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OPTIMIZING MANUFACTURING SCHEDULING WITH GENETIC ALGORITHM AND LSTM NEURAL NETWORKS

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Abstract
In response to Industry 4.0 and the rise of intelligent manufacturing, this study develops a system combining Long Short-Term Memory (LSTM) Neural Networks and a Multi-Objective Genetic Algorithm to improve prediction and optimization in manufacturing scheduling. A novel model predicts work-in-process (WIP) inventory using LSTM neural networks, accommodating dynamic changes in production. A manufacturing scheduling model is also created and solved using a multi-objective genetic algorithm, simplifying the resolution process and obtaining practical solutions. These methods provide a valuable approach to optimizing production scheduling in intelligent manufacturing, enhancing efficiency and economic gains.
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Key Words: Intelligent Manufacturing, Scheduling System, LSTM Neural Networks, Multi-Objective Genetic Algorithm, WIP Inventory Forecasting, Model Resolution

1. INTRODUCTION

In the era of Industry 4.0, manufacturing has transformed from a human-centric approach to an intelligence-guided one [1-4]. Central to this is the intelligent manufacturing scheduling system, aiming for automated and efficient production [5, 6]. Key components include precise forecasting of WIP inventory input and the development of optimization models [7-9].

Effective scheduling depends on logical production planning and accurate prediction of WIP inventory, having strategic importance for enterprises [10-13]. Proper prediction of WIP inventory assists in decision-making, optimal resource utilization, and prevention of resource waste, boosting production efficiency [14-17]. Moreover, rational model resolution provides a scientific foundation for decision-making, enhancing operational proficiency [18-20].

However, there are challenges in current scheduling methods mainly based on statistical and mathematical theories [21-23]. Issues include handling non-linear data, complex data patterns, and adapting to production changes [21-23]. Multi-objective optimization often results in conflicts between objectives, complicating the resolution process.

This research addresses two main areas. First, it presents a deep learning model, using LSTM Neural Networks, for WIP inventory prediction [7-9]. This model capitalizes on historical data for precise forecasting and adapts to production shifts. Secondly, a method using a Multi-Objective Genetic Algorithm resolves the manufacturing scheduling model. This approach manages conflicts between objectives, simplifying resolutions and yielding feasible results. These technologies have significant implications for enhancing production scheduling in intelligent manufacturing.

2. LSTM NETWORKS FOR MATERIAL INPUT PREDICTION

In intelligent manufacturing, accurately predicting turnover material input volume is essential. Influenced by factors such as production volume, product type, machinery capacity, and environmental conditions, this task is intricate. LSTM Neural Networks, a variant of RNNs, have emerged as a suitable solution.

LSTMs handle time-series data, capturing historical patterns of turnover material input. With its forget gate, input gate, output gate, and memory cell, LSTMs address gradient issues that traditional RNNs face, optimizing them for modern manufacturing predictions.

The forget gate is denoted by *d*, input gate by *u*, output gate by *p*, and internal memory cell by *v*, where *v* controls the degree of forgetting the current layer input z_u and the output of the previous hidden layer node g_{u-1}. The function of the forget gate is to determine how much previous information the LSTM unit should forget. By learning to remove certain information from the cell state, the LSTM can adaptively forget old, unnecessary information, making space for new, more relevant information. The expression for the forget gate function is given by:

$$d_y = \delta\left(Q_u z_y + I_u g_{y-1} + n_u\right) \tag{1}$$

The input gate regulates the flow of new information into the LSTM cell. It adjusts the update of the LSTM cell's internal state based on the required information. The function for the input gate is:

$$u_y = \delta\left(W_u z_y + I_u g_{y-1} + n_u\right) \tag{2}$$

$$v'_y = \tanh\left(Q_V z_y + I_V g_{y-1}\right) \tag{3}$$

The internal memory cell is the LSTM's core, holding its state information. With the forget and input gates, the LSTM can discard old data and incorporate new details, preserving long-term dependency information. The function for this cell is:

$$v_y = d_y * v_{y-1} + u_y * v'_y \tag{4}$$

The output gate determines to what extent the current state of the LSTM unit will affect other neurons. It controls when and how the LSTM unit outputs externally. The expression for the output gate function *p* is as follows:

$$p_y = \delta\left(Q_p z_y + I_p g_{y-1} + n_p\right) \tag{5}$$

$$g_y = p_y * \tanh\left(v_y\right) \tag{6}$$

Analysis shows that the turnover material input prediction model in intelligent manufacturing should incorporate 12 variables, including machine capacity, operation status, inventory, processing time, labour cost, and the past seven days' input volume. The number of hidden layer nodes, initially set at 12, was tested within the range [12-γ, 12+γ]. By comparing various node quantities, the optimal number was confirmed to be 12. For this model, predicting a scalar value for a specific time period, the output layer has one node. Typically, the nodes in input and output layers are determined by the problem's nature, while hidden layer nodes are set through trials or heuristic methods for best prediction results.

