

Evrencan ÖZCAN
Tuğba DANIŞAN
Rabia YUMUŞAK
Tamer EREN

AN ARTIFICIAL NEURAL NETWORK MODEL SUPPORTED WITH MULTI CRITERIA DECISION MAKING APPROACHES FOR MAINTENANCE PLANNING IN HYDROELECTRIC POWER PLANTS

PLANOWANIE UTRZYMANIA RUCHU W ELEKTROWNIACH WODNYCH W OPARCIU O MODEL SZTUCZNEJ SIECI NEURONOWEJ WSPARTY WIELOKRYTERIALNYMI METODAMI PODEJMOWANIA DECYZJI

Power plants are the large-scale production facilities with the main purpose of realizing uninterrupted, reliable, efficient, economic and environmentally friendly energy generation. Maintenance is one of the critical factors in achieving these comprehensive goals, which are called as sustainable energy supply. The maintenance processes carried out in order to ensure sustainable energy supply in the power plants should be managed due to the costs arising from time requirement, the use of material and labor, and the loss of generation. In this respect, it is critical that the fault dates are forecasted, and maintenance is performed without failure in power plants consisting of thousands of equipment. In this context in this study, the maintenance planning problem for equipment with high criticality level is handled in one of the large-scale hydroelectric power plants that meet the quintile of Turkey's energy demand as of the end of 2018. In the first stage, the evaluation criteria determined by the power plant experts are weighted by the Analytical Hierarchy Process (AHP), which is an accepted method in the literature, in order to determine the criticality levels of the equipment in terms of power plant at the next stage. In order to obtain the final priority ranking of the equipment in terms of power plant within the scope of these weights, Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is used because of its advantages compared to other outranking algorithms. As a result of this solution, for the 14 main equipment groups with the highest criticality level determined on the basis of the power plant, periods between two breakdowns are estimated, and maintenance planning is performed based on these periods. In the estimation phase, an artificial neural network (ANN) model has been established by using 11-years fault data for selected equipment groups and the probable fault dates are estimated by considering a production facility as a system without considering the sector for the first time in the literature. With the plan including the maintenance activities that will be carried out before the determined breakdown dates, increasing the generation efficiency, extending the economic life of the power plant, minimizing the generation costs, maximizing the plant availability rate and maximizing profit are aimed. The maintenance plan is implemented for 2 years in the power plant and the unit shutdowns resulting from the selected equipment groups are not met and the mentioned goals are reached.

Keywords: Artificial neural networks, hydroelectric power plants, failure period estimation, maintenance planning, AHP, TOPSIS.

Elektrownie to zakłady produkcyjne o dużej skali, których głównym celem jest nieprzerwane, niezawodne, wydajne, rentowne oraz przyjazne dla środowiska wytwarzanie energii. Utrzymanie ruchu stanowi jeden z kluczowych czynników pozwalających na osiągnięcie tych szeroko zakrojonych celów, które określa się wspólnym mianem zrównoważonych dostaw energii. W elektrowniach, procesami utrzymania ruchu, realizowanymi w celu zapewnienia zrównoważonych dostaw energii, zarządza się z uwzględnieniem kosztów związanych z wymogami czasowymi, kosztów materiałów i robocizny oraz strat wytwarzania energii. Ponieważ elektrownie wykorzystują tysiące różnych urządzeń, niezwykle ważne jest prognozowanie dat wystąpienia uszkodzeń oraz zapewnienie bezawaryjnego utrzymania ruchu. W przedstawionych badaniach, rozważano problem planowania utrzymania ruchu sprzętu o wysokim poziomie krytyczności na przykładzie jednej z dużych elektrowni wodnych, która na koniec 2018 r. pokrywała jedną piątą zapotrzebowania Turcji na energię elektryczną. W pierwszym etapie badań, kryteria oceny określone przez ekspertów zatrudnionych w elektrowni ważono za pomocą powszechnie stosowanej w literaturze metody procesu hierarchii analitycznej (AHP) w celu ustalenia poziomów krytyczności poszczególnych elementów wyposażenia elektrowni. Aby opracować ostateczny ranking priorytetowości elementów wyposażenia elektrowni na podstawie określonych wcześniej wag, zastosowano technikę TOPSIS, która polega na porządkowaniu preferencji na podstawie podobieństwa do idealnego rozwiązania. Techniki tej użyto ze względu na jej zalety, których nie mają inne algorytmy oparte na relacji przewyższania (ang. outranking algorithms). Na podstawie wyników otrzymanych dla 14 głównych grup urządzeń o najwyższym poziomie krytyczności, określonym na podstawie danych pochodzących z elektrowni, oszacowano czasy pomiędzy dwiema awariami, a na ich podstawie zaplanowano działania konserwacyjne. W fazie szacowania, opracowano model sztucznej sieci neuronowej (ANN) w oparciu o dane o uszkodzeniach, które wystąpiły w ostatnich 11 latach działania elektrowni, dla wybranych grup urządzeń. Przewidywane daty wystąpienia uszkodzeń szacowano, po raz pierwszy w literaturze, biorąc pod uwagę zakład produkcyjny jako system, bez uwzględnienia sektora

