes. In the dynamic production planning, all main internal and external parties need to participate in the production planning phase. Industry 4.0 virtual enterprise provides collaborative and win-win environment by implementing horizontal and vertical integration which allows all partners to participate in entire production planning [24, 25]. Keep in mind that the digital infrastructure that mostly is covered through real-time data management and their connectivity with the internet is the main enabler of Industry 4.0 virtual enterprise, the available ICT capabilities of manufacturing companies have a significant role through the network collaboration [26]. Inter-enterprise collaboration can be facilitated by using the Internet of Services (IoS) in which both internal and external services will be provided and utilized by all stakeholders through the entire value chain [27]. Decision-making through production planning refers to the cognitive process that leads to timely decisions that require many input variables for short-term planning based on real-time production data and non-production data [28]. Visual data mining is one of the industry 4.0 technology that supports decision-makers to search temporal data interactively, identify important relationships and use interesting models in dynamic decision-making [29]. Computational intelligence (CI) refers to the ability of a computer to learn to design from data or experimental observation. CI techniques can play a significant role in optimal production planning to solve a combinatorial optimization problem that requires to be efficiently modelled [30]. Through production planning, dynamic scheduling/rescheduling capability is required to automatically deal with any disruptions in the production process that may affect planning. Digital twin (DT) has great potential to make dynamic scheduling to be possible. DT utilise both real and simulated data to provide more information to predict the availability of the resources. It also compares the physical resources with the digital counterpart which is constantly updated in real-time to help to detect disturbances [31]. The smart ERP system along with data mining techniques enables digital twin model to provide a digital display of past and present behaviour of a single object up to the entire production system which plays a significant role to quickly respond to any disruptions in the production process [32].

3.3. Autonomous Execution Control

Autonomous production control through Industry 4.0 is characterized by decentralized and digitalized production control which aims to enhance production systems performance in which each element of the production can control autonomy and respond quickly to changes in dynamic production environments [33, 34]. In such a system, self-optimizing production control is required to constantly review the current production situation and as a result, the distribution of the jobs on the machines can be optimized at any time [35]. In this regard, Machine learning (ML) and

Artificial Intelligence (AI) can support control system to solve the real-time problems by extracting patterns from raw data which allow the machine to be adjusted based on products and produce small batch sizes [36]. To keep producing a single product profitable under industry 4.0 production, automated quality inspection is essential to not only ensure the delivery of best quality products but also allow customers to access the product quality data at real-time [37]. 3D scanning and smart camera are the technologies that allow SMEs to capture reliable and fast quality outputs and provide the opportunity to compare the final part/product with the initial design to guarantee fitting performance with other parts [37]. Peer collaboration in the control system is also needed so that components can communicate with peers to jointly help identify and respond to faults [38]. Many companies are already using Virtual Reality (VR) and Augmented Reality (AR) to offer new ways of improving Human-Machine collaboration. Maintenance and repair can be a good example which operator by using VR/AR glasses would be able to simply monitor the machine's performance parameters and adjust it without even physically touching it [39]. Also, Machine-to-Machine (M2M) communication let “smart devices” be able to communicate with each other independently and make joint decisions without direct human intervention [40].

