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BLOCKCHAIN-DRIVEN OPTIMIZATION IN INTELLIGENT MANUFACTURING

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Abstract
Intelligent manufacturing automation is a future trend, and optimizing production resource control using blockchain technology is a meaningful research topic. Existing studies have limitations, such as varying PSCO-PC models and insufficient flexibility in simulation models. This paper proposes a novel blockchain-based PSCO-PC strategy for intelligent manufacturing. It details the PSCO-PC model, improving the matching rationality and applicability of simulation system functions. The adaptive difficulty concept is introduced to address data throughput and consensus mechanism issues. Calculation steps for solving the optimal package revenue of PSCO matching records are provided. Experimental results confirm the effectiveness of the proposed simulation model and PSCO-PC strategy.
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Key Words: Blockchain Technology, Intelligent Manufacturing, Production-Service Combinatorial Optimization and Production Control (PSCO-PC), Simulation

1. INTRODUCTION

Intelligent manufacturing expands, extends, and partially replaces the brain work of humans during manufacturing process through cooperation between humans and intelligent machines [1-7]. It updates the concept of manufacturing automation to flexible, intelligent, and highly integrated manufacturing, and no doubt, smart (intelligent) is the future trend of manufacturing automation [8-12]. Now, global research on intelligent manufacturing intends to effectively improve manufacturing efficiency through data-driven means [13-15].

Nonetheless, as more intelligent perception devices such as sensors and distributed production devices have been widely used, the massive data generated from intelligent manufacturing production lines has gradually exposed a series of problems with these devices in data processing speed and data storage [16-19], and how to ensure the security of crucial data and the credibility of manufacturing resources has become a bottle neck for the development of intelligent manufacturing [20-25]. When solving the said problems, the blockchain technology [26-28] has exhibited certain advantages, so it’s a meaningful research topic to discuss how to optimize the control of production resources and services of intelligent manufacturing platforms in the meantime as efforts have been made to develop intelligent manufacturing devices and products.

Geng and Du [29] pointed out that intelligent manufacturing includes intelligent production and smart factory, and the phrase “Industry 4.0” is often used to represent intelligent manufacturing. Their paper aimed to improve the efficiency of conventional business mode, reduce production cost, and transform the commercial manufacturing mode towards the direction of automated, intelligent, timely, and on-demand distribution. The authors developed a deep reinforcement consensus algorithm by adjusting the blockchain consensus algorithm into intelligent manufacturing applications through deep reinforcement learning, and their experimental data provided a good reference for follow-up studies. Xu et al. [30] proposed a design scheme of integrated platform for information service provided by participants in supply chain and based on Ethereum blockchain. Authors designed system architecture and smart contracts to ensure that the security enhancement of blockchain can be fully exploited, then the paper discussed and solved some common and vital problems in the blockchain-based scheme, among which a data-driven credit evaluation scheme workable on chain was put forward and a cross-chain architecture was designed to make the system more secure, intelligent and scalable. Xu et al. [31] adopted a new Merkle-Patricia tree to extend the blockchain structure and provide fast query of node status. Since the conventional Merkle-Patricia tree does not support concurrent operation and the data operation performance deteriorates with high data volume, they designed a lock-free concurrent and cache-based Merkle-Patricia tree to support lock-free concurrent data operation, which can improve the data operation efficiency in multi-core system. Feng et al. [32] proposed an intelligent manufacturing information security sharing model based on blockchain technology. The blockchain system can store product information and transaction information in blocks, thereby achieving traceability of product information. This information sharing mechanism can strengthen information in real time, and it uses consensus mechanism and encryption algorithm to ensure that the products won't be tampered, to a certain extent, such information sharing mechanism has promoted the development of smart manufacturing.

