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# Artificial neural network application to a process time planning problem for palm oil production

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**Abstract**

The demand for palm oil is rapidly growing, but its production is faced with unreliable manufacturing indices, including processing time standards. In this study, an artificial neural network (ANN) model was developed as a solution for the prediction of standard time. The primary data were obtained through an industry survey and a direct time study measured at an oil mill using a stopwatch for each process and recorded on a standard time observation sheet. These direct time data collected over a 12-month period were standardized into numeric input data for ANN. A standard multilayered, feed-forward back-propagation type of neural network architecture was proposed. Direct time study data involving eleven different operations for a 22.5 tonne capacity Roche palm oil mill in Ohaji-Egbema were used in training, testing and validating the network. Time Processor software was developed in FORTRAN for investigating the quality of the trained network's output and standard time. Also, the labour and cost requirements of the mill were effectively optimized using linear programming (LP). Results from LP showed that optimal cost requirement of the mill was 6,330.16 USD per month. This amounts to a savings of 86.92%, compared with current requirement of 48,395.14 USD per month. The ANN model output was 423.666 mins compared with the current time of 540 mins for processing the same palm fruit. This shows that time standardization through ANN provides a savings of 21.54%. Thus, the developed ANN model has a reliable and good prediction capacity. It can be applied in a timely manner to medium and large scale oil mills or similar processes.

**Keywords:** Artificial neural network, Capacity planning, Labour requirements costing, Process control, Process standard time, Palm oil

## 1. Introduction

Palm oil is an important ingredient in the diet of many Sub-Saharan Africans, accounting for 38.5 million tonnes or 25% of the global edible oil and fat production [1]. Paradoxically, while the national and international demands for the product are never shrinking, local production capacity is declining. For example, the firm under study, the Roche Palm Oil Mill, is facing quality and productivity decline issues and to unravel the problem, production process time evaluation was explored.

The palm oil business process is highly time dependent and involves the following: harvesting of the fresh fruit bunches (FFB), reception and weighing of the FFB at the oil mill, sterilization, stripping the bunches to be free, digesting the fruit, pressing the mashed fruits to release oil, decanting and then pumping the oil to storage tank [2]. These post-harvest process stages are integral. They are time and labour intensive. As a result, economical processing requires a set of standard times for effective processing of palm fruits into oil. With standardized times, the process will be agile, capacity will boosted and respond to the ever increasing global market demand for the product in a shorter time and at reasonable costs. An agile production unit significantly reduces the time for planning, analysis and design [3].

Generally, the management of time in an industrial setting is important for productivity. The time required per unit of production is a key manufacturing index for reliable manufacturing operations. This index is necessary for scheduling, productivity analysis and cost calculations, [4] including capacity planning. Although there are a number of different techniques for work measurement, as reported by Muhlemann et al. [5], the prediction power of these techniques is marred by errors due to human actions. Kutschenreiter-Praszkiewicz [4] comprehensively reviewed these methods and concluded that they are ineffective. The current production time for palm oil processing is not exempted from the limitations of traditional work measurement techniques. This is because the processes of these mills are ill-planned, resulting in considerably

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lengthened through-put times. Consequences such as low productivity and non-sustainability of production capacity of oil mills are tied to poor standardization of processes and timing. Thus, there is need to develop new methods that provide standardized times in a faster and reliable way, particularly for palm oil processing. Considering the level of manual work involved in the mill activity, the choice of a new methods for standard time estimation should consider the evolution of decision making processes over time and artificial neural networks to meet these requirements.

Artificial neural networks (ANNs) are non-linear data driven self-adaptive approaches [self-learning, once supplied required data] as opposed to traditional model based methods [6]. ANN models may be used as an alternative method in engineering analysis prediction because they mimic the learning processes of a human brain [7]. ANNs typically are comprised of 3 layers, an input layer with input neurons, hidden layer(s) with hidden neurons and output layers with output neurons [8]. Each layer comprises one or more neurons. The neurons are interconnected using weighting factors [9]. The aforementioned characteristics of the ANN were considered in choosing it as an effective tool for an accurate determination of the time parameters for palm oil production.

ANNs have been applied by a number of researchers in various fields [10]. A synopsis of these applications is presented with a view to giving direction to the current study. An application in scheduling algorithms is presented by Akyol [11], modelling parameters by Ezugwu et al. [12], machine condition monitoring by Javadpour and Knapp [13] and manufacturing cost estimation by Jung [14]. Chituro et al. [15] proposed a new method for extracting global and simplified structures from a layered neural network. Its effectiveness was validated in three use cases, network decomposition, training assessments and data analysis. Ding et al. [16] established that a neural network based robust tracking control scheme for nonlinear systems involving matched uncertainties can be tackled using an adaptive critic technique. Also, Fadare [17] applied this technique in modelling the solar energy potential in Nigeria. Quite a few studies have been done in the area of production timing using ANN as a computational tool. Kutschenreiter-Praszkiewicz [4] applied a neural network for determination of standard times for machining and Eraslan [18] used an ANN in the estimation of production standard times in moulding. Due to their generalization capability, derived from its learning features, artificial neural networks can be successfully employed to solve problems involving predictive modeling and classification tasks [19]. In fact, artificial neural networks (ANN) can be used to process a wide variety of data from physical–chemical tests, macroscopic observations, specificities of fruit grinding processes, packaging material or even panel tasting to obtain highly accurate predictions as regards oil processing, adulteration and provenance [20]. More so, Astray et al. [21] used various computational models to develop a good authenticity tool to certificate wines. Their results show that the ANN model, with a sigmoidal function in the output neuron and Random forest model, permits determination of aging time with an average absolute percentage deviation below 1%. Also,

Martinez-Castillo et al. [22] developed a random forest model to determine the origin of honey produced and packaged within and outside Galicia, with an accuracy of 95.2% using Random forest, artificial neural network and support vector models. The aforementioned work presents various applications of ANN, but to the best of the authors' knowledge, no study has been done on processing palm fruits using ANNs. ANNs have advantages over traditional work measurement methods because they can serve in both operations planning and as control tools with higher levels of accuracy.

