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ORIGINAL ARTICLE

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# Due-date assignment in wafer fabrication using artificial neural networks

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**Abstract** Due-date assignment (DDA) is the first important task of shop floor control in wafer fabrication. Due-date related performance is impacted by the quality of the DDA rules. Assigning order due dates and timely delivering the goods to the customer will enhance customer service and competitive advantage. A new methodology for lead-time prediction, artificial neural network (ANN) prediction is considered in this work. An ANN-based DDA rule combined with simulation technology and statistical analysis is developed. Besides, regression-based DDA rules for wafer fabrication are modelled as benchmarking. Whether neural networks can outperform conventional and regression-based DDA rules taken from the literature is examined.

From the simulation and statistical results, ANN-based DDA rules perform a better job in due-date prediction. ANN-based DDA rules have a lower tardiness rate than the other rules. ANN-based DDA rules have better sensitivity and variance than the other rules. Therefore, if the wafer fab information is not difficult to obtain, the ANN-based DDA rule can perform better due-date prediction. The SFM_sep and JIQ in regression-based and conventional rules are better than the others.

**Keywords** Due-date assignment · Artificial neural network · Wafer fabrication · Simulation · Shop floor control

**Abbreviations**

| | |
|---|---|
| DDA | due-date assignment |
| ANN | artificial neural network |
| BPN | back-propagation network |
| SFC | shop floor control |
| AI | artificial intelligence |
| TWK | due-date prediction rule based on total amount of works |
| SLK | due-date prediction rule based on slack time |
| NOP | due-date prediction rule based on number of operations |
| JIQ | due-date prediction rule based on current queue length in system |
| JIBQ | due-date prediction rule based on queue length in bottleneck station |
| WIP | work in process |
| PSP | pre-shop-pool |
| KFM | regression-based due-date prediction rule considering key factor |
| SFM | regression-based due-date prediction rule considering significant factors |

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## 1 Introduction

A semiconductor chip is a complex device that consists of miniaturized electronic components and their connections. There are five steps in semiconductor manufacturing: wafer fabrication, wafer probe, device assembly, class test and final test. Wafer fabrication is the most technologically complex and capital-intensive industry. Because the required capital investment is extremely large, improved shop floor control strategy could result in a considerable increase in profit. However, it is challenging to develop SFC strategies for wafer fabs due to the long flow time, ever-changing product yield, re-entrant feature of the production sequence and stochastic wafer fab characteristics including machine failures. Due-date assignment is the first important task in shop floor control. Due-date related performance is impacted by the quality of the DDA rules. Assigning exact due dates and timely delivering the goods to customer will enhance customer service and competitive advantage. Assigning a due date is a difficult decision. As a jobs arrive at the shop, due dates are specified indicating when the job is expected to be completed.

This assignment is complicated by the fact that each arriving job has processing needs on various machines in the shop. Each machine continually experiences different and varying levels of congestion that changes as the jobs flow through the shop. We consider a new methodology for lead-time prediction, namely, artificial neural network (ANN) prediction. ANNs are an artificial intelligence (AI) approach that has been applied to such general problem areas as prediction, control, data compression and surface fitting. However, to date, most applications have been non-managerial scenarios such as robot control, visual systems and airport bomb detection. We will try to develop an ANN-based DDA rule combined with simulation technology and statistical analysis. We will model some regression-based DDA rules for wafer fabrication as benchmarking. Here, we attempt to determine if neural networks can outperform conventional, regression-based due-date assignment rules in wafer fabrication. The basic methodological approach employed is the statistical analysis of the data generated from a simulated shop.

The remainder of this paper is organized as follows. The second section will summarize the relevant literature on due-date assignment and artificial neural networks. The third section discusses the DDA methodology, including conventional rules, regression-based rules and ANN-based rules. The fourth section describes the simulation model and experimental design. In the fifth section, the statistical results are presented and the performance of DDA rules will be discussed. The conclusions and suggestions for future study are included in the last section.

## 2 Literature review

### 2.1 Due-date assignment rules

The DDA methods used in the related researches can be classified into four categories [1]:

1. Direct procedures (conventional rule);
2. Simulation method;
3. Analytical methods;
4. Statistical analysis.

Direct procedures assign due dates using such information such as the job characteristics, shop conditions and dynamic shop condition [2]. This method is convenient and easily computed; however, some parameters must be pre-determined in other ways.

