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Digital Transformation of Reconfigurable Production Systems for Advanced Manufacturing: Issues and Outlook

Mulang Song
Georgia Institute of Technology
Atlanta, USA
Msong84@gatech.edu

Jianxin (Roger) Jiao
Georgia Institute of Technology
Atlanta, USA
roger.jiao@me.gatech.edu

Abstract

This paper explores the evolution toward Digital Reconfigurable Production Systems (dRPS) to meet modern manufacturing demands for flexibility and customization. Fundamental challenges in implementing dRPS are identified, particularly in manufacturing load balancing across heterogeneous production entities with varying digitalization levels. A framework that integrates real-time, data-driven decision-making and advanced optimization techniques is proposed to address these issues. A case study on connector assembly demonstrates the framework's effectiveness. The paper concludes by outlining future research directions essential for advancing dRPS toward more adaptable and efficient production systems.

Keywords
Digital Twin, Reconfigurable Production System, Manufacturing System

1. Introduction

In today's fast-paced manufacturing landscape, the demand for customization and rapid market shifts is pushing companies to become more agile and responsive. Modern customers expect products tailored to their specific needs, and increasing pressure from supply chains and competitors is forcing manufacturers to reduce lead times. This scenario compels firms to move beyond traditional production models that prioritize high volume and uniformity. To address these challenges, many are adopting advanced manufacturing paradigm that can dynamically adapt to varying product specifications and fluctuating demands without sacrificing efficiency or driving up costs (Elmaraghy 2009). This shift is further supported by the integration of advanced digital technologies, enabling real-time, data-driven load balancing and planning—crucial for maintaining operational flexibility and optimizing resource utilization in reconfigurable environments (Bortolini et al. 2018; Tseng et al. 1996).

Driven by evolving demands, Flexible Manufacturing Systems (FMS) were initially developed to handle variability by quickly adapting to changes in product types and volumes (Florescu & Barabas 2020). While FMS represented a significant step toward flexibility, it soon became clear that even greater adaptability was needed to keep pace with fast-changing market conditions and customer requirements. This realization led to the development of Reconfigurable Production Systems (RPS), which not only retain the flexibility of FMS but also enhance it by offering more rapid and efficient reconfiguration capabilities. RPS are designed to swiftly adjust both capacity and functionality to accommodate different product specifications and production demands (Mehrabi et al. 2000). They achieve this through modular designs and advanced software controls that allow for quick recalibration of manufacturing processes.

Integrating Reconfigurable Production Systems (RPS) into modern manufacturing is essential for staying competitive. RPS enhance product customization, reduce lead times, and meet the dynamic demands of today's markets. To bridge the technological gap, manufacturers often adopt a nuanced approach: integrating new machines based on specific needs while modernizing existing ones. This strategy focuses on increasing the digitalization level of the production system, as higher digitalization significantly boosts overall performance. This ongoing process of digital transformation aligns with the principles of Industry 4.0, involving the integration of digital technologies into all aspects of manufacturing. It leads to the implementation of technologies like cyber-physical production systems (CPPS) and Industrial Internet of Things (IIoT) frameworks. CPPS leverages digital twins—virtual representations of physical assets, processes, and systems—along with real-time data analytics, machine learning, and cloud services. This enables intelligent decision-making and predictive maintenance through continuous analysis of production data (Borangiu et al. 2020; Kraus et al. 2021).

Based on the driven force and shift in the manufacturing paradigm, in the process of digital transformation of reconfigurable production systems (dRPS), where continuous digital transformation enhances the flexibility and responsiveness of traditional RPS to tackle the growing complexities of modern production environments. In dRPS, financial constraints often compel manufacturers to adopt a hybrid approach, combining highly digitalized production lines with those that have lower levels of digitalization. Instead of investing in entirely new production lines, they renovate or modernize existing machinery, which may still be functional but lacks advanced digital capabilities. This approach conserves resources and mitigates risks associated with full-scale automation by enabling incremental upgrades rather than wholesale replacements. Such incremental digital transformation is practical in complex production environments where committing to a complete overhaul is neither feasible nor economically viable (De Carolis et al. 2017; Zangiacomi et al. 2020). Challenges are faced during the digital transformation process such as integrating older machinery into complex management systems at low cost and managing production lines with varying levels of digitalization—all while maintaining efficiency and cost-effectiveness.

