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Job shop flow time prediction using artificial neural networks

Dissertation presented to achieve the degree of Master in Industrial Engineering and Management

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The path is made by walking.

Kafka F.,1883-1924

To my parents and brother.

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Resumo

Uma das maiores dificuldades de grande parte das empresas do setor produtivo é a definição de datas de entrega realistas e passíveis de serem atingidas. Entre uma grande variedade de métodos que se propõem a melhorar a previsão do tempo de fluxo, nem todos conseguem ter um bom desempenho em todas as circunstâncias.

As redes neuronais (ANN) têm sido implementadas com sucesso para previsão e deteção em diversas áreas tais como manufatura (p. ex. previsão de níveis de stock), medicina (p. ex. deteção de doenças), finanças e contabilidade (p. ex. previsão de falhas de bancos). Estudos anteriores sobre a utilização das ANN na previsão de tempos de fluxo, demonstraram que estas são capazes de obter melhores resultados do que as regras de atribuição de datas de entrega (DD) convencionais. A literatura relacionada com as regras de atribuição de DD, revela que as regras dinâmicas fornecem melhores resultados quando comparadas com as regras convencionais. Por estas razões, propomo-nos com este trabalho a estender a investigação sobre a utilização das ANNs para previsão de tempos de fluxo, comparando para esse efeito os resultados da ANN, com os resultados de duas regras dinâmicas de atribuição de DD: *Dynamic Process Plus Waiting* (DPPW) e *Dynamic Total Work Content* (DTWK). Além disso, duas regras de despacho são também utilizadas de forma a estudar o desempenho da ANN sob diferentes condições. Os resultados obtidos, tanto das regras dinâmicas de atribuição de DD como da ANN, foram avaliados em termos de atraso médio absoluto (MAL), atraso médio quadrático (MSL), percentagem de atraso (PT) e atraso médio (MT). Recorrendo a um software de simulação, foi implementado um sistema *job shop* dinâmico, com o objetivo de obter dados tanto para alimentar a ANN, como para estimar a data de entrega com recurso aos dois métodos dinâmicos.

Os resultados obtidos sugerem que as ANNs podem obter melhores resultados do que as regras dinâmicas de atribuição de DD, mesmo sob diferentes condições.

Palavras-chave: Job Shop Dinâmico, Atribuição de datas de entrega, Regras dinâmicas de atribuição de datas de entrega, Regras de despacho, Simulação, Redes Neuronais.

Abstract

One common problem for production companies is how to quote an realistic and attainable due date for an arriving costumer order. Among a wide variety of prediction methods proposed to improve due date (DD) assignment, it seems that not all perform well under all circumstances.

The artificial neural networks (ANN) as been successfully used for prediction in multiple areas such as: manufacturing (i.e. stocks level prediction), medicine (i.e. decease detection), finances and accounting (i.e. predicting bank failures). Previous studies on the use of the ANN as a flow time predictor shown that the ANN can outperform conventional DD assignment rules and are worthy of further experimentation. The literature on the DD assignment rules shown that the dynamic rules outdo the conventional DD assignment rules. For this reason, we propose to extended the research on the DD assignment by using an ANN model for flow time prediction and to comparing it to two dynamic DD assignment rules for flow time estimation: Dynamic Process Plus Waiting (DPPW) e Dynamic Total Work Content (DTWK).. Furthermore, two dispatching rules were also chosen to study the performance of the ANN under different conditions. The results from both DD assignment rules and ANN, were evaluated in terms of mean absolute lateness (MAL), mean square lateness (MAL), percentage tardiness (PT) and mean tardiness (MT). A hypothetical dynamic job shop system was implemented in a simulation software in order to generate data to feed the ANNs and to estimate the DD using the two dynamic DD setting rules.

Results suggest that the ANN outperform the DD assignment rules even under different conditions.

Keywords Dynamic Job Shop, Due date assignment, Dynamic due date setting rules, Dispatching rules, Simulation, Artificial Neural Networks.

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ABBREVIATIONS

ANN – Artificial Neural Network

CON – Constant

DD – Due Date

DPPW – Dynamic Processing Time Plus Waiting

DTWK– Dynamic Total Work Content

FIFO– First In First Out

NOP – Number of Operations

PPW – Processing Time Plus Waiting

SPT – Shortest Processing Time

SLK– Slack

TWK – Total Work Content

1. INTRODUCTION

With increasing globalization, competitiveness and current emphasis on costumers-oriented markets, the production companies face more challenges than ever. In order to gain competitive advantage in the intense market competition, companies must be able to provide to costumers with better quality, competitive pricing, reduced lead times, and reliable due dates (DD) when compared to its competitors (Li, 2009). Authors like Sha and Liu (2005) and Cheng and Jiang (1998) highlight the importance of meeting the DD claiming that it not only increases the customer service but also improves the resource utilization by making it more efficient. In fact, if an early conclusion of the orders, implies more inventory costs (i.e. storage costs and insurances), a delayed conclusion leads to a loss of reputation and clients to the company. For these motives and since providing an exact DD is a difficult task, the problem of DD assignment has been highly study on literature. However, its performance is dependent on the quality of the assigning models. (Hsu and Sha, 2004)

The DD is can be defined as the "date that the order is required to be delivered to the client" (Vinod and Sridharan, 2011). The DD can either be externally or internally set (Joseph and Sridharan, 2011). They are externally set when the DD is imposed by the client or internally set when is defined based on shop congestion levels. In the present investigation it will be study the DD assignment for the case of internally DD setting.

In literature, the DD assignment problem has been study in the context of job shops. The job shop term is commonly used to describe a system where a wide variety of products are produced, usually in small sizes and where each product can have different processing sequences (routings) and different processing times. This type of production system can be found on Make–To-Order (MTO) companies where the production only takes place after the costumer places an order. According with Kingsman *el al.,* (2005) , in these type of companies, the costumers often place several orders in different companies. To get the orders, these companies usually have to pass through a bidding system where the company that provides the most competitive DD, price and quality win the order. The company reputation, when it comes to providing realistic and reliable due dates, it is also considered by the costumer before choose to place the order. For example, if the company continuously fail in deliver the goods on the agreed time, the company will get to known as unreliable and get poor reputation, which will soon lead to costumers going elsewhere. However, this kind of workflow makes difficult to predict the demand and to produce of the goods on the agreed time. (Kingsman *et al.*, 1996) Thus, the problem of the DD assignment is especially important for these type of companies. (Thürer *et al.*, 2013)

In the most of the DD assignment models, the DD assignment of a job/order consists on predicting the flow time for that job, set a conclusion date based on that flow time and then evaluate the estimated flow time using for that purpose some performance measure. (Ragatz and Mabert, 1984; Joseph and Sridharan, 2011). However, the flow time prediction is a challenging task since every arriving job has its own processing needs, in different machines and it will experience different congestion levels which will consequently alter the flow of the jobs through the shop (Hsu and Sha, 2004).

Due to the complexity of the flow time prediction, we will study the use of artificial neural networks ANN as flow time estimator. From literature we use two due date assignment rules: Dynamic Total Work Content (DTWK) and Dynamic Process Plus Waiting (DPPW) to compare with performance of the Artificial Neural Network (ANN). Each of these three models will be evaluated in terms of mean absolute lateness (MAL), mean square lateness (MAL), percentage tardiness (PT), mean tardiness (MT).

This document is structured as follows: on Chapter 2 we present a literature review on due date setting rules, dispatching rules, performance measures and on the use of ANN as an flow time estimator; on Chapter 3 we describe our research methodology; on Chapter 4 we evaluate our results and provide a detailed discussion and analysis; on Chapter 5 we draw our final conclusions to retain from this work, as some guidelines for future work.

