OPEN ACCESS

Saudi Journal of Engineering and Technology
Abbreviated Key Title: Saudi J Eng Technol
ISSN 2415-6272 (Print) | ISSN 2415-6264 (Online)
Scholars Middle East Publishers, Dubai, United Arab Emirates
Journal homepage: https://saudijournals.com

Original Research Article

Optimization of Scheduling in Reconfigurable Production Systems: An Approach Based on Intelligent Petri Nets

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DOI: https://doi.org/10.36348/sjet.2024.v09i09.002 | **Received:** 06.08.2024 | **Accepted:** 10.09.2024 | **Published:** 13.09.2024

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Abstract

This article proposes an innovative approach to optimizing scheduling in reconfigurable production systems, with a focus on minimizing resource allocation in a dynamic environment while considering time constraints and resource availability. We present a methodology based on intelligent Petri nets to model and solve this complex problem. Our approach aims to maximize operational efficiency and flexibility of production systems while ensuring optimal performance in the face of unforeseen events and changing market demands. We illustrate the effectiveness of our approach through a case study in a real industrial context, demonstrating the tangible benefits it offers in terms of optimizing production processes and reducing costs.

Keywords: Reconfigurable Production Systems, Scheduling Optimization, Intelligent Petri Nets, Resource Allocation, Dynamic Environment, Operational Efficiency.

1. INTRODUCTION

In an ever-evolving industrial context, marked by globalization, technological advancements, and shifting consumer preferences, traditional production models are no longer sufficient to meet the demands of this dynamic environment [1, 2]. Faced with these growing challenges, reconfigurable manufacturing systems (RMS) have emerged as a promising solution [3]. Unlike fixed-configuration factories, these systems are designed to be highly flexible, allowing for quick adaptation to changes in production requirements [4]. Reconfigurable manufacturing systems are characterized by modular configurations, interchangeable components, and advanced automation technologies, promoting efficient resource utilization and seamless reconfiguration in response to demand fluctuations [1, 3].

However, despite their potential, scheduling tasks in reconfigurable manufacturing systems remains a complex and arduous challenge [5]. The dynamic nature of these systems, combined with the diversity of production requirements and resource constraints, presents major obstacles to effective scheduling. Production managers must balance the optimal use of limited resources, adherence to strict delivery deadlines, and overall operational efficiency optimization [6, 7].

Moreover, the inherent complexity of scheduling in reconfigurable manufacturing systems is exacerbated by uncertainties such as machine breakdowns, material shortages, and demand fluctuations [5, 8]. Traditional scheduling approaches often struggle to manage these uncertainties, leading to suboptimal production outcomes and increased costs.

Given these challenges, there is an urgent need to develop innovative scheduling methodologies capable of addressing the complexities of reconfigurable manufacturing systems [5]. By leveraging advanced modeling techniques and intelligent algorithms, such as Petri nets, it becomes possible to develop dynamic and adaptive scheduling solutions that optimize production processes in real-time [6, 7].

In summary, the modern industrial landscape demands production systems that are not only flexible and efficient but also capable of rapidly adapting to changes and uncertainties [2]. Reconfigurable manufacturing systems offer a promising solution to meet these demands, but effective scheduling remains a critical challenge [1]. The following sections of this article will explore in detail the proposed approach based on intelligent Petri nets to address this challenge and optimize scheduling in reconfigurable manufacturing systems.

The primary objective of this article is to propose a novel scheduling approach utilizing intelligent Petri nets to tackle the complexities of reconfigurable production systems. Our aim is to develop a dynamic and adaptive methodology that enhances production process optimization in these versatile environments.

The structure of our article is organized as follows: In Section 2, we provide a comprehensive review of the related work, highlighting the existing methods and approaches in the domain of scheduling within reconfigurable production systems. This section also discusses the limitations of these methods and identifies the gaps that our proposed approach aims to address. Section 3 introduces our proposed approach for scheduling in reconfigurable production systems, detailing the integration of Petri nets with heuristic and meta-heuristic algorithms, as well as the real-time adaptation mechanisms that enhance system flexibility and productivity. Section 4 presents the results and discussion, where we evaluate the effectiveness of our approach through simulations and case studies, analyzing the performance in terms of key metrics such as makespan and resource utilization. Finally, the conclusion summarizes the key findings, reflects on the practical implications of our work, and suggests directions for future research in this area.