While digital transformation has enhanced the technological capabilities of manufacturing systems, their integration into the strategic planning of manufacturing organizations remains underdeveloped. This gap primarily arises from the absence of robust and unified decision-making frameworks that incorporate reconfigurability into the overall production strategy. As highlighted by Han et al. (2020), effective decision-making in reconfigurable systems requires real-time data and advanced IoT technologies to optimize reconfiguration planning and execution. Moreover, the ability to plan and control these systems for maximum performance is critical, involving complex trade-offs between flexibility, cost, and productivity. Without these strategic capabilities, the potential production capabilities of dRPS cannot be fully realized, resulting in a disconnect between digital transformation and practical implementation.

In line with the vision of digital Reconfigurable Production Systems (dRPS), this paper aims to identify and address critical issues within this emerging manufacturing paradigm. We review methods and techniques that hold potential for balancing manufacturing loads in dRPS environments. Specifically, Section 2 examines the trends in manufacturing paradigm shifts and defines new requirements for dRPS. Section 3 articulates the problem of manufacturing load balancing in advanced dRPS based on existing literature. In Section 4, we explore the decision-making processes of advanced manufacturing systems. Building on these insights, Section 5 identifies fundamental challenges in dRPS. To tackle these challenges, Section 6 proposes a framework for manufacturing load balancing, demonstrated through a connector assembly case study. Finally, Section 7 discusses future research opportunities and offers concluding remarks.

2. Emerging Trend of Manufacturing Paradigm Shift

Elements in the manufacturing system have expanded over the decades which encompass various elements within the production process. Manufacturing systems were inferred as the arrangement of and operation of physical assets that are coordinated to produce value-added products (Suh et al. 1998). The research of manufacturing systems seeks to optimize its efficiency and performance by improving the system design, resource allocation, system planning and control. Integrating digital elements into manufacturing facilitates advancements in system design, resource allocation, and system planning and control. These areas have progressed concurrently, driven by the enhanced capabilities provided by digital integration.

Dedicated manufacturing systems (DMS) and flexible manufacturing systems are considered traditional manufacturing systems. Dedicated manufacturing lines are designed to fulfill the high-volume production requirement of a particular product (Mehrabi et al. 2000). On the other hand, flexible manufacturing systems are designed to handle varieties of product families, which is more responsive to the changed conditions. (Koren 2007). Digital control is one of the crucial digital elements introduced in flexible manufacturing systems (ELMaraghy 2005). It serves two roles in FMS: the central control unit and a key enabler of data exchange. Benefited by numerically controlled machines and processes, increased automation level in FMS enhances the degree of freedom in the system design which allows more complex and sophisticated solutions. Meanwhile, data exchange could be achieved based on the communication structure of the system, bridging the barrier between the physical system and the information system.

A Reconfigurable Manufacturing System (RMS) is designed to support rapid changes in both physical and software structures, enabling it to meet varying production capacities (ELMaraghy 2005., Koren 2007). RMS integrates both attributes from DMS and FMS which enable it to handle a product family while fulfilling high-volume production requirements. Several foundations and attributes are identified for RMS (Koren, 2005) are listed as (1) Modularity, (2) Scalability, (3) Integrability, (4) Convertibility, (5) Customization, and (6) Diagnosability. Modularity in the design allows the system to be reconfigured through modifying modules. Convertibility is related to changeover which is the system's ability to switch from producing one type of product to another. Convertibility and modularity both affect the system's performance in handling different product families. Scalability is the system's ability to adapt to different production capacities. Integrability refers to the system's ability to incorporate advanced technologies seamlessly into existing structures. Customization is the ability to fulfill specific customer requirements with minimal changes to the existing setup. Diagnosability is the ability to identify faults or inefficiencies in the system (Bortolini et al. 2018).

RPS extends those attributes further and broader from the manufacturing process to the production system which aims to optimize the entire production flow. To achieve reconfigurability and flexibility in the entire production system, challenges rely on manufacturing system design, logistics, and other production-related areas. The design of RPS is different from conventional fixed and rigid systems. Rösiö and Säfsten (2013) identify the lack of structured design methodologies as a critical challenge, highlighting the need for new tools and approaches that incorporate reconfigurability from the early stages of system design. This involves not just the physical design of machinery but also the integration of digital tools, such as digital twins and computer-integrated manufacturing (CIM) systems, to simulate and plan reconfigurations effectively (Bruccoleri et al. 2005). In the dynamic production environment of RPS, Jackson et al. (2016) demonstrate how digital manufacturing technologies allow for real-time tracking, adaptive routing, and seamless integration of new production lines or changes in product specifications.

