

Surveying the Sense of Urgency of the Tactical-Level Management to Adopt Industry 4.0 Technologies: Ranking of Three Sister Plants Based on BWM-CRITIC-TOPSIS

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Abstract:

Purpose: Although the decision to adopt Industry 4.0 technologies is commonly strategic, the selection and implementation of technology are the responsibilities of the tactical level management. The tactical level management will also directly experience the impact of adopting the technology towards the organizational performances in their functional areas. The comparative survey study aims to measure the tactical level management's sense of urgency of the nine pillars in three plants of a single manufacturing organization.

Design/methodology/approach: The research methodology starts with a literature review to collect the criteria pertaining to the pillars. Based on the 95 constituting criteria, the second step prepares and conducts a questionnaire survey with 32 participants on three sister plants. Next, rough BWM-CRITIC-TOPSIS ranks these plants at the pillar and criteria levels. The ranking method integrates Best-Worst Method (BWM), Criteria Importance Through Intercriteria Correlation (CRITIC), and technique for order performance by similarity to ideal solution (TOPSIS). The top management discussed and rendered insights into the results.

Findings: Results show that the high-mix and labor-intensive plant (Plant 1) has the highest urgency, whereas the largely automated plant (Plant 3) has the lowest urgency to adopt the nine pillars. The findings provide empirical evidence of the effect of the recent Industry 4.0 awareness programs in Plant 1 and advanced infrastructure would lead to organization inertia (Plant 3) to aggressively pursue technological change. The most urgent pillar is cybersecurity, and the least urgent pillar is additive manufacturing (AM), outlining the concern over cyber threats when product information is increasingly integrated into the supply chain and technology immaturity of AM in production.

Research limitations/implications: A limitation of this study is that the comparative survey only focused on three plants and the tactical level management of an organization.

Originality/value: This study contributes to the knowledge of Industry 4.0 readiness by being the first to show different levels in the sense of urgency of the tactical level managements on the relevant technologies, which potentially affect the direction and the pace of Industry 4.0 adoption.

Keywords: Industry 4.0, rough BWM-CRITIC-TOPSIS, management emphasis, multi-criteria-decision making

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1. Introduction

The essence of Industry 4.0 is to take advantage of digitization to achieve improvements in terms of automation and operational efficiency, including effectiveness (Ślusarczyk, 2018). Various research initiatives examine and assess different aspects of Industry 4.0 adoption in organizations. Such initiatives include Reference Architectural Model Industry 4.0 (RAMI 4.0) (Hankel & Rexroth, 2015), digital maturity and transformation study (Back & Berghaus, 2016), Industry 4.0 component model (Hoffmeister, Festo & Co, 2015), Roadmap Industry 4.0 (Pessl, Sorko & Mayer, 2017), Acatech Industry 4.0 Maturity Index (Schuh, Anderl, Gausemeier, ten Hompel & Wahlster, 2017), SPICE-based Industry 4.0-MM (Gökalp, Şener & Eren, 2017), Smart Industry Readiness Index (SIRI) (Singapore EDB, 2018), Industry 4.0 readiness assessment tool (Agca, Gibson, Godsell, Ignatius, Davies, C., & Xu, 2017), and 'Pathfinder 4.0' (Intechcentras, 2019). These initiatives define a set of Industry 4.0 and organizational components, and they are later assessed through suitable criteria commonly associated with the breadth and depth of Industry 4.0 adoption.

The Boston Consulting Group (BGC) identified the nine pillars in Industry 4.0: additive manufacturing (AM), cloud computing, augmented reality (AR), cybersecurity, Internet of things (IoT), advanced simulation, universal integration, big data, and autonomous systems. The research offers an alternative initiative, that is, to survey the sense of urgency at the tactical level toward these nine pillars in the different plants of a medical device manufacturing organization. The survey provides critical insights from the position of the tactical level management. Although the decision to adopt Industry 4.0 is commonly strategic, the selection and implementation of technology are the responsibilities of the tactical level management. In addition, the tactical level management will directly experience the impact of the adoption to the organization's performances at their functional areas. They are also the overseers to the operational level, where the Industry 4.0 technology affects the daily operational routines. Nechkoska (2015) defined the tactical managerial role, which includes how to achieve the expectation by utilizing what is given and following certain governing principles in the current context of the organization and environment. Therefore, as a leader (Day, 1999), the sense of urgency toward Industry 4.0 will be critical in any of the related initiatives. Kotter (1995, 2008) noted that the sense of urgency motivates the change process and greater participation of individuals in an organization. This sense drives for a sustained and lasting organizational change organization (Baxter, 2002). Managers with a sense of urgency would listen and communicate the vision with their subordinates.

The research methodology is based on a comparative survey study and divided into three stages. The first stage identifies the criteria of each pillar through a literature review of 205 journals. Approximately 10 to 12 criteria were selected for each pillar. These criteria are measurable elements in each pillar and relate to features and performances of the organization's operation. Nechkoska (2015) commented that tactical management operates in a complex adaptive system and needs to maintain a sense-and-respond system that is adaptable to the changes and unpredictability. Sado (2014) stressed the dependency of a tactical plan on how its implementation affects the continuity of operation and other functions of management. This finding motivates the research to underline the criteria instead of pillars to gauge the sense of urgency among tactical level personnel. The reason is that the criteria would be their primary consideration in the decision making of any technology (pillar) adoption and hence the urgency of the technology. The second stage develops a questionnaire and carries out the survey. Finally, the third part relates to analysis with two objectives. The first one is to identify the urgency of pillars or criteria in these plants individually. The second aim is to compare and rank the results between these plants, representing the urgency of individual plants to adopt the technology. The findings from the analysis are then reviewed by the focus group consisting of senior management personnel.

Considering that participants in the survey are of different departments and backgrounds, their knowledge and judgment of certain pillars and criteria may vary and reflect their functional perspectives. Additionally, precisely defining their knowledge is difficult. In this premise, we adopt rough BWM-CRITIC-TOPSIS proposed by Zhang, Fang and Song (2019). The ranking method integrates Best-Worst Method (BWM), Criteria Importance Through Intercriteria Correlation (CRITIC), and technique for order performance by similarity to ideal solution (TOPSIS). BWM, CRITIC and TOPSIS are well-known multi-criteria decision-making (MCDM) methods and have been

applied widely in different problems (Sadjadia & Karimi, 2018; Palczewski & Salabun, 2019; Pamučar, Ecer, Cirovic & Arlasheedi, 2020; Kumar, Saxena & Garg, 2021; Krishnan, Kasim, Hamid & Ghazali, 2021).

BWM is a multi-criteria decision-making method, which uses a pairwise comparison to determine the weights of criteria (Amiri & Emamat, 2020). Although BWM requires less comparison data, the comparisons are consistent, and the results are reliable (Rezaei, 2016). BWM only executes reference comparisons and employs a 1–9 scale to perform the pairwise comparisons. As BWM does not execute secondary comparisons, the procedure is much easier, more accurate, and less redundant (Guo & Zhao, 2017).

Diakoulaki, Mavrotas and Papayannakis (1995) proposed CRITIC to determine objective weights for criteria (Adalı & Işık, 2017). The objective weights obtained by CRITIC consider the conflict between criteria pair and contrast intensity of each criterion. The contrast intensity shows the difference between the criteria. Standard deviation is used to measure contrast intensity. Meanwhile, the conflict between criteria pairs can be measured by correlation coefficient (Zhang et al., 2019).

TOPSIS is a multi-attribute decision-making technique used for ranking and selection of several externally determined alternatives through distance measures (Shih, Shyur & Lee, 2007). TOPSIS can incorporate relative weights of criterion importance. Consequently, TOPSIS is attractive in that limited subjective input is needed from decision makers and applicable to cases where inter-criterion comparison is infeasible (Kumar et al., 2021). TOPSIS is quite close in accuracy except when equal weights were applied (Olson, 2004). Zavadskas, Mardani, Turskis, Jusoh and Nor (2016) presented that TOPSIS is the second most popular method among MCDM approaches. TOPSIS is relatively easy to implement and understandable and provides a well-structured analytical systematic process. TOPSIS is useful for qualitative and quantitative data and provides large flexibility in the definition of the choice set. A number of criteria can be applied during the decision process.

In MCDM, ranking involves identifying and ordering the priority (preference) of a given choices by assessing their relative importance using a set of criteria. MCDM methods assign weights to individual criteria for better and more accurate decision making (ranking). Assigning weights to qualitative criteria can be affected by decision maker preference and may vary considerably (Mareschal, 1998). In view of this, Rough BWM-CRITIC-TOPSIS determines the proper integrated weight of the selected criteria in Industry 4.0 assessment. In the method, objective weighting is generated purely from mathematical computation, and subjective weighting relies on the expert knowledge and judgment of the participants. Objective weighting is appropriate for the study of depriving reliable subjective weights (Deng, Yeh & Willis, 2000). From another perspective, subjective weights reflect the subjective judgment or intuition of the participant carrying sufficient, selective, or insufficient knowledge or experience. This integration mitigates the shortage that occurs in either a subjective or objective approach. The method is programmed in Microsoft Excel. The results are discussed with the top management after the analysis.

This paper is further organized as follows. Section 2 presents the literature review, which includes the nine pillars of Industry 4.0. Section 3 shows the selection of criteria. Section 4 introduces BWM-CRITIC-TOPSIS and its implementation steps. Section 5 presents the organization and plant profiles. Sections 6 and 7 present the results and discussion, respectively. Finally, Section 8 concludes the study.

2. Nine Pillars of Industry 4.0

AM refers to fabrication that uses a 3D CAD file, slices it to different thicknesses as a geometry of each layer, and orders the fabrication setup to deposit a layer regarding that geometry. AM has wide industry applications, for example, biomedical materials, disease models, medical instruments (Zadpoor & Malda, 2017), and aerospace part (Herzog, Seyda, Wycisk & Emmelmann, 2016). AM perfectly fits into the numerical design and manufacturing chain. Weller, Kleer and Piller (2015) presented AM technology's opportunities into technological and economic characteristics. The technological characteristics of AM are high manufacturing flexibility, less scrap, and no tools and molds necessary. The economic characteristics include acceleration and simplification of product innovation, reduction of assembly work, and lowering barriers to market entry. Research noted that AM technology is environmentally and ecologically promising (Bikas, Stavropoulos & Chryssolouris, 2016) and fully automated (Weng, Zhou, Lin., Senthil & Wu, 2016). From another perspective, the challenges of AM include the speed and

cost of production and intellectual property issues. Moreover, post-processing and the support structure materials cannot be recycled (Ford & Despeisse, 2016). Seifi, Salem, Beuth, Harrysson and Lewandowski (2016) also presented that missing quality standards and the presence of residual stress can limit AM's use in high-value or mission-critical applications. Tofail, Koumoulos, Bandyopadhyay, Bose, O'Donoghue and Charitidis (2018) presented that the considerations to invest in AM are the costs, the comparative benefits of AM over conventional manufacturing of the same part, and the rate at which such benefits occur. Watson and Taminger (2018) considered part complexity (as AM may be the preferred to produce a highly complex part), material property requirements, time (lead and manufacturing time), and material usage. Hällgren, Pejryd and Ekengren (2016) suggested that industries, where performance prevails over the part cost and series volumes are low, are more likely to adopt AM.

Cloud computing is Internet network-based computing allowing users to access their resources remotely around the world (Nandgaonkar & Raut, 2014). Its components include client, cloud network, and cloud application programming interface (Gupta, Beri, Behal, Gupta, Beri & Behal, 2016). The major cloud service models are infrastructure-as-a-service, platform-as-a-service, and software-as-a-service (Patel & Viradiya, 2016). The deployment models could be either public, private, community, and hybrid models, with each presenting a different level of security (Rashid & Chaturvedi, 2019). Cloud servers can store information, manage, and process a large volume of data because of their higher reliability, broad network access, fault tolerance, and on-demand usage (Gupta et al., 2016). These features provide advantages, such as cost-saving, mobile storage, scalability, anytime anywhere access, energy-saving, and better security (Sether, 2016; Xue & Xin, 2016). Cloud vendors provide their clients with platform back updates and the ease to recover their lost data anytime (Nandgaonkar & Raut, 2014). Coghlan (2016) presented that cloud computing is used for supporting production processes, enabling design and prototyping, and improving supply chain management. From another perspective, cloud computing is largely unstandardized and is subjected to accounts hacking (Xue & Xin, 2016), data breach, application program interface issues, and malicious insiders (Islam, 2017). When these incidents happen, cloud service providers often take no liability (Alzahrani, 2016). Other concerns of cloud computing include vendor lock-in, integration issues, unclear return of investment (ROI), compliance, legacy integration, immature technology, and lack of features (Xue & Xin, 2016).

Dini and Dalle-Mura (2015) defined AR as an innovative human-machine interaction that adds virtual components in a real-world environment. AR renders additional information textual, visual, and/or auditory for a specific task (Fraga-Lamas, Fernández-Caramés, Blanco-Novoa & Vilar-Montesinos, 2018). AR improves reliability, flexibility, speed, safety, adaptability, and new technology (Stoltz, Giannikas, McFarlane, Strachan, Um & Srinivasan, 2017). AR technology has been tested in real industrial settings, such as training (Makris, Karagiannis, Koukas & Matthaikakis, 2016; Martinetti, Rajabalinejad & van Dongen, 2017; Mourtzis, Xanthi & Zogopoulos, 2019), shop floor information visualization (Michalos et al., 2016), maintenance-assembly-repair (Fraga-Lamas et al., 2018; Mourtzis, Zogopoulos & Vlachou, 2017), picking assistance in a warehouse (Puljiz, Gorbachev & Hein, 2018; Stoltz et al., 2017), human-robot collaboration (Michalos, Karagiannis, Makris, Tokçalar & Chryssoulouris, 2016), products inspection, and building monitoring (De Pace, Manuri & Sanna, 2018). AR is used to monitor operation and modify the production plan (Wang, Yew, Ong & Nee, 2020). AR improves communication through the development of interactive and context-aware instructions for assembling products (Bottani & Vignali, 2019). Mobile AR techniques can filter and provide relevant information to the operators at the workplace to assist in making time-critical decisions (Whyte & Broyd, 2015). Stoltz et al. (2017) identified the factors of using AR in warehouse operations, including software challenges, hardware limitation, acceptance, and cost. AR technologies are yet to be realized for tracking all kinds of environments with reasonable cost and sufficient accuracy (Ishii, 2017). Similarly, Syberfeldt, Holm, Danielsson, Wang and Brewster (2016) asserted that AR is affected by lighting conditions and not precise enough for industrial applications. In addition, the affordable goggles and batteries in the market still cannot be used for a long period. Even with the improved ergonomics, many open issues are related to the visual perception of the mixed information (real plus virtual) (Masoni, Ferrise, Bordegoni, Gattullo, Uva, Fiorentino et al., 2017).

