Int j simul model 24 (2025) 1, 135-146
Original scientific paper

MANUFACTURING PROCESS BASED ON RECOGNITION RULES AND BAYESIAN NETWORKS

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Abstract
This study presents an optimization scheduling approach for automotive manufacturing processes using recognition rules and Bayesian networks (BN) to balance cost, time, and quality. The methodology includes a workflow model and a serial workflow scheduling algorithm, focusing on cost and quality within a set timeframe. The Bayesian Process Scheduling Optimization Algorithm (BPSOA) is evaluated against other algorithms, showing superior performance with an *MAE* of 0.1 and an *RMSE* of 1.2 after 20 iterations. Key results include process costs from 86,543 to 178,765 CNY, quality scores of 76.54 to 92.34, and handling times of 2.23 to 4.57 hours, with a resource utilization rate up to 95.43 % and failure rates between 1.23 % and 5.12 %. The study contributes to intelligent manufacturing by enhancing process adaptability and efficiency under uncertainty.
(Received in October 2024, accepted in January 2025. This paper was with the authors 1 month for 2 revisions.)

Key Words: Automotive Manufacturing Process Flow, Optimization Scheduling, Bayesian Network, Multi-Objective Optimization, Workflow Model

1. INTRODUCTION

Driven by globalization and technological innovation, the automobile manufacturing industry, as an important pillar of the national economy, is undergoing profound changes [1]. The optimization scheduling of automobile manufacturing process occupies a crucial position in improving production efficiency, reducing costs, and ensuring product quality [2]. Traditional optimization research often focuses on a single objective, such as minimizing costs or minimizing time, ignoring the fact that these objectives are often interrelated and influential in actual production [3]. For example, simply pursuing cost reduction may lead to longer production cycles and decreased quality, while overemphasizing time efficiency may increase costs and reduce product reliability. Meanwhile, traditional methods have limitations in dealing with uncertainty and complexity, especially in the face of rapid changes in market demand, technological advancements, and supply chain fluctuations, which often make it difficult for these methods to adapt [4, 5]. The existing scheduling algorithms, such as genetic algorithm, particle swarm optimization, and simulated annealing, have made progress in some aspects, but their adaptability and real-time performance in dynamic environments are still insufficient. These algorithms often struggle to balance the trade-offs between various objectives when dealing with large-scale, multi-stage, and multi-objective automotive manufacturing processes, and have insufficient response to uncertainties and dynamic changes in actual production [6, 7]. A novel framework leveraging recognition rules and Bayesian Networks (BN) has been proposed to optimize and schedule automotive manufacturing processes. This framework addresses the limitations of traditional methods by incorporating multi-objective optimization – encompassing cost, time, and quality – and by modelling uncertainties through BN. It also integrates big data and AI to enhance predictive accuracy and decision-making, offering innovative solutions for automotive manufacturing process optimization. The overall research is divided into the following steps: **Step 1**: Construct a workflow model capturing the dynamic characteristics of the automotive manufacturing process; **Step 2**: Define scheduling constraints for cost minimization and quality optimization using TMC; **Step 3**: Develop a Bayesian Process Scheduling Optimization Algorithm (BPSOA) for process optimization. The research is expected to provide innovative solutions for optimizing the automotive manufacturing process.

2. LITERATURE REVIEW

Recent research has focused on technological advancements in manufacturing. Niekurzak et al. [8] studied the impact of single minute rapid mould changing technology on automotive assembly lines, reducing mould change time and enhancing production efficiency. Liu et al. [9] examined the use of magnesium alloys in vehicles, addressing material challenges and predicting their growth due to environmental and consumer demands. Jahromi et al. [10] developed polypropylene composites for automotive repair, optimizing 3D printing processes and achieving improved material properties. Rubert et al. [11] applied the Quality Function Deployment method to improve automotive packaging quality and reduce costs. Lee et al. [12] proposed a framework for intelligent automotive factories, highlighting key technologies like digital twins and AI.

