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Dynamic Productivity Prediction and New Production Feature Selection Methods for Advanced Planning Scheduling

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Smart manufacturing is an important research field that is associated with production planning and scheduling, the Internet of Things and artificial intelligence technologies. Production lines use advanced planning and scheduling systems for production operations, time forecasting and planning; integrated manufacturing execution systems are used to collect real-time production information via the Internet of Things to strengthen scheduling control; and artificial intelligence machine learning technology is used to perform predictive maintenance to achieve high-accuracy planning and scheduling. Advanced planning and scheduling systems use genetic algorithms for planning with the aim of increasing speed and accuracy, and the integration of real-time production information from manufacturing execution systems and dynamic adjustments to shift planning are important issues in smart manufacturing. A traditional cyber-physical system integrates historical and real-time production information and carries out a machine learning analysis to improve the production scheduling efficiency, but the prediction of production times for new product orders is a topic that needs further research. This paper proposes new methods of dynamic productivity prediction and new production feature selection, with the aim of improving the performance of advanced planning and scheduling systems. A genetic ant colony algorithm is used to predict dynamic productivity based on real-time production information, to reduce the error between production time plans and actual operations. Historical production information is analysed, and the best correlation coefficient is used in new production feature selection, in order to reduce the discrepancy between production productivity forecasts and actual results. Our proposed dynamic productivity prediction method can reduce the error by at least 1.5% compared with other schemes in the literature, while the proposed production feature selection method can reduce the error by 0.08%.

Keywords: smart manufacturing, advanced planning and scheduling system, dynamic productivity prediction, new production feature selection, machine learning

1. INTRODUCTION

Smart manufacturing is an important trend in the development of traditional industries, and is used to achieve efficient production management. Automated production equipment uses Internet of Things technology to upload real-time production information to a cloud management platform, which provides a visual monitoring service that can control the equipment conditions and make adjustment to process planning. Artificial intelligence and machine learning technology can be integrated to predict and plan production

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operation times to improve the manufacturing efficiency. A cyber-physical system integrates historical data and real-time production information from the manufacturing execution system and carries out machine learning analysis and prediction, with the aim of improving advanced planning and scheduling system performance [1]. The development of integrated manufacturing execution systems that use real-time information for advanced planning and scheduling algorithm design can reduce forecast errors [2]. One study in the literature proposed an advanced planning and scheduling algorithm that used production information from the manufacturing execution system and passed it to a long short-term memory prediction model, in order to predict production operation times based on the energy consumption, resource utilisation and production time characteristics of each machine at a workstation [3]. The processing algorithm performed production operations by predicting the machine path with the lowest cost. Another study put forward a cloud management platform system that applied a manufacturing execution system to improve the performance of an advanced planning and scheduling system [4]. It used the ant colony algorithm to predict the production operation time based on the real-time production information from each machine at a workstation. This algorithm performed production operations by predicting the machine path with the shortest manufacturing time. However, the advanced planning and scheduling algorithms in the abovementioned articles did not take into account the time delay caused by the continuous processing of the machine, leading to differences between the predicted times for production operations and the actual operation times. Traditional advanced planning and scheduling systems cannot accurately plan machine paths for orders with unknown products, as advanced planning and scheduling algorithms cannot predict the production times for unknown products [5-8]. A scheme in one paper used the complex features of the production process to predict the production times for new products with a regression prediction model [9]. The authors considered the complex characteristics of product manufacturing and performed a linear regression analysis on the production times. However, the advanced planning and scheduling algorithms in the related literature do not take into account the learning bias caused by the low correlation coefficient feature, which leads to an error between the predicted production time for a new product and the actual operation time. In order to improve the efficiency of advanced planning and scheduling systems, we propose a dynamic productivity prediction method to predict the continuous processing delay time using linear regression, and develop a method of selecting new production features to predict production times using the best correlation coefficient feature. In Section 2 of this paper, we discuss research methods in the recent related literature. Section 3 describes our methods of dynamic productivity forecasting and new production feature selection, with the aim of improving the performance of advanced planning and scheduling systems. Section 4 presents a performance analysis of the proposed method and compares it with schemes in the literature. Finally, Section 5 summarises this paper.

