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A Reactive Prediction Based Dynamic Scheduling Method and its Performance Analysis

***Abstract**. The key problem of improving the efficiency of scheduling and the utilization of resource in manufacture system is the model of scheduling. However, the performance of the scheduling is disturbed by the uncertain elements in the system. This paper proposes a dynamic scheduling method which is based on reactive prediction to solve the interference. The mathematical statistics prediction theory is introduced in scheduling by using the mathematical statistics prediction model in the prediction scheduling. The time series data are obtained in the process of forecasting. The efficiency of distribution in the scheduling is improved by the forecasted data. There have three kinds of measurements consist of MSE, MAD and MAPE to analyze seven kinds of classics mathematical statistics prediction methods. The result shows that the dynamic scheduling method can eliminate the interference of the uncertain element in the scheduling*

***Streszczenie**. W artykule przedstawiono metodę optymalizacji harmonogramu zadań w procesie produkcyjnym w celu zwiększenia sprawności i wykorzystania dostępnych środków. Proponowane rozwiązanie oparte jest na predykcji biernej (matematyka statystyczna), która pozwala na dynamiczne szeregowanie zadań. Przeprowadzone badania, wykazały, że zastosowane szeregowanie zadań zapobiega ich interferencji. (**Opis i analiza metody harmonogramowania dynamicznego zadań na podstawie predykcji biernej**).*

Keywords: Prediction Model; Mathematical Statistics Theory; Reactive Prediction; Dynamic Scheduling.
Słowa kluczowe: model predykcyjny, matematyka statystyczna, predykcja bierna, harmonogramowanie dynamiczne.

Introduction

It is an important way to solve the uncertain problem in the process of scheduling by using the prediction scheduling. The prediction scheduling is captured more concerns as a new job scheduling method [1]. The prediction scheduling is a dynamic scheduling method. The study of the prediction scheduling method contributes to the solution of affection of the uncertain problem in practical production scheduling.

The prediction scheduling contains predictive control theory, the core content are three great mechanisms: prediction model, rolling optimization, feedback correct [2]. In recent years, the studies of the prediction scheduling are based on the mechanisms. Sadeghi.Naimeh [3] proposed an active prediction method to handle the scheduling problem in the construction plans. This method used a fuzzy logic method to simulate the uncertain problem in the construction plans. The result showed that the prediction method had a good robustness. Zhang [4] proposed some formulas for the mistaken prediction degree, which is defined as the probability that the predicted values for the performances of tasks and processors reveal different orders from their real values. The experiment showed that this method could predict the errors of some existing task scheduling algorithms. Ali Sk Ahad [5] developed a method for effective manufacturing scheduling by addressing manufacturing uncertainties. A manufacturing prediction algorithm is proposed based on a statistical methodology and feature recognition. This tool facilitates the development of lean manufacturing systems and enables practitioners to continuously improve these systems. There are more and more studies of prediction scheduling which focused on rolling optimization and feedback correction. There are only few reports which research the prediction model.

This paper focuses on prediction model in scheduling and proposes a dynamic scheduling method, which is based on the reactive prediction. The mathematical statistics theory is introduced in the dynamic scheduling by using the mathematical statistics forecasting model in the prediction scheduling. The mathematical statistics theory with high preciseness and strong applicability improves the ability of forecasting.

This paper is organized as follows. In section 2 the dynamic scheduling method is described and modeled. In section 3 the seven kinds of the mathematical statistics forecasting methods and three kinds of decision criterions will be reviewed as well as learning and inference. In section 4 the experiment shows that the influence of the parameters and the evaluation of the prediction results. The conclusion is given in section 5.

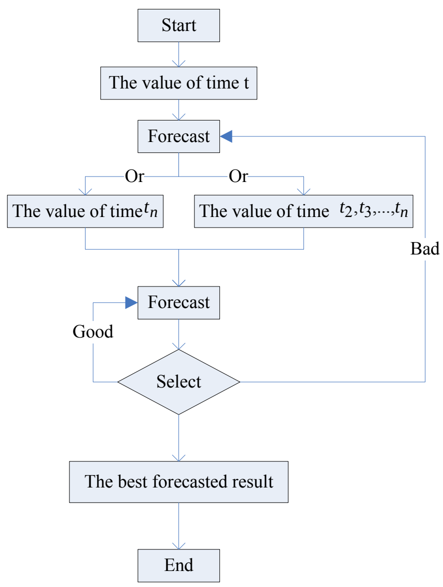

Fig.1. The process of forecasting

Prediction model

Method Description

The prediction scheduling is a method which uses the known information in the past to obtain the unknown information in the future for optimizing the scheduling. The mathematical statistics forecasting method which is used in the prediction scheduling is the core of the dynamic scheduling method. By using the mathematical statistics forecasting model in prediction scheduling, it is able to realize the purpose that used the mathematical statistics forecasting method to optimize the scheduling.

