# Determining optimal machine part replacement time using a hybrid ANN-GA model

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## Abstract

Companies must determine the replacement time of machine parts correctly since it affects their production costs and efficiencies. For this, it is aimed to determine the most appropriate replacement time to minimize cost per unit. In this study, it is proposed to develop a hybrid Artificial Neural Network (ANN)-Genetic Algorithm (GA) model to predict replacement time without using a cost model. At first, a replacement cost model is developed to calculate replacement times to use in training the neural network. Nevertheless, the cost model needs complex mathematical calculations. GA is used instead of the cost model to determine replacement time, and thus, to achieve fast learning for the neural network. The hybrid ANN-GA model was applied to predict replacement time of bladder in tire manufacturing. Furthermore, ANN and GA models, which were developed to increase the prediction accuracy of the hybrid model, were used. The hybrid ANN-GA model showed better solution according to the performance statistics than the other ANN and GA models. The values indicate that the hybrid model is in good agreement with the cost model. Thus, it is recommended that the hybrid model is used instead of the cost model.

**Keywords:** Replacement time; replacement cost model; artificial neural network; genetic algorithm; hybrid ANN-GA model.

# 1. Introduction

As the costs associated with machine parts correspond to a large proportion of the total cost of production, economical machine part replacement times are very important especially for expensive parts [1]. The optimal replacement time should be obtained to ensure minimization of the expected average cost per unit time. Replacement cost models are based on economic comparison between planned (preventive) and unplanned (failure) replacement actions. In planned replacement, machine parts may be changed at only scheduled times, and in this case, these parts might not have completed their useful life. In unplanned replacement, replacement is made on failed machine parts during operations. This case may damage the product that is being processed on the machine and therefore causes additional scrap product costs.

Machine part replacement time is regarded as a random variable that is usually modeled by Weibull distribution in replacement cost models. Weibull distribution is the most widely used probability distribution of reliability studies because it is highly flexible in compliance with random data and has the ability to be adapted for data with different distributions [2-4]. In a replacement cost model, Weibull distribution parameters, $\alpha$-scale and $\beta$-shape, need be updated with new replacement data to revise replacement strategies [5]. It is very time-consuming and labor-intensive to calculate the new replacement time based on the cost model involving complex mathematical operations every time.

This study proposes a hybrid Artificial Neural Network (ANN) - Genetic Algorithm (GA) model to predict a new replacement time without the need for a mathematical model. The ANN method is used to predict the machine part replacement time which minimizes the cost per unit. Since the ANN method evaluates not only present data but also past data, it predicts replacement time more accurately than cost models. A replacement time cost model is developed to provide the necessary data for the training of the ANN. The GA method is used instead of the developed cost model to find replacement times, and thus, to accelerate the learning of the neural network. The replacement times obtained with the GA method correspond to output data needed for the training of the neural network.

Replacement time cost model studies in the literature are mostly concerned with machine tool replacement [6-8] and machine replacement [9,10], rather than machine part replacement. A number of studies have been carried out with different criteria than those known in replacement cost models. In one of them, Wang et al. [11] used profit instead of cost as the criterion of economics in their replacement model. In another study, Sheikh et al. [12] used the number of products processed in the machine instead of the lifetime in the cost function to determine the optimal machine tool replacement interval.

Hybrid ANN-GA algorithms have been used in the past for the cost minimization problem by researchers. Hashami et al. [13] proposed a hybrid model including ANN optimized by GA for estimating power plant project costs. ANN was used to predict the costs, whereas GA was used to set the ANN's parameters such as number of hidden layers, number of nodes per each hidden layer and the corresponding weights and biases. Seo [14] developed a hybrid GA-ANN model to predict product life cycle costs. GA was used to improve ANN by eliminating irrelevant factors, determining the number of hidden nodes and processing elements and optimizing the connection weights between layers. Firouzi and Rahai [15] achieved a hybrid ANN-GA model optimizing risk-based repair and maintenance actions and yielding the minimum life cycle cost for concrete bridge decks.

There is a limited number of studies in the literature including the ANN method or GA method or hybridized ANN and GA methods in determining replacement times. Al-Chalabi et al. [16] presented a model-based ANN method to determine the economic replacement time (ERT) of production machines. Aldhubaib and Salama [17] illustrated an approach to link maintenance and replacement decisions. They used GA to optimally schedule maintenance activities. Liu et al. [18] conducted a study using ANN, GA and Weibull distribution together. They structured a model to determine long-run fuzzy expected replacement cost per unit time and the optimal preventive replacement interval. The ANN method was used for parameter estimation, reliability prediction and evaluation of the expected maintenance cost. The GA method was used to find the values for the membership function at any cut level. The effectiveness of the proposed method was illustrated using a two-parameter Weibull distribution.

In the literature, in cost-based hybrid ANN-GA models, GA was mostly used for tuning the parameter values of ANN. In this study, unlike others, GA is used to obtain replacement time, which is the neural network model's outputs, based on the cost model.

Application of the developed hybrid model in a real setting was illustrated on a bladder used in a curing press in tire manufacturing. ANN and GA models were individually created to increase the replacement time prediction performance of the developed hybrid model. The application results of the developed hybrid ANN-GA model, GA and ANN models were separately compared to the results obtained with the proposed replacement cost model. According to the performance statistics such as coefficient of determination ($R^2$), mean absolute percentage error (MAPE), and root mean square error (RMSE) the hybrid ANN-GA model had more similar results to the proposed replacement cost model's results than those of the ANN and GA models. Hence, the hybrid ANN-GA model is recommended to predict machine part replacement time instead of the cost model because it is more convenient and practical, as well.

