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A COMBINED SERVICE OPTIMIZATION AND PRODUCTION CONTROL SIMULATION SYSTEM

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Abstract
Manufacturing resources are the core resources for intelligent manufacturing enterprises. It is of great practical significance to improve the reliability and stability of production control in a dynamic production environment with long-term frequent disturbances. This paper explores the simulation system design and development for combined service optimization and production control of intelligent manufacturing. After specifying the system architecture, modelling and matching were carried out according to the specific requirements of intelligent manufacturing combined service objects in the production process. Next, a six-tuple was introduced into the service provided by the production control system combined with the Internet of things (IoT), the formal definition was given to the IoT service and intelligent manufacturing combined service, and the key parts were described in detail with the overall service description and combined service description of the six-tuple as examples. Through experiments, the results of the simulation system were outputted.
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Key Words: Intelligent Manufacturing, Combined Service Optimization, Production Control, Simulation System Design and Development

1. INTRODUCTION

Intelligence is the development direction of manufacturing automation. Intelligent manufacturing technology makes products traceable, identifiable, locatable and manageable, supports the comprehensive networking and communication of production equipment, enables the intelligent production for a small number of personalized products, and realizes the real-time interconnection between people, equipment, and products between isolated workshops [1-17]. Manufacturing resources are the core resources for intelligent manufacturing enterprises engaging in home appliances, food, automobiles, apparel, retail, electrical, energy and chemical industries. It is of great practical significance to improve the reliability and stability of resource allocation, intelligent monitor access, flexible packaging, and combined service optimization in a dynamic production environment with long-term frequent disturbances [18-24].

With the deepening application of information technology in manufacturing, the informatization of manufacturing systems has evolved from unit digital manufacturing to integrated networked manufacturing, and then to comprehensive digital, networked, and intelligent manufacturing. Modelling and simulation technology, as a comprehensive information technology integrating computer, model theory and scientific computing, plays an irreplaceable role in manufacturing informatization, and has been widely used in all stages of the product life cycle, including design, production, testing, maintenance, purchasing and sales. Murashima et al. [25] analysed the basic geometric features of innovation networks. Then, based on the small-world network, the evolution model of the advanced equipment manufacturing innovation network was established, and subjected to simulation. The simulation results show that the proposed model can emulate the evolution process of the advanced equipment manufacturing innovation network. Kostal et al. [26] reviewed and summarized the research and application of modelling and simulation technology in the manufacturing industry, and analysed the typical simulation technology in the industry from the aspects of manufacturing cell simulation, manufacturing integrated simulation and manufacturing intelligent simulation. For cloud-based simulation of large-scale complex manufacturing systems (CMSS), allocating appropriate service instances (virtual machines or nodes) is a promising approach to improve execution efficiency. Wang [27] built a performance estimation model (PEM) that uses executed event and synchronization algorithms to evaluate the runtime of CMS on different combinations of service instances. In addition, an intelligent scheduling algorithm with PEM as fitness function was developed to search for near-optimal allocation schemes for CMSS service instances. Experimental results show that PEMOA can reduce the running time by more than 7 %. In particular, improvements in PEMOA increased when manufacturing system simulations are communication-intensive or span a small number of service instance combinations. Manufacturers need to efficiently meet customer delivery requirements, and reduce manufacturing lead times as expected by customers. Rosen [28] compared and analysed three APC methods by simulation, namely pheromone (PHE), queue length estimator (QLE) and revised QLE (RQLE). Two kinds of job-shops were configured, namely, flexible flow job-shop and general flexible flow job-shop. Simulation results show that RQLE has superior performance in both configurations.

To sum up, domestic and foreign researchers explored the combined service optimization of intelligent manufacturing extensively. In the actual production environment, the manufacturing services and products vary with the time. It is necessary to further improve the adaptability of the combined services of intelligent manufacturing to disturbances. The current simulation systems for the combined services and production control algorithms of intelligent manufacturing mostly adopt the standalone architecture. To unify the simulation environment of different algorithms, it is necessary to design and develop flexible, autonomous, and expandable simulation systems.

Therefore, this paper explores the simulation system design and development for combined service optimization and production control of intelligent manufacturing. After specifying the system architecture, Section 2 carries out the modelling and matching according to the specific requirements of intelligent manufacturing combined service objects in the production process. Section 3 introduces a six-tuple into the service provided by the production control system combined with the Internet of things (IoT), gives the formal definition to the IoT service and intelligent manufacturing combined service, and details the key parts with the overall service description and combined service description of the six-tuple as examples. Through experiments, the results of the simulation system were outputted.

