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Data-driven decision making for engineering projects based on real-time IoT data and artificial intelligence algorithms

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Abstract The rapid development of the Internet of Things (IoT) has brought unprecedented opportunities and challenges to decision-making in engineering projects. This paper constructs intelligent decision-making method by utilizing the Internet of Things, artificial intelligence and other technologies. The Internet of Things is utilized to collect real-time engineering project status information and monitor the abnormal status. Then artificial intelligence is combined with operation research optimization algorithm to propose an intelligent decision-making method based on IoT data-driven. By verifying the overall performance of the system and analyzing the application examples, it can be found that the data delay of the IoT device is randomly distributed between 50ms-150ms, which is relatively smooth and has no obvious changing trend. The IoT device responds to the project 1000 data requests more accurately. The intelligent decision-making method based on artificial intelligence was adjusted at the 100th artifact. This ministry effectively reduces production performance loss, avoids the problem of inventory surge, and always maintains the inventory at a reasonable level.

Index Terms internet of things, artificial intelligence, operations optimization, data-driven, intelligent decision making

I. Introduction

Data-driven decision making is a data-based decision making approach [1]. Compared with the traditional way of making decisions based on experience and subjective judgment, data-driven decision-making is more objective, accurate and reliable [2]. Through in-depth analysis of a large amount of data, we can obtain more comprehensive and detailed information, so as to better understand the nature and trend of things [3], [4]. Such a way of decision making can reduce the risk of decision making and improve the success rate of decision making [5].

In engineering projects, decision-making is a complex and critical link [6]. In the era of artificial intelligence, the application of data-driven decision-making based on artificial intelligence technology can provide reliable support for decision-making in engineering projects [7], [8]. By comprehensively analyzing and modeling the data, enterprises can arrive at scientific and accurate decision-making results [9]. In terms of project schedule management, a reasonable construction progress and schedule can be developed by analyzing historical and real-time data [10], [11]. In terms of cost management, material procurement and resource utilization can be optimized based on the results of AI analysis to achieve cost control and reduction [12], [13]. In addition, artificial intelligence technology can help enterprises carry out risk assessment and prediction, and formulate response plans in advance to reduce losses and risks [14]. The use of artificial intelligence is not just a one-time event; it can also provide companies with opportunities for continuous improvement and innovation [15], [16]. By continuously collecting and analyzing data in the construction process, effective management experience and technical methods can be summarized to provide reference for the continuous improvement of engineering management [17]-[19].

In this paper, we mainly utilize the online intelligent decision-making system based on the Internet of Things with intelligent sensing devices, wireless communication technology, artificial intelligence and data-driven technology. Engineering projects generate a large amount of complex data during the implementation process. In order to capture potential consumption anomalies, IoT technology is utilized to collect data in real time and synthesize and analyze real-time project scenarios. Then artificial intelligence algorithms, i.e., machine learning, deep learning, and optimization algorithms, are integrated with theories related to operations research (project planning techniques, decision theory) to intelligently generate decision-making scenarios and achieve online intelligent scheduling for engineering projects. The system in this paper is applied to an automotive door welding production project to provide scheduling advice and guide the specific actions of on-site equipment and staff.

II. Data-driven decision support methodology based on Internet of Things (IoT)

II. A. Research on the application of IoT technologies in decision-making

The importance of IoT technology as a core driver cannot be overstated. IoT closely connects various fields such as facilities and environment through intelligent sensing devices, wireless communication technologies, cloud computing and big data analysis platforms, forming a huge intelligent network [20]. This network is capable of collecting real-time and accurate data on the operation of engineering projects.

In the IoT environment, the instantaneous explosion and influx of massive, unstructured data not only makes the application problem scenarios change rapidly, so that the data processing and feedback must have the characteristics of real-time, in-line, etc., and all kinds of application problems can only be effectively calculated under distributed conditions, and each terminal device must have real-time synergy and interaction with its peripheral devices or people to ultimately realize the Each terminal device must have real-time collaboration and interaction with its neighboring devices or people in order to realize effective support for online scheduling decision-making of various application problems. Therefore, how to carry out effective collaboration and interaction between devices and people, and how to analyze the effectiveness and robustness of the decision-making results after interaction have become the key issues to be solved in this field. In addition, the traditional decision mechanism design and decision-making method for scheduling problems, data real-time and data collection range is limited, the decision does not have a strong in-line and real-time characteristics, the necessity of online autonomous decision-making for each terminal device is often not very obvious. As a result, the traditional decision-making mechanism is difficult to meet the dynamic real-time requirements of the IoT environment, and cannot be applied to the rapidly changing scenario sequences of various application problems in the IoT environment.