2. LITERATURE REVIEW

Typically, the DD assignment process consists in making an estimate of the flow time for a job/order based on rules for flow time estimation, and then setting a completion date based on that estimation (Ragatz and Mabert, 1984; Joseph and Sridharan, 2011).The flow time can be defined as the time that a job spends in the production process/system from its release to its production and completion.

The DD assignment problems are mostly studied in the context of job shop systems. In broader terms a job shop system can be described as a composition of the following entities (Pettit, 1968)

- Production facilities (machines, workstations);
- Jobs (the tasks to be performed on the production facilities);
- Each job has a processing sequence;
- The processing sequences can be different from job to job;
- The jobs can have different processing times;
- Each production facility performs one or more tasks.

Moreover, job shop systems can be classified into two categories related to the job availability: dynamic and static job shop systems (Vinod and Sridharan, 2011). In the static job shop it is assumed that all the jobs are available for processing at the same time and therefore all the characteristics of jobs are previously known. In the dynamic job shop system, the jobs randomly arrive to the shop over time. In this case, the job shop becomes a queuing system: a job leaves one machine and proceeds on its route to another machine for the next operation. If other jobs already waiting for the machine to complete its current task can be found, a queue in front of that machine is formed.

The dynamic job shop system is widely used in literature to study the DD assignment problems since they provide a more accurate representation of the operating conditions in a real-world environment (Sha *et al.*, 2007). For this reason, in our investigation we will study dynamic job shop systems.

Modelling a dynamic job shop, often it involves deciding the order by which job will be processed first and for this purpose several dispatching rules can be used. However, the use of dispatching rules makes the flow time prediction in the dynamic job shops become a complex task. This complexity is often related to the uncertainty of the characteristics of the arriving jobs (Ragatz and Mabert, 1984; Joseph and Sridharan, 2011). To explain this complexity, Ragatz and Mabert (1984), divide the jobs into three temporal categories: jobs already in the system, the new arriving jobs and the future jobs. The characteristics of the jobs are only known at the time that the job arrive to the system. Here, the flow time for a new arriving job can be obtained using a flow time estimation model. However, if dispatching rules are allowed one arriving job can change the processing sequence of the jobs already at the system and by that change their flow time. Therefore, as we can see, without knowledge of the future arrivals it is impossible to predict exact flow times for all the jobs at the system. As the inclusion of dispatching rules are often used in real world environments, most of the study's in the DD assignment subject aims to study the effect of the dispatching rules on the flow time prediction and try to propose more efficient rules for flow time estimation. The flow time estimation can be also affected by other factors related to the shop condition such as: the use of transportation times, availability of raw materials, set up times, number of machines, number of tasks performed by each machine, number of jobs waiting to be processed on each machine and machine breakdowns (Baykasoğlu *et al.*, 2008). These factors can influence the time that the job spends at the system.

To evaluate the quality of the DD assignment rules, several performance measures can be used. These metrics depend on characteristics of the system, the shop conditions and the production objectives (Hua-ii *et al.*, 2015). The DD assignment rules can be evaluated in terms of earliness (the amount of jobs completed before the DD), tardiness (the amount of jobs completed after the DD) and in lateness (the difference between its actual completion date and its estimated DD, which includes both earliness and tardiness). However, there is no agreement on literature about what performance measure should be used for the DD assignment evaluation, since each metric is strongly related to the circumstances and would not perform the same on all cases (Ragatz and Mabert, 1984).

To sum up what has been previously said, and to deal with the flow time estimation problem three main decisions must be taken:

1. The definition of a DD setting rule, usually based on models for flow time estimation;
2. The definition of the dispatching rule followed in the shop floor;
3. The definition of a performance criteria to evaluate the quality of the DD setting rule when combined with a given dispatching rule.

The following subsections provide more information about these three decisions. The Section 2.1 starts by defining the flow time estimation concept. The type of information that can be used to make the flow time estimation is divided into two categories and the DD setting rules are also divide into two types of rules depending on the type of information that is used. The Section 2.2 provides an overview of the use of the dispatching rules on the DD setting and in the Section 2.3 several performance measures are discussed. Moreover, the Section 2.4 provides a discussion of the use of ANN as an DD assignment method.

2.1 Due date setting rules

According to Cheng (1994) the general flow time estimation for an order can be represented by the equation (1),

$$f_i = r_i + P_i + k_i \tag{1}$$

where f_i, r_i, P_i and k_i are the flow time estimation, the arrival time, the total processing time and the allowance factor for a given job i, respectively. Since in the dynamic job shop the arrival time and the processing time of a job are known at the moment that a job arrives to the system, the only variable that needs to be estimated is the allowance factor k.

The flow allowance is a variable used to control the tightness of the DD and which reflects the time that the job will experience at the system. As been previously said, the time that the job spends at the system can be affected by many factors and, it can also be estimated by multiple forms depending on the chosen DD assignment rule for the flow time estimation

(Sha *et al.*, 2007). In the flow time estimation, Baker and Trietsch (2015) states that choosing the proper allowance factor is a trade-off between the tightness of the due and the job earliness/tardiness. If the allowance factor provides a looser DD, it may be possible to complete all the work on time. However, this fact will lead to a higher amount of jobs completed before the DD (earliness). On other hand, given tighter flow allowances it will lead to a higher amount of jobs completed after the DD (tardiness). For this motive, choosing the right allowance factor is very important in order to establish a proper flow time.

The literature provides a wide variety of methods to estimate the flow time, ones simpler than others but the main difference among them, is the amount of factors that it is considered to make the estimation of the allowance factor k.

According to Thürer *et al.*, (2013) for the flow time estimation, two main of categories of factors can be used: job related information and shop related information. The first category is related to the job characteristics that can only be known at the time that the job arrives to the system. The second category is related to the shop condition in terms of congestion. The job related information include the: processing times and the number of operations and the routing. The job related information include several factors that are obtained before the job being released to the shop. This factors (Sha and Liu, 2005; Thürer *et al.*, 2013) can include:

- The number of jobs in in the queues of each machine on the route of the job;
- The number of jobs in the system;
- The number of jobs in each queue of each machine;

Not all the factors have the same influence in the flow time estimation. Alpay and Yüzügüllü (2006) made a study of the factors that affect the DD predictability for on time delivery. By comparing five DD assignment rules (Total Work Content (TWK), Process Plus Waiting (PPW), DTWK, DPPW and a proposed rule), under five dispatching rules, they conclude that the number of jobs in the queues of each machine on the route of the job, the total processing time of the job and the number of operations are the most important factors for the flow time estimation. However, they also point out that in order to increase the quality of the DD prediction, more factors should be considered.

For the purpose of our study, we will divide the DD assignment rules into two categories based on the type of information that its used to make the flow time estimation:

- Rules which consider job information only for flow time estimation (Subsection 2.1.1)
- Rules which consider both job information and shop information for flow time estimation (Subsection 2.1.2)

2.1.1 Due Date assignment rules based on job information

Earlier studies on the DD assignment subject, focused in the use of simple rules for flow time estimation. Five examples of these rules are Constant (CON), Number of operations (NOP), Slack (SLK), Total Work Content (TWK), and Processing Time Plus Waiting (PPW). These rules are presented bellow on Table 1.

Table 1 - Summary of DD assignment rules and respective formulas.

DD assignment rules	Formula
CON	$d_i = r_i + k$
NOP	$d_i = r_i + km_j$
SLK	$d_i = r_i + P_i + q$
TWK	$d_i = r_i + kP_i$
PPW	$d_i = r_i + kP_i + q$

Where d_i is the DD of a job and m_j is the number of operations for for a given job i. In this class of DD assignment rules, the constants k and q, the allowance factor and slack allowance respectively, are determined by linear regression based on historical data.