The contribution of this study may be summarized as follows:

- A machine part replacement cost model was developed,
- A hybrid ANN-GA cost model was structured to predict replacement time,

- It was presented that the hybrid model tended to provide more accurate prediction than the individual prediction models.

# 2. Methods

## 2.1. ANN Method

ANN is a machine learning method that can learn a mapping between an input and an output space and synthesize an associative memory that retrieves the appropriate output when presented new inputs [19]. Neural network is structured with three (input, hidden and output) layers and the interconnections between the neurons in the layers. Input layer receives features of input data and distributes them to the hidden layers without any processing. While the inputs are transmitted to the hidden layer, the net input of that cell is calculated by transfer function. The hidden layer shows the interactions between input layer and output layer. The net sum obtained from the transfer function is transmitted to the activation function to generate the output of the cell. The output value of the activation function is the output value of the neuron. ANN can has more than one layer and more than one neuron in this layer. The output layer indicating the output nodes of variables shows the output generating according to the input data by processing the information coming from the hidden layer. Then, neural network is trained to minimize the error between the present output and predicted output by the ANN model by adjusting the weights in a neural network. It is utilized from performance criteria in order to validate the performance of the developed ANN model.

## 2.2 GA Method

GA is a heuristic search technique that tries to obtain global solutions using random search techniques as opposed local solutions, introduced by Holland [20]. It includes various biological terms such as the population or the selection, crossover and mutation operators [21]. The individual (candidate) solutions and the individual traits of the chromosome are called as chromosomes and genes, respectively. GA algorithm starts by determining the parent chromosomes formed by random partitioning the population into the pairs of chromosomes. Then, crossover operator is used to produce more improved children chromosomes from the initial parent chromosomes. The process is evaluated by the fitness function, which reflects the goal of the optimization problem. Subsequently, the mutation procedure is applied to the children chromosomes to avoid not falling into a local optimum. In each iteration, the parent and the children chromosomes are combined and the best chromosomes from them are selected to update the current population.

### 2.3. Integrating ANN with GA

ANN has several disadvantages such as long training time, unwanted convergence to local optimal solution instead of global, and having large number of parameters. Therefore, it is requested to integrate ANN with another algorithm that can eliminate one of specific problem. An algorithm that has frequently been hybridized with ANN is GA. Recently the trend to hybridize GA and ANN has been getting common among researchers [13-15]. The advantage provided by forming an ANN-GA hybrid model is to make more accurate and fast prediction. ANN uses past data to predict future trend, while GA finds the better sets of input variables and input subsets for improving ANN training.

### 2.4. Model performance criteria

The prediction ability of the models can be usually evaluated by the statistical performance criteria such as $R^2$, MAPE and RMSE. $R^2$, RMSE and MAPE can be calculated by Eq.1, Eq.2 and Eq.3, respectively.

$$R^2 = \left[ \frac{\sum_{i=1}^{N} \left( (T_i - \bar{T}) (P_i - \bar{P}) \right)}{\sqrt{\sum_{i=1}^{N} (T_i - \bar{T})^2 \sum_{i=1}^{N} (P_i - \bar{P})^2}} \right]^2 \quad (1)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (T_i - P_i)^2} \quad (2)$$

$$MAPE(\%) = \frac{1}{N}\left[\sum_{i=1}^{N} \frac{|T_i - P_i|}{T_i}\right] x\ 100 \tag{3}$$

where $T_i$ is i-th period part life, $\bar{T}$ is mean part life, $P_i$ is i-th period predicted part life and $\bar{P}$ is i-th period predicted mean part life.

# 3. Proposed Hybrid ANN-GA Model

It is aimed to develop a hybrid ANN-GA model that makes the replacement cost per unit the minimum, for predict the machine part replacement time. This study consists of three phases. In the first phase a machine part replacement cost model was developed to determine replacement time minimizing cost per unit. However, since the cost model is stochastic, calculating replacement time is cumbersome and time consuming. Therefore, in the second phase, GA model was developed instead of cost model to obtain replacement time. In the third phase, the ANN model was created to determine the machine part replacement time without the need for the cost model. The replacement times obtained with GA was used in neural network training.

The end of each replacement period, it is needed revising α and β parameters of Weibull distribution in the light of data observed. It is difficult and time-consuming to determine replacement time with the replacement cost model contained complex function. In addition, the limited number of existing replacement time data are used to determine time. Since ANN learns from the past data, the number of data that used for prediction is more than the proposed replacement cost model. The hybrid model determines more precise approximate replacement time. The developed hybrid ANN-GA model is shown in Figure 1.

## 3.1. Replacement cost model

Proposed machine part replacement cost model was structured based on developed replacement cost models by Barlow and Hunter [22], Handlarski [23], Ahmad and

Kamaruddin [24]. Although the cost model is similar in terms of cost components into others models, but there are number of some assumptions that make the model different. The assumptions are:

- Only one of the machine parts is considered,
- If the machine part fails while the product is processed, it is caused product damage and be scrap product,
- When the machine is stopped to replace new machine part, the parallel other machine that works together also stops.

The model consists of the planned or unplanned replacement costs. The decision variable of the model is the machine part lifetime. Prior to introducing detailed description of cost model, some notations are given as Table 1.