The overall aim of this work is to determine a faster and more reliable approach to obtain solutions to production problems involving time restrictions in the case of process times using ANNs. Even though, the original design was implemented with data taken from an operational palm oil processing plant, the Roche Palm Oil Mill, in Southeastern Nigeria, the methodology can be applied to allied food processing plants. The specific objectives of the current study include determining standard times and estimating labour input requirements for palm oil processing at the Roche Palm Oil Mill. The result, if implemented, can provide reliable information on which planning and scheduling of production activities, estimates of tenders, selling prices and delivery promises can be based.

## 2. Materials and methods

### *2.1 Direct time study computation*

The primary data for this research was collected from Roche Palm Oil Mill in Ohaji of Imo State in Nigeria through and industry survey and a personnel direct time study measured at the oil mill using a stopwatch and recorded on standard time observation sheets. The direct time study measurements were conducted on each of the aforementioned post-harvest process stages. In line with industrial work measurement rules, the process observation should be over a number of cycles and an average of completion times is taken as representative times for individual work elements or processes. Questionnaires were typically used to collect information on identified factors, such as manning level, personnel allowances (personal, fatigue and delay allowances) and performance ratings that affect cost estimates and labour requirements of the organization. The time, cost and labour data were collected for a period of 12 months from January to December 2015.

Direct time study models were used to compute the standard time as [23] expressed in Equations 1 and 2. A FORTRAN program, Timeprocessor.exe (given in Appendix B) was developed for testing these standard time models. In this regard, three factors from the mill were taken into consideration, the average or observed time ($T_t$) worker's rating ($W_R$), the personnel, as well as delay and fatigue ($A_{PFD}$) allowances.

$$T_N = T_t \times W_R \tag{1}$$

$$T_{STD} = T_N(1+A_{PFD}) \tag{2}$$

where, $T_N$ = normal time, $T_t$ = average cycle time, $W_R$ = worker rating, $T_{STD}$ = standard time

### *2.2 ANN model building*

The ANN prediction model for oil palm processing was developed and analyzed using the MATLAB 2010 toolbox. A total of 264 data sets were collected at the oil mill for the study from January to December 2015. The neural network toolbox has data pre-processing function that includes normalization. It normalizes the inputs (scaling of inputs between -1 and 1) and removes constant rows so that the variances between each of the input and output values