The flow time estimation on these rules is obtained as follows (Baykasoğlu *et al.*, 2008):

- CON: the flow time of a job is the sum of his arrival time with a constant that gives equal allowance of each job;

- NOP: defines the flow time estimation of a job as function of number of operations to be performed;
- SLK: the flow time estimation is based on a common slack (q) that reflects equal waiting times or equal slacks. This slack is added to the sum of the release dates and processing times of individual jobs.
- TWK: the allowance factor is a multiple of the job processing time
- PPW: combines the CON, SLK and TWK into one model, where the due dates are linear functions of the processing time of the job.

In these class of rules, the same degree of the allowance factor is given to all the jobs, and for this reason they are also known as static rules. The accuracy of these rules depends on the determination of the most appropriate flow allowance for all the jobs. (Cheng and Jiang, 1998; Baykasoğlu *et al.*, 2008).

The main issue stated for this class of rules is that by given the same allowance factor to all the jobs, the shop load is not being taken into consideration. Yet, the shop load it will influence the time that the job will experience on the system. Therefore, if the shop load is heavy, an higher flow allowance should be assigned and in the other hand, if the shop load is moderate, a lower flow allowance should be assigned (Cheng and Jiang, 1998).

2.1.2 Due Date assignment rules based on job and shop information

To overcome the problem of the rules presented on the previous subsection, another class of rules denoted by dynamic DD setting rules, was developed by Cheng and Jiang (1998), where the allowance factor is dynamically updated as the job arrive to the shop. In their study, they proposed two dynamic rules based on static related: Dynamic Total Work Content (DTWK) based on the TWK rule and Dynamic Processing Plus Waiting (DPPW) based on the PPW rule. Both of these rules are capable of dynamically estimating the flow time by using feedback information about the current status of the shop and the characteristics of the arriving job to set an allowance factor at the moment that the job arrives to the shop. In this case the allowance factor will reflect the shop current conditions. They also have demonstrated that the dynamic DD assignment rules provide better results than their static counterparts. Similar results are presented in works done by (Baykasoğlu *et al.*, 2008; Alpay and Yüzügüllü, 2009; Vinod and Sridharan, 2011). For this reason our study will focus on the two dynamic DD assignment rules proposed by Cheng and Jiang (1998).

2.1.2.1 Dynamic Total Work Content

To establish the dynamic allowance factor for the DTWK rule, Cheng and Jiang (1998), assumed if the shop load is relatively steady for a short period of time, at any given time t, the flow allowance for a new arriving job in this period can be determined based on the current average flow time (2):

$$k_t = \frac{N_{st}}{\lambda \mu_g \mu_p} \tag{2}$$

where N_{st}, λ, μ_g, μ_p denote the number of the jobs in the shop at a time t, the average job arrival rate, the average number of operations and the mean processing time, respectively. To prevent allowance factors less than one it is used max $[1, k_t]$ instead of k_t.
Thus, the dynamic DD is given by the equation (3):

$$d_i = r_i + \max[1, k_t] \sum_{j=1}^{m_j} p_{ij} \tag{3}$$

where d_i, r_i, m_j and p_{ij} denote the due date assigned for the job i, the arrival time of job i, number of operations of job i and the processing time of the job i for operation j.

2.1.2.2 Dynamic Processing Time Plus Waiting

To obtain the dynamic processing time plus waiting, Cheng and Jiang (1998) applied the same concept where the allowance factor for a new job with m_j number of operations, can be given based on the average waiting time. The allowance factor is therefore given by the equation (4).

$$k_t = \frac{N_{qt} m_j}{\lambda \mu_g} \tag{4}$$

where N_{qt} is the total number of jobs in the queues of each machine. Thus, the dynamic DD is given by the (5).

$$d_i = r_i + k_t + \sum_{j=1}^{m_j} p_{ij} \tag{5}$$

2.2 Dispatching rules

Dispatching rules are very important on the topic of the DD assignment due to its influence at the flow of the jobs through the shop.

These rules have the mission to select the next job to be processed from a set of awaiting jobs in order to optimize the flow of jobs through the system (Blackstone *et al.*, 1982). In another words they give the jobs a certain priority value and the awaiting jobs are selected based on that priority. The priority value can be either the highest or the lowest value.

The dispatching rules can be classified in a number of ways. Holthaus and Rajendranb (1997) have proposed the following classification:

- Process-time based rules;
- Due Date Based Rules;
- Combination of rules;

- Rules that are neither process–time based nor DD based.

One example of a process-time based rule is shortest processing time (SPT) where the highest priority is given to waiting operation with the shortest processing time. This rule significantly reduces the flow time of the jobs through the shop and the mean tardiness of the jobs (Blackstone *et al.*, 1982). However, it will result in high values of tardiness to jobs with higher processing times.

The earliest due date (EDD) is an example of Due Dates Base-Rules where the highest priority goes to the job with the earliest DD. According to Holthaus and Rajendranb (1997) this type of dispatching rules performs well under light shop utilization levels but its performance decreases for an heavy shop utilization.

As stated by Blackstone *et al.*, (1982) there is no dispatching rule that can achieve the best performance under all circumstances since their efficiency depends on the characteristics of the system and the production objective.

Some authors have suggested to associate different dispatching rules by combining the best features from process-time and due date based rules. It has been found that these type of rules outperforms the process-time and due date based rules (Hua-ii *et al.*, 2015). However, they are more complex than the first two types of rules. Two examples of this type of rules are Least Slack (LS) and Critical Ratio (CR).

2.3 Artificial Neural Networks

Artificial neural networks (ANN) are computational systems inspired on biological functions of the human brain. The ANN consists in layers, processing elements (nodes) and connections. The ANN can be used to draw functions from observations. This characteristic can be useful in situations where the complexity of the data makes the design of such function by hand unattainable.

The ANN has been broadly employed in multiple areas such as manufacturing (i.e. prediction of production performance, stocks level prediction), medicine (i.e. decease detection), finances and accounting (i.e. predicting bank failures) (Patil, 2008).

As stated on the previous sections, the flow time prediction it is a difficult task due to the number of non-linearly related aspects that can affect it. As result on the advances on the computational systems, more recent studies on the DD assignment have attempt to include intelligent systems (IS) such as ANN to overcome the complexity of our problem (Hsu and Sha, 2004; Philipoom *et al.*,1994).

The motivations for the use of ANN in the DD assignment are explained by Hsu and Sha (2004) as follows:

- ANN can obtain plausible results even if the input data is incomplete or noisy;
- A well-trained ANN model can provide a real-time forecasting results;
- Creating a ANN model do not demand understanding the complex relationship among the input variables.

In the DD assignment problem, Philipoom *et al.*, (1994) is cited as one of the first researchers to study the use of ANNs for flow time prediction. They studied the effectiveness of ANNs when compared to the static DD assignment rules such as TWK and Jobs In Queue (JIQ) in a flow shop. These authors concluded that ANNs outperformed the TWK and JIQ rules in the performance measures of standard deviation of lateness and, in the performance measure related to the mean absolute deviation in most of the experiments.

Hsu and Sha (2004) studied the performance of ANN in DD prediction in a complex job shop under different dispatching rules and order review policies by comparing the ANN with TWK and JIQ rules. The results of their investigation have shown that the ANN had better results on-time delivery’s and mean tardiness than TWK and JIQ rules.