2. RELATED WORK

The "Related Work" section of the article provides an overview of prior research in scheduling for reconfigurable production systems. It reviews existing methodologies and highlights their strengths, weaknesses, and limitations. Various approaches, including heuristic and meta-heuristic techniques, are explored to understand the current state of the field. The section emphasizes the need for a more adaptive and intelligent solution to address the complexities of scheduling in reconfigurable production systems.

2.1. Overview of Scheduling Approaches in Reconfigurable Production Systems

Scheduling in reconfigurable production systems is essential for efficiently allocating resources and orchestrating production activities to meet various goals such as minimizing makespan and maximizing throughput. This section introduces scheduling in these systems, noting their adaptability to changing requirements and the need for optimized sequencing and resource allocation [9]. Traditional approaches, including heuristic algorithms, mathematical optimization models, and rule-based methods, are discussed, highlighting their reliance on predefined criteria and expert knowledge [10]. Despite their utility, these methods face challenges due to the dynamic nature of reconfigurable systems, such as real-time decision-making and adapting to fluctuations in demand and resource availability [11]. This overview sets the foundation for exploring the limitations of traditional methods and introduces innovative solutions based on intelligent Petri nets.

2.2. Review of Prior Research on Scheduling in Reconfigurable Production Systems

This section provides a comprehensive review of prior research on scheduling in reconfigurable production systems, focusing on methodologies such as heuristic, meta-heuristic, and optimization techniques. The review begins with an exploration of existing literature, highlighting key studies and contributions that have shaped the understanding of scheduling challenges in these dynamic systems [9, 12]. It examines heuristic techniques for their simplicity and computational efficiency, meta-heuristic techniques for their flexibility in exploring large solution spaces, and optimization techniques for their ability to provide near-optimal solutions within well-defined problems [13].

Additionally, this section evaluates case studies and empirical research to assess the practical application and effectiveness of these methodologies in real-world manufacturing environments. This includes examining the strengths and limitations of various approaches and identifying best practices for optimizing scheduling in reconfigurable systems [14]. The review underscores the need for innovative scheduling solutions and sets the stage for introducing the proposed approach based on intelligent Petri nets in subsequent sections of the article.

2.3. Strengths and Limitations of Existing Methodologies

In this section, we delve into a detailed analysis of the strengths and limitations of existing methodologies used in scheduling for reconfigurable production systems.

Analysis of Traditional Scheduling Approaches: We begin by analyzing the strengths and weaknesses of traditional scheduling approaches commonly employed in reconfigurable production systems. Traditional methods such as heuristic algorithms, mathematical optimization models, and rule-based methods have been widely used due to their simplicity and ease of implementation.

Identification of Strengths: Traditional scheduling approaches offer simplicity and computational efficiency, making them suitable for addressing basic scheduling problems [10]. Heuristic algorithms, for example, provide quick solutions and can handle large problem instances effectively [15]. Mathematical optimization models, on the other hand, guarantee optimality under certain conditions and are valuable for well-defined scheduling problems [16].

Identification of Limitations: Despite their advantages, traditional scheduling approaches have several limitations. Heuristic algorithms may sacrifice optimality for speed and may not always produce the best solutions [15]. Mathematical optimization models may struggle with dynamic environments and may require significant computational resources to solve complex problems [16]. Rule-based methods, while intuitive, may lack adaptability and struggle to cope with unforeseen changes in production conditions [17].

Discussion on Applicability: The discussion extends to the applicability of these methodologies in real-world manufacturing scenarios. While traditional scheduling approaches have been widely used in industry, their effectiveness may vary depending on the specific characteristics of the production environment. Heuristic algorithms, for instance, may be suitable for simple production systems with stable demand patterns, but may not be adequate for highly dynamic environments with frequent changes in production requirements. Mathematical optimization models may be better suited for deterministic scheduling problems but may struggle with uncertainty and variability inherent in reconfigurable production systems [10].