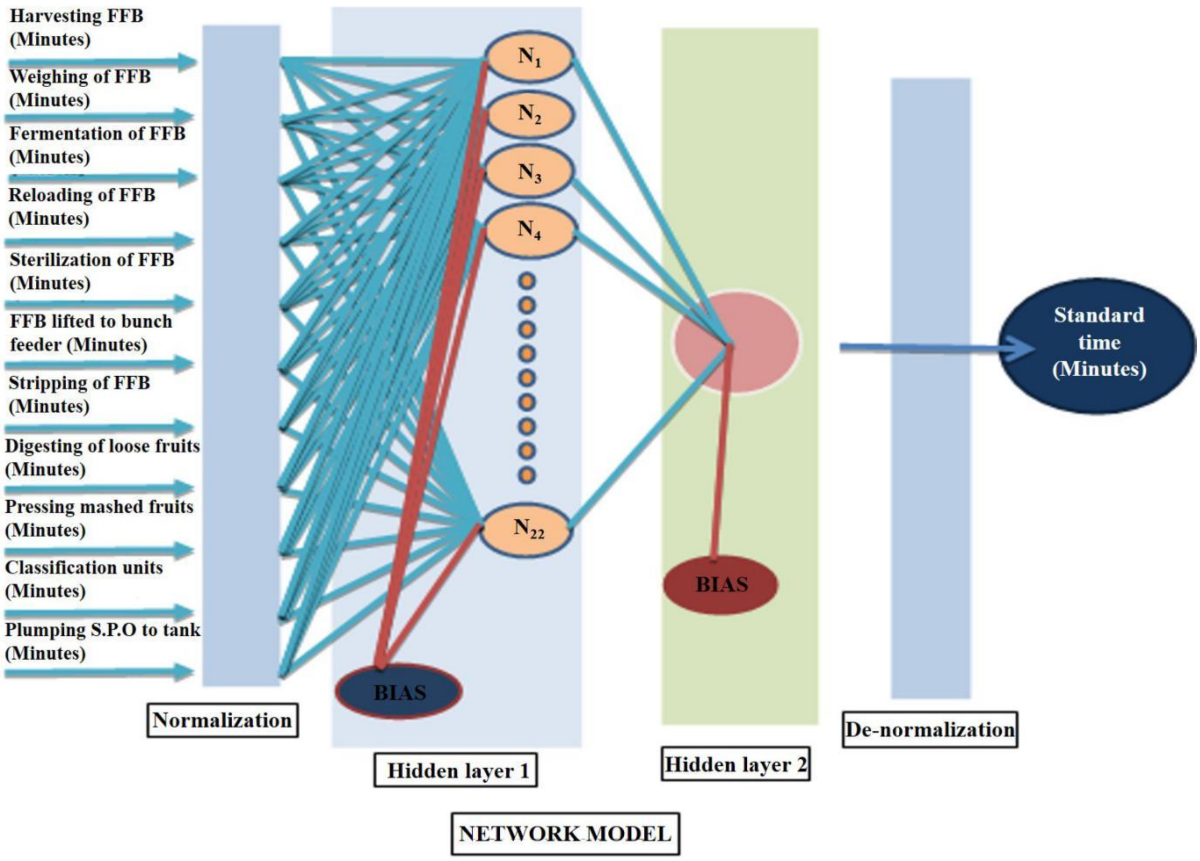


**Figure 1** Developed artificial neural network model used for determination of standard time (this work)

**Table 1** ANN model's design parameter and training criteria [2]

| **Design parameters** | | **Training criteria** | |
|---|---|---|---|
| Network Type | Feed-forward back propagation | Stop training when one of these is true about the training set | |
| Variable learning rate (Training function) | The Liebenberg-Marquardt with momentum and adaptive learning rate back propagation (TRAINLM) | Stop training when one of these is true about the test set | |
| Adaption learning function | Gradient descent with momentum weight and bias learning function (LEARNGDM) | Error (goal) | 0 |
| Performance function | Mean square error (MSE) | Epochs | 1000 |
| Number of layers | 2 | Time | Infinity |
| Number of neurons | 30 for the oil processing model | Max. fail | 1000 |
| Transfer (Normalization) function | Tangent-sigmoid transfer function (TANSIG) between -1 to 1 | Validation checks | 6 |

will be much smaller and easier for the model to identify. Thus, the factors' real numeric values were normalized according to the normalization method expressed in Equation 3 [24]:

$$Normalization = \frac{2(factor - minimum\ factor)}{maximun\ factor - minimum\ factor} - 1 \quad (3)$$

where, factor = the input data to be normalized, minimum factor = the minimum of input data and maximum factor = the maximum of input data.

In dividing the whole data range into training, validation and testing subsets, care was exercised to ensure that the data covered the entire spectrum of available information. There is no particular procedure for obtaining the optimum partitioning ratio as a combination with best training and testing results takes precedence [25]. A partitioning of 70:15:15 gave best model performance among other trials made.

The inputs are times recorded in each of the eleven processes, while the outputs represent standardized times. A standard time predicting model was developed using a Levenberg-Marquardt feed-forward back propagation network with tangent-sigmoid transfer function of the 11 inputs, a hidden layer, an output hidden layer and one output layer as shown in Figure 1.

The selection of the input and output (target) variables affects the ANN architecture immensely, depending on the nature of problem [26]. The training criteria include fixing the absolute error and the number of training cycles without improvements. It must be noted that, once the training criteria are met, model training is stopped. Table 1 shows the ANN model's design parameters and training criteria. However, if the training criteria are not met, a change in either of the activation functions, the number of neurons or data partitioning for enough training set was carried out. Figure 1 shows an interpretation of the neural network model designed in the current study and how it fits the overall process of matching the 11 inputs parameters to an output (standard time). The lines between each input after normalization and each of the 30 neurons (N) have different weights. There is also a bias layer (B) applied in the process. The neural network iteratively adjusts the weights and the bias until the inputs match the output of standard time. This is mathematically illustrated in equation (4):

[Standard time] = [Inputs] x [weights] + [bias] (4)

*2.3 Optimization of labour and cost requirements using linear programming*

To determine the labour and cost requirements at the mill, its process stages were optimized based on measured cycle times. The optimization was structured to reflect the constraints of the studied problem, as well as to balance its fidelity against expected values. The study employed MATLAB application software to solve the resulting linear programming (LP) problem developed with the computed standard times of each process, as well as current labour and cost requirements. The standard form of the LP problem is expressed in the compact form in Equations (5) and (6).

The objective function is of the form:

$$MinZ(x) = \sum_{j=1}^{n} c_j x_j + \sum_{i=1}^{m} 0 S_i \quad (5)$$

Subject to the linear constraints:

$$\sum_{j=1}^{n} a_{ij} x_j + S_i = b_i; i = 1, 2, 3, \dots, m \quad (6)$$

and $x_j, S_i \geq 0$, for all *i* and *j* (Non-negativity conditions)

where,
$a_{ij}$ = input coefficient for activity $x_j$
$X_j$ = activity (labour requirements)
$S_i$ = a non-negative constraint
$B_i$ = objective coefficient or total available resources

Since labour input was a major cost for daily processing of 22.5 tonnes of palm fruit, we considered three different categories of staff that currently work at this mill. They are senior, junior and casual staff. A simple linear programming model expressed in Equation 7 was applied:

[*x, fval, exitflag, output, lamda*] = *linprog* (f, A, b, [], [], lb) (7)

This input takes the values of *x*, *fval* and additionally uses a value *exitflag* that describes the exit condition. The structured output contains information about the optimization process and also returns a structured lambda whose fields contain Lagrange multipliers at the solution *x*.

