International Journal of Industrial Engineering & Production Research (2018)

International Journal of Industrial Engineering & Production Research

March 2018, Volume 29, Number 1
pp. 79- 90

DOI: 10.22068/ijiepr.29.1.79 http://IJIEPR.iust.ac.ir/

Availability Prediction of the Repairable Equipment using Artificial Neural Network, EWMA, AR, MA and ARMA Models

Hiwa Farughi*, Ahmad Hakimi and Reza Kamranrad

Hiwa Farughi, *Department of Industrial Engineering, University of Kurdistan Sanandaj*
Ahmad Hakimi, *Department of Industrial Engineering, University of Kurdistan Sanandaj*
Reza Kamranrad, *Department of Industrial Engineering, University of Science and Culture, Tehran*

KEYWORDS

Availability,
prediction,
artificial neural network,
exponentially weighted moving average,
time series model.

ABSTRACT

Availability is considered one of the most important criteria in public services quality. In this study, this criterion is evaluated using artificial neural network (ANN). In addition, availability values for future periods are predicted using exponential weighted moving average (EWMA) scheme and several time series models (TSM) including autoregressive (AR), moving average (MA), and autoregressive moving average (ARMA). Results obtained through the comparison of four methods based on ANN, considering several conditions for the effective parameters in ANN, show that the generalized regression method is the best method for predicting availability compared to other existing methods. Furthermore, results obtained from EWMA method and the three aforementioned TSMs demonstrate that MA model outperforms other models in predicting the availability values in future periods.

1. Introduction

Availability is a useful criterion to evaluate the performance of repairable systems. In any random moment of time, these systems are either working or disabled due to failure, which immediately repaired and restored to operational status in the least possible time. In this scope, a system is considered only in two possible statuses of working or being under repair. In other words, availability is the combination of two parameters of reliability and maintainability [1]. In this paper, the availability prediction of a system using ANN is proposed. To this end, several related studies concerning availability and reliability scopes and application of ANN to the maintenance are discussed.

Kiurghian et al. evaluated the systems with random failure and repairable parts [2]. Manzini et al. proposed a probabilistic function for unrepairable equipment and introduced the equivalent quality for parts and repairable systems [3].

The effectiveness of maintenance can be measured by several approaches, which are proposed in the study of Samat et al. paper. They proposed economical, technical, strategic and value-based approaches to maintenance concept [4]. Karbasian et al. improved the reliability of automatic manufacture systems using fault tree analysis (FTA) technique. In addition, they compared the results of FTA with two existing methods, including failure mode and effect analysis (FMEA), revealing the incorrect performance states (modes) [5]. Seyyed Esfahani

* Corresponding author: *Hiwa Farughi*

Email: h.farughi@uok.ac.ir

Received 5 August 2017; revised 4 December 2017; accepted 26 December 2017

proposed human resources scheduling based on machines maintenance planning and human reliability level. In this research, a mixed integer nonlinear model is proposed to schedule maintenance of machines and the rest of human resources based on reliability index in order to minimize cost of machines, idleness of human resources idleness, and cost of products quality [6]. Fattahi abd Ismailnezhad proposed a stochastic formation of manufacturing cell using queuing theory and reliability and solved this Np-hard problem by using two metaheuristic algorithms, including genetic and modified particle swarm optimization (MPSO) algorithms [7]. Jamshidi proposed a mathematical model that obtains the optimal work-rest schedule for humans based on fatigue-recovery models and the optimal maintenance policy for machines based on reliability level [8]. Karbasian et al. analyzed the input reliability of dynamic positioning system of a submarine considering common cause failures (CCF) with the aid of PBS and FFBD techniques. In addition, they allocated the above-mentioned reliability to the aid of a RBD [9]. Arabi et al. developed a new model for availability optimization applied to a series-parallel system using a Markovian process. In this research, the number of maintenance resources is located into the objective model under constraints, such as cost, weight, and volume [10]. In the following, the application of the ANN in the maintenance scope is discussed.

Liang et al. proposed a new scheme to predict the reliability of repairable systems by applying a combined model with two ANN and genetic algorithms [11]. Herzog et al. used the ANN method to predict the remaining life time of the machines and their parts. They improved capability prediction of the ANN using the situation monitoring data from the water pomp. Finally, they employed the multi-layer perceptron neural network (NN) based on the trained Lonberg-Marcuet algorithm to predict the remaining lifetime of the pomp [12]. Bahmanyar and Karami presented the stability voltage of power system using ANN with reduced setting of inputs [13]. Mayadevi et al. proposed a new technique to predict failure in powerhouse. They believed that powerhouse equipment should be monitored to prevent the disturbing failures of the availability. Hence, in this research, they used on-line monitoring technology with hybrid prediction techniques, including data mining, failure models, clustering and time series analyses, to predict the failure of powerhouse equipment [14]. A novel approach to failure prediction of robots based on ANN was proposed in the study of Diryag et al. using the perceptron neural network [15]. Raptisa et al. proposed a method to assess the power quality in the electrical network site using ANN. The main advantage of this method is implementation of fuzzy model on predicting the failure [16].