### 3.1.1. Planned replacement cost

The planned replacement cost ($C_p$) is incurred when the machine part is changed that its life is completed at the prescribed time. This cost consists of planned loss production cost($C_{lp}$), planned manning cost ($C_{mp}$) and replaced part cost ($C_r$). The loss production cost and manning cost are calculated using Eq.4 and Eq.5 respectively.

$$C_{lp} = \frac{MC_c t_r}{t} \tag{4}$$

$$C_{mp} = \frac{C_e(t_r + t_p)}{60} \tag{5}$$

The sum of these costs gives the planned replacement cost (Eq. 6).

$$C_p = \frac{MC_c t_r}{t} + \frac{C_e(t_r + t_p)}{60} + C_r \tag{6}$$

### 3.1.2. Unplanned replacement cost

Unplanned replacement cost *($C_{up}$)* occurs when machine part suddenly failed during processing on product. Thus, its useful life is shorter than predicted. Unplanned part replacement is usually more time-consuming than planned replacement. In addition, as the two machines are working in parallel, the breakdown of one machine causes to be disabled of the parallel machine. $C_{up}$ is obtained by adding scrap product cost *($C_{sup}$)*, unplanned lost production cost *($C_{lup}$)* and unplanned manning cost *($C_{mup}$)* which are calculated using Eq.7, Eq.8 and Eq.9 respectively.

$$C_{sup} = P\ C_s \tag{7}$$

$$C_{lup} = \frac{M\ C_c\ (t_d + t_r)}{t} \tag{8}$$

$$C_{mup} = \frac{C_e(t_r + t_{up})}{60} \tag{9}$$

$C_{up}$ is found by the following Eq.10.

$$C_{up} = P\ C_s + \frac{M\ C_c\ (t_d + t_r)}{t} + \frac{C_e(t_r + t_{up})}{60} + C_r \tag{10}$$

According to all these values, the average cost per unit ($C_U$)is given as in Eq.11.

$$C_{U=} \frac{C_p + \left(C_{up-}C_p\right)F(x)}{x\left(1 - F(x)\right) + E(x)} \tag{11}$$

$F(x)$ and $E(x)$ values of Weibull distribution in Eq. 11 are calculated using respectively Eq.12 and Eq.13. *x* is machine part replacement time or lifetime.

$$F(x) = 1 - e^{-(\frac{x}{\alpha})^{\beta}} \qquad 0 \le x \le \infty, \quad \alpha, \beta \ge 0 \tag{12}$$

$$E(x) = \alpha \int_0^{\infty} e^{-x}\, x^{n-1}\, dx\ (1 + 1/\beta\ ) \tag{13}$$

Maximum likelihood estimation method can be used to calculate α-scale and β-shape parameters of the Weibull distribution (Eq.14 and Eq.15).

$$\alpha = \frac{\sum_{i=1}^{n} x_i^{\beta}}{n} \tag{14}$$

$$f(\beta) = \left[\frac{\sum_{i=1}^{n} x_i^{\beta} ln x_i}{\sum_{i=1}^{n} x_i^{\beta}}\right] - 1/\beta - 1/n \sum_{i=1}^{n} ln x_i \tag{15}$$

# 4. Implementation of hybrid ANN-GA model

The proposed hybrid ANN-GA model was applied to predict in bladder replacement time, which is part of a curing press in a tire manufacturing company located in Turkey. The bladder is inflated with pressure in the tire during the change of the green tire in the mold, thereby ensuring that the tire takes shape of mold. Shaping method of tire curing depends on bladder with high elasticity and low rigidity to determine tire cavity profile [25]. Therefore, the bladder is considered as being important part of the curing process. The life and price of purchased bladder varies according to the manufacturer and model. If the predicted bladder life is smaller or larger than the actual value, it leads to extra cost. Replacement time of bladder is the number of tires that bladder has been used in during curing operation. In other words, bladder lifetime is the number of use of bladder or the number of tires per bladder.

The hybrid ANN-GA model was applied to predict replacement time of bladder with minimum deviation that will minimize average cost per tire.

## 4.1. Data collection and analysis

The bladder coded AXYZ was chosen because it is the most used type of bladder in the tire manufacturing company. A damaged bladder is a machine part that will not allow longer use. When the hole, folding and breakage occurred on bladder, its life is being completed. Bladder's lifetime, that is the number of tires in that used during curing process, is obtained from past recorded data. Number of tires varies from 1 to 1000. 1 indicates that the bladder is failed in the first tire after it is placed on the curing press, whereas 1000 indicates that bladder is failed after used in1000 tires. Bladder lifetime data were obtained by randomly choosing 30 of the recorded data. The data collecting process was repeated 120 times. Thus, 3600 ($120 \times 30$) replacement time data were collected. Anderson-Darling test applied to determine whether or fitting Weibull distribution of collected data. The values of parameters, α-shape and β -scale, of the Weibull distribution of the data for each period were calculated using Eq.14 and Eq.15, respectively. It was also calculated mean and standard deviation values for each period. The values of the first 3 and last 3 of the 120 periods are as in Table 2. Minitab 17 was used to determine whether data fit to the Weibull distribution and to determine the parameters values of the distribution.