Studies on application of blockchain technology in intelligent manufacturing platforms have attained certain results but still there are a few problems pending for further research, such as how to perform PSCO on intelligent manufacturing platforms established based on blockchain technology. Since there are great differences in PSCO-PC models established for different intelligent manufacturing systems, it's important to expand the monolithic architecture of simulation models and improve the flexibility of model simulation. Out of these concerns, this paper simulated the PSCO-PC of intelligent manufacturing based on block chain technology. In the second chapter, the PSCO-PC model was introduced in detail, through accurate simulation of on-site operating conditions, the simulation system functions' matching rationality and their applicability under different operating conditions were improved. Then, to solve the problem that the throughput of massive data and the confirmation time of consensus mechanism cannot keep up with the changes in the PSCO optimization goal, the third chapter introduced a concept called the adaptive difficulty of PSCO optimization goal into the constructed simulation system, and gave the steps for calculation nodes to solve the optimal solution of the package revenue of PSCO matching records. At last, experimental results verified the effectiveness of the constructed simulation model and the proposed PSCO-PC strategy.

2. MODELLING OF THE PSCO-PC PROBLEM

Modelling of the PSCO-PC problem of intelligent manufacturing is the basis for the design and development of corresponding simulation systems. The quality of model simulation of the actual operation conditions will directly affect the simulation system functions' matching rationality and their applicability under different operating conditions. The following texts introduced the PSCO-PC model in detail.

In terms of model entities, namely production equipment, production service, and production resource, assuming: there are I ($I \geq 1$) production equipment in an intelligent manufacturing platform, which are represented by $DF(I) = \{T_1, ..., T_i, ..., T_I\}$, all production equipment could provide J ($J \geq 1$) types of production service, which are represented by $SQ(J) = \{b_1, ..., b_j, ..., b_J\}$; each production equipment T_i could provide L_i ($1 \leq L_i \leq J$) types of production service, denoted as that $R_{i,l}$ is the l^{th} ($1 \leq l \leq L_i$) type of production service provided by production equipment T_i. The different types of production service provided by each production equipment involve multiple production resources of the same type. Assuming: production service $R_{i,l}$ has $K_{i,l}$ production resources, $PV_{i,lk}$ represents the k^{th} ($1 \leq k \leq K_{i,l}$) production resource of the l^{th} production service of production equipment T_i.

Assuming: production equipment has an address attribute, represented by VE_i, which is the basic logistics information of production equipment generated during the production process; production resources have several attributes including type, cost, efficiency, reliability, and state, etc., which are respectively represented by $b_{i,l,k}$, $d_{i,l,k}$, $DS_{i,l,k}$, $ZD_{i,l,k}$, and $UT_{i,l,k}(0,1)$; production services also have a few attributes, including type, quantity, cost, quality, efficiency, reliability, and state, which are respectively represented by $b_{i,l}$, $x_{i,l}$, $d_{i,l}$, $w_{i,l}$, $DS_{i,l}$, and $UT_{i,l}(0,1)$, wherein the type of production resource is the same with the type of production service it belongs; a production resource has two states: available and unavailable, and a production service has two states: can proceed, and cannot proceed. Because a production service can be equipped with multiple production resources of a same type, this production service is judged to be inactive only if all production resources of this production service are unavailable. The cost of production resource is the expense incurred by processing a single production resource within unit time, then the cost of production service can be defined as the sum of the costs of all available production resources, and its calculation formula is:

$$d_{i,l} = \sum_{k=1}^{k=K_{i,l}} \left(d_{i,l,k} \times UT_{i,l,k} \right) \tag{1}$$

The production resource efficiency is the amount of work load generated by a single production resource within per unit time, then the production service efficiency can be defined as the sum of the efficiency of available production resources, and its calculation formula is:

$$DS_{i,l} = \sum_{l=1}^{k=K_{i,l}} \left(DS_{i,l,k} \times UT_{i,l,k} \right) \tag{2}$$

The completion rate of production tasks or the qualified rate of products can be used to measure the quality of intelligent manufacturing production services.

Assuming: the intelligent manufacturing platform receives N production tasks at a same time, which are represented by $RW(N) = \{E_1, ..., E_n, ..., E_N\}$, wherein E_n represents the n^{th} $(1 \leq n \leq N)$ production task in the production task set; each E_n has a few attributes including task number, maximum cost, processing start time, and processing end time, which are represented by ex_n, $d^{max}{}_n$, $e^{start}{}_n$, and $e^{end}{}_n$, respectively, wherein ex_n describes the scale size of received production tasks, $d^{max}{}_n$ describes the maximum cost that the production service implementer is willing to pay to complete the production task. In order to grant the production service implementer with the right to adjust and cancel production tasks, the processing start time attribute had been added in the constructed simulation model, and the maximum completion time required by the production service implementer is the difference between the start time and the end time of the production task.