Ervural et al. proposed a forecasting method by integrating Genetic algorithms (GA) and Autoregressive Moving Average method to take advantages of the unique strength of ARMA and genetic algorithms model. The proposed method was applied to predict the consumption of natural gas in İstanbul, which is considered as the most important metropolitan city in Turkey, with a lower percentage error and greater sensitivity based on penalty function. According to the experimental results, the developed combined approach is more robust and outperforms classical ARMA models in terms of mean absolute percentage error (MAPE) and cost function values [17].

Forecasting solar irradiance is a key feature in increasing the penetration rate of solar energy inside the energy grids. Time series of solar irradiance and, more specifically, of clear sky index indicate a number of similarities to that of financial time series. David et al. assessed the performances of a commonly used combination of two linear models (ARMA and GARCH) in the context of econometrics in order to provide probabilistic forecasts of solar irradiance. In addition, they proposed a recursive estimation of the parameters of the models in order to provide a framework which could be easily applied in an operational context [18].

Wang et al. presented two new methods to estimate the observed noise variance accurately. In the first method, the lower lags of the auto-covariance function are used to estimate the observed noise variance with high estimation accuracy; however, it is valid only when the AR order is greater than the MA order. In the second method, the ARMA model is approximated as a high-order AR model so that it is effective even though the AR order is equal to or less than the MA order. They argued that if the observed noise variance is too small, its estimation error might become too large to validate the estimation [19].

Zheng and Chen proposed Dirichlet ARMA models for compositional time series. To this end, a new class of models was proposed by assuming that the proportions follow a time-varying Dirichlet distribution. Moreover, they assumed that, after a proper transformation, the corresponding time-varying parameters have

ARMA-type dynamic structure. This model was called the Dirichlet autoregressive moving average (DARMA) model [20].

Klepsch et al. presented an approximating vector model, based on functional PCA, for a functional ARMA(p,q) process. In addition, sufficient conditions were given for the existence of a stationary solution to both the functional and the vector model equations, and the structure of the approximating vector model was investigated. Furthermore, they used the stationary vector process to predict the functional process, where bounds for the difference between vector and functional best linear predictor are given. Finally, functional ARMA processes were applied to the modelling and prediction of highway traffic data [21].

In this paper, new approaches to predicting the availability of public services are proposed. For this purpose, the input variables of NN for training and testing are collected and analyzed. In addition, an approach based on EWMA model is proposed to predict availability in some future periods after initial prediction using ANN.

The remainder of this paper is organized as follows: problem definition is presented in the next section. In section 3, new methods are proposed for predicting the availability of public services based on ANN, EWMA, and some TSMs. In addition, a numerical example based on a real case study is presented in section 4 to evaluate the application of the proposed methods. Finally, concluding remark is presented in section 5.

2. Problem Definition

This paper proposes new methods based on ANN to predict the availability of the public services with focus on public transformation. The main reasons for using the ANN are the existence of a number of effective environmental factors, which have not been necessarily specified, and vagueness of the relationship between these factors. Hence, a technique is required to recognize the relation between these factors. ANN can be an efficient tool for this aim. In addition, the Mont-Carlo simulation method is applied فخ random data generation based on real data sets collected in the public transformation scope. These data are defined as the input variable of ANN, and the target value is related to input variables. Another contribution of this paper is to apply some predicting models, including EWMA and AR, MA and ARMA, to predict the availability of the future periods. A time series is a sequence of measurement of the same variable(s) made over time [22].

3. The Proposed Methods

In this section, the ANN-based approaches and EWMA method for prediction of the availability of public service equipment are explained.

3-1. Availability modelling and computation

In the availability modelling, there are several models including Markov models, fault tree models, minimal cut-set method, Petri net and Mont-Carlo simulation. In this paper, the Mont-Carlo simulation is applied to generate data set (for more details, see [23]). Availability means the probability that a system or equipment is in the operational condition at time point . To this end, a system should not be in the breakdown condition or should be repaired at time point t. Hence, availability includes both reliability and reparability.

3-2. Appling the ANN to prediction

The novel innovations in engineering and other science branches are being encouraged concerning problems in which the instability, non-linearity, uncertainty and complexity play important roles. Presenting the solution to these problems requires the application of non-linear techniques. ANN is the most powerful technique among the existing techniques.

3-3. The ANN inputs

In this subsection, all the input variables for training of ANN with mathematical equations are introduced. These variables include mean time to failure (MTTF), mean time to repair (MTTR), mean time to preventive maintenance (MTTP), and mean down time (MDT) which are discussed in the following subsections:

3-3-1. Mean time to failure

MTTF represents the periods in which system is working and equipment can satisfy their performance expectations. The main points are the separation of the time to first failure (TTFF) and time between next failures (TBF). This is due to the fact that TTFF represents the potential reliability of equipment, whereas the TBF is influenced by many parameters including maintenance policies, accuracy and effectiveness of the perform maintenance activity, maintenance personnel skills, etc. [4]. In this paper, by conducting separate analysis of these time periods, the behavior of system failure is modelled in each time duration using statistical tools. MTTF is one of the systems reliability measuring indicators that should not be confused with the mean time between failures (MTBF). MTTF could be calculated by the following equation:

$$'TTF = \int_0^{\infty} tf(t)dt = \int_0^{\infty} R(t)dt, \qquad (1)$$

where R (t) represents the system reliability in time period of zero to infinity.