Siers (2018) defined cybersecurity as the process of protecting information from unauthorized access, use, disclosure, disruption, modification, or destruction. With the increased connectivity and use of standard communication protocols, cybersecurity threats increase dramatically (Vaidya, Ambad & Bhosle, 2018). The risks

associated with any attack depend on three factors: threats (who is attacking), vulnerabilities (the weaknesses they are attacking), and impacts (what the attack does) (Zarreh, Saygin, Wan, Lee & Bracho, 2018b). Clim (2019) presented that the risk scenarios in an industrial setting include a vast range of cyber-attacks, including malicious programs causing machine malfunction and destruction. An organization invested in cybersecurity would secure the details of the employees, secure the flow of information within and outside the organization, and protect the system from hacking (Gurusamy & Hirani, 2018). Nevertheless, adoption of cybersecurity is expensive, and the economic returns on investments are often unpredictable (Conteh & Schmick, 2016).

IoT consists of smart machines interacting and communicating with other machines, environments, and infrastructures (Sharma & Tiwari, 2016; Bahga & Madiseti, 2016). IoT-enabling technologies include 5G, radio-frequency identification, sensors, low power and energy harvesting, robotics, sensor networks, and machine-type communication (Chaouchi & Bourgeau, 2018). Reka and Dragicevic (2018) presented the advantages of IoT, including instant data access for quick decision making, cost-effective for day-to-day activities, uniformity of tasks, and process transparency over the entire machine to machine (M2M) communication. IoT is being adopted for manufacturing applications, such as remote machine diagnostics (Soldatos, Gusmeroli, Malo & Di Orio, 2016), manufacturing automation, and supply chain management (Witkowski, 2017), oxygen and toxic gas levels (Sharma & Tiwari, 2016), energy consumption (Shrouf & Miragliotta, 2015), and overall equipment effectiveness (OEE) (Hwang, Lee, Park & Chang, 2017). The characteristics of IoT are participants, autonomous process, scalability, event sharing, semantic sharing, interconnectivity, and flexible structure (Reka & Dragicevic, 2018).

Naderi, Mohammadi and Nouri-Koupaei (2016) defined computer simulation as a comprehensive method for process design, manufacturing system study, and complex systems analysis. This simulation permits the transfer of the planning state to finally verify and validate the model (Uhlemann, Lehmann & Steinhilper, 2017). Advanced simulation allows scenario optimization and what-if analysis (Fakhimi & Mustafee, 2019). The simulation tool can model the entire product and production lifecycle aiming to reduce the corresponding costs and effort (Biermann, Bleckmann, Schumann & Iovkov, 2016). This tool helps shorten development cycles, improve the quality of products, reduce costs, and greatly facilitates knowledge management (Rodič, 2017). Advanced simulation helps to optimize flexible manufacturing system (FMS), for example, the allocation of a service provider (Naderi et al., 2016), dispatching (Freitag & Hildebrandt, 2016), machine choices, and messaging protocols (Nagadi, Rabelo, Basingab, Sarmiento, Jones & Rahal, 2018). Motlagh, Azimi, Amiri and Madraki (2019) presented advanced simulation challenges. First, users need to develop a clear procedure to collect data and determine uncontrollable parameters. Advanced simulation needs multiple assumptions regarding the parameters and cannot accurately reflect real-world problems. Full-featured and large-scale simulations involve considerable run time and powerful and expensive computer processing units (Xu, Huang, Chen & Lee, 2015). Simulation software tools usually offer only dedicated application object libraries, instead of the broad field of manufacturing (Mourtzis, Doukas & Bernidaki, 2014).

Integrated manufacturing enables effective coordination of all components (Chen, 2017). As the basis of the cyber-physical system, three levels of manufacturing integration are vertical integration, horizontal integration, and end-to-end integration (Hamdaoui & Bouayad, 2019; Chukalov, 2017). Vertical integration connects all elements in the product life cycle within an organization. Horizontal integration occurs between the company with its suppliers and partners. End-to-end integration covers M2M integration on the factory floor, customer integration (e.g., to obtain real-time feedback), and finally product-to-service integration to monitor the condition of the product in use. Manufacturing integration increases the flexibility of organizations on the IT level and manufacturing environments (Wieland, Hirmer, Steimle, Gröger, Mitschang, Rehder et al., 2016). Specifically, vertical integration widens product range and sharing of components among different products (Adkins & Patil, 2015). Data integration eliminates manual data-mapping errors and streamline business processes. Enterprise integration facilitates information flows, systems interoperability, organization's efficiency, and knowledge sharing among any kind of organization (Varela, Putnik, Manupati, Rajyalakshmi, Trojanowska & Machado, 2019; Bernardo, Farrero & Casadesús, 2016; Chansombat, Pongcharoen & Hicks, 2019). System integration enables a defective material to be detected early to minimize waste (Campion, 2017).

Big data refers to a large bulk of data that cannot be dealt with by traditional data-handling techniques (Mukherjee & Shaw, 2016). A big data value chain starts from data generation followed by data collection, data transmission, data processing, and data storage and ends with data analysis (Bhadani & Jothimani, 2016). Big data analytics help enterprises understand their business environments, customers' behavior and needs, and their competitors' activities (Vassakis, Petrakis & Kopanakis, 2018). Specifically, big data obtain insights, patterns, correlations, and associations, which could not be understood through traditional small data (Jeble & Patil, 2018). Big data improves existing capabilities, for fault detection, predictive maintenance (Moyné & Iskandar, 2017), and automating decision-making tasks (Müller, Fay & vom Brocke, 2018). Kapil, Agrawal and Khan (2016) explored a rather complete list of characteristics of big data for efficient handling, which will be used as the criteria. Moktadir, Ali, Paul and Shukla (2019) dissected barriers of using big data analytics into technology-related, expertise and investment-related, data-related, and organization-related.

The autonomous system is automated transporters, processes, and robots developed to support the operation in industrial enterprises, reduce human errors, gain high productivity with minimum cost, and deploy solutions that could be adjusted because of needs, adaptable production schedule, effective execution, or scalable model (Fitzgerald & Quasney, 2017; Joggerst, Knoll, Hoppe, Wendt & Groche, 2018; Fernandes, Martins & Carmo-Silva, 2018; Lu & Hasan, 2018; Truong, Ngo, Nguyen, Nguyen & Kim, 2019). EPSRC (2015) proposed a taxonomy so that automation providers and customers can define their current standing and expectation in the short, medium, and long terms. The taxonomy consists of six levels on two dimensions, which are the role of the human and the scope of automated tasks. Bauer, Schumacher, Gust, Seidelmann and Bauernhansl (2019) presented a model to describe and characterize autonomous production by five stages focusing on 12 features, such as manufacturing cell, material, and information flow. According to Bahrin, Othman, Azli and Talib (2016), autonomous systems are built in a greater range of capabilities that focus on intelligence, safety, flexibility, versatility, and collaboration. Autonomous production needs to be reliable to prevent rework, scrap, and accidents (Fox, 2018) and be trusted by consumers (Shahrdar, Menezes & Nojournian, 2018). Britton (2017) asserted that autonomous systems may equally be subjected to risks of system failure, human–system interaction breakdowns, and social disruptions.

3. Criteria of the Pillars

205 literatures were obtained through a paper search from two scientific publication databases, namely Scindirect and Scopus, using the key terms directly associated to the pillars. These literatures were briefly screened through and priority was given to works related to technology reviews. The following criteria for the pillars were then extracted from the remaining literatures (55 papers). Repeating or similar criteria were removed. The criteria must fulfill the following conditions: (1) measurable, (2) affects operations, and (3) specific to pillar technology. The criteria were screened to remove redundancy while maintaining generality and relevancy. They are listed below and numbered based on the sequence of appearance in the questionnaire.

AM (P1)

- i. C1-Manufacturing flexibility: expresses the objects that can be produced in any random order without cost penalty (Weller et al., 2015).
- ii. C2-Material usage: represents the amount of material required to produce the product (Watson & Taminger, 2018)
- iii. C3-Production cost: represents the total cost of AM machine cost, material cost, and labor cost (Tofail et al., 2018).
- iv. C4-Production time: represents the criteria to measure the speed of production, which includes lead and manufacturing time (Watson & Taminger, 2018).
- v. C5-Product quality: represents the measure of the percentage of rejection rate (Ford & Despeisse, 2016).
- vi. C6-Environmentally and ecologically promising: represents the environmental impact of the production process (Bikas et al., 2016).

- vii. C7-Material property requirements: includes the thermal field, dimensional stability, and residual stresses as these factors significantly affect the safety of the final product (Bikas et al., 2016).
- viii. C8-Product volume: represents the quantity of product produced (Hällgren et al., 2016).
- ix. C9-Energy efficiency: represents a measure of the energy conservation in the production process (Ford & Despeisse, 2016).
- x. C10-Automation: represents the process that requires no human involvement, and the equipment can be unattended (Weng et al., 2016).

Cloud computing (P2)

- i. C11-Cost efficiency: represents the ability to achieve the desired outcome with a small amount of investment (Nandgaonkar & Raut, 2014).
- ii. C12-Flexible with demand: represents the availability to withdraw the resources when no more requirements at any point of time (Nandgaonkar & Raut, 2014).
- iii. C13-Availability: a measure of the availability of cloud services to the users which allows users to access their resources anytime, anywhere (Alzahrani, 2016).
- iv. C14-Mobility: represents the ability to access resources anywhere on the globe (Nandgaonkar & Raut, 2014).
- v. C15-Agility: represents the ability to adapt quickly to respond to the changes in a business environment (Xue & Xin, 2016).
- vi. C16-Reliability: the criteria to measure the ability of cloud computing in maintaining data integrity (Alzahrani, 2016).
- vii. C17-Improve supply chain management: represents the increase in the collaboration between customers and suppliers (Coghlan, 2016).
- viii. C18-Contribution to design and prototyping: expresses the increase in the ability to manufacture customized products (Coghlan, 2016).
- ix. C19-Greener manufacturing: a measure of the sustainability of cloud computing (Varghese & Buyya, 2018).
- x. C20-Scalability: represents the ability to adjust the resources based on the changes of business needs (Xue & Xin, 2016).
- xi. C21-Speed of bandwidth: the ratio of the amount of data transfer to the time taken to transfer the data (Nandgaonkar & Raut, 2014).

AR (P3)

- i. C22-Human–robot collaboration: AR acts as an interface to allow users to interact with the robots. This criterion represents the user’s ability to understand the robot’s intentions (De Pace et al., 2018).
- ii. C23-Workspace visualization: represents the ability to monitor the production operation and modify the production plan (Wang et al., 2020).
- iii. C24-Training: represents the knowledge acquisition and transition from skilled experts to new technicians (Martinetti et al., 2017).
- iv. C25-Flexibility: a measure of the number of tasks that can be performed by using AR and the possibilities to shift from mass production to mass customization (Uva, Gattullo, Manghisi, Spagnulo, Cascella & Fiorentino, 2018).
- v. C26-Ergonomics: a measure of the affordability of using the AR technology (Masoni et al., 2017).
- vi. C27-Performance: a measure of the accuracy of the AR technology in production operation (Ishii, 2017).

- vii. C28-Data security: represents the ability of the AR technology to protect user's privacy against unauthorized access (De Pace et al., 2018).
- viii. C29-Cost: represents hardware and software cost for AR implementation (Stoltz et al., 2017).
- ix. C30-Safety: represents the degree of safety when using the AR technology (De Pace et al., 2018).
- x. C31-Speed: a measure of how much information can be accessed by the operator in a specific time period (Makris et al., 2016).

Cybersecurity (P4)

- i. C32-Reliability: represents the ability to protect the system from hacking (Gurusamy & Hirani, 2018).
- ii. C33-Data security: represents the ability of organizations in protecting their information to prevent data breaches (Siers, 2018).
- iii. C34-Cost: includes the amount of money needed to maintain a defense mechanism (Zarreh, Saygin, Wan, Lee & Bracho, 2018a).
- iv. C35-Prevention mechanisms: represents the adoption of the robot to identify and detect any misuses and send out reminders. (Pan & Yang, 2018).
- v. C36-Economic returns: a measure of the rate of return for the investment (Conteh & Schmick, 2016).
- vi. C37-Impact of cyber-attack: a measure of how cyber-attack affects the OEE of the organization (Zarreh, Wan, Lee, Saygin & Al Janahi, 2018).
- vii. C38-Education and training: represents the training that needs to be provided to the employee to raise their awareness about social engineering attack (Conteh & Schmick, 2016).
- viii. C39-Availability: represents the availability of the data and systems to authorized parties when they are needed (Siers, 2018).
- ix. C40-Integrity: represents the data and systems that are not altered without authorization (Siers, 2018).
- x. C41-Safety, health, and environment: represents the incidents of injuries and accidents caused by cyber threats (Zarreh, et al., 2018).

IoT (P5)

- i. C42-Interconnectivity: represents the interconnection of objects and people in the manufacturing industry (Reka & Dragicevic, 2018)
- ii. C43-Automation control: represents less human control on day-to-day activities and can maintain a transparent process over the entire M2M communication (Reka & Dragicevic, 2018).
- iii. C44-Performance: represents the scalability, availability, and response time of the system (Čolaković & Hadzialic, 2018).
- iv. C45-Technical concerns: represents the ability to store a huge amount of data for analysis and further final storage (Razzaq, Gill, Qureshi & Ullah, 2017).
- v. C46-Contribution to logistics and supply chains management: expresses the improvement in the carriage of goods and the accuracy in tracking and tracing the object (Witkowski, 2017).
- vi. C47-Security and privacy issues: represents the security of the information stored. The information might be opened for hackers and unauthorized concerns when many appliances are connected dynamically (Reka & Dragicevic, 2018).
- vii. C48-Ubiquitous computing: represents those engineers at multiple locations will be able to access and use resources in a "cloud" through thin clients to conduct engineering activities (Lu & Cecil, 2016).
- viii. C49-Energy consumption: a measure of the amount of energy used in the production (Reka & Dragicevic, 2018).

- ix. C50-Proactive Maintenance: represents the ability to predict when a breakdown will occur based on historic records and past service requests (Soldatos et al., 2016).
- x. C51-Interoperability: represents the ability to exchange the acquired data and make use of information (Hwang et al., 2017)
- xi. C52-Data collection: represents the ability to collect data and process the data either locally or send the data to centralized servers or cloud-based application back-ends for processing (Bahga & Madiseti, 2016).