Enabled technologies that push shift in the manufacturing paradigm and manufacturing services that are provided by paradigm are two crucial axes of manufacturing systems evolution (ElMaraghy et al., 2021). Figure 1 presents a comprehensive summary of the transformation of manufacturing systems which illustrates the progression in technology and manufacturing paradigm through an inverted pyramid structure. The enabled technologies are displayed on the left side of each layer which support and push the shifts in the manufacturing paradigm. In the bottom two layers, DMS is designed for high-volume production of a single product, while FMS is designed for flexibility to handle various product types with quicker adjustments. Starting from RPS, Technology forms the foundation for the establishment of manufacturing paradigms, and at times, new manufacturing paradigms drive or accelerate the emergence of new technologies. Evolved from DMS to RPS, on the technology side, starting with CNC and PLC systems for basic control, moving to IoT and sensors for enhanced data collection and utilization, then integrating digital twin technologies to visualize and simulate production processes.

As the required manufacturing technologies continue to advance, manufacturing systems inevitably become more complex, leading to higher costs and skill requirements. Due to financial and facility constraints, production systems, such as shop floors, consist of production lines and machines from different generations and technological capabilities. As introduced previously, dRPS represents a manufacturing paradigm that acknowledges and addresses these variabilities and complexities inherent in such diverse production environments. To operate dRPS effectively within environments where varying levels of technology coexist, creating the challenge of bridging the gap between older, less advanced production lines and newer, more technologically equipped ones. Therefore, dRPS leads to a critical question of how to compensate for disparities between different production lines which leads to new important characteristics in dRPS: Heterogenous Digital Integration (HDI).

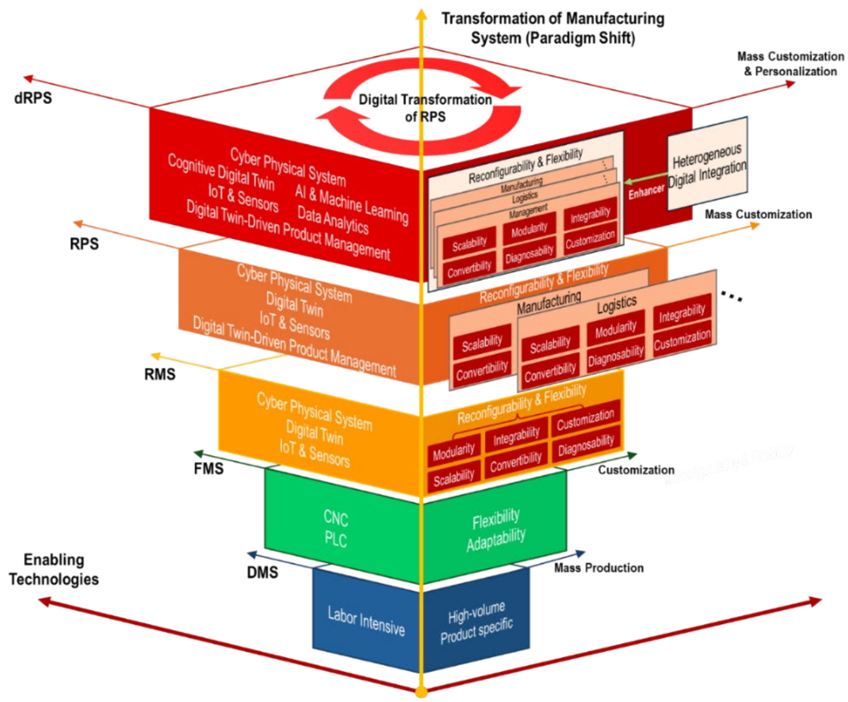

Figure 1. Transformation of Manufacturing Systems

3 From Order Acceptance and Scheduling to Manufacturing Load Balancing

As part of the field of Production and operation management (POM), order acceptance and task scheduling (OATS) evolved as manufacturing industries sought better approaches in resource management and order fulfillment. In the early stage, four key factors are identified as part of the systematic approach to order acceptance which are capacity constraints, order prioritization, scheduling integration, and feedback loop (Guerrero 1988). Integrated with scheduling problems, OAS requires an approach of optimization that incorporates data like machine availability, workload distribution, and processing times from the production system.

Driven by the increasing complexity of production environments, research in Order Acceptance and Scheduling (OAS) has evolved from addressing straightforward cases to tackling more complex scenarios. Initially focused on simple optimization goals, OAS research has progressed to consider multiple, often conflicting objectives, while also expanding from basic constraints to incorporate more intricate and interrelated constraints. Slotnick and Morton (2007) presented a combined order acceptance and sequencing model using branch-bound and heuristic methods to maximize production revenue while considering tardiness in a static single-machine environment. With similar assumptions, a Genetic Algorithm (GA) is employed to solve order acceptance and scheduling problems (Rom & Slotnick 2009). Cesaret et al. (2012) proposed a tabu search algorithm for order acceptance and scheduling to maximize total revenue on a single machine in a make-to-order production environment. Aouam et al. (2018) presented a production planning model integrated with order acceptance under demand uncertainty, utilizing a two-phase optimization approach combining capacitated lot sizing and load-dependent lead times.