2. RELATED WORK

The rise of Industry 4.0 has driven researchers towards the use of Internet of Things technology to communicate with manufacturing machinery and equipment in order to collect real-time data, and to use these data to improve the rules for dynamic production scheduling to improve the overall production efficiency of a workshop. One study in the literature has proposed a decision support system that can adjust the production sequence in real time, based on real-time data from workstations relating to the busy status of mechanical equipment, machines waiting for processing, and attributes of products waiting to be processed, in order to avoid idle time at workstations [10]. Another study reviewed and analysed research on manufacturing processing times. If mechanical equipment events and product specification differences were found to affect the manufacturing time, it was suggested that the production schedule time could be adjusted in real time, to avoid misjudgements in planning and scheduling [11]. Another study optimised the production planning and scheduling based on the total production time and energy consumption for the industrial category of high energy consumption and large orders in the forging industry. In this paper, the overall production time was optimised by applying different fitness calculation methods to genetic algorithms, and the energy consumption was minimized [12]. A further paper reported that customised manufacturing represented a future trend in smart manufacturing, as there has been a gradual transformation from large-scale production to large-scale customisation. New product manufacturing and assembly planning has become an important issue affecting scheduling planning, as the manufacture of new products increases the complexity of operations and reduces the accuracy of planning and scheduling forecasts [13].

There are many studies in the literature on the classification and discussion of advanced planning and scheduling system problems, including innovative models and methods, design optimisation methods, heuristic methods and genetic algorithms, advanced techniques involving the integration of RFID technology with cloud computing technology, and advanced planning, analysis and scheduling systems that provide spreadsheets and visual display platforms [14-18]. These systems have been developed for use in Industry 4.0 in the future. One study in the literature surveyed research results related to the modelling and implementation of advanced planning and scheduling systems over the past two decades, and proposed a collaborative filtering algorithm to solve the problems encountered between modelling and implementation [19]. Due to the growing pressure from industrial competition and limits arising from capital budgets and regulatory environments, traditional advanced planning and scheduling systems cannot reduce the production time and cost without compromising the production quality. Advanced planning and scheduling systems are therefore needed that can optimise calculation methods, data processing and method design. Another study explored the differences in the production process between product orders, and automatically allocated product orders to the production line based on the characteristics of the production process [20]. This automatic allocation method also considered the load balance of the mechanical equipment, and applied a tabu search and simulated annealing algorithms as part of an advanced planning and scheduling system. In another study, the manufacturing process was considered, including the use of automation and characteristic digital information in the field of metal manufacturing and mechanical equipment manufacturing [21].

A cloud-based advanced planning and scheduling system was proposed in which the scheduling engine was based on an intelligent dynamic planning and scheduling system. This system was capable of dynamically generating schedule plans for production and operation, and providing production planners in small and medium-sized enterprises with real-time visual information for analysis. Another set of researchers investigated the applicability of advanced planning and scheduling systems to the aluminum conversion industry, and reported that increasing product delivery delays, overproduction, waste and inventory could optimise the performance of the advanced planning and scheduling system [22]. Manufacturing plants generate huge amounts of data, and their complexity has increased significantly, meaning that extracting and using the characteristics of the manufacturing data curve to optimise the performance of an advanced planning and scheduling system can only yield limited increases in performance [23]. Deep learning technology has been proposed for analysing the manufacturing data curve of monitoring machinery, and for model training and identification. This approach can provide manufacturing plants with suitable methods for processing huge amounts of data and complex data volumes; it can improve the efficiency and accuracy of monitoring machinery and equipment, and enable the extraction of real-time visual information for analysis.

A study in the literature proposed a cloud management platform system that integrates manufacturing execution systems to improve the performance of advanced planning and scheduling systems [4]. The system framework consists of a client data preprocessing layer, an application user interface layer, a virtual entity resource integration layer and an advanced planning and scheduling service cloud layer. The client data preprocessing layer uploads the customer information, purchase details, manufacturing orders, production processes and real-time production information from a machine in the enterprise resource planning system to the cloud database via an API. The application user interface layer provides managers with updated information on production, machinery and equipment, and production lines, so that the advanced planning and scheduling system is aware of the actual operation conditions. The virtual entity resource integration layer is used to construct the software and hardware co-design required for entity sensing data and visual display. The advanced planning and scheduling service layer uses an ant colony algorithm to predict the overall production operation time based on the information from the three layers described above. However, the article does not consider the delay due to the continuous processing time of the machine and the inability to plan a machine path for unknown product orders, which leads to a discrepancy between the predicted times for production operations and the actual operation times of the advanced planning and scheduling algorithm.

The advanced planning and scheduling algorithm needs to be improved, since the machine path planning problem cannot be solved for orders for unknown products. A study in the literature therefore used a product complexity approach to predict the new production times, and the complex features of production including the quantity of components, the interconnections between subsystems, customisation of the final components, the variety of distinct knowledge for product design, the number of product functions and the variety of components [9]. A complexity analysis of the features of production in this paper is shown in Fig. 1. For instance, the quantity of components (A) has a complexity score of 2474 for Product 1, 1515 for Product 2, 46 for Product 3, and 2340 for Product 4. The algorithm normalises the maximum complexity of feature A to a value of 100 and adjusts the other products accordingly. After normalisation has been applied in the same way to the other products, we see that the interconnection between subsystems (B) has a score of 87 and the customisation of the final components (C) has a score of 100. The numerical score assigned to the variety of distinct knowledge for product design (D) is 100, the number of product functions (E) is 100, and the variety of components (F) is 100. The algorithm gives a normalised vaue for the feature complexity of 587 for Product 1, 436 for Product 2, 180 for Product 3, and 552 for Product 4. The production times for Products 1 to 4 are

