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# Generic Design Methodology for Smart Manufacturing Systems From a Practical Perspective. Part II—Systematic Designs of Smart Manufacturing Systems

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Article

# Generic Design Methodology for Smart Manufacturing Systems from a Practical Perspective. Part II—Systematic Designs of Smart Manufacturing Systems

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**Abstract:** In a traditional system paradigm, an enterprise reference model provides the guide for practitioners to select manufacturing elements, configure elements into a manufacturing system, and model system options for evaluation and comparison of system solutions against given performance metrics. However, a smart manufacturing system aims to reconfigure different systems in achieving high-level smartness in its system lifecycle; moreover, each smart system is customized in terms of the constraints of manufacturing resources and the prioritized performance metrics to achieve system smartness. Few works were found on the development of systematic methodologies for the design of smart manufacturing systems. The novel contributions of the presented work are at two aspects: (1) unified definitions of digital functional elements and manufacturing systems have been proposed; they are generalized to have all digitized characteristics and they are customizable to any manufacturing system with specified manufacturing resources and goals of smartness and (2) a systematic design methodology has been proposed; it can serve as the guide for designs of smart manufacturing systems in specified applications. The presented work consists of two separated parts. In the first part of paper, a simplified definition of smart manufacturing (SM) is proposed to unify the diversified expectations and a newly developed concept digital triad (DT-II) is adopted to define a generic reference model to represent essential features of smart manufacturing systems. In the second part of the paper, the axiomatic design theory (ADT) is adopted and expanded as the generic design methodology for design, analysis, and assessment of smart manufacturing systems. Three case studies are reviewed to illustrate the applications of the proposed methodology, and the future research directions towards smart manufacturing are discussed as a summary in the second part.

**Keywords:** smart manufacturing; information technologies (IT); system of systems (SoS); digital manufacturing (DM); digital twins (DT-I); digital triad (DT-II); cyber-physical systems; Internet of Things (IoT); Internet of Digital Triad Things (IoDTT); big data analytics (BDA); cloud computing (CC); axiomatic design theory (ADT)

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## 1. Introduction

Smart manufacturing (SM) has been identified as one of the prioritized areas to strengthen a nation's economy in both developed and developing countries. The studies in smart manufacturing technologies have attracted a great deal of attention from researchers in multiple disciplines. On the one hand, SM is a comprehensive solution to manufacturing systems with the integration of recent information technologies (IT); on the other hand, every smart manufacturing system is customized to the needs of a specific enterprise with limited resources and its own interests of business domains, strategies, and performance metrics. This leads to a high diversity for developers and users to understand the true meanings of SM, and accordingly, to select and integrate existing technologies adequately in the context of given circumstances of manufacturing businesses. To fill this gap, this paper attempts to unify the definition of SM with a newly proposed concept called digital triad (DT-II) to cover all common features of digital technologies towards system smartness; the contents of system smartness can be tailored to the needs of specific companies especially in terms of flexibility, scalability, adaptability, and resilience. Moreover, the concept of Internet of Digital Triad Things (IoDTT) is proposed as a system reference model to deal with the integrations of digital solutions at upper levels. The rationales of DT-II and IoDTT have been elaborated in the first part of the paper [1]. In the second part here, these concepts will be used to develop a systematic methodology for designs of smart manufacturing systems. To this end, the rest of the paper is organized as follow. In Section 2, the design of a smart manufacturing system is formulated to define a design space for the discussed functional requirements (FRs) of SM [1]; the design space consists of commonly adopted digital technologies including DT-I, CPS, IoT, CC, AI, VM, BDA, SoA, and BCT. In Section 3, the methods for the evaluation and comparison of design solutions (DS) are discussed, and the focus is put on the quantification as well as system performance indicators in dealing with the changes and uncertainties in dynamic business environments. In Section 4, axiomatic design theory (ADT) is adopted as a systematic methodology in designing a smart manufacturing system; a general design procedure is proposed with the detailed discussions of customizing FRs and DSs to specific applications. In Section 5, three case studies are introduced to illustrate how ADT can be applied in customizing a smart manufacturing systems when the performance indicators for system smartness are given. In Section 6, the innovation of the presented work is summarized for its theoretical and practical significance and the authors' future works in advancing the concepts of DT-II, IoDDT, and the ADT-based design methodology for smart manufacturing systems are outlined.

## 2. Design of Smart Manufacturing Systems

Since a smart manufacturing system aims for system adaptability in dealing with changes and uncertainties, and such a capability is achieved by either the flexibility of system elements or the configurability at system level, design of a smart manufacturing system involves three iterative phases in its system lifecycle, i.e., system design phase, system operation phase, and system reconfiguration phase, as shown in Figure 1. At the system design phase, a set of functional requirements (FRs) is defined, available physical assets and accessible virtual assets are considered to define a design space with all feasible design solutions (DSs), and system performances are ranked to define a set of prioritized performance metrics. At the system operation phase, design analysis and synthesis are performed to optimize a system, and thus implement it in application; all smart things in the system are monitored to determine if system elements or the whole system has to be reconfigured to meet the identified changes. At the system reconfiguration phase, either system elements or the whole system is reconfigured to make the smart manufacturing system sustainable.

Many researchers have investigated the design methodologies of intelligent manufacturing systems. Unglert et al. [2] proposed a computational design synthesis to analyze reconfigurable manufacturing cells where functional modules were reorganized to balance the capability and capacity of system. It was used in the concurrent design of system configurations. Kurgan et al. [3] proposed an integrated design methodology and considered manufacturing requirements at the phase of system design; it led to the cost saving of 18% and time reduction of 17% in the case study. SM is a type of reconfigurable systems that is sustainable over time. A system configuration of a reconfigurable system consists of a set of functional building blocks that are selected and assembled from available physical and virtual manufacturing assets for specific tasks [4–7]. A reconfigurable system allows the additions, removals, and modifications of functional modules without affecting the functions of other modules, and this helps scale the capacity of productions [8]. A reconfigurable system is characterized by its modularity, integrability, customization, convertibility, scalability, diagnosability, mobility, and adaptability. The high-level building blocks of SM were classified by Mittal et al. [9], and the most commonly used ones were intelligent controls, data-driven production managements, data analytics, smart products, smart materials, interoperability, data sharing, and standards.