Advanced simulation (P6)

- i. C53-Cost: includes the operating cost, installation cost, maintenance cost, and cost of the hardware, such as the powerful CPUs which are required for the simulation with complex processes and high product demand (Mourtzis et al., 2014).
- ii. C54-Usability: a measure of the degree of ease of use of the simulation software (Yu, 2018).
- iii. C55-Reliability: a measure of how accurately simulation reflects real-world production problems (Motlagh et al., 2019).
- iv. C56-Processing time: a measure of how long it takes to run the simulation (Xu et al., 2015)
- v. C57-Analysis: represents the ability to perform any what-if analysis and compare the optimized scenarios, all without affecting the operative environment (Fakhimi & Mustafee, 2019).
- vi. C58-FMS optimization: expresses the use of simulation in calculating the optimal number of service providers according to the facilities and service time per unit (Naderi et al., 2016).
- vii. C59-Process design: represents the ability in studying and designing manufacturing processes (Biermann et al., 2016)
- viii. C60-Production planning and control: expresses the ability to automatically develop improved dispatching rules specifically for control problems (Freitag & Hildebrandt, 2016).
- ix. C61-Performance evaluation: represents the evaluation of the performance of the machine, product, process chain, and factory in simulation (Alvandi, Li & Kara, 2017).
- x. C62-Verification and validation: represents the use of simulation to verify and validate new strategies and procedures in manufacturing (Kikolski, 2016).
- xi. C63-Decision support: represents the ability of the simulation in helping organizations to make wise decisions based on quantitative data analysis (Aqlan, Ramakrishnan & Shamsan, 2017).

Universal integration (P7)

- i. C64-Vertical integration: represents the connection of all of the elements that are included in the product life cycle within an organization (Chen, 2017).
- ii. C65-Horizontal integration: represents a company that is closely integrated with its suppliers and partners (Chen, 2017).
- iii. C66-End-to-end integration: includes machine-to-machine integration and integrates customers into the manufacturing system and product-to-service integration (Chen, 2017).
- iv. C67-Integration of products: expresses the ability to offer a wider product range and also achieve greater sharing of components among different products (Adkins & Patil, 2015).
- v. C68-Integration of competencies: represents the capability integration to deliver superior products with the best available skills (Adkins & Patil, 2015).
- vi. C69-Integration of management systems: represents the combination of the business components into one system to improve the organization's efficiency (Bernardo et al., 2016).

- vii. C70-Data integration: represents the combination of the data from different resources and provides users with a unified view (Xiang, Yin, Wang & Jiang, 2018).
- viii. C71-System integration: represents the combination of the different subsystems into one system. System integration meets lean manufacturing and propels the manufacturer toward continuous improvement for the benefit of the plant (Campion, 2017).
- ix. C72-Integrated monitoring system: represents the combination of all individual control systems into a single computer-controlled system. Monitoring data will be automatically acquisitioned and processed by dedicated applications and devices operating (Oborski, 2016).
- x. C73-Integrated production and preventive maintenance scheduling: The integration of production and maintenance aims to minimize total costs, which include the tardiness and earliness penalty costs, component and assembly holding costs, preventive maintenance costs, and set-up, production, transfer, and production idle time costs (Chansombat et al., 2019).

Big data (P8) (Kapil et al., 2016)

- i. C74-Versatility: represents the ability of big data to be flexible enough to be used differently for a different context.
- ii. C75-Verbosity: represents the redundancy of the information available at different sources.
- iii. C76-Volume: a measure of the quantity of collected and stored data.
- iv. C77-Velocity: a measure of the transfer rate of data between its source and destination.
- v. C78-Value: represents the business value to be derived from big data.
- vi. C79-Variety: expresses different types of data, such as pictures, videos, and audio, arriving at the receiving end.
- vii. C80-Veracity: represents the data quality. Accurate analysis of captured data is virtually worthless if not accurate.
- viii. C81-Validity: represents the correctness or accuracy of data used to extract results in the form of information.
- ix. C82-Volatility: big data volatility means the stored data and how long is useful to the user.
- x. C83-Variability: data arrive constantly from different sources. Variability is the criteria to measure how efficiently it differentiates between noisy and important data.
- xi. C84-Viscosity: a time difference between the event that occurred and being described.
- xii. C85-Virality: represents the rate at which the data are broadcast/spread by a user and received by different users for their use.

Autonomous systems (P9)

- i. C86-Efficiency: represents the ability to improve productivity and manufacturing resources utilization as a result of technology advances (Fernandes et al., 2018)
- ii. C87-Robot behavior: a measure of how the autonomous systems react to the inputs (Helle, Schamai & Strobel, 2016).
- iii. C88-Delivery speed: a measure of the rates of picking, packing, sorting, and labeling of items (Fitzgerald & Quasney, 2017).
- iv. C89-Functional efforts and expertise: represents the expertise required in the organization to communicate with the autonomous systems (Fitzgerald & Quasney, 2017).
- v. C90-Robustness: represents the ability to overcome or withstand hazardous environments (Wong, Yang, Yan & Gu, 2018).

- vi. C91-Safeguards: a measure of the safety of the technologies. Sufficient assurances have to be provided before an autonomous system is allowed to operate in a shared environment with people (Dennis, Fisher, Slavkovik & Webster, 2016).
- vii. C92-Level of automation: measures the degree of maturity of the technology (EPSRC, 2015).
- viii. C93-Investment: represents the amount of money that needs to be invested (Fitzgerald & Quasney, 2017).
- ix. C94-Reliability: measure of how long a machine performs its intended function. Autonomous production needs to be reliable to prevent rework, scrap, and accidents. Outputs from reliable production systems consistently conform to performance requirements (Fox, 2018).
- x. C95-Capabilities: represents the ability of the autonomous system to complete tasks intelligently, with the focus on safety, flexibility, versatility, and collaboration (Bahrin et al., 2016).

4. Rough BWM-CRITIC-TOPSIS

The proposed method consists of two phases. First, the rough BWM and CRITIC methods are used to calculate the integrated weight considering the subjective and objective weight. Second, the rough TOPSIS method is used to evaluate and rank the plants. Figure 1 shows the research framework.

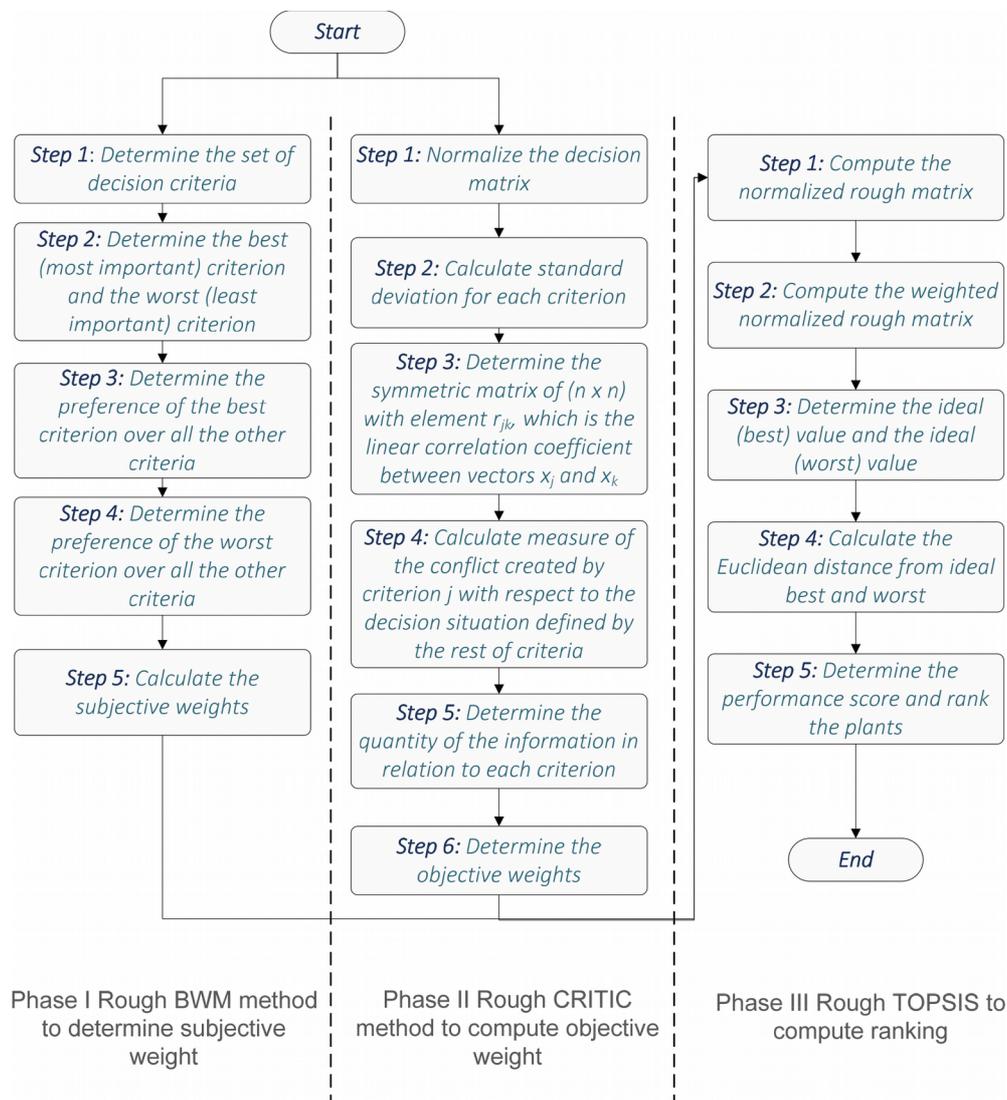


Figure 1. Research framework

4.1. Phase I Rough BWM Method to Determine the Subjective Weight

Step 1: Determine the set of decision criteria. The survey respondents are requested to decide the set of criteria $C = \{C_1, C_2, \dots, C_n\}$ for Industry 4.0 maturity evaluation, where n is the amount of criteria.

Step 2: Determine the best (most urgent) criterion and the worst (least urgent) criterion. Experts are requested to identify the best criterion and the worst criterion from the criteria set.

Step 3: Determine the preference of the best criterion over all the other criteria. The preferences of the best criterion are scored comparing with the other criteria. The preferences are scored from 1 to 9 (1: equally urgent ... 9: is extremely more urgent).

Step 4: Determine the preference of the worst criterion over all the other criteria. The preferences of other criteria are scored compared with the worst criterion. The preferences are scored from 1 to 9 (1: equally urgent ... 9: is extremely more urgent).

Step 5: Calculate the subjective weights, W_j . To obtain the optimal weights, we need to solve the following linear programming model.

Min ξ

Subject to

$$|W_B - a_{Bj}W_j| \leq \xi, \text{ for all } j$$

$$|W_j - a_{jW}W_W| \leq \xi, \text{ for all } j$$

$$\sum W_j = 1$$

$$W_j \geq 0, \text{ for all } j$$

where W_B is the weight for the best criterion, W_W is the weight for the worst criterion, j is the number of criterion, a_{Bj} is the preference score of best criterions with respect to the other criteria, a_{jW} is the preference score of other criteria with respect to the worst criterion, W_j is the weight for the particular criterion, and $\sum W_j$ is the sum of all of the weights.

4.2. Rough CRITIC Method to Determine Objective Weight

Step 1: Normalize the decision matrix.

$$X_{ij}^r = \frac{X_{ij} - X_j^{worst}}{X_j^{best} - X_j^{worst}} \quad (1)$$

where X_{ij} is the particular value of itself, X_j^{worst} is the worst value for the criterion, and X_j^{best} is the best value for the criterion.

Step 2: Calculate standard deviation, σ_j for each criterion.

Step 3: Determine the symmetric matrix of $n \times n$ with element r_{jk} , which is the linear correlation coefficient between the vectors x_j and x_k .

Step 4: Calculate the measure of the conflict created by criterion j with respect to the decision situation defined by the rest of the criteria by using the following formula:

$$\sum_{k=1}^m (1 - r_{jk}) \quad (2)$$

Step 5: Determine the quantity of the information, C_j , in relation to each criterion by using the following:

$$C_j = \sigma_j * \sum_{k=1}^m (1 - r_{jk}) \quad (3)$$

Step 6: Determine the objective weights, W_{oj} , by using the following:

$$W_{oj} = \frac{C_j}{\sum_{k=1}^m C_k} \quad (4)$$

Step 7: Compute the integrated weights by combining the subjective and objective weights

$$W_j = \frac{W_{sj} * W_{oj}}{\sum_{t=1}^n W_{st} * W_{ot}} \quad (5)$$

where

W_j represents the comprehensive weight of each criterion, W_{sj} represents the subjective weight, and W_{oj} represents the objective weight.

4.3. Rough TOPSIS to Compute Ranking

Step 1: Compute the normalized rough matrix by using the following:

$$x_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^n x_{ij}^2}} \quad (6)$$

Step 2: Compute the weighted normalized rough matrix by multiplying the integrated weights, W_j to x_{ij} .

Step 3: Determine the ideal (best) value, V_j^+ and the ideal (worst) value, V_j^- .

For beneficial criteria, a highest value is desired (maximum value = ideal best value, minimum value = ideal worst value). For non-beneficial criteria, the lowest value is desired (minimum value = ideal best value, maximum value = ideal worst value).

Step 4: Calculate the Euclidean distance from the ideal best and worst by using the following equations:

$$d_i^+ = \sqrt{\sum_{j=1}^n (V_{ij} - V_j^+)^2} \quad (7)$$

$$d_i^- = \sqrt{\sum_{j=1}^n (V_{ij} - V_j^-)^2} \quad (8)$$

Step 5: Determine the relative closeness of the plants, c_i , and rank the plant

$$c_i = \frac{d_i^-}{d_i^+ + d_i^-} \quad (9)$$

5. Questionnaire Design and the Organization Profiles

Three sections exist in a questionnaire form. The first section is about plant numbers. The second part assesses the urgency of individual criteria of a pillar to the organization's operations. Scaled questions are used in the second section—responses are graded on a continuum (rate the urgency of the criterion on a Likert scale of 1 to 9, with 9 being the most urgent criterion). A brief description of each pillar and criterion in the questionnaire is given. The questionnaire form is developed in a Google form and distributed to the three manufacturing plants through email. Each plant would have at least three respondents to participate in the survey. The criteria for the respondents are that they must be holding a managerial and works more than five years in the organization. This category of personnel would involve in mid-term decision making. Additionally, they have a corporate view of the organization,

including organization strategy and long-term decision making. The Google form application presents the survey results in the form of a spreadsheet.

The survey is conducted in a manufacturing organization producing medical products. Three plants in Malaysia under the organization are selected for the study. These manufacturing plants are located within one manufacturing site. Each of the reviewed plants had a size of each between 500 and 1,000 employees. Considering the product portfolio and their respective production volumes manufactured in the individual plants, their productions differ from each other. Plant 1 produces mainly small lot sizes with a high variation of products. Overall demands are relatively stable, whereas, within the product portfolio, the plant faces considerably varying demands that require high flexibility in production. The architecture of the production, therefore, follows a “job shop discrete manufacturing type.” Plant 2 focuses on a high production volume with a mid-size variety. Considering the requirements of the products, its production flow follows a “repetitive discrete manufacturing archetype.” Finally, Plant 3 is a plant with a high volume and very low flexibility as product variety is also very low. The plant is highly automated with a considerably low percentage of manual work contents. The manufacturing archetype follows the principle of “repetitive process manufacturing” All plants are running independently from one another but are connected through main central functions, such as Production Planning or Logistics.