The bladder's average changing time was 13 min. From the observations, the planned preparing time was determined average 5 min. and the unplanned preparing time was determined average 15 min. The average curing time of a tire is 20 min. Due to the fact that the two curing presses operate in parallel with each other, the failure of any bladder causes stop the other parallel press at same time. Curing press downtime is average 45 min. If the one bladder is damaged, on average 3 tires are be scrap. The cost of a scrap was an average of €74 per tire. The unit cost of the AXYZ coded bladder is €94. The average replacing cost of a bladder is €35 and the compensation cost is €25 per hour.

### 4.2. Determination replacement time using GA

GA, based on the developed cost model, provided to determine replacement time for each period to minimize unit cost. These data were used for training ANN model. The equation of average replacement cost per tire that given in Eq. 11 was accepted as the objective function of GA. The GA model is as shown in Figure 2.

The values of parameter in the GA are given in Table 3. These values were determined from other studies in literature [26- 28] and by experts' opinions.

## 4.3. Prediction of replacement time using ANN

The replacement time that is obtained from GA and the parameters' values of Weibull distribution were used to train ANN. In testing phase of ANN model, the parameters of the Weibull distribution are the inputs and the replacement time obtained from GA is the output. The ANN model is as following (Figure 3).

ANN model with feed forward backpropagation that consists of 2-inputs, 1-output, was structured to predict the replacement time. Multilayer perceptron (MLP) model was chosen which was the best model for prediction problems [29]. $80\ \%$, $10\ \%$ and $10\ \%$ of the data were used for training, testing and validation, respectively.

After the initial weight values and threshold values of the inputs were determined, the data in the training set were shown to the network. These data were the replacement time belonging to 96 periods $(120 \times 0.80)$. Selected seven training algorithm (Table 4) was tested to determine the best one of among them.

The test performance results of each algorithm according to $R^2$ are given in Table 5. Traingdx algorithm seems to provide the best performance according to these results.

ANN performance also is effected from number of hidden layer. Therefore, neural network was tested for different number of layers to determine the most suitable layer number. The results are illustrated in Table 6. From the table, it appears that a single layer provides the best performance for validation and testing with respect to $R^2$. This case can be considered a good result because in the literature it has been explained that having more than one hidden layer slows learning [30].

Other parameter values of ANN model were determined from studies in literature [31-33] and by experts' opinions (Table 7).

Figure 4 shows the ANN model's structure providing to predict replacement time.

It was utilized MATLAB12 software for ANN and GA calculations.

The performance of the network was measured on using the test data set that has not used before. The network's prediction accuracy shows the performance of the neural network model. 12 (10 %) and 12 (10 %) out of the 120 periods were used for testing and validation, respectively. Regression graphs related to training, validation and testing show the similarity between the network output values and the target values (Figure 5). The results can be interpreted as perfect because of the values are located on line with a 45-degree angle. The calculated $R^2$ value for the all data set was about 0.943. The results indicate that the hybrid model is sufficient to predict machine part replacement time.

The replacement times obtained with ANN model for the first 3 and the last 3 out of 120 periods are shown in Table 8.

## 5. Results and Discussion

ANN and GA models were individually developed to increase their prediction capability to hybrid model' s one. The replacement time values which are obtained from proposed cost model were separately compared with each model for 120 periods. The inputs (α and β parameter' values) and output (replacement time values) of models for the first 3 and last 3 out of 120 periods are as in Table 8.

The statistical performance criteria values of models are given in Table 9. The prediction capability of the proposed hybrid ANN-GA, ANN and GA models were compared the replacement cost model's one. Results indicated the hybrid ANN-GA model's performance is better than the other ANN and GA models. Higher $R^2$, lower RMSE and MAPE values were obtained by hybrid model compared to other models. Hybrid model proposed in this study are in good agreement with proposed cost model. The correlation value, $R^2$ shows that the model has high explanatory power [34]. Hence, the hybrid ANN-GA prediction data is approximate to the proposed replacement cost model data. The verification analysis confirmed the hybrid model to be highly accurate, reliable and practical for predicting replacement time. These results are similar to the results of the studies in the literature [35, 36].

## 6. Conclusion

In this study, it was aimed to determine the machine part replacement time that minimized the cost per unit product. The study included three main issues:

- A machine part replacement cost model was developed
- A hybrid ANN-GA model was developed to provide prediction of the replacement time without the stochastic replacement cost model requiring complex mathematic operations. The hybrid model would predict a replacement time for the new data.
- ANN and GA models were separately developed to increase the prediction capability of the hybrid ANN-GA model. The prediction results of each model were compared to the proposed replacement cost model's results based on prediction performance statistics. It was determined that the hybrid model's prediction capability was better than the single ANN and GA models.

The developed hybrid ANN-GA model is more convenient and practical than the replacement cost model. So, the hybrid model may be successfully used for determining replacement times.

In a future study, it is aimed to use different machine learning algorithms such as support vector machine, regression trees and random forest.