Studies of OAS problems have also been extended to more dynamic and complex production environments. Combining machine learning (hype-heuristic method) with genetic algorithm (meta-heuristic method), Nguyen et al. (2016) proposed a learning and optimization system. The system generates initial solutions based on historical data and refines initial solutions using genetic algorithms. In hybrid environments of Make-to-Stock (MTS) and Make-to-Order (MTO), an algorithm is presented consists of both variable dimensional particle swarm optimization for order acceptance and modified Gliffler-Thompson algorithm for scheduling to balance the competing demands of maintaining inventory levels of stock while fulfilling customized orders (Wang et al. 2019). A bi-level nested heuristic algorithm is proposed to solve the OAR problem in a flexible and modular production system that involves the management of multiple divisions with various capabilities and capacities. In the bi-level heuristic algorithm, the upper level makes decisions in order of acceptance and the lower-level schedules accepted tasks (Wang et al. 2023).

Compared with the OAS problem, load balancing is a more general term that refers to the amount of work or tasks assigned to various resources within a system. Load balancing aims to distribute the load to optimize the system performance. In the semiconductor industry, the performance of fabrication lines can be improved by balancing task loads between lines based on their line constraints (Toba et al., 2005 & Shr et al. 2007). In cloud manufacturing systems, genetic algorithms are employed for balancing workloads assigned to each cloud service provided based on task process time (Ghomi et al.2019). Shifts to a new manufacturing paradigm, D. Li et al. (2017) used big data and IoT to balance "load" across shop-floor entities, defined as the dynamic distribution of manufacturing tasks, to improve real-time system performance in cloud manufacturing. Gong et al. (2024) advance the discussion to crowdsourced manufacturing, where "load" refers to the manufacturing tasks assigned across a network of manufacturers, optimized through bi-level coordination between product planning and load balancing to maximize efficiency.

In dRPS, the decision-making process involving task selection, allocation and scheduling remains crucial. However, the optimized planning and control in dRPS are inherently more complex due to the system's dynamic and reconfigurable nature. This complexity gives rise to the problem of Manufacturing Load Balancing (MLB), which extends beyond traditional OAS by extending its evaluation criteria such as resource heterogeneity, real-time adaptability, and the integration of advanced technologies. Unlike traditional OAS, where decisions are typically made in more static environments, load balancing in dRPS must dynamically distribute workloads across various production lines and machines with varying digitalization levels. Thus, MLB in dRPS is not just an extension of OAS but a broader, more intricate challenge that incorporates the principles of load distribution to optimize overall system performance in a constantly evolving production environment.

4 Real-time Data-driven Decision-making

Through the advancement in IoT technologies, smart sensing, and data analytics, real-time data-driven decision-making in production systems is supported by the seamless collection, processing, and integration of data. Real-time data can significantly improve production efficiency, product quality, and overall system responsiveness by providing services of predictive maintenance, real-time monitoring and control, quality management, energy management, and production optimization (Tao et al. 2019). Augmented reality (AR), IoT, system integration, cloud computing, big data analytics, autonomous robots, simulation, and cyber security are identified as key areas of research in real-time data-driven decision-making (Bousdekis et al. 2021). As part of system integration, scheduling, and planning draws lots of attention from researchers. Furthermore, these studies heavily rely on simulation and IoT.

Pires et al. (2018) presented a simulation-based optimization to improve the operational performance of complex manufacturing systems. Real-time data is used to adjust the simulation model for adaptive control. An intelligent collaborative mechanism is proposed to monitor the assembly process and adjust resource configuration dynamically based on collected data in complex assembly systems. The intelligent collaborative mechanism utilizes Petri-net models for assembly workflow management and employs dynamic optimization in task scheduling and resource assignment (Qian et al.2020). Discrete event-driven model predictive control has also been employed for real-time work-in-process optimization in serial production systems, showing significant improvements in production efficiency (Zhou et al. 2020). These methods demonstrate the potential for improved responsiveness and reduced lead times in manufacturing. A bilevel interactive optimization approach for real-time order acceptance and scheduling in data-enabled permutation flow shops has also been proposed. This method involves a bilevel interactive optimization model that simultaneously addresses order acceptance and job release planning, integrating data-driven representations of dynamic production statuses (Chen et al. 2020).