In other fields, Xu et al. [13] focused on the evolutionary behaviour and the equilibrium strategy of the digital platform and manufacturing enterprises. Abdelhamid et al. [14] used data mining to identify cardiovascular risk factors in diabetic patients. Ebrahimi and Mojtahedi [15] combined association rule mining and Bayesian Networks (BN) to assess automotive part failures. Kar et al. [16] applied fuzzy analytic hierarchy process and BN to identify key process variability factors. Tian et al. [17] proposes a new method for quality prediction and control of multistage production and manufacturing processes based on big data analysis and neural networks. By combining big data technology with neural network algorithms, it achieves precise monitoring and quality control of production processes. In the study by Chen [18], a novel model for language training assessment is proposed, which leverages data mining and Bayesian network techniques. This research introduces a new approach to evaluating language training effectiveness, offering insights into how advanced analytical methods can be applied to enhance language learning and assessment. The findings contribute to the field of educational technology and have potential implications for improving language training programs. Ojstersek et al. [19] explored effective methods for optimizing smart manufacturing systems using digital twin technology. The study achieved real-time analysis and optimization of smart manufacturing system performance by creating a data-driven simulation model based on real production system. The research results demonstrate that digital twin technology can significantly improve the efficiency, flexibility, and sustainability, providing new ideas and solutions for the development of the smart manufacturing field. This study not only showcases the enormous potential of digital twin technology in production system optimization but also offers valuable references for the design and optimization of future smart manufacturing systems. In the study by Küçüker and Yet [20], a Bayesian network model is introduced for reliability prediction in aircraft fleet operations. By integrating supplier estimates, maintenance data, and expert judgement, the model provides a comprehensive approach to assessing the reliability of aircraft fleets. This research contributes significantly to the field of operational research, offering a practical tool for aircraft operators to improve their maintenance strategies and enhance operational safety. The findings underscore the importance of leveraging data-driven methods to enhance decision-making in complex and safety-critical environments such as aviation.

In summary, many experts have conducted research on technological innovation and material applications in the manufacturing industry. However, existing research still lacks adaptability to complex dynamic environmental changes, systematic methodological frameworks, and comprehensive performance evaluation of new materials. Therefore, the research proposes an optimization scheduling model for automotive manufacturing process based on recognition rules and BN to address issues such as lack of flexibility in manufacturing processes, efficiency in material application, and insufficient production decision support. It is expected to contribute to the intelligent transformation of the manufacturing industry and the promotion of new material applications.

3. RESEARCH METHODOLOGY

3.1 Optimization and scheduling model for automotive manufacturing

In the manufacturing industry, especially in automobile manufacturing, the goal of workflow scheduling is to optimize the three interdependent parameters of cost, time, and quality [20]. Extending the process time can improve product quality, but there is an upper limit. Similarly, long-term service in the early stages may reduce costs, but beyond a certain point, costs will increase. This study mainly explores how to effectively arrange schedules to achieve cost and quality optimization, as shown in Fig. 1.

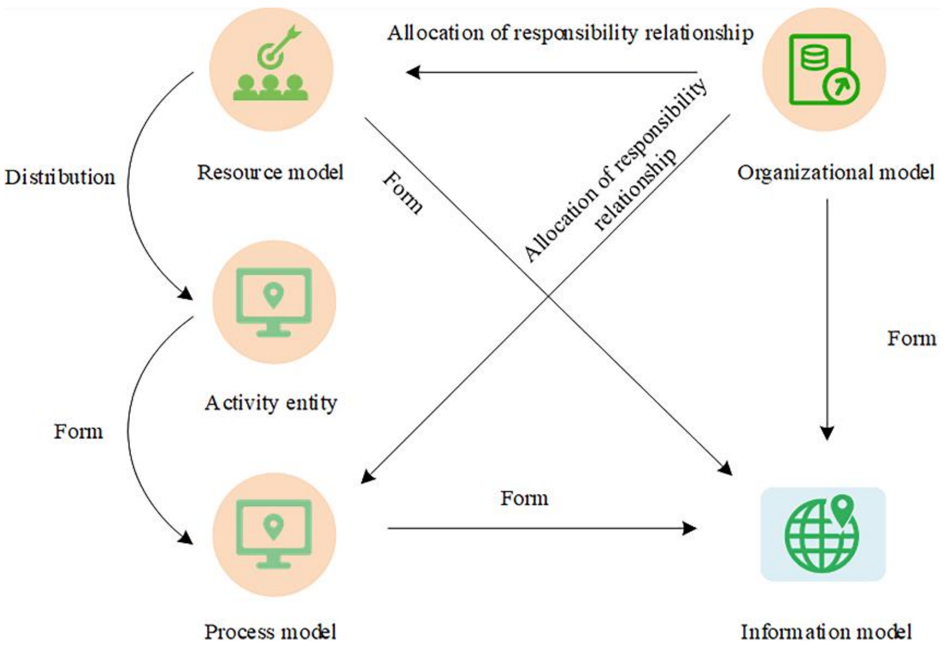

Figure 1: Composition of workflow model.