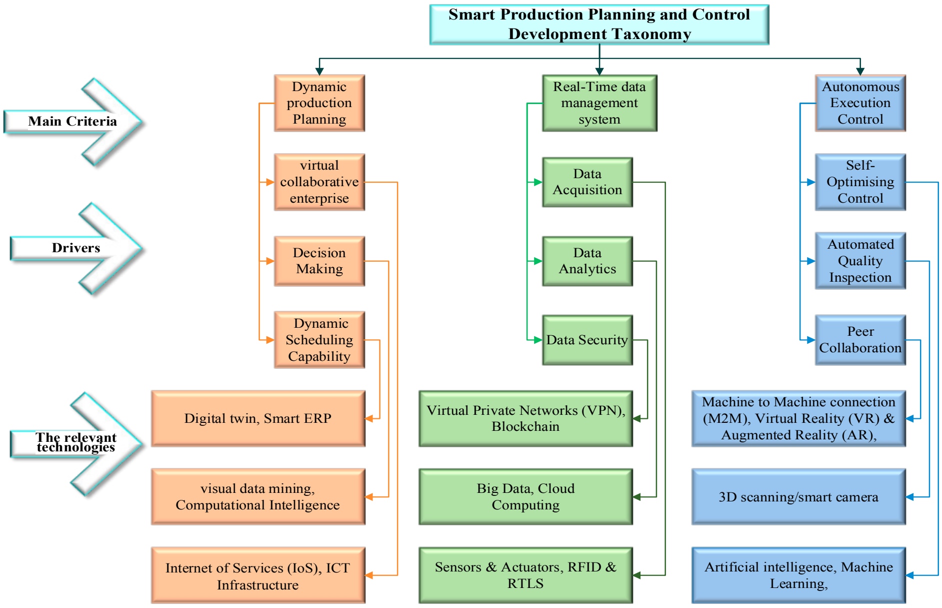

Fig. 2. The hierarchical requirement for smart production planning & control

4. Validation of the proposed hierarchical requirements model

To validate the proposed model, a questionnaire was designed for data collection purposes from 50 industrial SMEs. The questionnaire was developed based on the criteria and levels in the smart production planning & control requirements capture hierarchy (i.e. Fig. 2.). Experts who have been asked to make pairwise comparisons between the two factors/criterion in each level at a time, decide which factor is more important and then specify the degree of importance on a scale between one (equal importance) and nine (absolutely more important) of the most important factor/criteria [41]. All the responders agreed about the proposed model and showed positive responses towards smart production planning & control and its necessity. Most importantly, this can also be considered as a validation of the model. For example, the judgement output of the three main criteria located in top-level showed that Real-Time Data Management was the most important criterion (0.57) for SMEs followed by Autonomous Execution Control (0.29), and Dynamic Production Planning with the least ranking (0.14). In addition, global priorities of technologies are given in Fig.3. in which Machine Learning received the highest ranking (16.6%), followed by Big Data (15%), Sensors & Actuators (14.5%) and Computational Intelligence (0.9%) was the lowest ranking with respect to the ‘main goal’. Later, this model is contributed as a benchmark in this field to the industrial application of the SSTRA methodology while it could be modified based on the nature of SME during the requirement capture workshops (see Section 5).

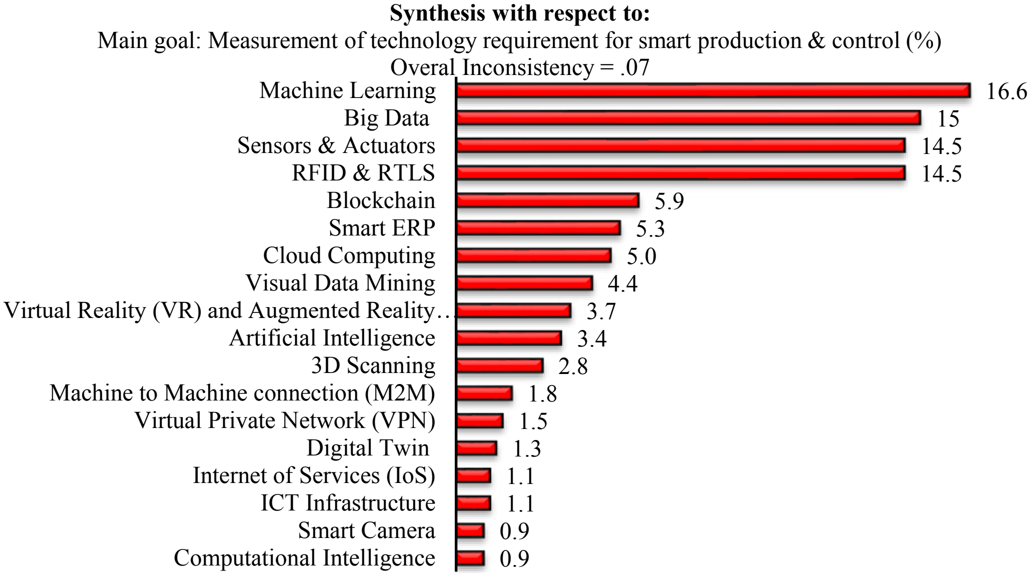

Fig. 3. Global priorities of technologies (%)

5. Industrial application of the SSTRA

In this paper, SSTRA was applied in the SME manufacturer in the sanitary ware industry in the form of the case study. According to the signed confidentiality agreement, the name of the company remains anonymous. But some results were allowed to be presented by extracting real names and, etc. SSTRA implementation was carried out by the planning of a set of meetings and workshops to obtain and analyze the collected data. However, to follow social distancing guideline (i.e. COVID 19), all meeting and workshops were conducted online by the researchers rather than on-site company visits. In total, two meeting and three workshops were held.

In the first meeting with the company senior managers, the objective of the practice is explained, the participants were recognized, and subsequently, the project team was formed. Then, in the second meeting with all participants, a solid knowledge base regarding the SSTRA framework and the matters related to Industry 4.0 within the company was created. In the first workshop, during the requirements data collection phase, the proposed hierarchical requirements model (i.e. Fig. 2) was provided to the project team as the benchmark to be evaluated. The project team was free to do any modification if necessary, to be more compatible with the nature of the company and its operation. The research team was available during the workshop for any clarification and support. There was no conflict among the project team members that the benchmark model is completely fit with company operation. Subsequently, AHP was used for ranking the main criteria, drivers and technologies to reflect the current priorities of the SME. In this regard, Expert Choice Software was used to drive the local weight of each element of each level in the benchmark model ($i.e. W_{ti}$, W_{dj}, and W_{mcz}). Finally, the output of this phase was documented (see Table 1) to be used through the assessment phase. In the second workshop, the technology benchmarking phase was completed using a graphical interface to assess the SME technology readiness position based on technologies' benchmarks (Si). As an example, technologies benchmarks under Automated Quality Inspection driver is provided in Table 2. The given score to each technology benchmarks was documented (see Table 3) and later used as input to the assessment phase to measure the transition readiness. Finally, in the third workshop, based on transmitted outputs from prior phases, equation 4 was used by assessors' team to calculate the total readiness score (R) and identify the company position. The outcome proved that R =1.08, and in this case, the company was classified as "Beginner". Beside quantitative readiness score, visual representation of matrix data was also provided to help company decision-makers in understanding the relative readiness of each main criterion by technology (see Fig. 4.).