3-3-2. Mean time to repair

Maintenance activities, including preventive maintenance or corrective activities, are completed in accordance with components and involved subsystems in different times. Physical characteristics of components, level of personnel's maintenance skills, available maintenance equipment, etc. are effective factors affecting the required time to complete repair activities. Therefore, the completion time of maintenance activities, even for the same components and in the same conditions, might be different. Accordingly, the time of maintenance activities often follows a probability distribution such as Exponential, normal, log-normal, Weibull and Gamma.

MTTR is widely used in maintainability measurement. This measure calculates the required elapsed time to perform a maintenance activity by using the following equation. Note that repair times usually follow exponential, log-normal, and normal distribution.

$$MTTR = {\left(\sum_{i=1}^{k} \lambda_i \, CMT_i\right)}\Big/{\sum_{i=1}^{k} \lambda_i} \qquad (2)$$

where k represents the number of components or system parts. In addition, λ_i is a failure rate of each unit or part, and CMT_i is the required time to repair the i^{th} unit or part.

3-3-3. Mean time to preventive maintenance

In order to maintain the equipment in a specified performance level, performing preventive maintenance activities, including inspection, regulation, and calibration, is necessary. A suitable preventive maintenance planning plays a significant role in reducing the downtime of equipment and improving their performance. MPMT could be computed by the following equation:

$$MPMT = {\left(\sum_{i=1}^{m} FPM_i \times ETPMT_i\right)}\Big/{\sum_{i=1}^{m} FPM_i} \qquad (3)$$

where μ demonstrates the total number of preventive maintenance activities, and FPM_i represents the frequencies of the i^{th} maintenance activities.

3-3-4. Mean downtime

MDT denote the downtime including preventive maintenance, bureaucratic delays and logistic delay times. MDT is caused by the queue in the maintenance service process which is one of the most important factors in prolongation of the maintenance time. The aforementioned variables are introduced as ANN inputs. Note that another variable as a target variable is required for training the ANN. Since the main purpose of this study is to predict the system availability, the target variable can be calculated by the following equation:

$$T\arg et = \frac{MTTF + MTTR}{MTTF + MTTR + MPMT + MDT}. \qquad (4)$$

3-4. Fuzzy approach in waiting time analysis

Waiting time is an important and effective parameter for the equipment availability, in which the required data do not exist in the company. Hence, five experts' opinions are considered for collecting data. Due to the uncertain nature of the waiting time, the experts' opinions regarding the waiting time and corresponding weights are stated in the form of triangular fuzzy numbers. Because fuzzy numbers are defined as fuzzy sets, verbal expressions of experts concerning waiting time are stated as triangular fuzzy numbers.

3-4-1. Fuzzy delphi

In this method, experts are asked to express their opinions in order to form minimum possibility and maximum possibility values for the waiting time, as shown in the following notation:

$$\left(A_1^{(i)}, B_1^{(i)}, C_1^{(i)}\right) \quad i=1,\ldots,n$$

where i represents the i^{th} expert, and $A_1^{(i)}$, $B_1^{(i)}$ and $C_1^{(i)}$ are the minimum possibility value and maximum possibility value, respectively. In addition, "1" is the first stage in the estimation process. Since the experts' opinions look at different weights, the corresponding weights are expressed as fuzzy numbers shown by the following figure.

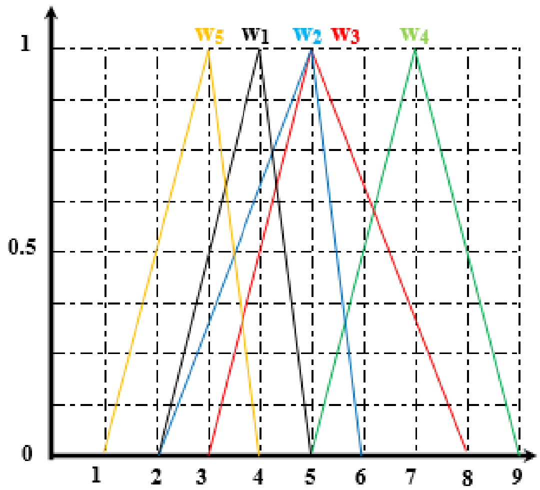

Fig. 1. Fuzzy show of the opinion weight

Each of the experts' opinion weights is presented by $\tilde{w}_i = (\tilde{w}_a^i, \tilde{w}_b^i, \tilde{w}_c^i)$. Accordingly, the average of each category of the experts' opinions is calculated by the following equation:

$$A_1^m = \frac{\sum_{i=1}^{5} A_1^{(i)} \tilde{w}_a^i}{\sum_{i-1}^{5} \tilde{w}_a^i}, \quad B_1^m = \frac{\sum_{i=1}^{5} B_1^{(i)} \tilde{w}_a^i}{\sum_{i-1}^{5} \tilde{w}_a^i}, C_1^m = \frac{\sum_{i=1}^{5} C_1^{(i)} \tilde{w}_a^i}{\sum_{i-1}^{5} \tilde{w}_a^i} \qquad (5)$$

In addition, the difference between the average categories for each expert are as follows:

$$\left(A_1^m - A_1^{(i)}, B_1^m - B_1^{(i)}, C_1^m - C_1^{(i)}\right) \qquad (6)$$

In this stage, each expert presents a new estimation according to the obtained information from afore-mentioned stage; if not appropriate, the previous opinion can be revised. When the average of the fuzzy number category is stable enough, the process ends.