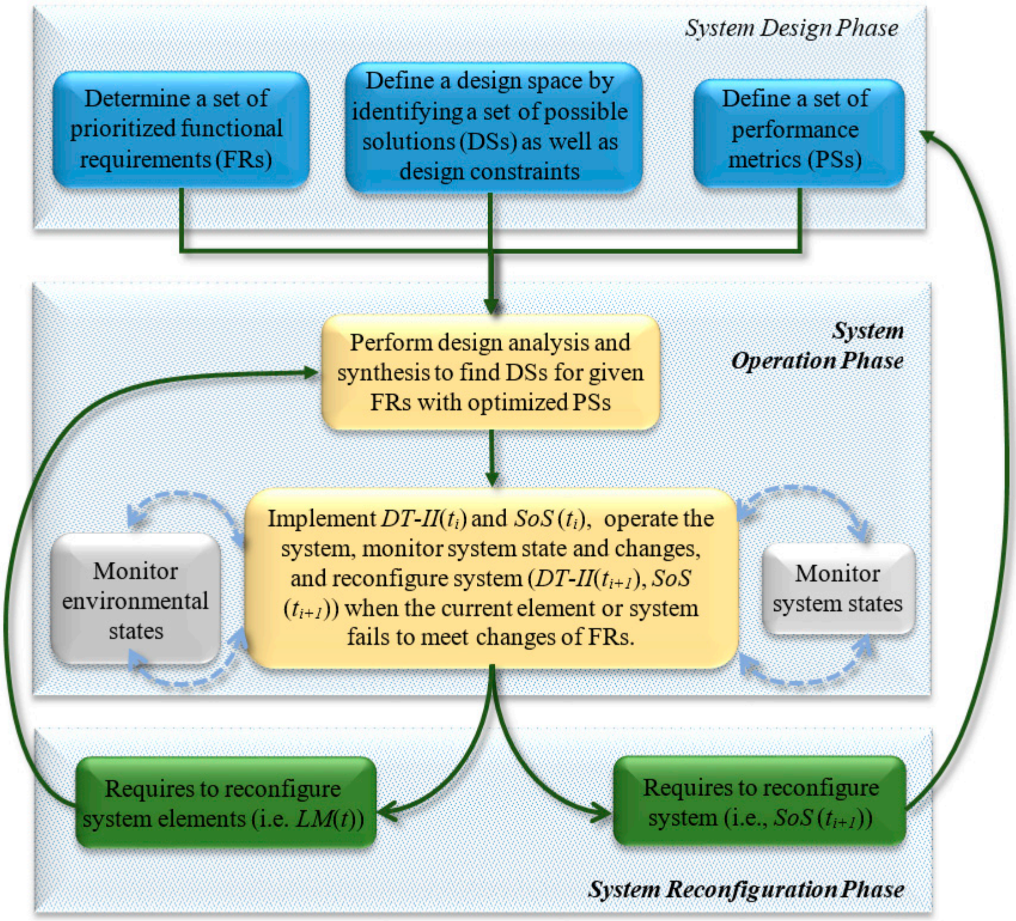

**Figure 1.** Three phases in design of a smart manufacturing system.

Here, the axiomatic design theory (ADT) is used to describe the design procedure of smart manufacturing systems. However, the authors' main interests are (1) the determinations of functional requirements (FRs) and design spaces by the solutions, and (2) the evaluation of the mappings from design solutions (DSs) to functional requirements (FRs). How to decompose FRs to meet the independence principle and minimized information principle is of less interest in this section. As the matter of fact, for a complex and multidisciplinary system, every system element is conceptually coupled with others, which makes it impractical to achieve the independence of functional requirements in decomposition. Since FRs have been discussed in part I, we discuss common digital technologies as design solutions (DSs) and performance evaluations (PSs) for system smartness as follows.

A smart manufacturing system has been modelled as an instance of the Internet of Digital Triad Things (IoDTT), and the system consists of a set of networked digital triads. Therefore, various digital technologies are the essential enablers to satisfy the functional requirements of smart manufacturing systems. Here, commonly used digital technologies as well as the roles in SM are discussed.

### *2.1. Digital Technologies for Smart Materials and Processes*

Similar to traditional manufacturing, SM aims to make and deliver products to users. However, products from SM are generally more advanced in terms of their intelligence level, functionalities, and more importantly, their sustainability from the perspectives of economy, environment, and human society. Akrivos et al. [10] argued that future products should be sustainable, and products from SM should be made to enhance their sustainability, especially the self-healing properties of materials, products, and systems. A smart product could sense occurred damage and heal the damage autonomously to sustain the product life, so that the product life is extended, even lasting permanently. The most advanced digital technologies such as extreme ultraviolet lithography (EUV) [11] and 4D or 5D printing [12] became commercially available to prepare raw materials for smart products.

### *2.2. Digital Twins (DT-I)*

To practice the first-time right in decision-making processes, decisions should be verified and validated before they are executed in the physical world. Modelling and simulation tools used to be standalone system that were widely applied to predict system behaviors based on assumed conditions, changes, disturbances, and randomness [13]. DT-I has been advanced from traditional modelling and simulation approaches in the sense that physical and virtual models are connected and interacted directly. The concept of digital twins (DT-I) has enabled the interactions and integrations of information and physical worlds in real-time manners. For example, augmented reality was adopted specifically for the interaction interfaces in smart manufacturing [14]. DT-I could be multidimensional: for example, geometric, physical capability, rule, and behavior models in the five-dimensional model [15]. DT-I could be expanded to represent reconfigurable systems at different granularities and for corresponding missions. In a recent literature review by Semeraro et al. [16], DI-I itself was treated as a system paradigm where virtual models were embedded as indispensable components to model the behaviors of physical components and make smart decisions for system operations.

### *2.3. Cyber-Physical Systems (CPS)*

CPS is related closely to DT-II; while the former focuses on the interactions of digital and physical twins in the cyber and physical worlds, respectively. CPS supports real-time communication and interaction of cyber and physical systems to close control loops, monitor system states in real-time, and adjust system behaviors promptly when the changes are detected [17,18]. The CPS-based system elements are applicable to many tasks such as communication, controls, scalability, validation and verifications, and system managements [19,20]. CPS can be data-driven to optimize system controls using real-time data collected from the physical world; CPS makes a manufacturing system smart by improving the responsiveness, adaptability, and predictivity of system elements and facilitating the collaboration of stakeholders in the entire process of mass customization of products [21].

### *2.4. Human Cyber-Physical Systems (HCPS)*

Due to a high-level of uncertainty and complexity, many fully automated solutions involve in a high cost, and such solutions become impractical due to limited cost-effectiveness. Therefore, humans still play indispensable roles in making manufacturing systems flexible and adaptable. D'Addona et al. [22] analyzed the needs of human operations for cognition in practicing adaptive automation through case studies. Cognition was utilized to respond out-of-the-loop conditions such as abnormal transitions, and skill loss, automation-induced errors, adaptable behaviors, and inappropriate trusts in collaborative manufacturing processes. Humans must be in the loop to achieve the desired performances of production. In such a way, the safety and comfortableness of workers were well balanced in uncertain environments. Humans are integrated with CPS and human cyber-physical systems (HCPS). Enabling technologies such as augmented reality (AR) are critical to support human-machine collaborations and interactions. Baroroh et al. [23] showed that AR were used in SM in implementing interactions, manufacturing processes, machine functions, and knowledge explorations.