II. B. Data-driven anomaly sensing methods

Intelligent decision-making in the IoT environment faces the challenges of multiple and continuous system data, complex and diverse abnormality patterns, and variable future trends, and is susceptible to factors such as seasonality, cyclicity, and multifactor superposition [21].

The decision-making system needs to use the Internet of Things to collect the corresponding state information in real time during the operation process, so as to judge and screen whether the system is in a normal state or abnormal state, or in a non-stationary state between normal and abnormal. Abnormal state is the state that causes the system to fail and makes the system unable to operate normally, and immediate measures must be taken to reschedule the system back to normal.

II. C. Core methods for intelligent decision making

A data-driven anomaly perception method and a trend analysis and decision-making method based on "scenario-focus" are proposed by combining artificial intelligence and operations research optimization, and a data-driven "scenario-focus" online intelligent scheduling decision-making method is formed, which provides a new system based on the Internet of Things to solve dynamic and complex intelligent scheduling problems [22].

II. C. 1) Trend projections

In this paper, trend analysis will be combined with uncertainty decision making, firstly, the probability distribution of future states will be given by the prediction model, and then the uncertainty decision model will be constructed by combining the possible outcomes of each state, so as to advance the utilization of data in the IoT environment from prediction to real-time decision making.

II. C. 2) Focus selection

Uncertainty handling in the IoT environment should be oriented towards solving practical problems and adapting to the real-time requirements of online decision-making. Uncertainty handling varies from scenario to scenario, and uncertainty handling that reflects the purpose of decision-making should be selected based on the scenario.

Definition 1: Suppose a typical scenario state x_i^* of a suspected anomaly has n possibilities for its next state $x_{i+1}^i (1 \le i \le n)$, where x_{i+1} occurs with probability $p(x_{i+1}^i) = p_i$, and $(x_{i+1}^i, p_1; x_{i+1}^i, p_i; \cdots; x_{i+1}^a, p_a)$ is said to be a state to be collapsed.

For a to-be-collapsed state $(x_i+1, p_1; x_{i+1}^i, p_i; \cdots; x_{i+1}^n, p_n)$, when the system is running up to $t+1$ $x_i+1, \cdots, x_{i+1}^i, \cdots, x_{i+1}^n$ one and only one of them will be realized, and the outcome (gain or loss) when x_{i+1}^l occurs is recorded as $y(x_{i+1}^l) = y_i$. The combination of each possible outcome and its probability of occurrence $(y_1, p_1; y_1, p_i; \cdots; y_a, p_a)$ is called the outlook. The core of uncertainty handling is to evaluate the effect of a choice when its future state is uncertain, i.e., to construct the prospect function $F(y_1, p_1; y_i, p_1; \cdots; y_n, p_n)$. Noting that

$y=(y_1,y_2,\cdots,y_n)$, $p=(p_1,p_2,\cdots,p_n)$, the prospect function can be shortened to $F(y,p)$, which means: by weighing the likelihood of the occurrence of each state and the outcome it will generate The meaning is: by measuring the likelihood of each state occurring and the outcome it will produce, the state is assigned an appropriate "value" for the purpose of decision making. Since the collapsed state is collapsed to a unique state when the collapsed state is realized, if the decision-making process is difficult to repeat many times and the possible states are more dispersed, the mean value (or expected utility) naturally loses its significance, and it is difficult to reflect the decision-maker's actual pursuit. In this paper, we will consider the possible outcomes and their likelihood of occurrence, and measure the degree of attention to be paid to various states to deal with uncertainty: $F(y,p)=\alpha(y,p)\cdot y$, where $\alpha(y,p)=(\alpha_1(y,p),\cdots,\alpha_i(y,p),\cdots,\alpha_a(y,p))$ is the attention vector, and $\alpha_i(y,p)$ is called the attention coefficient of the state x_{i+1}^i, which satisfies $\sum_{i=1}^{n}\alpha_i(y,p)=1$. The coefficient of interest differs from probability in that it is determined by both the likelihood of the event occurring and the outcome of the event. The process of uncertainty handling reflects the decision-making purpose, and the attention coefficient $\alpha_i(y,p)=0$ implies that the state x_{i+1}^i is not attended to in decision-making, regardless of whether the probability of its occurrence is greater than 0. Similarly, the attention coefficient $\alpha_i(y,p)>0$ implies that the state x_{i+1}^i is attended in decision making, and the nodes corresponding to those states that are attended are called focuses.

