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# A Neural Network Approach to Predict Duration in Conformity for Predictive Manufacturing

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**Abstract.** Currently, expert knowledge is sometimes the only way to predict the duration of the manufacturing process in relation to conformity. While expert knowledge is difficult to come by and often limited to experience. This paper aims to predict the duration of the manufacturing process by utilizing machine learning and big data. This paper utilizes a real industrial case with the use of neural network regression model that aims to expand the body of knowledge available in the area of predictive manufacturing research. The result of the model suggests the neural network regression model can result in a feasible outcome, while in the meantime overfitting did occur. Mean-squared error ,relative squared error, relative absolute error and the correlation coefficient was computed.  The paper also addresses the limitations and limited scope of findings and makes suggesting moving forwards.

**Keywords.** Machine Learning, Neural Network, Predictive Scheduling, Predictive Manufacturing

## 1. Introduction

Scheduling is important once there are resources like machines and material in manufacturing which require to be shared to perform totally different tasks. Producing scheduling is to initially assign machines and resources to jobs and conjointly determine the duration on the corresponding machines [1].

For our purposes, it is important to note that these scheduling steps may be performed in different factories or warehouses, thus a point of pride for the management of a specific manufacturing facility. Also note that, as explained above, as these working days can be extended by a single scheduling action. The production schedule can be adjusted according to the needs of such a manufacturing job. In some cases, factories may require additional schedules just for the schedule they hold, to compensate for shifts which occurred in the previous week.

For a clear prospect first scheduling problems need defining. Components are needed, and they are namely, job, characteristics, machine environment and optimality criteria [2]. This is the most important component which determines the work quality of a schedule plan. Firstly, the production quality and the second is the flow quality. In

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practice, most schedule planners use one or the other of the previously mentioned three components. While it is possible for them to find the optimum solution, the only way to achieve the best performance is to have an automated process. The best schedule planner knows the difference between the production quality and the optimization quality. In the production process, the schedule planner can show that only a certain amount of job is completed in order to know a work level [3].

In order to achieve optimization criteria, schedules are generated statically or dynamically. However, a schedule is based on the current state of the system and may not be robust, meaning it cannot guarantee what will happen in the future. Manufacturing system environments are dynamic. Machine failures, postponements of the due date and the arrival of urgent orders can occur [4]. These unforeseeable and unavoidable events can render a previously feasible plan unviable [5]. Therefore, estimating the availability of orders in manufacturing can be helpful. First, when a job is unlikely to be completed on time, the schedule plan can give you more flexibility to avoid not being able to complete the entire plan. Secondly, if factors affecting deliverability can be identified in advance, issues can be resolved in advance to avoid delays.

Currently, the estimated ability to deliver is mainly based on expert knowledge. This is usually sufficient for small businesses because of their simple production environment. However, for large-scale production with diverse products, the manufacturing system is complex, dynamic, and even chaotic [6]. In this case, human experts do not seem promising [7]. Many scholars believe that there are no real human experts when it comes to programming problems [8]. Scholars in the field of operational research believes that most real production environments are too complex for humans to analyze [9]. Human cognitive capacity is unable to extract knowledge fast enough to adapt to dynamic manufacturing environments. In addition, it can sometimes be difficult to obtain expert knowledge, which can lead to delays in decision-making [10].

Machine learning is a relatively new concept, and the field consists of artificial intelligence, statistics, probability theory, and optimization techniques to enhance computation to identify patterns and make prediction accordingly by utilizing past training data to predict desired feature output [11]. Machine learning models when it is supervised learning are either a regression or a classification model. The deployment of machine learning operates by finding hidden patterns which is difficult otherwise when compared to human expert or the use of expert knowledge or fuzzy systems[12], [13].

Machine learning specifically deep learning is a model which has selection of application with good quality performance indicators and performance outputs[14], [15]. This research article uses a neural network regression model to predict duration in an industrial case study. The previous work carried, utilized MLP to predict deliverability in manufacturing [1]. In a neural network model which has representing a weight is the combination between the lines connecting to the nodes and input values it receives to calculate its own output value [16]. This study was undertaken to examine if a machine learning algorithm can be utilized to solve scheduling in the manufacturing area. The purpose can be thought of as enhancing the body of knowledge in the manufacturing area.

## 2. Problem formulation

The data set utilized can be described as Big Data due size being over 13Mega bite full of 100,000 orders instances. The data was queried from large databased over 1Gb and no minimum amount of data needed for it to be categorized as Big Data from the literature available. The data also has n products to be delivered to factory floor and processed by m machine in said factory floor. Each machine is programmed to preform different preform different types of productions and each product may have multiple processing stages. The location on the staging area p has different configuration with its unique id code.