### 2.5. Internet of Things (IoT)

IoT seems essential to SM due to two main reasons: (1) SM is data-driven, and real-time data about smart things, stakeholders, and business environments must be available to support the decision-making processes at any level and scope of manufacturing businesses and (2) SM requires the access to virtual resources over the Internet to deal with manufacturing businesses over product lifecycles. SM adopts IoT as the information infrastructure to network manufacturing assets such as products, parts, machine tools, sensors, and decision-making units in the heterogeneous environment. IoT allows a smart manufacturing system to sense system elements and environment, access virtual services over the Internet, and provide abundant data to drive decision-making processes at all levels and scopes of manufacturing businesses in system lifecycles [24–26]. IoT consists of countless smart things that are built over the Internet with wired and wireless communications [27,28].

### 2.6. Cloud Computing (CC)

Modern manufacturing systems tend to be decentralized and distributed, while decision-making activities for smart manufacturing are facing a number of challenges, such as (1) sharing and accessing data in distributed environments, (2) storing and maintaining an ever-increasing amount of data in the network, (3) the high demand of computing to optimize decisions with the limited local computing resources, and (4) the complexity of coordination, collaboration, and interoperation of manufacturing resources over the Internet. Cloud computing (CC) is built upon service-oriented architecture (SoA); every task that manipulates data, accesses virtual resource, or run a model for decision-making can be treated as a service (XaaS), and any system element with a limited computing capability can utilize CC to support its decision-making activities [29] To select services to meet manufacturing needs in cloud manufacturing, Huang and Wu [30] developed a two-layer trust fuzzy model which consisted of time, cost, availability, reliability, and safety at the first-layer and 13 other indexes at the second-layer.

### 2.7. Artificial Intelligence (AI)

In making a decision for a manufacturing business, it is an ideal scenario that (1) an explicit mathematic model is available to represent the relations of inputs, outputs, and system parameters, (2) all of the required data of the decision model are available and accurate when a decision is made, and (3) the computation is manageable by the system to reach decisions in time. Unfortunately, most of decision-making processes are too complex to develop explicit mathematic models, and the required data in decision-making are often incomplete, ambiguous, and not free of error. Artificial intelligence (AI) is a cognitive science for data mining and decision-making support in the fields of data analytics, image processes, robotics, natural language processes, and machine learning. AI became the frontier of manufacturing technologies in future industrial systems, and was integrated with industrial IoT (IIoT), BDA, CC, and CPS to support industrial operations in an efficient, flexible, and sustainable way [31].

### 2.8. Virtual Manufacturing (VM)

Utilizing virtual assets over the Internet transferred certain manufacturing businesses into services, and, accordingly, the manufacturing system became a product-service system. This leveraged the flexibility and capability of a smart manufacturing system to deal with the complexity and changes [32]. To access virtual assets over the Internet, manufacturing assets must support interoperations. Adamczyk et al. [33] introduced a knowledge-based expert system to support the semantic interoperations in SM; note that the semantic interoperations must address the divergence and misinterpretation of heterogenic data from various sources. Landolfi et al. [34] referred to the use of virtual assets as manufacturing as a service (MaaS). A MaaS based platform was developed to connect service vendors, suppliers, and customers to enterprises directly for system-level optimization.

### *2.9. Big Data Analytics (BDA)*

SM is built upon IoT. To achieve a high system diagnosability, predictivity, and responsiveness, SM must rely on big data connected over the Internet to support its decision-making systems at all levels and scopes. SM applications involved the challenges to assure integrity, quality, privacy, availability, scalability, transformation, legitimacy, surveillance, and governance of data [19]. BDA and SM used to be investigated in the fields of information technologies and intelligent manufacturing, respectively. These concepts were recently bridged due to close correspondences [35]. Ren et al. [36] analyzed emerging issues and potential solutions when BDA is integrated as one of critical technologies to deal with big data and data-driven decision-makings from the perspective of product lifecycles. Tao et al. [37] discussed the importance of big data analytics from the historical perspective, identified the bottlenecks of BDA in utilizing abundant data in developing SM, and proposed a conceptual framework to integrate BDA tools for effective data-driven SM.

SM fully utilized advanced data analytics tools to support decision making activities at various domains and levels of manufacturing businesses. Accordingly, with the increase of volume, velocity, and variety of data acquired from business environment, it posed the challenge of processing data efficiently [38]. On the other hand, BDA also relies on reliable and trustworthy data from IoT to reduce knowledge and information for decision makings; therefore, BDA relates to numerous activities in an information flow including data collection, sharing, processing, and fusion. Wang and Luo [39] proposed a reference framework to take advantage of digital-twin models to fuse the data from virtual and physical models seamlessly.

### *2.10. Blockchain Theologies (BCT)*

SM applications involved the challenge of assuring integrity, quality, privacy, availability, scalability, transformation, legitimacy, surveillance and governance of data, value transfer, and manufacturing services [19]. In contrast to traditional standalone information systems, SM is networked and its system boundaries are open; SM is more vulnerable in terms of security, privacy, and safety. Tuptuk and Hailes [40] discussed the challenges in securing smart manufacturing systems in terms of existing vulnerability, potential cyber-attacks, awareness and preparations for security loopholes, and security measures. The blockchain technology (BCT) has been explored to embed trustworthiness and visibility in SM. Viriyasitavat et al. [41–43] developed a few algorithms to (1) select partners and compose them as virtual enterprises over the Internet and (2) assure the privacy, trustiness, and security in value transfer and interoperations of business partners.

## **3. Performance Metrics (PMs) for System Smartness**

The expectations for SM can be classified into functional requirements (FRs) and performance metrics (PMs). On the one hand, FRs are a set of hard goals that a manufacturing system must achieve; FRs are treated as design constraints in developing DSs. On the other hand, PMs are a set of soft goals for which DSs of a smart manufacturing system should be optimized. Since a system solution is specific to given applications, the classification of system expectations for FRs and PMs is different from one system to another. The common FRs of smart manufacturing systems have been discussed in Section 3.2; in this section, the commonly used PMs will be discussed.