produkcyjnego. Plan obejmuje działania konserwacyjne, które mają być przeprowadzone przed przewidywanymi datami awarii, w celu zwiększenia wydajności wytwarzania energii, przedłużenia żywotności elektrowni, minimalizacji kosztów wytwarzania energii, maksymalizacji wskaźnika dostępności elektrowni oraz maksymalizacji zysków. Opracowany plan konserwacji wdrażano w omawianej elektrowni przez 2 lata. W tym okresie nie odnotowano przerw w pracy jednostek wytwórczych spowodowanych awarią rozważanych grup urządzeń, co oznacza, że wspomniane cele zostały osiągnięte.

Słowa kluczowe: sztuczne sieci neuronowe, elektrownie wodne, szacowanie czasu między uszkodzeniami, planowanie utrzymania ruchu, AHP, TOPSIS.

1. Introduction

In today's conditions where competition is increasing, enterprises need to increase their profitability in order to ensure their continuity in their activities or to include plans aimed at minimizing the total cost resulting from these activities. These plans are of great importance in order to manage the operational activities that can be classified under the titles of production, personnel, material and maintenance in a systematic and effective manner. Especially in order to realize these targets, it is critical that the machinery, equipment and devices in the production facilities perform the expected functions in a timely, uninterrupted, high quality and reliable manner. In this respect, planning of the maintenance activities contributes greatly to the effective management of the other three main processes (production, personnel and material), while systematic management of maintenance planning activities plays an important role in achieving improvements in operational efficiency.

Besides contributions provided by the mentioned maintenance planning activities, it is necessary to optimize all the costs in accordance with the operating conditions as maintenance costs can reach 15-70% of the various production costs varying according to the type of operation [11]. According to the most commonly used method, maintenance cost is composed of labor, spare parts and service costs which are spent for maintenance [19]. In case of stoppages caused by malfunction or any maintenance application in the enterprise, the losses for each time period in which production cannot be realized should be considered as cost and included in the management process. The most important point to be considered here is the monitoring, inspection and follow-up taking them under control of maintenance performance parameters such as the mean time between failures (MTBF), failure stop rate (FSR) and fault repair time (FRT). Recording the data in which the maintenance performance indicators are mentioned in the maintenance practices realized by the enterprises is one of the important factors that will contribute to this process.