Furthermore, the need to predict duration is the output feature and can be extracted from the data set and subsequently, preform data normalization as can be previewed in the methodology section.

### *2.1 Industrial Case Study*

This project is supported by an Italian company, Gruppo Fabbricazione Meccanica (GFM) SrlGroup. They provided data for this research as raw data; they work with many small independent machine shops. For each order that GFM receives from customers, a decision must be made on how these orders are allocated to these workshops. A very important task of GFM is to decide how to distribute these tasks in order to achieve the best performance indicators such as shortest lead time, cost and quality. The dataset used in this study contains information on 100,000 orders, including requested delivery date, actual production start date, machine code, product code, work location, etc. This data includes all GFM orders from 2015 to 2017.

### *2.2 Benefits to industry*

- To prevent expensive machining equipment to fail in the manufacturing process which is costly and resulting in scheduling downtime. Machine learning enables for industry to preemptively asses' conditions before failure.
- Maximize efficiency of equipment fleet and factories by taking proactive measures strategically.
- Collect big data to enable fine-tuning the manufacturing processes and make modification accordingly.

## 3. Methodology

In this research paper it seeks to address the neural network regression model to be deployed into production and differs from the work carried on A multilayer perceptron (MLP) utilizing a classification problem in doing so there are technical milestones it must address [1]. The work was carried out using Microsoft Azure Machine learning in the cloud.

## 4. Experiment setup

Technical milestones for the setup of experiment can be duly summarized by 9 steps. Firstly, collect data from SQL data base then select columns in data set followed by normalize data by seeking missing and distorted data. The next step is the filter-based feature selection where the input and output features are selected. This is followed by splitting data into training and testing data where 0.7 is for training the model and the remaining 0.3 is testing the model. Selecting neuron network regression model is the following step to be used with the training data previously mentioned. Then use the training data model to compute the process, which will take a significant time. Then we have the last two milestones which are evaluating the model is it successful and measuring the neural network which was built.

## 5. Theory utilized

The neural network has nodes in layered format. Each node does connect to the previous nodes and in this model, it utilized 10 hidden layers as this is the optimum layers due to computational time. If there are many nodes it can result in data overfitting and the computational time will run into days. Each input can be thought of having a numerical value and is multiplied by w each time it is passed to the subsequent neural node. For input values it receives it is correspondingly processed by an activation function that limits the output feature.

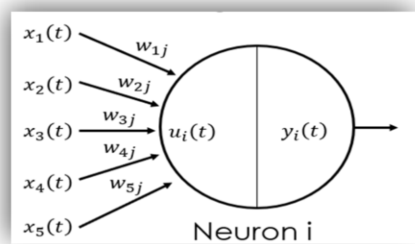


**Figure 1.** Artificial neuron

Stimulus $$u_i(t) = \sum_{j=1}^{N} w_{ij} \cdot x_j(t) \quad (1)$$

Response $$y_i(t) = f\big(u_{rest} + u_i(t)\big) \quad (2)$$

$u_{rest}$ = resting potential
$x_j(t)$, $y_i(t)$ = output of neuron $i, j$ at time $t$ (Action potential)
$w_{ij}$ = connection strength between neuron $i$ and neuron $j$ (neurotransmitters and receptors)
$u_i(t)$ = total stimulus at time $t$

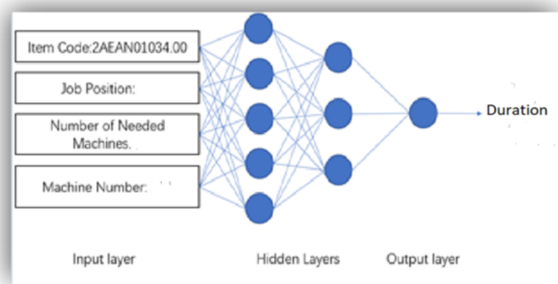


**Figure 2.** Illustrates the NN Regression model inner workings

### *5.1 Performance measures for Numeric Prediction*

The way in which results sand the model can be valued it must pass through the following equations. The predicted instance can be thought of as $p_1, p_2, \dots p_n$ correspondingly $a_1, a_2, \dots a_n$ are the actual values [2].