Researchers have proposed many evaluation models and performance metrics for manufacturing systems from different perspectives. However, performance metrics can conflict with each other. Jiang et al. [44] discussed the contradictions of metrics in multi-objective optimizations (MOO). Based on their relevance, the metrics were classified into capacity, convergence, diversity, and convergence-diversity, and one performance evaluation model was developed to achieve the consistencies of Pareto fronts in (MOO). In evaluating system sustainability, Moldavska and Welo [45] emphasized the importance of sustainable development goals and proposed incorporating these goals in evaluating system sustainability. Auer et al. [46] assessed manufacturing systems from the perspective of products, and life-cycle assessment and life-cycle costing was used to determine the impact of manufacturing systems on the eco-environment. Jung et al. [47] tried to map strategy-level performance metrics to the structure of SM, and the identified challenges were the selection of performance metrics, the correspondences of performance metrics and manufacturing activities, and the representation of system models for comparisons. Some researchers investigated the impact of certain information technologies on the performances of a smart manufacturing system. For example, Kiesel et al. [48] discussed the roles of 5G in reducing the latency of critical applications since 5G was able to accelerate digital transformation in the sense that the latency could be below 1 milliseconds (ms) in monitoring and controlling complex production processes. The potential economic benefits were quantified. Barletta et al. [49] valued SM for its contribution to environmental sustainability, and they presented the assessment model and tools to evaluate sustainability readiness of smart manufacturing systems. Ante et al. [50] proposed a hierarchical structure of key performance indicators (KPIs) to measure the performance of smart manufacturing systems; the performances were evaluated at strategic, tactical, and operational levels, and the dependences of system elements were taken into consideration in quantifying KPIs. Zhang et al. [51] emphasized the impact of disposed products on economy and environment, and they suggested combining the gray correlation decision-making trials to evaluate products in layout designs of manufacturing plants. Both centralized and decentralized production systems were modelled by Moutzis et al. [52] and system performances were evaluated from the perspectives of lead time, cost, flexibility, throughout, and environmental impact relevant to transportation. It is a difficult challenge for a small and medium-sized enterprise (SME) to choose an appropriate digital solution for specific decision-making. Martin et al. [53] argued that the core value of smart manufacturing was to utilize data to predict behaviors of cyber physical production systems, and they adopted the value stream mapping method (VSM) to analyze and compare smart manufacturing solutions.

Quantitative evaluations are critical in the analysis and synthesis of system designs. Georgoulias et al. [54] indicated that existing empirical evaluation models were only applicable to specific applications, and they argued that an evaluation model or algorithm should be generic, holistic, and quantitative. Georgoulias et al. [55] further developed an evaluation model to quantify the system flexibility (i.e., product flexibility, capacity flexibility, and operation flexibility) in dealing with the changes of management processes in manufacturing organization; the developed model was used to optimize the system for better effectiveness and competitiveness. Youssef et al. [56] used the universal generation function to evaluate the availability of manufacturing assets; it considered the changes of production rates and demands in assessing system configurations. Cagno et al. [57] proposed a framework to measure the sustainability of enterprises and the sustainability was assessed based on economic, social, and environmental indicators. In the framework by Farias et al. [58], the green performance and leanness were emphasized in determining the assessment criteria and metrics of manufacturing systems. Junior et al. [59] proposed a balanced scorecard method to evaluate system sustainability based on the correspondences of economic, environmental, and social lines to the learning and growing, process, and market and financial perspectives. Cai and Lai [60] evaluated the system sustainability from the perspective of energy flow within manufacturing plants. Unfortunately, the information for the assessment model would not be available until the physical system was built and in operation and the statistical data were collected and available for use. Brennan [61] discussed the need for holonic manufacturing systems to develop corresponding performance metrics. A holonic system was required to handle disturbance, support human integration, and provide reliability, robustness, and flexibility in coping with changes, and a system design was evaluated based on reliability, responsiveness, flexibility, cost, and assets. Mahmood et al. [62] used modeling and simulation to assess the performance of applied technologies in integrated production lines while only the performances at shop-floor level were evaluated without the consideration of external partners and end-users. Burggra et al. [63] compared the performances of artificial intelligence (AI) and human beings in job-shop scheduling of a cyber-production management system using a reinforcement learning algorithm. Ottesjo et al. [64] proposed an assessment tool to measure the level of digitization of SMEs, and it aimed to analyze administrative awareness and technical capabilities and identify digitalization gaps for SMEs to advance their manufacturing systems from the system lifecycle perspective.

The following section will focus on the smartness of system that is exhibited in its system lifecycle.

### *3.1. Visibility, Diagnosability, and Predictivity*

A smart manufacturing system must be a closed system that is responsive to internal and external changes; the primary condition is that the system possesses an ability to understand the past, present, and future of the system. Visibility, diagnosability, and predictivity reflect the levels of system smartness in detecting changes and disturbances, diagnosing and troubleshooting problems, and predicting the trends of changes based on data collected from various sources over manufacturing systems. System visibility relies on the sensors and instrumentations installed on smart things, and diagnosability and predictivity rely on the capabilities of advanced information technologies such as AI, CC, and BDA [1].

### *3.2. Upgradability*

Upgradability measures how easily a system or system element can be upgraded to newly developed technologies. Manufacturing technologies are essential tools to run manufacturing businesses, and manufacturing technologies are continuously evolving with the advance of fundamental science and technologies, especially digital technologies. To prolong the lifecycle, manufacturing systems should be modularized so that individual functional modules can be maintained and upgraded with a minimized impact on systems [65,66]. The smartness of a system can be measured by the upgradability of adopting technologies, enterprise systems, and decision-making units at various levels and domains.

### *3.3. Adaptability*

Adaptability measures the capability of a system to deal with changes and uncertainties [67]. Adaptability is measured from system outputs; correspondingly, adaptability is achieved by the flexibility of system elements and the reconfigurability among system elements. Internal or external changes and uncertainties can only be tackled by the changes that can be possibly implemented on system elements or system configurations; therefore, system adaptability can alternatively be measured on (1) internal adjustable components, (2) modular system architecture, and (3) a combination of adjustable and modular components and use of external assets [68,69]. In particular, a modularized architecture makes a system reconfigurable to meet new manufacturing needs by reconfiguring its physical and logical structures. Note that aiming at high-level adaptability involves in an increased cost and complexity in general. The challenges in developing a reconfigurable system are high initial investments, long-term of investment returns, limited system performances at reconfiguration and ramp up phases, and the complexity of task-oriented configuration designs [66,70–72].

### *3.4. Resilience*

The wish-list of future manufacturing systems provided by O'Connell et al. [73] emphasized system resilience. Resilience refers to the system ability to achieve high-level objectives (i.e., adaptation, sustainability, and reliability) in the presence of unpredicted changes and disturbances [74–77]. In particular, adaptation referred to the enhanced ability to achieve desired goals in a dynamic environment, including the ability to reduce vulnerability to threats and adverse disturbances. To improve system resilience, Zhang et al. [78] developed a dynamic model to control a reconfigurable electronic assembly line that was subjected to spatio-temporal disruptions. Resilience dynamics were analyzed by max-plus algebra, the analyzed results were used to generate digital twins, and the control of the assembly line was implemented over an open reconfigurable architecture.