For activation functions, *sigmoid* and *tanh* functions are chosen, as expressed below:

$$SM\left(z\right) = \frac{1}{1+e^{-z}} \tag{7}$$

$$\tanh\left(z\right) = \frac{\sin\left(z\right)}{\cos\left(z\right)} \tag{8}$$

The predicted turnover material input volume at the u^{th} hour of the day is denoted by W_u, machine production capacity by Y_u, machine operation status by G_u, inventory by Q_u, processing time by E_u, labour cost by R_u, and accumulated turnover material input volume from the 1st to 7th day in the k^{th} period by W_{k-1} to W_{k-7}. The final non-linear relationship established by the LSTM neural network is given by:

$$W_u = d\left(Y_u, G_u, Q_u, E_u, R_u, W_{k-1}, W_{k-2}, ..., W_{k-7}\right) \tag{9}$$

3. INTELLIGENT MANUFACTURING SCHEDULING: MODEL AND SOLUTION

3.1 Model construction

In intelligent manufacturing, interconnected production stages have unique cycles and turnover materials. Ensuring material availability is crucial. Once scheduled, material cycles can be determined, setting stage deadlines, as shown in Fig. 1. Dependencies, like how the assembly might impact fabrication, are vital. The model aims to optimize the schedule, minimizing production time and costs. It identifies a schedule vector within a deadline, coordinating activities and reducing costs.

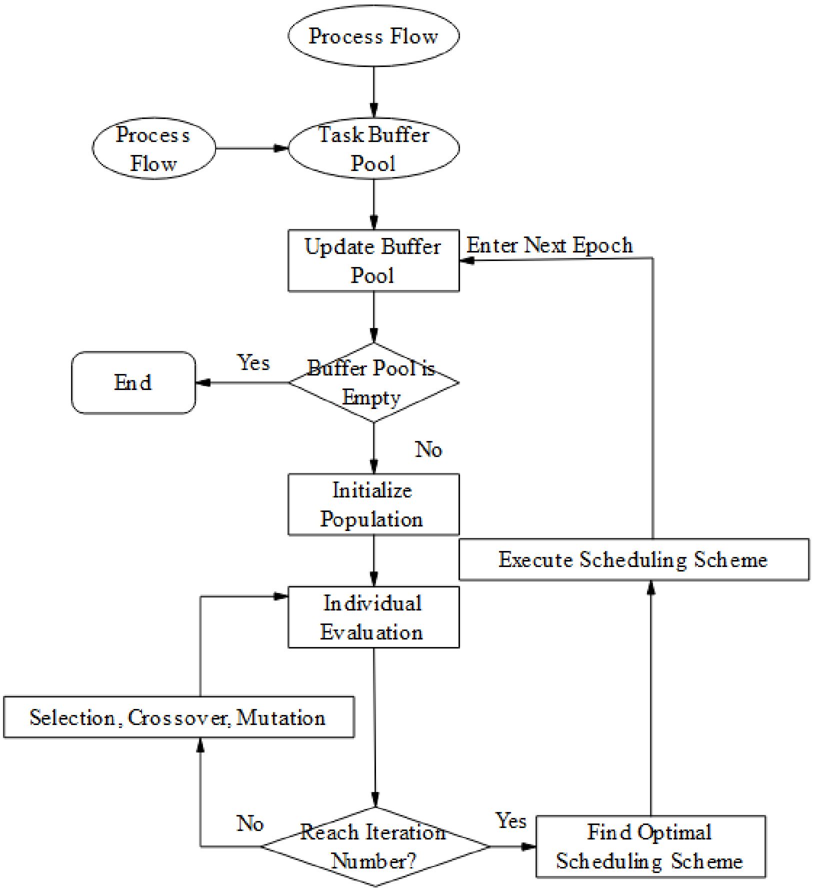

Figure 1: Execution flow of intelligent manufacturing scheduling simulation model.