Table 1. The output of requirements data collection phase

Main Criteria (MC)	W_{mcz}	Driver (D)	W_{dj}	Technology (T)	W_{ti}
Real-time Data Management System	0.53	Data Acquisition	0.44	Sensors & Actuators	0.67
				RFID & RTLS	0.33
		Data Analytics	0.30	Big Data	0.75
				Cloud Computing	0.25
		Data Security	0.26	Virtual Private Network (VPN)	0.33
				Blockchain	0.67
Dynamic Production Planning	0.31	Virtual Collaborative Enterprise	0.30	Internet of Services (IoS)	0.50
				ICT Infrastructure	0.50
		Decision Making	0.22	Visual Data Mining	0.50
				Computational Intelligence	0.50
		Dynamic Scheduling Capability	0.48	Digital Twin	0.25
				Smart ERP	0.75
Autonomous Execution Control	0.16	Self-Optimizing Control	0.34	Machine Learning	0.50
				Artificial Intelligence	0.50
		Automated Quality Inspection	0.37	3D Scanning	0.50
				Smart Camera	0.50
		Peer Collaboration	0.29	Virtual Reality (VR) and Augmented Reality (AR)	0.67
				Machine to Machine connection (M2M)	0.33

Table 2. Automated Quality Inspection technologies benchmarks

Automated Quality Inspection					
	Benchmark				
Technology	***Outsider*(*S*=0)**	***Beginner* (*S*=1)**	***Learner* (*S*=2)**	***Experienced* (*S*=3)**	***Leader* (*S*=4)**
3D Scanning	No use of 3D scanning ☐	Hand-held laser 3D scanners are used ☐	Triangulation 3D scanning technology is used ☒	Offline industrial computed tomography scanning and structured-light 3D scanners are connected to the central production planning and control system ☐	Industrial computed tomography scanning and structured-light 3D scanners are connected to the central production planning and control system via Cloud ☐
Smart Camera	No use of industrial vision systems ☐	Conventional (2D visible light) imaging is used ☒	PC-based vision systems are used (i.e. the vision system is connected to a computer) ☐	An offline self-contained, standalone vision system with a built-in image sensor is used ☐	A self-contained, standalone vision system with a built-in image sensor is connected to the central production planning and control system via Cloud ☐

Table 3. The output of the benchmarking phase

Technology (T)	S_i
Sensors & Actuators	1
RFID & RTLS	1
Big Data	2
Cloud Computing	0
Virtual Private Network (VPN)	0
Blockchain	1
Internet of Services (IoS)	2
ICT Infrastructure	2
Visual Data Mining	1
Computational Intelligence	0
Digital Twin	1
Smart ERP	1
Machine Learning	1
Artificial Intelligence	1
3D Scanning	2
Smart Camera	1
Virtual Reality (VR) and Augmented Reality (AR)	0
Machine to Machine connection (M2M)	0

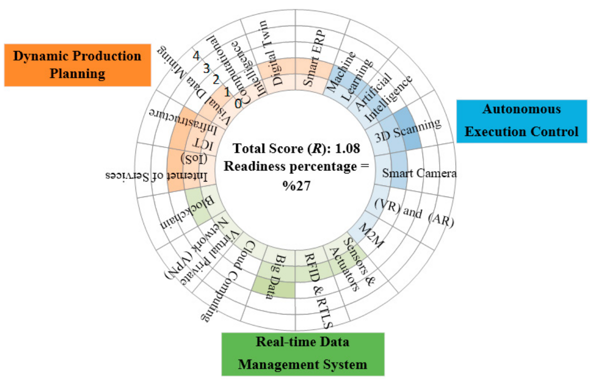

Fig. 4. Visual Presentation transition readiness

6. Conclusion

In this study, the Smart SME Technology Readiness Assessment (SSTRA) methodology was adapted and utilized to examine SMEs level of technology readiness to implement Industry 4.0 from a smart production planning & control point of view. The benchmark for smart production planning & control taxonomy was proposed and validated based on data collected from 50 industrial SMEs concerning the weights of each criterion, driver, and technology in their workplace. The SSTRA methodology was implemented in the SME manufacturer in the sanitary ware industry. The application of SSTRA has effectively supported the company to evaluate its current situation regarding Industry 4.0 requirements to identify what technologies were needed to be implemented to address the smart production planning & control requirement. Subsequently, gave company decision-makers a clear perspective to decide in which areas or technologies need to focus more to keep its operation compatible towards the digital era with minimum risk of investment and implementation. The studied company showed a willingness to implement SSTRA methodology throughout the company entire value chain to support its transition to Industry 4.0. As a road map for future research, the SSTRA would be alignment with Strategic Technology Alignment Roadmapping (STAR) methodology [42] to provide guiding and justifying investment in industry 4.0 transition R&D projects to achieve the optimum project portfolio.

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