### *3.5. Flexibility*

Flexibility is similar to adaptability, but it is measured on system elements rather than system outputs. Lafou et al. [79] defined flexibility as the ability of a manufacturing system to deal with variations of products, and system flexibility was quantified based on the mappings of products and manufacturing assets. They commented that modularity and standardization of manufacturing resources and products generally minimized the introduction costs of new variations. System flexibility can be achieved by software, hardware, or a combination of both. The flexibility of a hardware system must be supported by the corresponding software system. Keddis et al. [80] discussed the flexibility of data-driven communication to match the flexibility of adaptable hardware system.

All of the performance indicators are driven from manufacturing systems; therefore, performance indicators are associated with each other in certain ways. It is important to understand their correspondences. For example, Lufi and Besenfelder [81] investigated the dependence of robustness on system flexibility of manufacturing systems since system flexibility tackled with volatile and unpredictable environments and a manufacturing system should make a trade-off between optimization and robustness for the best interest of system performance. Mass personalization needs high-level flexibility and responsiveness of a manufacturing system to make personalized products in small batch sizes cost-effectively. Traditional manufacturing systems have their limits in reconfiguring systems to accommodate changes, and SM should be capable of self-reconfiguring and optimizing to achieve flexible, autonomous, and error-tolerant productions in turbulent business environments. System elements in a self-organizing system are distributed, adaptable, self-autonomic, and supportive to bottom-up reconfiguration [82].

### *3.6. Sustainability*

Alike to humankind, a smart manufacturing system aims ultimately at a long system lifespan; manufacturing enterprises are facing an increasing pressure to optimize system sustainability in addition to traditional performance measures such as reliability, cost, and productivity. Sustainability becomes necessary to consider in decision-making processes over system lifecycles. A manufacturing process is a type of mechanical, chemical, electrical, or biological transformation that can be modelled by energy generation, transfer, storage, or consumption. Hoang et al. [83] developed a mathematic model with thermodynamic, physical-thermodynamic, and economic-thermodynamic indicators to estimate energy efficiency of manufacturing systems. Huang and Badurdeen [84] investigated the impacts of products and processes respectively in evaluating system sustainability; the framework for sustainability evaluation included the metrics involved at five stages. In the assessment by Jiang et al. [85], system sustainability was quantified for decomposing system-level mission into device-level manufacturing processes and integrating data from device-level to enterprise-level executions. Sustainability was evaluated comprehensively from economic, environmental, and social perspectives. SMEs have limited resources to pursue system sustainability as prioritized business objectives; the required sustainability is treated as the constraint of business rather than the performance to be optimized. Singh et al. [20] introduced an expert system to quantify system sustainability for SMEs. Sustainability becomes mandatory simply because the ecosystem of the earth and desired quality of humankinds could not be maintained without sustainable manufacturing [86].

Zhang et al. [87] developed a business case to make system-level decisions in SMEs; it considered system dynamics in assessing sustainability and lifecycle costing of products.

## 4. Systematic Methodology for Design of Smart Manufacturing Systems

The main functional requirements enabling digital technologies and a complete list of expectations of a smart manufacturing system have been discussed in Sections 3 and 4; however, it is extremely rare that an enterprise has the access to any digital technologies when the enterprise needs, and a manufacturing system can be designed and implemented from scratch. It is impractical to design an ideal smart manufacturing system without physical constraints. In practice, the smartness of a manufacturing system will be iteratively improved by upgrading and incorporating more digital methodologies in continuous improvement (CI).

To make system complexity manageable at each iteration, the axiomatic design theory (ADT) is adopted in Figure 1 to narrow down a set of FRs, DSs, and PMs that are most critical to given applications, and the rest of FRs, DSs, and PMs should be formulated as design constraints based on available manufacturing assets and current system states. In other words, design of a smart manufacturing system at each iteration only involves (1) one or a few metrics relevant to system smartness (i.e., flexibility, visibility, sustainability, resilience, and even some traditional metrics such as efficiency and agility) and (2) one or a few corresponding digital triads (DT-II) or the configuration in IoDTT. Available manufacturing assets and given marketing conditions are formulated as design constraints.

## 5. Case Studies

Three examples of manufacturing system designs by the authors and their collaborators are introduced here to illustrate how the proposed methodology was applied in the system development to increase system smartness in continuous improvement (CI). Note that the application scenarios were specified, the design solutions (DSs) were limited to certain digital technologies, and system smartness was associated with the system performance of interests in achieving specified functional requirements (FRs) in the given applications. In all of these three cases, FRs and system smartness were interpreted and defined based on customers' needs. The design space of DSs were for digital technologies and determined by system developers based on accessible manufacturing resources, and the following discussions were limited to using the proposed methodology to formulate a smart system design problem. Interested readers might find the details and rad data of these design examples in the corresponding publications [5,7,88–90].

### *5.1. Case Study 1: BDA for Visibility and Diagnosability in Continuous Improvement (CI)*

The purpose of the first case study was to show that the definition of system smartness in a smart manufacturing system can be customized to the prioritized key performance indicators (KPIs). In other words, pursuing a smart manufacturing system is a long-term effort of continuous improvement, and targeted system smartness should be as specific as possible to be measured quantitatively. The process was applicable to system design in any sectors. With real-time data collected from the things in the physical world and simulation models in the digital world, the decision-making processes at any level and domain could be data driven to improve system responsiveness, since big data helps to improve system smartness in terms of the visibility of system states and changes and the diagnosability of defects and malfunctions.

Figure 2 shows a case where system smartness was defined for visibility and diagnosability, and digital technologies for data collection and analysis were identified as the design solutions of interest. In the developed solution, BDA was incorporated in an enterprise system, heterogeneous and data were analyzed and processed to make the scale of the datasets manageable, and the decisions for the actions in continuous improvement could be made promptly. Note that the data of past, present, and prediction could be maintained in a life model together with digital and physical things as DT-II in system implementation [88–90].