At the same time, hydroelectric power plants are critical with about one fifth share in Turkey's energy mix [21]. Therefore, a large-scale hydroelectric power plant in Turkey is selected as application field, and this plant has 6,111 equipment. It is not possible to carry out maintenance so many equipment in terms of continuity of generation and minimization of the costs. In fact, every equipment in the power plant does not directly affect sustainable energy generation. In other words, the level of impact of equipment on sustainable energy supply can be expressed as the level of risk (criticality level) of equipment in terms of power plant. For this reason, prioritization of maintenance activities according to criticality levels of equipment would not be deviated the power plant from its sustainable energy supply goal but would serve this comprehensive purpose. Furthermore, considering that the purpose of the maintenance is to extend the time of the fault-free operation of the equipment, it will be possible for an equipment to reach this goal in the most appropriate way (especially in terms of cost efficiency) by the maintenance before the possible downtime. From this point of view in this study, a new maintenance planning methodology is proposed for the efficient maintenance management and hence an efficient power plant management, which includes the maintenance performance indicators in a big-scale hydroelectric power

plant with the aim of achieving continuous, reliable, efficient, economic and environmentally friendly electricity generation [58].

First, 9 criteria which affect the criticality level of the equipment in the power plant are weighted by AHP, and the obtained weights are used in TOPSIS algorithm for calculating the risk levels of equipment in terms of sustainable energy supply in the power plant. It is determined that 14 equipment groups have the maximum risk level in this ranking obtained for 6,111 equipment. This calculation is consistent with real life in terms of threatening the uninterrupted, reliable, efficient, economic and environmentally friendly power generation when 14 equipment groups fail. Then, an ANN model is established by using 11-years fault data including maintenance performance indicators for selected equipment groups and possible fault dates are estimated, and maintenance schedule is based on the estimated date of the failure for each equipment for the first time in the literature. As a result of the implementation of this schedule in the power plant for 2 years, the generation stoppages resulting from the lack of maintenance in the selected equipment groups are reduced by 100%. In addition, increasing the generation efficiency, extending the economic life of the power plant, minimization of generation costs, maximization of power plant availability and profit maximization are achieved.

In the second section of the study, the studies in literature about the problem in a broad perspective are included. In the third section, the methods used in the study are given with use case and the application phase is described in section 4. The study is completed with section 5 where the results and recommendations are presented.

2. Related literature

Multi-Criteria Decision Making (MCDM) is an approach that makes decision-making more effective when there are often conflicting and/or related, qualitative and quantitative criteria [31]. The fact that the problem parameters are qualitative or quantitative in the decision-making process and that these parameters should be evaluated together make the MCDM a practical and comprehensive evaluation strategy. For this reason, in many studies in the literature, many MCDM methods, such as AHP [33,39,77], Analytic Network Process (ANP) [73], TOPSIS [10], ELimination Et Choix Traduisant la REalité (ELECTRE) [24], Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) [9] and Vlsekriterijumska Optimizacija I KOmpromisno Resenje (VIKOR) [26] are used in different problem areas such as location [36], project [44,66], staff [4], supply chain [81] and strategy selection [15], and health applications [47]. Furthermore, energy related decision-making problems have also intrinsically multiple criteria structures and therefore, analytical approaches for effective solutions for these problems are needed. In this context and within the frame of the advantages of MCDM stated above, this approach provides effective results in solving many problems related with energy. Especially, the reviews performed by Mardani et al. [50] and Kumar et al. [40] have proved the importance of the MCDM to be very important for the problems in energy related studies. Another point that is noteworthy is that the usage of method combinations composed of one more than techniques under MCDM approach for problem solving have enabled us to receive effective results. For example, Zyoud and Fuchs-Hanusch [92] have proved that the studies in which AHP and TOPSIS which are also used in

this study are integrated, are more effective than the separate usage of the methods. The studies performed by Özcan et al. [58] and Kumar et al. [41] in the hydroelectric power plants, and Sindhu et al. [72] in the solar power plant are the important studies that integrate these two methods. In this study, the solution is started with AHP method due to the subjectivity reduction, ease of application, widespread use and flexibility of integration with linear programming, fuzzy logic and especially sorting algorithms [39,77,82]. In the second phase, the TOPSIS method is preferred because of the easy and effective way to perform the alternative ranking [10]. Another method used in the study, the ANN is used together with these MCDM methods in a few studies in the literature [8,42,76,84]. Today, ANN frequently encountered among artificial intelligence methods such as fuzzy logic, genetic algorithms etc. is used for solving the many types of problems about classification [46,90], diagnostics [3,91], scheduling [45] and prediction [2,80,89] in the wide sectoral range such as atmospheric sciences [23], transportation [20], finance [87], health [69] and energy [37].

