Research on Automatic Flow-shop Planning Problem Based on Data Driven Modelling Simulation and Optimization

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Abstract. With the increasing demand for individualization, new smart manufacturing models are implemented in order to adapt to the market demands of high quality, multi-variety and fast delivery. However, new problems in production and operation are urgently needed for research. It is especially significant to study the automatic flow workshop planning based on data-driven modelling and simulation. Firstly, according to the rapid analysis of various data of the workshop, UML-based object-oriented data model is formulated. Then the application module of data-driven simulation modelling is established by using the simulation platform. The bottleneck recognition based simulation optimization module for the tabu search algorithm with guiding rules is designed. Data-driven modelling makes the model more flexible and reusable which can run a variety of different experiments by modifying the external data to drive simulation model. Finally, experiments are conducted to verify the effectiveness of the simulation optimization method proposed in current study. In addition an optimized production line configuration plan is provided.

1. Introduction

With the aggravation of the industry competition, how to quickly seize the growing market becomes a critical task for enterprises. Through the upgrade of the current production mode, many companies adopt advanced intelligent hardware and software systems to implement a new mode of intelligent manufacturing. Thereby increasing production capacity and product quality, enhancing the company’s own competition, expanding the market and reducing production costs [1]. For the planning of intelligent manufacturing lines, simulation technology could handle complex systems that cannot be processed using mathematical models, accurately describe real-world conditions and identify key factors that affect the system. It performs simulation and solution verification quickly and gives a variety of resource allocation schemes and compares various indicators. Modelling is the premise and basis for conducting simulation experiments, which is also one of the most complicated stages in the implementation of simulation projects. However, traditional simulation technology consumes a lot of manpower and time costs, and cannot respond quickly to changes in the production floor [2]. There is an urgent need for a fast, real-time simulation system to accurately evaluate and optimize the production system.

However, the construction cost of smart manufacturing workshops is very high, because the imbalance of resource allocation leads to high cost of redesign and construction. At the beginning of
the design, it is necessary to not only express the physical structure of the system, but also describe the operational logic of the production system. Therefore, the application of data-driven modelling and simulation technology is proposed.

Data is the driving force for modelling, directly serving the development, operation, and evaluation of automated modelling and simulation. Reconstruction of the production line depends on the data changes. Data-driven modelling allows modelers to provide modifications and corresponding additions at the input data level, which can lead to rapid construction of simulation models.

Generally, the simulation system and various simulation softwares have dedicated formats to provide data import and export interfaces. It takes a lot of time to convert according to the interface. Therefore, it is necessary to establish a unified data model storage. The research has proposed different CMSD frameworks to solve the problem that different simulation softwares can’t be converted according to different formats [3]. Lee [4] builds data transfer mechanism through XML and ODBC to realize shop floor data to simulation model Data conversion. Fournier J et al [5] divided the data transformation into two steps. First map to the XML data model, and then convert to simulation code through XML and XSLT data model to realize the interactive integration of MRP, ERP and other systems with simulation models.

James Tannock et al [6] used data-driven simulation to support the design and improvement of supply chains. Based on the physical layout data of assembly line, Wang Junfeng [7] implemented the data-driven generation simulation model for the automobile assembly line using the Arena software. Wang Guoxin et al [8] described the system structure hierarchically and establishes corresponding control models respectively. Dynamically complete simulation, experimentation, verification and optimization based on production data, experimental parameters, control parameters, statistical data. Meng et al [9] developed a data-driven modelling and simulation framework for MHS of coal mines to automatically generate a discrete-event simulation model based on current MHS structural and operational data.

Data-driven modelling and simulation technology is a system integration application. The integration of simulation with other information systems helps advance the study of system modelling and simulation. Modelling and simulation optimization is an organic whole. While considering the versatility and reusability of the model, the robustness, the parameterization of the optimization algorithm, and the customization characteristics are also needed to consider.