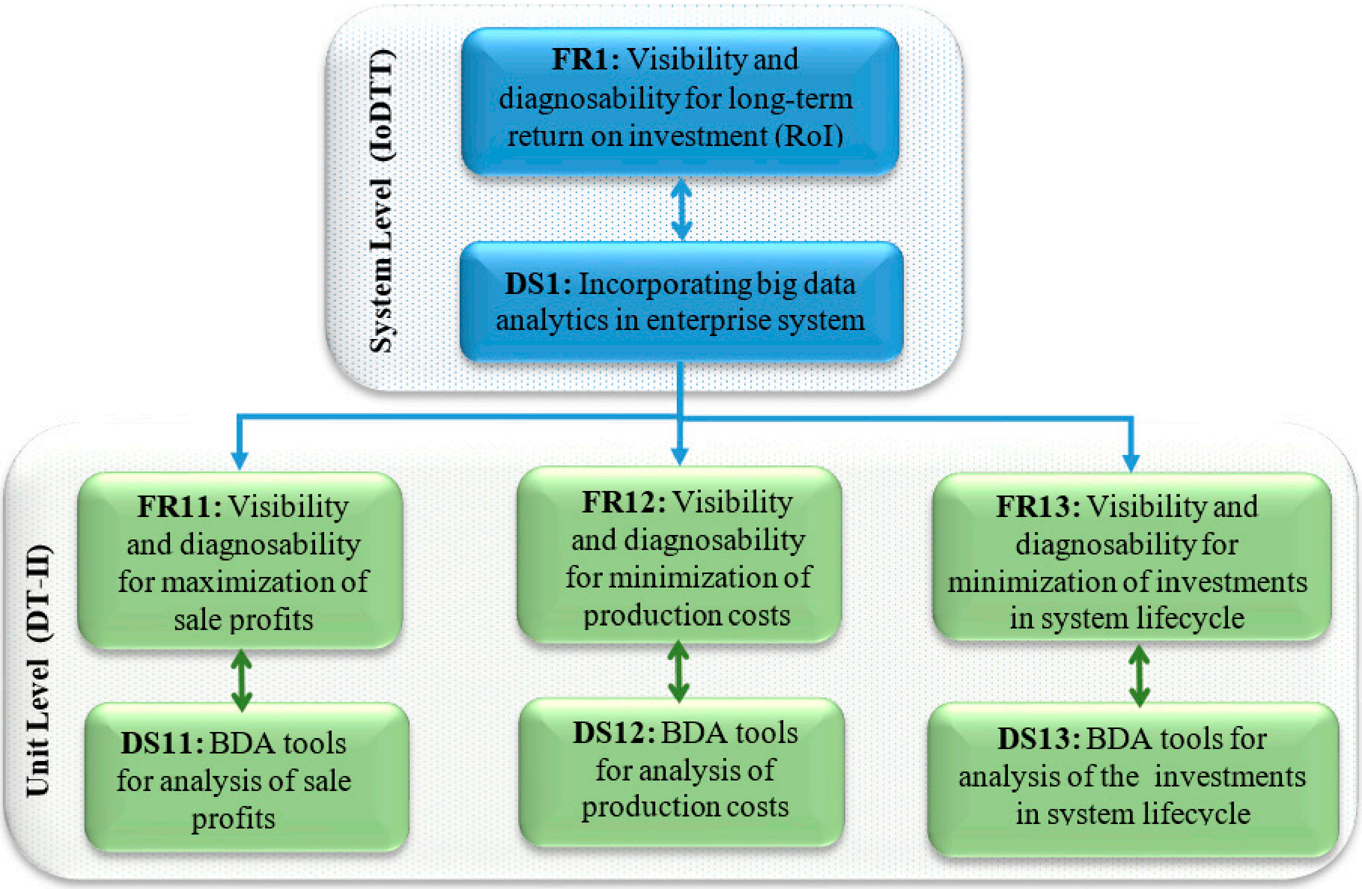

**Figure 2.** Case study I–Improve visibility and diagnosability by big data analytics (BDA).

### *5.2. Case Study 2: Incorporating Additive Manufacturing for Flexibility and Adaptability*

The purpose of the second case study was to show that the proposed design methodology was ready to be applied at the phase of system operations when some system performances were found unsatisfactory, and the solution to critical processes must be obtained in enhancing system smartness. In such a case, DSs were for certain manufacturing processes, and system smartness was related to unsatisfactory performances of interests. The process was applicable to design problems in system operations in any continuous improvement practice. In general, a manufacturing system transfers raw materials into final products through a series of manufacturing processes. When an enterprise aims at system smartness for dealing with the changes and disturbance in its material flow, the hardware systems must have flexibility and capabilities to accommodate these changes in manufacturing processes. From this perspective, incorporating more and more advanced digital technologies in production systems helps to improve system smartness in terms of the adaptability and robustness.

Figure 3 showed a case where system smartness was defined for high-level flexibility and adaptability in dealing with unavoidable defects occurring to production lines; system flexibility and adaptability was directly measured by the direct run rate (DRR) of products, i.e., the percentage of products that meet the requirements of quality at the first try. A product might be damaged due to numerous potential interactions of tooling and products over production lines. System flexibility and adaptability was measured by a set of decomposed FRs shown in Figure 3 and Table 1. Additive manufacturing (AM) was introduced as the design solutions (DSs) to enhance the capabilities of the manufacturing system in producing protective tools when they are needed. In the developed solution, 3D printers were introduced to make protective parts for problematic tools where product defects occurred. A number of DT-II units were developed to implement the whole process from monitoring production lines to detecting defects on products, identifying problematic tools, generating and verifying digital models for protective parts, producing parts, and finally to mounting parts on assembling tools in the production lines. According to ADT, the design solutions (DSs) in Figure 4 were developed to fulfill the identified FRs [7].

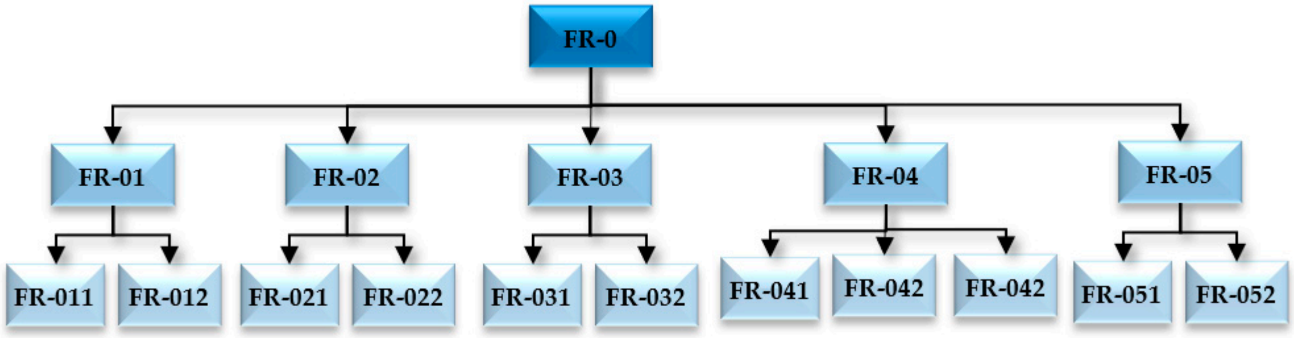

**Figure 3.** Decomposition of system smartness (flexibility and adaptability) in case study 2 (Reprinted with permission from ref. [7]. 2021 Taylor & Francis).