Initially, researchers examined due-date rules that considered only the job characteristics. These methods include: TWK, where the due dates are based on the total amount of works; SLK, where the jobs are given flow allowances that reflect equal waiting times or equal slacks; and NOP, where the due dates are set according to the number of operations to be performed in the job. More recently, another class of due-date assignment methods was proposed that includes job-characteristic information and shop-status information. As Cheng and Gupta [3] noted, many researchers reported improved performance from these methods. This includes JIQ, where the due dates are determined based on the current queue lengths in the system [4].

Computer technology advances have made simulations to be one of the public methods used in due-date assignment research. Vig and Dooley [5], Weeks [6], Kaplan and Unal [7] adopted simulations in their research. Simulations allow evaluating the effects of different polices without actual execution.

Analytical methods, based on queuing theory, estimate the mean and standard derivation of order flow time [8]. Because analytical method assumptions usually conflict with the conditions of the real world, analytical method applications are restricted.

Statistical analysis uses the regression method [9] and relation analysis [7] to find the relations between order flow times and other variables. The deficiency in statistical analysis is that past trends may not exist in the future.

Chung et al. [1] used both the simulation method and queuing theory to estimate flow time and establish control parameters for flow time. They tried to assign an achievable due date for an order. Their method used queuing theory to estimate system status, such as WIP and throughput.

In recent years, many artificial intelligent and soft computing methods have been used for decision support and forecasting. Philipoom et al. [10] considered a new procedure for internally setting due dates, namely, neural network prediction, in a simple flow shop.

### 2.2 Artificial neural networks

Artificial neural networks (ANN) are computing systems that incorporate a simplified model of the human neuron, organized into networks similar to those found in the human brain. ANNs are computer simulations of biological neurons. They are not programmed; rather, they learn by example. Neural networks are composed of processing elements (nodes) and connections. Each processing element has an output signal that fans out along the connections to the other processing elements. Each connection is assigned a relative weight. A node's output depends on the specified threshold and the transfer function. ANNs are used in pattern recognition, speech recognition, group technology, scheduling, prediction, optimisation, etc. An ANN is characterized by its architecture, activation function and learning method. There are many different types of ANNs that model how the human brain uses thought to learn. These ANN types include the Hopfied, Brain-State-in-a-Box, Bidirectional Associative Memory, Boltzmann, Adaptive Resonance Theory, Hamming, and Hamming and Spation-temporal Networks (p. 7 in [11]).

ANNs are becoming better well known and have been successfully implemented in manufacturing [12]. For instance, Philipoom et al. [10] used neural network models to forecast the order due-date in a simple flow shop manufacturing system. The neural network model yields better forecasting results than conventional due-date assignment approaches [10]. Their research pointed out that neural networks could outperform conventional, regression-based due-date assignment rules. They concluded that neural networks are worthy of further experimentation as the methodology of choice in due-date prediction. However, order due dates in a flow shop are stable and the system deviation is smaller than that in a job shop.

Huang et al. [13] constructed an ANN model to predict production performance for a wafer fabrication factory. They used a three-layer back-propagation neural network. It allowed more accurate prediction of the WIP level and move volume in the next time period for each wafer fabrication operation stage [14]. Using neural network models to predict wafer fabrication production performance has the following merits.

1. Neural networks can obtain a probable result even if the input data are incomplete or noisy.
2. A well-trained neural network model can provide a real time forecasting result.
3. Creating a neural network model does not necessitate understanding the complex relationship among the input variables.

Back-propagation neural networks (BPN) are widely used and produce good results in prediction and pattern recognition. This work constructed BPN model for order due-date prediction in wafer fabrication. We integrated the artificial neural network, simulations and statistical tools for modelling an ANN based due-date assignment rule in wafer fabrication.

## 3 DDA methodology

In general, the internally set due-dates can be represented using the following Eq. 1 [15]:

$$d_i = r_i + p_i + q_i \tag{1}$$

$d_i$: internally-set due-date of order $i$
$r_i$: arrival time of order $i$
$p_i$: total processing time for order $i$
$q_i$: total queuing time in the system for order $i$

In Eq. 1,$r_i$ and $p_i$ are the known nearly constants after order $i$ arrives. The total queuing time for order ($q_i$) is the only variable that needs to be estimated for predicting $d_i$ in Eq. 1. Hence, the manager must establish an applicable prediction model for $q_i$ to precisely predict the due-date for an order.