2. SIMULATION EXAMPLE

This paper designs the architecture of simulation system (Fig. 1) to better simulate the service composition structure of intelligent manufacturing, and meet the simulation requirements for the service needs in different production stages, serving different goals of production control. The system encompasses six subsystems: the abstract service flow generation module, service demand generation module, service composition algorithm execution module, manufacturing history record management module, abstract service flow generation module, and simulation and execution module of service composition results. Each subsystem cooperates and completes the simulation task by transmitting execution results to other subsystems or providing interfaces or transmitting data files, and thus completes the entire experimental process.

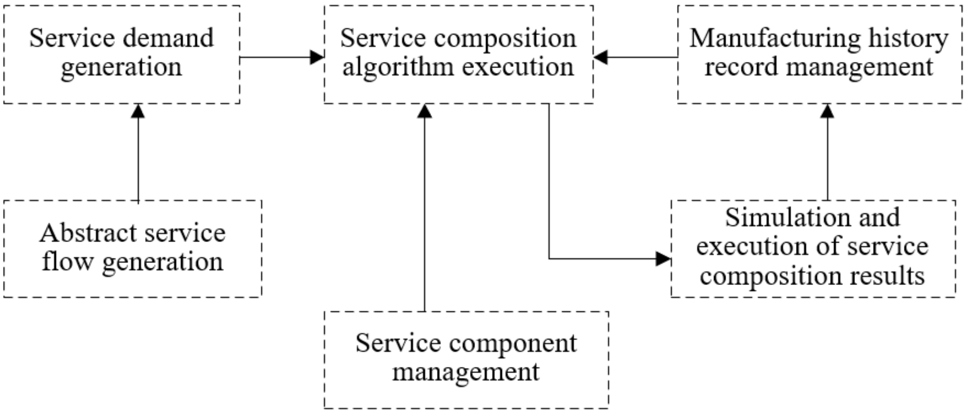

Figure 1: Architecture of simulation system.