*2.3.1 Formulation of the objective function and constraints*

In formulating the LP algorithm with objective function and constraint components, there are several assumptions for the palm production line. (a) The process is largely manual. (b) As a work principle, each work unit flows smoothly through the production line travelling minimum distances between stations. (c) In line pacing, the work units complete their assigned tasks on each product unit within a certain cycle time, which paces the line to maintain a specified production rate. (d) Mill capacity is 100% utilized and this is very optimistic. However, at each unit, a certain portion of the total work elements is performed on the work-in-process until oil emerges.

*2.3.2 Objective function*

In the data obtained from the Roche Palm Oil Mill, payment schedules for the three personnel categories, senior, junior and causal staff were 0.019 USD, 0.014 USD and 0.01 USD per minute, respectively. These parameters have been expressed as (cost/min) coefficients of the objective function in Equation 8. However, in the formulation, an instructive exercise would have been to divide these coefficients by 22.5 tonnes (per day). However, this idea was not implement because the firm currently operates as a public corporation. The public corporation perspective is evident by its currently high staff level which discourages competition. The 22.5 tonnes of capacity was not reflected on the coefficients to align the overall labour cost with the firm's outlook.

Minimized total daily manpower cost, is expressed in Equation 8.

$$MinZ(x) = \frac{\cos t}{\min} x_1 + \frac{\cos t}{\min} x_2 + \frac{\cos t}{\min} x_3 \quad (8)$$

where, $x_1$, $x_2$ and $x_3$ represent senior, junior and casual staff (decision variables), respectively. Thus, by substituting the unit cost per minute values into Equation 8, the objective function is as expressed as Equation 9.

$$MinZ(x) = 7x_1 + 5x_2 + 3x_3 \quad (9)$$

*2.3.3 Constraint formulation*

The number of staff at the Roche Palm Oil Mill in each process and the computed time of task completion were obtained. The main constraint is time, thus, each process was subject to the contribution of each staff member to the average time (total time) recorded. For each process, the available man-minutes must be at least equal to or greater than the required total time, expressed in Equation 10. Hence, ten constraints are expressed in time relations to represent their connection with decision variables.

$$\frac{total\ time}{number\ staff} x_1 + \frac{total\ time}{number\ staff} x_2 + \frac{total\ time}{number\ staff} x_3 \geq total\ time \quad (10)$$

Thus, Equations 11 to 20 were derived by substituting the values of each process in Equation 10 and the quotient becomes the constraint equation for the designated process.

$$29.301\ x_1 + 0\ x_2 + 2.930\ x_3 \geq 293.01 \quad (11)$$

$$5.357\ x_1 + 3.214\ x_2 + 8.035\ x_3 \geq 16.07 \quad (12)$$

$$7.024\ x_1 + 3.512\ x_2 + 1.171\ x_3 \geq 35.12 \quad (13)$$

$$9.101\ x_1 + 18.202\ x_2 + 45.505\ x_3 \geq 91.01 \quad (14)$$

**Table 2** Summary of processes, number of staff and average completion time

| S/N | Processes | Number of staff $x_1$ | $x_2$ | $x_3$ | Average completion time (minutes) |
|---|---|---|---|---|---|
| 1. | Harvesting FFB | 10 | - | 100 | 293.01 |
| 2. | Weighing of FFB | 3 | 5 | 2 | 16.07 |
| 3. | Fermentation | - | - | - | - |
| 4. | Reloading FFB | 5 | 10 | 30 | 35.12 |
| 5. | Sterilization | 10 | 5 | 2 | 91.01 |
| 6. | Bunch feeder | 5 | 5 | 1 | 12.62 |
| 7. | Stripping FFB | 3 | 5 | 1 | 12.61 |
| 8. | Digesting fruits | 14 | 4 | 14 | 13.00 |
| 9. | Pressing mashed fruits | 64 | - | 64 | 64.79 |
| 10. | Decanting Oil | 20 | 10 | - | 56.41 |
| 11. | Pumping to storage tank | 6 | 9 | 3 | 65.53 |
| | **Total number of staff** | **140** | **53** | **217** | |

Source: Survey 2015 at Roche Palm Oil Mill

$$2.524\ x_1 + 2.524\ x_2 + 12.62\ x_3 \geq 12.62 \quad (15)$$

$$4.203\ x_1 + 2.522\ x_2 + 12.61\ x_3 \geq 12.61 \quad (16)$$

$$0.929\ x_1 + 3.250\ x_2 + 0.923\ x_3 \geq 13.00 \quad (17)$$

$$1.012\ x_1 + 0\ x_2 + 1.012\ x_3 \geq 64.79 \quad (18)$$

$$2.821\ x_1 + 5.641\ x_2 + 0\ x_3 \geq 54 \quad (19)$$

$$10.922\ x_1 + 7.281\ x_2 + 21.843\ x_3 \geq 65.53 \quad (20)$$

where, $x_1$, $x_2$, $x_3 \geq 0$.

Process 3, fermentation, was abstracted out without loss of fidelity in the constraints for computability. It must be noted that fermentation is a natural process and no staff performed any work on it. Sometimes, the fruits are fermented while still attached to the palm tree. Therefore, using MATLAB linprog solver, the $X_n$ coefficients of Equations 9, 11 to 20 are cued into the Equation 7 for the optimization.