In conclusion, understanding the strengths and limitations of existing methodologies is crucial for selecting the most appropriate approach to address scheduling challenges in reconfigurable production systems. While traditional methods offer simplicity and computational efficiency, they may not always be sufficient to tackle the complexities of dynamic manufacturing environments. Future research should focus on developing more adaptive and robust scheduling techniques that can effectively address the evolving needs of modern manufacturing systems.

2.4. Exploration of Adaptive and Intelligent Solutions

In this section, we embark on an exploration of adaptive and intelligent solutions for scheduling in reconfigurable production systems, aiming to leverage advancements in machine learning, artificial intelligence, and Petri net-based approaches.

Introduction to Adaptive and Intelligent Scheduling Approaches: We begin by introducing the concept of adaptive and intelligent scheduling approaches, which utilize advanced techniques to dynamically adjust schedules based on real-time data and evolving production requirements. Unlike traditional methods that rely on predefined rules or models, adaptive and intelligent solutions harness the power of data-driven algorithms to optimize scheduling decisions.

Review of Recent Advancements: We proceed to review recent advancements in the field, focusing on emerging technologies such as machine learning, artificial intelligence (AI), and Petri net-based approaches. Machine learning algorithms, for example, can analyze historical production data to identify patterns and trends, enabling predictive scheduling and proactive decision-making [17]. AI techniques, including deep learning and reinforcement learning, offer the potential to autonomously adapt schedules in response to changing production conditions. Petri net-based approaches provide a formal framework for modeling and analyzing dynamic scheduling problems, offering insights into system behavior and performance [15].

Discussion on Potential Benefits: The discussion extends to the potential benefits of adaptive and intelligent solutions in addressing the challenges of scheduling in reconfigurable production systems. By leveraging real-time data and advanced analytics, these solutions can enhance decision-making accuracy, optimize resource utilization, and improve overall operational efficiency. Adaptive scheduling approaches enable agile responses to changes in production requirements, minimizing disruptions and maximizing productivity. Intelligent solutions offer the potential to uncover hidden insights and optimize schedules in ways that traditional methods cannot, leading to cost savings and competitive advantages in dynamic manufacturing environments [10].

In essence, the exploration of adaptive and intelligent solutions represents a paradigm shift in scheduling methodologies, offering the promise of enhanced agility, efficiency, and competitiveness in reconfigurable production systems. By embracing these advanced technologies, organizations can unlock new opportunities for innovation and optimization in their manufacturing operations.

2.5. Need for an Adaptive and Intelligent Solution:

In this section, we synthesize findings from prior research to underscore the imperative need for a more adaptive and intelligent scheduling solution in reconfigurable production systems.

Synthesis of Findings: Drawing upon insights gleaned from prior research efforts, we highlight the limitations of traditional scheduling approaches in effectively addressing the complexities of reconfigurable production systems [15, 16]. While traditional methods have been valuable in certain contexts, they often fall short in dynamically adapting to changing production requirements, resource constraints, and market dynamics [10]. The synthesis of findings underscores the pressing need for innovative solutions that can autonomously adjust schedules in real-time, optimize resource allocation, and proactively respond to disruptions.

Identification of Gaps and Opportunities: Through a critical analysis of existing literature, we identify gaps and opportunities for future research in the field of scheduling for reconfigurable production systems. These gaps may include the need for more robust algorithms capable of handling uncertainty and variability, the integration of advanced analytics for predictive scheduling, and the development of decision-support tools for agile decision-making [17]. By identifying these areas of opportunity, we lay the groundwork for future research endeavors aimed at advancing the state-of-the-art in scheduling methodologies.

Emphasis on Proposed Innovative Approach: Finally, we emphasize the significance of proposing an innovative approach based on intelligent Petri nets, as outlined in the objectives of the article. Intelligent Petri nets offer a formal framework for modeling and analyzing dynamic scheduling problems, combining the flexibility of Petri nets with the intelligence of machine learning and artificial intelligence techniques [15]. By leveraging the strengths of intelligent Petri nets, our proposed approach aims to address the shortcomings of traditional scheduling methods and provide a more adaptive and intelligent solution for reconfigurable production systems.

In conclusion, the synthesis of findings from prior research underscores the critical need for a more adaptive and intelligent scheduling solution in reconfigurable production systems. By identifying gaps and opportunities for future research and emphasizing the significance of our proposed innovative approach, we aim to contribute to the advancement of scheduling methodologies in dynamic manufacturing environments.