1580, 814, 245 and 1332, respectively. The algorithm is used to train a linear regression analysis model for the normalised sum of the feature complexities of Products 1 to 3 (587, 437, 180) and their production times (1580, 814, 245) to predict the feature complexity of Product 4. The normalised sum of 552 values has a production time of 1319 values. However, the advanced planning and scheduling algorithms in the related literature do not take into account the learning bias caused by the characteristics of the low correlation coefficients, which leads to an error of 13 days between the predicted times for production operations on new products and the actual operation times.

Indicator	Characteristics and complexity of products							
	Product 1		Product 2		Product 3		Product 4	
A. Quantity of components	2474	100	151	61	46	2	2340	95
B. Interconnection between subsystems	324	87	374	100	72	19	345	92
C. Customisation of the final components	475	100	150	32	25	5	400	84
D. Variety of distinct knowledge for product design	4	100	4	100	2	50	4	100
E. Number of product functions	1	100	1	100	1	100	1	100
F. Variety of components	927	100	404	44	30	3	750	81
Complexity of products	587		436		180		552	

Fig. 1. Feature complexity analysis for product manufacturing.

3. DYNAMIC PRODUCTIVITY PREDICTION AND NEW PRODUCTION FEATURE SELECTION METHODS

3.1 System Architecture

This paper proposes new methods for dynamic productivity forecasting and new production feature selection, with the aim of improving the efficiency of advanced planning and scheduling systems. The architecture of our system is shown in Fig. 2. The proposed system performs production planning and scheduling based on a genetic ant colony algorithm for multiple product order information, and a dynamic productivity forecasting algorithm is applied to predict the production times based on real-time production data from mechanical equipment. The genetic ant colony algorithm uses a highly random combination of mating and mutation to achieve high coverage; it calculates the different permutations and combinations of mechanical equipment used for each process, applies an iterative process to implement the ant colony pheromone mechanism and a rule of thumb, and calculates each for the production route with the shortest total manufacturing time of permutations and combinations. The path selection weight value is given positive feedback for permutations and combinations with excellent performance; otherwise, negative feedback is given to ensure gradual convergence to the optimal production route. The dynamic productivity forecasting algorithm uses a linear regression machine learning approach to analyse the product complexity and predict the time required by mechanical equipment to produce an order, with the aim of reducing the error between the predicted production time and actual production operations. If an order includes a new product, the new product feature selection algorithm is first applied to predict the production time for the new product. The correlation coefficient is used to calculate the degree of linear correlation between each feature of the production complexity of new products and the two variables of historical production time, and features with a low degree of correlation are filtered to improve the prediction accuracy of the manufacturing time for the new product. A genetic ant colony algorithm is used to predict the machine path with the shortest manufacturing time based on the order information, and a machine learning linear regression analysis is used to predict the time delay for the continuous processing path of the machine. The prediction method for the dynamic production productivity is applied to reduce the error between the predicted production time and the actual production operations. The system calculates the correlation coefficient between the complex features of production and the historical production time to obtain the best correlation coefficient feature; the best value of this feature is passed to a machine learning linear regression analysis to predict the new product production time and to apply the new production feature selection method, in order to reduce the error between the predicted production time and the actual operation.

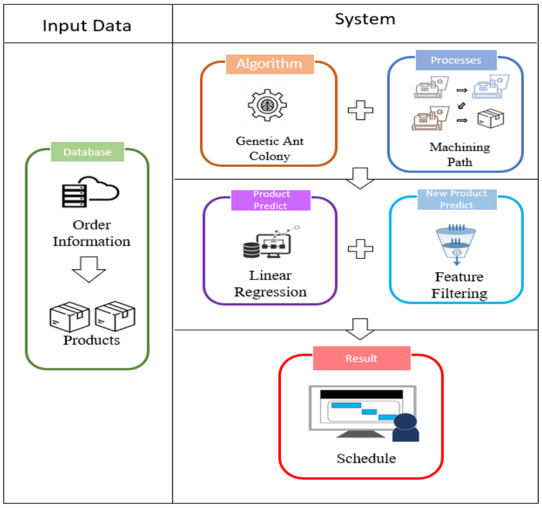


Fig. 2. System architecture.