First, there is a value of the parameter of a known work piece at time t. The forecasting value of the time t_n or the time sequence $t_1, t_2, \ldots, t_n$ could be obtained by using the mathematical statistics forecasting method. Second, the forecasted value is forecasted to obtain the other value in the future. Third, all the forecasted values are compared with each other and the next fundamental of forecasting is decided with the result of the comparison. Finally, these forecasted values form a set. The best forecasted values are selected according to the constraints. The process of forecasting as Fig. 1:

The scheduling which uses the mathematical statistics forecasting method is dynamic and responsive. First of all, the forecasted values of time sequence are changing. Then, the result of comparison and selection is needed to be feedback in the process of forecasting. The feedback makes the prediction method as a reactive intelligent iterative process. This method could ensure that the scheduling is able to make an appropriate adjustment when the inference of the uncertain is changing.

Model Building

The prediction scheduling is described with triple notation which is denoted by *A & B & C*. The three elements correspond to the machine, the work piece and the objective function. The elements of the triple group are on behalf of three fields. The domain *A* is expressed as the number, the type and the status of the machine. The domain *B* is expressed as the nature, the number, the processing requirement, the restriction, the processing affection and the type of the work piece. The domain *C* is expressed as the optimization of the objective function.

There is an assumption as follows. The number of the work pieces and the machines is limited in the domain *A*. A machine can process one work piece or complete one process in the domain *B*. The purpose of prediction scheduling is to use the forecasting method to minimize the objective function in the domain *C*.

Definition 1: A work piece set N consists of n work pieces. A work piece is N_n. The time is T. The work piece N_n which is processed in the interval of time is T_n. The production order of the work piece N_n is M_n.

Definition 2: The constraint set is F. The limit of production is f. The element of interference is j. There have many kinds of j such as specification, temperature, air humidity and so on. There is an equation as follows:

$$F = \sum_{j=1}^{\infty} f_j \qquad (1)$$

Definition 3: The goal of forecasting is N_f which is a kind of parameter of work piece N_n. The actual value of N_f is S_t. The forecasted value of N_f is Y_t.

Definition 4: The predictive window is a time window. There is the unknown information of the unprocessed work piece or the unfinished process in the window. The predictive window is W_t and the window about known information is G_t at time T.

Definition 5: In the window W_t, the time of the first predictive information is $I_t^1 = min\{I_k \ / \ k \in w_t\}$, the time of the second predictive information is $I_t^2 = min\{I_k \ / \ k \in w_t,\ I_k > I_k^{\ 1}\}$. Similarly, the time of the n predictive information is $I_t^n = min\{I_k \ / \ k \in w_t,\ I_k > I_k^{n-1}\}$.

By these definitions, the process of forecasting runs as follows:

Step 1: The work piece N_n arrives at time T;

Step 2: The target of forecasting N_f, the predictive window W_t and the window G_t are chosen according to actual situation;

Step 3: The value Y_t of forecasting is obtained at time I_k^n in the window W_t by using the actual value S_t in the widow G_t at time t. The values $Y_1, Y_2, \ldots, Y_t$ of time sequence of forecasting are obtained at time $I_t^1, I_t^2, \ldots, I_k^n$ in the window G_t by using the actual value $S_1, S_2, \ldots, S_t$ in the widow W_t at time $t_1, t_2, \ldots, t_n$;

Step 4: The best forecasted value is selected in the set Y. There has a judgment condition to decide that whether repeat step 3;

Step 5: The predictive window W_t and the window G_t are changed as next time coming. Go back to step 3;

Step 6: When the error of forecasting is smallest, the forecasting is finishes.

Step 7: The scheduling decision is determined by combining the known information S_t and predictive information Y_t.