In the intelligent manufacturing multi-mode time-cost trade-off model constructed in this context, a project is composed of b+2 fabrication processes, each of which can be considered an activity. These activities are assembled into a set $C = \{1, ..., b+2\}$, where activity 1 and activity b+2 are virtual activities, representing the start and completion of the project.

Each non-virtual activity $k \in C$ has L_k execution modes. Each mode has its own start time A_k, execution time o_{kl}, and direct costs v_{kl}. Moreover, the fabrication cost of precast components includes both direct costs $v_{kl}\, z_{kl}$ and indirect costs $e \times f$.

To meet the project deadline σ, the objective is to derive an optimal scheduling plan that curtails the project's duration and costs. Key components of this model include:

- Activities and modes: each non-virtual activity has varied execution modes with distinct start times, durations, and costs.
- Costs: precast component fabrication costs encompass direct and indirect expenses.

- Optimization goal: The aim is to formulate a schedule minimizing time and costs within the deadline constraints.
- Expressions: The model provides expressions with a focus on schedule minimization, given by:

$$MIN\sum_{k=1}^{b+2} f_{kl} \tag{10}$$

Assuming indirect costs are *e*, and production schedule is represented by *f*, the objective function to minimize project costs is given by:

$$MIN\sum_{k=1}^{b+2}\sum_{l\in L_k} v_{kl} z_{kl} + \sum_{k=1}^{b+2} e\times f_{kl} \tag{11}$$

Constraints for decision variable z_{kl} are provided by:

$$s.t \sum_{l\in L_k} z_{kl}, k=1, k=1,...,b+2 \tag{12}$$

Precedence constraints for production activities are given by:

$$a_u + \sum_{l\in L_k} f_{kl} z_{kl} \le A_k, \forall, \langle u,k\rangle \in S(y) \tag{13}$$

Completion time must meet the project deadline σ:

$$A_{b+2} \le \sigma \tag{14}$$

Each activity's start time must be non-negative:

$$A_K \ge 0, \forall K \in C \tag{15}$$

The decision variable must take a value of 0 or 1:

$$z_{kl} \in \{0,1\}, \forall l \in L_k \tag{16}$$

This model analyses the project in detail, considering various activity execution modes and costs, aiming to optimize scheduling to reduce both time and expenses. This is vital for intelligent manufacturing's scheduling system.

3.2 Model solution

For the intelligent manufacturing multi-mode time-cost trade-off model, a solution approach based on the multi-objective genetic algorithm is suitable due to its global search traits and multi-objective optimization properties. This ensures the optimal solution meets the set constraints.

This model uses a two-tier encoding method, which includes "production sequence" and "execution modes." The "production sequence" reflects the order of all non-virtual activities within a project. The genetic algorithm's goal in this encoding is to arrange activities to optimize both time and cost. Each activity gets a unique identification number, symbolizing its execution order.

"Execution mode," on the other hand, relates to the various methods available for performing each non-virtual activity. This encoding focuses on choosing the best execution method for each activity to achieve time and cost optimization. The genetic algorithm works on both encoding levels simultaneously, finding the best solution per time and cost standards. This dual-layer encoding is significant because it considers both activity order and execution method, aligning more with real-world production scheduling.

NSGA-II (Non-dominated Sorting Genetic Algorithm II) is employed, a popular multi-objective optimization genetic algorithm. Optimal solutions are identified using rapid non-dominated sorting and crowding distance computation.

NSGA-II's hallmark is its non-dominated sorting process. Solutions are initially categorized based on dominance, creating different dominance layers. No solution in a tier dominates another in the same tier, but those in higher tiers do dominate those below. The sorting begins with the top dominance layer's solutions, followed by the next, and so on. The specific steps include:

Step 1: Set $u = 1$.

Step 2: For any $k = 1, 2, ..., b$ and $k \neq u$, compare the superiority relation between z_u and z_k.

Step 3: If no z_k is better than z_u, then z_k is a non-dominated solution of the model.

Step 4: Let $u = u + 1$ and go to *Step 2* until all non-dominated solutions of the model are found.

Repeating *Steps 1-4* while excluding solutions from the first non-dominated layer produces the next non-dominated layer. This process continues until all populations are ranked.

If a dominance layer contains a large number of individuals, NSGA-II uses crowding distance calculation for further selection. Crowding distance measures the density around an individual, calculated by summing distances between neighbours across all objectives. A higher crowding distance suggests a less dense area and superior solution quality. The specific steps are detailed next:

Step 1: Set the crowding distance b_f for each point to 0.