Aiming at the rapid planning and design of intelligent manufacturing workshop, the current research proposed a data-driven modelling and simulation and optimization planning method to study the practical application of data-driven simulation modelling technology in the field of intelligent manufacturing. Focusing on the execution layer of the intelligent workshop, analyze the characteristics of the line and building a data model in the database including workshop layout data and simulation running logic data, and design a data-driven simulation modelling module on the simulation software platform. The fast and accurate generation, reusability, maintainability and other performance of the data-driven simulation model enhances the rapid analysis of the manufacturing floor. Finally, the simulation optimization based on the tabu search algorithm in the simulation model is designed to optimize the automated production line configuration. Through the simulation model design optimization program, the planning and design efficiency of the on-site workshop is improved, and the intelligent level of the manufacturing enterprise is continuously promoted. Production line planning framework based on data-driven modelling and simulation as shown in Figure 1.
2. Data-driven modelling and simulation for the automated production line workshop

Current research formulated a data model in the database after analyzing the characteristics of the data through object-oriented analysis, and then analyzed the simulation modelling logic and running logic of the automated production line workshop. The layered modelling method is used to build the customized entity in the simulation platform. And the physical layout of the workshop is automatically generated, running through the logical data driven model.

2.1 Data model of the workshop

The production line workshop model consists of two parts: the production line and the logistics system. The production line mainly completes the material processing process, and the logistics system is responsible for the entire transportation process of the materials in the entire workshop. The robot is responsible for the refueling action of the auxiliary machine, and the different number of machines and robots constitute the smallest production unit of the production line. The incoming and finished products of the production line are stored in the line buffer of each assembly line to form a complete production line module.

After sorting out the basic components and processes of the workshop, the workshop is modeled from the perspective of data modelling. Use the class diagram in UML to represent the elements of the workshop, which describes the abstract classes in the workshop and the relationship between classes and classes. The data model of the workshop is constructed through the relational data table of the database management system.

2.2 Data driven modelling and simulation of the workshop

At the beginning of the simulation, modeling must be based on the entity of the workshop. Then a complete workshop model should be established after the analysis of the logical flow of the complete and accurate workshop elements.

Using the layered modelling method, the resource model is transformed into the simulation input data from the Access data interaction platform to establish the simulation model in the automatic pipeline workshop. The data-driven simulation model generation module is developed in the simulation software platform, and the product order data in the data model is imported for dynamic simulation to drive the simulation model to build and run.

There are three modules in automatic modelling and simulation: model generation module, data import module, and operation control module. The model generation module is shown in Figure 2. The model generation module automatically generates the static simulation model of the workshop by reading the physical layout data in the data-model, automatically generating the necessary elements such as the intelligent entity, elements, data tables and simulation logic of the simulation model. Data import module: The data table in the simulation model is associated with the data table of the database. The module calls the data import module before the simulation runs, and the data in the database is
imported into the simulation model to drive the simulation model to run.

![Diagram of simulation model generation process](image)

**Figure 2. Automatic generation of static models**

The essential to data-driven modelling is to accurately map the data in the data-model. Design a data-driven simulation model generation module developed by API, and drives the simulation model to build and run by importing data from the data-model, as shown in Figure 3.

![Diagram of data-driven simulation modelling and simulation](image)

**Figure 3. Data driven simulation modelling and simulation**

The simulation needs to be defined separately operating logic (Process) to implement complex logic simulation model. In the data-driven modelling, the XML file which saving the pre-defined simulation logic is imported into the model. Then the Process processing flow is automatically generated in the model, so that the simulation model is organized in accordance with predetermined rules.

3. **Data-driven simulation optimization of machine allocation planning**

Based on the data-driven simulation modelling, the optimization algorithm library is added to optimize the simulation model for the unreasonable allocation of resources. The results of the simulation experiment are evaluated by the specified indicators. The optimization program feeds back the output of the simulation and adjusts the configuration parameter data of the simulation model if optimization is needed. By repeatedly performing the above process, the parameters of the model are continuously optimized. Finally simulation gives the scheduling scheme to be executed.

In the planning and design, it is easy to ignore the influence of the manipulator on the production line process resulting in the unreasonable configuration of the assembly line, machine and robot, which makes it impossible to identify the real bottleneck on the assembly line. Aiming at the problem of unreasonable allocation of production line resources, the current research designed an algorithm simulation optimization module with guiding rules based on bottleneck recognition which obtains the optimization plan of production line configuration.

The process that defines the maximum load on the machine is the bottleneck process [10]. The bottleneck identification method in the simulation model with process load and robot load as indicators is used to determine the bottleneck position on the production line.