3-4-2. DE-fuzzy process

Since, in many fuzzy modellings, output of fuzzy systems should be crisp values called defuzzification process, where the center of gravity method is widely used method defined in the following equation:

$$X^* = \frac{\int_a^b \mu(x).x \, dx}{\int_a^b \mu(x) dx} \qquad (7)$$

Note that after calculating the certain value of waiting time, this value is added to non-operating time as an input variable of NN. In other words, a fuzzy value will be added to non-operating time caused by maintenance time.

3-5. Time series models for predicting availability

Time series analysis comprises methods for analyzing time series data in order to extract meaningful statistics and other characteristics of the data. Time series forecasting is the use of a model to predict future values based on previously observed values. While regression analysis is often employed in such a way as to test theories whose current values of one or more independent time series affect the current value of another time series, this type of analysis of time series is not called "time series analysis". It mainly focuses on comparing values of a single time series or multiple dependent time series at different points of time. When modeling variations in the level of a process, three broad classes of practical importance are the autoregressive (AR) models, the integrated (I) models, and the moving average (MA) models. These three classes depend linearly on previous data points [24]. Combinations of these ideas produce autoregressive moving average (ARMA).

In this subsection, some TSMs are developed to predict the availability of repairable equipment based on three models: AR, MA, and optimal ARMA. In doing so, these models are stated as follows:

3-5-1. The AR model

This model is used for forecasting when there is a certain correlation between values in a time series. AR(p) model is an autoregressive model, and *p* is called the order and is defined as a "*p*th order autoregressive process". AR(p) model is defined by the following equation:

$$y_t = \delta + \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \ldots + \varphi_p y_{t-p} + A_t$$

where $y_1, y_2, \ldots, y_{t-p}$ are the past series values, and A_t is a white noise. In addition, δ is calculated by the following equation:

$$\delta = \left(1 - \sum_{i=1}^{p} \varphi_i\right)\mu,$$

where μ is the process mean. Note that, in this paper, value of availability for the first period is calculated by ANN-based models; then, AR model predicts the availability of future periods. Indeed, in this paper, the new combined ANN and AR model is developed to predict the availability of repair equipment.

3-5-2. The MA model

Instead of using past values of the forecast variable in an AR model, a moving average model applies past forecast errors as follows:

$$y_t = \mu + A_t + \theta_1 A_{t-1} + \theta_2 A_{t-2} + \ldots + \theta_q A_{t-q},$$

which is called MA (q) model. Note that each value of y_t can be considered as a weighted moving average of the past few forecast errors. Note that, in this paper, MA model is initially designed by ANN-based models' outputs and, then, the availability for future periods is predicted.

3-5-3. The ARMA model

ARMA model is the mixture of AR (p) and MA (q) models, which is often described by ARMA (p,q). These define the structure of the model in terms of the order of AR and MA models to be used. The general form of ARMA (p,q) is defined as follows:

$$y_t = \mu + \varphi_1 y_{t-1} + \ldots + \varphi_p y_{t-p} A_t - \theta_1 A_{t-1} - \ldots - \theta_q A_{t-q},$$

where all of the ARMA(p,q) model's parameters are defined in AR(p) and MA(q) models. It should be noted that ARMA (p,q) was first developed by the ANN-based models' outputs and, then, availability of the future periods is predicted. In addition, in this paper, all three TSM models are applied to predict the availability of repairable equipment. In the following, a real numerical example is used to show the efficiency of the proposed methods.

4. A Numerical Example Based on the Real Case

In this section, the performances of four ANN-based methods are evaluated using the four mentioned inputs and an output variable. First, Mont-Carlo simulation is used to generate data randomly based on correspondence probability distributions as an ANN input. Then, the ANN technique is applied to predict the availability of the public service system. Finally, the EWMA approach is used to predict the availability of the second and third future periods.

4-1. Mont-Carlo simulation's application to data generation

As mentioned, in this paper, four variables, including MTTF, MTTR, MTTP, and MDT, are selected as input variables of ANN. Note that, first, 62 real data are collected for each variable in the related unit. Then, statistical analysis is used to detect the distribution of each variable with the corresponding parameters. Finally, using Mont-Carlo simulation, 1000 samples are generated for each variable by considering the corresponding parameters by MATLAB software (See Figure 2).