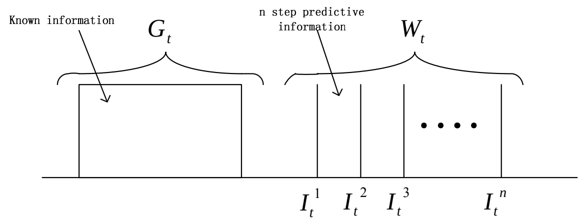

Fig.2. *N* steps scheduling decision

The predictive window W_t , the known window G_t, the actual value S_t , the actual value Y_t and the scheduling decision are adjusting as the constraint is changing, so the scheduling method is reactive and dynamic.

Forecasting Method

The prediction model is an important point in prediction scheduling. In this paper, the mathematical statistics theory is introduced in the dynamic process of scheduling by using the mathematical statistics forecasting model as the prediction model. The seven kinds of classics mathematical statistics prediction methods are analyzed. The decision criterion is used to monitor the process of forecasting and compare the result of forecasting. The most accurate forecasting method of the seven forecasting methods is sought to identify by experiment.

Selection of Forecasting Methods

The prediction model is the basis of prediction scheduling, which is even more important than rolling optimization and feedback in many cases. However, the specific knowledge about the prediction model is limit in the existing researches.

The seven kinds of classics mathematical statistics prediction methods are selected to be analyzed in this paper. The five kinds of the method contain simple models, such as: NM (Naive Method), MAM (Moving Average Method), WMAM (Weighted Moving Average Method), SESM (Simple Exponential Smoothing Method), MLR (Multiple Liner Regression). The two kinds of the method contain complex models, such as: HM (Holt's Method), WM (Winter's Method).

Naive method: This method uses the recent information to forecast the needed value directly [6]. The formulation as follows:

$$F_{t+1} = Y_t \qquad (2)$$

F_{t+1}= the forecast value for the next period, Y_t= the actual value for previous period. The method dose not limit the chosen time of the process of forecasting. The actual value and the forecasted value could be at any time in the past and the future. The value of time *t* is used to forecast the value of time *t+1* in the experiment.

Moving Average Method: This method uses the average of the observations to forecast the value. The MAM mainly depends on the number of terms selected [7]. The formulation as follows:

$$F_{t+1} = (Y_{t-1} + Y_{t-2} + Y_{t-3} + ... + Y_{t-n+1})/n \quad (3)$$

F_{t+1}= the forecast value for the next period, Y_t= the actual value for previous period, *n*= the number of terms. The method dose not limit the chosen times of the process of forecasting. The actual value and the forecasted value could be at any time in the past and the future. The values of times *t-1* and t are used to forecast the value at time *t+1* in the experiment.

Weighted Moving Average Method: This method uses the exponentially weighted observation to forecast the value. The change of weight highly impact on the forecast [8]. The formulation as follows:

$$F_{t+1} = w_1 Y_t + w_2 Y_{t-1} + w_3 Y_{t-2} + ... + w_n Y_{t-n+1} \quad (4)$$
$$(w_1 + w_2 + w_3 + ... + w_n = 1 \text{ and } 0 < w < 1)$$

F_{t+1}= the forecast value for the next period, Y_t= the actual value for previous period, *w*= the weight of the actual value. The method dose not limit the chosen times of the process of forecasting. The actual value and the forecasted value could be at any time in the past and the future. The values of times t-1 and t are used to forecast the value at time t+1 in the experiment.

Simple Exponential Smoothing Method: This method uses a weighted moving average of past values to forecast the value. The procedure gives different weights to recent forecasted value and past observation [9]. The formulation as follows:

$$F_{t+1} = \alpha Y_t + (1-\alpha)F_t, \quad (0 < \alpha < 1) \quad (5)$$

F_{t+1}= the new smoothed value or the forecast value for the next period, F_t= the forecast value for period t, Y_t = the new observation or the actual value for previous period, *α* =smooth constant. The method dose not limit the chosen times of the process of forecasting. The actual value and the forecasted value could be at any time in the past and the future. The values of times *t-1* and *t* are used to forecast the value at time *t+1* in the experiment.