In the context of dRPS, real-time data-driven decision-making plays a critical role in optimizing production processes across machines with varying levels of digitalization. Achieving HDI is essential to ensure that all machines, regardless of their digital capabilities, can contribute to the overall decision-making process

5. Fundamental Issues in dRPS

The evolution of manufacturing systems, the transition from Order Acceptance and Scheduling (OAS) to Manufacturing Load Balancing, and the integration of Real-Time Data-Driven Decision-Making in production systems have highlighted significant gaps and challenges in the implementation of Digital Reconfigurable Production Systems (dRPS). These challenges arise from the need to optimize performance in highly dynamic and heterogeneous environments where machines differ in digitalization levels and data capabilities. Fundamental issues in Real-Time Data-Driven Manufacturing Load Balancing and Planning within dRPS are identified in this section.

Data-Driven Representation of the Production Digital Thread Enabled by HDI: The varying levels of digitalization across machines in dRPS create significant challenges for data-driven approaches. Older machines, often retrofitted, may provide limited types of data and lack sophisticated Digital Twin models or Discrete Event Simulations (DES). More advanced machines, however, offer comprehensive real-time data, creating a disparity in available information. To address this, the development of a unified Data-Driven Representation of production digital threads for HDI is essential. Digital threads, which serve as interconnected data pathways linking physical assets to their digital counterparts (digital twins), can harmonize data from diverse sources, enabling seamless integration between legacy and modern systems. The challenge lies in creating representation methods that can handle incomplete data from less digitalized machines while leveraging the detailed data from advanced systems. These methods must be capable of inferring missing information, adapting to variable data quality, and ensuring decision-making processes remain accurate and efficient despite data heterogeneity.

Hierarchical Interactive Decision-Making: As dRPS integrates both legacy and advanced systems, there is a need for a multi-level decision-making process that can effectively manage the complexity of the reconfigurable production environments. A Hierarchical Interactive Decision-Making framework becomes essential because decisions made at the load acceptance level (e.g., which orders to accept based on capacity and potential revenue) directly impact the subsequent planning and scheduling activities (e.g., how to allocate tasks across different production lines). The challenge lies in designing a unified framework that can seamlessly integrate these hierarchical levels, where the first level focuses on strategic decisions about order acceptance, and the second level manages the operational load balancing and scheduling. This interaction is complex because it requires real-time coordination and optimization across multiple levels, each with its own objectives and constraints.

Coordinated Optimization of Manufacturing loads balancing and planning: In large-scale production systems, ensuring optimal performance in load balancing and planning is crucial. However, defining and achieving the appropriate criteria for performance evaluation becomes a challenge. The Coordinated Optimization of Load Balancing and Planning requires a sophisticated approach that considers not just the immediate outcomes (e.g., minimizing operational costs or processing time) but also long-term system performance. The challenge is to develop optimization models that can balance multiple objectives simultaneously, such as maximizing throughput, minimizing delays, and reducing inventory holding costs. Moreover, these models must be capable of adapting to real-time data inputs and adjusting to the dynamic conditions of the production environment. Establishing the right performance metrics and ensuring that the optimization process can meet these criteria under varying conditions are key challenges that need to be addressed.

Game-theoretical decision-making with equilibrium solutions: In dRPS, where multiple performance evaluation criteria (followers) interact with a central decision-making system (leader), achieving optimal system performance often requires Game-Theoretical Decision-Making and Equilibrium Solutions. This approach is necessary to manage the interactions between different criteria that may have competing objectives, such as maximizing throughput, minimizing costs, or improving quality. The leader-follower dynamics in this context require the development of models that can balance these criteria while ensuring overall system efficiency. The challenge lies in constructing these models to include feedback loops that allow the central system to make informed decisions based on the evaluation of different criteria, ensuring that these decisions lead to a stable and optimal equilibrium. This becomes particularly important when unexpected events, such as machine breakdowns or shifts in production demands, require the system to dynamically adjust task allocations and schedules to maintain performance across all criteria.

6. A Case Example of Load Balancing in dRPS for Connector Assembly

In this section, a case of manufacturing load balancing in a production line that produces certain connector families in dRPS on a shop floor is defined. At different levels of the shop floor hierarchy, the focus varies. Top management is primarily concerned with overall revenue and the number of orders fulfilled on time, as these metrics are critical indicators of shop floor performance and profitability. In contrast, production, operations, and logistics management are more focused on minimizing engineering costs and work-in-progress (WIP) costs (Boyer & Lewis 2002). This differentiation in focus underscores the importance of a bilevel optimization approach, where strategic and operational priorities are managed concurrently to achieve optimal performance. Effective machine load balancing is critical to reduce both operational and engineering costs by reducing line overburden or idle situations (Li et al. 2017). Manufacturing load balancing of production lines minimizes machine downtime, extends the lifespan of equipment by preventing overuse, and optimizes resource allocation which directly cuts engineering costs tied to maintenance and repair.