Step 2: Conduct non-dominated sorting for all objectives, and set the boundary individual B_f to ∞.

Step 3: Assuming that the crowding distance is represented by b_f, the value of the k^{th} objective function for the $X + 1$ point is represented by $d^{b+1}{}_k$, and the value of the k^{th} objective function for the $u - 1$ point is represented by $d^{b+1}{}_k$, with the maximum value of the objective function value d_k represented by $d^{MAX}{}_k$ and the minimum value by $d^{MIN}{}_k$. Crowding distance is then calculated for other individuals based on the following formula:

$$b_f = \sum_{k=1}^{l} \left(\frac{\left| d_k^{b+1} - d_k^{b-1} \right|}{d_k^{MAX} - d_k^{MIN}} \right) \tag{17}$$

In NSGA-III's selection process, if two individuals belong to the same domination layer, the one with the larger crowding distance is deemed superior. The elitist preservation strategy in genetic algorithms ensures the best individuals aren't lost due to random operations like crossover and mutation. Preferred parents V_u and offspring F_u form the population E_u. Infeasible solutions are discarded, and the population is ranked into V_{u+1} based on non-domination values. Individuals are added to V_{u+1} using calculated crowding distances until the number reaches B.

(1) Selection: Genetic algorithms use selection based on an individual's fitness, dictating its representation in the next generation. Multi-objective genetic algorithms first rank individuals based on non-domination sorting. Those in superior levels are prioritized for the next generation. If two individuals are on the same level, the one with a larger crowding distance is prioritized.

(2) Crossover, Mutation: These operations generate new individuals. The elitist preservation strategy ensures the best individuals remain undamaged. In crossover, the best individual can have a higher chance of being selected as a parent, preserving its genes. In mutation, mechanisms can prevent optimal individual genes from random changes, or a reduced mutation rate can be applied.

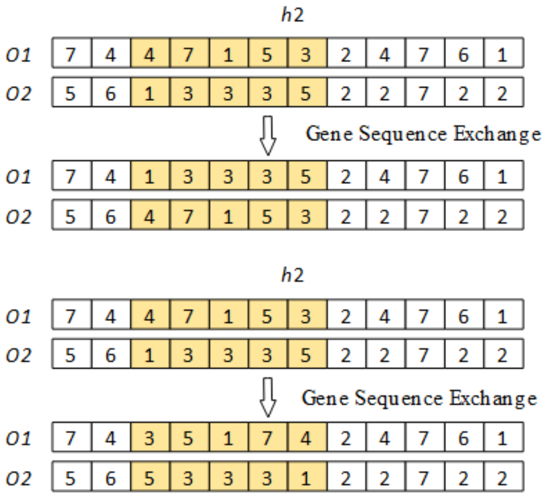

Figure 2: Improved crossover mutation operator diagram.

Fig. 2 depicts the refined crossover and mutation operators. The crossover operation might set a probability ensuring optimal individuals are more likely chosen as parents, retaining their genetic quality. During mutation, protection for optimal individuals can be in place, or a reduced mutation rate can be set. Fig. 3 provides a crossover example from this study's context.

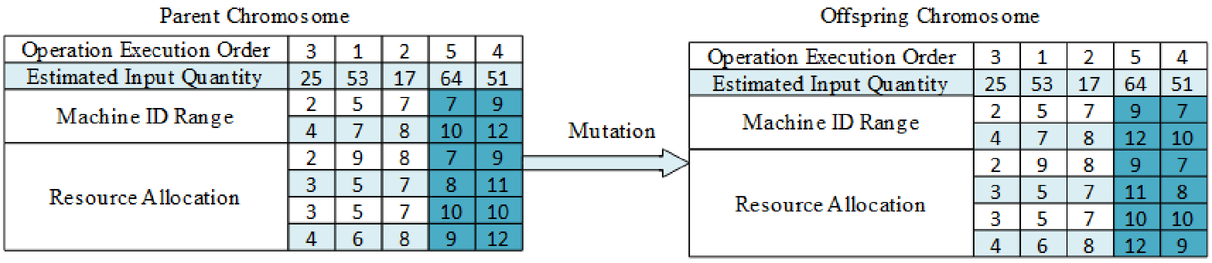

Figure 3: Crossover schematic diagram.