Fig. 1 illustrates the optimization framework for automotive manufacturing process flow and resource allocation. The framework includes resource, activity, organizational, and information models, which interact to enhance process efficiency and resource utilization. The resource model outlines the allocation of manpower and equipment, supporting task links in the manufacturing process. Activity entities are the specific tasks that form the process's basic units, working with the process model to define task sequences and ensure process efficiency. The organizational model details the structure and hierarchy, assigning responsibilities to departments and roles, and linking them with resources through responsibility relationships for task allocation. The information model facilitates the flow of information between activities and processes. In optimizing automotive manufacturing, these models are interconnected, particularly with workflow models like process, function, and organization.

The collaborative effect between the resource allocation model and the workflow model is shown in Fig. 2.

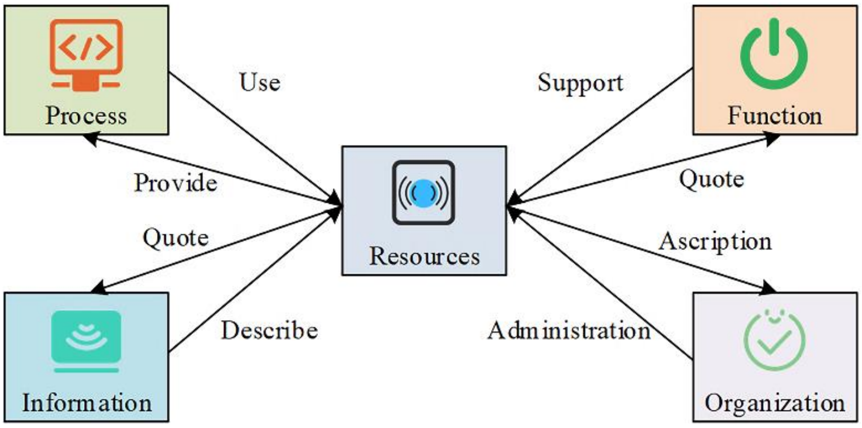

Figure 2: The synergy between resource allocation model and workflow model.

Fig. 2 highlights the pivotal role of the resource model in the workflow model. It interfaces with other models – processes, functions, information, and organization – via relationships like "use," "support," "reference," "description," and "management," ensuring efficient resource allocation. The resource model aligns resources with task demands through "use" and "support" links with processes and functions. It clarifies responsibilities and ensures resource management standardization by "referencing" and "attributing" to functions and organizations. By "describing" with the information model, it records and communicates resource usage and attributes, providing data support. Integrating BN analysis, the model predicts and optimizes resource demand and allocation, enhancing process efficiency and reducing waste. A Directed Acyclic Graph (DAG) can be employed to delineate the sequence and dependencies among process steps, based on the resource model's interactions with workflow models.

3.2 Optimization of auto manufacturing flow

After completing the workflow model design for automotive manufacturing processes, the research focuses on optimizing the cost and quality of automotive manufacturing processes within a specified time frame. To this end, a workflow model was constructed to capture the dynamic characteristics of the manufacturing process, and a Time-constrained Minimum Cost identification rule (TMC) was proposed to achieve cost minimization and quality optimization [21, 22]. Minimize the total process cost as shown in Eq. (1):

$$A_c = min\left(\sum_{i \in N'} \rho_{ij} c_{ij}\right) \tag{1}$$

In Eq. (1), i refers to each node in the process flow. N' is a collection of process nodes. ρ_{ij} is a decision variable. C_{ij} refers to the cost incurred when selecting service j at process node i. Maximizing the overall process quality is shown in Eq. (2):

$$A_q = max\left(\prod_{i \in N'} \rho_{ij} a_{ij}\right) \tag{2}$$

In Eq. (2), a_{ij} refers to the quality generated when selecting service j at process node i. The three constraints that need to be met in automotive manufacturing process scheduling correspond to the limitations of process cost, process quality, and process time, as shown in Eq. (3):

$$\begin{cases} A_c \le V_c \\ A_q \ge V_q \\ A_t \le V_t \end{cases} \tag{3}$$

In Eq. (3), V_c represents the upper limit value set by the enterprise for process costs. V_q represents the lower limit value set by the enterprise for process quality. V_t represents the upper limit value set by the enterprise for process time. The entire algorithm process is shown in Fig. 3.