Recently, prediction studies focused on ANN [70,89] and obtaining effective results is one of the factors that highlight this method. In addition, traditional prediction methods have been sufficient due to the long-term linear problems in the prediction studies in previous years [13,59]. Nowadays it is not reasonable to assume that the problems are linear because of the dynamic and variable structure of real-life problems [25]. Therefore, these methods are incomplete in some respects in nonlinear problems. In contrast to the traditional prediction models, ANN models learn the structure of the problem from historical data on the problem and captures a fine functional relationship between the parameters even if the problem is difficult. This is the most important feature of ANN models, which shows their superiority compared to traditional ones in nonlinear problems. Therefore, the use of ANN models is more effective for problems that are especially difficult to solve where sufficient data or observation can be obtained [18,62,86]. In addition, it is necessary to transfer large amounts of data from the system examined in deep learning applications [61]. However, there are 285 faults in the hydroelectric power plants, where the problem is addressed, in the 11-year period. While this size of data set is insufficient for deep learning methods, it is sufficient for ANN method. Therefore, ANN method was preferred in this study instead of both traditional statistical methods and deep learning methods. Energy-related problems are often complex, and therefore the ANN method is used effectively in forecasting problems related to energy. The literature reviews performed by Suganthi and Samuel [74] on electricity demand, Weron [85] on electricity prices, and Wang and Srinivasan [83] on energy usage, evidence by the fact that the ANN is frequently used in the energy related studies.

ANN can learn the process based on historical data and obtain highly accurate estimation results even if changes occur in the process [55]. In addition, the applications of artificial intelligence, including the ANN, in power plants aim to minimize human intervention in processes. In other words, these practices aim to reduce the dependence on staff in all process management, including maintenance planning, because of the threats that they may cause [51]. As a result of these objectives and the advantages mentioned above, ANN has taken place in the maintenance planning problem in the energy sector. Examples of maintenance planning literature in the energy sector are summarized below:

Messai et al. [53] performed a system design that forecasts the temperature of the fuel rod temperature sensor in the nuclear reactor core by a Bayesian Network, which is a special ANN model. Ayo-deji et al. [6] assessed the performance of the simulation with two ANN models predicting the location and size of the fault before the malfunction occurred in the operator support system. As with these studies, ANN models not only use environmental variables such as outdoor temperatures or radiation, but also the condition variables of

the equipment as internal temperature for different operating times. In this way, faults can be detected before affecting production and a quantitative risk measurement can be realized. From this point of view, Polo et al. [57] made the malfunction mode and energy production estimation of critical equipment for photovoltaic power plant with ANN.