In intelligent manufacturing, a production task is usually composed of multiple production services, so in order to match with production services in intelligent manufacturing platforms, this paper divided a production task into several smaller sub-tasks. Assuming a production task can be broken down into M_n $(M_n \geq 1)$ sub-tasks, $rE_{n,m}$ represents the m^{th} $(1 \leq m \leq M_n)$ sub-task of production task E_n, then the sub-task set of production task E_n can be denoted as $E_n = \{rE_{n,1}, ..., rE_{n,m}, ..., rE_{n,Mn}\}$, each sub-task has a few attributes including the type of required production service, number of sub-tasks, unit workload, minimum production service quality, and minimum reliability, which are respectively represented by $sb_{n,m}$, $rx_{n,m}$, $vqk_{n,m}$, $w^{min}{}_{n,m}$, and $retk^{min}{}_{n,m}$; assuming the total workload of sub-task $rE_{n,m}$ is $qk_{n,m}$ and it satisfies $qk_{n,m} = vqk_{n,m} \times rx_{n,m}$; $w^{min}{}_{n,m}$ represents the index of minimum quality completed by the production service implementer of this sub-task, $retk^{min}{}_{n,m}$ represents the minimum reliability index of the production service implementer for completing the production service of this sub-task when PSCO is applied.

One thing should be noted is that during the actual production process of intelligent manufacturing, the PSCO has different forms of organizational optimization structures such as sequential, selective, branched, or cyclic processing procedures. To highlight the advantage of PSCO, the model needs to fully consider multiple organizational optimization structures so that the architecture could be expanded for different simulation requirements.

The intelligent manufacturing production platform has the function to perform centralized management and control of the scattered production resources, since production equipment separate in different locations, the different sub-tasks of a same production task may be performed on different equipment in different locations, so the logistics of materials or parts in the production equipment workshop is unavoidable, especially the time and cost of production logistics cannot be ignored in case that the distance between production equipment is long.

Assuming: production equipment is distributed in P ($P \geq 1$) different places, $X(P) = \{X_1, ..., X_o, ..., X_P\}$ represents the set of equipment addresses; logistics between production equipment is directly or indirectly accessible, and the distance from X_{p1} to X_{p2} is equal to the distance from X_{p2} to X_{p1}, $c(X_{p1} \leftrightarrow X_{p2})$ represents the distance between X_{p1} and X_{p2}; the logistics between production equipment involves two attributes: logistics cost $kd_{p1,p2}$ and logistics speed $ke_{p1,p2}$. $kd_{p1,p2}$ measures the logistics cost of per unit distance, it can be calculated as follows:

$$kd_{p1,p2} = c(X_{p1} \leftrightarrow X_{p2}) \times kvo \tag{3}$$

$ke_{p1,p2}$ measures the logistics time of per unit distance, it can be calculated by the following formula:

$$ke_{p1,p2} = \frac{c(X_{p1} \leftrightarrow X_{p2})}{kr} \tag{4}$$

Assuming: a sub-task $rE_{n,m}$ ($m < M_n$) is subjected to PSCO and matched to the production service at address X_{p1}, the next sub-task $rE_{n,m+1}$ is subjected to PSCO and matched to the production service at address X_{p2}, then the logistics cost from $rE_{n,m}$ to $rE_{n,m+1}$ can be represented by $kd^{m,m+1}{}_n$, and it satisfies $kd^{m,m+1}{}_n = kd_{p1,p2}$; likewise, the logistics time from $rE_{n,m}$ to $rE_{n,m+1}$ can be represented by $Ie^{m,m+1}{}_n$, and it satisfies $It^{m,m+1}{}_n = lt_{p1,p2}$.

Another thing should be noted is that during the actual production process of intelligent manufacturing, the logistics involves different logistics networks, different logistics speeds, and different logistics costs. In order to simplify the PSCO-PC process, the simulation model constructed in this paper ignored the choice of production service implementer for logistics, and only set two assignable free variables of logistics speed and logistics cost.