Definition 2: For a to-be-collapsed state $(x_{i+1}^1,p_1;x_{i+1}^l,p_i;\cdots;x_{i+1}^n,p_a)$, the state with attention coefficients $\alpha_i(y,p)>0$ x_{i+1}^i corresponding to a node is called a focus.

For situations where there are states where serious consequences may occur and only one of them is sufficient for the decision maker to make a choice (e.g., an interruption in the oil distribution system occurs in a state sufficient to cause the decision maker to initiate a rescheduling, a lottery win is sufficiently rewarding to cause the buyer to ignore the cost and make a purchase), the focus is on the state of maximal gain (or loss) $x^*=\arg\max_{x_{i+1}^i} y(x_{i+1}^i)$, when the state with the largest gain (or loss) has a focus coefficient of 1, and the rest are 0.

For scheduling decisions that are not repeatable multiple times or where a state is of sufficiently high concern, if a strategy is chosen that gives a larger payoff with a larger likelihood, the way the focus is chosen in one-shot decision theory and multi-stage one-shot theory: $x^*=\arg\max_{x_{i+1}^i}\min(\pi(x_{t+1}^i),u(x_{t+1}^i))$, where $\pi(x_{t+1}^i),u(x_{t+1}^i)$ are the normalization functions of $p(x_{t+1}^i),y(x_{t+1}^i)$ respectively. The focus x^* indicates that there does not exist a state in which the probability and the return are both greater than the focus, and if one is dissatisfied with the status quo the pursuit of a higher return requires a higher risk. The focus is assigned a coefficient of concern of 1, and the other states are 0. For such problems, the choice of focus changes accordingly when the decision goal is different, but it is a simple operation of probability and gain (or loss).

For routine decisions that can be repeated many times (or the decision process is very similar), when the decision process is repeated enough times, the frequency of each state will converge to its probability, at this time each state can not be ignored, and become the focus of attention, x_{i+1}^i of the attention coefficient and its probability of occurrence is equal to the $\alpha_i(y,p)=p_i$. When the decision process is repeatable enough times, the focus-based uncertainty treatment converges to the mean-based treatment and the two are equivalent.

Uncertainty handling depends on the scenario, i.e., system state and decision purpose. When the decision purpose is clear, the computational process of choosing the focal point is all a simple computation of probabilities and gains (or losses), and the choice of focal point allows for a fast implementation of uncertainty handling that reflects the decision purpose and meets real-time requirements. Handling uncertainty also solves the preference ranking of alternative strategies.

When the decision-making objective is clear, the premise of focus selection is to determine the scenario of the scheduling problem through data in order to determine the appropriate uncertainty handling. During the operation of the system, the scenarios may also change at different stages, and the decision-making goals are not the same, and different types of focuses can be used to meet the evolutionary needs of each stage.

Intelligent scheduling decision-making cannot be separated from artificial experience and knowledge, and the decision-making goal is the accumulation of experience and the embodiment of domain knowledge. The implementation of the system integrates the use of artificial intelligence and operations research in a variety of knowledge representation methods, in the system to achieve the problem knowledge representation, model knowledge representation, and algorithmic knowledge representation, with the support of the knowledge representation of the various parts of the realization of the modeling process of online intelligence is shown in Figure 1.