**Table 1.** The meanings of decomposed *FRs* in case study 2 (Reprinted with permission from ref. [7]. 2021 Taylor & Francis).

| *FRs* | **Description** |
|---|---|
| ***FR-0:*** | Develop the solution to improve DRR of truck assembly line by integrating AM processes |
| ***FR-01:*** | Utilize the data of truck quality inspection for surface defects, identify the sources (workstations and assistive tools) of defects.<br>***FR-011:*** Detect surface defects.<br>***FR-012:*** Identify problematic assembling processes and assistive tools. |
| ***FR-02:*** | Develop and model parts as the protective solutions to identified defects.<br>***FR-021:*** Utilize information of assistive tools.<br>***FR-022:*** Optimize design for strength, fabrication time, and cost. |
| ***FR-03:*** | Provide the tested physical solutions to assembly workstations in less than 24 h.<br>***FR-031:*** Perform tests on physical parts for material strength.<br>***FR-032:*** Perform simulation for functional validation and process optimization. |
| ***FR-04:*** | Standardize the procedure and practice of AM processes.<br>***FR-041:*** Maintain normal operations of AM machines.<br>***FR-042:*** Provide guides and training manuals for operators and procedure.<br>***FR-043:*** Standardize the interactions of functional modules. |
| ***FR-05:*** | Routinize the operations of AM machines with the aid of inventory, design library, planning and scheduling of printing jobs for cost reduction.<br>***FR-051:*** Build and maintain design libraries for knowledge-based engineering<br>***FR-052:*** Manage the inventory of protective parts. |

### *5.3. Case Study 3: Using IoT for Automation*

The purpose of the third case study was to show that the proposed design methodology can be extended to design any systems or products as long as FRs, DSs, and performance metrics (PMs) could be tailored to the specified applications. The proposed design methodology is generally applicable to designs of any smart systems or products, since the systems are tailored to given applications by defining system smartness and feasible design solutions of most interests. As mentioned before, system smartness can be defined for high-level adaptability and sustainability in dynamic environment; system smartness can also be defined for some traditional performance metrics such as efficiency, agility, robustness, cost-effectiveness, and degree of automation. Such design types have a significant advantage in practice since adopting digital technologies has a direct impact on these system metrics.

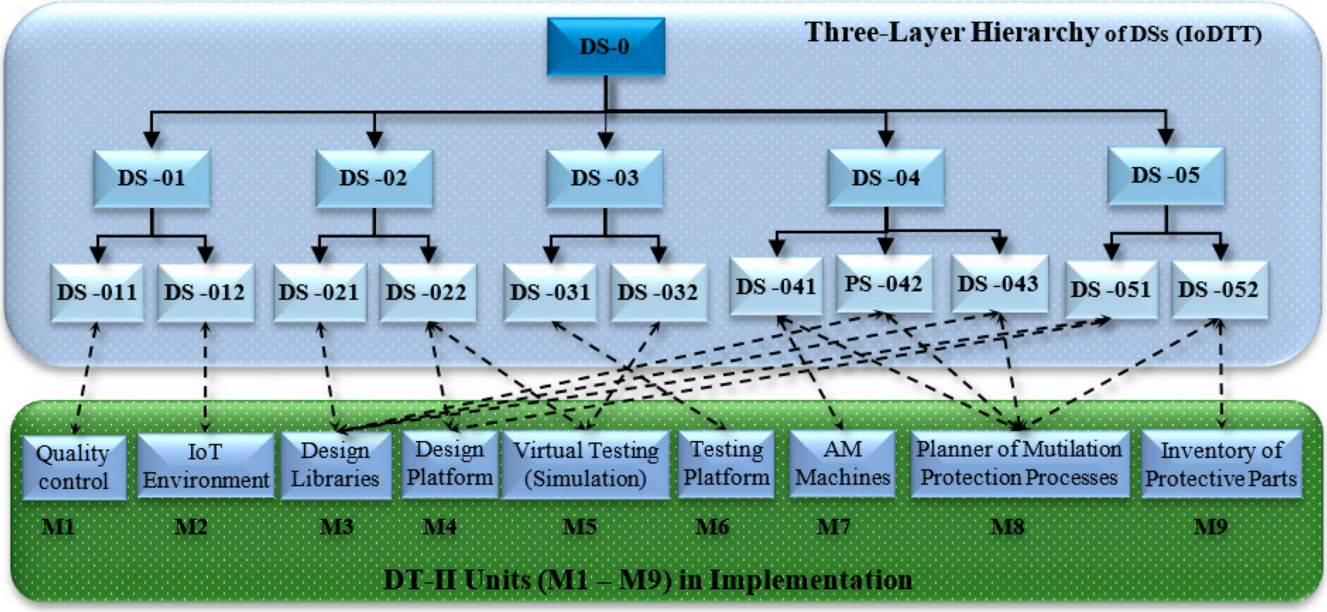

**Figure 4.** Proposed digital solutions in case study 2 (Reprinted with permission from ref. [7]. 2021 Taylor & Francis).

Figure 5 showed a case of designing an automatic fuel-recharging system. System smartness was defined for the degree of automation in performing relevant tasks for drivers to refill gas on vehicles. System smartness was measured by the minimized cost for fully automated refueling services at gas stations. The IoT-based technologies were explored as the design solutions to minimize users' interferences cost-effectively. The system-level goal was decomposed into four FRs, i.e., FR11 for 'data collection and processing', FR12 for 'controls for abnormal events', FR13 for 'refueling operation', and FR14 for 'controls for normal events'. To meet FR11, various sensors and instrumentations such as vision, laser scanning, bar-code scanning, compliant sensors, and controllable platform were used as DSs to detect incoming vehicles and determine the relative position and orientation of fuel spout; embedded chips and apps on phones can be integrated with the Internet of Things (IoT) database to obtain customers' intent and payment information and collect information about vehicle and fuel. To meet FR13, gantry systems, robots, and sophisticated mechanisms were integrated with multi-functional tools to access a fuel port, open a fuel-filler cover, retrieve a refueling tool, close a fuel-filler cover, and reset the refueling tool. To meet FR12 and FR14, the system-level controls for normal and abnormal events were implemented as stand-alone systems or IoT-enabled apps; in addition, all processing parameters could be specified manually through the interfaces of programmable logic controllers (PLC) or IoT-based apps.