6. Results

We obtained 15 respondents from Plant 1, 10 from Plant 2, and seven from Plant 3. Ten sessions of rough BWM-CRITIC-TOPSIS were performed, following the procedures outlined in Section 4. These sessions include the ranking of plants following the overall emphasis of pillars, rankings plants in accordance with each pillar. For each session, results were presented in two tables. The first table shows the computation of four steps in BWM-CRITIC-TOPSIS, and the second table shows distance, closeness coefficient, and the rank of each plant. Finally, we also obtained descriptive statistics of pillars (Table 21) and criteria (Table 22) at the organization level.

| Criteria | Subjective weight | Plant 1 | Plant 2 | Plant 3 | C_j | Objective weight | Integrated weight | V_j^+ | V_j^- |
|----------|-------------------|---------|---------|---------|--------|------------------|-------------------|---------|---------|
| Cpt at. | Step 1 | Step 2 | | | Step 3 | | | Step 4 | |
| P_1 | 0.0498 | 1.0000 | 0.6548 | 0.0000 | 0.7552 | 0.0641 | 0.0280 | 0.0191 | 0.0119 |
| P_2 | 0.1480 | 1.0000 | 0.5953 | 0.0000 | 0.7008 | 0.0595 | 0.0772 | 0.0463 | 0.0425 |
| P_3 | 0.0682 | 1.0000 | 0.8146 | 0.0000 | 0.9996 | 0.0848 | 0.0507 | 0.0338 | 0.0210 |
| P_4 | 0.1831 | 1.0000 | 0.0000 | 0.0000 | 1.2664 | 0.1075 | 0.1725 | 0.1009 | 0.0989 |
| P_5 | 0.1372 | 1.0000 | 0.2632 | 0.0000 | 0.7812 | 0.0663 | 0.0797 | 0.0481 | 0.0445 |
| P_6 | 0.0946 | 1.0000 | 1.0000 | 0.0000 | 1.4403 | 0.1222 | 0.1013 | 0.0625 | 0.0495 |
| P_7 | 0.1175 | 1.0000 | 0.0000 | 0.8823 | 4.3034 | 0.3652 | 0.3762 | 0.2229 | 0.2073 |
| P_8 | 0.1067 | 1.0000 | 0.5612 | 0.0000 | 0.6789 | 0.0576 | 0.0539 | 0.0342 | 0.0276 |
| P_9 | 0.0949 | 1.0000 | 0.7328 | 0.0000 | 0.8572 | 0.0727 | 0.0605 | 0.0385 | 0.0295 |

Note: Cpt at = compute at.

Table 1. Computation of rough BWM-CRITIC-TOPSIS for the nine pillars

| Plant | d^- | d^+ | Closeness coefficient | Rank |
|---------|--------|--------|-----------------------|------|
| Plant 1 | 0.0281 | 0.0000 | 1.0000 | 1 |
| Plant 2 | 0.0191 | 0.0169 | 0.5310 | 2 |
| Plant 3 | 0.0138 | 0.0234 | 0.3717 | 3 |

Table 2. Distance, closeness coefficient and the rank of each plant (the nine pillars)

| Criteria | Subjective weight | Plant 1 | Plant 2 | Plant 3 | C_j | Objective weight | Integrated weight | V_j^+ | V_j^- |
|----------|-------------------|---------|---------|---------|--------|------------------|-------------------|---------|---------|
| Cpt at. | Step 1 | Step 2 | | | Step 3 | | | Step 4 | |
| C_1 | 0.0832 | 1.0000 | 0.6410 | 0.0000 | 0.4043 | 0.1243 | 0.1072 | 0.0670 | 0.0553 |
| C_2 | 0.1102 | 1.0000 | 0.1470 | 0.0000 | 0.3115 | 0.0957 | 0.1093 | 0.0661 | 0.0612 |
| C_3 | 0.1293 | 1.0000 | 0.3571 | 0.0000 | 0.1611 | 0.0495 | 0.0664 | 0.0421 | 0.0351 |
| C_4 | 0.0930 | 1.0000 | 0.2232 | 0.0000 | 0.2270 | 0.0698 | 0.0673 | 0.0446 | 0.0345 |
| C_5 | 0.1293 | 1.0000 | 0.2976 | 0.0000 | 0.1768 | 0.0543 | 0.0728 | 0.0461 | 0.0387 |
| C_6 | 0.1061 | 1.0000 | 0.7353 | 0.0000 | 0.6010 | 0.1847 | 0.2032 | 0.1247 | 0.1066 |
| C_7 | 0.0911 | 1.0000 | 0.4545 | 0.0000 | 0.1844 | 0.0567 | 0.0536 | 0.0349 | 0.0269 |
| C_8 | 0.0839 | 1.0000 | 0.0000 | 0.1485 | 0.8277 | 0.2544 | 0.2213 | 0.1462 | 0.1152 |
| C_9 | 0.0796 | 1.0000 | 0.4779 | 0.0000 | 0.1993 | 0.0613 | 0.0506 | 0.0339 | 0.0242 |
| C_{10} | 0.0944 | 1.0000 | 0.3658 | 0.0000 | 0.1606 | 0.0494 | 0.0484 | 0.0308 | 0.0254 |

Note: Cpt at = compute at.

Table 3. Computation of rough BWM-CRITIC-TOPSIS (AM)

| Plant | d^- | d^+ | Closeness coefficient | Rank |
|---------|--------|--------|-----------------------|------|
| Plant 1 | 0.0429 | 0.0000 | 1.0000 | 1 |
| Plant 2 | 0.0170 | 0.0344 | 0.3304 | 2 |
| Plant 3 | 0.0046 | 0.0397 | 0.1039 | 3 |

Table 4. Distance, closeness coefficient and the rank of each plant (AM)

| Criteria | Subjective weight | Plant 1 | Plant 2 | Plant 3 | C_j | Objective weight | Integrated weight | V_j^+ | V_j^- |
|----------|-------------------|---------|---------|---------|--------|------------------|-------------------|---------|---------|
| Cpt at. | Step 1 | Step 2 | | | Step 3 | | | Step 4 | |
| C_{11} | 0.0754 | 0.3201 | 1.0000 | 0.0000 | 1.8449 | 0.0948 | 0.0779 | 0.0464 | 0.0439 |
| C_{12} | 0.0911 | 0.0000 | 1.0000 | 0.1861 | 3.7552 | 0.1930 | 0.1915 | 0.1166 | 0.1065 |
| C_{13} | 0.1078 | 1.0000 | 0.5000 | 0.0000 | 1.7791 | 0.0914 | 0.1073 | 0.0626 | 0.0613 |
| C_{14} | 0.1078 | 1.0000 | 0.7353 | 0.0000 | 1.2552 | 0.0645 | 0.0757 | 0.0450 | 0.0419 |
| C_{15} | 0.1045 | 0.5000 | 1.0000 | 0.0000 | 1.3346 | 0.0686 | 0.0781 | 0.0478 | 0.0422 |
| C_{16} | 0.1078 | 0.4500 | 1.0000 | 0.0000 | 1.4529 | 0.0747 | 0.0877 | 0.0527 | 0.0486 |
| C_{17} | 0.0964 | 1.0000 | 0.1388 | 0.0000 | 3.3479 | 0.1720 | 0.1806 | 0.1091 | 0.1012 |
| C_{18} | 0.0624 | 1.0000 | 0.8163 | 0.0000 | 1.1623 | 0.0597 | 0.0406 | 0.0254 | 0.0201 |
| C_{19} | 0.0706 | 1.0000 | 0.6452 | 0.0000 | 1.4097 | 0.0724 | 0.0557 | 0.0341 | 0.0296 |
| C_{20} | 0.0849 | 0.7000 | 1.0000 | 0.0000 | 1.0425 | 0.0536 | 0.0496 | 0.0297 | 0.0272 |
| C_{21} | 0.0915 | 0.9834 | 1.0000 | 0.0000 | 1.0774 | 0.0554 | 0.0552 | 0.0344 | 0.0263 |

Note: Cpt at = compute at.

Table 5. Computation of rough BWM-CRITIC-TOPSIS (cloud computing)

| Plant | d^- | d^+ | Closeness coefficient | Rank |
|---------|--------|--------|-----------------------|------|
| Plant 1 | 0.0142 | 0.0109 | 0.5646 | 2 |
| Plant 2 | 0.0162 | 0.0071 | 0.6942 | 1 |
| Plant 3 | 0.0019 | 0.0178 | 0.0958 | 3 |

Table 6. Distance, closeness coefficient and the rank of each plant (cloud computing)

| Criteria | Subjective weight | Plant 1 | Plant 2 | Plant 3 | C_j | Objective weight | Integrated weight | V_j^+ | V_j^- |
|----------|-------------------|---------|---------|---------|--------|------------------|-------------------|---------|---------|
| Cpt at. | Step 1 | Step 2 | | | Step 3 | | | Step 4 | |
| C_{22} | 0.0767 | 0.9939 | 1.0000 | 0.0000 | 0.9143 | 0.1079 | 0.0771 | 0.0496 | 0.0320 |
| C_{23} | 0.0895 | 1.0000 | 0.5682 | 0.0000 | 0.4135 | 0.0488 | 0.0407 | 0.0267 | 0.0196 |
| C_{24} | 0.1249 | 1.0000 | 0.0000 | 0.2000 | 2.0125 | 0.2376 | 0.2763 | 0.1695 | 0.1526 |
| C_{25} | 0.0861 | 1.0000 | 0.6633 | 0.0000 | 0.4276 | 0.0505 | 0.0405 | 0.0257 | 0.0203 |
| C_{26} | 0.0789 | 1.0000 | 0.6000 | 0.0000 | 0.4117 | 0.0486 | 0.0357 | 0.0228 | 0.0179 |
| C_{27} | 0.0977 | 1.0000 | 0.6349 | 0.0000 | 0.4173 | 0.0493 | 0.0449 | 0.0291 | 0.0217 |
| C_{28} | 0.1249 | 1.0000 | 0.0000 | 0.0909 | 1.7198 | 0.2030 | 0.2361 | 0.1460 | 0.1305 |
| C_{29} | 0.1049 | 1.0000 | 0.9322 | 0.0000 | 0.7623 | 0.0900 | 0.0879 | 0.0551 | 0.0418 |
| C_{30} | 0.1222 | 1.0000 | 0.8000 | 0.0000 | 0.5470 | 0.0646 | 0.0735 | 0.0459 | 0.0367 |
| C_{31} | 0.0941 | 1.0000 | 0.9722 | 0.0000 | 0.8445 | 0.0997 | 0.0874 | 0.0555 | 0.0390 |

Note: Cpt at = compute at.

Table 7. Computation of rough BWM-CRITIC-TOPSIS (AR)

| Plant | d^- | d^+ | Closeness coefficient | Rank |
|---------|--------|--------|-----------------------|------|
| Plant 1 | 0.0391 | 0.0001 | 0.9973 | 1 |
| Plant 2 | 0.0289 | 0.0235 | 0.5513 | 2 |
| Plant 3 | 0.0037 | 0.0372 | 0.0897 | 3 |

Table 8. Distance, closeness coefficient and the rank of each plant (AR)

| Criteria | Subjective weight | Plant 1 | Plant 2 | Plant 3 | C_j | Objective weight | Integrated weight | V_j^+ | V_j^- |
|----------|-------------------|---------|---------|---------|--------|------------------|-------------------|---------|---------|
| Cpt at. | Step 1 | Step 2 | | | Step 3 | | | Step 4 | |
| C_{32} | 0.0472 | 1.0000 | 0.3572 | 0.0000 | 1.9940 | 0.0637 | 0.0289 | 0.0172 | 0.0163 |
| C_{33} | 0.1164 | 1.0000 | 0.5263 | 0.0000 | 2.1952 | 0.0702 | 0.0784 | 0.0469 | 0.0435 |
| C_{34} | 0.1164 | 1.0000 | 0.9706 | 0.0000 | 3.5846 | 0.1146 | 0.1280 | 0.0824 | 0.0544 |
| C_{35} | 0.1164 | 0.9750 | 1.0000 | 0.0000 | 3.7340 | 0.1193 | 0.1333 | 0.0811 | 0.0684 |
| C_{36} | 0.0220 | 1.0000 | 0.6928 | 0.0000 | 2.5778 | 0.0824 | 0.0174 | 0.0117 | 0.0075 |
| C_{37} | 0.1164 | 1.0000 | 0.0000 | 0.4117 | 2.2369 | 0.0715 | 0.0799 | 0.0504 | 0.0421 |
| C_{38} | 0.1164 | 0.3999 | 0.0000 | 1.0000 | 5.6381 | 0.1802 | 0.2013 | 0.1187 | 0.1140 |
| C_{39} | 0.1164 | 1.0000 | 0.1041 | 0.0000 | 2.0249 | 0.0647 | 0.0723 | 0.0443 | 0.0402 |
| C_{40} | 0.1164 | 0.6000 | 0.0000 | 1.0000 | 4.9105 | 0.1569 | 0.1752 | 0.1026 | 0.0995 |
| C_{41} | 0.1164 | 1.0000 | 0.0000 | 0.5002 | 2.3931 | 0.0765 | 0.0854 | 0.0503 | 0.0483 |

Note: Cpt at = compute at.

Table 9. Computation of rough BWM-CRITIC-TOPSIS (cybersecurity)

| Plant | d^- | d^+ | Closeness coefficient | Rank |
|---------|--------|--------|-----------------------|------|
| Plant 1 | 0.0326 | 0.0031 | 0.9130 | 1 |
| Plant 2 | 0.0302 | 0.0111 | 0.7316 | 2 |
| Plant 3 | 0.0066 | 0.0319 | 0.1723 | 3 |

Table 10. Distance, closeness coefficient and the rank of each plant (cybersecurity)

| Criteria | Subjective weight | Plant 1 | Plant 2 | Plant 3 | C_j | Objective weight | Integrated weight | V_j^+ | V_j^- |
|----------|-------------------|---------|---------|---------|--------|------------------|-------------------|---------|---------|
| Cpt at. | Step 1 | Step 2 | | | Step 3 | | | Step 4 | |
| C_{42} | 0.1015 | 0.1200 | 0.0000 | 1.0000 | 6.1679 | 0.1247 | 0.1410 | 0.0868 | 0.0781 |
| C_{43} | 0.1003 | 0.6002 | 0.0000 | 1.0000 | 4.3267 | 0.0875 | 0.0978 | 0.0567 | 0.0561 |
| C_{44} | 0.1058 | 0.4668 | 0.0000 | 1.0000 | 4.6758 | 0.0946 | 0.1115 | 0.0654 | 0.0634 |
| C_{45} | 0.0871 | 1.0000 | 0.3947 | 0.0000 | 3.6126 | 0.0731 | 0.0709 | 0.0445 | 0.0377 |
| C_{46} | 0.0839 | 1.0000 | 0.7857 | 0.0000 | 4.7829 | 0.0967 | 0.0904 | 0.0553 | 0.0473 |
| C_{47} | 0.1058 | 1.0000 | 0.0000 | 0.0000 | 3.4949 | 0.0707 | 0.0833 | 0.0499 | 0.0472 |
| C_{48} | 0.0677 | 0.9524 | 1.0000 | 0.0000 | 5.8363 | 0.1180 | 0.0890 | 0.0554 | 0.0429 |
| C_{49} | 0.0445 | 1.0000 | 0.8036 | 0.0000 | 4.8612 | 0.0983 | 0.0487 | 0.0309 | 0.0235 |
| C_{50} | 0.0938 | 1.0000 | 0.1786 | 0.0000 | 3.4301 | 0.0694 | 0.0725 | 0.0449 | 0.0398 |
| C_{51} | 0.1037 | 0.6308 | 0.0000 | 1.0000 | 4.2657 | 0.0863 | 0.0997 | 0.0611 | 0.0532 |
| C_{52} | 0.1058 | 0.9201 | 0.0000 | 1.0000 | 3.9895 | 0.0807 | 0.0951 | 0.0569 | 0.0512 |

Note: Cpt at = compute at.