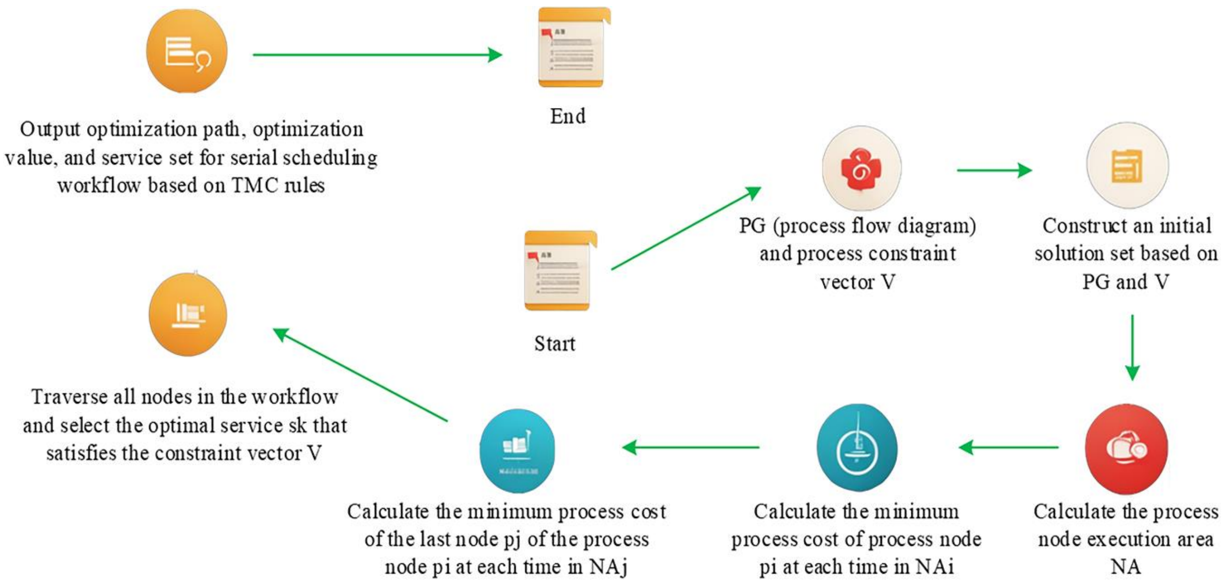

Figure 3: Scheduling algorithm process.

Fig. 3 describes the serial workflow scheduling algorithm's steps, beginning with the receipt of the process flow diagram (PG) and the process constraint vector (*V*) to create an initial solution set. The deadline *D* is used to establish the execution area (NA) for process nodes. The algorithm calculates the minimum process cost at each time point within this area. For each node p_i and its successor node p_j, the algorithm assesses the minimum process cost in their respective execution areas. The aim is to optimize node scheduling to reduce costs and meet deadlines. The algorithm traverses all nodes to identify the optimal service s_k that fulfils the constraint vector *V*. The process ends with the output of the optimized path, values, and service set.

3.3 Optimization and scheduling of auto manufacturing flow using BN

Serial workflow scheduling algorithms are crucial for optimizing process flows under both deterministic and uncertain conditions [23, 24]. In automotive manufacturing, BN models simplify complex processes by representing steps as random variables in a DAG, capturing dependencies and allowing for the quantification of factors like equipment performance and material quality [25, 26]. The root node, critical for scheduling, initiates the process. Variables may represent parameters like temperature, aiding in process prediction and optimization. DBN is adept at modelling time-evolving relationships by dividing time series into slices with conditional probability distributions [27, 28]. Each variable's state is influenced by others in the same slice and its previous state, enabling DBN to predict future states or infer past ones based on current and historical data. In automotive manufacturing, DBN can optimize production by analysing process impacts and adjusting steps according to prior states. Most research fields on optimizing and scheduling automotive manufacturing processes may involve the triangulation process of the Moral diagram, as shown in Fig. 4.

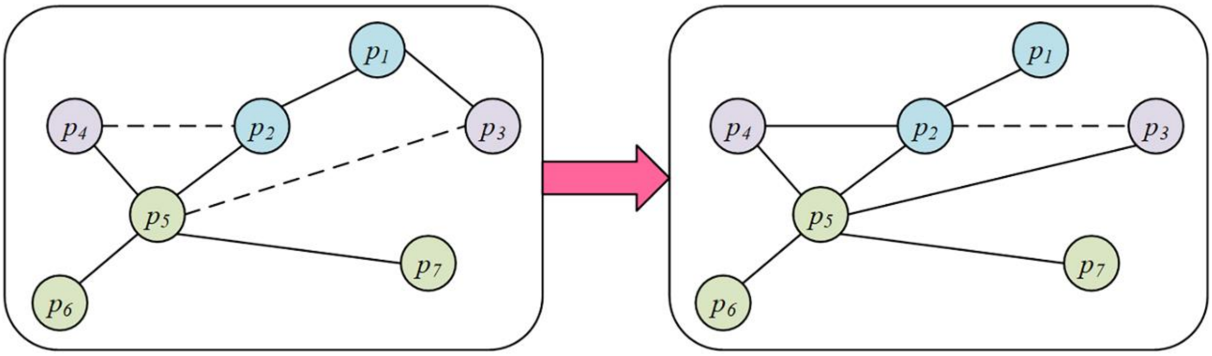

Figure 4: The process of triangulation.