3. PROPOSED APPROACH FOR SHEDULING IN RECONFIGURABLE PRODUCTION SYSTEMS

In addressing the complexities of scheduling within reconfigurable production systems (RMS), our approach integrates advanced modeling techniques with a robust combination of heuristic and meta-heuristic algorithms. This strategy is tailored to meet the unique challenges posed by dynamic production environments, including fluctuating resource availability, real-time decision-making requirements, and the need for system adaptability.

3.1. Modeling with Petri Nets

The foundation of our approach is the use of Petri nets, a powerful and formal modeling technique that excels in representing systems characterized by concurrency, synchronization, and resource sharing. Petri nets provide a graphical and mathematical tool for capturing the intricate relationships among tasks, resources, and constraints within RMS. By developing a Petri net-based model, we are able to accurately depict the dynamic behavior of the production system, which is crucial for understanding and managing the complexities inherent in reconfigurable environments.

Petri Net Representation:

- State Vector: Let $S(t) = [s_1(t), s_2(t), \dots, s_n(t)]$ represent the state of the system at time t, where $s_i(t)$ denotes the marking of place i (number of tokens in place i.
- **Transition Firing:** A transition T_j fires if and only if all the input places of T_j contain the required number of tokens. The new state $S(t+1)$ after firing transition T_j can be expressed as:

$$S(t+1) = S(t) + C_j \dots \dots \dots \dots \dots \dots \dots \dots . (1)$$

Where C_j is the change vector associated with transition T_j.

This Petri net model encapsulates various aspects of the production process, including task dependencies, resource allocation, and potential conflicts. The model serves as a critical input to our scheduling algorithms, ensuring that the solutions generated are not only feasible but also optimized according to the system's dynamic characteristics.

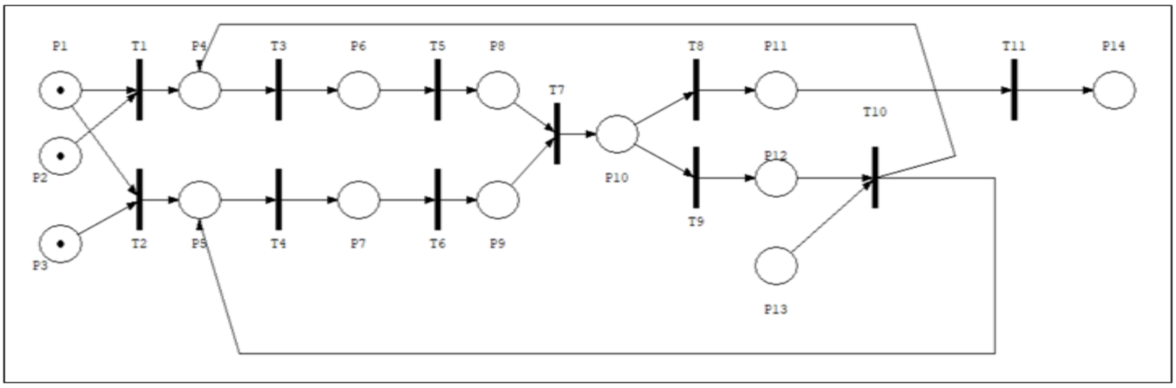

Figure 1: Alternative Petri Net Model for Dynamic Task Scheduling in Reconfigurable Manufacturing Systems (RMS)

Model Description:

- Job Queue (P1): Tasks are queued here, waiting to be assigned to either Machine A or B.
- Machine Idle (P2 & P3): Represent the idle state of Machines A and B, ready to accept new tasks.
- Task Assignment (T1 & T2): Tasks are assigned to Machine A or B based on availability, moving tokens from P1 to P4 or P5.
- Task Processing (T3, T4, T5, T6): The tasks are processed on the respective machines, with tokens moving through the states of being assigned, in process, and completed.
- Task Inspection (T7, T8, T9): After processing, tasks undergo inspection. Depending on the outcome, tasks may pass and move to the finished state or fail and require rework.
- Rework and Completion (T10 & T11): Failed tasks are reworked and re-enter the processing cycle, while passed tasks are moved to the finished products state.