| | | |
|---|---|---|
| Mean-squared error | $\frac{(p_1 - a_1)^2 + \cdots + (p_n - a_n)^2}{n}$ | (3) |
| Root mean-squared error | $\sqrt{\frac{(p_1 - a_1)^2 + \cdots + (p_n - a_n)^2}{n}}$ <br> $\bar{a}$ is the mean over the training data | (4) |
| Relative squared error | $\frac{(p_1 - a_1)^2 + \cdots + (p_n - a_n)^2}{(a_1 - \bar{a})^2 + \cdots + (a_n - \bar{a})^2}$ | (5) |
| Root relative squared error | $\sqrt{\frac{(p_1 - a_1)^2 + \cdots + (p_n - a_n)^2}{(a_1 - \bar{a})^2 + \cdots + (a_n - \bar{a})^2}}$ | (6) |
| Relative absolute error | $\frac{\lvert p_1 - a_1\rvert + \cdots + \lvert p_n - a_n\rvert}{\lvert a_1 - \bar{a}\rvert + \cdots + \lvert a_n - \bar{a}\rvert}$ | (7) |
| Correlation coefficient | $\frac{S_{PA}}{\sqrt{S_P S_A}}$ <br> $S_{PA} = \frac{\sum(p_i - \bar{p})(a_i - \bar{a})}{n-1}$, <br> $S_p = \frac{\sum(p_i - \bar{p})^2}{n-1}$ <br> $\bar{a}$=mean value over the test data | (8) |

## 6. Results and Discussion

In the extensive area of operational research, the deployment of machine learning is relatively new area of research. In operational research the literature contains insufficient data as benchmark used as performance measurements in shopfloor. In the current contemporary era for medium and small size enterprises the availability large data pool is abundant for data mining, hence the use of machine learning comes into the equation.

The output performance measure for this paper is a neural network regression model that is split 0.3 of all the data is used for testing the performance of said model and the remaining 0.7 is utilized for training the model. It must be noted that the computational time must be taken into consideration as the running of data set can considerably increase the time for the results to show. The disadvantage of the computational time along with the lack of any previous data nor publication present, thus results are not comparable.

The true meaning of the results is that it is possible to use a neural network regression model to predict duration given the diverse input features used. There is no literature available on the duration comparable in the fields of expert and fuzzy systems. The function of this section is to interpret the results in Table 1.

Mean-squared error illustrates how close a regression line is to a set of points predefined. This is undertaken by taking the distances from the points to the regression line defined as the errors and by squaring it removes any negative signs.

Table 1: Illustrates Results for Numeric Performance

| *Numeric Prediction* | *Results* |
|---|---|
| *Mean-squared error* | 614.644188 |
| *Root mean-squared error* | 1567.977505 |
| *Relative squared error* | 1.001527 |
| *Root relative squared error* | 1.040630 |
| *Relative absolute error* | 1.08291 |
| *Correlation coefficient* | -0.001527 |

The value given is 614.644188 and is in isolation with no other machine learning algorithms to compare to. The limitation of this paper is that it only utilizes only one model. Root mean-squared error is the second performance metrics and is root of equation 1. Root mean-squared error RMSE is improved in terms of reflecting performance when dealing with large error values. The results from equation 2 is 1567.9. Root mean-squared error tends to highlight the outliers and it can be said that relative is sometimes preferable to absolute error.

Relative squared error RMSE is a standard formula to measure the error rate of a regression model, which was used. Nevertheless, it can only be compared between models whose errors are measured in the same units. The result from the model shows a value of 1.0406.

Root relative squared error is root of Relative squared error and measure of the differences between values and can be thought of as the standard deviation of the differences between predicted values and observed values which resulted in a value of 1.0829. Correlation coefficient measures the correlation between a's and p's and ranges from 1 to -1 which is negatively correlated. We have a value of -0.001527 which indicates no correlation.

Future research is needed where multiple machine learning models utilized whereby patterns, contradictions and exemptions are examined and explained. The next phase into this field of research is compare logistic regression model compared with the neural network regression model.

## 7. Conclusion

The conclusion to this paper is it addressed the niche in modelling and validating the results which is regression model not a classification model. Technical milestones were followed from raw data obtained by Gruppo Fabbricazione Meccanica (GFM) SrlGroup.

A neural network regression model was chosen to perform a regression computation, to predict the duration of the production scheduling. Results obtained show some level of data overfitting which can occur and in the next iteration adjustments are needed. There are no other models to compare to obtain overarching view. Future research into wider applications of machine learning models. New data are needed which in its nature is a classification data to solves two-class classification problem.

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