Most of the maintenance planning studies carried out with ANN in the renewable energy field are carried out in wind power plants which are advantageous due to simple production structure according to other renewable energy plants. The study of Schlechtingen and Santos [67], which deals with offshore wind turbines, is based on the Supervisory Control and Data Acquisition (SCADA) data of 10 wind turbines of the same type with 2 MW installed capacity. By using these data, two different ANN models are constructed for fault estimation and the results are compared. Faults are evaluated as first and second faults on a day-by-day basis and temperature values are estimated. Based on these estimations, the fault is detected at the earliest 50 days ago. Kusiak and Li [43], the other researchers working on the estimation of faults, estimated the failures in three phases based on data from SCADA of 4 wind turbines. In this study, the first stage is to determine the presence of the fault, the second stage is the estimate of the severity of the fault and the final stage is the specific fault estimation. Three-phase fault estimation is modeled by using Neural Network (NN), Neural Network Ensemble (NN Ensemble), Boosting Tree Algorithm (BTA) and Support Vector Machine (SVM) methods and it was able to find the problem 5-60 minutes before failure occurred. Another study on wind turbines is performed by Chen et al. [16]. In this study, Adaptive-Network Based Fuzzy Inference Systems (ANFIS) which is a smart approach to classify faults in wind turbines is used unlike fault estimation. There are other studies using the ANFIS method. The second study of Schlechtingen and Santos [68] is also an example to the ANFIS usage for maintenance planning. In this study, a system for monitoring wind turbines with ANFIS which is a combination of ANN and fuzzy logic analysis, is proposed according to SCADA data. In the continuation of the study, some sample applications of the system such as hydraulic failure, cooling system failure, anemometer failure and turbine control device failures are shown. Sun et al. [75] presented a generalized ANN model to estimate deviations of parameter data such as rotor speed, output power and component temperature collected in SCADA. Instead of testing the model on two states and using a single estimation model, multiple prediction models which are trained with different types of sample data are integrated to determine the deviations of the status parameters of the wind turbine. It is shown that the proposed method is more effective than the traditional single model-based method in the definition of turbine deviation values. In another study about wind turbines, Bi et al. [12] developed a new system that gives an alarm 13-20 hours before the current system by using SCADA data for generator with ANN and ANFIS integration. Bangalore and Patriksson [7] carried out an exemplary study of hybrid models on wind turbines. In this study, implementation of ANN based status monitoring method is presented for a wind turbine and the system has been able to detect the fault 2 months in advance. They also proposed a mathematical optimization model for preventive maintenance scheduling. Finally, Lu et al. [49] predicted the economic life of rotor, transmission and generator equipment in the wind turbine with ANN.

When the studies are examined in the literature, the ANN method is frequently used in fault prediction studies without considering the sector. The review on fracture mechanics using artificial intelligence methods by Nasiri et al. [56] classified the studies under the titles of fault mode and mechanism identification, damage and fault detection and diagnosis, error and error detection, the diagnosis and mechanical fracture parameters. As a result of the review, they confirmed that the ANN method is used in 46% of the studies examined. This finding

proves that the ANN method is effectively used in the failure estimation problems.

In this study, the time estimation between the two faults (in other words, mean time between failures-MTBF) is discussed, and in the literature, studies on maintenance planning based on fault estimations based on maintenance performance parameters and evaluating the system in the light of these parameters come to the fore. For example, in order to investigate system reliability, Komal and Sharma [38] applied three techniques based on ANN and genetic algorithm for the washing system in a paper factory, Jiang et al. [34] modeled the effect of climate and environmental conditions in wind turbines using the regression method, and Vedachalam and Ramadass [78] carried out an exemplary design for dynamic command system. For the prediction of MTBF, which is effective in maintenance planning [34], Chen et al. [17] performed the MTBF estimation for a CNC machine using the DGM model because MTBF is an important parameter in the reliability of complex equipment. Braglia et al., presented a multivariate statistical approach that supports the classification of mechanical components in terms of MTBF [14]. They proposed a new approach to differentiate the operating parameters due to the differences in MTBF, and the determination of MTBF of mechanical parts, depending on the specific operating conditions. Unlike other authors, Jones et al. [35], Adoghe et al. [1] and Illias et al. [32] performed their studies by conducting investigations on malfunctions. Jones et al. [35] calculated the failure rate of the system with Bayesian Network for maintenance planning in a manufacturing industry and used $1 / \text{MTBF}$ ratio in this calculation. Adoghe et al. [1] performed the statistical analysis of the failure data using the serial correlation coefficient and Laplace test methods, and thus, they provided the selection of critical components having the highest risk index in terms of system reliability, and they presented an effective maintenance planning program to address these critical components. Thus, they proposed a reliability-centered maintenance methodology based on statistical analysis for an electrical distribution system. Illias et al. [32] used dissolved gas analysis with a combination of ANN and three PSO techniques to estimate the initial failure of the transformer. In the ANN model, they used 100 input data from 6 gas types, and considered the fault data, thermal error, low density and high-density parameters as output data. They categorized these data as training, verification, and test sets. Apart from these studies, Liu et al. [48] used the MTBF for the reliability of the CNC grinder and Yang et al. [88] used the maintenance failure repair time parameter.