For multi-attribute decision-making in intelligent manufacturing scheduling, management personnel can follow these steps. Given that attributes may vary in units and dimensions, normalization is vital to prevent biases. Linear normalization adjusts all data between 0-1, while zero-mean normalization standardizes data using mean and standard deviation, setting a new mean of 0 and standard deviation of 1. This balances the significance of different attributes. If the dimensionless value of the l^{th} objective function is denoted by $d_l(b)$ from the b^{th} optimal solution, the normalization formula is provided as:

$$d_l(b) = \frac{s_l^{MIN}}{s_l} \tag{18}$$

$$s_l^{MIN} = MIN\{s_{l1}, \ldots, s_{lb}\} \tag{19}$$

For effective manufacturing scheduling, it's essential to assign appropriate weights to each attribute. Weighting can be subjective, based on decision-maker experience, or objective, derived from data characteristics. Methods like intuitive weighting and comparative judgment are subjective, while information entropy or variance-based methods are objective. These weights help in emphasizing each attribute's significance in decision-making.

After normalization and weight determination, a weighted evaluation is conducted. Here, scores for each decision scheme are computed using attribute weights and values. The scheme with the highest total score is deemed optimal.

In summary, to achieve effective multi-attribute decision-making in intelligent manufacturing scheduling, management must normalize attributes, calculate their weights, and perform a weighted evaluation. Depending on the scenario, the methods and parameters can be adjusted. The formula to compute this is:

$$Q = \beta d_1(b) + \alpha d_2(b) \tag{20}$$

4. SIMULATION RESULTS

In Fig. 4, the predicted turnover material input, using an LSTM neural network model, aligns closely with actual values, demonstrating the model's accuracy. Especially during peak and trough periods, the model adeptly captures the fluctuations, underscoring its predictive strength. While the model generally provides precise forecasts, there are intervals where noticeable deviations occur, likely due to noise in the sample data.

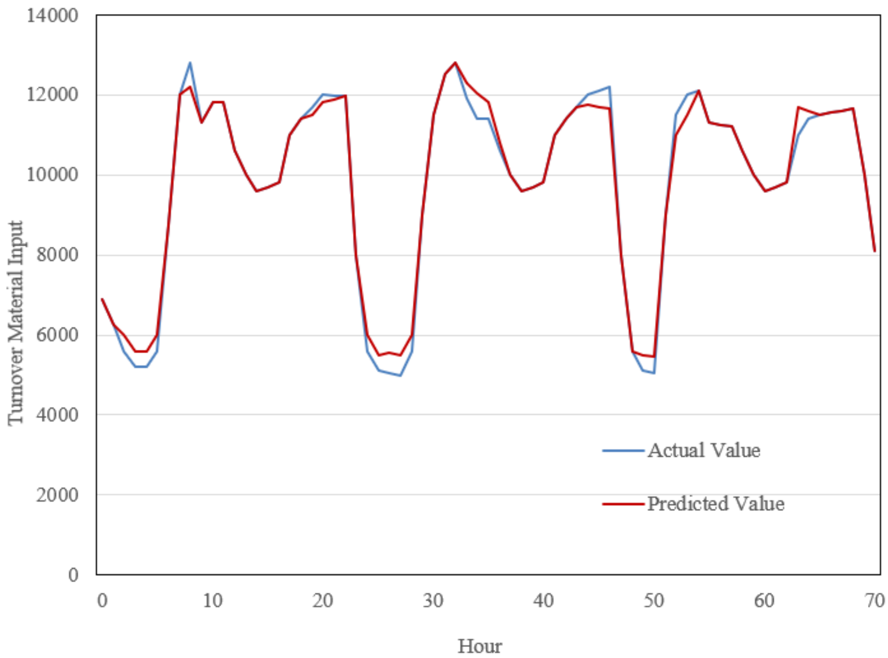

Figure 4: Comparison of predicted and actual cumulative input quantity in the manufacturing workshop.

Analysing the simulation data in Table I reveals that most predicted values align closely with actual ones, with deviations staying within a 5 % threshold. However, there were instances, like during specific hours on the 1st and 2nd days, where deviations surpassed this limit. Such variations could result from unforeseen circumstances, including equipment issues or staffing changes. The data also suggests that the model tends to overestimate, likely due to its emphasis on higher input points during training.

Fig. 5 shows a decline in population fitness values as iterations increase, demonstrating the effectiveness of the multi-objective genetic algorithm. The initial phases, specifically from iterations 0 to 25, display a sharp decline, reflecting a broad exploration of potential solutions. Between iterations 25 and 50, a plateau suggests the discovery of a potential optimal solution. From iteration 50 onwards, there's a steady reduction in fitness, indicating the algorithm's capability to move past local optima. By iterations 100 to 200, fitness values stabilize around 24, hinting at the attainment of an optimal solution. Overall, while the algorithm showcases notable efficiency, it's crucial to remember that global optima are not always guaranteed, especially in complex scenarios. Choosing appropriate algorithms and parameters based on the problem's characteristics remains vital.