3. THE PSCO MECHANISM BASED ON QUEUING DELAY

In case that the implementation rate of PSCO-PC records of the intelligent manufacturing platform is fixed, since the success rate of production services of the simulation system defaults to the sum of production service success rates of all production equipment participating in the production within a fixed period of time, so it can be considered that the increase of production service success rate of a single production equipment has a positive effect on the increase of production service success rate of the entire platform, and increasing the number of production equipment participating in production services will effectively increase the overall production service success rate of the entire platform.

In the intelligent manufacturing platform, performing hash operations based on the technology of blockchain can attain random number that meets the PSCO goal, its maintenance is realized by the consistency of platform production data through the consensus mechanism of blockchain technology, and the difficulty of PSCO can be adjusted by controlling the block generation time. However, the above strategy will make the computing power of those calculation nodes with higher computing power to enhance further, and the computing power of calculation nodes with lower computing power can hardly find a match. In the meantime, the throughput of massive data and the confirmation time of consensus mechanism cannot keep up with the changes in the PSCO goal. To solve these matters, this paper introduced a concept called the adaptive difficulty of PSCO goal into the constructed simulation system. Fig. 1 shows the PSCO mechanism of intelligent manufacturing platform based on blockchain.

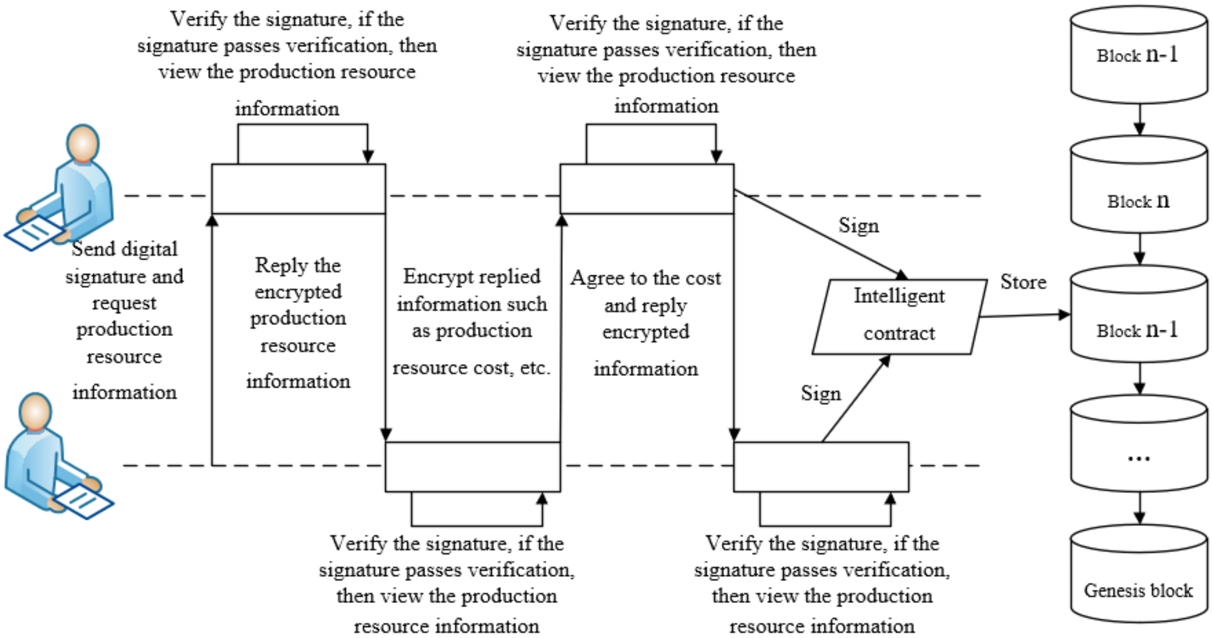

Figure 1: PSCO mechanism of intelligent manufacturing platform based on blockchain.