On the left side of Fig. 4 is the original network, where nodes represent different process steps and edges represent the dependencies between each step. In the case of uncertain information, this dependency relationship may be complex and difficult to infer directly. Through the triangulation process, some edges are added to ensure that the network can form an acyclic graph decomposition structure when constructing the BN model, making conditional independence clearer and facilitating probability calculations [29]. The designed algorithm will be named Bayesian Process Scheduling Optimization Algorithm (BPSOA).

In order to verify the effectiveness of the optimization scheduling algorithm in the automotive manufacturing process, a series of systematic simulation experiments were designed and studied. The experiment was conducted on a computer equipped with an Intel Core i7 processor and 16 GB RAM, using AWS cloud platform for parallel computing to improve performance. The software tool was simulated and modelled using AnyLogic platform. The experimental data is sourced from a standard dataset of historical fault records and manufacturing processes to ensure its representativeness and reliability. When initializing parameters, set the initial population size to 50, the maximum number of iterations to 200, the crossover rate of the genetic algorithm to 0.8, and the mutation rate to 0.02. The upper and lower limits of time, cost, and quality are set according to the actual production requirements of the manufacturing enterprise. The experiment first constructs a Directed Acyclic Graph (DAG) model with process nodes as the core to describe the dependency relationships between each process step. Next, establish constraints for scheduling optimization, including time constraints, cost constraints, and quality constraints, to ensure that the scheduling plan meets enterprise standards. In terms of algorithm configuration, experiments compared the performance of Bayesian Process Scheduling Optimization Algorithm (BPSOA), Ant Colony Optimization (ACO), Simulated Annealing Algorithm (SA), Particle Swarm Optimization (PSO), and Genetic Algorithm (GA). Among them, the evaluation indicators include mean absolute error (*MAE*), root mean square error (*RMSE*), processing time, resource utilization rate, and failure rate to verify the adaptability and stability of BPSOA in uncertain environments, and to compare its advantages and disadvantages with traditional optimization algorithms in terms of convergence speed, scheduling accuracy, and resource utilization efficiency.

4. RESULTS AND DISCUSSION

4.1 Policy analysis of optimization scheduling for auto manufacturing

The study first compares the errors in the process, as shown in Fig. 5.

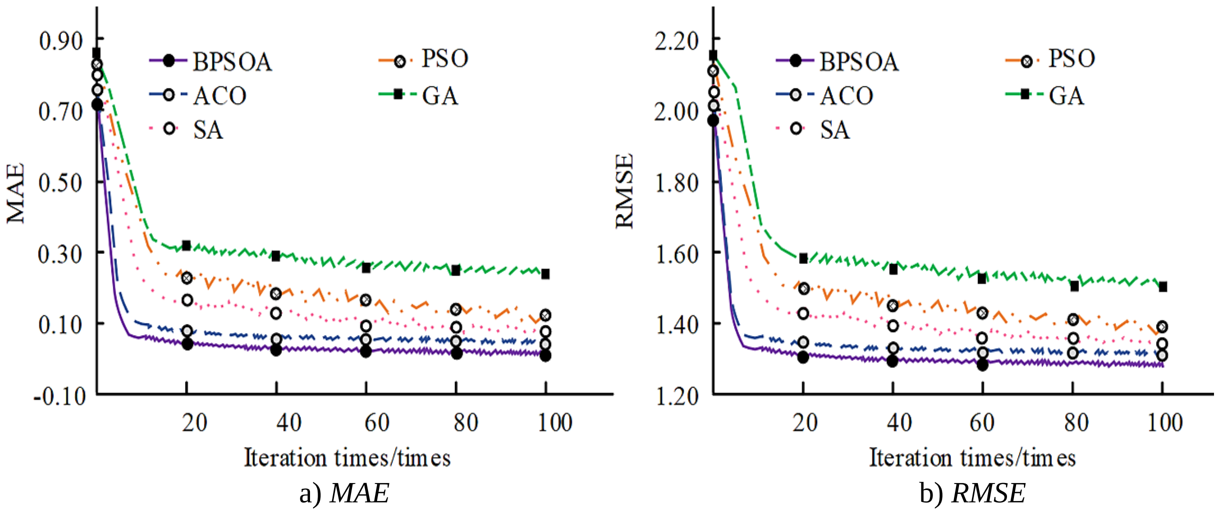

Figure 5: Error comparison of different algorithms in process optimization.