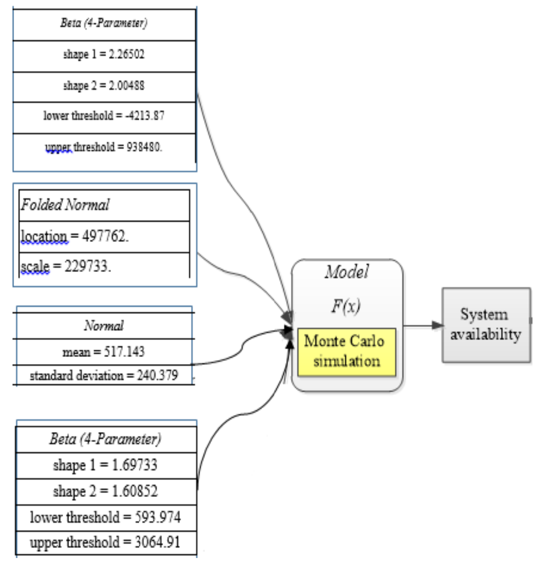

Fig. 2. Mont-Carlo simulation process

As can be seen from Figure 2, the first input variable follows *4-parameter Beta* distribution with two shape parameters equal to 2.26502 and 2.00488, respectively, and -4213.87 and 938480 for lower and upper thresholds. The second variable follows *Folded normal* distribution with 497762 and 229733 for location and scale parameters, respectively. In addition, the third variable follows *Normal* distribution with mean and standard deviation equal to 517.143 and 240.379, respectively. The forth variable also follows *4-parameter Beta* distribution with 1.69733 and 1.60852 for two shape parameters and 593.974 and 3064.91 for lower and upper thresholds, respectively. Note that data are generated by Matlab software. These distributions and the correspondence parameters are as follows:

$$\begin{aligned} &MTTF \sim Beta(2.26502, 2.00488, -4213.87, 938480) \\ &MTTR \sim FoldedNormal(497762, 229733) \\ &MPMT \sim Normal(517.143, 240.379) \\ &MDT \sim Beta(1.69733, 1.60852, 593.974, 3064.91) \end{aligned} \tag{8}$$

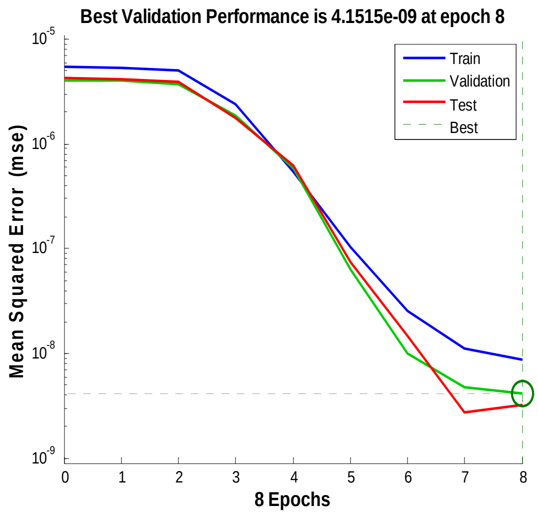

Fig. 3. Feed forward-backprop method with two layers and 10 neurons

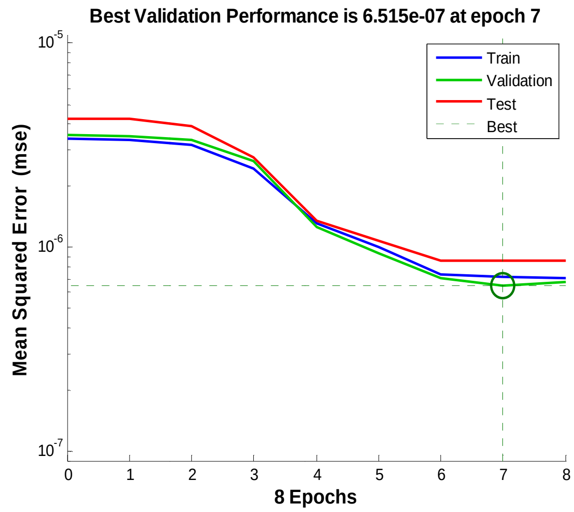

Fig. 5. Feed forward-backprop method with two layers and 15 neurons

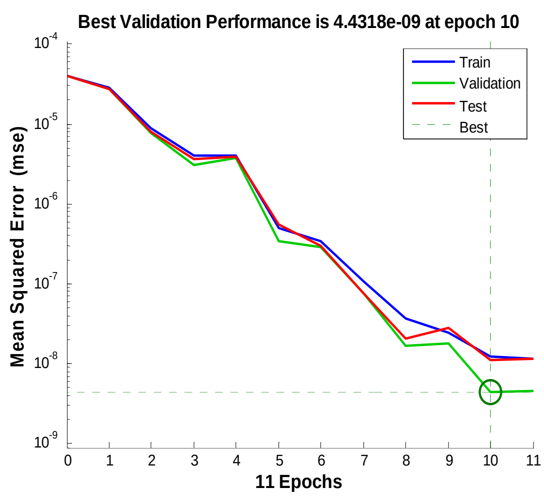

Fig. 4. NARX method with two layers and 10 neurons

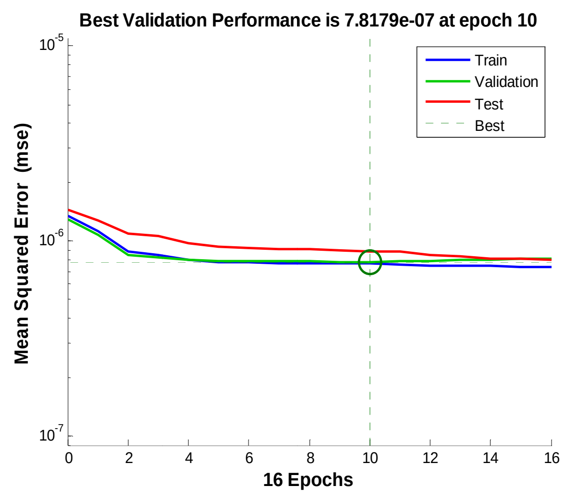

Fig. 6. NARX method with two layers and 15 neurons

Figures 3 and 4 show the number of epochs of training, validation, and testing for two Feed forward-backprop and NARX methods with two layers and 10 Neurons. Results state that Feed forward-backprop method achieves the convergence and suitable validation in shorter time rather than NARX method in terms of MSE; this is because the initial MSE for Feed forward-backprop is between 10^{-6} and 10^{-5}; however, the corresponding MSE for NARX is larger than 10^{-5}. This criterion shows that the initial error obtained by NARX method is greater than Feed forward-backprop. Note that the best validation of the two mentioned methods is obtained in 8 and 10 epochs.