Table 11. Computation of rough BWM-CRITIC-TOPSIS (IoT)

| Plant | d^- | d^+ | Closeness coefficient | Rank |
|---------|--------|--------|-----------------------|------|
| Plant 1 | 0.0199 | 0.0083 | 0.7058 | 1 |
| Plant 2 | 0.0155 | 0.0149 | 0.5094 | 2 |
| Plant 3 | 0.0132 | 0.0188 | 0.4126 | 3 |

Table 12. Distance, closeness coefficient and the rank of each plant (IoT)

| Criteria | Subjective weight | Plant 1 | Plant 2 | Plant 3 | C_j | Objective weight | Integrated weight | V_j^+ | V_j^- |
|----------|-------------------|---------|---------|---------|--------|------------------|-------------------|---------|---------|
| Cpt at. | Step 1 | Step 2 | | | Step 3 | | | Step 4 | |
| C_{53} | 0.0802 | 1.0000 | 0.2083 | 0.0000 | 0.8575 | 0.0997 | 0.0870 | 0.0549 | 0.0469 |
| C_{54} | 0.0862 | 1.0000 | 0.8333 | 0.0000 | 0.6180 | 0.0719 | 0.0674 | 0.0403 | 0.0367 |
| C_{55} | 0.1072 | 0.7199 | 1.0000 | 0.0000 | 1.6662 | 0.1938 | 0.2261 | 0.1334 | 0.1266 |
| C_{56} | 0.0794 | 1.0000 | 0.5405 | 0.0000 | 0.3850 | 0.0448 | 0.0387 | 0.0241 | 0.0204 |
| C_{57} | 0.1072 | 1.0000 | 0.7143 | 0.0000 | 0.4534 | 0.0527 | 0.0615 | 0.0368 | 0.0337 |
| C_{58} | 0.0929 | 1.0000 | 0.3125 | 0.0000 | 0.6266 | 0.0729 | 0.0737 | 0.0473 | 0.0385 |
| C_{59} | 0.0687 | 0.9895 | 1.0000 | 0.0000 | 1.0056 | 0.1170 | 0.0875 | 0.0540 | 0.0429 |
| C_{60} | 0.0893 | 1.0000 | 0.3030 | 0.0000 | 0.6446 | 0.0750 | 0.0729 | 0.0454 | 0.0394 |
| C_{61} | 0.0968 | 1.0000 | 0.0000 | 0.0000 | 1.5147 | 0.1762 | 0.1856 | 0.1141 | 0.1035 |
| C_{62} | 0.0850 | 1.0000 | 0.7052 | 0.0000 | 0.4445 | 0.0517 | 0.0478 | 0.0296 | 0.0248 |
| C_{63} | 0.1072 | 1.0000 | 0.5555 | 0.0000 | 0.3824 | 0.0445 | 0.0519 | 0.0310 | 0.0288 |

Note: Cpt at = compute at.

Table 13. Computation of rough BWM-CRITIC-TOPSIS (advanced simulation)

| Plant | d^- | d^+ | Closeness coefficient | Rank |
|---------|--------|--------|-----------------------|------|
| Plant 1 | 0.0223 | 0.0019 | 0.9218 | 1 |
| Plant 2 | 0.0145 | 0.0146 | 0.4985 | 2 |
| Plant 3 | 0.0000 | 0.0228 | 0.0000 | 3 |

Table 14. Distance, closeness coefficient and the rank of each plant (advanced simulation)

| Criteria | Subjective weight | Plant 1 | Plant 2 | Plant 3 | C_j | Objective weight | Integrated weight | V_j^+ | V_j^- |
|----------|-------------------|---------|---------|---------|--------|------------------|-------------------|---------|---------|
| Cpt at. | Step 1 | Step 2 | | | Step 3 | | | Step 4 | |
| C_{64} | 0.1102 | 0.6000 | 0.0000 | 1.0000 | 1.5310 | 0.0886 | 0.1017 | 0.0615 | 0.0554 |
| C_{65} | 0.0938 | 0.6000 | 0.0000 | 1.0000 | 1.5310 | 0.0886 | 0.0866 | 0.0518 | 0.0479 |
| C_{66} | 0.1102 | 1.0000 | 0.0000 | 0.7143 | 0.9573 | 0.0554 | 0.0636 | 0.0381 | 0.0348 |
| C_{67} | 0.0887 | 0.7200 | 0.0000 | 1.0000 | 1.3014 | 0.0753 | 0.0696 | 0.0420 | 0.0376 |
| C_{68} | 0.0554 | 1.0000 | 0.1087 | 0.0000 | 3.0351 | 0.1757 | 0.1014 | 0.0623 | 0.0563 |
| C_{69} | 0.1102 | 1.0000 | 0.0000 | 0.7895 | 0.9487 | 0.0549 | 0.0630 | 0.0381 | 0.0337 |
| C_{70} | 0.1102 | 0.4286 | 0.0000 | 1.0000 | 2.0225 | 0.1171 | 0.1344 | 0.0805 | 0.0749 |
| C_{71} | 0.1011 | 1.0000 | 0.0000 | 0.0000 | 2.8127 | 0.1628 | 0.1714 | 0.1032 | 0.0968 |
| C_{72} | 0.1102 | 0.8500 | 0.0000 | 1.0000 | 1.1506 | 0.0666 | 0.0764 | 0.0455 | 0.0418 |
| C_{73} | 0.1102 | 1.0000 | 0.0000 | 0.2000 | 1.9850 | 0.1149 | 0.1319 | 0.0809 | 0.0728 |

Note: Cpt at = compute at.

Table 15. Computation of rough BWM-CRITIC-TOPSIS (universal integration)

| Plant | d^- | d^+ | Closeness coefficient | Rank |
|---------|--------|--------|-----------------------|------|
| Plant 1 | 0.0148 | 0.0045 | 0.7647 | 1 |
| Plant 2 | 0.0007 | 0.0169 | 0.0373 | 3 |
| Plant 3 | 0.0118 | 0.0110 | 0.5164 | 2 |

Table 16. Distance, closeness coefficient and the rank of each plant (universal integration)

| Criteria | Subjective weight | Plant 1 | Plant 2 | Plant 3 | C_j | Objective weight | Integrated weight | V_j^+ | V_j^- |
|----------|-------------------|---------|---------|---------|--------|------------------|-------------------|---------|---------|
| Cpt at. | Step 1 | Step 2 | | | Step 3 | | | Step 4 | |
| C_{74} | 0.0990 | 1.0000 | 0.0000 | 0.4545 | 1.8141 | 0.0587 | 0.0672 | 0.0408 | 0.0369 |
| C_{75} | 0.0727 | 1.0000 | 0.6818 | 0.0000 | 2.7140 | 0.0878 | 0.0739 | 0.0465 | 0.0374 |
| C_{76} | 0.0844 | 1.0000 | 0.9722 | 0.0000 | 4.2359 | 0.1370 | 0.1338 | 0.0794 | 0.0729 |
| C_{77} | 0.0990 | 1.0000 | 0.4167 | 0.0000 | 1.8633 | 0.0603 | 0.0691 | 0.0416 | 0.0383 |
| C_{78} | 0.0990 | 0.6941 | 0.0000 | 1.0000 | 4.9624 | 0.1605 | 0.1838 | 0.1144 | 0.0946 |
| C_{79} | 0.0742 | 1.0000 | 0.6757 | 0.0000 | 2.6882 | 0.0869 | 0.0746 | 0.0464 | 0.0386 |
| C_{80} | 0.0983 | 1.0000 | 0.0000 | 0.5932 | 2.1899 | 0.0708 | 0.0805 | 0.0493 | 0.0431 |
| C_{81} | 0.0990 | 0.9111 | 0.0000 | 1.0000 | 4.2965 | 0.1389 | 0.1591 | 0.0982 | 0.0798 |
| C_{82} | 0.0457 | 1.0000 | 0.0000 | 0.0562 | 1.5441 | 0.0499 | 0.0264 | 0.0173 | 0.0140 |
| C_{83} | 0.0772 | 1.0000 | 0.0000 | 0.1515 | 1.5101 | 0.0488 | 0.0436 | 0.0276 | 0.0236 |
| C_{84} | 0.0802 | 1.0000 | 0.0961 | 0.0000 | 1.5521 | 0.0502 | 0.0466 | 0.0290 | 0.0256 |
| C_{85} | 0.0713 | 1.0000 | 0.1389 | 0.0000 | 1.5529 | 0.0502 | 0.0414 | 0.0264 | 0.0222 |

Note: Cpt at = compute at.

Table 17. Computation of rough BWM-CRITIC-TOPSIS (big data)

| Plant | d^- | d^+ | Closeness coefficient | Rank |
|---------|--------|--------|-----------------------|------|
| Plant 1 | 0.0279 | 0.0063 | 0.8160 | 1 |
| Plant 2 | 0.0104 | 0.0292 | 0.2632 | 3 |
| Plant 3 | 0.0274 | 0.0161 | 0.6303 | 2 |

Table 18. Distance, closeness coefficient and the rank of each plant (big data)

| Criteria | Subjective weight | Plant 1 | Plant 2 | Plant 3 | C_j | Objective weight | Integrated weight | V_j^+ | V_j^- |
|----------|-------------------|---------|---------|---------|--------|------------------|-------------------|---------|---------|
| Cpt at. | Step 1 | Step 2 | | | Step 3 | | | Step 4 | |
| C_{86} | 0.0383 | 1.0000 | 0.0000 | 1.0000 | 2.0394 | 0.1200 | 0.0455 | 0.0264 | 0.0261 |
| C_{87} | 0.1150 | 1.0000 | 0.0000 | 0.8491 | 1.5568 | 0.0916 | 0.1043 | 0.0628 | 0.0559 |
| C_{88} | 0.1150 | 1.0000 | 0.0000 | 0.1851 | 1.0464 | 0.0616 | 0.0701 | 0.0418 | 0.0396 |
| C_{89} | 0.1150 | 1.0000 | 0.0000 | 0.4386 | 0.9067 | 0.0533 | 0.0607 | 0.0372 | 0.0329 |
| C_{90} | 0.1150 | 1.0000 | 0.3677 | 0.0000 | 2.0346 | 0.1197 | 0.1363 | 0.0847 | 0.0734 |
| C_{91} | 0.1150 | 1.0000 | 0.0000 | 0.7447 | 1.2925 | 0.0760 | 0.0865 | 0.0519 | 0.0471 |
| C_{92} | 0.1150 | 1.0000 | 0.4167 | 0.0000 | 2.1827 | 0.1284 | 0.1462 | 0.0900 | 0.0792 |
| C_{93} | 0.0421 | 1.0000 | 0.0000 | 0.1351 | 1.1189 | 0.0658 | 0.0274 | 0.0166 | 0.0153 |
| C_{94} | 0.1150 | 0.6001 | 0.0000 | 1.0000 | 3.0571 | 0.1799 | 0.2049 | 0.1205 | 0.1157 |
| C_{95} | 0.1150 | 1.0000 | 0.2586 | 0.0000 | 1.7601 | 0.1036 | 0.1180 | 0.0729 | 0.0645 |

Note: Cpt at = compute at.

Table 19. Computation of rough BWM-CRITIC-TOPSIS for autonomous systems

| Plant | d^- | d^+ | Closeness coefficient | Rank |
|---------|--------|--------|-----------------------|------|
| Plant 1 | 0.0204 | 0.0019 | 0.9138 | 1 |
| Plant 2 | 0.0065 | 0.0157 | 0.2925 | 3 |
| Plant 3 | 0.0086 | 0.0181 | 0.3209 | 2 |

Table 20. Distance, closeness coefficient and the rank of each plant (autonomous systems)

| | Most urgent pillar | Least urgent pillar | Most consistent pillar | Least consistent pillar |
|--------------|--------------------|---------------------|------------------------|-------------------------|
| Industry 4.0 | P ₄ | P ₁ | P ₄ | P ₃ |

Table 21. Descriptive statistics of pillars at the organization level.

| Aspect | Most urgent criterion | Least urgent criterion | Most consistent criterion | Least consistent criterion |
|-----------------------|-----------------------|------------------------|---------------------------|----------------------------|
| AM | C5 | C9 | C2 | C9 |
| Cloud Computing | C13 | C18 | C13 | C21 |
| AR | C28 | C22 | C24 | C22 |
| Cybersecurity | C32 | C36 | C40 | C36 |
| IoT | C47 | C49 | C43 | C49 |
| Advanced Simulation | C55 | C59 | C55 | C59 |
| Universal Integration | C70 | C68 | C71 | C69 |
| Big Data | C78 | C82 | C77 | C82 |
| Autonomous Systems | C86 | C93 | C86 | C90 |

Table 22. Descriptive statistics of criteria at the organization level based on pillars.

7. Discussion

Three members in senior management, including the vice-president of the organization reviewed the results in a focus group session and agreed on the findings. They also provided the insights that help to explain the findings. In the discussion, the plants are first compared in terms of emphasis in the nine pillars of Industry 4.0. Table 1 shows the computation of BWM-CRITIC-TOPSIS, and Table 2 presents the distance, closeness coefficient, and the rank

of each plant. In Table 2, Plant 1 is at the highest maturity level among the three manufacturing plants. This result indicates that Plant 1 has the highest receptiveness among the tactical level management in implementing the nine pillars of Industry 4.0. The maturity of Plant 2 ranks second followed by Plant 3.

The plants are then compared in terms of emphasis in the criteria for each pillar of Industry 4.0. Tables 3, 5, 7, 9, 11, 13, 15, 17, and 19 show the computation of BWM-CRITIC-TOPSIS, and Tables 4, 6, 8, 10, 12, 14, 16, 18, and 20 present the distance, closeness coefficient, and the rank of each plant. The ranking between the plants is directly linked to the maturity in rolling out a horizontal integration of various systems. In seeking for improvement, Plants 2 and 3 would have more exposure and infrastructure setup on Industry 4.0 elements. From another perspective, Plant 1 has always been more labor-intensive and higher product mix. Not until recently, a roadmap with a more prescriptive path of Industry 4.0 is determined in Plant 1 to improve its competitiveness. The initial efforts of the roadmap were placed to integrate and digitize performance measures at the plant level. Management discussion and awareness workshops on Industry 4.0 were regularly conducted. The results show that Plant 1 is rather consistent in pursuing all pillars of Industry 4.0. From another perspective, the findings also provided empirical evidence that advanced infrastructure would lead to organization inertia (in this case, Plants 2 and 3) to further aggressively pursue technological change. Harraf, Soltwisch and Talbott (2016) noted that the newly invested technologies and capabilities may become the source of complacency for the organizations as they become less responsive to opportunities and threats in their environment. Therefore, the top management would require to plan and deploy a long-term strategy to inspire tactical level management under such a scenario to break the organization's inertia.