Fig. 5 a shows that BPSOA started with a *MAE* near 0.8 and quickly dropped to around 0.1 in the first 20 iterations, then stabilized at a low error level. ACO and SA began with high *MAE* values, converging slowly to around 0.2, while PSO was slower, stabilizing at 0.3 *MAE*. GA had the slowest decrease, ending at about 0.4 *MAE*. Fig. 5 b indicates that BPSOA's initial *RMSE* was around 2.1, which quickly decreased to 1.3 after 20 iterations and later stabilized at 1.2. ACO and SA both saw significant reductions in the first 20 iterations, converging at 1.4 *RMSE*. PSO had a slower convergence, stabilizing at 1.5 *RMSE*, while GA had the slowest decline, with a final *RMSE* of around 1.6. The loss variations of different optimization algorithms on three automotive manufacturing datasets are shown in Fig. 6.

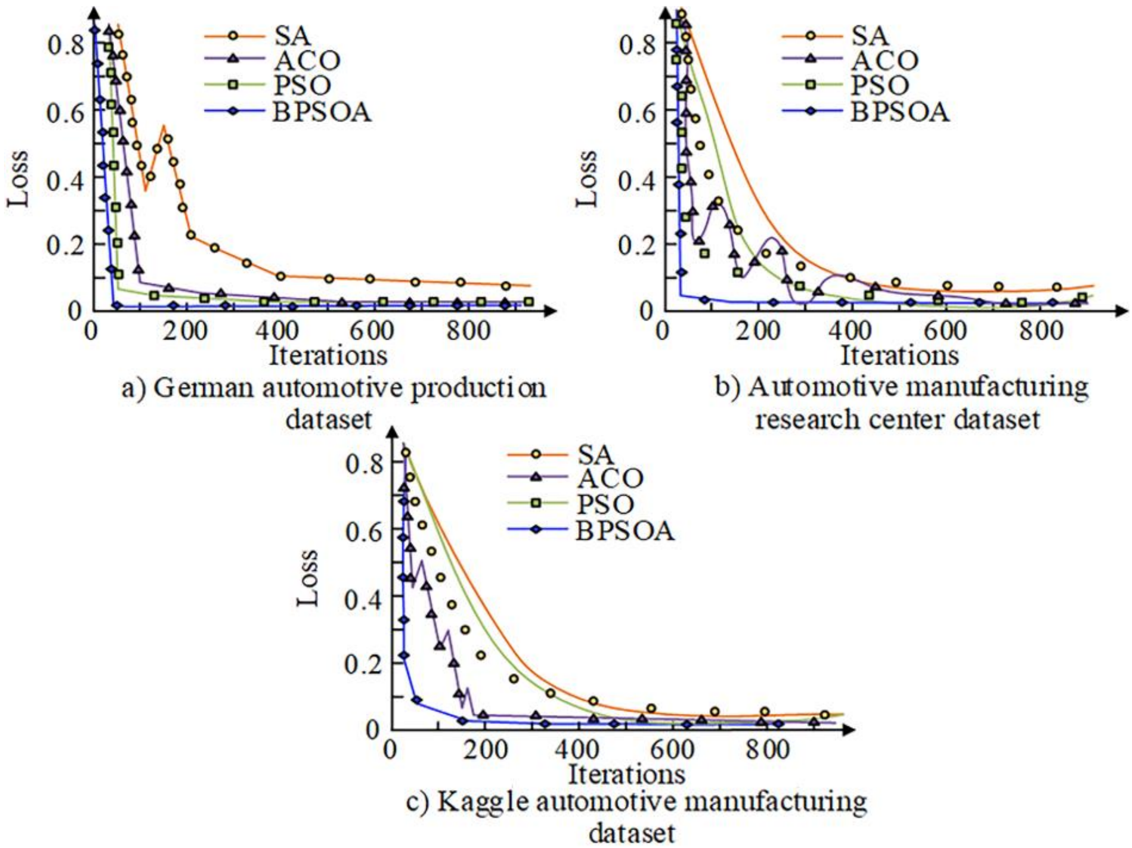

Figure 6: Loss variation of different optimization algorithms on three automotive manufacturing datasets.