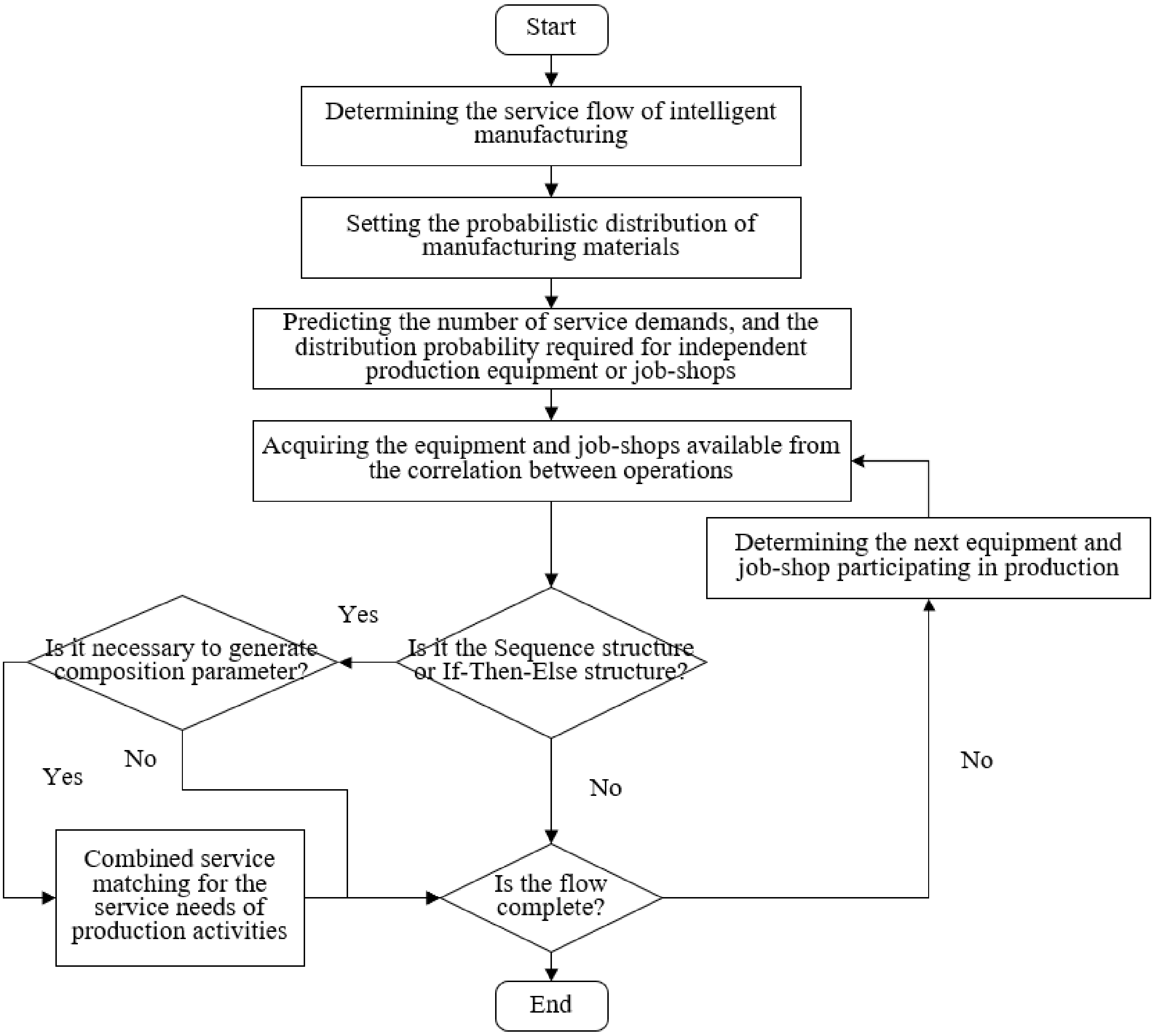

Figure 2: Generation flow of intelligent manufacturing service demands.

This paper firstly models and matches the combined service objects of intelligent manufacturing according to their specific demands in the production process. That is, the service objects are descripted from the angle of demand, subjected to comparative analysis, and their mapping relationship is characterized. Then, the judgement rules are determined for the matching between the service demands of the objects and the service functions provided by the production control system. The degree of matching is measured by similarity. Fig. 2 shows the generation flow of intelligent manufacturing service demands.

Let *SOD_X* denote the demand of a service object; *IMPS_X* and *IMPS_Y* denote the available combined service of intelligent manufacturing. Then, the similarity can be calculated by the following instance.

The degree of matching between *SOD_X* and *IMPS_X* can be calculated in the following steps:

SIM(*IMPS_X's input contrast* 1,*SOD_X's input contrast* 1)
=*SIM*(*ParallelComputingFile*1,*ParallelComputingFile*1)=1

SIM(*IMPS_X's input contrast* 1,*SOD_X's input contrast* 2)
=*SIM*(*ParallelComputingFile*1,*PIPEI NO.*1)=0

SIM(*IMPS_X's input contrast* 2,*SOD_X's input contrast* 1)
=*SIM*(*PIPEI NO.*1,*ParallelComputingFile*1)=0

SIM(*IMPS_X's input contrast* 2,*SOD_X's input contrast* 2)
=*SIM*(*PIPEI NO.*1,*PIPEI NO.*1)=1

The similarity matrix of input parameters can be expressed as:

InputParameterSimilarityMatrix(*IMPS_X's input,SOD_X's input*)=[1001]

Further, we have:

FIT Of InputParameterSimilarity(*IMPS_X*,*SOD_X*)=0.5**MAX*(1,0)+0.5**MAX*(0,1)=1

Similarly,

FIT Of OutputParameterSimilarity(*SOD_X*,*IMPS_X*)=1

FIT Of PrerequisiteParameterSimilarity(*IMPS_X*,*SOD_X*)=1

FIT Of QoS-ParameterSimilarity(*SOD_X*,*IMPS_X*)=1

FIT Of IOTServiceParameterSimilarity(*RDsx*,*RDry*)=
0.25**FITOf InputParameterSimilarity*(*IMPS_X*,*SOD_X*)+
0.25**FIT Of PrerequisiteParameterSimilarity*(*IMPS_X*,*SOD_X*)+
0.25**FIT Of PrerequisiteParameterSimilarity*(*IMPS_X*,*SOD_X*)+
0.25**FIT Of QoSParameterSimilarity*(*SOD_X*,*IMPS_X*)=1

The degree of matching between *SOD_X* and *IMPS_Y* can be calculated by:

SIM(*IMPS_Y's input contrast 1,SOD_X's input contrast* 1)
=*SIM*(*ParallelComputingFile*2,*ParallelComputingFile*1)=0

SIM(*IMPS_Y's input contrast 1,SOD_X's input contrast* 1)
=*SIM*(*ParallelComputingFile*2,*PIPEI NO.*1)=0

SIM(*IMPS_Y's input contrast 2,SOD_X's input contrast* 1)
=*SIM*(*PIPEI NO.*1,*ParallelComputingFile*2)=0

SIM(*IMPS_Y's input contrast 2,SOD_X's input contrast* 2)
=*SIM*(*PIPEI NO.*1,*PIPEI NO.*1)=1

Let *RDsx* be the combined service object of intelligent manufacturing; *RDry* be the service provided by the production control system of the IoT. Then, the similarity matrix of the input parameters can be obtained as:

InputParameterSimilarityMatrix(*IMPS_Y's input,SOD_X's input*)=[0001]

Thus, we have:

FIT Of InputParameterSimilarity(*IMPS_Y*,*SOD_X*)=0.5**MAX*(1,0)+0.5**MAX*(0,1)=0.5

Similarly, we have:

FIT Of OutputParameterSimilarity(*SOD_X*,*IMPS_Y*)=0.5

FIT Of PrerequisiteParameterSimilarity(*IMPS_Y*,*SOD_X*)=0.25(0+0+0+0)=0

FIT Of QoSParameterSimilarity(*SOD_X*,*IMPS_Y*)=0.25(0+0+0.5+1)=0.375

FIT Of IOTServiceParameterSimilarity(*RDsx*,*RDry*)=0.25(0.5+1+0+0.5)=0.5

Figs. 3 and 4 show the structure of the set of files and set of service objects, respectively. The basic data of *isCompleted*, an output parameter, adopt the Boolean type of XML Schema, which illustrates the structure of XML files.

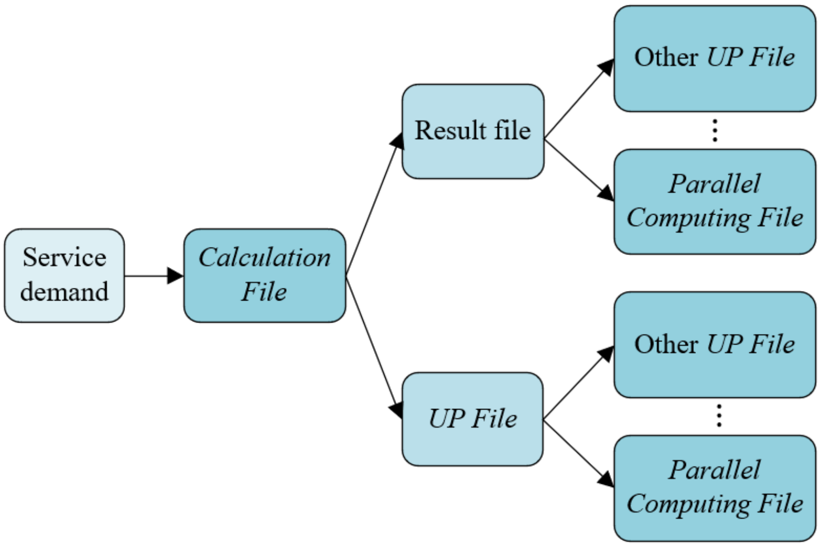

Figure 3: Structure of file set.

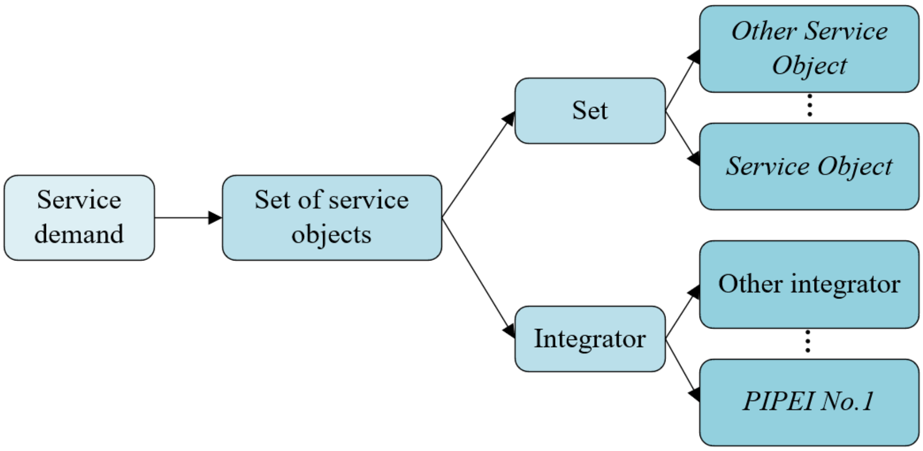

Figure 4: Structure of service objects.

3. CASE ANALYSIS OF SERVICE COMBINATION FOR INTELLIGENT MANUFACTURING

To illustrate the service combination of intelligent manufacturing, this paper introduces a 6-tuple to the services *RDry* provided by the production control system integrated with IoT, and illustrated in OWL. In this way, the formal definition could be given for the IoT services and the combined service of intelligent manufacturing, making various services capable of automatic combination. Referring to the language design idea of PNML, this paper proposes the semantic-based PNML to illustrate the IoT service and the combined service of intelligent manufacturing. The engineering realization of IoT service is depicted by WSDL, the IoT service is implemented in the open-source software Tuscany, and the IoT service component is realized on Spring. This paper takes the operation and calculation process of actual production control simulation as an example to verify the description flow and technical ideas of intelligent manufacturing service combinations. Besides, the relevant algorithm is compiled to automatically convert PNML with semantic features into the description files for the component and combination in Tuscany.