With these studies in mind we can settle that ANNs can outperform conventional DD assignment rules and are worthy of further experimentation. The literature on the DD assignment rules shown that the dynamic rules outdo the rules based only on job information. For this reason, we propose to extended the research by using an ANN model for flow time prediction and comparing it to the dynamic DD assignment rules for flow time estimation (DPPW and DTWK).

2.4 Performance measures for DD assignment

According to Cheng and Jiang (1998) the missed DD of a job can be defined as the absolute deviation of the job completion date from its DD, regardless the job is actually late or early. The missed DD of a job can be expressed in terms of lateness (which includes both earliness and tardiness), equation (6),

$$\mathrm{L_i} = \mathrm{c_i} - d_i \tag{6}$$

where L_i, c_i, denote the lateness and the real completion time of the job i, respectively.

To evaluate the quality of the DD assignment rules, several performance measures have been employed in the literature. The most commonly used are related to the flow time and lateness (Cheng and Jiang, 1998; Alpay and Yüzügüllü, 2009). However, there is a greater emphasis in selecting among the performance measures, those related to the lateness and tardiness such as mean tardiness (MT) and percentage of tardy jobs (PT) (Vinod and Sridharan, 2011). This can be explained by the fact that a tardy conclusion of the jobs can lead to the loss of costumer trust and further costs or even penalizations. On the other hand, earliness although not so critical on the customer relationship, is also undesirable due to the fact that an early conclusion of the jobs will lead to increasing storage related costs. This means that the quality of the DD should be evaluated not only in terms of tardiness but also in terms of lateness.

The mean absolute lateness (MAL) has been defined by several authors (Cheng and Jiang, 1998; Sha and Liu, 2005; Alpay and Yüzügüllü, 2009; Vinod and Sridharan, 2011) as an appropriate linear measure of the missed DD. MAL is always equal to the sum of absolute values of lateness. A smaller MAL value suggests a better DD prediction aptitude and therefore a better accuracy. However, a DD prediction can be accurate but not precise. For this reason, Mean Squared Lateness (MSL) is also used in the evaluation of the DD assignment rules. The MSL measures the average squared difference between the actual completion dates and the estimated due dates for jobs. A smaller MSL value implies a smaller deviation from a designated due date occurrence.

For these reasons in our investigation we will measure the quality of the DD assignment rules in terms of accuracy and precision by employing the MAL and the MSL performance measures. Furthermore, we will also evaluate the MT and the PT to study the impact of the tardy jobs since in real world environments, tardiness is a critical issue to companies.

3. RESEARCH METHODOLOGY

To address the question on how ANN can be used as a DD assignment method and how well it can predict due dates when compared to the dynamic due date assignment methods, we built a dynamic job shop simulation model (described on Section 3.1) and an ANN model (described on Section 3.2).

The simulation model serves two purposes: to generate and provide the necessary data set for modelling the DD assignment rules and generate the necessary input data to train and test the ANN. In the simulation model, the jobs were prioritized based on two dispatching rules: FIFO and SPT. From literature, two dynamic DD assignment methods were chosen for flow time prediction but also to be compared with our ANN model: DTWK and DPPW.

The performance measures used to evaluate the flow time prediction of the two DD assignment rules and the ANN were: mean absolute lateness (MAL), mean squared lateness (MSL), percentage of tardy jobs (PT), mean tardiness (MT).

The dynamic job shop model was implemented using the simulation software *Simul8*, and the ANN model was built using the *Artificial Neural Network Toolbox* of *Matlab*.

The Figure 1 provides an overview of the research methodology and the relationships between each model.

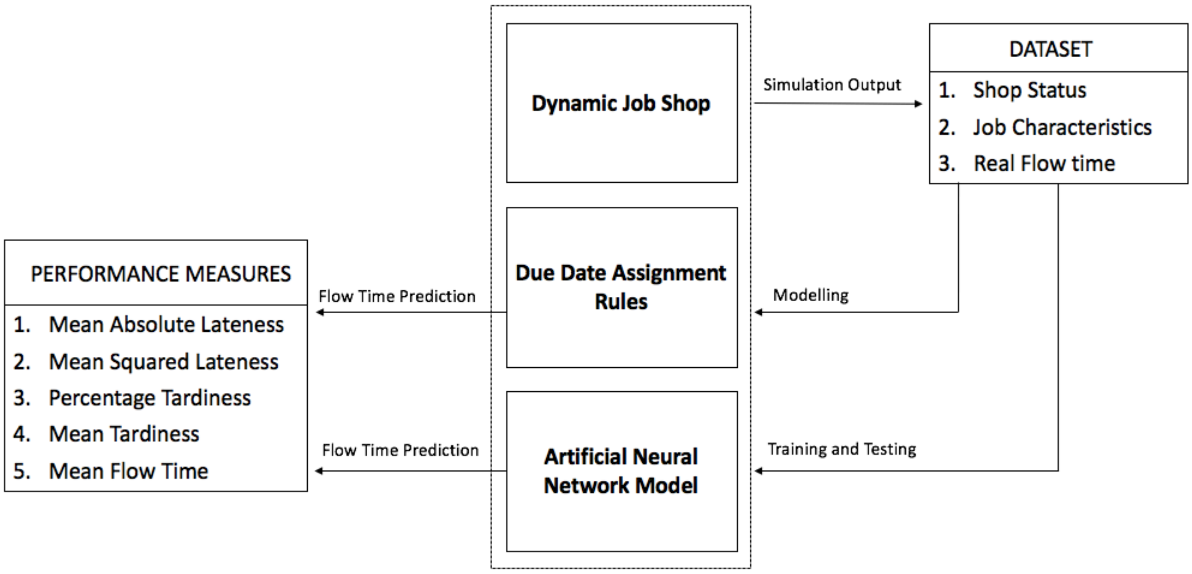

Figure 1 - Overview of the research methodology and the relationships between each model (Based on Hsu and Sha, 2004). **.**

3.1 Simulation Model

In this investigation we developed a simulation model for a dynamic job shop system, using the simulation software *Simul8*. In order to build the simulation model, several decisions regarding to the dynamic job shop configuration, job characteristics and dispatching rules had to be made. Moreover, in order to simplify the dynamic job shop model several assumptions were also made. These assumptions are presented below on Subsection 3.1.1. The job characteristics are described on Subsection 3.1.2 and a brief description of the dispatching rules applied is given on Subsection 3.1.3. The Subsection 3.1.4 provides a description of the simulation model and its implementation on *Simul8* software.

3.1.1 Dynamic Job Shop Model

Our dynamic job shop system consists in six non-identical machines under constant utilization, performing six different operations. The system was built under the following assumptions based on the research of Vinod & Sridharan (2011).

- All the machines have the same probability of being visited;
- Each machine can perform only one operation at a time on any job;
- Pre-emption is not allowed (once an operation as begun, it cannot be interrupted);
- There are no machine breakdowns: each machine is continuously available for production;
- All materials are continuously available for the operations;
- Setup times and transportations are not considered;
- There is no restriction on queue length at any machine and all the jobs are accepted for production.

3.1.2 Job Characteristics

Jobs arrive to the system following an exponential distribution with a mean of 0.648 time units which leads to a 90% utilization level. This utilization level corresponds to a heavy shop utilization.

Each job consists in a set of operations to be performed on the machines in the shop. The routings of the jobs are made by random assignment and a machine will be included only once in the routing. Therefore, a job cannot visit the same machine more than once. Each machine has the same probability to be the first in the routing sequence. The number of operations of each job is uniformly distributed in the range 1-6, which mean that a job can have a number of operations that can be between 1 and 6. Operation processing times follows an exponential distribution with a mean of 1time unit. The Table 2 summarise the job characteristics.