The basic parameters are shown as following Table 1.
Table 1. Model parameters

| L | Distribution of workstations on the production line |
| Q | Number of processes |
| S | Number of workstations |
| N | Number of robots |
| P | Sequence of operations, "i" indicates the number of iterations |
| R | Robot sequence, "j" indicates the number of iterations |
| P₀ | Initial value of the sequence of operations |
| R₀ | Initial value of the robot sequence |
| φ | The random transformation number of the solution in the algorithm |
| TP | Output of the production line at the ith iteration |
| t_p | Processing time in the process |
| t_r | The time taken by the robot to replace the material in the process |
| t_n | The time taken by the robot to transfer the tray at the end of the production line |
| t_c | Material cleaning time in the process |
| r_j | robot in the production line |
| m | machine in the production line |
| a_i | Number of materials replaced by r_i during simulation |
| t_x | Total robot movement time during simulation |
| p_i | Process in the production line |
| ω | Work load rate of machine m_i |
| n_1 | Number of machines included in the process p_k |
| T | Total output of machine m_i during simulation |
| ω_r | Work load rate of robot r_i |
| ω_p | Resource load rate of process p_k |

The calculation for load factor of processing machine and robot is given in Equations (1) and (2). By calculating the workload of each machine, the average load of all machines in the process is taken in Equation (3) which determine the position of the bottleneck process.

\[
\omega_{m_i} = TP_{m_i} \times \left(t_p + t_r + t_c + t_m/2\right)/t_{run} \tag{1}
\]

\[
\omega_{r_j} = a_{r_i} \times \left(t_r + t_x + t_m/2\right)/t_{run} \tag{2}
\]

\[
\omega_{p_k} = \sum_{i=1}^{n_p} \omega_{m_i}/n_{p_k} \tag{3}
\]

According to the workload, the process and the robot are sorted. The process with the largest workload is known as the bottleneck process. At the same time, the robot with the largest workload will also affect the production capacity of the production line. Therefore, the guiding rules based on the workload rate of the robot and the process could adjust the machine allocation plan including the assignment of processes, robots, and workstations.

The simulation input is controlled by the external program. And the simulation model is continuously called for calculation to optimize the production line configuration. When adjusting input parameters, set up a rule bootstrap to quickly find an optimized configuration of the production line. The tabu search algorithm optimization process is shown in Figure 4. Through the work load of the production line process and the robot, the machine distribution plan is adjusted to obtain a better distribution plan of the production line machine.

![Figure 4. Optimization algorithm flowchart](image-url)
4. Experimental result
It is considered that model verification and validation is extremely important in simulation practice. The data-driven simulation modelling is verified through simulation experiments. The simulation logic and output comparison of the model are verified to test the feasibility of the data-driven modelling technology and the effectiveness of the simulation model.

Experiment 1: Design a simplified assembly line workshop with 2 production lines, 6 robots, 1 AGV trolley and 2 loading points. The workshop processes both products P1 and P2. The work of P1 is j1, j2, j3, and the work of P2 is j4, j5, j6, which are processed on the production line LineA and the production line LineB respectively.

Run the simulation model for 48 hours, and the output and utilization of each machine and the robot utilization are imported into the Result during operation. The simulation output for comparison with the theoretical output calculated according to the formula.

| Process id | Product | Work | Experimental output | Theoretical output | Error(%) |
|------------|---------|------|---------------------|--------------------|---------|
| pro1       | P1      | j1   | 1247                | 2362               | -       |
| pro2       | P1      | j2   | 1290                | 2310               | -       |
| pro3       | P1      | j3   | 1328                | 1470               | -9.66   |
| pro4       | P2      | j4   | 922                 | 934                | -       |
| pro5       | P2      | j5   | 911                 | 1020               | -       |
| pro6       | P2      | j6   | 901                 | 932                | -3.33   |

As shown in the Table 2, the yellow marked data in the table is the process with the lowest processing capacity meaning the production line bottleneck which need be compared when comparing the errors. The comparison error between the simulated output and the theoretical output of the bottleneck process are -9.66% and -3.23% of pro3 and pro6 within acceptable limits. The overall output of each process in a pipeline is roughly equal due to the JIT production in the simulation logic. The validity and correctness of data-driven modelling is verified.

| Robot id | r1 | r2 | r3 | r4 | r5 | r6 |
|----------|----|----|----|----|----|----|
| Utilization (%) | 65.36 | 64.41 | 66.35 | 50.63 | 28.79 | 41.17 |

The theoretical output is larger than the simulation output because the theoretical output calculation does not take into account the situation where the robot services multiple machines. As shown in Table 3, the maximum utilization rate of the robot reached 66.35%. The influence of the manipulator on the output of the processing machine cannot be neglected. Therefore, an emergency search algorithm flow with guiding rules is designed to adjust the machine allocation plan. Finally a better production line machine distribution plan is obtained.