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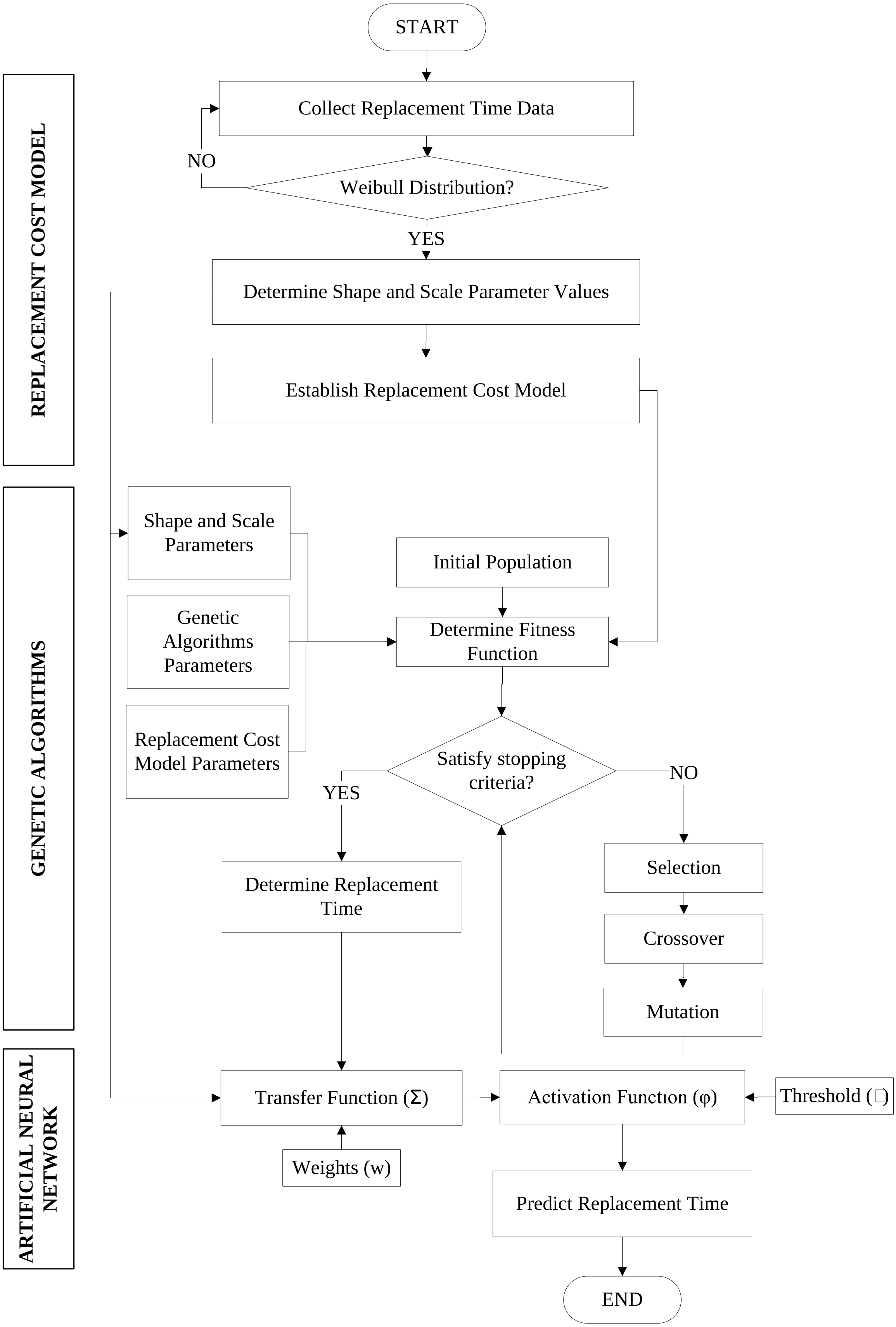