Table 2 – Summary of job characteristics

Number of operations	Uniform Distribution [1,6]
Routing	Made by random assignment
Processing Time	Exponential Distribution, μ=1
Inter-arrival Time	Exponential Distribution, μ=0,684

3.1.3 Dispatching Rules

When a machine becomes free, if there is more than one job on the queue to that machine, it is necessary to decide which waiting job will be processed first. This decision is normally taken on the basis of certain dispatching rules, already in the shop floor. As been previously said on Section 2.2, the dispatching rules gives to each of one of the waiting jobs some priority value. The selected job will be the one with the higher priority value which can be the smallest value or the higher one depending on the dispatching rule applied. In this investigation, two different dispatching rules were used: FIFO and SPT. The characteristics of the selected dispatching rules are as follow:

- First Come First Out (FIFO): the jobs are processed in the order they arrive at the queue. FIFO is a random priority rule.
- Shortest Processing Time (SPT): the priority value is given based on the operation processing time. The job with the highest value, and therefore the selected one, it will be the job with the lowest operation processing time for that machine.

These dispatching rules were chosen based on the following motives:

- The FIFO rule is usually used as a standard to compare the effects of other dispatching rules;

- Tardiness is often point out as the major concern in production companies and SPT rule significantly reduces the flow time of the jobs through the shop and the mean tardiness;

3.1.4 Description of the Simulation Model

The first stage in development of the simulation model, was the definition of the simulation time and the warm up time which is the time that the simulation will run before start collecting results. The warm-up time is used to let the system reach to the desired conditions. The simulation runs for 2000 time units and the warm up time is 200 time units.

The dynamic job shop model can be divided into three routines that are executed each time that a job arrives to the system:

1. Initial Routine: collect the required information;
2. Cycle Routine: repeated until the job is completed;
3. Final routine: record the real completion date.

These routines are programed on *Visual Logic* which is the *Simul8* programming language. *Visual logic* allows to incorporate detailed logic into the simulation in order to describe exactly how it will behave. The Figure 2 describes the flow of the routines and the relationship among them. When the simulation reach to the end, all the results are stored in an excel sheet to be loaded into the *Matlab*.

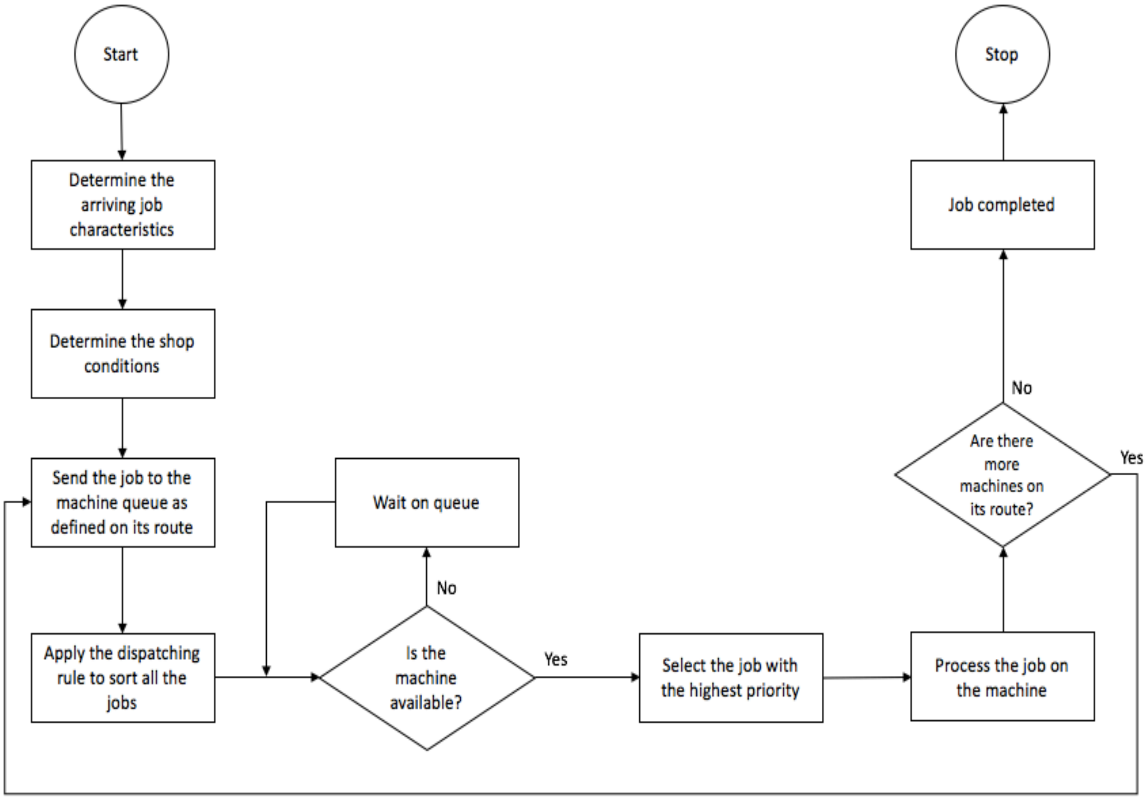

Figure 2 - Dynamic job shop simulation flowchart

3.1.4.1 Initial Routine

When a job arrives to the shop and before being released to the shop, the system identifies its characteristics, record its arrival time and verify the shop status.

The job characteristics collected at the moment that the job arrive to the shop are the routing sequence, the processing times on each machine of its route, the total processing time and number of operations. The shop status is given by the total number of jobs in the system, total number of the jobs in the queues and number of jobs in the queue of each machine on its route.

3.1.4.2 Cycle Routine

This routine is performed each time that a job is released to the shop to be processed according to its route. When the job is released to the shop, the system puts it into the related queue for its first operation. Before joining the queue, the system verifies if is there any jobs already on the queue waiting to be processed on the machine. If there is already jobs on that queue, the system sorts all the jobs by assigning to each one of them a priority value that depends of the dispatching rule applied. The job is added to the corresponding sorted position and waits in the queue till the corresponding machine becomes available. When the machine becomes available, the job on the first position (and therefore with the highest priority value), enters on the machine for processing. After the work is completed the job leaves the machine and the system verifies if there are any more machines on its route. If there are more machines on its route, the job proceeds to the queue of the next machine and all the process is repeated.

3.1.4.3 Final Routine

The job leaves the shop if there are no more machines on is route. Before leaving the shop its actual completion time is recorded.

3.2 Artificial Neural Network Model

As previously stated in section 2.3, an artificial neural network is a computational system inspired on biological functions of human brain. These networks allow us to estimate complex functions that are dependent on a large number of inputs. Biologically a neuron is a cell that takes several inputs and its activated by some outside process, depending on the stimulation the neuron starts its own process and passes the information to other neurons. Depending on the "amount" of activation some input or output paths may have stronger impact or higher weight than other connections. Taking into account these assumptions a human brain is a simple network of neurons and we can emulate it by modelling several neurons and connecting them via a weighted graph. The neuron receives a set of weighted inputs, processes their sum by its activation function ϕ and passes the result to the following neurons (Figure 3). We form a network by chaining these neurons together in layers.

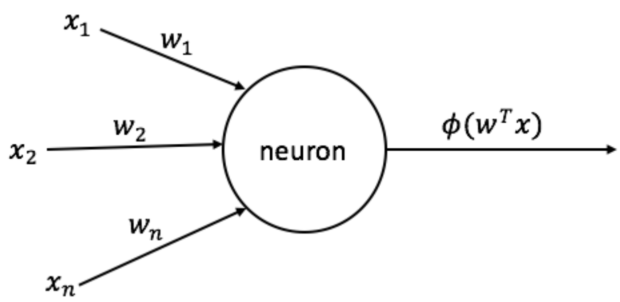

Figure 3- Structure of an simple neuron.