As shown in Fig. 6 a, initially, the loss of all four algorithms is about 0.8. BPSOA performs better than other algorithms, losing 0.02 in the first 100 iterations and stabilizing. ACO and PSO reached 0.05 after 200 iterations, while SA remained stable at 0.08 after 800 iterations. As shown in Fig. 6 b, on this dataset, BPSOA rapidly reduced the loss to below 0.05 in the first 100 iterations and remained stable. ACO and PSO reached 0.15 and 0.2, respectively, after 200 iterations, while SA slowly stabilized at 0.09. As shown in Fig. 6 c, in the Kaggle dataset, BPSOA decreased to about 0.07 and stabilized in the first 100 iterations. ACO and PSO reached 0.1 and 0.15, respectively, after 200 iterations, while SA remained stable at 0.07 after 800 iterations. The evaluation of BPSOA performance on process results is shown in Table I.

Table I: Evaluation of BPSOA performance on process results.

Process node	**Average processing cost** (10,000 CNY)	**Minimum quality score**	**Maximum handling time** (Hours)	**Resource utilization ratio** (%)	**Overall failure rate** (%)
p1	11.68	76.54	3.45	88.77	4.82
p2	9.54	89.35	2.68	87.79	3.20
p3	14.88	82.23	4.12	93.46	2.64
p4	10.46	90.57	3.57	89.12	5.12
p5	15.29	85.89	3.90	91.23	2.79
p6	8.65	92.12	2.23	85.68	1.87
p7	12.35	83.46	4.46	92.57	3.46
p8	11.23	87.12	3.89	94.01	4.57
p9	13.46	86.54	2.68	90.10	1.23
p10	17.88	81.68	4.57	95.43	2.35

The data in Table I shows that the average processing cost of the ten process nodes ranged from 86543 yuan to 178765 yuan. The observed minimum mass fraction ranged from 76.54 to 92.12, while the maximum processing time fluctuated between 2.23 hours and 4.57 hours. The resource utilization rate was generally high, reaching up to 95.43 %. The overall failure rate indicated a good trend in operational efficiency, with failure rates ranging from 1.23 % to 5.12 %. These performance results reflected the effectiveness of BPSOA in optimizing automotive manufacturing workflows, which can improve quality and efficiency while reducing costs.

4.2 Application analysis of optimization scheduling for auto manufacturing

The fluctuation comparison of key performance indicators of different algorithms in the optimization and scheduling of automotive manufacturing process flow is shown in Fig. 7.

Fig. 7 a shows the SA algorithm with stable task completion times, averaging 5 to 6 hours, with the minimum at 4.5 hours and the maximum at 6.5 hours. Fig. 7 b indicates the ACO algorithm had significant cost fluctuations, averaging around 1 unit, with values ranging from -1 to 3 units, including negative costs in some experiments. Fig. 7 c reveals the PSO algorithm's stable resource utilization, averaging between 5.0 and 6.0, with a minimum of 4.0 and a maximum of 6.5. Fig. 7 d demonstrates the SA algorithm's stable output quality, with an average score near 1.0, fluctuating slightly between 0.9 and 1.1. Although the score was slightly lower, the stability was high, indicating that the BPSOA can maintain consistent output quality under different experimental conditions. The simulation results of optimization scheduling for automotive manufacturing processes are shown in Table II.