### *2.4 Model validation*

The performance of the model was validated using the following statistical measures, the coefficient of determination ($R^2$), root mean square error (*RMSE*) and maximum average error percentage (*MAEP*) [24, 27]. These are expressed in Equations 21, 22 and 23, respectively.

$$R^2 = 1 - \left[ \frac{\sum_{i=1}^{i=N} (E_a - E_p)^2}{\sum_{i=1}^{i=N} (E_a - E_m)^2} \right] \quad (21)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{i=N} (E_a - E_p)^2}{N}} \quad (22)$$

$$MAEP = \frac{1}{N} \sum_{i=1}^{i=N} \left( \frac{|E_a - E_p|}{E_a} \times 100 \right) \quad (23)$$

where,
$E_a$ = actual/field result; computed by direct time study
$E_p$ = predicted result
$E_m$ = mean value and N = number of data points

If the value of $R^2$ is close to 1 and that of $RMSE$ is close to zero, the model is considered to have good prediction capability. When the value of *MAEP* is sufficiently small, there is minimal error. These conditions imply that the model is satisfactory and will be acceptable for standard time determination.

## 3. Results and discussion

A representative of the process data recorded at the oil mill is shown in Appendix A. The normal time estimates of completion of each process are shown in Table 2. The optimized results of the linear programming minimization are displayed by the Editor Solver in MATLAB as the number of senior staff ($x_1$), junior staff ($x_2$) and casual staff ($x_3$) as 4, 8 and 60 persons, respectively. These are the decision variables and when substituted into Equation 9 yielded the optimal solution of the problem or value of objective function required to minimize labour requirements at this mill and process 22.5 tonnes of fresh palm fruit into oil products each day. This is displayed as *fval.* The minimum labour cost was 0.69 USD per minute, from the program iteration results.

In the program, the optimization was terminated after 11 iterations with an *exitflag* of 1, meaning that the result converged to a solution x, with a sufficiently small first-order optimality measure, $5.8934e^{-09}$, which was less than the optimality tolerance function, $1.00e^{-06}$ (default) and a constraint violation of zero. The parameters of the linear programming solution were within range, indicating a good optimization [28]. Multiplying the optimal solution (0.69 USD per minute) by 7 hours per day, 22 working days per month and 60 minutes/hour, an overall labour cost of 6,330.17 USD per month was achieved. Compared with the initial labour cost, which is 48,395.14 USD per month, it is implied that the firm will save up to 42,064.97 USD per month, which is an approximately 86.92% savings in the monthly labour costs.

From Figure 2, the performance plot shows no over fitting. The validation and test curves are very similar and are close to the best fit curve. The best validation performance is 0.0126 at epoch 13 of 19 epochs. This agrees with literature [29], where the *MSE* value was found to be 0.0024. It is notable that as the *MSE* value tends to zero, the more satisfactory the prediction performance [28].

The correlation coefficient (*R*-values) between the computed linear programming (TimeProcessor.exe software) and ANN predicted standard time values for palm oil processing are shown in Figure 3 and Table 3. They are very high, above 0.98. The *R*-values for the training,