Figures 5 and 6 show the number of epochs of training, validation and testing for two Feed forward-backprop and NARX methods with two layers and 15 neurons. Results state that Feed forward-backprop and NARX methods achieve the convergence and suitable validation in 8 and 16 epochs, respectively, in terms of MSE. In addition, the best validation of the two mentioned methods is obtained in 7 and 10 epochs, respectively. Results from Figures 3 to 6 also show that by increasing the number of neurons, the time of convergence increases; meanwhile, NARX needs more epochs to achieve the convergence and validation.

Note that, in four parameter's Beta distribution, the first two values are the shape and other two values are the boundary parameters, respectively. The

Beta-based data with four parameters are generated by the following equation:

$$X = L + (U - L) \times Beta\,(a,b) \qquad (9)$$

where L and U are the lower and upper bounds of the Beta distribution, respectively. In addition, a and b are also the shape parameters of the Beta distribution. For example, regarding the MTTF, L and U are -4213.87 and 938480, respectively. Furthermore, a and b are 2.26502 and 2.00488, respectively. Accordingly, 1000 random samples for each of four input variables are generated; consequently, 1000 target values have been calculated by Equation (9).

4-2. Results of the ANN

In this subsection, a comparative study between four methods, including Feed Forward-backprop, NARX, generalized regression, and Perceptron, is done. These comparisons are applied based on neuron number, different layers, and type of fitness (SSE or MSE); results are reported in Table 1.

Tab. 1. Comparative evaluation between four ANN-based methods based on Neuron and layer number

Fitness	Training time	Number of iteration	Criterion	Neuron number	Layer number	Method
4.1515e-9	0:00:00	11	MSE	10	2	Feed Forward-backprop
4.6128e-9	0:00:00	13		10	3	
1.6992e-8	0:00:00	12		10	5	
1.1553e-8	0:00:00	10		15	2	
2.6701e-8	0:00:00	8		20	2	
1.1016e-8	0:00:00	11		20	3	
5.4639e-8	0:00:03	66	SSE	10	2	
6.0358e-8	0:00:07	168		10	3	
2.9206e-8	0:00:04	88		15	2	
1.4707e-8	0:00:04	48		20	2	
9.1979e-9	0:00:03	102		20	3	
4.4318e-9	0:00:01	10	MSE	10	2	NARX
6.0385e-9	0:00:01	12		10	3	
1.3353e-8	0:00:01	10		15	2	
1.6943e-8	0:00:01	11		20	3	
1.0325e-7	0:00:02	50	SSE	10	2	
1.6430e-8	0:00:01	44		10	3	
8.5020e-7	0:00:02	34		15	2	
3.0215e-8	0:00:13	131		20	3	
2.2936e-3	0:28:31	1000	MSE	-	-	Perceptron
0.0000	0:00:00	-	SSE	-	-	Generalized Regression

Table 1 shows that the generalized regression has better performance than the other methods do. This is due to the fact that the fitness criterion obtained by generalized regression method is zero, which is less than the corresponding fitness values from three mentioned methods. The other priority of generalized regression is in the time of training, such that this item is much less than the other methods. In addition, results show that the perceptron method has an inappropriate performance in terms of both time of training and fitness criteria. Furthermore, in order to accurately clarify the evaluation of the test of NN, the performance charts are shown in Figures 3 to 6.

4-3. Prediction availability of the future periods

As mentioned in the previous sections, the aim of ANN is to predict the availability of public services. To this end, the best trained method is used to predict availability of the future periods. Due to the fact that the ANN has higher error in the period after the first period, in this paper, the EWMA and three TSMs are applied to make a more accurate prediction of availability in the second and third periods. For this purpose, first, the system availability in the first period (A_1) is predicted by ANN and, then, availability of the next periods is calculated by the following equation:

$$A_{t+1} = \lambda Y_{t+1} + (1-\lambda) A_t \quad (10)$$

where A_{t+1} is the availability of the (t+1)th period. In addition, λ and Y_{t+1} are the smoothing parameters of the ($0 \le \lambda \le 1$) and (t+1)th observations, respectively. Furthermore, the above equation shows that availability of each period is related to the previous period (A_t). Accordingly, the availability of the second and third periods can be calculated by the following equation:

$$\begin{aligned} A_2 &= \lambda Y_2 + (1-\lambda) A_1 \\ A_3 &= \lambda Y_3 + (1-\lambda) A_2 \end{aligned} \quad (11)$$