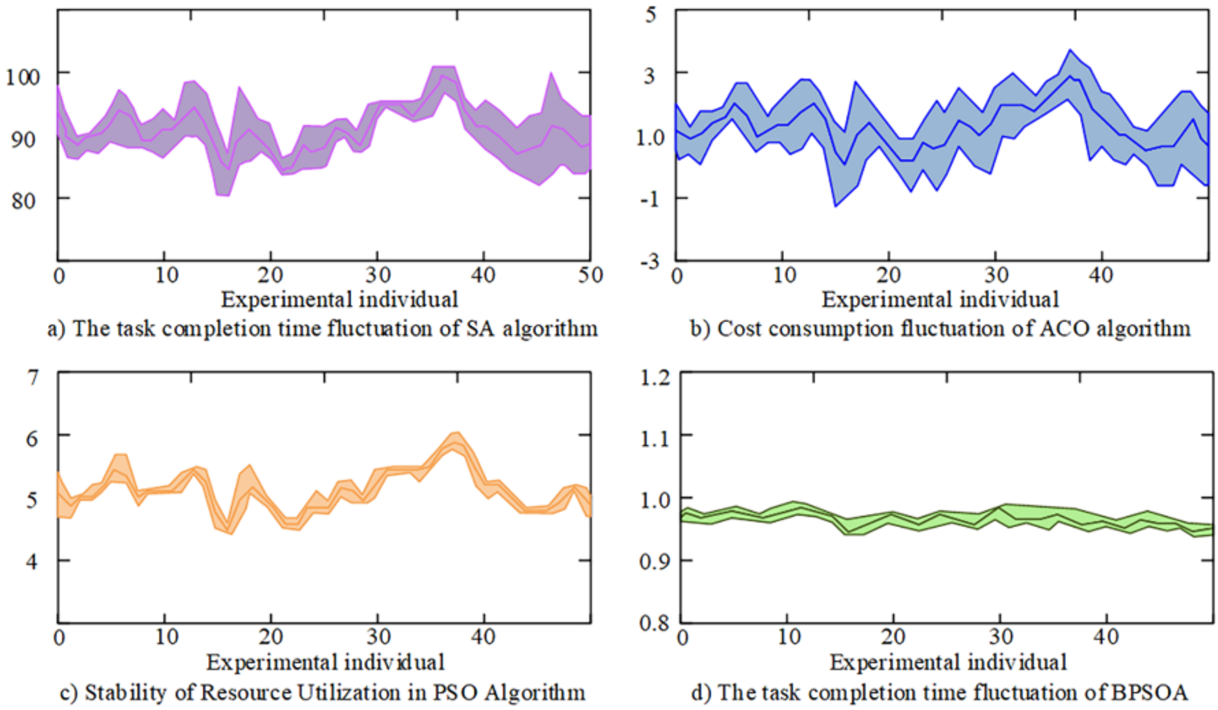

Figure 7: Comparison of key performance index fluctuations of different algorithms in automotive manufacturing process optimization scheduling.

Table II: Results of optimized scheduling simulation for automotive manufacturing processes.

Process node	**Minimum processing cost** (10,000 CNY)	**Maximum quality score**	**Average handling time** (hours)	**Resource utilization rate** (%)	**Failure rate** (%)
p1	12.49	85.63	2.14	90.12	3.43
p2	8.77	90.54	1.99	85.46	2.91
p3	15.46	78.12	3.46	92.20	1.71
p4	9.23	88.99	2.18	88.65	4.57
p5	14.99	82.46	3.68	91.54	3.88
p6	7.54	92.35	1.46	87.12	2.15
p7	10.88	89.65	2.57	90.99	2.43
p8	11.12	80.88	3.89	93.23	5.68
p9	13.46	85.23	2.89	89.88	2.35
p10	18.77	86.54	4.12	94.32	1.23

Table II indicates that the minimum process cost for each node fluctuated between 754,321 and 1,876,543 yuan, while the maximum process quality ranged from 78.12 to 92.35 points. The average processing time varied from 1.46 to 4.12 hours. The resource utilization rate was high, peaking at 94.32 %, and the failure rate remained stable within a few percentage points. These results suggest that the probabilistic reasoning of Bayesian Networks can enhance the adaptability and efficiency of the process flow under uncertain conditions.

5. CONCLUSION

This study addresses the optimization and scheduling challenges in the automotive manufacturing industry, a sector that is crucial for industrial efficiency and innovation. A framework that integrates recognition rules and Bayesian networks has been proposed to balance the competing objectives of cost, time, and quality. Utilizing a workflow model and the Bayesian Process Scheduling Optimization Algorithm (BPSOA), the factors were optimized within defined time constraints. The BPSOA demonstrated a Mean Absolute Error (*MAE*) of 0.1 and a Root Mean Square Error (*RMSE*) of 1.2 after 20 iterations, outperforming other algorithms. The algorithm achieved average processing costs ranging from 86,543 to 178,765 CNY, quality scores between 76.54 to 92.35, and handling times from 2.23 to 4.57 hours. The resource utilization rate reached up to 95.43 %, with failure rates between 1.23 % and 5.12 %. This algorithm has better performance in ensuring scheduling accuracy. This performance improvement is mainly attributed to the modelling ability of Bayesian networks in dynamic environments, which enables scheduling results to more flexibly respond to real-time changes and complex dependencies. In addition, by adjusting the parameters of the genetic algorithm, such as crossover rate and mutation rate, the scheduling process was further optimized, and the convergence speed of the algorithm was improved. Meanwhile, according to the results, BPSOA has a lower failure rate in extreme situations, reflecting its stability under high loads and complex constraints. This is crucial for practical production applications, as it can effectively reduce production stagnation and resource waste caused by improper handling. The study's limitations include the potential for improvements in data quality and the necessity of testing the algorithm in dynamic, real-world scenarios. Future work should focus on enhancing the model with more detailed data and integrating advanced analytics to improve prediction accuracy and adaptability to changing conditions.

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