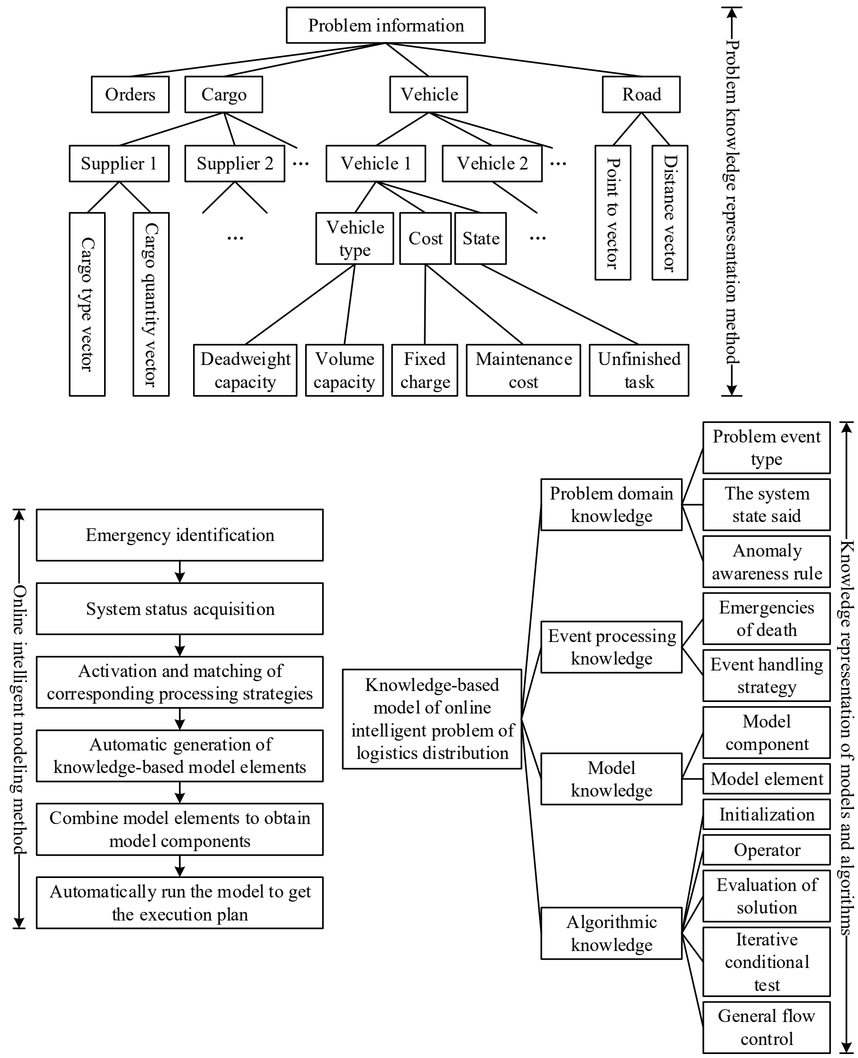

Figure 1: The core module of intelligent modeling and optimization method

III. Application of Artificial Intelligence Algorithms Combined with Operations Research Theory in Intelligent Decision Making

Scheduling optimization methods combining artificial intelligence and operations research optimization techniques mainly focus on the development of artificial intelligence models and corresponding algorithms for complex scheduling problems, especially NP-hard problems, which decompose the complexity of the problem and can find a better solution in a limited time.

III. A. Operations Research Theory

The main contents of operations research include: planning theory (including linear planning, nonlinear planning, integer planning and dynamic planning, etc.), graph and network analysis, project planning techniques, decision theory, countermeasure theory, queuing theory, storage theory and so on.

(1) Planning Theory. Planning theory, also known as "mathematical planning", is an important branch of operations research. The study of the given conditions, how to the most reasonable and effective use or deployment of limited human resources, material resources, financial resources, and time, in order to better achieve the desired goals of the system. It can be expressed as the problem of finding the maximum and minimum values of a function under satisfying constraints. Usually referred to as the amount of problem solving needs to control the "variable" or "decision variable", the decision variable must meet the conditions of the "constraints", to achieve the expected target for the "objective function".

(2) Graph and network analysis. Graph and network analysis is an old but very active branch, it is the foundation of network technology. The founder of graph and network analysis was the mathematician Euler.

(3) Storage Theory. Storage Theory, also known as Inventory Theory, is a theory that focuses on material inventory strategies, i.e., determining the amount of material inventory, the frequency of replenishment, and the amount of material to be replenished at one time. Reasonable inventory is a necessary guarantee for the smooth running of production and life, which can reduce the occupation of funds, reduce expenses and unnecessary turnover links, shorten the material circulation cycle and accelerate the process of reproduction.

(4) Project planning technology. Project planning technology is a kind of scientific plan management technology developed in the mid-1950s, which is an integral part of operations research.