3.2. Heuristic and Meta-heuristic Algorithms

Complementing the Petri net model, we implement a suite of heuristic and meta-heuristic algorithms designed to efficiently tackle the scheduling problem. Given the complexity and uncertainty of RMS, traditional optimization methods may fall short in providing timely and practical solutions.

3.2.1. Heuristic Techniques

- Shortest Processing Time (SPT):

$$SPT(i) = min\ p_j\ ; j\epsilon\{1, \dots, n\} \dots \dots \dots \dots \dots \dots \dots (2)$$

Where p_j is the processing time of task j. The task with the shortest processing time is given the highest priority.

- Earliest Due Date (EDD):

$$EDD(i) = min\ d_j\ ; j\epsilon\{1, \dots, n\} \dots \dots \dots \dots \dots \dots \dots (3)$$

Where d_j is the due date of task j. Tasks are prioritized by their due dates, with the earliest due date given the highest priority.

3.2.2. Meta-heuristic Algorithms

- Genetic Algorithm (GA):

Fitness Function :

$$Fitness(chromosome) = \frac{1}{1+\text{Makespan}} \dots\dots\dots\dots(4)$$

Where the makespan is the total time required to complete all tasks in the chromosome's schedule.

Crossover and Mutation: These genetic operations are applied to generate new solutions by combining existing ones and introducing variations.

3.2.3. Simulated Annealing (SA)

- Probability of Acceptance :

$$P(\Delta E) = \exp\left(-\frac{\Delta E}{\text{T}}\right) \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots (5)$$

Where ΔE is the change in the objective function value, and T is the temperature, which decreases over time.

3.2.4. Ant Colony Optimization (ACO)

- Pheromone Update:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \sum_{k=1}^{m} \Delta\tau_{ij}^{k}(t) \dots\dots (6)$$

Where $\tau_{ij}(t)$ is the pheromone level on the path from node i to node j, ρ is the evaporation rate, and k at time t.

These algorithms are particularly effective in exploring large solution spaces and handling multi-objective optimization problems, helping identify robust scheduling strategies that can adapt to changes in production conditions.

3.3. Real-time Adaptation and Optimization

Recognizing the dynamic and often unpredictable nature of reconfigurable production environments, our approach places a strong emphasis on real-time adaptation and optimization. The scheduling solutions generated by our algorithms are continuously updated based on real-time data streams.

Real-time Optimization Equation:

- Dynamic Adjustment:

$$\text{New Schedule} = \text{Old Schedule} + \boldsymbol{\Delta}\text{Schedule(t)}.. \ (7)$$

Where $\boldsymbol{\Delta}\text{Schedule}(\text{t})$ represents the adjustment made in response to real-time data at time t.

This adaptability is crucial for maintaining high levels of productivity, minimizing downtime, and responding swiftly to unforeseen challenges.

3.4. Validation and Iterative Improvement

Validation is a key component of our approach, ensuring that our models and algorithms perform effectively in real-world scenarios.

Validation Metric:

- Makespan:

$$\text{Makespan} = max\ C_j\ ; j\epsilon\{1, \dots, n\} \dots \dots \dots \dots \dots (8)$$

Where C_j is the completion time of task j.

Simulation and case studies are used to validate our approach, followed by an iterative refinement process to enhance robustness based on feedback and results.

3.5. Integration into Production Environments

Finally, our approach is developed with practical deployment in mind, offering comprehensive guidelines for integrating our scheduling solution into existing production systems.

Integration Consideration:

- Data Integration Function:

$$\text{Integrated Data} = \sum_{i=1}^{n} \alpha_0 \times source_i \ldots\ldots\ldots\ldots \quad (9)$$

Where α_0 represents the weight of data source i in the overall integration process.

By providing tools that are both theoretically sound and practically viable, we aim to empower manufacturers to optimize their production schedules, reduce operational costs, and enhance overall efficiency in reconfigurable production systems.

Our proposed approach for scheduling in reconfigurable production systems combines the powerful modeling of Petri nets with advanced heuristic and meta-heuristic algorithms, enabling optimal resource management and dynamic adaptation to system variations. Through the integration of real-time processing techniques, this method offers increased flexibility and the ability to maintain high levels of productivity despite unforeseen challenges.