Following the above explanations of the studies using ANN about maintenance planning, the differences of this study from other studies in the literature are as follows:

- In the literature, different artificial intelligence methods are used for maintenance planning problem, and the fault can be detected at the earliest 2 months ago. This study is based on the MTBF parameter, which presents a different philosophy between fault estimation studies. In this study, it is detected the faults earlier than other studies in the literature, and the estimation is made in periods between 201 and 1461 days. Predicting the faults in such an early stage proves the applicability of the model developed in real life problems, considering the length of the preliminary preparation and implementation process required for maintenance.
- In this study, maintenance planning is performed based on MTBF estimation. Similar studies in terms of MTBF estimation in maintenance planning are often carried out for wind turbines. In these studies, a few equipment (such as turbine rotor, transmission, generator or generally turbine for other power plants) is considered because these machines have not complex structure. However, hydroelectric power plants are the most complex one among the all renewable energy power plants. In this respect, this is the first study on maintenance planning based on

the MTBF parameter in the literature, which deals with complex hydroelectric power plants in a system.

- Furthermore, hydroelectric power plants are the most mature renewable energy technology and therefore, these big-scale and complex plants affect the countries' energy mix more than the wind turbines (e.g. the shares of hydro and wind in total electricity generation in Turkey as of the end of 2018 are 20% and 6.3% respectively [21]). Accordingly, hydroelectric power plants are the most critical renewable resource for sustainable energy supply in the world. Therefore, it can be said that the effect of maintenance at these facilities on the sustainable energy supply is much higher than the wind turbines.
- Another fact that makes this study stand out is the use of AHP-TOPSIS-ANN method integration in terms of increasing the level of analyticalness in this problem field, which together with all these features make the study different. It is thought that this study will contribute significantly to the literature due to all these differences.

3. Methods

3.1. AHP

The AHP method developed by Saaty is used as a singular or supportive method in many decision-making problems and its popularity is increasing day by day. This method allows people to define priorities between criteria and alternatives in the decision-making process, together with qualitative and quantitative judgments [79].

The following are the implementation steps of AHP [65]:

Step 1: Determination of goal, criteria, sub-criteria, alternatives and hierarchical structure

This phase includes the aim of the decision maker, the criteria affecting this goal, and the determination of the relationships between them through the addition of alternatives (Figure 1).

Step 2: Performing the pairwise comparison for criteria and alternatives for each criterion

It is carried out by experts by comparing all criteria and alternatives according to their severity. At this stage, the 1-9 preference scale, which is developed by Saaty and given in Table 1 is used.

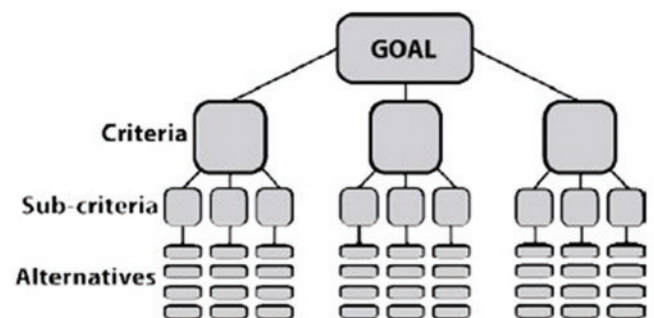


Fig. 1. Hierarchical structure [65]

Step 3: Calculation of priority vector

The vector weights (w) are calculated using the pairwise comparison matrix, normalization of $A.w = \lambda_{max}.w$, and the following equation:

Table 1. Saaty's preference scale [65]