In our study we use a multilayer feed forward network architecture where the information flows from one layer to another until the last layer. Usually we have three different types of layers on any ANN architecture:

- **Input layer**- The first layer of every architecture and it receives the input data, it has as many neurons as the number of features that we use to train our model.
- **Hidden layer**- It can be one or more of these type of layer on the network. For most of problems one hidden layer is sufficient since adding more layers adds more complexity to the network but with no significant gains on performance. The number of neurons are usually set by empirical experimentation although there is a general rule of thumb by considering the mean between the number of input and output neurons. Most the hard computation is performed on this kind of layer. In our ANN architecture we use one hidden layer with 15 neurons.

- **Output layer-** the last layer of every ANN and it makes sense of the output from the previous hidden layer by returning a class label (i.e male or female) or a value (i.e house price estimation). The number of neurons in this layer is then dependant of the model configuration for example for the first case a classification model we would have one neuron: the class prediction or two neurons one probability for each class male or female; in the second example a regression model it will only be a single neuron: the predicted price. In our case the output layer has one neuron only which will return the flow time prediction.

The network receives an input vector x on the input layer which is passed to the following hidden layer where activations values, h are computed then it flows to the output layer to give us the prediction, y. The network has the ability to map a function f from x to h and a function g that maps from h to y. Then the hidden layer activation is given by $f(x)$ and the output of the network is $g(f(x))$, this allows us to compute things that either f or g would not be able to do individually. A general architecture of regression ANN model is presented on Figure 4.

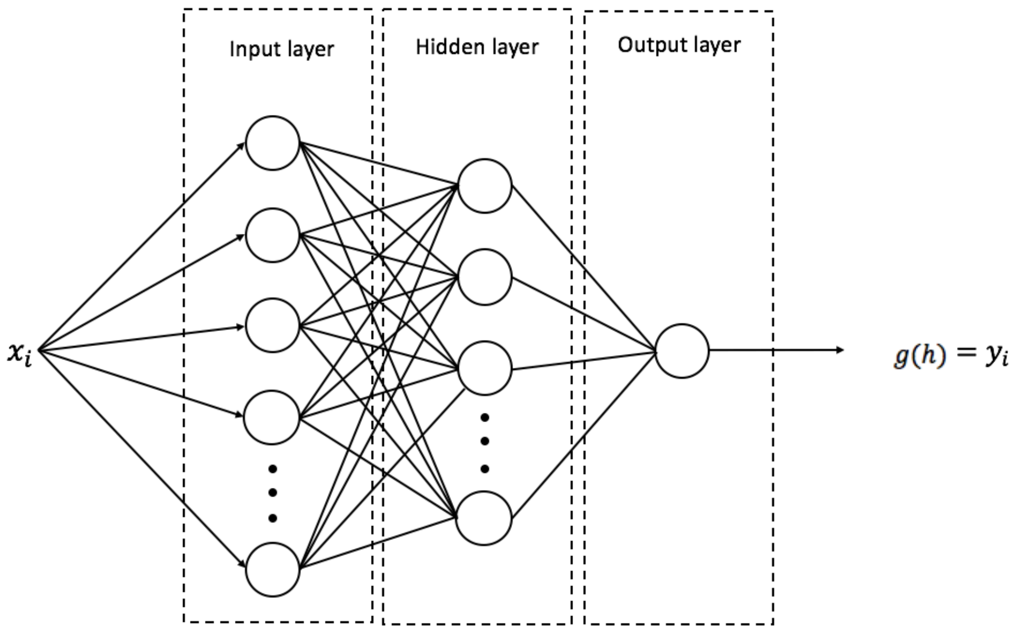

Figure 4 - A general architecture for a ANN regression model.

3.2.1 Training and Testing

Our goal is to train a model on labelled data (supervised learning). For this purpose, we feed the network with a set of inputs in order to produce a set of predictions for our data. This is accomplished by having both input x and the associated target output y obtained from our simulation model. In this case the input x will be the job characteristics and shop condition at the time that each job i arrive to the shop. The output will be the flow time prediction for each job i. Training the model will involve learning the correct edge weights to produce the desired target output.

In Section 2 we described the importance of factors like the number of jobs in the queues of each machine, the total processing time and the number of operations of a job as the most relevant factors for flow time predication. For this reason, it seems natural to use them as features to train our model. Additionally, we have also considered other information like the processing time in each machine, the processing sequence and the total number of jobs in the queues (Table 3). Similar datasets have been used in previous studies such as Philipoom *et al*., (1994) and Hsu and Sha (2004).

Table 3 - Structure of the input data set.

Main class	Sub class	Number of features
Job information	Number of operations	1
	Total of processing time	1
	Processing time in each machine	6
	Processing sequence on the machines	6
Shop status	Number of Jobs in each queue	6
	Total number of jobs in the queues	1
	Total number jobs in the system	1
Total number of features		**22**

The Matlab Neural Network Toolbox has already an implementation of a regression/fitting network which uses linear regression as activation function and the Levenberg-Marquardt back propagation algorithm as learning algorithm. The objective of this training algorithm is to minimize the error (the difference between the actual and expected results) by estimating the weight on forward process and update those weights on the backwards process.

3.3 Performance mesures

The performance measures allow us to compare the performance of the two dynamic due date assignment rules (DTWK and DPPW) and the performance of the ANN in the flow time estimation. The performance measures used to evaluate the quality of the flow time estimations were: mean absolute lateness (MAL), mean squared Lateness, mean tardiness (MT), mean absolute lateness (MAL) and percentage of tardy jobs (PT). The performance measures are described above as follow:

1. **Mean Absolute Lateness** (MAL): measures the mean absolute difference between the real completion date and the due date of jobs.

$$MAL = \frac{1}{n}\left[\sum_{i=1}^{n} |L_i|\right] \tag{7}$$

2. **Mean Squared Lateness** (MSL): measures the average squared difference between the actual completion dates and the promised due dates for orders.

$$MSL = \frac{1}{n}\left[\sum_{i=1}^{n} {L_i}^2\right] \tag{8}$$

3. **Mean Tardiness** (MT)**:** measures the average tardiness of jobs When a job is finished after the assigned due date, a delay occurs. The positive difference between his completion time and the due date is the tardiness (T_i)

$$T_i = Max\ \{0, c_i - d_i\} \tag{9}$$

$$MT = \frac{1}{n}\left[\sum_{i=1}^{n} T_i\right] \tag{10}$$

where n is the number of completed jobs.

4. **Percentage of tardy jobs** (PT): measures the percentage of jobs that are complete after the assigned due date.

$$PT = \frac{n_T}{n}\ x\ 100 \qquad (11)$$

where n_T is the number of tardy jobs .

4. EXPERIMENTS AND RESULTS

The sample used to train the ANNs comprised the information of 2000 different periods of time generated by the simulator. The tests were performed with a different sample with data regarding 200 jobs generated by a different run. In order to compare results between the ANN and the DD assignment methods, the test sample was also used for flow time estimation by using both of the DD assignment rules.

The results regarding to the performance measures of the dynamic DD assignment rules and to the ANN are comprised on Table 4. Moreover, the

Figure 5 and Figure 6 provides information about the distribution of the lateness values (in time units) around the DD, which its useful to explain the results of the performance measures.

Since the present study involves a hypothetical dynamic job shop system, the results were compared to similar studies in dynamic job shops in order to ensure the correct implementation of these methods. The comparison is presented on the Appendix A.