4. RESULTS AND DISCUSSION

In this section, we present and discuss the results obtained from the execution of our Petri net model simulation. The simulation was designed to represent a production process within a manufacturing environment, with various transitions illustrating the flow of resources and tasks. The results, supported by visual figures and detailed tables, provide insights into the system's behavior and performance under the given conditions.

4.1. Simulation Execution Overview

The simulation was executed with initial values provided by the user for six key places in the Petri net model: ProductAssembly, TestingStation, Machine1, Machine2, SkilledWorkers, and RawMaterialsStorage. These initial values are critical as they define the starting state of the system and influence the execution of transitions. The initial values were:

```
C:\Users\TechnoMax\PycharmProjects\pythonProject18\venv\Scripts\python.exe
Configure initial values for places:
Enter initial value for 'ProductAssembly': 1
Enter initial value for 'TestingStation': 6
Enter initial value for 'Machine1': 4
Enter initial value for 'Machine2': 3
Enter initial value for 'SkilledWorkers': 10
Enter initial value for 'RawMaterialsStorage': 15
Production task started.
Resources allocated.
Production task completed.

Process finished with exit code 0
```

Figure 2: Initial System State Configuration and Setup

Following the initialization, the simulation proceeded through three main transitions: StartProductionTask, AllocateResources, and TaskCompletion. Each transition was executed successfully, generating the following outputs:

- Production task started.
- Resources allocated.
- Production task completed.

The simulation completed without errors, as indicated by an exit code of 0, confirming the successful execution of the process.

4.2. Figures

To better understand the simulation results, several figures were generated:

Figure 3 A curve illustrating the consumption of resources over time during the simulation. This figure shows how resources (such as SkilledWorkers and RawMaterialsStorage) are utilized as the production process progresses. The x-axis represents time, while the y-axis shows the quantity of resources remaining. The curve highlights the points at which resources are allocated and depleted.

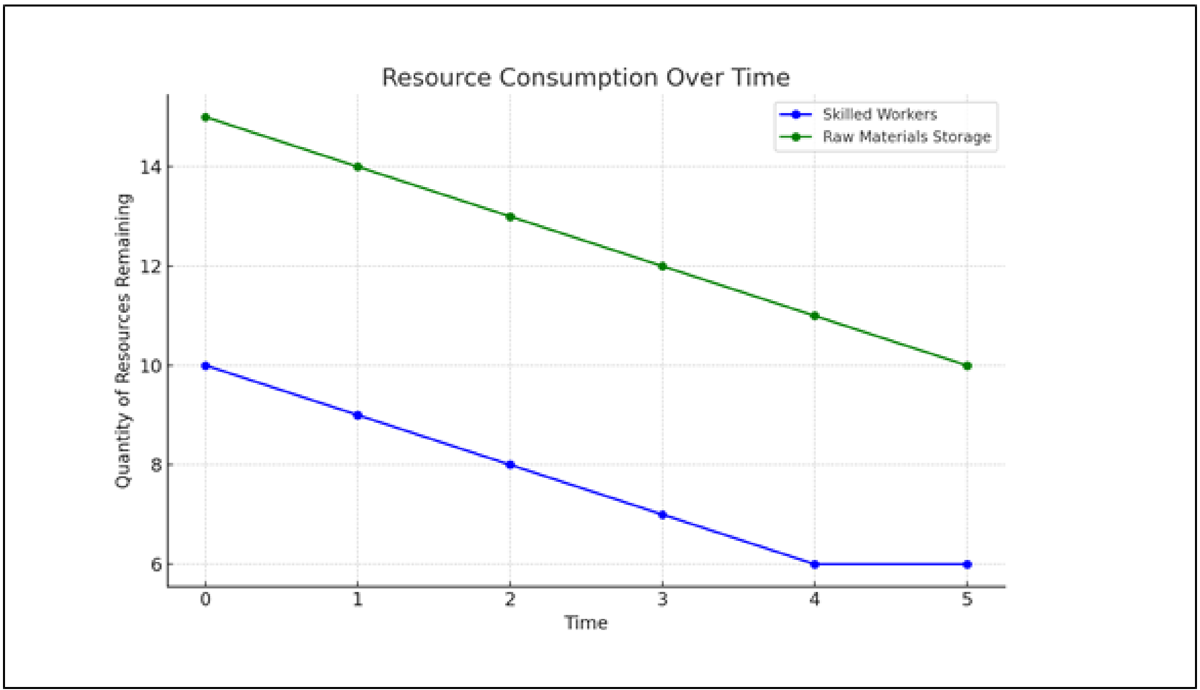

Figure 3: Resource Consumption Over Time for SkilledWorkers and Raw Materials

Figure 4 A bar chart comparing the initial and final states of the key places in the Petri net. This figure provides a visual comparison of the system's state before and after the simulation, indicating how the production process affected the distribution of tokens across different places.