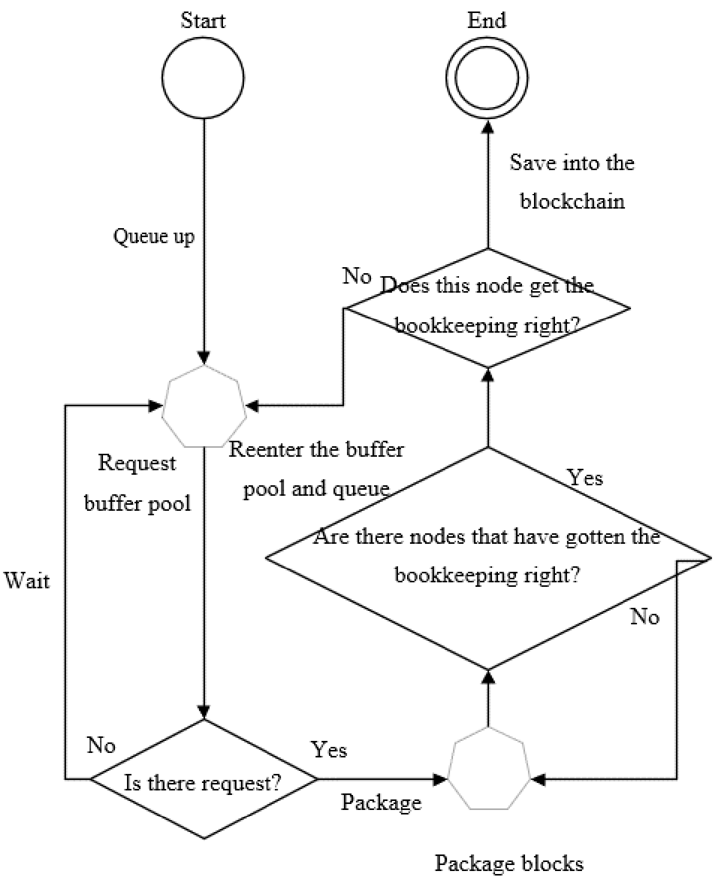

Figure 2: Processing flow of PSCO request of intelligent manufacturing platform based on blockchain.

Fig. 2 gives the flow for processing PSCO request of intelligent manufacturing platform based on blockchain. Before running, generally the intelligent manufacturing platform sets an initial difficulty for the PSCO goal, to avoid waste of computing power caused by competition among calculation nodes, assuming: in the system, there are r calculation nodes that match with production equipment participating in the mining, and x_i represents the computing power of calculation node i, then the formula for calculating the adaptive difficulty c_i of i is:

$$c_i = \frac{x_i}{\sum_{j=i}^{r} x_j} \times C \tag{5}$$

For the blockchain-based intelligent manufacturing platform, the computing power of calculation nodes participating in mining is counted and the mining difficulty of each calculation node is adjusted based on the computing power.

To encourage calculation nodes to actively participate in mining, the platform needs to give certain rewards to successful mining nodes. If there are a pieces of production service record in the buffer pool, the size of a production service record j is n_j KB, $j = 1, 2, 3, ..., a$. The reward given by the platform is composed of two parts: the fixed reward s, and the contribution value of PSCO $\Sigma^c_{j=i} u_{i,j}$, $c \leq a$. Assuming: o_{ni} represents the probability of calculation node i getting the bookkeeping right during one-time mining, then the formula for calculating the reward S_i of production equipment i is:

$$S_\mathrm{i} = o_{ni} \times s + \sum_{j=i}^{c} u_{i,j} \tag{6}$$

o_{ni} can be calculated by the following formula:

$$o_{ni} = \frac{x_i}{\sum_{j=i}^{r} x_j} \tag{7}$$

To stimulate calculation nodes to package PSCO matching records with a large information volume, let Δ_j be directly proportional to the square of the size of PSCO matching record j, the proportion coefficient is set to x, then the greater the information volume of a PSCO matching record, the higher its probability of being packaged by calculation nodes, there is:

$$\Delta_\mathrm{j} = x \times n_j^2 \tag{8}$$

Generally, there is an upper limit to the block capacity, which is set as N_d KB, then there is:

$$\sum_{j=i}^{c} n_j < N_d \tag{9}$$

Assuming: d_i represents the cost of unit computing power of calculation node i within per unit time, in case that a calculation node i needs to provide a computing power of β_i, the cost $t_{i,j}$ for processing PSCO matching record j can be calculated by the following formula:

$$t_{i,j} = \frac{d_i \times \beta_i \times n_j}{\lambda_{ni}} \tag{10}$$

Assuming: $u_{i,j}$ represents the value of a PSCO matching record j to calculation node i, then there is:

$$u_{i,j} = \Delta_j - t_{i,j} \tag{11}$$

Calculation nodes attain PSCO success rate by consuming their computing power, then the ratio α_i between the two satisfies:

$$\alpha_{\mathrm{i}} = \frac{\beta_i}{\lambda_{ni}} \tag{12}$$

To get the maximum package revenue U, under the constraint of block capacity, calculation nodes need to selectively determine PSCO matching records to be packaged, that is:

$$\begin{gathered} U = \max \sum_{j=i}^{c} u_{i,j} \\ s.t. \sum_{j=i}^{c} n_j < N_D, n_j \geq 0 \end{gathered} \tag{13}$$

In order to attain the optimal solution of package revenue of PSCO matching records, this paper solved this problem by employing dynamic planning, and the solution idea is introduced below:

Step 1: In the initial state, let the capacity of calculation node i be null, for any PSCO matching record, it can be selected or packaged, and its value can be calculated.

Step 2: Traverse the buffer pool for remaining PSCO matching records, if the capacity of calculation node i after packaging is greater than N_d, then compare the packaging value of the calculation node before and after deleting some other records, if the value after deleting is higher, then choose to delete other records; if the value after deleting is lower, then choose to delete this record; if the capacity of calculation node i after packaging is smaller than N_d, then it's packaged directly.

Step 3: Repeat *Step 2* until all content in the buffer pool of PSCO matching records has been traversed.

4. EXPERIMENTAL RESULTS AND ANALYSIS

To verify the impact of adaptive difficulty of PSCO goal of calculation nodes in the consensus stage on the queuing delay of the service response of production equipment corresponding to each calculation node in the platform, in this paper, based on IntelliJ IDEA, the Java language was adopted to realize the POW consensus algorithm of blockchain-based intelligent manufacturing platform. The three calculation nodes with a computing power of 20, 30, and 40 respectively were used to run the algorithm for 30, 60 and 90 times under two conditions: the initial difficulty of PSCO goal was 3.5, and the adaptive difficulty of PSCO goal, and the queuing delay of service response of calculation nodes in the consensus stage was counted, the statistical results are given in Table I.

Table I: Production service queuing delay of calculation nodes in consensus stage.

Computing power	**Consensus times**	**Time consumption of consensus for initial difficulty** /ms	**Time consumption of consensus for adaptive difficulty** /ms
20	30	19.3	1.02
	60	43.8	2.59
	90	96.2	4.57
30	30	14.6	14.3
	60	32.76	32.74
	90	72.3	72.6
40	30	11.54	209
	60	26.1	531.6
	90	57.69	1107.8

As can be seen from the table, the time consumption for the adaptive difficulty of PSCO goal was almost proportional to the computing power of calculation node. The main reason is that after adopting the adaptive difficulty of PSCO goal of blockchain-based intelligent manufacturing platform, the chance for calculation nodes with lower computing power has greatly increased, which has increased the probability of consuming less queuing time for production services to complete consensus, and this has further sped up the response of blockchain-based intelligent manufacturing platform to the service requirements of production equipment, and improved the production efficiency of production equipment.

Table II: Memory and CPU consumption.