3.2 Dynamic Productivity Prediction Method

We propose a dynamic production productivity prediction method that uses a genetic ant colony algorithm to plan the machine path with the shortest manufacturing time. The algorithm, entitled ‘Finding the Best Planning Scheduling’, obtains the machine path with the shortest total manufacturing time for a complex order, and an algorithm entitled ‘Combining Dynamic Productivity Prediction’ is supplemented by the dynamic productivity machine learning prediction method to predict the production time. The system randomly generates order sorting (order_of_population) groups based on the multiple order information (order_of_population) using a genetic algorithm, and applies the concept of a pheromone (Ant_update_weight) from the ant colony algorithm to set the weight value (art_ weights_list) for each machine in the product production path. The weight of the iterative process of finding the path ω_t will gradually volatilise and decrease with the number of iterations according to the volatility coefficient ($\omega_t = (1-\alpha)\omega_t$), and the weight of the optimal path for this time will increase by a constant Q divided by the best solution worktime ($\omega_t = (1-\alpha)\omega_t$ + Q / best_solution.worktime). This is done to speed up the convergence of the genetic algorithm to obtain the machine path with the shortest total manufacturing time for the overall order. Pseudocode for the 'Finding the Best Planning Scheduling' algorithm is shown in Fig. 3. At the machine path planning stage (Choose_machine), we take into consideration the fact that the production time needed by a machine to continuously produce the same product includes a delay: the production time for the second reproduction is greater than for the first reproduction. The system uses a machine learning linear regression analysis model to predict the dynamic production productivity based on real-time machine information to obtain the production time for a third product in the future. Our advanced planning and scheduling system use the future production time (working_time) obtained by the dynamic production productivity prediction method (Machine Learning_Predict) to predict the machine path, and reduces the error in the actual time caused by the use of only the last rework production time to predict the machine path in previous schemes.

Finding the best planning schedule algorithm

```
Requires: Genetic algorithm [CROSS_RATE = 0.1, MUTATE_RATE = 0.01]
Requires: planning_to_circuit
Requires: ML algorithm
Requires: count variable supervised_iteration = 0
Requires: art_weights_list
Requires: machine weights as ωt
Requires: volatility coefficient as α = 0.03
Requires: constant as Q = 10
def Ant_update_weight (best_solution):
    get machine weight: art_weights_list
    get machine weight form best_solution path: best_machine _list
    for ωt in art_weights_list:
        if ωt in best_machine_list:
            ωt = (1 – α)ωt + Q / best_solution.worktime
        else:
            ωt = (1 – α)ωt
main():
    set the number of iterations: Iteration
    get order list: order_list
    order_of_population = random permutations from order_list
    while (true):
        if Iteration _sup == Iteration:
            break
        else:
            order_of_population.total_working_time = planning_to_circuit (or
             der_of_population)
```

```
    set the number of iterations: Iteration
    get order list: order_list
    order_of_population = random permutations from order_list
            fitness = 1 / order_of_population.total_working_time
            if best_solution.fitness < fitness:
                best_solution = order_of_population
            if top 3 fitness:
                Ant_update_weight (best_solution)
            order_of_population = Genetic Algorithm (order_of_population, fitness)
            supervised_iteration += 1
   return best_solution
```

Fig. 3. Pseudocode for the 'Finding the Best Planning Schedule' algorithm.

The 'Combined Dynamic Productivity Prediction' algorithm is shown in Fig. 4. Our scheme incorporates real-time production information from the manufacturing execution system, which is passed to a machine learning algorithm to predict future productivity (predict_model). This enhances the prediction accuracy of the advanced planning and scheduling system. An ant colony algorithm is used to dynamically adjust the machine selection weights of the product production path in real time (Ant_update_weight), and to find the machine path with the shortest total manufacturing time for the overall order, with a fast convergence speed.

Combined dynamic productivity prediction algorithm

```
Requires: ML algorithm
Requires: process_array
Requires: sklearn.linear_model import LinearRegression
Requires: ordered_insert_list
def Choose_machine (process):
            machine = choose (machine_list, weights _list)
            machine_path.append (machine)
     return machine_path
def MachineLearning_Predict (machine,order):
     machine_time = 0
     get machine historical data: machine_date
     get production quantity: product_count
     predict_model = LinearRegression (machine_date)
     machine_time += predict_model (product_count)
     return machine_time
def planning_to_circuit (order_of_population):
     working_time = 0
     total_working_time = 0
     for order_list in order_of_population:
        for order in order_list:
           product process sequence: manufacturing_process
```

```
        for process in manufacturing_process:
            machines_path = Choose_machine (process)
            for machine in machines_path:
                working_time = MachineLearning_Predict (machine, order)
                total_working_time += working_time
    order_of_population.total_working_time = total_working_time
return order_of_population
```

Fig. 4. Pseudocode for the 'Combined Dynamic Productivity Prediction' algorithm.