Figure 2. illustrates the production line manufacturing load balancing of production lines in dRPS. The shop floor can produce products from several product families $PF_1, PF_2, \dots, PF_\lambda$ of connectors. The shop floor contains m production lines for producing those product family, which includes L_i types of product variants in each product family. As shown in figure 2, product family modular architecture PF on the top left side of dRPS task load balancing and panning system, contains information of the product structure and process specification. For each product family variant, it contains its production process on a certain type of production line. PF demonstrate the relationship between product variants and production lines for reference. The production lines vary in their capabilities: some advanced lines can handle a wide range of product variants in one production family, while others are limited to fewer types. PF provides significant information to dRPS production line load evaluation system. Meanwhile, several other components are also connected to the load evaluation system.

During the control time window, v unprocessed manufacturing tasks await assignment and scheduling to production lines. Each manufacturing task comprises a different number of jobs. The task pool contains v unprocessed manufacturing tasks $(T_1, T_2, \dots, T_v)$ defined by parameters such as the due date d_j (due date of manufacturing task j), cost related coefficients w_{c_j} and w_{tj}, and revenue r_j for fulfilling the task j. Each manufacturing task j includes J_j multiple jobs $\left(t_1^j, t_2^j, \dots, t_j^{J_j}\right)$ that require planning. Information in the task pool is transferred to the evaluation system first. Besides the task pool, the MES database and historical machine database are connected to the evaluation system. MES database contains non-detailed information on the execution status of the production process and the machine database stores machine-level data (For example, data from PLC or SCADA). The load evaluation algorithm also utilizes machine data from the machine database, and machine production status from the MES database to generate the current machine load $\theta_{M_1}, \theta_{M_2}, \dots, \theta_{M_m}$. The current machine load is sent to the manufacturing load balancing system as one of the important evaluation criteria.

The task loading balancing and planning manager is pivotal in distributing and balancing task loads across the shop floor's production lines. The current task load balancing plan details the current distribution of tasks $\left(T_1, T_2, \dots, T_f\right)$ across M_1, M_2,…, M_m production lines. While the shop floor is fulfilling the existing task loads, jobs in the task load may be reassigned for shopfloor performance optimization, and loads balancing plan reconfiguration is triggered by an event. This manufacturing load balancing system is triggered by the new arrival batch of manufacturing tasks, or a disruption event of the machine as introduced in the previous sub-section. In the process of load balancing, the earliest available time of each production line A_j is obtained from the real-time production status update and predicted time for finishing processing jobs in the digital-physical layer. The earliest available time for each production line is the time when the machine finishes the processing job or recovers from a disruptive event. The task load balancing plan reconfiguration is generated based on a balancing and planning algorithm to dynamically redistribute tasks, ensuring optimal load balancing and resource utilization. This section emphasizes real-time adaptation, where the plan is continually updated based on new task arrivals and unexpected changes in machine status. This real-time decision-making process ensures that the production system remains flexible and responsive to any disruptions or changes in operational conditions.