Table 4 - Performance measures for all methods.

	FIFO			**SPT**		
	DTWK	**DPPW**	**ANN**	**DTWK**	**DPPW**	**ANN**
MAL	15,5	9,5	7,0	13,4	15,6	10,8
MSL	6359,4	164,6	94,3	1713,2	2108,3	860,6
PT	58,0%	52,5%	50,5%	22,0%	16,5%	39,0%
MT	7,6	5,1	3,9	6,4	7,4	3,4

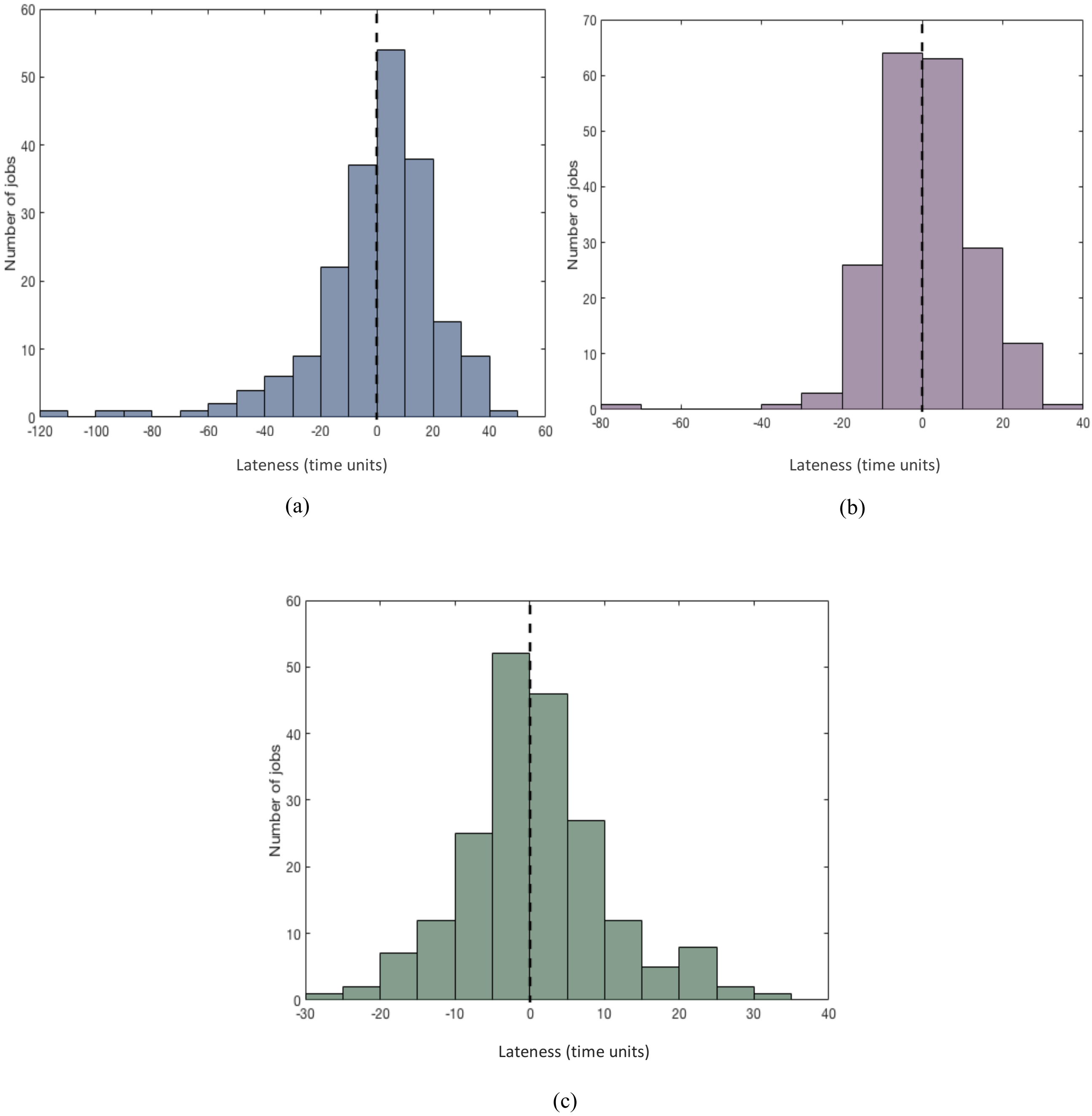

Figure 5 - Histogram of the lateness values from (a) DTWK, (b) DPPW and (c) ANN, for FIFO rule.

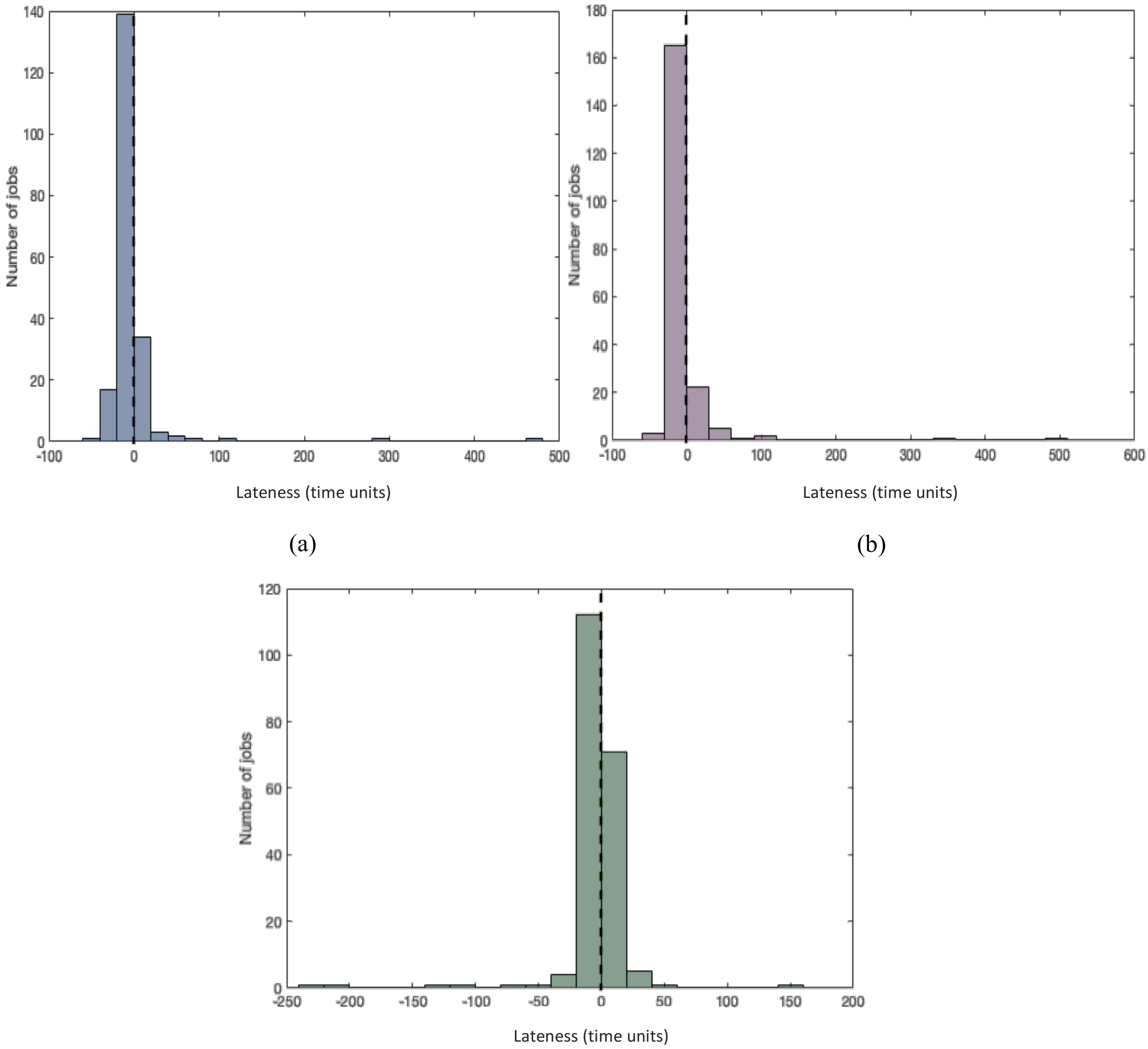

Figure 6 - Histogram of lateness values from (a) DTWK, (b) DPPW and (c) ANN for the SPT rule.