Importance Values	Value Definitions
1	Equal importance of both factors
3	Factor 1 is more important than factor 2
5	Factor 1 is much more important than factor 2
7	Factor 1 has a very strong importance compared to factor 2
9	Factor 1 has an absolute superior importance to factor 2
2, 4, 6, 8	Intermediate values - when compromise is needed

$$w_i = \sum_{j=1}^n a_{ij} / n \quad (1)$$

Step 4: Calculation and control of the consistency ratio (CR)

CR is calculated as the result of the ratio of the consistency index (CI) to the random consistency index (RI - Table 2) (Eq.3). Eq.2 is used to calculate the CI:

$$CI = (\lambda_{max} - n) / (n - 1) \quad (2)$$

Table 2. RI values for different n values [65]

n	1	2	3	4	5	6	8	9	10	11	12	13
RI	0	0	0,58	0,9	1,12	1,24	1,41	1,45	1,49	1,51	1,48	1,56

$$CR = CI / RI \quad (3)$$

If CR<0.1, the pairwise comparison matrix is consistent. Otherwise, pairwise comparisons should be checked and revised, and the above calculations should be repeated.

Step 5: Analysis of the scores

The highest value alternative is chosen as the best alternative.

3.2. TOPSIS

TOPSIS was developed by Hwang and Yoon in 1981 and is a method commonly used in real life multi-criteria decision problems. This method allows decision-makers to compare and sort alternatives. TOPSIS ranks the alternatives based on the maximum distance from the negative ideal solution, and minimum distance to the positive ideal solution. After all, the method chooses the closest alternative to the ideal solution. The method consists of 6 steps [31].

Step 1: Creating the decision matrix

In the rows of the decision matrix, the alternatives are listed and the criteria which affects the decision-making process are given in the columns.

Step 2: Creating the standard decision matrix

A standard decision matrix is created with Eq. 4:

$$r_{ij} = a_{ij} / \sqrt{\sum_{k=1}^m a_{kj}^2} \quad (4)$$

Step 3: Creating the weighted standard decision matrix

The weighted standard decision matrix is obtained by multiplying each weight value calculated for the criteria by the value of the relevant criterion in the standard decision matrix.

Step 4: Creating the positive ideal (A*) and negative ideal (A-) solutions

According to the assumption that the criteria show a tendency to monotonous increasing and monotonous decreasing, the maximum and minimum ones of the values in the weighted standard decision matrix are determined for obtaining the positive and negative ideal solution sets.

Step 5. Calculating the separation measures

The distance of the criteria values of each decision point in the matrix to the ideal and negative ideal solution is calculated by using Eq. 5. and Eq. 6:

$$S_i^+ = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^+)^2} \quad (5)$$

$$S_i^- = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2} \quad (6)$$

Step 6: Calculating the relative closeness to ideal solution

The relative closeness to the ideal solution C_i^* is calculated by using the separation measures according to the Eq. 7:

$$C_i^* = \frac{S_i^-}{S_i^- + S_i^+} \quad (7)$$

C_i^* is in the range 0-1. If $C_i^*=1$, the corresponding decision point is absolutely close to the ideal solution. On the other hand, $C_i^*=0$ represents the absolute closeness of the decision point to the negative ideal solution [5].

3.3. Artificial neural network

ANN is a processor that has a natural tendency to put into practice the stored information based on experience. The ANN is similar to the human brain in two respects: the information is obtained by the network through a learning process and the so-called synaptic weight between neurons is used to store information [28]. The emergence and development of this method is as follows: McCulloch and Pitts [52] are taken the first steps for the ANN by setting up a simple neural network with a small electrical circuit. This network is emerged by imitating the computational ability of the human brain. In 1949, Hebb [30] described the basic theory of learning in his book, The Organization of Behavior. Rosenblatt [63] found the perception of perceptron in 1958 is an important development for ANN. In 1969, Minsky and Papert [54] proved that the perceptron sensors could not solve the

XOR problem and suggested that two-layer feed-forward networks could be used. Rumelhart et al. [64] developed the back-propagation algorithm for multi-layered neural networks in 1986. After this process, progress has also been made so far [29,89].