The total queuing time in the system for an order ($q_i$) consists of two major parts (Eq. 2). First, $q_{psp}$ is the time from order acceptance to order release into the shop (i.e. the queuing time in the pre-shop pool). $q_s$ is the total queuing time in the shop (from order released into shop to order finished). To provide an exact customer due-date, the manager must establish precise prediction models for $q_{psp}$ and $q_s$. Most researchers used regression-based rules to predict the due-date. One or more factors, including job characteristics or system status, are considered in building a regression model for due-date prediction, such as TWK, NOP and JIQ. Regression-based and ANN-based rules are used to predict the due-date ($d_i$) in this research.

$$q_i = q_{psp} + q_s \tag{2}$$

$q_{psp}$: total queue time in the pre-shop pool for order $i$.
$q_s$: total queue time in the shop of order $i$.

### 3.1 Conventional DDA rules

Most of the conventional DDA rules consider only one factor related job characteristic or system status. We will compare some of these rules with the regression-based and ANN-based rules. In conventional DDA models, TWK, JIQ, and JIBQ are public and adapted in our research. Ragatz and Mabert [13] published a comprehensive comparison of different due-date assignment rules. They considered the performance of eight different assignment rules in a simulated specific shop. We will consider two public DDA rules, TWK and JIQ, in our simulation model.

The methodology is described as follows.

#### *3.1.1 Total work content (TWK)*

This method assigns due dates to each order as a multiple of the order's total processing time. TWK is widely used in practice. The TWK rule is as follows:

$$d_i = r_i + k * p_i \tag{3}$$

Where $d_i$ denotes the assigned due date for order $i$ and $k$ is the parameter that reflects the expected queue time that order $i$ will experience in the system. The $k$ value is estimated based on the regression models.

#### *3.1.2 Jobs in queue (JIQ)*

This method assigns due dates to each order as a multiple of the number of orders in the queue. JIQ is widely used in practice. The JIQ rule is as follows:

$$d_i = r_i + p_i + k * q_s \tag{4}$$

Where $d_i$ denotes the assigned due date for order $i$ and $k$ is the parameter that reflects the expected queue time that order $i$ will experience in the system. The $k$ value is estimated based on the regression models.

### 3.1.3 Jobs in bottleneck queue (JIBQ)

This method is used in the system have the significant bottleneck. The due date of each order is assigned just considering the length of the queue in the bottleneck workstations. The JIBQ rule is as follows:

$$d_i = r_i + p_i + k * q_{\text{bottleneck}} \quad (5)$$

Where $d_i$ denotes the assigned due date for order $i$ and $k$ is the parameter that reflects the expected queue time that order $i$ will experience in the system. The $k$ value is estimated based on the regression models.

## 3.2 Regression-based DDA rules

In TWK, JIQ and JIBQ, $q_i$, the total queuing time, including $q_{psp}$ and $q_s$, will be predicted considering just a single factor. Most of the conventional DDA rules consider just one or more factors building a regression-based model for predicting the order due date. Owing to the complexity of wafer fabrication, many factors affect due-date prediction. Ninety-two factors are considered in this research in building two regression-based DDA rules, the key factor prediction model (KFM) and significant factor prediction model (SFM). KFM uses the most important factors under statistics analysis. SFM uses the significant factors.

The 92 factors can be classified into three classes including: the system conditions, order characteristics and pre-shop-pool (PSP) condition. There are some subclasses in the system and PSP conditions. The classification structure of the prediction factors is shown in Table 1.

The prediction model for $q_s$ was built by choosing one or more significant factors from main classes 1 and 2. The $q_{psp}$ prediction model considers all of these factors in main classes 1, 2 and 3.

### 3.2.1 KFM_sep

KFM_sep considers only the factor that has the highest statistical analysis correlation coefficient value. The queuing times, $q_s$ and $q_{psp}$, are forecasted separately. The due date for each order is assigned as follows:

**Table 1** The classification structure of the prediction factors

| Main class | Subclass | Number of factors included |
|---|---|---|
| 1. System Condition | 1.1 Shop status | 8 |
| | 1.2 Bottleneck status | 10 |
| | 1.3 Constraint resource status | 50 |
| | 1.4 Recently completed orders | 8 |
| 2. Order Characteristics | | 8 |
| 3. PSP Condition | 3.1 PSP status | 4 |
| | 3.2 Recently completed orders | 4 |
| Total | | 92 |

$$d_i = r_i + p_i + q_{KFM(PSP)} + q_{KFM(S)} \quad (6)$$

Where $d_i$ denotes the assigned due date for order $i$, $q_{KFM(PSP)}$ and $q_{KFM(S)}$ are the $q_{psp}$ and $q_s$ estimations in the KFM regression models.