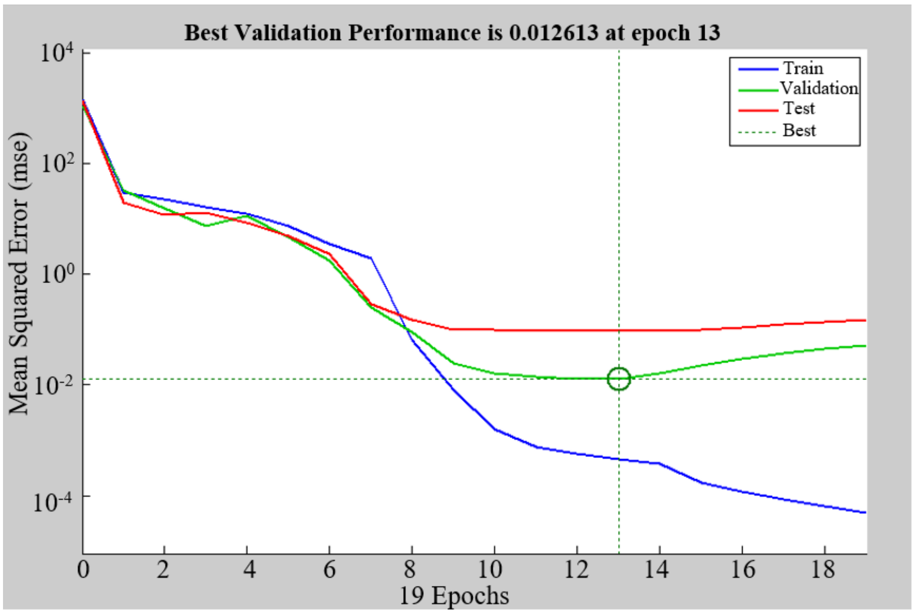


**Figure 2** Performance plot of the ANN model at 19 Epochs

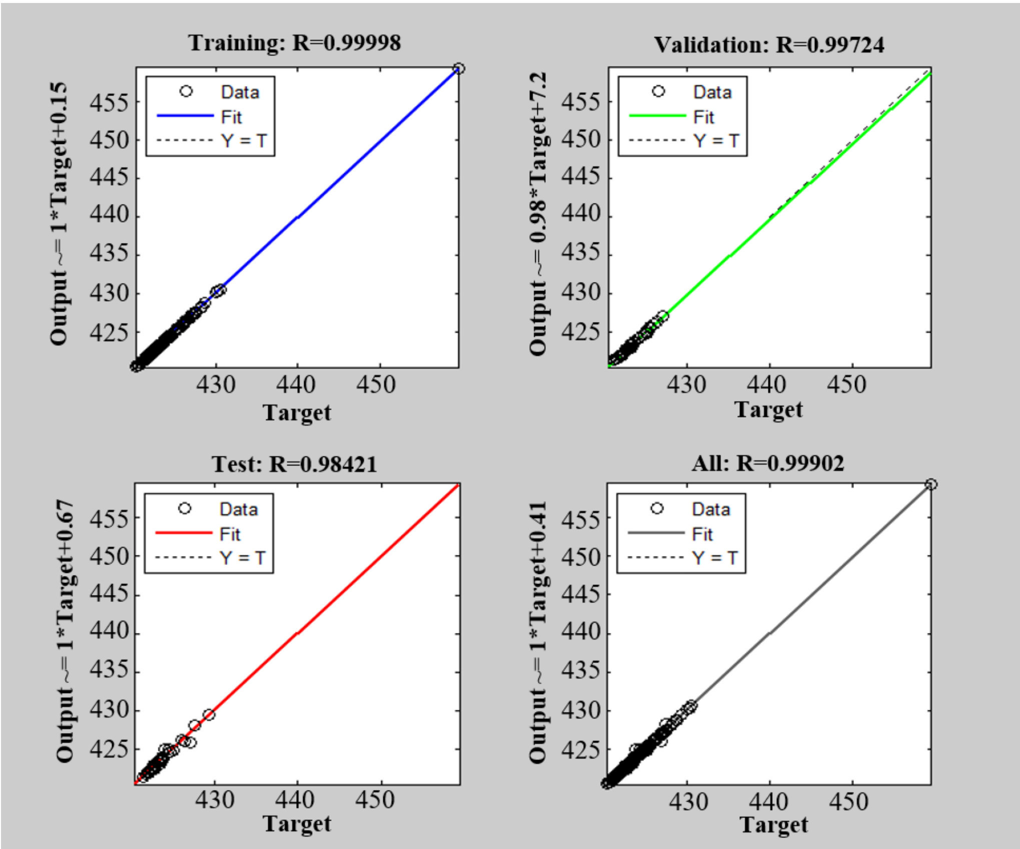


**Figure 3** Regression plot of the ANN model at 19 Epochs

validation, testing and the whole dataset are 0.9997, 0.9972, 0.9842 and 0.9990, respectively. These *R*-values agree with literature [17] where the training, test and overall data set for its ANN model were found to be 0.978, 0.971 and 0.956, respectively. These showed that the ANN predicted values are very close to the actual values of the standard time computed using TimeProcessor.exe in FORTRAN. Also, Table 3 shows that the *MSE* values for training, validation, testing and the whole dataset are 0.0004478, 0.01261, 0.09523 and 0.01261, respectively. This implies that the error in the prediction of the ANN from the direct or actual computation is minimal.

From Figure 4, the plots of field and ANN model data have similar trends. Both are linear and follow the same trend. The two lines are almost indistinguishable. Table 4 shows the statistical analysis to validate the developed ANN

**Table 3** Summary of ANN model regression analysis

| S/N | Data sets | Random Partition (%) | Samples | *R* | *MSE* | Linear Relationship Output vs Targets |
|---|---|---|---|---|---|---|
| 1 | Training | 70 | 184 | 0.99979 | 0.0004478 | Strong |
| 2 | Validation | 15 | 40 | 0.99724 | 0.01261 | Strong |
| 3 | Testing | 15 | 40 | 0.98421 | 0.09523 | Strong |
| 4 | All | 100 | 264 | 0.99902 | 0.01261 | Strong |