Hence, by using the best-proposed method (with minimum error), availability values of the second and third periods for different values of λ from 0.05 to 0.2 are predicted and reported in Table 2. In addition, EWMA model is designed by ANN-based models' outputs for the first periods and, then, the availability for future periods is predicted. Note that, in this paper, AR(2), MA(2), and ARMA (2,2) models are applied to predict availability of repairable equipment. To this end, Minitab software is used to estimate the coefficients of each TSM, and results are stated in the following equations:

AR(2):

$$y_t = -0.0331 + 0.0013\, y_{t-1} + 1.0287\, y_{t-2} \quad (12)$$

MA(2):

$$y_t = 0.0320 + A_t + 0.0012 A_{t-1} + 0.9970\, A_{t-2} \quad (13)$$

ARMA(2,2)

$$\begin{aligned} y_t &= -1.4456 - 0.9721\, y_{t-1} - 1.4260\, y_{t-2} \\ &- A_t - 0.9673\, A_{t-1} - 3.4078\, A_{t-2} \end{aligned} \quad (14)$$

Tab. 2. The predicted values of availability for the first, second and third periods

Model	λ	Availability values	Method			
			Feedforward-backprop	NARX	Generalized Regression	Perceptron
EWMA	0.05	A_1	0.99694	0.99696	0.99577	1.00000
		A_2	0.9969	0.9970	0.9958	0.9998
		A_3	0.9969	0.9969	0.9958	0.9996
		SSE	0.2011e-5	0.2064e-5	0.1315e-5	0.0263e-3
	0.10	A_1	0.99694	0.99696	0.99577	1.00000
		A_2	0.9969	0.9970	0.9959	0.9997
		A_3	0.9968	0.9968	0.9959	0.9993
		SSE	0.3814e-5	0.3911e-5	0.2534e-5	0.0484e-3
	0.15	A_1	0.99694	0.99696	0.99577	1.00000
		A_2	0.9969	0.9970	0.9960	0.9995
		A_3	0.9967	0.9967	0.9959	0.9989
		SSE	0.5419e-5	0.5554e-5	0.3659e-5	0.0673e-3
	0.20	A_1	0.99694	0.99696	0.99577	1.00000
		A_2	0.9969	0.9970	0.9961	0.9994
		A_3	0.9966	0.9967	0.9959	0.9986
		SSE	0.6838e-5	0.7005e-5	0.4695e-5	0.0833e-3
TSM	AR	A_1	0.99694	0.99696	0.99577	1.00000
		A_2	0.997069	0.997068	0.997107	0.996974
		A_3	0.997063	0.997063	0.997059	0.997072
		SSE	2.7952E-06	2.80E-06	2.7956E-06	2.8023E-06
	MA	A_1	0.99694	0.99696	0.99577	1.00000
		A_2	0.997065	0.997065	0.997104	0.996970
		A_3	0.997063	0.997064	0.997063	0.997062
		SSE	2.7955E-06	2.80E-06	2.8093E-06	2.7699E-06
	ARMA	A_1	0.99694	0.99696	0.99577	1.00000
		A_2	0.997100	0.997100	0.997123	0.997042
		A_3	0.997133	0.997134	0.997104	0.997206
		SSE	3.0465E-06	3.05E-06	2.9547E-06	3.2855E-06

Table 2 shows the predicted values of availability for the first, second, and third periods using EWMA and TSM based on four NN methods in Matlab software. Results show that the generalized regression has higher efficiency than the other proposed methods in predicting the availability with both EWMA and TSMs. This is because the SSE of generalized method is lower than the other methods under different values of λ and also for three mentioned TSMs. In addition, the perceptron method has a weaker performance to predict the availability in terms of SSE in both EWMA and TSM algorithms. Also, results show that each model from TSM has better performance than EWMA method in terms of SSE for predicting availability.

5. Conclusion and Future Researches

In this paper, an ANN-based approach, EWMA and TSMs were proposed to evaluate and predict the availability of the public services by considering the impact of environmental parameters, not necessarily specified. According to the real study, four variables, including MTTF, MTTR, MPMT, and MDT, were considered for training and modeling the ANN-based approach. In addition, waiting times corresponding to weights are stated as triangular fuzzy numbers. Results show the suitable efficiency of the ANN-based methods in predicting of the availability for the first and future periods. Furthermore, comparative studies showed that TSMs-based models (i.e., AR, MA, and ARMA) had better performance than EWMA-based model in all four ANN-based methods (i.e., Feed forward-backprop, NARX, Perceptron, and generalized regression). This is because of the fact that TSM models could establish a better relationship between future and past availabilities. Hence, managers of public services could consider our proposed methods in their decision-making in order to improve service quality. As a future research, developing the proposed methods to an integrated criterion for reliability, availability, and maintainability can be investigated. In addition, due to the seasonality of failures in this paper, comparing the proposed prediction method with ARIMA and SARIMA can be an interesting field of study for other researches.

Acknowledgments

A special thanks to the staff of the technical office of Sazeh Pouyesh Co. in Tehran for their kind cooperation. Also, thanks to Mrs. Mohammadi for the help she provided in the gathering information.

References

[1] Pham, H., DOD guide for archiving Reliability, Availability, and maintainability, System engineering for Mission Success, Handbook of Reliability Engineering, Springer, (2003).