III. B. Machine Learning Algorithms

Machine learning techniques play a central role in intelligent decision making, especially in the field of analyzing and predicting production data. By applying different machine learning methods, such as decision trees, support vector machines (SVMs), and random forests, it is possible to predict core metrics such as the health of equipment, location distribution of resources, and production efficiency [23]. A typicalized prediction formula is:

$$Y = f(X) + \grave{o} \tag{1}$$

III. C. Deep Learning Algorithms

Deep learning techniques are mainly used for monitoring and parsing of the environment. Especially in security monitoring, the image analysis capability of deep learning is fully applied [24]. The commonly used target detection formula in deep learning is:

$$L(\theta) = \sum_{i=1}^{N}((y_i - \hat{y}_i)^2 + \lambda \| \theta \|^2) \tag{2}$$

where $L(\theta)$ is the loss function, y_i is the actual value, $\hat{y}_i$ is the predicted value, θ is the model parameter, λ is the regularization term, and N is the data sample size.

III. D. Optimization algorithms

In the intelligent decision-making process, the application of optimization algorithms focuses on improving the quality of scheduling plans. Scheduling involves resource allocation, equipment usage efficiency, and manpower arrangement, and optimization algorithms are able to seek the optimal scheduling solution by constructing mathematical models [25]. Mathematical models with specific constraints and objective functions are often used in intelligent decision making to find the best solution using optimization algorithms. For example, a specific linear programming method can be used to optimize the scheduling plan, and the set objective may be to maximize the efficiency of resource use or minimize the operating cost, and at the same time, it needs to satisfy the constraints such as the output volume of the mine, the state of the equipment, and the allocation of human resources. It not only improves operational efficiency, but also ensures the effective use of resources. The common optimization model formula is:

$$\min\left(\sum_{i=1}^{N} c_i x_i\right) s.t, Ax \le b, x \ge 0 \tag{3}$$

where c_i denotes the cost of each resource, x_i is the decision variable, A is the matrix of constraint coefficients, and b is the vector of constraints.

IV. Analytical study of data-driven decision-making method for engineering projects

IV. A. System Test Methodology

The system testing method is to collect specified data from 10 devices of the project through IoT devices and sensors, and verify whether the serial port rate, data sharing service and other functions of the module meet the design requirements and actual needs through the configuration and collection capability of the terminal. The overall performance of the system is verified by recording the collected data and analyzing the key parameters such as response delay, collection interval and BER.

(1) Hardware Installation: 10 data acquisition modules are installed on 10 devices, connected to PLC through the serial cable terminal serial port, and the upper serial port is connected to the touch screen.

(2) module parameter configuration: module power-up, according to the port parameters connected to the PLC, with the AT command to configure the serial port parameters, including the baud rate, parity bit, data bits, stop bits, etc.; in the computer log in the module WiFi configuration page, configure the wireless connection parameters and

set up the module to the STA mode; reboot the module, the PLC and the touch screen is normally connected, WiFi is normally connected, then the configuration is complete.

(3) Software deployment: install the data acquisition software on the acquisition host and deploy the local database; add 10 terminal information in the software and configure the terminal parameters; test whether the terminal is normally on-line.

(4) Response delay test: after the terminal connection is normal, carry out the response delay test; the test method is as follows: send a data request to a single module, and record the interval time between the data collection host sending a request and receiving a reply, and then calculate the average response delay; after receiving a reply, immediately send the same request again, repeat 200 times to get 200 groups of response delay data, and then calculate the average response delay; respectively, select 4 devices for testing, and get 4 sets of data collection hosts to get the average response delay. The average response delay of the four devices is obtained.

(5) BER test: select a device, set a certain parameter value, send data request to the device 1000 times at the monitoring end, receive data recorded into the database, and automatically check whether there is any error according to the set value; test the 4 units selected in 4) respectively.

(6) Data collection interval test: select 1 device, set the serial port baud rate to 115200bps, send 20bytes, 100bytes of data requests, and set the sending interval to 150ms, 100ms, 50ms; each combination of sending 300 times, record the data and analyze the data with or without anomalies.

Use the serial port debugging assistant to configure the serial port parameters and network parameters of 10 data acquisition modules through AT commands.

The data acquisition software and database are deployed on the acquisition host. After debugging 10 devices are successfully connected, the acquisition information is shown in Table 1, you can query the data acquisition information of 10 devices in real time on the software.

Table 1: Verification results of data acquisition software

Equipment	Alarm status	x-code	x-code	x-code	Running state
1	0009	0000	0001	0001	00
2	000	0000	0001	0001	00
3	0001	0001	0001	0001	00
4	0008	0001	0001	0001	00
5	0009	0001	0001	0001	00
6	0009	0001	0000	0001	00
7	0007	0001	0000	0001	00
8	0001	0001	0000	0001	00
9	0000	0001	0000	0001	00
10	0000	0001	0000	0001	00
......					