3.3 Proposed Production Feature Selection Method

Since no historical information is available for predicting the production operation time for new products using existing advanced planning and scheduling algorithms, we consider the correlation coefficient [24] between the characteristics of artificial intelligence machine learning technology and the target to adjust the prediction results from our algorithm. Our scheme predicts the production time for new products based on the characteristics of the best correlation coefficient between the original product and the production time, supplemented by a machine learning linear regression analysis model. Our new productivity prediction algorithm is shown in Fig. 5. A production feature selection method is proposed that uses a product moment correlation coefficient detector to calculate the p-value (which ranges from zero to one). The more highly the product features are correlated with the production time, the smaller the p-value. Our new production feature selection method is based on an analysis of the correlation coefficient p-value between the original product and the production time. The best correlation coefficient characteristics of the original product and its production time are passed to the machine learning linear regression analysis prediction model to calculate the production times for new products, which can be used for advanced planning and scheduling operations. The novel production feature selection method proposed in this paper can avoid the problem of analysis error caused by overfitting of the prediction model, and can provide professionals to recommend feature selection to add machine learning linear regression analysis prediction model training for new production operation times.

New product productivity prediction algorithm

```
Requires: scipy.stats import pearsonr
def feature_filtering (list_of_features_new_product):
    get machine production time: product_time
    get product features: product_features
    for fn in product_features:
        p = pearsonr (fn, product_time)
        if p < TH:
            Train_Feature.append (fn)
            TH = p
    for new_feature_data in list_of_features_new_product:
        if new_feature_data in Train_Feature:
            new_feature.append (new_feature_data)
```

```
predict_model = ML algorithm (Train_Feature, product_time)
new_order_time = predict_model (new_feature)
return new_order_time
```

Fig. 5. Pseudocode for the 'New Product Productivity Prediction' algorithm.

3.4 Example Involving the Proposed Methods

To illustrate our advanced planning and scheduling algorithm, we take three orders (Order_1, Order_2 and Order_3) as an example. In this case, three, one and two products need to be produced, respectively. Order_2 is a new product. The system uses the 'Finding the Best Planning Schedule' algorithm to create 20 solutions in the form of groups of random permutations and combinations using genetic algorithms. It executes three iteration process, and uses the above group solutions to use the 'Combined Dynamic Productivity Prediction' algorithm for dynamic productivity prediction method scheduling operations. For Order_1, the production process list has the order [laser, welding, grinding], and the Choose_machine function is used to select the machine path. If each machine produces a specific product, there are nearly three manufacturing times, such as Laser_machine_1 = [20, 20, 21], Laser_machine_2 = [23, 22, 23] and Laser_machine_3 = [21, 22, 21] values, which will give the machine weight values in an average reciprocal manner as [1/20, 1/23, 1/21] values, to implement the ant colony algorithm to obtain the machine path. The higher the value of a machine weight, the higher the selection probability. Since Order_1 requires the production of three products, if the genetic ant colony algorithm chooses Laser_machine_1, then the dynamic productivity prediction algorithm predicts the follow-up production time to be 21, based on the real-time data of [20, 20, 21]. The system applies the 'New Product Productivity Prediction' algorithm to predict the production operation time for new products for Order_2. The laser process similar product features [feature A, feature B, feature C], the complex features of similar product 1 [2000, 500, 810] and production operations 15 minutes, the complex features [1500, 200, 400] of similar products 2 and the production operation 8 minutes and the complex features [50, 25, 30] of similar products 3 and the production operation 2 minutes information to carry out the best correlation coefficient characteristic analysis to get. The above example gives the feature C [810, 400, 30] and the production operation time with the best correlation coefficient of 0.0094. Using a feature value of 700, the above machine learning linear regression prediction model gives the production operation time as 9.7 min. If the abovementioned characteristics have a threshold value for the correlation coefficient that is lower than 0.05, we use the complex correlation coefficient characteristics to predict the production time of new products. Otherwise, we use all of the existing product complexity and production times to predict the manufacturing times for new products. The system uses the Ant_update_weight function to update the weight of each machine selection based on the path planning of the top three machines with the highest fitness. Taking the best solution as an example, we see that the total manufacturing time is 350 min, and the weight τ_t of of Laser_machine_1 is updated from the original value of 1/20 to a value of 0.077. Our approach achieves dynamic productivity forecasting accurately and quickly, and can carry out machine path planning with the shortest total manufacturing time for the complex overall order.