**Table 4** Data for statistical analysis to validate the ANN model

| Days | Actual time , $E_a$ (Minutes) | Predicted time by ANN, $E_p$ (Minutes) | Difference $E_a$-$E_p$ | $(E_a - E_p)^2$ | $E_a$-$E_m$ | $(E_a$-$E_m)^2$ | $[E_a$-$E_p]$ |
|---|---|---|---|---|---|---|---|
| 1 | 421.4674 | 421.520833 | -0.0534325 | 0.002855034 | 421.4674 | 177634.8 | 0.053433 |
| 2 | 421.9961 | 421.994809 | 0.0012908 | 0.000001666 | 421.9961 | 178080.7 | 0.001291 |
| 3 | 421.90175 | 421.917566 | -0.0158165 | 0.000250161 | 421.9018 | 178001.1 | 0.015816 |
| 4 | 421.2311 | 421.224334 | 0.0067659 | 0.000045777 | 421.2311 | 177435.6 | 0.006766 |
| 5 | 421.57195 | 421.539590 | 0.0323600 | 0.001047169 | 421.572 | 177722.9 | 0.03236 |
| 6 | 423.24305 | 423.245448 | -0.0023983 | 0.000005752 | 423.2431 | 179134.7 | 0.002398 |
| 7 | 420.7092 | 420.726576 | -0.0173758 | 0.000301919 | 420.7092 | 176996.2 | 0.017376 |
| 8 | 422.15335 | 422.181067 | -0.0277172 | 0.000768242 | 422.1534 | 178213.5 | 0.027717 |
| 9 | 422.6268 | 422.610010 | 0.0167901 | 0.000281908 | 422.6268 | 178613.4 | 0.01679 |
| 10 | 422.8138 | 422.844015 | -0.0302154 | 0.000912971 | 422.8138 | 178771.5 | 0.030215 |
| 11 | 421.87115 | 421.861408 | 0.0097420 | 0.000094906 | 421.8712 | 177975.3 | 0.009742 |
| 12 | 422.47125 | 422.480537 | -0.0092874 | 0.000086255 | 422.4713 | 178482 | 0.009287 |
| 13 | 422.5911 | 422.545766 | 0.0453342 | 0.002055190 | 422.5911 | 178583.2 | 0.045334 |
| 14 | 422.8648 | 422.810260 | 0.0545400 | 0.002974616 | 422.8648 | 178814.6 | 0.05454 |
| 15 | 422.00885 | 422.065374 | -0.0565243 | 0.003194997 | 422.0089 | 178091.5 | 0.056524 |
| 16 | 422.0726 | 422.076161 | -0.0035615 | 0.000012684 | 422.0726 | 178145.3 | 0.003561 |
| 17 | 421.4504 | 421.441564 | 0.0088358 | 0.000078071 | 421.4504 | 177620.4 | 0.008836 |
| 18 | 421.9604 | 421.913232 | 0.0471684 | 0.002224855 | 421.9604 | 178050.6 | 0.047168 |
| 19 | 421.7955 | 421.830215 | -0.0347154 | 0.001205158 | 421.7955 | 177911.4 | 0.034715 |
| 20 | 422.64635 | 422.803832 | -0.1574824 | 0.024800696 | 422.6464 | 178629.9 | 0.157482 |
| 21 | 421.88135 | 421.908385 | -0.0270355 | 0.000730918 | 421.8814 | 177983.9 | 0.027035 |
| 22 | 421.4504 | 421.434822 | 0.0155782 | 0.000242680 | 421.4504 | 177620.4 | 0.015578 |
| 23 | 422.6523 | 422.667373 | -0.0150733 | 0.000227205 | 422.6523 | 178635 | 0.015073 |
| 24 | 422.4857 | 422.368653 | 0.1170466 | 0.013699895 | 422.4857 | 178494.2 | 0.117047 |
| 25 | 421.4623 | 421.457136 | 0.0051643 | 0.000026670 | 421.4623 | 177630.5 | 0.005164 |
| 26 | 423.02375 | 423.036015 | -0.0122645 | 0.000150419 | 423.0238 | 178949.1 | 0.012265 |
| 27 | 422.38965 | 422.385599 | 0.0040513 | 0.000016413 | 422.3897 | 178413 | 0.004051 |
| 28 | 422.0777 | 422.066506 | 0.0111938 | 0.000125301 | 422.0777 | 178149.6 | 0.011194 |
| 29 | 422.5452 | 422.821603 | -0.2764032 | 0.076398724 | 422.5452 | 178544.4 | 0.276403 |
| 30 | 422.6489 | 422.686382 | -0.0374822 | 0.001404912 | 422.6489 | 178632.1 | 0.037482 |
| 31 | 421.2906 | 421.370236 | -0.0796357 | 0.006341846 | 421.2906 | 177485.8 | 0.079636 |
| 32 | 422.82485 | 422.813189 | 0.0116607 | 0.000135972 | 422.8249 | 178780.9 | 0.011661 |
| 33 | 422.6438 | 422.852968 | -0.2091679 | 0.043751192 | 422.6438 | 178627.8 | 0.209168 |
| 34 | 422.400275 | 422.411598 | -0.0113229 | 0.000128207 | 422.4003 | 178422 | 0.011323 |
| 35 | 421.719 | 421.738718 | -0.0197180 | 0.000388801 | 421.719 | 177846.9 | 0.019718 |
| 36 | 421.99185 | 421.948144 | 0.0437059 | 0.001910209 | 421.9919 | 178077.1 | 0.043706 |
| 37 | 422.6965 | 422.467692 | 0.2288083 | 0.052353247 | 422.6965 | 178672.3 | 0.228808 |
| 38 | 421.14355 | 421.125498 | 0.0180523 | 0.000325884 | 421.1436 | 177361.9 | 0.018052 |
| 39 | 422.47635 | 422.468381 | 0.0079690 | 0.000063505 | 422.4764 | 178486.3 | 0.007969 |
| 40 | 421.83375 | 421.846210 | -0.0124605 | 0.000155263 | 421.8338 | 177943.7 | 0.01246 |
| 41 | 422.25365 | 422.256938 | -0.0032876 | 0.000010808 | 422.2537 | 178298.1 | 0.003288 |
| 42 | 421.63825 | 421.648307 | -0.0100568 | 0.000101139 | 421.6383 | 177778.8 | 0.010057 |

model, showing 1 to 42 data of 264 data sets. The statistical measures were calculated and found to be 0.99804, 0.1290 and 0.011%. for $R^2$, *RMSE* and *MAEP* respectively. Since the value of $R^2$ is close to 1 and that of *RMSE* is close to zero, and *MAEP* value implies minimum error, then the ANN model is considered to have good prediction capability.

Finally, these results show a very high coefficient of determination ($R^2$) 0.99804 and close to 1, while the *RMSE* and *MAEP* were low enough, 0.1290 and 0.011%, respectively, as shown in Table 5. This agrees with literature [30, 20], where the average errors was found to be less than 0.4% and 1%, respectively. These results validate the prediction performance of the developed ANN model according to Equations 21 to 23 [24, 27]. This shows that the developed ANN model yields predictions that are acceptable for palm oil processing.