Based on the production control simulation system, the combined service flow of intelligent manufacturing is developed and designed as follows: Firstly, the calculation demands of the service object are submitted, namely, the number of CPUs, the memory capacity, the real-time requirement, and the solution form. The simulation system then pre-integrates the independent service objects based on the calculation demand. Next, the simulation system compiles the computing requirements provided by the service object into files and inputs them, and the input results are used for parallel computing in CAE simulation. After the calculation is completed, the scores of the service object will be accumulated. If the calculation fails, the scores of the object will be returned. The simulation system also provides the service object with the function of downloading calculation results.

Pre-integration can be achieved by the following statement:

Public Boolean PrepaidCredits();//Return whether the score accumulation is successful.

The six-tuple introduced by *RDry* described in the OWL language is represented by:

$$STA_{PC} = \left(CSL, H, U, D, UF, SPM\right) \tag{1}$$

where:

1) The input of the combined service, the output repository $CSL=\{in,out\}$;

2) Transition of combined service $H=\{IMPS\}$;

3) Arc set $U=\{(in,IMPS),(IMPS,out)\}$;

4) Assuming that the Boolean expression of the precondition is represented by P-exp, and the Boolean expression of the output effect is represented by E-exp. The finite non-empty set of "Token Color" and data type is:

$$D = \left\{ \begin{matrix} IP(R), \text{dataType} \\ OP(R), \text{dataType} \\ \text{P-exp, Bool expression} \\ \text{E-exp, Bool expression} \end{matrix} \right\} \tag{2}$$

(1) The input satisfies $IP(R_{in})=IP(r_1)\Lambda IP(r_2)\Lambda IP(r_3)\ldots\Lambda IP(r_m)$;

(2) The service input of intelligent manufacturing satisfies:

R_{in}={*ServiceObject*, *ServiceDemand*, *InputCalculationFile*, *Counter*}

(3) The output satisfies $OP(R_{out})=OP(r_1)\Lambda OP(r_2)\Lambda OP(r_3)\ldots\Lambda OP(r_n)$;

(4) Whether the score accumulation is successful is indicated by *IsPrepaidCreditsCompleted*. Then, the service output of intelligent manufacturing satisfies: R_{out}={*ServiceObject*, *ServiceDemand*, *InputCalculationFile*, *Counter*, *IsPrepaidCreditsCompleted*}

(5) *P-exp*=*DemandSatisfaction*(*ServiceDemand*);

(6) *E-exp*=*IsPrepaidCreditsCompleted*;

5) The arc set function *UF*={*UF*(*in-IMPS*), *UF*(*IMPS-out*)} corresponding to the arc set U of the combined service, where *UF*(*in-IMPS*)=*IP*(*R*)Λ*P-exp*; *UF*(*IMPS-out*)=*OP*(*S*)Λ*E-exp*

6) Assume that the combined service in the model is represented by *COS*, the atomic service is represented by *ATS*, and the structure set of *COS* and *ATS* is represented by *ST*. The intelligent manufacturing service process model *SPM*=(*COS*, *ATS*, *STS*); *COS*, *ATS*, and *STS* are all non-empty sets.

Without loss of generality, take the overall service description and combined service solution description in the introduced six-tuple as an example to describe the key definitions.

In the overall service description, the service name is represented by *SIN*, and there are:

(1) Service type: *Combined service*

(2) The intelligent manufacturing service input satisfies:

R_{in}={*ServiceObject*, *ServiceDemand*, *InputCalculationFile*, *Counter*}

(3) The intelligent manufacturing service output satisfies:

R_{out}={*ServiceObject*, *ServiceDemand*, *InputCalculationFile*, *OutputCalculationFiles*, *Counter*}

(4) The preconditions satisfy *P-exp*=*true*

(5) The output effect satisfies *E-exp*=*true*

(6) The combined service in the model satisfies $COS=\{SIN_{COU}\}$
(7) The atomic service in the model satisfies $ATS=\{SIN_{PrepaidCredits}, SIN_{Credits}, SIN_{BackCredits},\}$
(8) The structure set STS of COS and ATS in the model satisfies:

$$STS=\{Sequence\ (SIN_{PrepaidCredits},\ SIN_{COU},\ IFThenElse\ (SIN_{Credits},\ SIN_{BackCredits},\ IsCounteCompleted)),\ IFThenElse(SIN_{Credits},\ SIN_{BackCredits},\ IsCounteCompleted)$$