The results of the response delay test are shown in Figure 2. All the data delay is randomly distributed between 50ms-150ms, the overall is relatively smooth, there is no overall change in the trend, it can be considered that the system response line is relatively stable in a certain range.

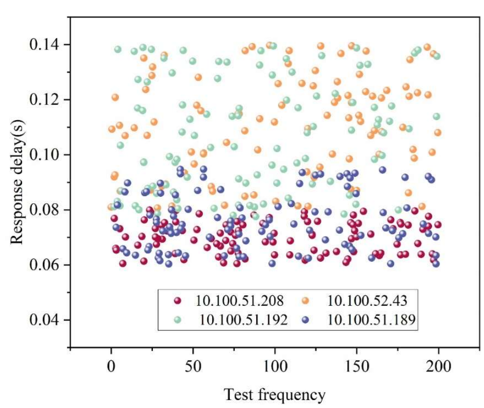

Figure 2: Results of response delay test

The response delay data of each device is counted to get the minimum, maximum and average values. The response delay data statistics are shown in Table 2, and the average response delay of the four devices are 95ms, 95ms, 75ms and 76ms, respectively, and the average response delay of the four devices is 84ms.

Table 2: Results of response delay test(ms)

Unit:ms	Equipment1	Equipment2	Equipment3	Equipment4	Total
Mean	95	95	75	76	85
Min	72	75	64	55	86
Max	140	135	98	100	138

The results of the BER test are shown in Table 3, where all four devices responded to 1000 data requests with accurate data.

Table 3: Results of error rate Test

	Equipment1	Equipment2	Equipment3	Equipment4	Total
Error rate	0%	0%	0%	0%	0%

The results of the collection interval test are shown in Table 4, under the baud rate of 115200bps, the actual test 100bytes is sent at an interval of 100ms, and no abnormality occurs. In common industrial automation protocols generally do not use a single packet 500bytes length of data packets, so according to the actual situation, only tested to 100bytes.

Table 4: Results of data collection interval test

Sending interval/ms	Data length/byte	
	20	100
50	Slight loss	Slight loss
100	normal	normal
150	normal	normal

Table 5: car door welding line dynamic disturbance event list

Disturbing event	Workstation number	Change	Disturbance duration(s)
1	4	44	320
2	2	66	500
3	7	85	360
4	3	96	300
5	5	122	710
6	1	250	1264
7	6	389	440
8	4	430	700
9	3	482	320

IV. B. Example of application of big data-driven customized production method optimization for engineering projects

IV. B. 1) Case Description and Base Parameter Collection

The automotive door welding line consists of seven stations and six buffer zones. The transfer of workpieces between adjacent processes is realized by automated conveyors. The function of each station of the line is described as follows: station 1 - welding of reinforcement plates, station 2 - welding of window frames, station 3 - welding of bumpers, station 4 - gluing and edging, station 5 - induction curing, station 6 - welding of hinges, station 7 - testing. Each station has multiple sets of fixtures, thus allowing for mixed line production of multiple products.

In order to realize automated decision-making, each station of the welding line is installed with RFID system, sensor system, image recognition system, etc.; RFID system is used to collect real-time data related to the operation, such as material shortage data, workpiece flow data, workpiece position data, etc.; the sensor network mainly senses the robot status data, and the sensor network mainly senses the robot status data such as the number of robot failures as Table 5 shown in Table 5.

Robot processing time data is shown in Table 6. The welding line suffers from bottleneck drift during multi-species mixed flow production.

Table 6: car door welding line (s)

Product variety	m1	m2	m3	m4	m5	m6	m7
Variety A	252	278	230	200	220	254	250
Variety B	179	230	264	246	196	236	236
Variety C	230	245	263	184	187	241	227
Variety D	200	218	254	246	187	214	247

Multi-product mixed-flow production and automated in-process control: In order to deliver multiple products in a short period of time, the welding line is designed with mounting fixtures for different products to realize fast changeover of the robot, including switching between front and rear doors of multiple vehicle models. The changeover time of the robot between four types of doors is shown in Table 7.