Experiment 2: 7 kinds of production lines with different configurations, respectively processing 2 kinds of products. The initial data is as shown in Table 4.

| Line id | L | Q | S | N | t_p | t_p | t_p | t_p |
|---------|---|---|---|---|-----|-----|-----|-----|
| LineA   | [2,2,2,2,2,2,2] | 3 | 8 | 8 | [180,300,400] | [30,30,30] | [25,25,25] | [0,0,15] |
| LineB   | [2,2,2,2,2,2,2] | 3 | 11 | 11 | [180,300,400] | [30,30,30] | [25,25,25] | [0,0,15] |
| LineC   | [1,2,2,2,2,1,2,1] | 3 | 11 | 4 | [180,300,400] | [30,30,30] | [25,25,25] | [0,0,15] |
Run the model by importing the production process and the machine-assigned data. Then the tabu search algorithm is optimized for production line configuration. Initial solution and optimization solution are shown in Table 5.

Table 5. Initial solution and optimization solution

| Line id | $P_0$    | $R_0$    | $\varphi$ | $TP_0$ | $P_i$       | $R_i$       | $TP_i$ |
|--------|----------|----------|-----------|--------|-------------|-------------|--------|
| LineA  | [2,3,3]  | [1,1,1,1,1,1,1] | 2         | 1153   | [2,3,3]     | [1,1,1,1,1,1,1] | 1153   |
| LineB  | [3,3,5]  | [1,1,1,1,1,1,1,1,1] | 3         | 1495   | [2,4,5]     | [1,1,1,1,1,1,1,1,1] | 1154   |
| LineC  | [2,4,5]  | [3,3,3,2]       | 13        | 886    | [3,4,4]     | [2,3,3,3]    | 1275   |
| LineD  | [2,4,5]  | [2,2,2,2,3]     | 19        | 1298   | [3,4,4]     | [1,3,3,2,2]  | 1515   |
| LineE  | [2,4,3]  | [1,1,1,1,1,1,1,1,1] | 2         | 973    | [2,3,4]     | [1,1,1,1,1,1,1,1] | 1205   |
| LineF  | [2,3,4]  | [3,3,3]       | 4         | 751    | [2,4,3]     | [2,4,3]     | 886    |
| LineG  | [2,3,4]  | [2,2,2,3]      | 7         | 960    | [2,4,3]     | [2,2,3,2]   | 1174   |

Table 6. Optimized production lines capacity

| Line id | LineA | LineB | LineC | LineD | LineE | LineF | LineG |
|--------|-------|-------|-------|-------|-------|-------|-------|
| Increase (%) | 0     | 3.3   | 43.9  | 16.7  | 23.8  | 18    | 22.3  |

The production line optimization scheme is obtained through the optimization of the simulation algorithm. As shown in Table 6, the results of the simulation optimization are compared. The average productivity through algorithm optimization has increased by 18.3%, and the production line has increased by up to 43.9%. The results show that the algorithm can improve the production capacity of the production line by adjusting the machine allocation plan under the existing pipeline configuration.

5. Conclusion

In current research, a data-driven modelling and simulation method is proposed to effectively simulate the intelligent workshop simulation system. Data-driven modelling technology integrates data with other systems. The technology automatically generates and runs real-time data-driven simulation models which could respond to requirements to assist the site in making more accurate decisions. When the planning and design scheduling does not achieve the predetermined aim, different simulation experiments can be run by modifying the external database data-driven model, which can not only promote the accuracy of modelling and reduce the complexity of re-modelling, but also enhance the flexibility of the simulation model. Generality and portability improve planning efficiency. The combination of modelling techniques and optimization methods extend the range of applications for simulation optimization. It is not only effective for the intelligent workshop production line design, but also valuable for production lines with diverse order requirements, similar production line structure, scale and occasional differences.

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