Multiple Linear Regressions: This method is used to estimate the nature of the relationship between independent variable and dependent variable [10]. The dependent is the value predicted, and the independent is the observation. The formulation as follows:

$$Y_n = \beta_0 X_1 + \beta_1 X_2 + ... + \beta_{n-1} X_n + \omega \quad (6)$$

$\beta_0 X_0 + \beta_1 X_2 + ... + \beta_n X_n$= the mean response with the independent *X*. *w*= independent and distributed with 0 and standard deviation. $\beta_0, \beta_1, ...\beta_{n-1}$ and *w* are unknown constant. The actual value and the forecasted value could be at any time in the past and the future. The value of any time is used to forecast the value of any time in the future. The values of times *t-1* and *t* are used to forecast the value at time *t+1* in the experiment.

$$L_t = \alpha Y_t + (1-\alpha)(L_{t-1} + T_{t-1}), \quad 0 < \alpha < 1 \quad (7)$$

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1}, \quad 0 < \beta < 1 \quad (8)$$

$$F_{t+P} = L_t + PT_t \quad (9)$$

L_t= new smoothed value, *α*= smoothing constant for the minute, Y_t= new observation or actual value of series in period *t*, *β*= smoothing constant for trend estimate, T_t = trend estimate, *P*= periods to be forecast into future, F_{t+P} = forecast for p period into the future. The original values for the smoothed value and the trend estimate must be set to start the forecast. In this paper, the initial value of the smoothed series is assigned the same as the first observation. The first value of the trend is estimated equal 0. The smoothing constants alpha and beta are required to optimize. The values of alpha and beta are optimized by the trial and error.

Winter's Method: WM is helpful for explaining the seasonality when the data have the seasonal pattern [11]. The formulation as follows:

$$L_t = \alpha Y_t / S_{t-l} + (1-\alpha)(L_{t-1} + T_{t-1}), \quad 0 < \alpha < 1 \quad (10)$$

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1}, \quad 0 < \beta < 1 \quad (11)$$

$$S_t = \gamma Y_t / L_t + (1-r)S_{t-l} \quad (12)$$

$$F_{t+P} = (L_t + PT_t)S_{t-l*p} \quad (13)$$

L_t= new smoothed value, *α*= smoothing constant for the minute, Y_t= new observation or actual value of series in period t, beta =smoothing constant for trend estimate, T_t = trend estimate, S_t= seasonal estimate, *γ*= smoothing constant for seasonal estimate, *l*= length of seasonality, *P*= periods to be forecast into future, F_{t+P}= forecast for *p* period into the future. As HM, the original values for the smoothed value, the trend estimate and seasonal indices must be given to start the forecast. In this paper, the first smoothing value is considered as the first observation. The trend estimate is set as 0. The first seasonal estimate is assigned as 1. The smoothing constants *α*, *β* and *γ* are required to optimize. The values of alpha, beta and gamma are optimized by the trial and error.

Forecasting Accuracy Measurement

In this study, the accuracy of each method is assessed by using MSE (Mean Squared Error), MAD (Mean Absolute Deviation) and MAPE (Mean Absolute Percentage Error). The three kinds of measurements have some advantages: indicate the error, provide information on relative change, and compare the accuracy of results across different forecasting models.

Mean Squared Error: MSE is one commonly used approach to evaluate the exponential smoothing methods. This evaluation defines the sum of squares of the forecasting error to be error when divided by the number of periods of the date [7]. The formulation as follows:

$$MSE = \frac{1}{n}\sum_{t-1}^{n}(Y_t - F_t)^2 \quad (14)$$

F_t= the forecast value in time period t, Y_t= the actual value in time period *t*, *n*= the number of periods. This technique which is employed to determine the average size of all errors can not indicate the positive or negative errors.

Mean Absolute Deviation: MAD uses the average of the absolute error to assess the exponential smoothing method. The error is defined as the absolute error [9]. The formulation as follows:

(15) $$MAD = \frac{1}{n}\sum_{t-1}^{n}|Y_t - F_t|$$

F_t = the forecast value in time period t, Y_t = the actual value in time period t, n= the number of periods. This technique is helpful for evaluating the variability parameters which makes a difference to forecast.

Mean Absolute Percentage Error: MAPE is the mean of all of the percentage errors for observations set taken without regard to sign [9]. The formulation as follows:

(16) $$MAPE = \frac{1}{n}\sum_{t-1}^{n}\frac{|Y_t - F_t|}{Y_t}$$

F_t= the forecast value in time period t, Y_t= the actual value in time period t, n= the number of periods. This technique is useful for comparing the accuracy of the same or different forecasting model on two entirely different series.