From the perspective of the AM aspect, Table 4 shows that Plant 1 has the highest urgency in implementing AM technology, and Plant 3 has a relatively lesser urgency to adopt AM technology. This result is expected because the AM technology is mainly beneficial for small lot sizes with a high focus on customization. This context would perfectly fit into the job shop discrete manufacturing archetype implemented in Plant 1. Plants 2 and 3 represent a repetitive archetype, in which, in combination with a low variety and big production volumes, a competitive advantage is not yet expected when applying AM technologies. From the perspective of the cloud computing aspect, Table 6 shows that Plant 2 has the highest urgency in adopting cloud computing technology. Considering the high degree of automation in Plant 2, considerable data are generated and collected daily for further processing. The usage of cloud computing is foreseen to lift efficiency in such a production environment. From the perspective of AR (Table 8) and cybersecurity (Table 10) aspects, the results show that Plant 1 has the highest urgency in adopting the technology, whereas Plant 3 has the lowest urgency in implementing technology of AR and cybersecurity. AR is applied mainly in Plant 1 today already as a digital assistant system for manual operations. The potential however also had been explored in Plant 3, in which the main application can be found for maintenance activities. The urgency of cybersecurity can be concluded as a result of system interconnectivity projects running in each of the plants.

From the perspective of IoT and advanced simulation, Plant 1 has the highest urgency in adopting these technologies compared with the other two plants, whereas Plant 3 has the lowest urgency in implementing these technologies. From the perspective of the universal integration aspect, Table 16 shows that Plant 1 has the highest urgency, whereas Plant 2 has the least urgency in adopting universal integration. The main contribution for this difference is linked to the inventory replenishment system applied in the various plants. Plant 1 is directly linked to the customer needs as the inventory is comparably low and a fast reaction time on customer peak demands is required. Plant 2 however reacts on a forecast planning with a relatively stable demand distributed on the various products produced. From the perspective of big data and autonomous systems, Tables 18 and 20 show that Plant 1 has the highest sense of urgency in implementing these technologies, whereas Plant 2 has the lowest sense of urgency. Given the highly mature automation level in Plant 2, the usage of big data and autonomous systems had become the normal practice, which stands in comparison to Plant 1, in which a manual operation represents the majority of the shop floor.

The study also reveals the urgency of pillars and criteria at the organization level. In Table 21, the most urgent pillar is "Cybersecurity (P4)." This result underlines the commitment of the tactical level management to be vigilant on data management and data security within the organization. Additionally, the organization mandates regular training on handling data safely and appropriately, which explains the most consistent criterion from the cybersecurity

aspect being the “Integrity (C40).” The constant emphasis on cybersecurity may explain why the most urgent criterion for the organization to implement cybersecurity is “Reliability (C32),” the most urgent criterion for the organization to implement IoT is “Security and privacy issues (C47),” the most urgent criterion for the organization to implement universal integration is “Data integration (C70),” and the most urgent criterion for the organization to implement big data is “Value (C78).” Generally, the cost and efficiency of the underlying process (backend process) are often not highly considered by the middle-level management as the least urgent criterion for cybersecurity is “Economic returns (C36).” The impact of a cybersecurity incident may be viewed as costlier than the investment.

The result reveals that the least urgent pillar is AM(P1),” indicating the general concerns by the tactical level management on the maturity of AM technology to produce reliable and quality high-end medical products. The current development of AM only accommodates small quantity production and customization approach. Therefore, the technology of AM is explored cautiously by the organization through preliminary and small-scale exploratory studies to support research and development. As urgent manufacturing of products in Plant 1 is observed, AM is rather seen as a possibility to manufacture spare parts or fixtures in Plants 2 and 3. The most consistent criterion from the AM aspect is “Material usage (C2),” and the most urgent criterion for the organization in AM technology is “Product quality (C5).”

The most consistent criterion from the cloud computing aspect is “Availability (C13),” whereas the least consistent criterion is “Contribution to design and prototyping (C18).” The main reason for the consistency of “Availability (C13)” can be linked to a centralized training approach and the common user experience in cloud computing across the various plants. On the contrary, the functional linkage to design and prototyping differs from plant to plant, explaining the least consistent criterion for (C18). The most consistent criterion from the AR aspect is “Training (C24),” which confirms again the experiences at the organization level, whereas the least urgent and consistent criterion is “Human–robot collaboration (C22).” The latter criterion is undermining the heterogeneous level of automation in the different plants, and with this, the variation needs further human–robot interactions. The most consistent criterion from the IoT aspect is “Automation control (C43),” underlining not only the central training approach but also the user experience in all plants. By contrast, the least consistent criterion is “Energy consumption (C49),” which directly links to the inconsistent impact of energy consumption in the individual plants. The most urgent criterion for the organization to implement advanced simulation is “Reliability (C55),” as the results must be fully proven because of the huge impact on, for example, quality, costs, and delivery. Moreover, the least urgent criterion is “Process design (C59).” The most consistent criterion from the universal integration aspect is “system integration (C71)” as this underlines the consistent user experience in all plants. The least consistent criterion is “Integration of management systems (C69),” which links back again to the variation on the level of automation and transparency in the various plants. The most consistent criterion from the big data aspect is “Velocity (C77),” confirming the overall expected capability for fast decision making, whereas the least consistent criterion is “Volatility (C82).” The most urgent and most consistent criterion for the organization to implement autonomous systems is “Efficiency (C86).” This result confirms the effectiveness of the strategic target setting process, which is aligned across the organization and cascaded down to the various plants, driving the common understanding and synergies of an expected outcome for autonomous systems. The least consistent criterion from the autonomous systems aspect is “Robustness (C90),” and the least urgent criterion is “Investment (C93),” which testify once more to the heterogeneous level of automation in the various plants.

The results have been corroborated by the senior management, and therefore suggest the suitability of BWM-CRITIC-TOPSIS to provide ranking in this comparative study to elicit perception-based information. The three constituent methods in BWM-CRITIC-TOPSIS play different roles. BWM leads to reliable subjective weights in group decision-making where respondents may be from diverse backgrounds. Taking in the same set of inputs, CRITIC takes into account of the contrast intensity and the conflicting relationship held by individual criteria to generate objective weights (Peng, Zhang & Luo, 2020). Consequently, higher weight is assigned to a criterion with a higher degree of conflict or a lower degree of redundancy. Finally, TOPSIS has demonstrated the ability to integrate weights, which provides moderation effects to the subjective and objective weights. In a simple mathematical form, the integrated weights provide a final scalar value to rank the criteria based on the sense of urgency to implement each I4.0 pillar.

8. Conclusion

The research conducted a comparative study to survey and compare the sense of urgency of tactical-level management in three sister plants to adopt different Industry 4.0 technologies, based on a comprehensive list of related criteria. To cater for varying knowledge and judgment of participants to certain pillars and criteria, the rough BWM-CRITIC-TOPSIS method which considered objective and subjective weights in the analysis was used to rank the plants based on the urgency to adopt a particular technology. The results indicate that a high-mix, low-volume, and labor-intensive plant (Plant 1) is at the highest urgency level among the three plants, whereas a largely automated plant (Plant 3) has the lowest urgency in adopting Industry 4.0 technologies. Despite recent Industry 4.0 awareness programs in Plant 1 contributing to the findings, the finding also provides empirical evidence that advanced infrastructure would lead to organization inertia (in the case of Plant 3) to aggressively pursuing technological change. Among the nine pillars of Industry 4.0, the most urgent pillar is cybersecurity, and the least urgent one is AM. This result outlines the concern over cyber threats when the product information is increasingly integrated into the supply chain and the technology immaturity of AM in production. In term of research contribution, the study demonstrated differing senses of urgency of tactical level management of different sister plants in technology adoption. The research also demonstrated the usefulness of BWM-CRITIC-TOPSIS to generate an integrated hence fairer weights to rank Industry 4.0 pillars and the sister plants. The results help the company management to understand the position of tactical level management and potentially facilitate a better Industry 4.0 strategy planning. The limitation of the research is that the data collection was obtained exclusively from an identified groups of employees from different plants in the manufacturing organization. The results therefore are empirical and may reflect the idiosyncrasy of the organization.

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References

- Adalı, E.A., & Işık, A.T. (2017). CRITIC and MAUT methods for the contract manufacturer selection problem. *European Journal of Multidisciplinary Studies*, 2(5), 93-101. <https://doi.org/10.26417/ejms.v5i1.p93-101>
- Adkins, M., & Patil, R. (2015). Data Integration Challenges and Solutions for Life Science Industry. *Pharma Bio World*, July, 60-66. Available at: <https://www.emerson.com/documents/automation/data-integration-challenges-solutions-for-life-science-industry-en-38212.pdf>
- Agca, O., Gibson, J., Godsell, J., Ignatius, J., Davies, C., & Xu, O. (2017). *An Industry 4 readiness assessment tool*. Warwick: The University of Warwick. Available at: https://warwick.ac.uk/fac/sci/wmg/research/scip/reports/final_version_of_i4_report_for_use_on_websites.pdf
- Alvandi, S., Li, W., & Kara, S. (2017). An integrated simulation optimisation decision support tool for multi-product production systems. *Modern Applied Science*, 11(6), 56. <https://doi.org/10.5539/mas.v11n6p56>
- Alzahrani, H. (2016). A brief survey of cloud computing. *Global Journal of Computer Science and Technology*. 151(3), 11-15. Available at: https://globaljournals.org/GJCST_Volume16/3-A-Brief-Survey-of-Cloud-Computing.pdf
- Amiri, M., & Emamat, S.M.M. (2020). A Goal Programming Model for BWM. *Informatica*. 31(1), 21-34. <https://doi.org/10.15388/20-INFOR389>
- Aqlan, F., Ramakrishnan, S., & Shamsan, A. (2017). Integrating data analytics and simulation for defect management in manufacturing environments. *Proceedings of the 2017 Winter Simulation Conference* (3940-3951). Available at: <http://simulation.su/uploads/files/default/2017-aqlan-ramakrishnan-shamsan.pdf> <https://doi.org/10.1109/WSC.2017.8248104>

- Back, A., & Berghaus, S. (2016). Digital Maturity & Transformation Studie: Über das Digital Maturity Model. In *Institut für Wirtschaftsinformatik*, Universität St.Gallen und Crosswalk AG. Available at: https://iwi.unisg.ch/wp-content/uploads/digitalmaturitymodel_download_v2.0-1.pdf
- Bahga, A., & Madiseti, V.K. (2016). Blockchain platform for industrial internet of things. *Journal of Software Engineering and Applications*, 9(10), 533-546. <https://doi.org/10.4236/jsea.2016.910036>
- Bahrin, M.A.K., Othman, M.F., Azli, N.N., & Talib, M.F. (2016). Industry 4.0: A review on industrial automation and robotic. *Advances on Intelligent Control and Robotic*, 78(6-13), 137-143. <https://doi.org/10.11113/jt.v78.9285>
- Bauer, D., Schumacher, S., Gust, A., Seidelmann, J., & Bauernhansl, T. (2019). Characterization of Autonomous Production by a Stage Model. *Procedia CIRP*, 81, 192-197. <https://doi.org/10.1016/j.procir.2019.03.034>
- Baxter, B.K. (2002). The relationship between a sense of urgency implementation and successful change strategies in organizations, *OTS Master's Level Projects & Papers*, 191. Available at: https://digitalcommons.odu.edu/ots_masters_projects/191
- Bernardo, M., Farrero, J.M.C., & Casadesús, M. (2016). The Impact of Management Systems Integration Through the Value Chain. *1st International Conference on Quality of Life* (179-185). Univerisity of Kragujevac. Available at: http://cqmq.rs/2016/cd1/pdf/papers/focus_1/25.pdf
- Bhadani, A.K., & Jothimani, D. (2016). Big data: challenges, opportunities, and realities. In Singh, M.K., & Kumar, D.G. (Eds.), *Effective big data management and opportunities for implementation* (1-24). Pennsylvania: IGI Global. <https://doi.org/10.4018/978-1-5225-0182-4.ch001>
- Biermann, D., Bleckmann, T., Schumann, S., & Iovkov, I. (2016). Advanced Simulation-based Design of High-Performance Machining Processes. *Procedia CIRP*, 46, 165-168. <https://doi.org/10.1016/j.procir.2016.03.167>
- Bikas, H., Stavropoulos, P., & Chryssolouris, G. (2016). Additive manufacturing methods and modelling approaches: a critical review. *International Journal of Advanced Manufacturing Technology*, 83(1-4), 389-405. <https://doi.org/10.1007/s00170-015-7576-2>
- Bottani, E., & Vignali, G. (2019). Augmented reality technology in the manufacturing industry: A review of the last decade. *IISE Transactions*, 51(3), 284-310. <https://doi.org/10.1080/24725854.2018.1493244>
- Britton, D.P. (2017). A systems engineering approach to regulating autonomous systems. *Master Thesis*, Duke University, UK.
- Campion, S. (2017). System Integration Meets Lean Manufacturing. *Quality Magazine*. Available at: <https://www.qualitymag.com/articles/93746-system-integration-meets-lean-manufacturing>
- Chansombat, S., Pongcharoen, P., & Hicks, C. (2019). A mixed-integer linear programming model for integrated production and preventive maintenance scheduling in the capital goods industry. *International Journal of Production Research*, 57(1), 61-82. <https://doi.org/10.1080/2F00207543.2018.1459923>
- Chaouchi, H., & Bourgeau, T. (2018). Internet of Things: Building the New Digital Society. *IoT 2020*, 1, 1-4. <https://doi.org/10.3390/iot1010001>
- Chen, Y. (2017). Integrated and intelligent manufacturing: Perspectives and enablers. *Engineering*, 3(5), 588-595. <https://doi.org/10.1016/J.ENG.2017.04.009>
- Chukalov, K. (2017). Horizontal and vertical integration, as a requirement for cyber-physical systems in the context of industry 4.0. *International Scientific Journal Industry 4.0*, 2(4), 155-157. Available at: <https://stumejournals.com/journals/i4/2017/4/155.full.pdf>
- Clim, A. (2019). Cyber Security Beyond the Industry 4.0 Era. A Short Review on a Few Technological Promises. *Informatika Economica*, 23(2), 34-44. Available at: <http://revistaie.ase.ro/content/90/04%20-%20clim.pdf> <https://doi.org/10.12948/issn14531305/23.2.2019.04>
- Čolaković, A., & Hadzialic, M. (2018). Internet of Things (IoT): A Review of Enabling Technologies, Challenges, and Open Research Issues. *Computer Networks*, 144, 17-39. <https://doi.org/10.1016/j.comnet.2018.07.017>