In the description of the combined service solution, the service name is represented by SIN_{COU}, then there are:

(1) Service type: *Combined service*
(2) Intelligent manufacturing service input satisfies:
$R_{in}=\{ServiceObject, ServiceDemand, InputCalculationFile, Counter, IsCounteCompleted\}$
(3) Intelligent manufacturing service output satisfies:
$R_{out}=\{ServiceObject, ServiceDemand, InputCalculationFile, OutputCalculationFiles, Counter, IsCounteCompleted\}$
(4) The prerequisites satisfy $P\text{-}exp=IsPrepaidCreditsCompleted$
(5) The output effect satisfies $E\text{-}exp=IsCounteCompleted$
(6) The combined service in the model satisfies $COS=\{SIN_{UC}, SIN_{UON}\}$
(7) The atomic service in the model satisfies $ATS=\{SIN_{UIC}\}$
(8) The structure set STS of COS and ATS in the model satisfies:

$$STS=\{Sequence\ (SIN_{UC},\ IFThenElse\ (SIN_{UON},\ SIN_{UIC},\ IsUpCompleted)),\ IFThenElse\ (SIN_{UON},\ SIN_{UIC},\ IsUpCompleted)$$

4. EXPERIMENTS AND RESULTS ANALYSIS

To generate the service demand of each service object in the simulation model, the first step is to configure the matching quality indices of service demands. Table I shows the configuration of indices, including bounds and probabilistic distribution.

Table I: Indices of matching quality of service demands.

Index	Max	Min	Probabilistic distribution
Time cost	52	0	Uniform distribution
Reliability	3	0	Normal distribution
Response time	114	0	Uniform distribution
Effectiveness	5	0	Uniform distribution

According to the service demands {*SOD_Equipment*, *SOD_Parts*, *SOD_FinishedProducts*, *SOD_Processes*} for each workshop or equipment following the production workflow of intelligent manufacturing, the proposed simulation system generates five service demands. Table II provides the indices of matching quality of the five service demands.

From the provided intelligent manufacturing combined services, our simulation system chooses 120 services in OWL, and processed these services based on Euclidean distance, using our algorithm and the distance-based similarity matching algorithm separately. Figs. 5 and 6 present the precision ratios and recall ratios of different matching algorithms. It can be seen that our algorithm surpassed the similar matching algorithms in both precision ratio and recall ratio. The main reason is that the simulation and description abilities of intelligent manufacturing production control are improved by adding the comparison and calculation of matching quality indices.

Based on the five service demands that have been generated, the authors ran the service composition algorithm program given in Section 4, yielding the service composition optimization results of the five service demands. Table III shows the optimization schemes for intelligent manufacturing service composition.

Table II: Index data of matching quality of service demands.

Demand	Service demands	Time cost	Reliability	Response time	Effectiveness
Demand 1	*SOD_Equipment*	25.61	0.1473	92.58	0.3415
	SOD_Parts	13.29	0.3958	56.32	0.7362
	SOD_FinishedProducts	17.42	0.9147	81.69	0.9158
	SOD_Processes	25.16	0.9261	25.37	0.3627
Demand 2	*SOD_Equipment*	15.28	0.3579	74.51	0.6152
	SOD_Parts	32.65	0.7185	66.37	0.3047
	SOD_FinishedProducts	21.08	0.9138	72.05	0.6251
	SOD_Processes	22.52	0.3424	82.91	0.3274
Demand 3	*SOD_Equipment*	14.37	0.1926	15.38	0.7169
	SOD_Parts	24.69	0.4281	35.62	0.2518
	SOD_FinishedProducts	25.37	0.5327	22.05	0.6263
	SOD_Processes	20.48	0.5061	85.37	0.1025
Demand 4	*SOD_Equipment*	32.06	0.4213	24.59	0.6142
	SOD_Parts	34.19	0.6947	15.26	0.5819
	SOD_FinishedProducts	30.52	0.2819	55.38	0.6352
	SOD_Processes	22.48	0.7481	91.25	0.4185
Demand 5	*SOD_Equipment*	12.37	0.8168	23.68	0.9142
	SOD_Parts	16.20	0.9382	61.21	0.9385
	SOD_FinishedProducts	19.68	0.5249	92.38	0.8472
	SOD_Processes	14.46	0.2415	55.15	0.8169