4. EXPERIMENTAL RESULTS

4.1 Performance of Dynamic Productivity Prediction

The proposed advanced planning and scheduling system was developed and implemented using the Anaconda development environment in Python, and was based on the Scikit-learn machine learning suite. To verify our dynamic productivity prediction method, experiments were carried out using five, 10 and 15 orders for analysis. The data included actual production time information on six products, which were used for a performance analysis, and some of the open data are shown in Fig. 6 [25]. The number of system iterations is equal to the number of orders: when there are five orders, the algorithm will undergo five iterations, each of which will give 20 random solutions. In order to verify the effectiveness of the proposed model, a public dataset is considered in this paper. Using an exhaustive method, the changes in machine production times in this public dataset are input to the proposed model to obtain a theoretical value (Theoretical optimum for the total time) for optimal production planning and scheduling. Advanced research is carried out for five orders, and the theoretical value is found to be 20.3 h for the best production planning and scheduling scheme. The results from our advanced planning and scheduling system for five orders are shown in Fig. 7, and the theoretical optimal total time is 20.3 h. Existing schemes in the related literature [4] do not consider the continuous processing time delay of the machine, and the total pre-scheduling time is 19.8 h. The method proposed in this paper uses a dynamic productivity forecasting method, which gives a total pre-arrangement time of 20.5 h. From this, we can observe that the prediction error for the existing scheme in the literature is 2.5%, whereas the prediction error for our method is 1.0%. The proposed dynamic productivity prediction method can therefore reduce the error by 1.5% compared with the existing scheme.

	Order	Sum	Product	Deadline
0	JOB1	10	IPB51222S	2020/11/19
1	JOB1	10	IPFUELS	2020/11/20
2	JOB1	10	IPG2211A2N	2020/11/20
3	JOB10	3	IPFUELS	2020/11/12
4	JOB10	5	IPNMAT	2020/11/12
5	JOB11	10	IPB51222S	2020/11/19
6	JOB11	10	IPFUELS	2020/11/20
7	JOB11	10	IPG2211A2N	2020/11/20
8	JOB12	10	IPG2211A2N	2020/11/12
9	JOB12	10	IPNCONGD	2020/11/17
10	JOB12	10	IPNMAT	2020/11/18
11	JOB13	10	IPNCONGD	2020/11/30
12	JOB13	5	IPB51222S	2020/11/15
13	JOB13	8	IPG2211A2N	2020/11/17
14	JOB14	3	IPB51222S	2020/11/12
15	JOB14	5	IPNMAT	2020/11/12
16	JOB14	6	IPNCONGD	2020/11/12
17	JOB15	3	IPFUELS	2020/11/12
18	JOB15	5	IPNMAT	2020/11/12
19	JOB2	10	IPG2211A2N	2020/11/12
20	JOB2	10	IPNCONGD	2020/11/17
21	JOB2	10	IPNMAT	2020/11/18
22	JOB3	10	IPNCONGD	2020/11/30
23	JOB3	5	IPB51222S	2020/11/15
24	JOB3	8	IPG2211A2N	2020/11/17
25	JOB4	3	IPB51222S	2020/11/12
26	JOB4	5	IPNMAT	2020/11/12
27	JOB4	6	IPNCONGD	2020/11/12
28	JOB5	3	IPFUELS	2020/11/12
29	JOB5	5	IPNMAT	2020/11/12
30	JOB6	10	IPB51222S	2020/11/19

realtime_start	realtime_end	date	value
Leaser			
2019/12/23	2019/12/23	1954/1/1	12.9547
2019/12/23	2019/12/23	1954/2/1	12.872
2019/12/23	2019/12/23	1954/3/1	13.0098
2019/12/23	2019/12/23	1954/4/1	13.2579
2019/12/23	2019/12/23	1954/5/1	13.3406
2019/12/23	2019/12/23	1954/6/1	13.4509
2019/12/23	2019/12/23	1954/7/1	13.4233
2019/12/23	2019/12/23	1954/8/1	13.4509
2019/12/23	2019/12/23	1954/9/1	13.6438
2019/12/23	2019/12/23	1954/10/1	13.947
2019/12/23	2019/12/23	1954/11/1	14.1124
2019/12/23	2019/12/23	1954/12/1	14.1675
2019/12/23	2019/12/23	1955/1/1	14.0572
2019/12/23	2019/12/23	1955/2/1	14.3329
2019/12/23	2019/12/23	1955/3/1	14.4983
2019/12/23	2019/12/23	1955/4/1	14.5258
2019/12/23	2019/12/23	1955/5/1	14.6085
2019/12/23	2019/12/23	1955/6/1	14.5534
2019/12/23	2019/12/23	1955/7/1	14.6361
2019/12/23	2019/12/23	1955/8/1	14.9668
2019/12/23	2019/12/23	1955/9/1	15.27
Bench Drilling			
2019/12/23	2019/12/23	1955/10/1	15.5181
2019/12/23	2019/12/23	1955/11/1	15.711
2019/12/23	2019/12/23	1955/12/1	15.904
2019/12/23	2019/12/23	1956/1/1	16.0142
2019/12/23	2019/12/23	1956/2/1	16.0969
2019/12/23	2019/12/23	1956/3/1	16.2623
2019/12/23	2019/12/23	1956/4/1	16.5655
2019/12/23	2019/12/23	1956/5/1	16.9514
2019/12/23	2019/12/23	1956/6/1	16.8963

Fig. 6. Example of prediction problem.