- Coghlan, W. (2016). Ascending Cloud: The adoption of cloud computing in five industries, *The Economist Intelligence Unit executive summary*, 1-12. Available at: https://www.vmware.com/radius/wp-content/uploads/2015/08/EIU_VMware-Executive-Summary-FINAL-LINKS-2-26-16.pdf
- Conteh, N.Y., & Schmick, P.J. (2016). Cybersecurity: risks, vulnerabilities and countermeasures to prevent social engineering attacks. *International Journal of Advanced Computer Research*, 6(23), 31-38. <https://doi.org/10.19101/IJACR.2016.623006>
- Day, G. (1999). Creating a Market - Driven Organization. *MIT Sloan Management Review*. 41(1), 11-22. <https://sloanreview.mit.edu/article/creating-a-market-driven-organization/>
- De Pace, F., Manuri, F., & Sanna, A. (2018). Augmented reality in industry 4.0. *American Journal of Computer Science and Information Technology*, 6(1), 1-7. <https://doi.org/10.21767/2349-3917.100017>
- Deng, H., Yeh, C.H., & Willis, R.J. (2000). Inter-company comparison using modified TOPSIS with objective weights. *Computers and Operations Research*, 27, 963-973. [https://doi.org/10.1016/S0305-0548\(99\)00069-6](https://doi.org/10.1016/S0305-0548(99)00069-6)
- Dennis, L., Fisher, M., Slavkovik, M., & Webster, M. (2016). Formal verification of ethical choices in autonomous systems. *Robotics and Autonomous Systems*, 77, 1-14. <https://doi.org/10.1016/j.robot.2015.11.012>
- Diakoulaki, D., Mavrotas, G., Papayannakis, L. (1995). Determining objective weights in multiple criteria problems: the CRITIC method. *Computers and Operations Research*, 22, 763-770. [https://doi.org/10.1016/0305-0548\(94\)00059-H](https://doi.org/10.1016/0305-0548(94)00059-H)
- Dini, G., & Dalle-Mura, M. (2015). Application of augmented reality techniques in through-life engineering services. *Procedia CIRP*, 38, 14-23. <https://doi.org/10.1016/j.procir.2015.07.044>
- EPSRC (2015). Autonomous Manufacturing, *Research proposal*. Available at: <https://epsrc.ukri.org/files/funding/calls/2015/autonomousmanufacturing/>
- Fakhimi, M., & Mustafee, N., (2019). Sustainability Analysis in Industry 4.0 using Computer Modelling and simulation, In Gunal, M.M. (Ed.), *Simulation for Industry 4.0* (97-109). https://doi.org/10.1007/978-3-030-04137-3_6
- Fernandes, N.O., Martins, T., & Carmo-Silva, S. (2018). Improving materials flow through autonomous production control. *Journal of Industrial and Production Engineering*, 35(5), 319-327. <https://doi.org/10.1080/21681015.2018.1479895>
- Fitzgerald, J., & Quasney, E. (2017). *Using Autonomous Robots to Drive Supply Chain Innovation*. Deloitte Perspectives. Deloitte Development LLC. Available at: <https://www2.deloitte.com/content/dam/Deloitte/us/Documents/manufacturing/us-manufacturing-autonomous-robots-supply-chain-innovation.pdf>
- Ford, S., & Despeisse, M. (2016). Additive manufacturing and sustainability: an exploratory study of the advantages and challenges. *Journal of Cleaner Production*, 137, 1573-1587. <https://doi.org/10.1016/j.jclepro.2016.04.150>
- Fox, S. (2018). Reliable autonomous production systems: Combining industrial engineering methods and situation awareness modelling in critical realist design of autonomous production systems. *Systems*, 6(3), 26-41. <https://doi.org/10.3390/systems6030026>
- Fraga-Lamas, P., Fernández-Caramés, T.M., Blanco-Novoa, Ó., & Vilar-Montesinos, M.A. (2018). A review on industrial augmented reality systems for the industry 4.0 shipyard. *IEEE Access*, 6, 13358-13375. <https://doi.org/10.1109/ACCESS.2018.2808326>
- Freitag, M., & Hildebrandt, T. (2016). Automatic design of scheduling rules for complex manufacturing systems by multi-objective simulation-based optimization. *CIRP Annals*, 65(1), 433-436. <https://doi.org/10.1016/j.cirp.2016.04.066>
- Gökalp, E., Şener, U., & Eren, P.E. (2017). Development of an Assessment Model for Industry 4.0: Industry 4.0-MM. In Mas, A., Mesquida, A., O'Connor, R., Rout, T., & Dorling, A. (Eds.), *Software Process Improvement and Capability Determination* (128-142). https://doi.org/10.1007/978-3-319-67383-7_10

- Guo, S., & Zhao, H. (2017). Fuzzy best-worst multi-criteria decision-making method and its applications. *Knowledge Based Systems*, 121, 23-31. <https://doi.org/10.1016/j.knosys.2017.01.010>
- Gupta, K., Beri, R., Behal, V., Gupta, K., Beri, R., & Behal, V. (2016). Cloud computing: a survey on cloud simulation tools. *International Journal for Innovative Research in Science & Technology*, 2(11), 430-434.
- Gurusamy, V., & Hirani, B. (2018). Cyber Security for Our Digital Life. *Proceeding of National Conference on Innovations in Computer Technology and its Applications (NCICTC'18)* (1-6). Guru Nanak College, Chennai.
- Hällgren, S., Pejryd, L., & Ekengren, J. (2016). (Re) Design for additive manufacturing. *Procedia CIRP*, 50, 246-251. <https://doi.org/10.1016/j.procir.2016.04.150>
- Hamdaoui, M., & Bouayad, B. (2019). Determinants and Effects of Vertical Integration on the Performance of Moroccan Manufacturing. *Athens Journal of Mediterranean Studies*, 5(1), 57-78. <https://doi.org/10.30958/ajms.5-1-4>
- Hankel, M., & Rexroth, B. (2015). *The reference architectural model industrie 4.0 (RAMI 4.0)*. ZVEI – German Electrical and Electronic Manufacturers' Association. Germany. Available at: <https://przemysl-40.pl/wp-content/uploads/2010-The-Reference-Architectural-Model-Industrie-40.pdf>
- Harraf, A., Soltwisch B.W., & Talbott, K. (2016). Antecedents of Organizational Complacency: Identifying and Preventing Complacency in the Work Environment. *Managing Global Transitions*, 14(4 (Winter)), 385-401. University of Primorska, Faculty of Management Koper.
- Helle, P., Schamai, W., & Strobel, C. (2016). Testing of autonomous systems—Challenges and current state of the art. *Proceeding of 26th Annual INCOSE International Symposium* (1-14). Edinburgh, Scotland. <https://doi.org/10.1002/j.2334-5837.2016.00179.x>
- Herzog, D., Seyda, V., Wycisk, E., & Emmelmann, C. (2016). Additive manufacturing of metals. *Acta Materialia*, 117, 371-392. <https://doi.org/10.1016/j.actamat.2016.07.019>
- Hoffmeister, M., Festo, A., & Co, K.G. (2015). *The Industrie 4.0 Component*. ZVEI-German Electrical and Electronic Manufacturers' Association, Germany. Available at: https://www.zvei.org/fileadmin/user_upload/Themen/Industrie_4.0/Das_Referenzarchitekturmodell_RAMI_4.0_und_die_Industrie_4.0-Komponente/pdf/ZVEI-Industrie-40-Component-English.pdf
- Hwang, G., Lee, J., Park, J., & Chang, T.W. (2017). Developing performance measurement system for Internet of Things and smart factory environment. *International Journal of Production Research*, 55(9), 2590-2602. <https://doi.org/10.1080/00207543.2016.1245883>
- Ishii, H. (2017). Industrial Application of Augmented Reality. *International Journal of Nuclear Safety and Simulation*, 8(3), 183-192. Available at: <http://hdl.handle.net/2433/236047>
- Islam, K.V.N. (2017). Review on Benefits and Security Challenges of Cloud Computing. *International Journal of Computer Science and Information Technologies*, 8(2), 224-228.
- Intechcentras (2019). *Pathfinder i4.0*. Available at: <https://pathfinder.i40.de/en/demo/>
- Jebble, S., & Patil, Y. (2018). Role of Big Data in Decision Making. *Operations and Supply Chain Management: An International Journal*, 11(1), 36-44. <https://doi.org/10.31387/oscm0300198>
- Joggerst, L., Knoll, M., Hoppe, F., Wendt, J., & Groche, P. (2018). Autonomous Manufacturing Processes under Legal Uncertainty. *Applied Mechanics and Materials*, 885, 227-239. <https://doi.org/10.4028/www.scientific.net/AMM.885.227>
- Kapil, G., Agrawal, A., & Khan, R. (2016). A study of big data characteristics. Paper presented at the 2016 *International Conference on Communication and Electronics Systems (ICCES)* (1-4). <https://doi.org/10.1109/CESYS.2016.7889917>
- Kikolski, M. (2016). Identification of production bottlenecks with the use of Plant Simulation software. *Ekonomia i Zarządzanie*, 8(4), 103-112. <https://doi.org/10.1515/emj-2016-0038>

- Krishnan, A.R., Kasim, M.M., Hamid, R., & Ghazali, M.F. (2021). A modified CRITIC method to estimate the objective weights of decision criteria, *Symmetry*, 13(6), 1-21. <https://doi.org/10.3390/sym13060973>
- Kotter, J.P., (2008). *A Sense of Urgency*. Boston, Massachusetts: Harvard Business School Press.
- Kotter, J.P., (1995). Leading change: Why transformation efforts fail?, *Harvard Business Review*, March/April, 59-67.
- Kumar, V., Saxena, P., & Garg, H. (2021). Selection of optimal software reliability growth models using an integrated entropy-Technique for order preference by similarity to an ideal solution (TOPSIS) approach. *Mathematical Methods in the Applied Science*, 1-21 <https://doi.org/10.1002/mma.7445>
- Lu, M., & Hasan, M. (2018). Productivity improvement in operating autonomous plants subject to random breakdowns in construction. Paper presented at the 2018 *Winter Simulation Conference (WSC)* (3885-3896). <https://doi.org/10.1109/WSC.2018.8632430>
- Lu, Y., & Cecil, J. (2016). An Internet of Things (IoT)-based collaborative framework for advanced manufacturing. *The International Journal of Advanced Manufacturing Technology*, 84(5-8), 1141-1152. <https://doi.org/10.1007/s00170-015-7772-0>
- Makris, S., Karagiannis, P., Koukas, S., & Matthaiakis, A.S. (2016). Augmented reality system for operator supports in human–robot collaborative assembly. *CIRP Annals*, 65(1), 61-64. <https://doi.org/10.1016/j.cirp.2016.04.038>
- Mareschal, B. (1998). Weight stability intervals in multicriteria decision aid, *European Journal of Operational Research*, 33, 54-64. [https://doi.org/10.1016/0377-2217\(88\)90254-8](https://doi.org/10.1016/0377-2217(88)90254-8)
- Martinetti, A., Rajabalinejad, M., & van Dongen, L. (2017). Shaping the future maintenance operations: reflections on the adoptions of Augmented Reality through problems and opportunities. *Procedia CIRP*, 59, 14-17. <https://doi.org/10.1016/j.procir.2016.10.130>
- Masoni, R., Ferrise, F., Bordegoni, M., Gattullo, M., Uva, A.E., Fiorentino, M. et al. (2017). Supporting remote maintenance in industry 4.0 through augmented reality. *Procedia Manufacturing*, 11, 1296-1302. <https://doi.org/10.1016/j.promfg.2017.07.257>
- Michalos, G., Karagiannis, P., Makris, S., Tokçalar, Ö., & Chryssolouris, G. (2016). Augmented reality (AR) applications for supporting human-robot interactive cooperation. *Procedia CIRP*, 41, 370-375. <https://doi.org/10.1016/j.procir.2015.12.005>
- Moktadir, M.A., Ali, S.M., Paul, S.K., & Shukla, N. (2019). Barriers to big data analytics in manufacturing supply chains: A case study from Bangladesh. *Computers & Industrial Engineering*, 128, 1063-1075. Available at: <http://hdl.handle.net/10453/123309> <https://doi.org/10.1016/j.cie.2018.04.013>
- Motlagh, M.M., Azimi, P., Amiri, M., & Madraki, G. (2019). An efficient simulation optimization methodology to solve a multi-objective problem in unreliable unbalanced production lines. *Expert Systems with Applications*, 138, 112836. 1-22. <https://doi.org/10.1016/J.ESWA.2019.112836>
- Mourtzis, D., Doukas, M., & Bernidaki, D. (2014). Simulation in manufacturing: Review and challenges. *Procedia CIRP*, 25, 213-229. <https://doi.org/10.1016/j.procir.2014.10.032>
- Mourtzis, D., Zogopoulos, V., & Vlachou, E. (2017). Augmented reality application to support remote maintenance as a service in the robotics industry. *Procedia CIRP*, 63, 46-51. <https://doi.org/10.1016/j.procir.2017.03.154>
- Mourtzis, D., Xanthi, F., & Zogopoulos, V. (2019). An adaptive framework for augmented reality instructions considering workforce skill, *Procedia CIRP*, 81, 363-368. <https://doi.org/10.1016/j.procir.2019.03.063>
- Moyne, J., & Iskandar, J. (2017). Big data analytics for smart manufacturing: Case studies in semiconductor manufacturing. *Processes*, 5(3), 39. 1-20. <https://doi.org/10.3390/pr5030039>
- Müller, O., Fay, M., & vom Brocke, J. (2018). The effect of big data and analytics on firm performance: An econometric analysis considering industry characteristics. *Journal of Management Information Systems*, 35(2), 488-509. <https://doi.org/10.1080/07421222.2018.1451955>