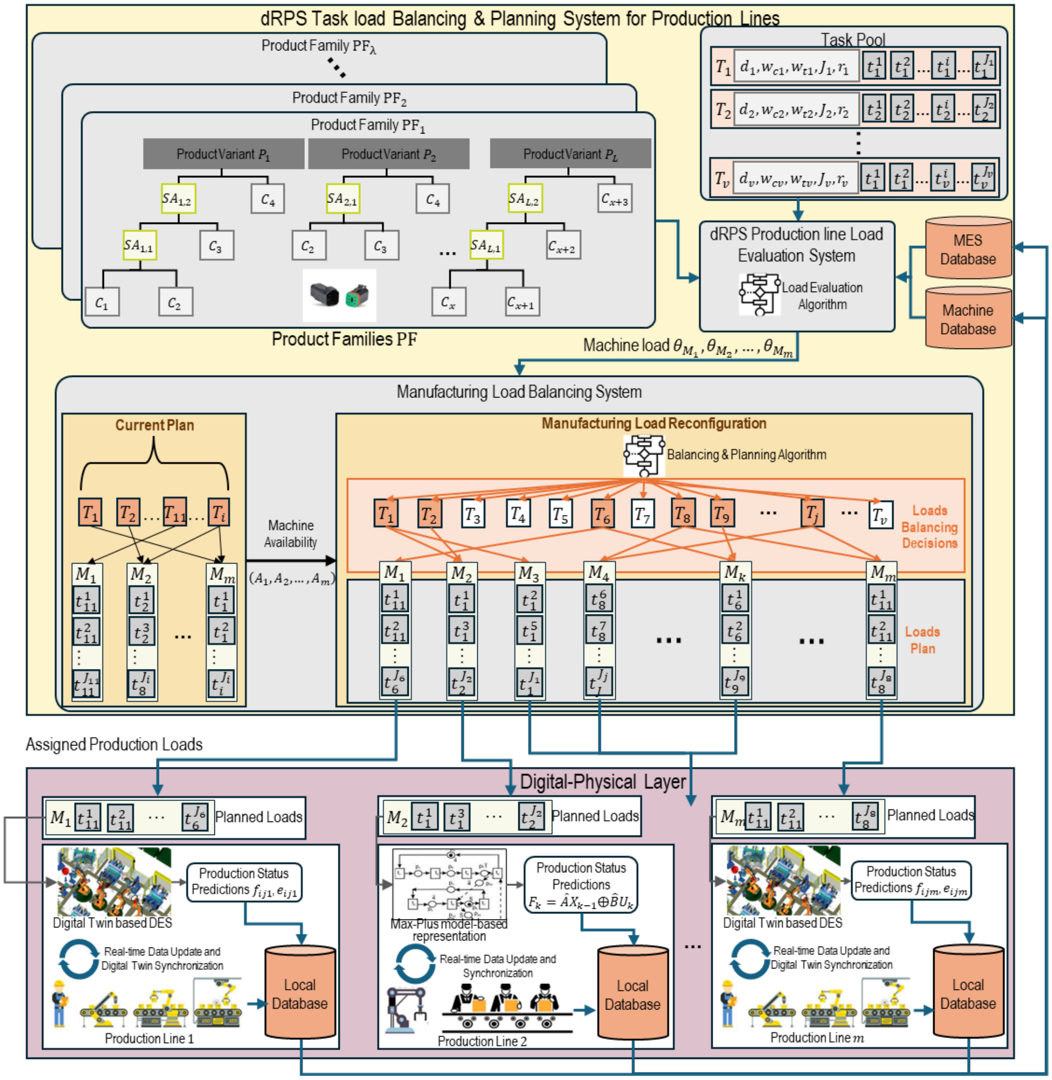

Figure 2. Machine manufacturing load balancing and planning in dRPS

The bottom section illustrates the digital-physical layer in a dRPS, incorporating digital twin technology and Max-plus algebraic representation to facilitate real-time data updates and synchronization between the actual production line and models. Each production line $(M_1, M_2, \dots, M_m)$ executes planned loads that are assigned by the task loads balancing and panning system. For advanced high automation level production lines that utilize advanced technology in intralogistics systems, material handling, and processing control. Discrete event simulation built based on digital twins can estimate the finish time of the jobs that are assigned to the production line. For production line that contains relatively low digitalization level. The max-plus algebraic representation provides a mathematical model for production status predictions, ensuring precise and dynamic adjustments to the production schedule based on the current system status. This real-time synchronization enables the system to swiftly respond to any disruptions or changes, maintaining optimal production flow and efficiency. Both digital twin-based DES and Max-Plus models are employed for predicting the task finish time of the currently assigned task load. The predictions are calculated locally and stored in the local database. The local database also stores machine data from the production line. The local database of each production line is uploaded to the MES database and machine database in the dRPS task load balancing and planning system.

dRPS manufacturing load balancing and planning system for connector production lines has the capability to manage and optimize production tasks in a hybrid reconfigurable environment. By integrating real-time data through digital twin technology and employing advanced balancing algorithms, the system ensures that strategic objectives of revenue maximization and timely order fulfillment are met, alongside operational goals of cost efficiency and effective WIP management. This holistic approach facilitates the assignment of tasks to the most suitable production lines, maximizing the capabilities of advanced lines for complex product variants, and maintaining a balanced, efficient, and responsive production system

7. Outlook and Future work

dRPS are envisioned to be highly adaptable to complex production environments which aims for achieving advanced and optimized management through balancing manufacturing loads across production entities. Based on fundamental issues identified in the paper, several research areas are crucial for facilitating the emergence and effective implantation of dRPS.