### 3.2.2 KFM_com

KFM_com considers only the key factor. The queuing time ($q_i$), including $q_s$ and $q_{psp}$, is forecasted using a regression model. The due date for each order is assigned as follows:

$$d_i = r_i + p_i + q_{KFM(total)} \quad (7)$$

Where $d_i$ denotes the assigned due date for order $i$, $q_{KFM(total)}$ is the $q_i$ estimation using the KFM regression models.

### 3.2.3 SFM_sep

SFM_sep considers the significant factors under statistical analysis. The queuing time, $q_s$ and $q_{psp}$, are forecasted separately. The due date for each order is assigned as follows:

$$d_i = r_i + p_i + q_{SFM(PSP)} + q_{SFM(S)} \quad (8)$$

Where $d_i$ denotes the assigned due date for order $i$, $q_{SFM(PSP)}$ and $q_{SFM(S)}$ are the $q_{psp}$ and $q_s$ equations using the SFM regression models.

### 3.2.4 SFM_com

SFM_com considers all of the significant factors. The queuing time ($q_i$), including $q_s$ and $q_{psp}$, are forecasted using a regression model. The due date for each order is assigned as follows:

$$d_i = r_i + p_i + q_{SFM(total)} \quad (9)$$

Where $d_i$ denotes the assigned due date for order $i$, $q_{SFM(total)}$ is the $q_i$ estimation using the SFM regression models.

Using historical data as the input variables, the regression model and neural network model represent the properties and variations in a system. When a system is stable, acceptable forecasting accuracy using the two models is expected. However, finding a nonlinear regression model that can correspond to the historical data and represent the system's status is difficult. Many independent variables must be considered in our case. Furthermore, some of the data do not fit the basic assumptions in regression models. Thus, additional data transformations are necessary to generate our regression model. Alternatively, creating neural network models does not have the above conditions. Moreover, in practice, neural network models can yield better results than regression models [10, 16].

## 3.3 ANN-based DDA rule

In our research, an artificial neural network, simulations and statistical analysis tools are integrated to model an ANN-based DDA rule. The structure of the rule is shown in Fig. 1. Two types of ANN-based DDA rules are developed. The first rule, ANN_com, adopts one neural network to predict the wait time (including waiting time in PSP and waiting time in the shop) in a wafer fab. The second rule, ANN_sep, uses two neural networks to predict the wait time in PSP and the shop separately. The prediction difference between the ANN_com and ANN_sep is investigated.

### *3.3.1 Virtual wafer fabrication*

To obtain adequate data for modelling the DDA rules a virtual wafer fabrication system was modelled based on a real wafer fab. The wafer fab configuration considered in this study is a wafer fabrication factory in Taiwan. The fab consists of 53 workstations and 301 machines. The fab has three types of products with a product mix of 0.2, 0.35, and 0.45. The entire process requires 16, 18 and 17 loops. That is, a lot visits photolithographic exposure workstations 16,18, and 17 times. The processing time for a lot is randomly generated from a uniform distribution between 0.95×MPT and 1.05×MPT, where the MPT (mean processing time) is given for each workstation. The set-up time is included in the processing time. The virtual fab takes into account the downtime, which includes unscheduled breakdowns. The time between failure and repair for each workstation is randomly generated from exponential distributions with given mean values. A lot (a cassette for wafers) contains 24 wafers and the transfer time between workstations is ignored in the simulation. The virtual wafer fab was built on personal computers with Pentium III 800 processors using the eM-plant, a simulation package developed by Tecnomatix Technologies Corp.

### *3.3.2 Data set*

We can collect a lot of data using a simulation experiment in the virtual fab. A data set consists of 92 variances and the real flow time for each lot (containing the processing time and actual waiting time in the PSP and shop). This data set was used for training our ANN and regression model. It is necessary to guarantee statistical independence among the data before the test is performed. To insure this, only one in every 10 outputs from the shop simulation was randomly selected to be included in the sample of 33,000 jobs. The simulation was designed for a simulation time period of 24 hours a day and the data was collected after 150 warm days.