Table I: Comparison of machine turnover material input predictions and actual values.

Date	Hour	Actual value	Predicted value	Deviation	Date	Hour	Actual value	Predicted value	Deviation
	1	66.25	67.21	1.12 %		1	67.21	67.27	0.51 %
	2	54.26	53.27	3.61 %		2	56.22	58.24	3.56 %
	3	52.36	51.30	5.62 %		3	52.37	51.35	5.1 %
	4	51.88	52.83	6.21 %		4	53.85	53.81	5.56 %
	5	53.94	52.95	3.28 %		5	55.93	54.91	3.89 %
	6	96.34	95.36	4.25 %		6	98.34	97.34	1.25 %
	7	121.42	119.49	4.69 %		7	120.45	119.45	0.72 %
	8	128.30	127.35	4.26 %		8	122.37	121.34	1.33 %
	9	121.42	122.47	3.05 %		9	121.45	112.40	1.23 %
	10	118.23	117.26	2.65 %		10	115.21	114.25	0.68 %
	11	121.05	122.07	0.25 %		11	122.08	122.02	2.92 %
Day 1	12	114.23	115.24	1.38 %	Day 2	12	116.24	115.27	1.31 %
	13	116.32	115.35	0.89 %		13	117.38	118.32	2.78 %
	14	97.36	96.38	0.24 %		14	97.37	96.31	3.56 %
	15	96.24	95.22	0.61 %		15	94.21	93.27	1.29 %
	16	98.36	99.35	0.35 %		16	98.37	97.33	1.89 %
	17	106.03	104.01	0.71 %		17	101.01	101.05	1.69 %
	18	121.45	122.43	0.54 %		18	121.45	121.46	0.51 %
	19	116.28	115.22	0.53 %		19	115.27	114.26	1.02 %
	20	110.88	111.81	1.89 %		20	112.87	113.88	0.23 %
	21	121.56	122.55	1.26 %		21	120.51	121.57	0.02 %
	22	115.36	116.32	0.82 %		22	114.37	114.33	3.81 %
	23	105.23	104.25	2.54 %		23	107.28	108.27	0.55 %
	24	84.26	82.27	2.61 %		24	80.25	81.22	0.88 %

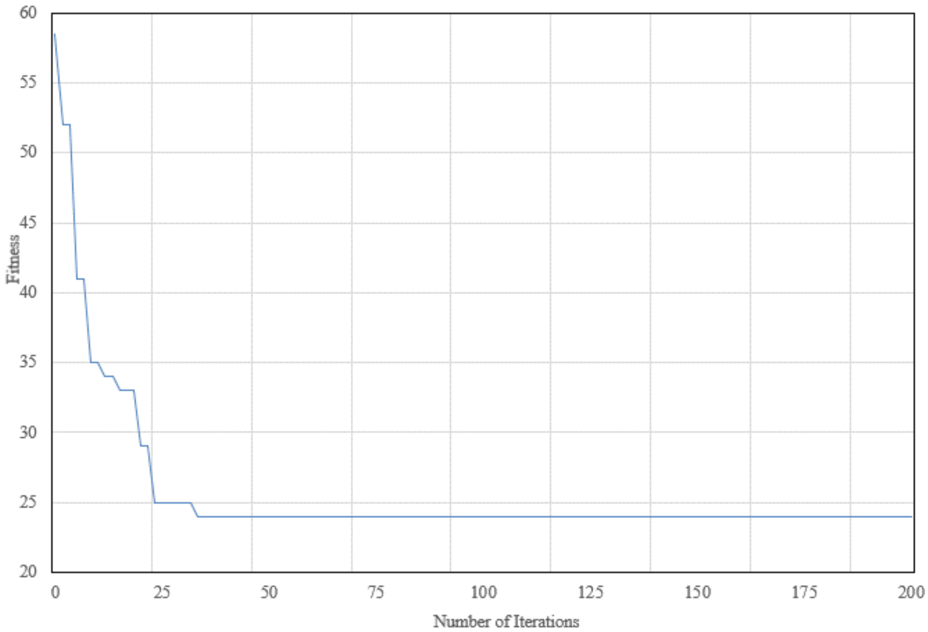

Figure 5: Genetic algorithm population iteration curve.