Stakeholders such as suppliers and external manufacturers are important to dRPS for extending the scope from internal operational management of production lines to the entire production ecosystem. To enhance flexibility and responsiveness, close collaboration with external manufacturers and suppliers. The emergence of crowdsourced manufacturing introduces a new dimension to dRPS where production tasks are distributed among a network of independent manufacturers. This approach leverages cyber platforms to coordinate and manage production through open calls, enabling flexible manufacturing capacity and resource sharing across different clusters of manufacturers (Jiao et al. 2024). By integrating crowdsourcing with smart manufacturing, dRPS benefits from enhanced collaboration, balancing fulfillment capacities, and optimizing production processes in a dynamic and competitive environment (Song et al. 2024). By incorporating crowdsourcing into the digital transformation of reconfigurable production systems, dRPS benefits from enhanced collaboration, balanced fulfillment capacities, and optimized production processes in a dynamic and competitive environment. This integration accelerates the digital transformation journey, fostering innovation, supporting small and medium-sized enterprises, and aligning with Industry 4.0 principles where digital integration and stakeholder engagement are key drivers of competitiveness.

dRPS are established within production environments featuring varying production capabilities. Achieving seamless integration across different systems necessitates rapid implementation of production line modeling. Discrete event modeling methods, such as Max-Plus algebra, play a crucial role in integrating conventional production lines into advanced load-balancing systems. For advanced production lines with higher complexity, the swift construction of Discrete Event Simulation (DES) models based on digital twins is essential for the effective functioning of dRPS. Recent advancements in Generative AI (GenAI) have enabled researchers to explore its applications in industrial settings. Applications such as GPT-powered smart manufacturing systems enhance design, communication, and operational efficiency (Fei et al. 2023). Additionally, GenAI combined with knowledge graphs improves defect mitigation strategies, streamlining production processes (Shu et al. 204). GenAI has the potential to automate and expedite the creation of accurate and detailed simulation models of production lines. By learning from existing production data, configurations, and operational parameters, Generative AI can generate DES models that closely mirror the real-world behavior and dynamics of complex production systems.

Another promising area for future research in dRPS is the application of game-theoretic decision-making to the problem of load balancing among various production entities, including machines, operators, and engineers. To optimize overall system performance, it is essential to evaluate and balance the load on these entities effectively, handling multiple evaluation criteria such as efficiency, cost, quality, and resource utilization, which often have complex interdependencies and may conflict with one another. Game theory offers a robust framework for addressing these complexities by modeling the strategic interactions among rational decision-makers with potentially competing objectives. In dRPS, each production entity can be considered a player in a game, where their decisions on task acceptance, processing priorities, and resource allocation impact both individual and system performance. By formulating the load balancing problem as a game-theoretic model, it becomes possible to analyze and predict the behavior of these entities under various scenarios and identify equilibrium solutions that optimize overall system performance. This approach is particularly valuable due to the dynamic and reconfigurable nature of dRPS, as game-theoretic models can accommodate varying capabilities and preferences, allowing for adaptive strategies that respond to real-time changes in production demands and resource availability. Incorporating game theory into the decision-making process enables handling multiple evaluation criteria simultaneously, balancing trade-offs between objectives such as minimizing costs while maximizing throughput and quality. Future research should focus on developing specific game-theoretic models tailored to dRPS load balancing, exploring concepts like Nash equilibrium, cooperative games, and bargaining solutions to find optimal strategies for load distribution. Additionally, integrating these models with real-time data analytics and machine learning could enhance their predictive power and adaptability, leading to more sophisticated and effective load balancing mechanisms that ultimately improve efficiency, flexibility, and competitiveness in complex production environments.

8. Conclusions

The advancement of Digital Reconfigurable Production Systems represents a significant step toward meeting the increasing demands for flexibility, customization, and efficiency in modern manufacturing. By addressing the fundamental issues identified in this paper and pursuing the proposed avenues for future research, the manufacturing industry can move closer to realizing the full potential of dRPS. This will involve not only technological innovations but also strategic planning, cross-disciplinary collaboration, and a commitment to continuous improvement. As manufacturing systems become more interconnected and data-driven, the integration of advanced digital technologies with human expertise will be key to achieving resilient, adaptable, and high-performing production environments.

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Biographies

Mulang Song is a graduate student in the School of Mechanical Engineering, Georgia Institute of Technology (USA). His research interest is mainly related to Engineering Design, Blockchain, and the associated applications in Crowdsourced Manufacturing.

Dr. Jiao is the editor-in-chief of Journal of Engineering Design and an associate professor of mechanical and industrial engineering at Georgia Tech, USA. Prior to joining the School of Mechanical Engineering at Georgia Tech in December 2008, he was an Assistant Professor and then Associate Professor in the School of Mechanical and Aerospace Engineering at Nanyang Technological University, Singapore. Before his career in Singapore, he was a Visiting Scholar in the Department of Industrial Engineering and Engineering Management at the Hong Kong University of Science and Technology from 1998 to 1999. From 1993 to 1994, he was a Lecturer of Industrial Engineering in the School of Management at Tianjin University, China, and from 1988 to 1990, he worked as an Associate Lecturer in the Department of Industrial Design at Tianjin University of Science and Technology, China. More info about his research: https://scholar.google.com/citations?user=9yikEHAAAAAJ&hl=en&oi=ao.