### *3.3.3 Statistics analysis*

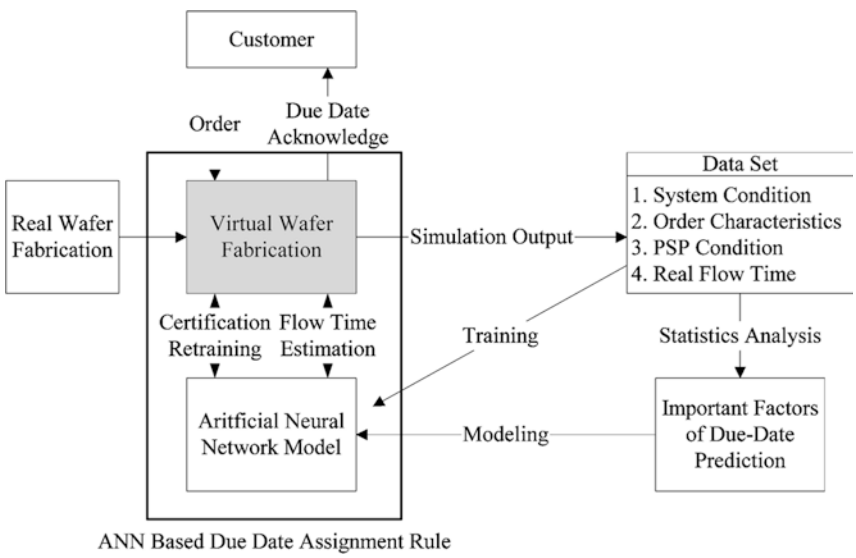
Creating an ANN initially involves determining the input variables. Based on the data obtained, a correlation analysis was performed to help determine the input variables. Forty-two variables (i.e. the significant factors of due-date prediction) were modelled in our ANN model. These variables had significant correlation with flow time.

### *3.3.4 Modelling and training*

Our research constructed three BPN prediction models using the neuralworks professional II/Plus, a neural network package developed by NeuralWare Technological Corp. The first BPN focused on the total wait time in the system, including the wait time in the PSP and shop. The other two BPNs focused on predicting the wait time in the PSP and shop separately.

Modelling a BPN must apply the experimental design method to determine the optimum BPN structure. Figure 2 is an example of a three-layer back-propagation neural network. The number of hidden layers in a BPN model and the number of nodes on the hidden

**Fig. 1** The structure of the ANN based DDA rule



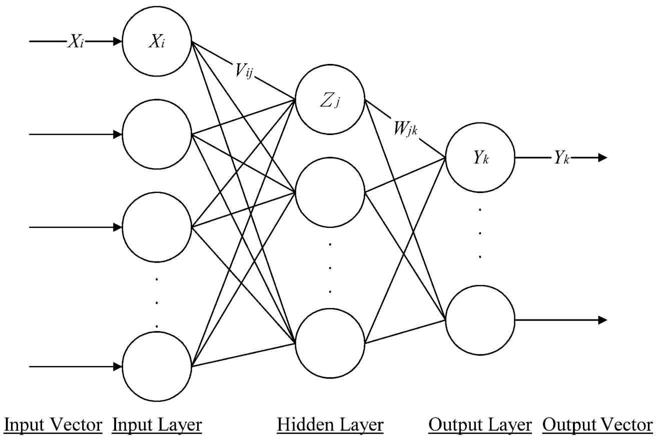



**Fig. 2** An example of three-layer back-propagation neural network

layer must be determined. The momentum and learning rate for the model must also be determined.

Supervised learning is adopted in our BPN model. The gradient-descent algorithm is employed ([13], pp 322–328). Through a supervised learning rule, the collected data set (training data) comprises an input and an actual target output. The gradient-descent learning algorithm enables a network to enhance the performance by self-learning. Two phases are available for computing: forward and backward. In the forward phase of back-propagation learning the input data pattern is directly passed into the hidden layer. Each element in the hidden layer calculates an activation value by summing up the weighted inputs and then transforms the weighted input into an activity level using a transfer function (the sigmoid function is broadly used). The resulting activity is allowed to spread through the network to the output layer. If a difference arises, i.e. an error term, the gradient-descent algorithm is used to adjust the connected weights in the backward phase. This learning process is repeated until the error between the actual and desired output (target) converges to a predefined threshold. A trained neural network is expected to predict the output when a new input pattern is provided to it.

### *3.3.5 Certification and retraining*

The BPN model training occurs off-line. The data set is separated into two parts before model training. The first set is the training data (30,000 records). The second set (3,000 records) is used for certification. To improve the prediction accuracy different data set should be used in training and certification. To assure that the model is suitable for prediction, on-line retraining is designed in the BPN model. That is, the model is retrained using recently completed data lots.