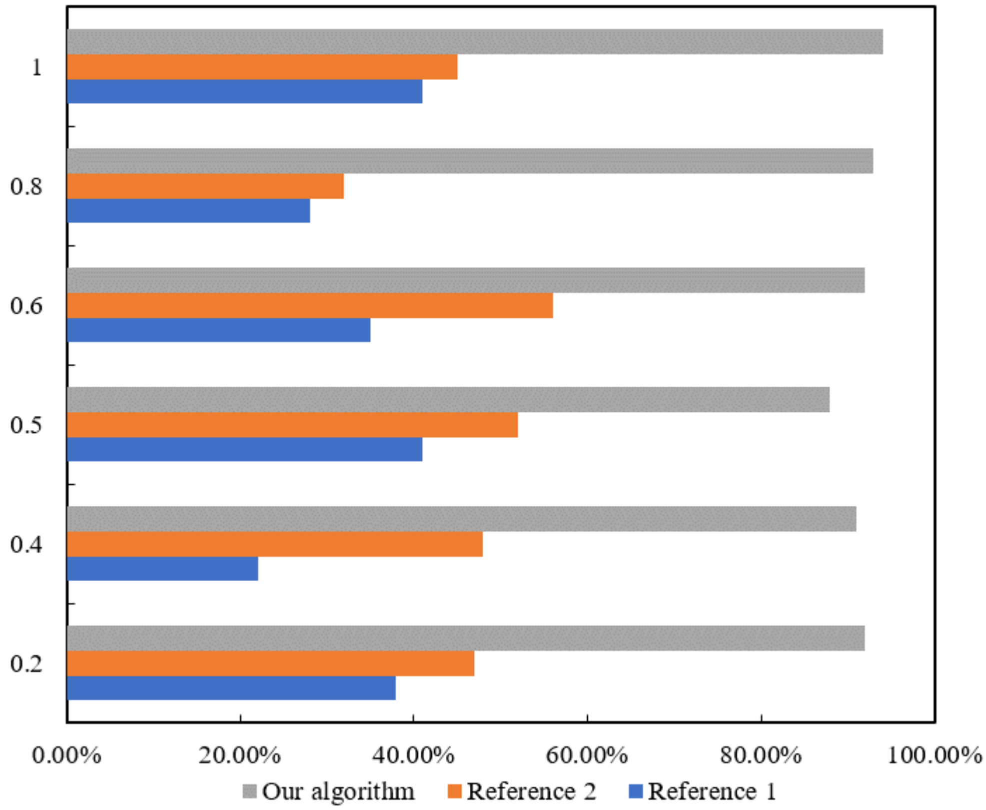

Figure 5: Precision ratios of different matching algorithms.

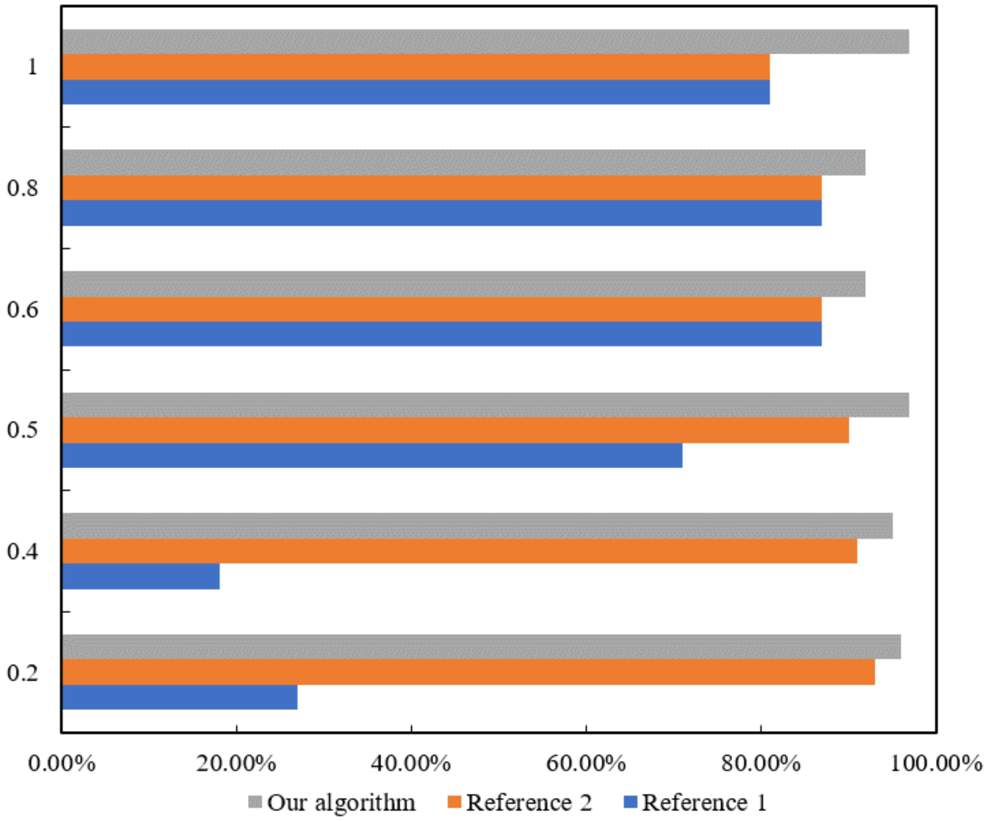

Figure 6: Recall ratios of different matching algorithms.