When the method is analyzed and tested, a tracking signal is applied to monitor the performance of the forecasting. A tracking signal which takes advantage of the deviation of the forecasting values shows the performance of the forecasting, no change in parameters as alpha is necessary. If the forecasting value falls outside the range, the alpha value needs to be updated. In this case, the range of permissible deviation is defined $\pm 2(MSE)^{(1/2)}$.

Experiments

The experiment is divided into two parts. The first part shows the influence of the parameters changing in the process of forecasting. The second part shows the result of forecasting.

Influence of Parameters Changing

The parameter which is changing in a range affects the process of forecasting. The four methods are tested in the experiment, such as: WMAM, SESM, HM, WM. The results of the experiment show the influence of the parameter changing.

In this study, the diameter of work piece is selected in a factory to be the forecasted object. A stable machine selected can produce 500 one day. The values of the work pieces which are selected are to experiment.

Influence of Parameters Changing in WMAM

The process of WMAM depends on the choice of *w*. The values of times *t-1* and *t* are used to forecast the value of time *t+1* in the experiment.

Table 1. Value of parameter

Method	Value
WMAM	W_1=0.7 W_2=0.3
WMAM2	W_1=0.4 W_2=0.6
WMAM3	W_1=0.2 W_2=0.8

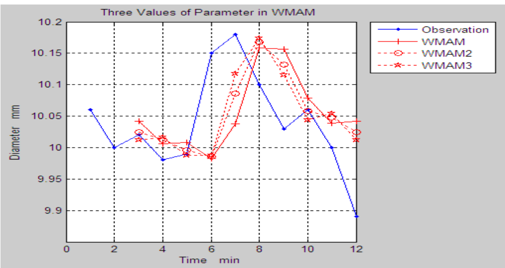

Fig.3. Result of forecasting in WMAM

Table 1 and Fig 3 show that :

(1) Because of $w_1+w_2=1$,one value increases, the other will decrease.

(2) The error of forecasting is closing to 0 when w_2 is closing to 1.

In the process of WMAM, the error of forecasting is smaller as *w* is more closing to 1 when the distance between the forecasting time and the actual time is smaller.

Influence of Parameters Changing in SESM

The process of SESM depends on the choice of *alpha*. The values of times *t-1* and *t* are used to forecast the value of time *t+1* in the experiment.

Table 2. Value of parameter

Method	Value
SESM	α=0.2
SESM2	α=0.5
SESM3	α=0.8

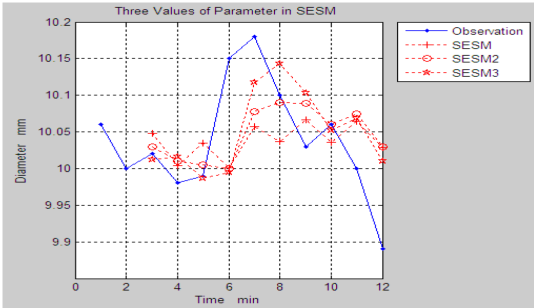

Fig.4. Result of Forecasting in SESM

Table 2 and Fig 4 show that :

(1) Because of $0<\alpha<1$, one value increases, the other will decrease.

(2) The error of forecasting is closing to 0 when α is closing to 1.

In the process of SESM, the error of forecasting is smaller as α is closing to 1

Influence of Parameters Changing in HM

The process of HM depends on the choices of α and β. The values of times t-1 and t are used to forecast the value of time t+1 in the experiment.

Table 3. Value of Parameter

Method	Value
HM	α=0.2 β=0.4
HM2	α=0.4 β=0.6
HM3	α=0.6 β=0.8

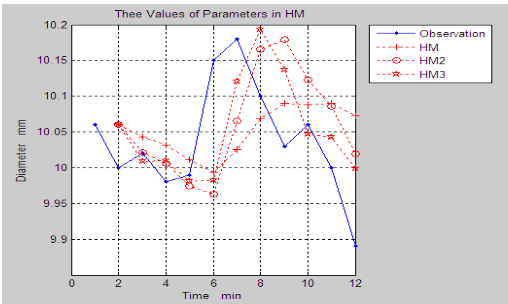

Fig.5. Result of Forecasting in HM

Table 3 and Fig 5 show that :

(1) In the range of $0<\alpha<1$ and $0<\beta<1$, α and β are increased or reduce at the same time.

(2) The error of forecasting is closed to 0 when α or β is closed to 1.

In the process of HM, the error of forecasting is smaller as α or β is closed to 1.