- Mukherjee, S., & Shaw, R. (2016). Big data—concepts, applications, challenges and future scope. *International Journal of Advanced Research in Computer and Communication Engineering*, 5(2), 66-74. <https://doi.org/10.17148/IJARCCCE.2016.5215>
- Naderi, B., Mohammadi, M., & Nouri-Koupaei, M. (2016). Optimizing flexible manufacturing system: A developed computer simulation model. *International Journal of Engineering*, 29(8), 1112-1119. <https://doi.org/10.5829/idosi.ije.2016.29.08b.11>
- Nagadi, K., Rabelo, L., Basingab, M., Sarmiento, A.T., Jones, A., & Rahal, A. (2018). A hybrid simulation-based assessment framework of smart manufacturing systems. *International Journal of Computer Integrated Manufacturing*, 31(2), 115-128. <https://doi.org/10.1080/0951192X.2017.1407449>
- Nandgaonkar, S.V., & Raut, A. (2014). A comprehensive study on cloud computing. *International Journal of Computer Science and Mobile Computing*, 3(4), 733-738.
- Nechkoska, R.P. (2015) Tactical management in focus: adaptability and information systems. In: *Proceedings of the CAiSE'2015 Doctoral Consortium at the 27th International Conference on Advanced Information Systems Engineering (CAiSE 2015)* (19-27). Stockholm, Sweden. Available at: <http://hdl.handle.net/1854/LU-6890611>
- Oborski, P. (2016). Integrated monitoring system of production processes. *Management and Production Engineering Review*, 7(4), 86-96. <https://doi.org/10.1515/mper-2016-0039>
- Olson, D.L. (2004). Comparison of weights in TOPSIS models. *Mathematical and Computer Modelling*, 40(7-8), 721-727. <https://doi.org/10.1016/j.mcm.2004.10.003>
- Pan, J., & Yang, Z. (2018). Cybersecurity challenges and opportunities in the new edge computing + IoT world. *Proceedings of the 2018 ACM International Workshop on Security in Software Defined Networks & Network Function Virtualization* (1-4). <https://doi.org/10.1145/3180465.3180470>
- Palczewski, K., & Salabun, W. (2019). The fuzzy TOPSIS applications in the last decade. *Procedia Computer Science*, 159, 2294-2303. <https://doi.org/10.1016/j.procs.2019.09.404>
- Pamučar, D., Ecer, F., Cirovic, G., & Arlasheedi, M.A. (2020). Application of improved Best Worst Method (BWM) in real-world problems. *Mathematics*, 8,1342, 1-29. <https://doi.org/10.3390/math8081342>
- Patel, R., & Viradiya, J. (2016). A Review on Divisible Load Scheduling and Allocation on Cloud Computing. *International Research Journal of Engineering and Technology*, 3(3), 489-492.
- Peng, X., Zhang, X., & Luo, Z. (2020). Pythagorean fuzzy MCDM method based on CoCoSo and CRITIC with score function for 5G industry evaluation. *Artificial Intelligence Review*, 53, 3813-3847. <https://doi.org/10.1007/s10462-019-09780-x>
- Pessl, E., Sorko, S.R., & Mayer, B. (2017). Roadmap Industry 4.0—implementation guideline for enterprises. *International Journal of Science, Technology and Society*, 5(6), 193-202. <https://doi.org/10.11648/j.ijsts.20170506.14>
- Puljiz, D., Gorbachev, G., & Hein, B. (2018). Implementation of Augmented Reality in Autonomous Warehouses: Challenges and Opportunities. *Proceedings of 1st International Workshop on Virtual, Augmented, and Mixed Reality for HumanRobot Interactions (VAM-HRI'18)* (1-7). Available at: <https://arxiv.org/ftp/arxiv/papers/1806/1806.00324.pdf>
- Rashid, A., & Chaturvedi, A. (2019). Cloud computing characteristics and services: a brief review. *International Journal of Computer Sciences and Engineering*, 7(2), 421-426. <https://doi.org/10.26438/ijcse/v7i2.421426>
- Razzaq, M.A., Gill, S.H., Qureshi, M.A., & Ullah, S. (2017). Security issues in the Internet of Things (IoT): a comprehensive study. *International Journal of Advanced Computer Science and Applications (IJACSA)*, 8(6), 383-388. <https://doi.org/10.14569/IJACSA.2017.080650>
- Reka, S.S., & Dragicevic, T. (2018). Future effectual role of energy delivery: A comprehensive review of Internet of Things and smart grid. *Renewable and Sustainable Energy Reviews*, 91, 90-108. <https://doi.org/10.1016/j.rser.2018.03.089>
- Rezaei, J. (2016). Best-worst multi-criteria decision-making method: Some properties and a linear model. *Omega*, 64, 126-130. <https://doi.org/10.1016/j.omega.2015.12.001>

- Rodič, B. (2017). Industry 4.0 and the new simulation modelling paradigm. *Organizacija*, 50(3), 193-207.
<https://doi.org/10.1515/orga-2017-0017>
- Sadjadia, S.J., & Karimi, M. (2018). Best-worst multi-criteria decision-making method: A robust approach, *Decision Science Letters*, 7, 323-340. <https://doi.org/10.5267/j.dsl.2018.3.003>
- Sado, S.Y. (2014). The role of tactical plans in achieving organizational growth and objectives: A case study of zenith bank PLC Damaturu Branch. *Mediterranean Journal of Social Sciences*, 5(17), 59-66.
- Schuh, G., Anderl, R., Gausemeier, J., ten Hompel, M., & Wahlster, W. (2017). *Industrie 4.0 maturity index. Managing the digital transformation of companies*. Munich: Herbert Utz. Available at: <https://en.acatech.de/publication/industrie-4-0-maturity-index-managing-the-digital-transformation-of-companies/download-pdf?lang=en>
- Seifi, M., Salem, A., Beuth, J., Harrysson, O., & Lewandowski, J.J. (2016). Overview of materials qualification needs for metal additive manufacturing. *Journal of the Minerals, Metals & Materials Society*, 68(3), 747-764.
<https://doi.org/10.1007/s11837-015-1810-0>
- Sether, A. (2016). Cloud Computing Benefits. *JSRN Electronic Journal*, 1-19. <https://doi.org/10.2139/ssrn.2781593>
- Shahrdar, S., Menezes, L., & Nojoumian, M. (2018). A survey on trust in autonomous systems. *Intelligent Computing* (368-386). https://doi.org/10.1007/978-3-030-01177-2_27
- Sharma, V., & Tiwari, R. (2016). A review paper on “IOT” & It’s Smart Applications. *International Journal of Science, Engineering and Technology Research (IJSETR)*, 5(2), 472-476.
- Shih, H.S., Shyur, H.J., & Lee, E.S. (2007). An extension of TOPSIS for group decision making. *Mathematical and Computer Modelling*, 45(7-8), 801-813. <https://doi.org/10.1016/j.mcm.2006.03.023>
- Shrouf, F., & Miragliotta, G. (2015). Energy management based on Internet of Things: practices and framework for adoption in production management. *Journal of Cleaner Production*, 100, 235-246.
<https://doi.org/10.1016/j.jclepro.2015.03.055>
- Siers, R. (2018). *Cybersecurity: An Introduction. Security Studies* (3rd ed.) (556-568). Routledge, Abingdon, Oxon.
<https://doi.org/10.4324/9781315228358-38>
- Singapore EDB (2018). The Singapore Smart Industry Readiness Index. Catalysing the transformation of manufacturing. *Singapore Economic Development Board White paper*, 1-48. Available at: <https://speta.org/wp-content/uploads/2019/08/SIRI-White-Paper.pdf>
- Ślusarczyk, B. (2018). Industry 4.0-are we ready? *Polish Journal of Management Studies*, 17(1), 232-248.
<https://doi.org/10.17512/pjms.2018.17.1.19>
- Soldatos, J., Gusmeroli, S., Malo, P., & Di Orio, G. (2016). Internet of things applications in future manufacturing. *Digitising industry-internet of things connecting the physical, digital and virtual worlds* (153-183). River Publishers .
- Stoltz, M.H., Giannikas, V., McFarlane, D., Strachan, J., Um, J., & Srinivasan, R. (2017). Augmented reality in warehouse operations: opportunities and barriers. *IFAC-PapersOnLine*, 50(1), 12979-12984.
<https://doi.org/10.1016/j.ifacol.2017.08.1807>
- Syberfeldt, A., Holm, M., Danielsson, O., Wang, L., & Brewster, R.L. (2016). Support systems on the industrial shop-floors of the future—operators’ perspective on augmented reality. *Procedia CIRP*, 44, 108-113.
<https://doi.org/10.1016/j.procir.2016.02.017>
- Tofail, S.A., Koumoulos, E.P., Bandyopadhyay, A., Bose, S., O’Donoghue, L., & Charitidis, C. (2018). Additive manufacturing: scientific and technological challenges, market uptake and opportunities. *Materials today*, 21(1), 22-37. <https://doi.org/10.1016/j.mattod.2017.07.001>
- Truong, Q.T., Ngo, H.Q.T., Nguyen, T.P., Nguyen, H., & Kim, W.H. (2019). A Novel Infrastructure Design of Industrial Autonomous System. *International Journal of Fuzzy Logic and Intelligent Systems*, 19(2), 103-111.
<https://doi.org/10.5391/IJFIS.2019.19.2.103>

- Uhlemann, T.H.J., Lehmann, C., & Steinhilper, R. (2017). The digital twin: Realizing the cyber-physical production system for industry 4.0. *Procedia CIRP*, 61, 335-340. <https://doi.org/10.1016/j.procir.2016.11.152>
- Uva, A.E., Gattullo, M., Manghisi, V.M., Spagnulo, D., Cascella, G.L., & Fiorentino, M. (2018). Evaluating the effectiveness of spatial augmented reality in smart manufacturing: a solution for manual working stations. *The International Journal of Advanced Manufacturing Technology*, 94(1-4), 509-521. <https://doi.org/10.1007/s00170-017-0846-4>
- Vaidya, S., Ambad, P., & Bhosle, S. (2018). Industry 4.0—a glimpse. *Procedia Manufacturing*, 20, 233-238. <https://doi.org/10.1016/j.promfg.2018.02.034>
- Varela, M.L., Putnik, G.D., Manupati, V.K., Rajyalakshmi, G., Trojanowska, J., & Machado, J. (2019). Integrated process planning and scheduling in networked manufacturing systems for I4. 0: A review and framework proposal. *Wireless Networks*, 27(6), 1-13. Available at: <https://link.springer.com/article/10.1007/s11276-019-02082-8>
- Varghese, B., & Buyya, R. (2018). Next generation cloud computing: New trends and research directions. *Future Generation Computer Systems*, 79, 849-861. <https://doi.org/10.1016/j.future.2017.09.020>
- Vassakis, K., Petrakis, E., & Kopanakis, I. (2018). Big data analytics: Applications, prospects and challenges. *Mobile big data* (3-20). Springer. https://doi.org/10.1007/978-3-319-67925-9_1
- Wang, X., Yew, A., Ong, S., & Nee, A. (2020). Enhancing smart shop floor management with ubiquitous augmented reality. *International Journal of Production Research*, 58, 2352-2367. <https://doi.org/10.1080/00207543.2019.1629667>
- Watson, J., & Taminger, K. (2018). A decision-support model for selecting additive manufacturing versus subtractive manufacturing based on energy consumption. *Journal of Cleaner Production*, 176, 1316-1322. <https://doi.org/10.1016/j.jclepro.2015.12.009>
- Weller, C., Kleer, R., & Piller, F.T. (2015). Economic implications of 3D printing: Market structure models in light of additive manufacturing revisited. *International Journal of Production Economics*, 164, 43-56. <https://doi.org/10.1016/j.ijpe.2015.02.020>
- Weng, Z., Zhou, Y., Lin, W., Senthil, T., & Wu, L. (2016). Structure-property relationship of nano enhanced stereolithography resin for desktop SLA 3D printer. *Composites Part A: Applied Science and Manufacturing*, 88, 234-242. <https://doi.org/10.1016/j.compositesa.2016.05.035>
- Whyte, J., & Broyd, T. (2015). Viewing Asset Information: Future Impact of Augmented Reality. Paper presented at *the Proceeding of 32nd CIB W78 Conference (754-761)*. Eindhoven, The Netherlands. Available at: <http://itc.scix.net/paper/w78-2015-paper-078>
- Wieland, M., Hirmer, P., Steimle, F., Gröger, C., Mitschang, B., Rehder, E. et al. (2016). Towards a rule-based manufacturing integration assistant. *Procedia CIRP*, 57, 213-218. <http://doi.org/10.1016/j.procir.2016.11.037>
- Witkowski, K. (2017). Internet of things, big data, industry 4.0—innovative solutions in logistics and supply chains management. *Procedia Engineering*, 182, 763-769. <https://doi.org/10.1016/j.proeng.2017.03.197>
- Wong, C., Yang, E., Yan, X.T., & Gu, D. (2018). Autonomous robots for harsh environments: a holistic overview of current solutions and ongoing challenges. *Systems Science & Control Engineering*, 6(1), 213-219. <https://doi.org/10.1080/21642583.2018.1477634>
- Xiang, F., Yin, Q., Wang, Z., & Jiang, G.Z. (2018). Systematic method for big manufacturing data integration and sharing. *The International Journal of Advanced Manufacturing Technology*, 94(9-12), 3345-3358. <https://doi.org/10.1007/s00170-017-0575-8>
- Xu, J., Huang, E., Chen, C.H., & Lee, L.H. (2015). Simulation optimization: A review and exploration in the new era of cloud computing and big data. *Asia-Pacific Journal of Operational Research*, 32(03), 1550019, 1-34. <https://doi.org/10.1142/S0217595915500190>
- Xue, C.T.S., & Xin, F.T.W. (2016). Benefits and challenges of the adoption of cloud computing in business. *International Journal on Cloud Computing: Services and Architecture*, 6(6), 01-15. <https://doi.org/10.5121/ijccsa.2016.6601>

- Yu, U.J. (2018). Examination of students' acceptance and usage of simulation software technology in an advanced-level merchandising class. *International Journal of Fashion Design, Technology and Education*, 11(1), 1-11. <https://doi.org/10.1080/17543266.2017.1280090>
- Zadpoor, A.A., & Malda, J. (2017). Additive manufacturing of biomaterials, tissues, and organs. *Annals of Biomedical Engineering*, 45, 1-11. <https://doi.org/10.1007/s10439-016-1719-y>
- Zarreh, A., Saygin, C., Wan, H., Lee, Y., & Bracho, A. (2018a). Cybersecurity Analysis of Smart Manufacturing System Using Game Theory Approach and Quantal Response Equilibrium. *Procedia Manufacturing*, 17, 1001-1008. <https://doi.org/10.1016/j.promfg.2018.10.087>
- Zarreh, A., Saygin, C., Wan, H., Lee, Y., & Bracho, A. (2018b). A game theory-based cybersecurity assessment model for advanced manufacturing systems. *Procedia Manufacturing*, 26, 1255-1264. <https://doi.org/10.1016/j.promfg.2018.07.162>
- Zarreh, A., Wan, H., Lee, Y., Saygin, C., & Al Janahi, R. (2018). Cybersecurity Concerns for Total Productive Maintenance in Smart Manufacturing Systems. *Procedia Manufacturing*, 38, 532-539. <https://doi.org/10.1016/j.promfg.2020.01.067>
- Zavadskas, E.K., Mardani, A., Turskis, Z., Jusoh, A., & Nor, K.M. (2016). Development of TOPSIS method to solve complicated decision-making problems—An overview on developments from 2000 to 2015. *International Journal of Information Technology & Decision Making*, 15(03), 645-682. <https://doi.org/10.1142/S0219622016300019>
- Zhang F, Fang, H., & Song, W. (2019). Carbon market maturity analysis with an integrated multi-criteria decision-making method: A case study of EU and China, *Journal of Cleaner Production*, 241, 1-15. <https://doi.org/10.1016/j.jclepro.2019.118296>

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