[2] Kiureghian, A., Ditlevsen, O., Song, J., "*Availability, reliability and downtime of systems with repairable components'*, Reliability Engineering and System Safety, Vol.12, No.92, (2007), pp. 231–242.

[3] Manzini, R., Regattieri, A., Pham, H., Ferrari, E., Maintenance for Industrial Systems, Springer series in Reliability Engineering, (2010).

[4] Samat, H.A., Kamaruddin, S., and Azid, I.A., "*Maintenance Performance Measurement: A Review*", Pertanika J. Sci. & Technol. Vol.2, No.19, (2011), pp. 199– 211.

[5] Karbasian, M., Rostami Mehr, M., Agharajabi, M., "*Improvement of the Reliability of Automatic Manufacture Systems by Using FTA Technique*", International Journal of Industrial Engineering, Vol. 23, No.2, (2012), pp. 85-89.

[6] Jamshidi, R. & Seyyed Esfahani, M. M., "*Human Resources Scheduling Based on Machines Maintenance Planning and Human Reliability Level*". International Journal of Engineering Science, Vol. 26, No. 1, (2015), pp. 2008-4870.

[7] Fattahi, P., & Ismailnezhad, B., "*Formation of manufacturing cell using queuing theory and considering reliability*", International Journal of Industrial Engineering & Production Research, Vol. 27, No .2, (2016), pp. 121-139.

[8] Jamshidi, R., "*Maintenance and work-rest scheduling in Human-machine system according to fatigue and reliability*", International Journal of Industrial Engineering & Production Research, Vol. 27, No .3, (2016), pp. 263-272.

[9] Karbasian, M., Eghbali Babadi, A., Hasani, F., "*Calculation and Analysis of Reliability with Consideration of Common Cause Failures (CCF)(Case Study: The Input of the*

Dynamic Positioning System of a Submarine)", International Journal of Industrial Engineering & Production Research, Vol. 28, No. 2, (2017), pp. 175-187.

[10] Yahyatabar Arabi, A., A. Eshraghniaye Jahromi, A., Shabannataj, M., "*Developing a New Model for availability Optimization Applied to a Series-Parallel System*", International Journal of Industrial Engineering, Vol. 24, No.2, (2013), pp. 101-106.

[11] Liang, Y., "*Combining neural networks and genetic algorithms for predicting the reliability of repairable systems*", International Journal of Quality&Reliability Management, Vol.3, No.25, (2008), pp. 201-210.

[12] Herzog, M.A., Marwala, T., Heyns, P.S., "*Machine and component residual life estimation through the application of neural networks*", Reliability Engineering and System Safety Vol.14, No.94, (2009), pp. 479– 489.

[13] Bahmanyar, A.R., Karami, A., "*Power system voltage stability monitoring using artificial neural networks with a reduced set of inputs*", Electrical Power and Energy Systems Vol.20, No.58, (2014), pp.246-256.

[14] Mayadevi, N., Vinodchandra, S., Ushakumari, S., "*Failure Forecast Engine for Power Plant Expert System Shell, Advanced Communication Control and Computing Technologies*', IEEE International Conference, (2012).

[15] Diryag, A., Mitic´, M., Miljkovic, Z., "*Neural networks for prediction of robot failures*", Mechanical Engineering Science, Vol.36, No.228, (2014), pp.1444-1458.

[16] Raptisa, T.E., Vokas, G.A., Langouranis, P.A., Kaminaris S.D., Total Power Quality Index for Electrical Networks Using Neural Networks, Energy Procedia, (2015).

[17] Ervural, B.C., Beyca, O.F., Zaim, S., "*Model Estimation of ARMA Using Genetic Algorithms: A Case Study of Forecasting Natural Gas Consumption*". Procedia-Social and Behavioral Sciences, Vol. 235, (2016), pp. 537-545.

[18] David, M., Ramahatana, F., Trombe, P.J., Lauret, P.,"*Probabilistic forecasting of the solar irradiance with recursive ARMA and GARCH models*", Solar Energy, Vol.133, (2016), pp.55-72.

[19] WANG, K., Wu, Y., Gao, Y., Li, Y., "*New methods to estimate the observed noise variance for an ARMA model*". Measurement, Vol.99, (2017), pp.164-170.

[20] Zheng, T., Chen, R., "*Dirichlet ARMA models for compositional time series*", Journal of Multivariate Analysis, Vol. 158, (2017), pp. 31-46.

[21] Klepsch, J., Kluppelberg, C., Wei, T., "*Prediction of functional ARMA processes with an application to traffic data*". Econometrics and Statistics, Vol.1, (2017), pp.128-149.

[22] Brockwell, P.J., Davis, R.A., Introduction to time series and forecasting, springer text in statistics, 3rd edition, (2016).

[23] Bauer, E., Zhang, X., Kimber, D.A., Practical System Reliability, John Wiley & Sons, Ltd, (2009).

[24] Gershenfeld, N.A., The Nature of Mathematical Modeling, New York: Cambridge University Press. (1999).

Follow This Article at The Following Site

farughi H, hakimi A, kamranrad R. Availability Prediction of the Repairable Equipment using Artificial Neural Network and Time Series Models. IJIEPR. 2018; 29 (1) :79-90
URL: http://ijiepr.iust.ac.ir/article-1-778-en.html