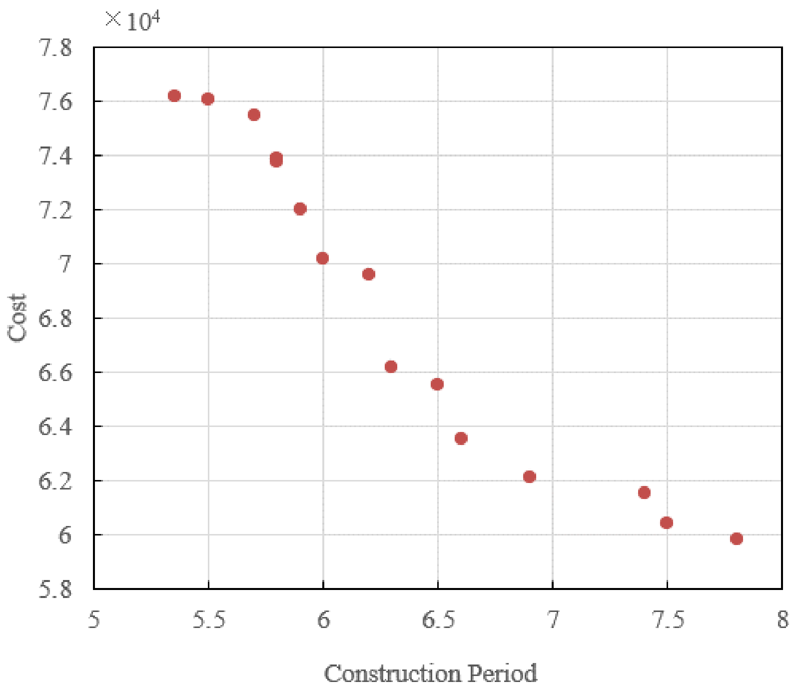

Figure 6: Pareto optimal solutions.

Pareto optimal solutions represent the pinnacle in multi-objective optimization, marking solutions where improving one objective may worsen another. In our context, the twin objectives are minimizing both duration and cost. Fig. 6 depicts a simultaneous decline in both, signifying a balance between them. However, it's essential to recognize that a decrease in duration might raise costs, and vice versa. Manufacturers must choose suitable solutions from the Pareto set based on specific business needs, aiming for the best balance between duration and cost.

Table II lists the mean and standard deviation (*std*) for various enhanced genetic algorithms (SAGA, PGA, FGA, QGA, DAGA) and the proposed method across different operation quantities. The mean indicates solution quality, while the std shows stability; lower values are preferred for both. The data suggests that the proposed method consistently boasts the lowest mean across all operation quantities, pointing to its superior ability in identifying optimal solutions. Additionally, its consistently low standard deviations indicate impressive stability.

Table II: Experimental results of different genetic algorithms.

Number of operations	Method in this paper		SAGA		PGA	
	mean	*std*	*mean*	*std*	*mean*	*std*
20	9.51 E1	6.58	9.45 E1	7.41	1.03 E2	8.56
40	1.66 E2	1.94 E2	1.62 E2	2.42 E2	1.55 E2	2.51 E2
60	2.96 E2	2.25 E2	2.96 E2	2.89 E2	2.02 E2	2.78 E2
80	4.81 E2	3.06 E2	4.72 E2	3.85 E2	3.89 E2	4.31 E2
100	9.28 E2	5.56 E2	8.85 E2	6.77 E2	7.99 E2	7.36 E2
Number of operations	FGA		QGA		DAGA	
	mean	*std*	*mean*	*std*	*mean*	*std*
20	1.25 E2	7.58	1.45 E2	1.35 E1	1.29 E2	1.31 E1
40	1.64 E2	1.69 E1	1.92 E2	1.42 E1	1.85 E2	1.85 E1
60	3.28 E2	2.41 E1	3.87 E2	2.32 E1	3.63 E2	2.53 E1
80	5.39 E2	4.33 E1	5.69 E2	3.88 E1	5.48 E2	3.24 E1
100	1.09 E3	8.49 E1	1.23 E3	7.26 E1	1.08 E3	7.88 E1