## 4. Conclusions

In the current study, artificial neural network application for process time planning for palm oil production was done. From our results, the computed standard time ($T_{STD}$) for 22.5 tonnes of FFB in the oil mill, with $A_{PFD}$ and $W_R$ values of 0.1 and 0.85, respectively, was found to be 423.6625 minutes using the TimeProcessor.exe software. The predicted result by the ANN model was 423.6663 mins and that recorded at Roche Palm Oil Mill was 540 mins for the same processes. This implies a time savings of 116.22 mins (21.54%).

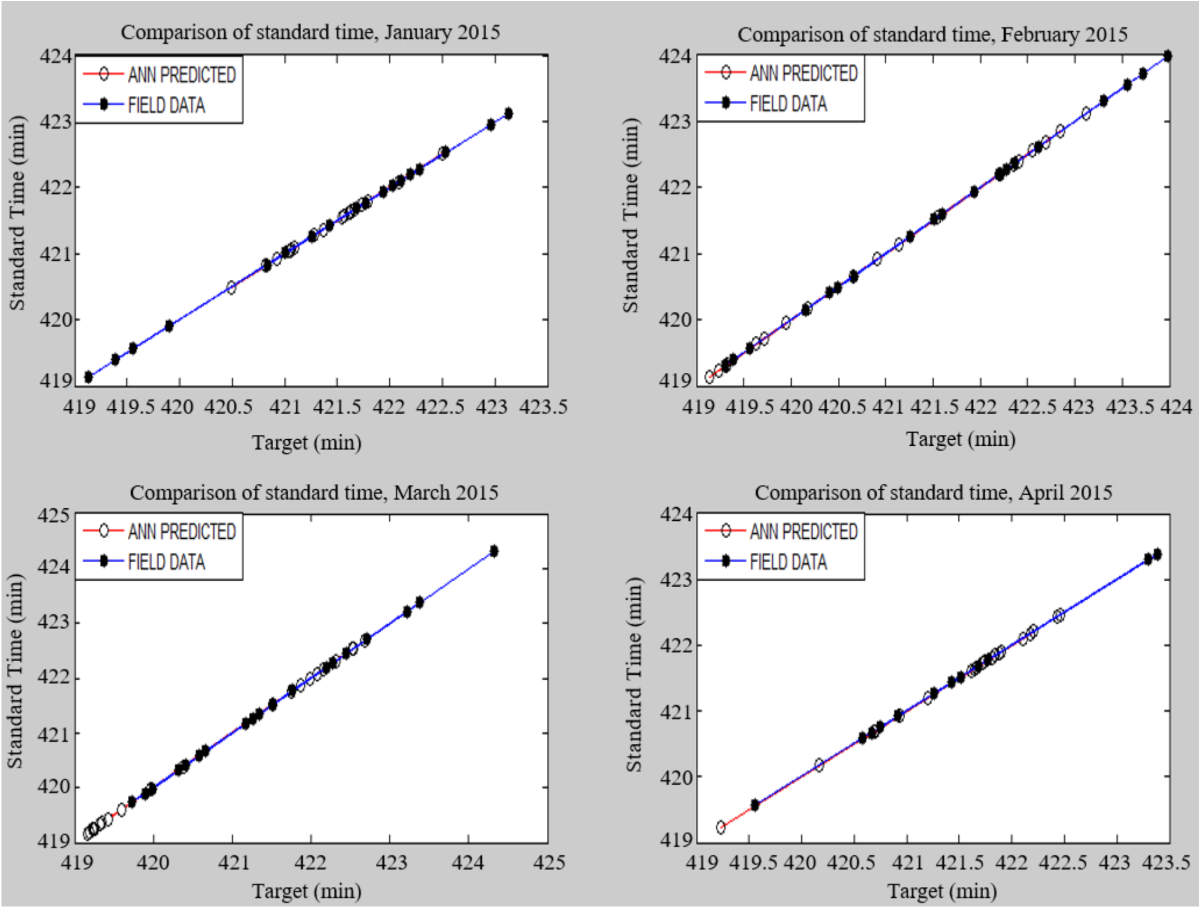


**Figure 4** Plot of field data vs ANN predicted data for the January-April 2015.

**Table 5** ANN model validation

| Model developed | $R^2$ | *RMSE* | *MAEP (%)* |
|---|---|---|---|
| ANN model for predicting Standard time | 0.99804 | 0.1290 | 0.011 |

However, after optimization, the required labour for a 22.5 tonne capacity of the mill were found to be 4, 8 and 60 senior, junior and casual staff, respectively. Thus, cost requirements were optimized at the mill, showing a savings of 42064.97 USD, an 86.92% reduction of the original monthly labour costs.

The objective of achieving a faster and reliable method of determining standard time for palm oil production is met in the developed ANN model, since the prediction errors are very minimal, as shown in Table 4. Therefore, with the developed ANN model, subsequent years' prediction of the standard time can be made without difficulties. The input parameters are the time recorded for each process stage. Once the standard time is determined, planning and scheduling of production activities at the oil mill can be efficiently achieved. It will provide information for labour-control, estimates on tenders, delivery promises and forms a basis for incentive schemes for staff. Standardizing of manufacturing processes can boost productivity by reducing variability in production.

However, the results cannot be directly compared to any similar work elsewhere since there was no exact known replica of these processes. Our future research efforts will consider solving the problem with broader computational techniques and offering a one-to-one comparison, where possible. Thus, the developed ANN model has a reliable and good prediction capacity. It can be applied in a timely manner to medium and large scale oil mills or similar processes.

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