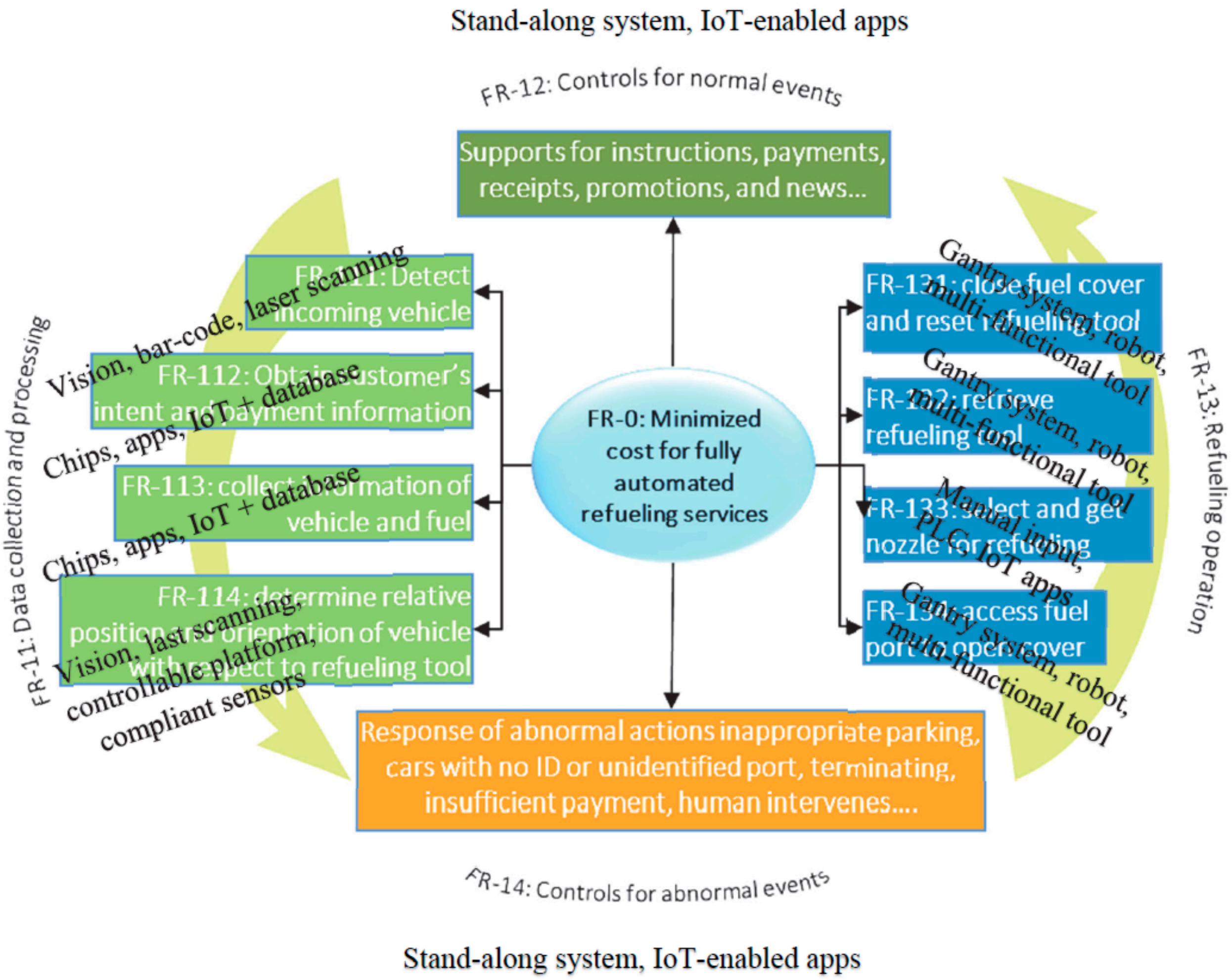

**Figure 5.** Design solutions (DSs) to fully automated refueling (Reprinted with permission from ref. [5]. 2021 Emerald Publishing Limited).

## 6. Conclusions and Future Directions

To the authors' knowledge, limited works are available on the development of systematic methodologies for designs of smart manufacturing systems. The novel contributions of the presented work were made at two aspects: (1) unified definitions of digital elements and manufacturing systems have been proposed; they are generalized to have all of the digitized characteristics and they are customizable to be applied in any manufacturing system with specified manufacturing resources and goals of smartness and (2) a systematic design methodology has been proposed; it can serve as the guide for designs of smart manufacturing systems in certain applications from a practical perspective. Note that 'practical perspective' here refers to the views of specific enterprises with given resources, technology accesses, and the interests of business domains, strategies, and performance indicators including costs.

The proposed design methodology deals with the high diversified systems by some customizing efforts in defining prioritized goals of system smartness and affordable digital technologies in achieving system goals; in addition, the performance metrics for system smartness must be quantifiable so that different design solutions can be analyzed, evaluated, and compared to optimize system solutions. Future research efforts will be needed in many areas such as (1) developing quantifiable performance metrics for system smartness of interest and synergizing multiple performance metrics when they are considered simultaneously; (2) establishing design libraries which include commonly design solutions (DSs); (3) developing some design templates which correspond to design solutions (DSs) and functional requirements (FRs) with consideration of the sustainability at both of component and system levels; (4) using BDA and AI in dealing with the combinatory complexity in tailoring digital solutions to specific manufacturing applications' effective computing; (5) making a trade-off between system reconfigurations and the utilization of virtual assets in system lifecycle; (6) developing some systematic approaches to verify and validate a system before it will be actually implemented in physical world; (7) developing the standardized procedures for design of smart manufacturing systems based on the proposed methodology; (8) reshaping the proposed design methodology as a standardized procedure in designing smart manufacturing systems; (9) adapting the proposed design methodology to supply network systems since they are a model of the social-technological-economic system—a reality of mankind.

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## Abbreviations

| | |
|---|---|
| ADT: | Axiomatic Design Theory |
| AI: | Artificial Intelligence |
| AM: | Additive Manufacturing |
| AR: | Augmented Reality |
| BCT: | Blockchain Technology |
| BDA: | Big Data Analytics |
| BPM: | Business Process Management |
| CC: | Cloud Computing |
| CI: | Continuous Improvement |
| DM: | Digital Manufacturing |
| DSs: | Design Solutions |
| DT-I: | Digital Twins |
| DT-II: | Digital Traid |
| ERP: | Enterprise Resource Planning |
| FRs: | Functional Requirements |
| HCPS: | Human-Cyber Physical Systems |
| HRI: | Human-Robot Interactions |
| IoDTT: | Internet of Digital Triad Things |
| IoT: | Internet of Things |
| IIoT: | Industrial Internet of Things |
| IT: | Information Technologies |
| KPIs: | Key Performance Indicators |
| MaaS: | Manufacturing as a service |
| ML: | Machine Learning |
| MOO: | Multi-Objective Optimizations |
| PLC: | Programmable Logic Controller |
| PMs: | Performance Metrics |
| SM: | Smart Manufacturing |
| SME: | Small to Midsize Enterprises |
| SoA: | Service-oriented Architecture |
| SoS: | System of Systems |
| VSM: | Value stream mapping |
| SaaS: | Any decision making as a service |

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