Type	**Name**	***CPU***	**Average memory**	**Maximum memory**
Process	*N Bertl-client1*	9.47 %	65.8 MB	69.7 MB
Process	*N Bertl-client2*	8.31 %	66.7 MB	68.8 MB
Process	*N Bertl-client3*	8.44 %	65.41 MB	67.2 MB
Docker	*Xys1.case.com*	14.18 %	368.7 MB	389.7 MB
Docker	*Xys1.case.com*	13.45 %	385.6 MB	395.6 MB
Docker	*Xys2.case.com*	13.75 %	374.9 MB	392.5 MB
Docker	*Bert.case.com*	5.62 %	7.6 MB	7.6 MB
Docker	*Nuhje.case.com*	6.89 %	19.8 MB	19.8 MB
Docker	*Guhne.case.com*	7.91 %	22.9 MB	24.5 MB

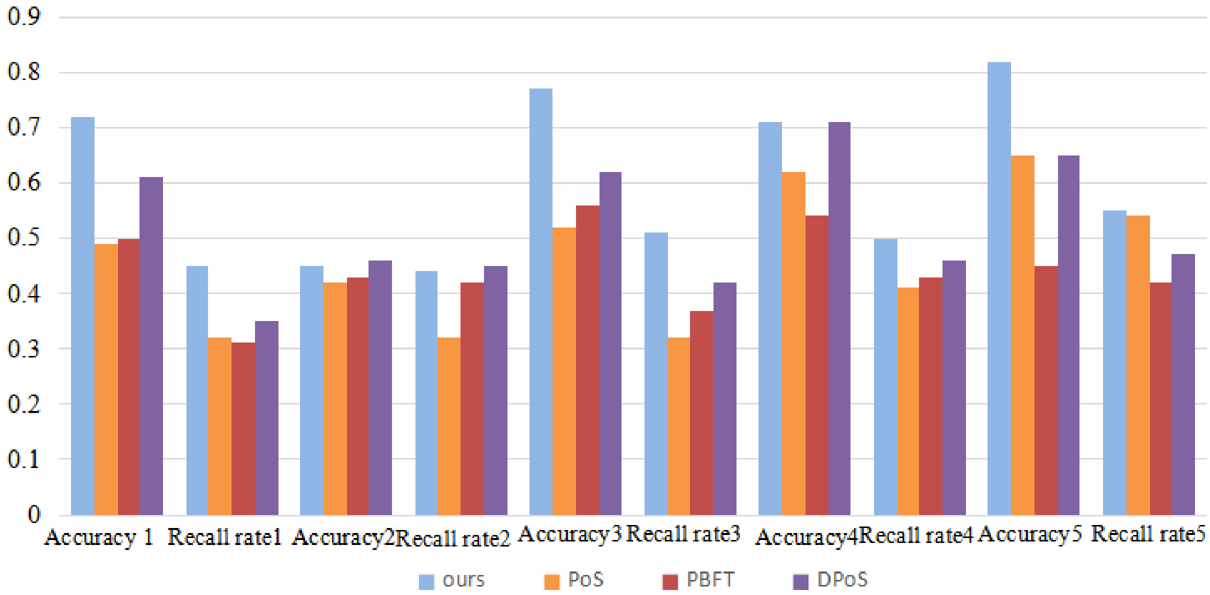

Figure 3: PSCO effects of different methods.

Based on the data content of constructed blocks, the memory and CPU consumption of each module and the service response of production equipment of the intelligent manufacturing platform during operating process were counted, and the statistical results are listed in Table II. The comprehensive statistical results showed that, in terms of data throughput, PSCO efficiency, and CPU consumption, the simulation system could support the normal simulation operation of the platform and it basically met the workshop-level performance requirements of the blockchain-based intelligent manufacturing platform for production management.

Further, the PSCO effects attained by the proposed method and other consensus methods including PoS, PBFT, and DPoS were compared. Two indicators, accuracy and recall rate were used to evaluate the PSCO effects, and the experimental results of sample datasets coming from

5 different production lines were given in Fig. 3. According to the figure, the proposed method outperformed other methods in terms of the two indicators, which had verified that the PSCO effect of the proposed method was better.

The simulation system constructed in this paper also has the function of simulation management, which can test operations such as manage the simulation parameters of production equipment, adjust the processing sequence, confirm the PSCO information, click the menu of Gantt chart, and click to generate Gantt chart, Table III gives the specific content of function operations of simulation management.

Table III: Function operations of simulation management.

Function	Test operation	Expected result
Simulation management	Manage the simulation parameters of production equipment Adjust processing sequence Confirm the PSCO information Click the menu of Gantt chart Click to generate Gantt chart	Display information list of simulation process Adjust the processing sequence successfully Complete PSCO and attain implementation results Generate Gantt chart successfully

Fig. 4 shows the Gantt Chart generated by the system after implementing PSCO.