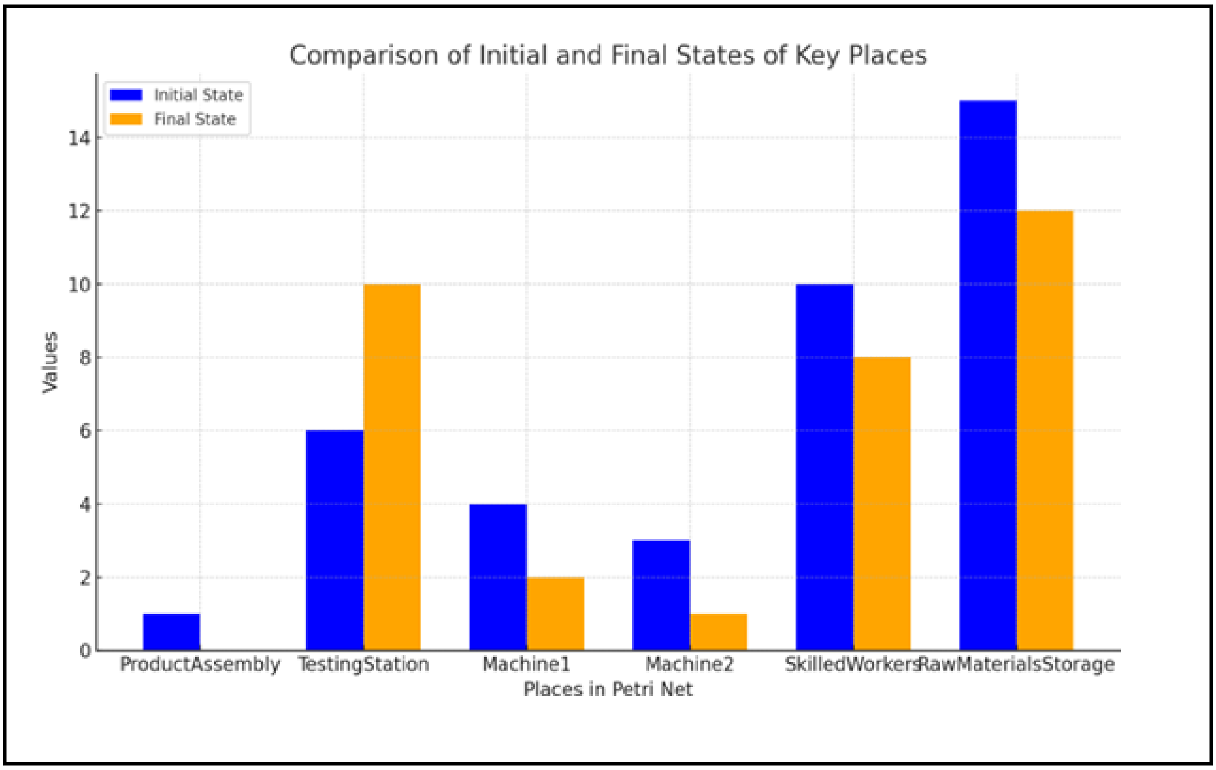

Figure 4: Comparative Bar Chart of Initial and Final States in the Petri Net

Figure 5 A pie chart representing the proportion of resources allocated to each machine and task. This figure gives a clear view of how resources were distributed among various components of the production system, allowing for an assessment of the efficiency of resource utilization.