**Figure 1.** Flow chart of proposed hybrid ANN-GA model

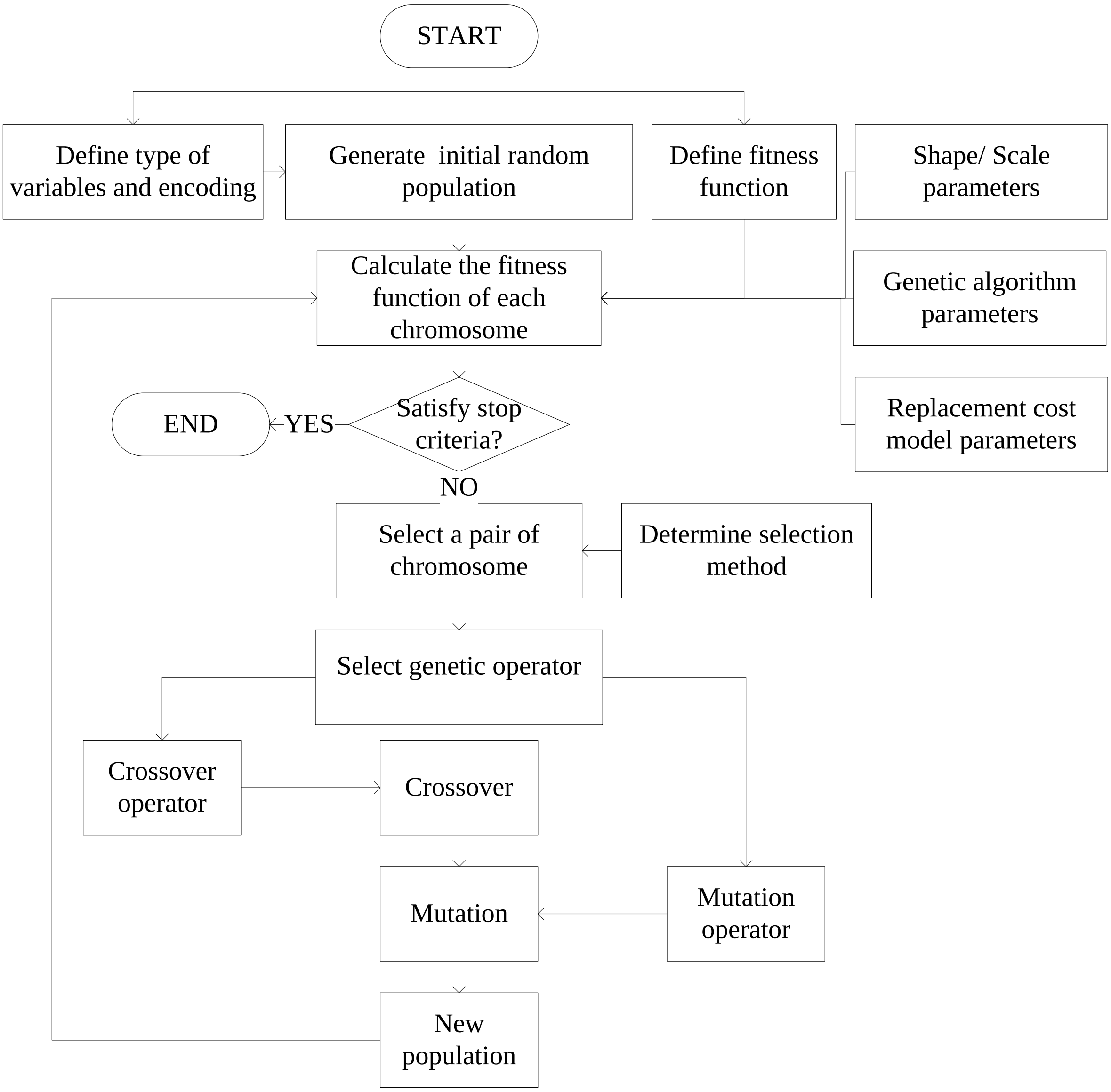


**Figure 2.** Flow chart of GA model

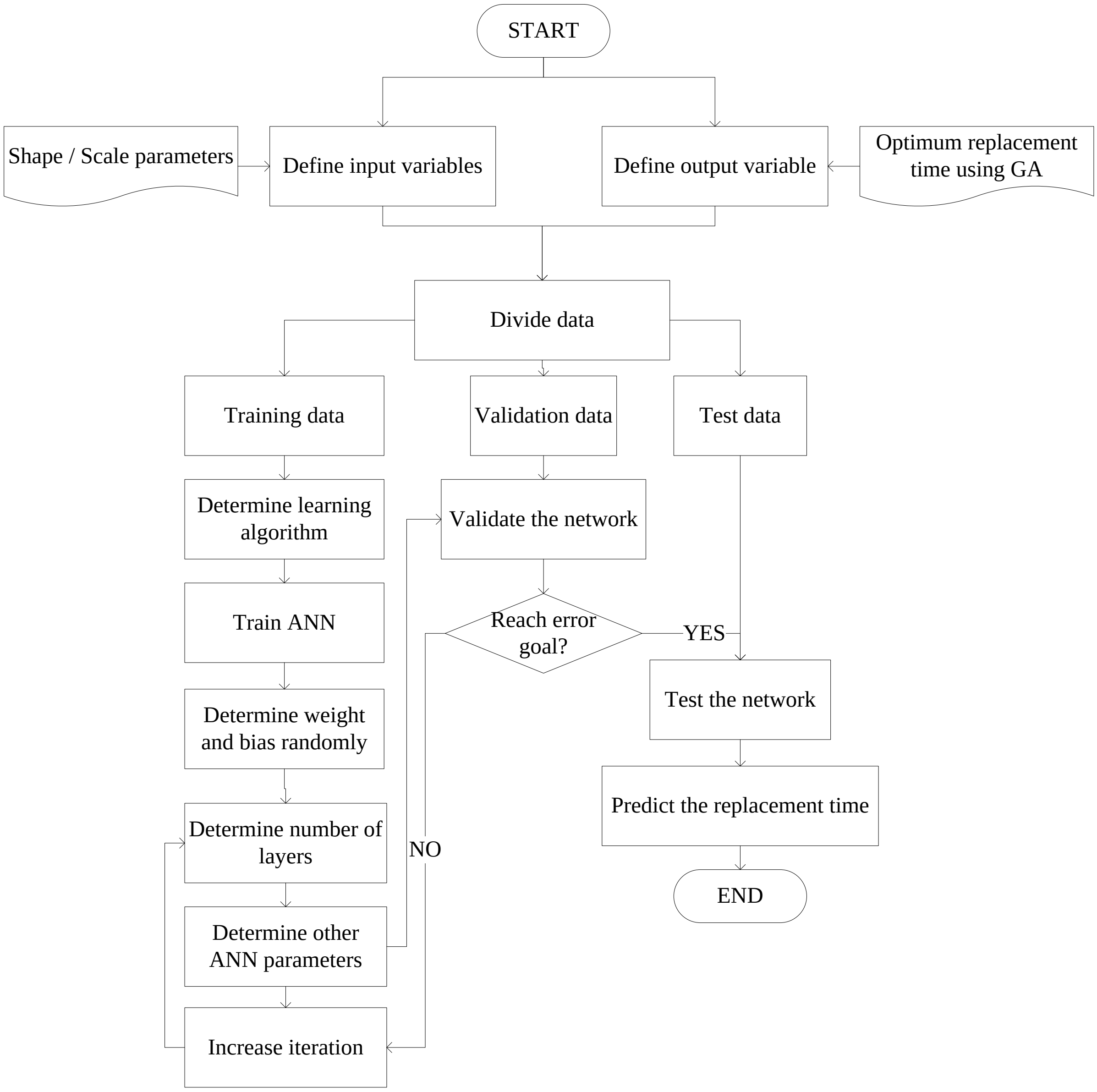


**Figure 3.** Flow chart of ANN model

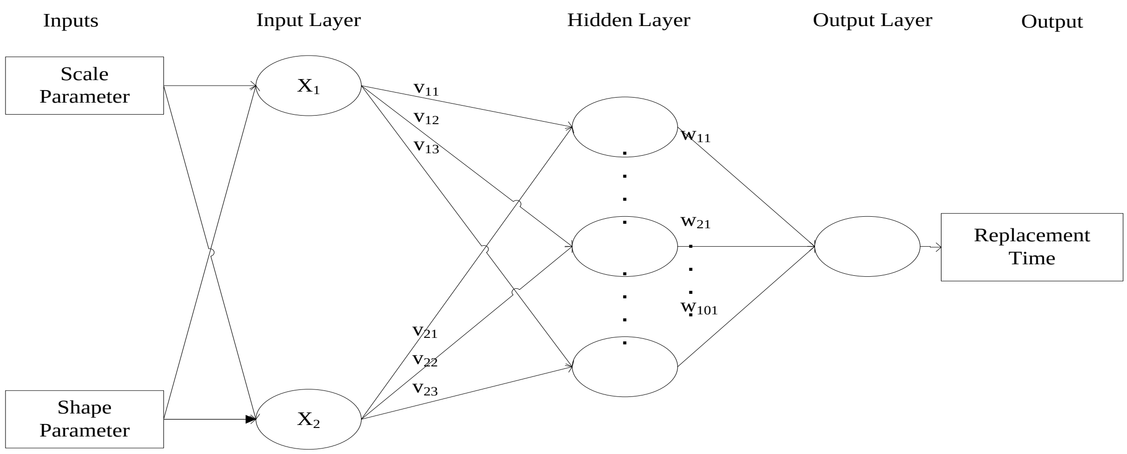


**Figure 4.** ANN model structure

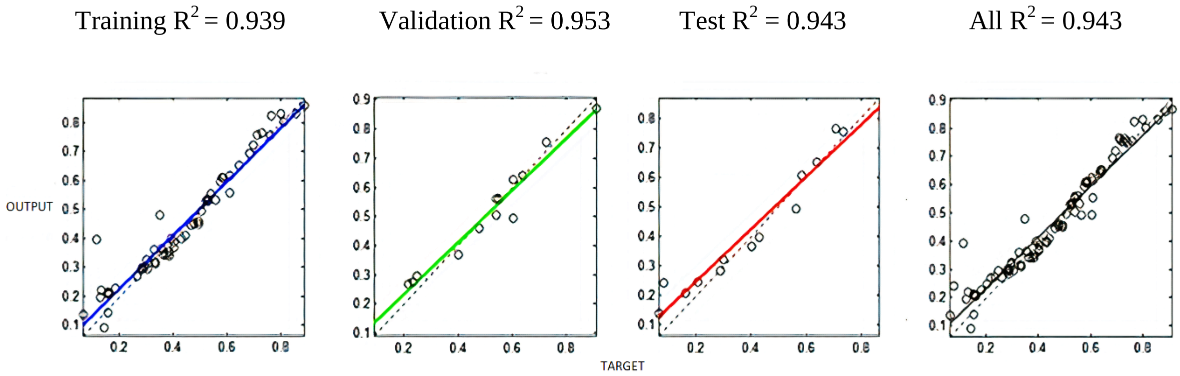


**Figure 5.** The best performance of ANN

## List of tables' captions



**Table 1.** Notations of the cost model

| Notation | Cost elements | Unit |
|---|---|---|
| $P$ | Failure detection performance | Scrap product / part failure |
| $C_s$ | Product scrap unit value | € |
| $C_c$ | Conversion cost | € |
| $T$ | Cycle time | Min |
| $M$ | Machine cavities empty machine | 1, 2 |
| $C_e$ | Compensation | Cost/hr. |
| $t_d$ | Machine down time (waiting time) | Min |
| $t_r$ | Replacing time | Min |
| $t_p$ | Preparing time planned | Min |
| $t_{up}$ | Preparing time unplanned | Min |
| $C_r$ | Replaced parts cost | € |
| $C_{lp}$ | Loss of production cost (Planned replacement) | € |
| $C_{mp}$ | Manning cost (Planned replacement) | € |
| $C_p$ | Planned replacement cost | € |
| $C_{sup}$ | Scrap product cost (Unplanned replacement) | € |
| $C_{lup}$ | Loss of production cost (Unplanned replacement) | € |
| $C_{mup}$ | Manning cost (Unplanned replacement) | € |
| $C_{up}$ | Unplanned replacement cost | € |
| $C_U$ | Average cost per unit | € |
| $F(x)$ | Cumulative probability function of Weibull distribution | |
| $E(x)$ | Arithmetic mean of Weibull distribution | |
| α | Scale parameter of Weibull distribution | |
| Β | Shape parameter of Weibull distribution | |