Table 7: The car door welding line is the replacement time (s)

Transposition	m1	m2	m3	m4	m5	m6	m7
$A \to B$	200	160	130	264	--	140	--
$A \to C$	--	190	130	264	80	120	--
$A \to D$	140	--	160	252	80	160	--
$B \to A$	180	160	160	132	--	140	--
$B \to C$	220	170	130	232	60	100	--
$B \to D$	170	130	--	212	--	170	--
$C \to A$	100	210	205	252	60	140	--
$C \to B$	140	130	160	192	60	120	--
$C \to D$	--	210	210	92	--	170	--
$D \to A$	170	190	170	232	60	140	--
$D \to B$	200	140	--	192	--	140	--
$D \to C$	--	220	210	--	--	160	--

The diagnostic results of permanent capacity loss of the manufacturing system under the effect of different dynamic disturbance events are shown in Table 8. In addition to the AI model, the diagnostic results of manufacturing system performance loss under two other process control strategies are also listed. In the table, Y and N denote the presence and absence of permanent capacity loss, respectively. The results show that the AI is slightly less responsive than the Kanban mechanism when the dynamic disturbance event lasts for a longer period of time. The responsiveness of the AI can be improved if the work-in-process inventory constraint is increased moderately, i.e., the necessary work-in-process inventory is maintained in the manufacturing system.

Table 8: car welding line capacity loss diagnosis results

Disturbing event	MPS	Kanban	e-MPC	Artificial intelligence
1	N	N	N	N
2	N	N	Y	N
3	N	N	N	Y
4	N	N	N	N
5	N	Y	N	N
6	N	N	Y	Y
7	N	N	N	N
8	N	N	Y	N
9	Y	N	N	N

IV. B. 2) Workpiece waiting time

As shown in Fig. 3, the average waiting time of workpieces under Kanban, e-MPC and AI are 3234s, 2243s and 2695s respectively, and combined with the results of the production line output rate, it can be seen that AI can achieve almost the same output rate as that of MPS and Kanban with less WIP inventory. Combined with the above results, it can be shown that the AI model proposed in this paper can show better performance under endogenous event perturbation.

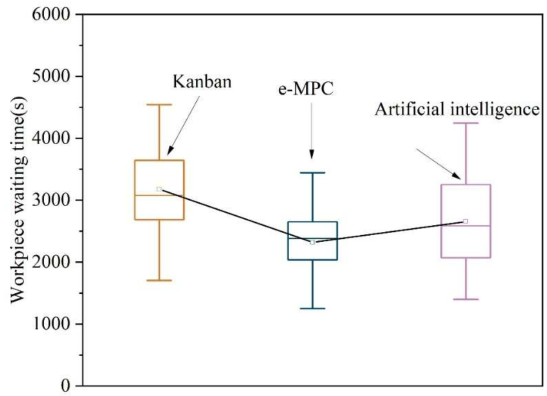

Figure 3: Workpiece waiting time

IV. B. 3) Change of workpiece machining sequence

It is assumed that the optimal machining order of workpieces under the effect of different exogenous perturbation events is shown in Table 9 (the results are given according to the rescheduling model). Each element in the table represents: the point at which processing order II, III and IV changes compared to processing order I. For example, A→C means that the 116th-135th workpiece in processing order II changes from product A to product C, etc.

Table 9: Change of artifact processing order

Numbering	Process order I	Process order II	Process order III	Process order IV
116-135	--	A→C	A→C	A→C
153-178	--	C→B	C→B	C→B
179-198	--	B→A	B→A	B→A
224-250	--	--	A→D	A→D
251-275	--	--	C→A	C→A
276-298	--	--	A→C	A→C
406-440	--	--	--	B→A
441-470	--	--	--	A→D
471-500	--	--	--	D→C

The workpiece release time and workpiece waiting time corresponding to different machining sequences are shown in Fig. 4. Where, the graph represents the difference in workpiece release time corresponding to different machining sequences, i.e., $\{u_{II}(k)-u_I(k), u_{III}(k)-u_{II}(k), u_{IV}(k)-u_{III}(k)\}$, $u_I(k)$, $u_{II}(k)$, $u_{III}(k)$ and $u_{IV}(k)$ are the optimal release times of the workpieces corresponding to different machining sequences, respectively. As can be seen from the figure, the AI can dynamically adjust the workpiece release schedule before the scheduling scheme changes to better cope with the perturbations that will occur. For example, the machining sequences II, III, and IV are changed only when 116 workpieces are machined, but the optimal control scheme of the AI is adjusted when the 100th workpiece is machined. This ex ante dynamic control mechanism can be effective in minimizing manufacturing system performance loss or avoiding work-in-process inventory spikes.