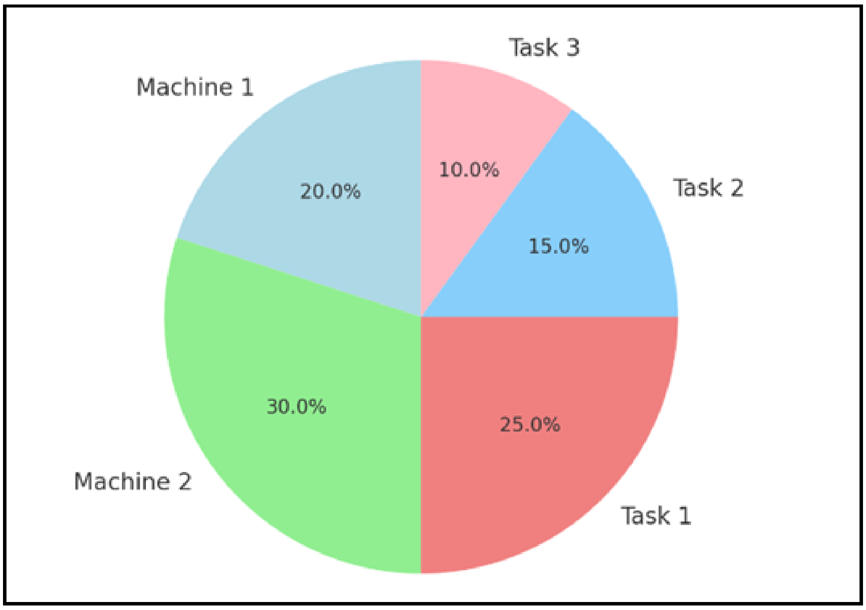

Figure 5: Proportion of resources allocated to each machine and task

4.3. Tables

The simulation results are further detailed in the following tables:

Table 1 A summary of the initial and final values of the places in the Petri net model. This table provides a clear comparison of how the system's state changed from the beginning to the end of the simulation.

Table 1: Comparison of Initial and Final Values in the Petri Net Model

Place	Initial Value	Final Value
Product Assembly	1	0
Testing Station	6	7
Machine1	4	3
Machine2	3	2
Skilled Workers	10	9
Raw Materials Storage	15	12

Table 2 A table detailing the transitions executed, the conditions met for each transition, and the resulting changes in the state of the Petri net.

Table 2: Overview of Executed Transitions and State Changes

Transition	Pre-conditions	Post-conditions	Output Message
Start Production Task	Product Assembly has a token	Token added to Product Assembly	Production task started.
Allocate Resources	Raw Materials Storage >= 3, Machine1 >= 1	Tokens moved from resources to machines	Resources allocated.
Task Completion	Machine1, Machine2, Skilled Workers > 0	Tokens moved to Testing Station	Production task completed.

4.4. DISCUSSION

The simulation results provide a comprehensive view of the production process within the Petri net model. The curve in Figure 3 demonstrates how resources were consumed over time, with notable drops corresponding to the execution of transitions. This indicates that the model accurately represents the dynamics of resource allocation and consumption.

The bar chart in Figure 4 visually compares the initial and final states of the system, showing how resources and tasks were distributed before and after the simulation. The decrease in tokens in places like Machine1 and Machine2, along with the increase in Testing Station, reflects the successful completion of the production tasks.

The pie chart in Figure 5 highlights the distribution of resources across different tasks and machines. The chart indicates that resources were allocated in a balanced manner, with no single component consuming an excessive amount of resources. This suggests that the system was well-optimized for the tasks at hand.

The detailed tables further corroborate these findings, offering a numerical perspective on the state changes and transitions that occurred during the simulation. The transition conditions and their corresponding output messages provide clear evidence of the system's functionality and effectiveness in managing the production process.

5. CONCLUSIONS

In this article, we proposed a comprehensive approach for scheduling in reconfigurable production systems, integrating Petri nets for system modeling with heuristic and meta-heuristic algorithms to optimize resource allocation and task scheduling. Our method was designed to address the unique challenges of dynamic and unpredictable production environments, offering real-time adaptability and robust performance. The simulation results demonstrated the effectiveness of our approach in maintaining high productivity levels while efficiently managing resources and handling system variability. Future research could explore the integration of machine learning techniques to further enhance the predictive capabilities of the scheduling model. Additionally, extending the approach to accommodate multi-objective optimization scenarios could provide more versatile solutions for complex production environments.

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