### *3.3.6 Due-date acknowledgement*

When the trained BPN is on-line, the ANN based DDA rules can immediately assist the due-date acknowledgement. When a customer asks for a due-date quote for an order, a new input pattern consists of all of the input variables provided to the BPN for predicting the total wait time. The due date is confirmed based on Eqs. 10(ANN-com) and 11 (ANN_sep):

$$d_i = r_i + p_i + q_{ANN\_com(total)} \tag{10}$$

$$d_i = r_i + p_i + q_{ANN\_sep(PSP)} + q_{ANN\_sep(S)} \tag{11}$$

$q_{ANN\_com(total)}$ is the estimation of the total wait in the system under the trained BPN model. $q_{ANN\_sep(PSP)}$ and $q_{ANN\_sep(S)}$ are the wait time estimations in PSP and the shop under the trained BPN model.

## 4 Experimental design

Our research included three types of DDA methodology with nine rules in our simulation model. Table 2 shows a summary of these DDA rules:

The required parameter values for each rule were predetermined. The regression and ANN models were built before the rule comparison.

A simulation experiment was performed to compare the DAA rules used in this study. The performance measures used for the comparison were tardiness, lateness, earliness and the correlation between the predicted flow time and actual flow time. Tardiness is the absolute difference between the actual completion date and the promised due date for orders. This method was used as the primary performance measure. A smaller tardiness implies a better due-date prediction capability. Tardiness is always equal to the sum of the lateness and earliness. The formulas used for the performance index are as follows:

**Table 2** The summary of DDA rules

| Types | Rules | Information required | Formula |
|---|---|---|---|
| Conventional | TWK | Total PT | $d_i = r_i + k^* p_i$ |
| | JIQ | Queue in system | $d_i = r_i + p_i + k^* q_s$ |
| | JIBQ | Queue in bottleneck | $d_i = r_i + p_i + k^* q_{\mathrm{bottleneck}}$ |
| Regression-based | KFM_com | Key factor | $d_i = r_i + p_i + q_{KFM(total)}$ |
| | KFM_sep | Key factor | $d_i = r_i + p_i + q_{KFM(PSP)} + q_{KFM(S)}$ |
| | SFM_com | Significant factors | $d_i = r_i + p_i + q_{SFM(total)}$ |
| | SFM_sep | Significant factors | $d_i = r_i + p_i + q_{SFM(PSP)} + q_{SFM(S)}$ |
| ANN-based | ANN_com | Significant factors | $d_i = r_i + p_i + q_{ANN\_com(total)}$ |
| | ANN_sep | Significant factors | $d_i = r_i + p_i + q_{ANN\_sep(PSP)} + q_{ANN\_sep(S)}$ |

$$\text{Tardiness} = \left\{ \sum_{i=1}^{n} \left[ \max(0, d_i - f_i) + \max(0, f_i - d_i) \right] \right\} / n \tag{12}$$

$$\text{Earliness} = \left[ \sum_{i=1}^{n} \max(0, d_i - f_i) \right] / n \tag{13}$$

$$\text{Lateness} = \left[ \sum_{i=1}^{n} \max(0, f_i - d_i) \right] / n \tag{14}$$

$f_i$: is the actual finish date of order $i$.
$d_i$: is the internally set due date for order $i$
$n$: is the number of orders

The configuration of the wafer fab considered in this study is a wafer fabrication factory in Taiwan. The fab consists of 53 workstations and 301 machines. Product type, processing time and other information related the virtual wafer fab is shown in Sect. 3.3.

The order releasing mechanism releases new lots into the fab at a constant rate, e.g. 16 lots/day (i.e. UNIF). Under the order release mechanism, the fab utilization is nearly 90%. Before a lot is released, the lot orders are kept in the pre-shop pool. First-In-First-Out (FIFO) is adopted as the dispatching rule at each work centre. UNIF and FIFO are in widespread use in practice. Only one in every 10 outputs from the virtual fab was randomly selected to be included in the sample of 600 jobs for measuring the DDA rule performance. The simulation was designed for a simulation time period of 24 hours a day and the data was collected after 150 warm days. A due date is quoted immediately when the order is accepted. All of the information used in these DDA rules is collected at that time.