**Table 2.** Replacement times obtained cost model

| Sample | Period | | | | | | |
|---|---|---|---|---|---|---|---|
| Number | 1 | 2 | 3 | … | 119 | 118 | 120 |
| 1 | 101 | 304 | 447 | … | 410 | 321 | 669 |
| 2 | 369 | 112 | 325 | … | 315 | 293 | 442 |
| 3 | 525 | 674 | 387 | … | 591 | 468 | 301 |
| 4 | 489 | 249 | 267 | … | 577 | 415 | 80 |
| 5 | 896 | 301 | 505 | … | 385 | 329 | 612 |
| … | … | … | … | … | … | … | … |
| 26 | 544 | 495 | 491 | … | 448 | 484 | 382 |
| 27 | 488 | 594 | 125 | … | 443 | 381 | 630 |
| 28 | 985 | 798 | 293 | … | 617 | 550 | 451 |
| 29 | 222 | 459 | 544 | … | 407 | 662 | 548 |
| 30 | 720 | 229 | 287 | … | 631 | 236 | 378 |
| Maximum | 985 | 798 | 621 | … | 765 | 791 | 707 |
| Minimum | 101 | 112 | 125 | … | 248 | 236 | 80 |
| Mean | 455 | 377 | 425 | … | 488 | 468 | 437 |
| Standard Deviation | 234 | 175 | 123 | … | 118 | 130 | 151 |

**Table 3.** Parameter settings for GA

| Setting type | Value |
|---|---|
| Encoding Scheme | Double vector |
| Population Size | 500 |
| Evolution Generation | 50 |
| Selection | Roulette Wheel |
| Crossover | One Point |
| Mutation | Uniform |
| Crossover Probability (Pc) | 0.6 |
| Mutation Probability (Pm) | 0.01 |
| Generations | 100 |

**Table 4.** The utilised ANN training algorithms in this study

| Abbreviation | Algorithm | Description |
|---|---|---|
| CGF | traincgf | Fletcher-Powell Conjugate Gradient |
| CGP | traincgp | Polak-Ribiére Conjugate Gradient |
| GD | traingd | Gradient Descent |
| GDA | traingda | Gradient Descent with Adaptive Learning Rate |
| GDX | traingdx | Gradient Descent with Variable Learning Rate |
| LM | trainlm | Levenberg-Marquardt |
| RP | trainrp | Resilient Backpropagation |

**Table 5.** Performance results of training algorithms

| Training algorithm | $R^2$ | | | |
|---|---|---|---|---|
| | Training | Validation | Test | All |
| CGF | 0.803 | 0.933 | 0.774 | 0.817 |
| CGP | 0.845 | 0.733 | 0.719 | 0.823 |
| GD | 0.837 | 0.750 | 0.806 | 0.817 |
| GDA | 0.857 | 0.935 | 0.789 | 0.872 |
| GDX | 0.939 | 0.953 | 0.943 | 0.943 |
| LM | 0.935 | 0.924 | 0.884 | 0.924 |
| RP | 0.920 | 0.931 | 0.904 | 0.910 |

CGF: Fletcher-Powell Conjugate Gradient CGP: Polak-Ribiére Conjugate Gradient GD: Gradient Descent
GDA: Gradient Descent with Adaptive Learning Rate GDX: Gradient Descent with Variable Learning Rate
LM: Levenberg-Marquardt RP: Resilient Backpropagation

**Table 6.** Results of ANN performance for different number of layer

| Number of layer | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Training $R^2$ | 0.939 | 0.307 | 0.935 | 0.691 | 0.762 |
| Validation $R^2$ | 0.953 | 0.163 | 0.955 | 0.671 | 0.904 |
| Test $R^2$ | 0.943 | 0.283 | 0.863 | 0.773 | 0.542 |
| All $R^2$ | 0.943 | 0.268 | 0.927 | 0.677 | 0.738 |

$R^2$ : Coefficient of determination

**Table 7.** Parameters values of the neural network model

| Setting Type | Value |
|---|---|
| Network type | Feed-forward backpropagation |
| Training function | Levenberg-Marquardt |
| Learning rate | 0.4 |
| Momentum rate | 0.7 |
| Total function | Weighted sum |
| Transfer function | Tansig |
| Number of neuron | 10 |

**Table 8.** Inputs and outputs of models

| | | 1 | 2 | 3 | … | 119 | 118 | 120 |
|---|---|---|---|---|---|---|---|---|
| Input | α –scale | 516,33 | 404,94 | 447,94 | … | 609,15 | 517,34 | 486,24 |
| | β-shape | 2,0521 | 2,2522 | 4,0334 | … | 4,5544 | 2,7818 | 3,1617 |
| Output | Cost model | 325 | 245 | 269 | … | 374 | 301 | 283 |
| | Hybrid ANN-GA | 323 | 220 | 276 | … | 376 | 302 | 288 |
| | GA | 326 | 175 | 260 | … | 378 | 305 | 286 |
| | ANN | 248 | 200 | 234 | … | 286 | 260 | 245 |

**Table 9.** Performance comparison of models

| Model | $R^2$ | RMSE | MAPE |
|---|---|---|---|
| Hybrid ANN-GA | 0.943 | 9.1240 | 2.5280 |
| GA | 0.908 | 14.760 | 2.9450 |
| ANN | 0.799 | 45.654 | 16.389 |

$R^2$: Coefficient of determination MAPE: Mean absolute percentage error RMSE: Root mean square error

## Technical Biography of Each Author

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