Table III: Optimization results of intelligent manufacturing service composition.

Scheme	**Corresponding demand**	***SOD_Equipment***	***SOD_Parts***
Scheme 1	Demand 1	*Equipment*915241228	*Parts*851724256
Scheme 2	Demand 2	*Equipment*975482161	*Parts*913526841
Scheme 3	Demand 3	*Equipment*936251844	*Parts*802157496
Scheme 4	Demand 4	*Equipment*948571527	*Parts*830261524
Scheme 5	Demand 5	*Equipment*902152847	*Parts*842517548
Scheme	**Corresponding demand**	***SOD_FinishedProducts***	***SOD_Processes***
Scheme 1	Demand 1	*FinishedProducts*862519234	*Processes*847571472
Scheme 2	Demand 2	*FinishedProducts*812504219	*Processes*862531457
Scheme 3	Demand 3	*FinishedProducts*857484752	*Processes*895647841
Scheme 4	Demand 4	*FinishedProducts*884512746	*Processes*803261527
Scheme 5	Demand 5	*FinishedProducts*815247169	*Processes*874518242

The above optimization schemes were selected for simulation. The simulation system automatically extracts the intelligent manufacturing process parameters and service demand input variables. Table IV presents the simulation results. It can be seen from the execution steps of the simulation that the SOD_Equipment services of workshop 2 and workshop 3 belonged to two branches. Only one of them can be selected for execution when the simulation system is running. It can be seen that the results of the simulation system are basically consistent with the intelligent manufacturing process.

Table IV: Execution results of simulation.

Scheme	Service demands	Time cost	Reliability	Response time	Effectiveness
Scheme 1	*SOD_Equipment*	35.17	0.1285	162.3	0.9584
	SOD_FinishedProducts	3.125	0.1957	34.15	0.1507
	SOD_Processes	1.629	0.4152	162.3	0.6253
	Overall matching quality	34.25	0.0623	357.9	0.1847
Scheme 2	*SOD_Equipment*	22.17	0.1248	85.41	0.9471
	SOD_FinishedProducts	3.524	0.1953	31.62	0.1625
	SOD_Processes	1.629	0.4158	195.8	0.6374
	Overall matching quality	31.52	0.02152	254.2	0.1842
Scheme 3	*SOD_Equipment*	36.29	0.1724	162.9	0.9547
	SOD_FinishedProducts	3.201	0.5169	84.57	0.7418
	SOD_Processes	1.415	0.4352	163.2	0.6295
	Overall matching quality	39.28	0.05127	352.6	0.6314
Scheme 4	*SOD_Equipment*	6.512	0.1562	23.24	0.8152
	SOD_FinishedProducts	14.95	0.7485	25.16	0.7416
	SOD_Processes	1.352	0.3629	185.9	0.5293
	Overall matching quality	15.68	0.02154	195.6	0.5847
Scheme 5	*SOD_Equipment*	12.41	0.1846	65.28	0.9152
	SOD_FinishedProducts	3.495	0.5342	84.15	0.7019
	SOD_Processes	1.528	0.7958	159.1	0.9174
	Overall matching quality	26.52	0.06325	352.7	0.7482

5. CONCLUSIONS

This paper explores the simulation system design and development for combined service optimization and production control of intelligent manufacturing. Firstly, the authors gave the architecture of the simulation system, and modelled and matched the specific demands of the compound service objects in the production process. Then, a six-tuple was introduced to the services of the IoT-based production control system, realizing the formal definition of IoT services and the combined services of intelligent manufacturing. In addition, the key parts were described in detail with the overall service description and combined service description of the six-tuple as examples. According to the service demands {*SOD_Equipment*, *SOD_Parts*, *SOD_FinishedProducts*, *SOD_Processes*} for each workshop or equipment following the production workflow of intelligent manufacturing, the proposed simulation system generates five service demands. Besides, the matching quality indices corresponding to the five service demands were obtained. Further, the precision ratios and recall ratios of different matching algorithms were compared, revealing that our algorithm has better precision and recall ratios than the other similarity matching algorithms. In addition, the execution results of the optimization scheme and simulation for the intelligent manufacturing service composition were presented, indicating that the results are basically in line with the production process of the intelligent manufacturing process.

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