## 5 Discussion and analysis

The performance of the nine DDA rules is shown in Table 3 and Fig. 3. The ANN-based DDA rules are shown to be superior to the regression-based and conventional

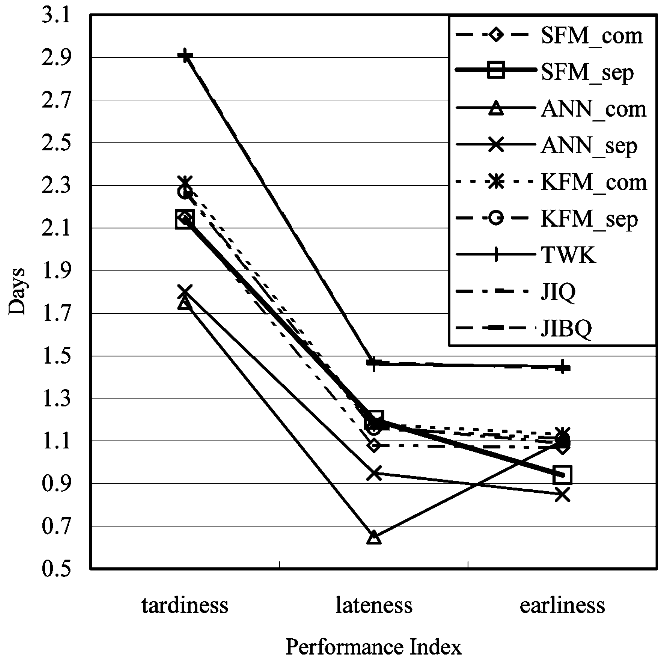



**Fig. 3** The performance of DDA rules

rules. The ANN_com and ANN_sep tardiness rate is lower than the other methods. The difference is greater than 2 days. In the regression-based rules, SFM_com and SFM_sep are superior to KFM_sep and KFM_com. That is, more information used will improve the prediction performance. The conventional rules, including TWK, JIQ, and JIBQ, are inferior to the others. Owing to the complexity of wafer fabrication, the conventional DDA rules, including single information, are inadequate. The ANN-based rules are better than others in lateness and earliness. SFM_sep and SFM_com are better than the conventional rules. The tardiness variance is significant in the DDA rules. In the ANN-based rule the maximum tardiness is more than 17 days. The regression-based and conventional rule had more than 18 days tardiness. It is very significant that the DDA rule, using simple methodology, is not sensitive to the due date. Due-date quoting based on these rules will not have the capability to reflect the reality in the fab. ANN-based rules have a smaller

**Table 3** The performance of DDA rules

| Performance Index | | SFM_com | SFM_sep | ANN_com | ANN_sep | KFM_com | KFM_sep | TWK | JIQ | JIBQ |
|---|---|---|---|---|---|---|---|---|---|---|
| Mean of predicted flow time (variance) | | 43.37 (5.23) | 43.13 (5.12) | 43.43 (5.33) | 43.38 (5.12) | 43.33 (3.59) | 43.34 (4.02) | 43.38 (0.43) | 43.31 (4.04) | 43.35 (0.01) |
| Correlation[a] | | 0.66 | 0.68 | 0.78 | 0.82 | 0.55 | 0.55 | 0.21 | 0.57 | 0.04 |
| Tardiness | Average | 2.15 | 2.14 | 1.75 | 1.8 | 2.31 | 2.27 | 2.91 | 2.26 | 2.91 |
| | Max. | 18.89 | 18.9 | 16.92 | 15.79 | 18.65 | 19.11 | 17.89 | 18.6 | 18.46 |
| Lateness | Average | 1.08 | 1.2 | 0.65 | 0.95 | 1.18 | 1.16 | 1.46 | 1.17 | 1.47 |
| | Max. | 18.89 | 18.9 | 16.92 | 16.79 | 18.65 | 19.11 | 17.89 | 18.6 | 18.46 |
| Earliness | Average | 1.07 | 0.94 | 1.1 | 0.85 | 1.13 | 1.11 | 1.45 | 1.09 | 1.44 |
| | Max. | 6.31 | 6.71 | 6.04 | 6.92 | 7.58 | 7.12 | 9.78 | 7.66 | 10.51 |
| % of late | | 0.29 | 0.28 | 0.18 | 0.2 | 0.3 | 0.24 | 0.37 | 0.29 | 0.37 |
| % of early | | 0.42 | 0.36 | 0.43 | 0.41 | 0.42 | 0.4 | 0.44 | 0.42 | 0.4 |
| % of on time | | 0.29 | 0.36 | 0.39 | 0.39 | 0.28 | 0.36 | 0.19 | 0.29 | 0.23 |

[a] The correlation coefficients between real flow time and predict flow time of lots

**Table 4** Duncan's multiple range test for the DDA rules[a]

| Performance | DDA Rule |
|---|---|
| Tardiness | 3[b], 4, 2, 1, 8, 6, 5, 7, 9 |
| Lateness | 3, 4, 1, 6, 8, 5, 2, 7, 9 |
| Earliness | 4, 2, 1, 8, 3, 6, 5, 9, 7 |

[a] The $\alpha$ of Duncan's test is 0.05
[b] The number is DDA rule: 1. SFM_com, 2. SFM_sep, 3. ANN_com, 4. ANN_sep, 5. KFM_com, 6. KFM_sep, 7. TWK, 8. JIQ, 9. JIBQ

tardiness value and variance. The ANN-based rule due-date prediction capability is better than others.