The workpiece waiting times corresponding to different machining sequences are shown in Fig. 5. The results show that the AI can always maintain the work-in-process inventory of the manufacturing system at a reasonable level with small fluctuation when coping with the change of machining sequences, and the workpiece waiting times corresponding to the four machining sequences in the figure are [1974, 2054s].

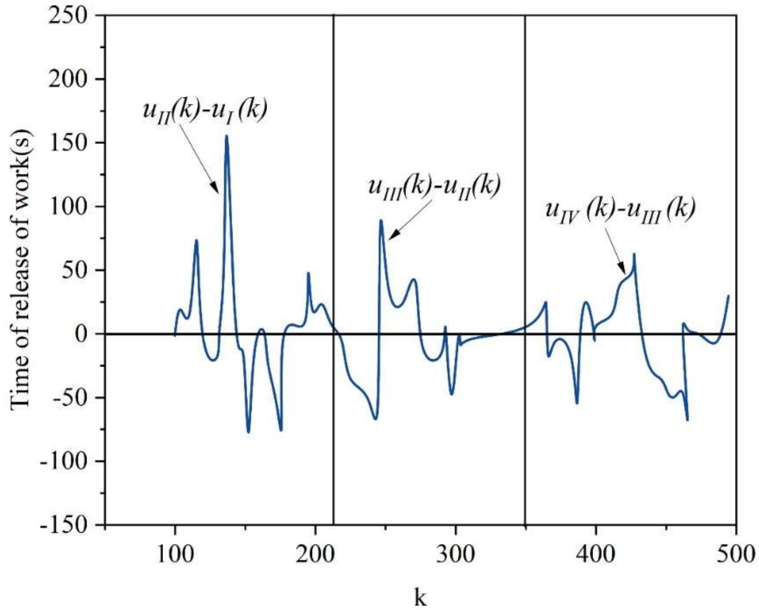

Figure 4: Time of release of work

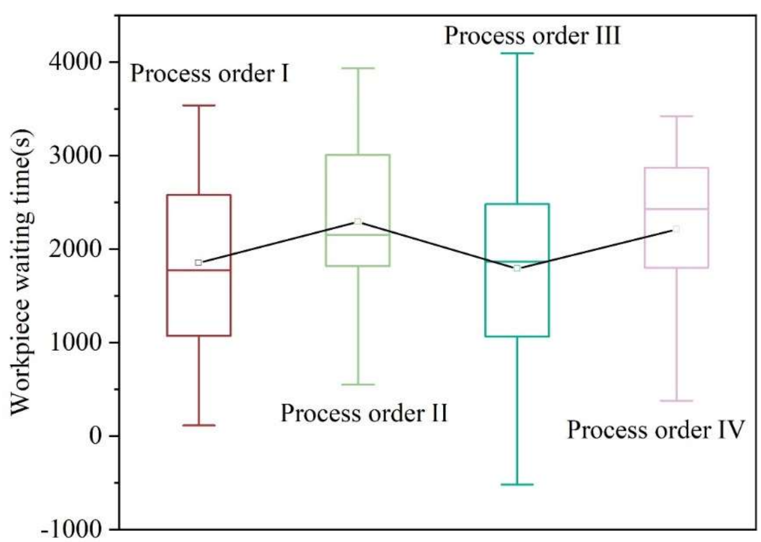

Figure 5: Workpiece waiting time

V. Conclusion

This paper mainly utilizes IoT devices (intelligent sensing devices, wireless communication technology, cloud computing), artificial intelligence, data-driven technology, etc., to design an online intelligent scheduling decision-making method based on IoT, so as to realize the search for optimal scheduling solutions based on engineering project data. Empirical analysis can get the following conclusions: the delay of IoT devices collecting engineering project data is randomly distributed between 50ms-150ms, therefore, the response of IoT devices is relatively stable in a certain range. Its requests for data are answered and data are accurate, and the BER is low. Artificial intelligence algorithms can dynamically adjust the workpiece release schedule, always maintaining the product inventory at a reasonable level with small fluctuations when the machining sequence changes.

The conclusion of this paper provides a new decision-making method for intelligent scheduling system in the environment of IoT and AI, and provides new ideas for solving complex scheduling decision problems in the environment of IoT.

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