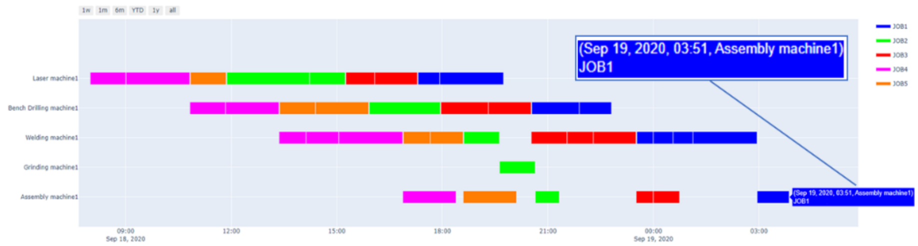


Fig. 7. (a) Results for five orders: Existing scheme in [4].

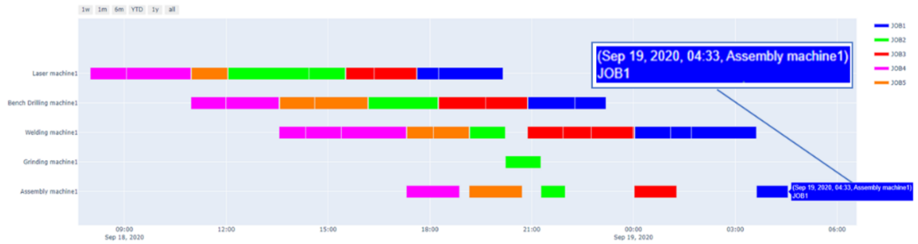
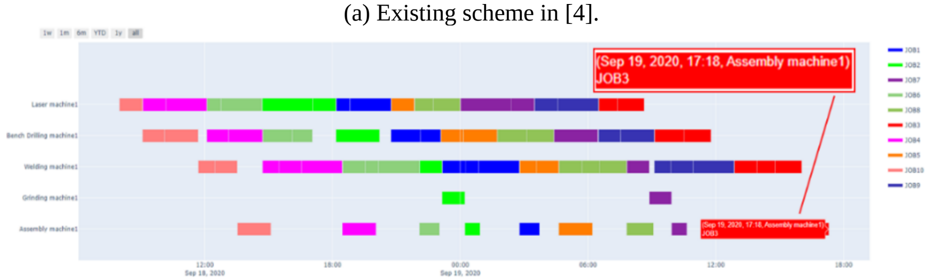


Fig. 7. (b) Results for five orders: Proposed method.

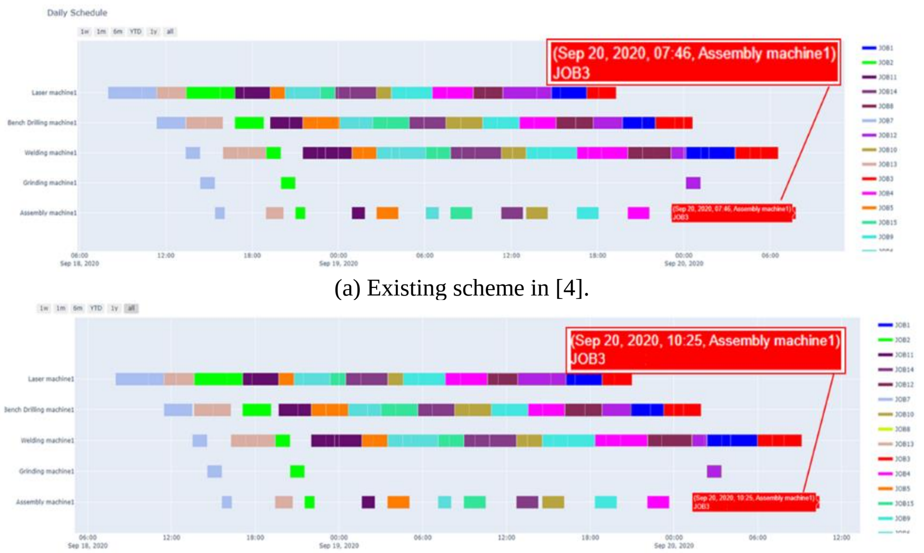
The results from our advanced planning and scheduling system for ten orders are shown in Fig. 8, and the theoretical optimal total time is 33.8 h. Existing schemes in the related literature do not consider the continuous processing time delay of the machine, and the total pre-scheduling time is 31.9 h. The method proposed in this paper uses a dynamic productivity forecasting method, which gives a total pre-arrangement time of 33.3 h. From this, we can observe that the prediction error for the existing scheme in the literature is 5.6%, whereas the prediction error for our method is 1.5%. The proposed dynamic productivity prediction method can therefore reduce the error by 4.1% compared with the existing scheme. The results from our advanced planning and scheduling system for fifteen orders are shown in Fig. 9, and the theoretical optimal total time is 75.6 h. Existing schemes in the related literature do not consider the continuous processing time delay of the machine, and the total pre-scheduling time is 71.7 h. The method proposed in this paper uses a dynamic productivity forecasting method, which gives a total pre-arrangement time of 74.4 h. From this, we can observe that the prediction error for the existing scheme in the literature is 5.2%, whereas the prediction error for our method is 1.6%. The proposed dynamic productivity prediction method can therefore reduce the error by 3.6% compared with the