From Table 4, it is possible to observe that the results regarding to the DD assignment rules only, shows that when the FIFO rule is applied, the DPPW achieves better results for all the performance measures. However, when the SPT rule is applied, the DPPW rule stills achieves the best results for tardiness related measures, but is outperformed by the

DTWK rule for both MAL and MSL. From our understanding, this can be explained from two perspectives:

1. As the SPT rule minimizes the flow time of the jobs in the system by giving priority to the jobs with the lowest processing times, it will consequently reduce the number of the jobs in the system. The allowance factor of the DTWK rule considers the number of the jobs in the system to estimate the current average flow time for each arriving job**,** which makes it sensible to the reduction of the number of jobs in the shop accomplished by the SPT rule. The less jobs are in the shop, the lower the flow allowance it will be and therefore, tighter the estimated DD it will be. This explains the reduction of the MAL and MSL values of DTWK rule from FIFO to SPT and the fact that the DTWK achieves better results that DPPW for these measures.

2. SPT rule tend to delay the conclusion of the jobs with the highest processing times. Thus, this jobs will have higher flow times than the rest of the jobs. For the jobs with the highest processing times, the DD estimation will be more inefficient and will produce higher lateness values. This is possible to observe through Figure 6(a) and (b) were the larger values of lateness correspond to the jobs with the highest processing times. Moreover, it is possible to observe that for these jobs, the lateness values are higher for the DPPW rule. The MAL of the DPPW is sensible to the increasing values of lateness for this jobs, which explains the increased values of MAL and MSL from FIFO case to SPT case.

Regarding to the ANN, from Table 4 we can observe that for the FIFO case the ANN outperforms both of the DD assignment methods by providing better values in terms of MAL, MSL, PT and MT. This can be explained by the lateness values provided by each method. In fact as we can see in Figure 5, the lateness values provided by the ANN (Figure 5 (c)) are lower than the lateness values from the DTWK (Figure 5 (a)) and DPPW rule (Figure 5 (b)) which revels an better DD capability.

For the SPT case the results are quite interesting for the ANN since it achieves better results than the DD assignment methods for all the performance measures except for PT jobs. This fact could mean that the ANN has a poor performance in terms of tardiness. However, this is discussable: by comparing the lateness values regarding to DTWK rule, DPPW rule and to the ANN, presented on Figure 6(a), Figure 6(b) and Figure 6(c) respectively, we can observe that lateness values are lower for the ANN, which naturally implies lower values of tardiness. Therefore, as we can observe from Table 4, although the number of completed jobs after the DD is higher for the ANN, the MT of these jobs is lower than the DD assignment rules. Moreover, as we can see from Figure 6, there is an higher number of jobs completed before the DD for both DTWK (Figure 6(a)) and DPPW(Figure 6 (b)) when comparing to the number of jobs completed before the DD for the ANN (Figure 6 (c)). This means that higher percentages of early jobs is being obtained from both DD assignment methods, which as being previously referred is undesirable. For these motives, in spite of the value of PT, we can also consider that ANN has a better DD capability than the dynamic DD assignment rules for the SPT rule. Another remarkable outcome from the ANN is that was able to reduce the lateness values for the jobs with the highest processing times, Figure 6 (c). This means that for these jobs, the flow time prediction from the ANN was more accurate than the dynamic DD assignment rules.

5. CONCLUSIONS

In this study we investigate the use of ANN for flow time prediction in a hypothetical dynamic job shop model. In order to compare the performance of the ANN for flow time estimation, we select from literature two dynamic DD assignment rules, and to investigate the performance of the ANN under different dispatching rules, two dispatching rules has been selected: FIFO and SPT.

Through our study it was possible to conclude that the same DD assignment rule do not perform well under all the circumstances. This also been appointed as one particular issue of the DD assignment rules. However, it seems that in general, the ANN was able to overcome this problem, since it performs equally better under the use of both of dispatching rules.

Moreover, for SPT case, the ANN was able to predict more accurately the flow time for the jobs with the highest processing times. For these type of jobs, the DD assignment rules shown a poor performance. One particular issue related to the ANN could be the higher value of PT for the SPT case. However, the lateness values provided by the ANN are lower than the lateness values provided by the DD assignment rules and for this reason the MT is lower for the ANN, which is a good characteristic. This study also highlights that earliness, although not so critical for companies should be taken in consideration to evaluate the quality of DD assignment rules.

As future work, research efforts could be dedicated to (1) evaluate the quality of the ANN under lighter shop conditions, (2) evaluate the performance of the ANN under the use of several others dispatching rules, (3) study if performance of the ANN could be improved if a larger dataset its provided and (4) test the use of the ANN for flow time prediction in more complex dynamic job shops.

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APPENDIX A - COMPARISSON OF THE RESULTS WITH THE RESULTS FROM PREVIOUS WORKS ON DYNAMIC JOB SHOPS

Reference	DD assignment rules	ANN	Dispatching rules	Performance Measures	Results					
					FIFO			SPT		
					DTWK	DPPW	ANN	DTWK	DPPW	ANN
(Cheng and Jiang, 1998)	DPPW DTWK	NO	FIFO SPT	MAL MSL	MAL:20,58 MSL: 881,0	MAL:13,5 MSL:355,9	-	MAL:12,7 MSL:1181,1	MAL:14,7 MSL:1376,5	-
(Vinod and Sridharan, 2011)	DPPW DTWK	NO	FIFO SPT	MAL PT MT	MAL: ≅490,0 PT: ≅68,0%. MT: ≅320 ,0	MAL: ≅310,0 PT: ≅63,0% MT: ≅210,0	-	MAL: ≅300,0 PT: ≅ 39,0% MT: ≅320 ,0	MAL: ≅400,0 PT: ≅30,0% MT: ≅210,0	-
(Alpay and Yüzügüllü, 2006)	DPPW DTWK	NO	FIFO SPT	MAL MSL	MAL: 20,68 MSL: 881,9	MAL: 14,77 MSL: 413,9	-	MAL: 13,03 MSL: 1191,6	MAL: 18,09 MSL: 1442,0	-
(Hsu and Sha, 2004)	-	YES	FIFO	MT	-	-	MT:2,76	-	-	-
Ours	DPPW DTWK	YES	FIFO SPT	MAL MSL PT MT	MAL: 15,47 MSL:6359,4 PT: 58,0% MT: 7,56	MAL: 9,47 MSL: 164,6 PT: 52,5% MT: 3,91	MAL:7,00 MSL:94,32 PT:50,5% MT: 5,10	MAL: 13,40 MSL: 1713,2 PT: 22,0% MT: 6,37	MAL: 15,56 MSL: 2108,3 PT: 16,5% MT: 7,41	MAL:10,84 MSL:860,55 PT: 39,9% MT: 3,35