Influence of Parameters Changing in WM

The process of WM depends on the choices of α, β and γ. The values of times t-1 and t are used to forecast the value of time t+1 in the experiment.

Table 4. Value of parameter 1

Method	Value
WM	α=0.1 β=0.2 γ=0.3
WM2	α=0.3 β=0.4 γ=0.3
WM3	α=0.3 β=0.2 γ=0.4
WM4	α=0.5 β=0.5 γ=0.5

Table 5. Value of parameter 2

Method	Value
WM	α=0.5 β=0.6 γ=0.7
WM2	α=0.7 β=0.6 γ=0.7
WM3	α=0.7 β=0.8 γ=0.8
WM4	α=0.5 β=0.5 γ=0.5

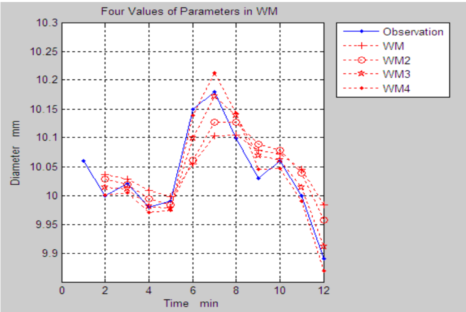

Fig.6. Result of forecasting in WM 1

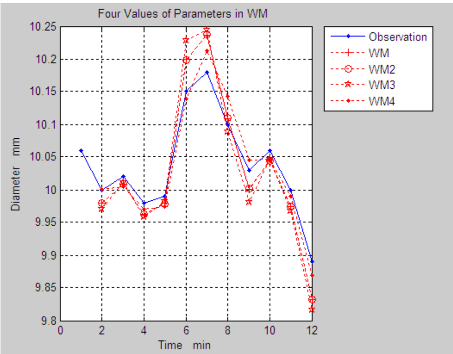

Fig.7. Result of forecasting in WM 2

Table 4, Table 5 and Fig 5-7 show that :

(1) In the range of $0<\alpha<1$, $0<\beta<1$ and $0<\gamma<1$, α, β and γ are increased or reduced in [0.0.5] and [0.5,1].

(2) The error of forecasting is closed to 0 when α or β or γ is closed to 0.5.

In the process of WM, the error of forecasting is smaller as α or β or γ is closed to 0.5.

Experiment of Foresting Methods

The seven kinds of classics mathematical statistics prediction methods are performed in the experiment. The results will show the best one in mathematical statistics prediction the methods.

In this study, the productivity of grinding is selected in a factory to be the forecasted object. There have 1000 actual values of the productivity of grinding which are selected in the experiment.

Experiment Set

In the experiment, the approaches of the forecasting methods mentioned in the section II are used in this study. Then, the values of kinds of parameters are needed to set as Table 6.

:

Table 6. Value of parameters in the forecasting model

Method	Values of Parameters
NM	
MAM	n=1,2,...11
WAM	w_1=0.3 w_2=0.7
SES	α=0.3
MLR	β_0=0.31 β_1=0.45 w=1
HM	α=0.3 β=0.4 p=1
WM	α=0.3 β=0.4 p=1γ=0.3 $p=1$ l=1

Experiment Results

The results of experiment consist of tables and figures. Table 7 shows the value of forecasting methods.Figure 8 shows the accuracy of forecasting methods. Table 8 shows the value of measurements of forecasting methods. Figure 9 shows the error of forecasting methods.

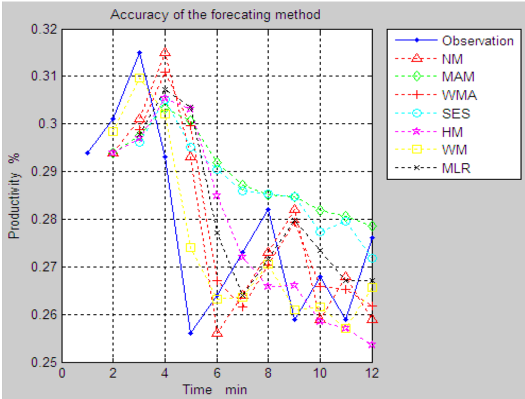

Fig. 8. The accuracy of forecasting methods

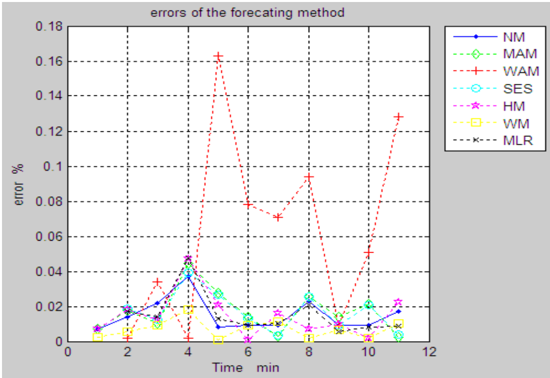

Fig.9: Errors of forecasting methods

The experiment shows that:

(1) Table 7, Table 8 and Fig 8, Fig 9 reveal that the winter's method is the best among the seven kinds of the forecasting methods.

(2) Table 1~Table 5 and Fig 3~Fig 7 reveal that the result of the forecast is closing the observation as the value of variable parameter (α, β, γ…) is more closing to a certain value. The variable parameters have a great affection to the forecasting method. The parameters in the forecasting method are needed a further optimization.

(3) The mathematical statistics forecasting models proposed to be used in the prediction scheduling perform well in the experiment. The dynamic scheduling is feasible.

Table 7. Value of Forecasting Methods

Value	Naïve		MAM		WAM		SES		HM		WM		MLR	
	Forecast	Error	Forecast	Error	Forecast	Error	Forecast	Error	Forecast	Error	Forecast	Error	Forecast	Error
0.294														
0.301	0.2940	0.0070	0.2940	0.0070					0.2940	0.0070	0.2984	0.0026		
0.315	0.3010	0.0140	0.2975	0.0175	0.0161	0.0020	0.2961	0.0189	0.2969	0.0181	0.3097	0.0053	0.2977	0.0173
0.293	0.3150	0.0220	0.3033	0.0103	0.0178	0.0340	0.3052	0.0122	0.3054	0.0124	0.3021	0.0091	0.3072	0.0142
0.256	0.2930	0.0370	0.3007	0.0447	0.0436	0.0020	0.2952	0.0392	0.3032	0.0472	0.2740	0.0180	0.3036	0.0476
0.264	0.2560	0.0080	0.2918	0.0278	0.0031	0.1630	0.2904	0.0264	0.2849	0.0209	0.2632	0.0008	0.2771	0.0131
0.273	0.2640	0.0090	0.2872	0.0142	0.0114	0.0780	0.2858	0.0128	0.2720	0.0010	0.2637	0.0093	0.2640	0.0090
0.282	0.2730	0.0090	0.2851	0.0031	0.0117	0.0710	0.2852	0.0032	0.2658	0.0162	0.2706	0.0114	0.2717	0.0103
0.259	0.2820	0.0230	0.2848	0.0257	0.0203	0.0940	0.2847	0.0257	0.2661	0.0071	0.2610	0.0020	0.2798	0.0207
0.268	0.2590	0.0090	0.2819	0.0139	0.0021	0.0090	0.2773	0.0093	0.2585	0.0095	0.2616	0.0064	0.2734	0.0054
0.259	0.2680	0.0090	0.2805	0.0215	0.0063	0.0510	0.2797	0.0207	0.2571	0.0019	0.2571	0.0019	0.2672	0.0081
0.276	0.2590	0.0170	0.2785	0.0025	0.0143	0.1280	0.2718	0.0042	0.2536	0.0224	0.2658	0.0102	0.2672	0.0089

Table 8. Value of Measurements of Forecasting Methods

Method	Naive	MAM	WAM	SES	HM	WM	MLR
MSE	0.0003003	0.0004338	0.0003103	0.0003731	0.0003727	0.0000737	0.0003389
MAD	0.0528	0.0171	0.0133	0.0157	0.0149	0.0070	0.0141
MAPE(%)	-0.0038	0.0615	0.0465	0.0549	0.0531	0.0250	0.0487

Conclusion

The uncertain problems have serious implications on the scheduling in the process of the practical production. The dynamic scheduling method which is based on the reactive scheduling is proposed to solve the uncertain problem. This method uses the advantage of the mathematical statistics forecasting method to eliminate the interference. The experiment shows the influence of the parameters to the forecasting method and proves that the method is feasible in the scheduling.

The dynamic scheduling method is used in the process of production of the work piece. The result shows that WM is the best method in the prediction scheduling. The purpose which could reduce production cost and optimization resource will be achieved by using this dynamic scheduling method.

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