(a) Existing scheme in [4].



(b) Proposed method.

Fig. 8. Results for 10 orders.



(a) Existing scheme in [4].

(b) Proposed method.

Fig. 9. Results for 15 orders.

existing scheme. The dynamic productivity prediction method can reduce the error between the predicted production time and the actual production time, and is better than the existing scheme from the literature by at least 1.5%, as shown in Table 1.

Table 1. Summary of experimental results.

Number of orders	Methods	Total prescheduling time (h)	Theoretical optimum (Exhaustive method) for the total time (h)	Prediction error (%)	Error reduction (%)
5	Existing scheme [4]	19.8	20.3	2.5	1.5
	Proposed method	20.5		1.0	
10	Existing scheme [4]	31.9	33.8	5.6	4.1
	Proposed method	33.3		1.5	
15	Existing scheme [4]	71.7	75.6	5.2	3.6
	Proposed method	74.4		1.6	

4.2 Performance of New Production Feature Selection

To verify our new production feature selection method, we used real data on production times from the literature to conduct a performance analysis. This included four product samples and six feature indicators [9]. The system uses the scipy.pearsonr correlation coefficient detector in Python to provide data analysis for the relevant literature. The correlation coefficient obtained in this way is shown in Fig. 10. The equation used in the existing scheme in the literature to predict the new product production time is shown in Eq. (1), while the equation used by our proposed new production feature selection method is shown in Eq. (2). This paper proposes a new production feature selection method using the best correlation coefficient F feature for prediction with a value of 0.0074, so using the original three product F features [927, 404, 46] and their manufacturing time [1580, 814, 245]. A machine learning linear regression prediction model was built and the production time was predicted to be 1320 days using the new product F feature [750]. The actual production time for the new product provided by the relevant literature is 1332 days and its method prediction are 1319 days, this paper effectively improves the 0.08% value ((1320 – 1319) / 1332) of the prediction error of the relevant literature.

$$y_{Related} = 0.0071x_{Related}^2 + 2.146x_{Related} + 402.11 \tag{1}$$

$$y_{Method} = 1.511x_{Related} + 185.83 \tag{2}$$

Indicator	Pearsonr
A. Quantity of components	0.13
B. Interconnection between subsystems	0.48
C. Customisation of the final components	0.10
D. Variety of distinct knowledge for product design	0.3
E. Number of product functions	NAN
F. Variety of components	0.007

Fig. 10. Correlation coefficient.

5. CONCLUSIONS

Smart manufacturing is an important trend in the development of traditional industries, and relies on efficient production management. Automated production equipment uses Internet of Things technology to upload real-time production information to a cloud management platform, which provides a visual monitoring system for control over all the equipment conditions and adjustments to process planning. Artificial intelligence and machine learning technology needs to be integrated into production operation time prediction planning in order to improve manufacturing efficiency. In this paper, we have proposed dynamic productivity prediction and new production feature selection methods that can improve the performance of advanced planning and scheduling systems. A genetic ant colony algorithm is used to predict dynamic productivity based on real-time production information to reduce the discrepancy between production time plans and actual operation. Historical production information is analysed and the best correlation coefficient is used for new production feature selection to reduce the error between the forecast productivity and the actual operation. The dynamic productivity prediction method put forward in this paper can reduce this error by 1.5% compared with an existing scheme in the literature, and our proposed new production feature selection method can reduce the error by 0.08% compared with the alternative scheme. From the experimental results presented in this paper, it can be seen that obtaining strong correlation features after filtering the features can effectively improve the prediction performance; however, when the product model has high complexity and many features, the improvement in the prediction results will be limited. In future work, we will effectively normalise the threshold used for the strong correlation features, and will apply deep learning for model training and prediction in order to eliminate those features that will not affect the results and improve the prediction accuracy.

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