The on-time delivery percentage is another important performance index. On-time delivery is defined as the order's tardiness is smaller than 1 day. That is, the forecasted due date is not larger or smaller than one day of the actual flow time. ANN-based DDA rules have 39% on-time delivery. More than 80% of the orders can be delivered before the predicted due date. The percentage of on time delivery is not derived from a greater buffer on the due-date prediction. The due-date prediction accuracy using ANN-based rules is better than that using regression-based and conventional rules.

Table 4 shows the Duncan's multiple test result at $\alpha = 0.05$. The ANN-based rules are superior to the other rules.

## 6 Conclusion and future work

In this research regression-based and ANN-based DDA rules were developed and tested in a virtual fab. The conventional DDA rules, TWK, JIQ, and JIBQ, were used as the benchmark in the simulation model. The simulation result and statistics showed that the ANN-based DDA rules produce a better due-date prediction. The ANN-based DDA rule tardiness is smaller than that from the other rules. Their sensitivity and variance are also better than the others. If the wafer fab information is not very difficult to obtain, the ANN-based DDA rule can perform due-date prediction. The regression-based and conventional rules, SFM_sep and JIQ are better than the other rules. SFM_sep, like the ANN-based rule, is based on lots of information about the wafer fab. If the cost of obtaining this information is too expensive, KFM-com, KFM-sep, and JIQ are suitable for due-date prediction in wafer fabrication.

There are some other topics that can be discussed in the future, including the integration of the due-date assignment rule and shop floor control strategies, such as order review/releasing and dispatching. Because the interaction among the shop floor control strategies is significant, the effect of order review/release and dispatching on due-date prediction cannot be ignored. Due-date prediction based on capability planning in place of a prediction model can be developed.

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## References

1. Chung SH, Yang MH, Cheng CM (1997) The design of due date assignment model and the determination of flow time control parameters for the wafer fabrication factories. IEEE Transaction on Component, Packaging, and Manufacturing Technology—Part C 20:278–287
2. Smith ML, Seidman A (1993) Due date selection procedure for job shop simulation. Comput Ind Eng 7:297–320
3. Cheng TCE, Gupta MC (1989) Survey of scheduling research involving due date determination decisions. Eur J Oper Res 38:156–166
4. Eilon S, Chowdhury IG (1976) Due-date in job shop scheduling. Int J Prod Res 14:223–138
5. Vig MM, Dooley KJ (1991) Dynamic rules for due-date assignment. Int J Prod Res 29:1361–1377
6. Weeks JK (1979) A simulation study of predictable due-dates. Manage Sci 25:363–373
7. Kaplan AC, Urnal AT (1993) A probabilistic cost-based due date assignment model for job shops. Int J Prod Res 31:2817–2834
8. Enns ST (1993) Job shop flow time prediction and tardiness control using queue analysis. Int J Prod Res 31:2045–2057
9. Smith CH, Minor ED, Wen HJ (1995) Regression-based due date assignment rules for improved assembly shop performance. Int J Prod Res 33:2375–2385
10. Philipoom PR, Rees LR, Wiegmann L (1994) Using artificial neural networks to determine internally-set due-date assignments for shop scheduling. Decis Sci 25:825–847
11. Fausett L (1994) Fundamentals of neural networks. Prentice-Hall, New York
12. Udo GJ (1992) Neural networks applications in manufacturing process. Comput Ind Eng 23:97–100
13. Ragatz GL, Mabert VA (1984) A simulation analysis of due date assignment rules. J Oper Manage 5:27–39
14. Huang CL, Huang YH, Chang TY, Chang SH, Chung CH, Huang DT, Li RK (1999) The construction of production performance prediction system for semiconductor manufacturing with artificial neural networks. Int J Prod Res 37:1387–1402
15. Chang FCR (1994) A study of factors affecting due-date predictability in a simulation dynamic job shops. J Manuf Syst 13:393–400
16. Shyur HJ, Luxhoj JT, Williams TP (1996) Using neural networks to predict component inspection requirements for aging aircraft. Comput Ind Eng 30:257–267
17. Rumelhart DE, Mcclelland JL (1989) Parallel distributed processing: explorations in the microstructure of cognition, vol. 1. MIT Press, Cambridge