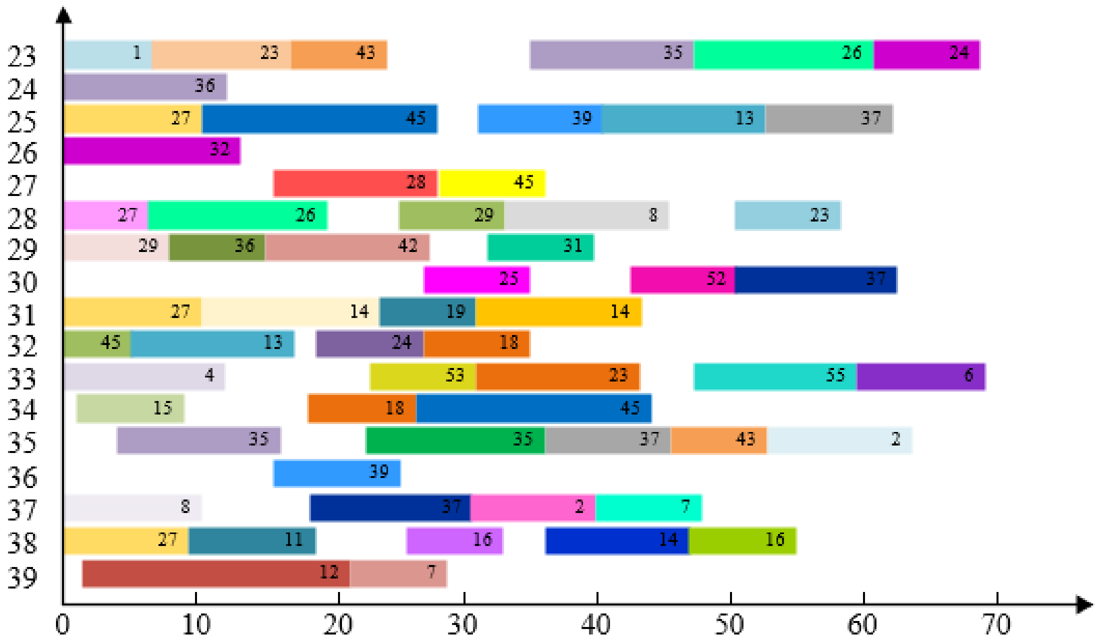

Figure 4: Gantt Chart generated by the system after implementing PSCO.

5. CONCLUSION

This paper studied the SPCO of intelligent manufacturing and simulated the production control and management of blockchain-based intelligent manufacturing platform. At first, the PSCO-PC model was introduced in detail, through accurate simulation of on-site operating conditions, the simulation system functions' matching rationality and their applicability under different operating conditions were improved. Then, to solve the problem that the throughput of massive data and the confirmation time of consensus mechanism cannot keep up with the changes in PSCO goal, this paper introduced a concept called the adaptive difficulty of PSCO goal into the constructed simulation system, and gave the steps for calculation nodes to solve the optimal solution of the package revenue of PSCO matching records. The experimental results showed that the production service success rate has an impact on the package quantity of calculation nodes, an effective strategy to enhance the service capacity and throughput of the blockchain-based intelligent manufacturing platform is to improve the production service success rate of calculation nodes or to increase the number of calculation nodes. After that, the queuing delay of service response of calculation nodes in the consensus stage was counted, and the results verified the impact of adaptive difficulty of PSCO goal of calculation nodes in the consensus stage on the queuing delay of the service response of production equipment corresponding to each calculation node in the platform. Also, the memory and CPU consumption of each module and the service response of production equipment were counted, the PSCO effects attained by the proposed method and other consensus methods including PoS, PBFT, and DPoS were compared, and the results proved that in terms of data throughput, PSCO efficiency, and CPU consumption, the simulation system could support the normal simulation operation of the platform and it basically met the workshop-level performance requirements of the blockchain-based intelligent manufacturing platform for production management, and the proposed method exhibited better PSCO effect than other methods.

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