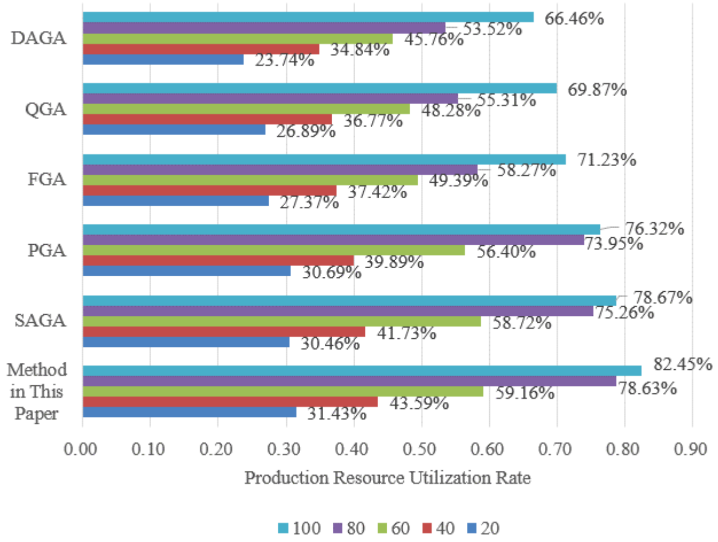

Figure 7: Comparison of resource utilization rates in intelligent manufacturing production for different genetic algorithms.

Fig. 7 presents a comparison of resource utilization rates among various genetic algorithms, including the proposed method, SAGA, PGA, FGA, QGA, and DAGA, over different operation quantities. A clear increase in resource utilization rates is evident as the number of operations grows for all algorithms. Significantly, the proposed method showcases the highest resource utilization rates, particularly for 80 and 100 operations, outperforming its counterparts. This highlights the proposed method's strength in enhancing resource utilization and manufacturing efficiency, especially for large-scale operational challenges.

In conclusion, the proposed method excels in various aspects of intelligent manufacturing production, from prediction accuracy to optimization and resource utilization, outmatching other genetic algorithms. These observations affirm the research's proposition that the introduced methodology offers a promising approach to boosting efficiency in intelligent manufacturing production.

5. CONCLUSION

In the present study, a comprehensive examination was conducted, principally focused on artificial neural networks and genetic algorithms within the context of intelligent manufacturing production, with particular emphasis on their efficacies in process scheduling and resource utilization optimization. Through a meticulous comparison and analysis of several genetic algorithms (including the method delineated herein, alongside SAGA, PGA, FGA, QGA, and DAGA), a multifaceted conclusion was drawn:

(1) Regarding Process Scheduling and Multi-Objective Optimization: It was demonstrated that the method proposed in the present study exhibits preeminence, especially in aspects of multi-objective optimization and population iteration. A scrutiny of the population iteration process revealed that the method could achieve lower fitness values with fewer iterations, a testament to its superior efficiency in pinpointing optimized solutions. An analysis of Pareto optimal solutions further corroborated a judicious equilibrium between schedule and cost, the two cardinal objectives, as facilitated by the method under investigation.

(2) Concerning Resource Utilization in Intelligent Manufacturing Production: The method delineated herein was found to manifest the highest performance, particularly noticeable with an augmentation in the number of processes. An appreciable enhancement in resource utilization rate was unveiled, underscoring its proficiency in managing larger-scale process scheduling dilemmas, thereby amplifying production efficiency.

(3) Pertaining to Prediction Accuracy: A comparative analysis between actual values and predicted values yielded evidence of an admirable accuracy rendered by the method in this study. A negligible divergence between the predicted outcomes and the actual values was discerned, indicative of an aptitude for precise prognostication of process completion status.

(4) Implications and Future Perspectives: While the proposed method has been shown to outperform other genetic algorithms in areas such as multi-objective optimization, efficiency of population iteration, resource utilization rate, and prediction accuracy, it must be noted that the applicability of such a method necessitates a careful consideration of actual production conditions and environments. Necessary selections and adaptations must be judiciously effected, contingent on specific exigencies in practical implementations. Furthermore, potential extensions of this research could delve into the integration of real-time data, a broader array of intelligent algorithms, or a more diversified set of industry applications.

In summation, evidence has been accrued to support the superior performance of the method proposed in this research, relative to other genetic algorithms, across various facets of intelligent manufacturing production. It has been empirically substantiated that the method in question constitutes an efficacious avenue for the augmentation of efficiency and precision in intelligent manufacturing production. The conclusions herein are resonant with the overarching tenets of the research, contributing to a broader understanding of the field, yet they are also mindful of the real-world complexities and nuances that must guide the application of these findings.

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