A simple neural network structure consists of inputs, weights, aggregation function, activation function and output element (Figure 2). The inputs consist of numerical values from the outside of the system or from neurons. The effect of input to the cell on the network refers to weights. Aggregation function performs a linear combination of the inputs of the neuron by calculating the net input to the cell. The numerical sum of these two vectors gives the net input and it is sent to the activation function [28]. The activation function is a non-linear function that shows the network's data structure [22]. There are many activation functions such as sigmoid, hyperbolic tangent, logarithmic sigmoid and purelin.

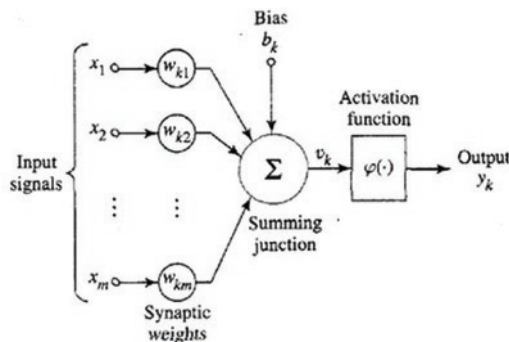


Fig. 2. A simple ANN structure [28]

ANN architecture is divided into single-layer and multi-layer artificial neural networks. The multi-layered structure is used in more complex problems and the single-layered structures are used in simpler problems. Due to the use of multi-layered networks in the complex problems of energy [74,83,85], multi-layered structure is utilized in this study.

4. Case Study

In particular, population growth, industrialization and urbanization with constantly evolving technology, the demand for electricity in Turkey is increased by an annual average rate of 5.6% in the last decade. At the same period, electricity consumption per capita in Turkey has reached from 2,052 kWh to 3,373 kWh with 64,4% increase. Hydroelectric power plants met about one-fifth of electricity consumption, which realizes 292,171,618 kWh as of the end of 2018 [21], in Turkey with these significant increasing rates. Therefore, uninterrupted electricity generation in hydroelectric power plants has critical importance in terms of energy supply security for Turkey. Considering the fact that one of the two pillars of sustainable energy supply in electricity generation power plants is maintenance management, the critical importance of maintenance planning in hydroelectric power plants is seen.

In this context, especially the unwanted stoppages in the large-scale hydroelectric power plants and the damages caused by them have to be considered as important problems. Because, these stoppages affect the energy supply security of the country negatively, not only the plant owner organization. Considering that the power plant with 5 units of 200 MW and 6,111 equipment is operated in accordance with the operational directives, it is focused on the maintenance planning problem in this study, and it is reached the result of not carrying out the maintenance within a systematic plan is concluded with undesirable long-term stoppages in the plant.

It is not possible to apply a standard maintenance policy for all equipment in such a large plant, due to the high level of impact of

maintenance on costs. For this reason, first, the most critical equipment groups which stop the electricity generation in the power plant and interfere with the generation quality and reliability are determined with AHP-TOPSIS combination. Based on the fact that the plant can provide sustainable energy supply with appropriate maintenance to be applied to these equipment groups, an ANN model is proposed by using 11-years fault data of them. As a result, possible fault periods of the most critical equipment of the power plant are obtained by using this model. Maintenance before the estimated breakdown dates is an accepted strategy that prevents the occurrence of faults, and consequently, a maintenance plan is prepared in line with this strategy and the results of the application are presented. The implementation stages of the study are presented in Figure 3.

4.1. Determining the critical equipment

At this stage, which is carried out according to the TOPSIS methodology, the evaluation criteria specified in Table 3 are determined first. The evaluation criteria are determined by referring to the opinions of the experts working in the plant and by taking into account all factors affecting the criticality level of each equipment for the plant and are determined to be related to each equipment.

In Table 3, the verbal value is assigned to each equipment according to each criterion using the parameters column specified under the criteria. The numerical equivalents of the parameters are created by utilizing the views of the power plant experts when considering the assumption of "all indicators must be numerical" for implementing the TOPSIS method. While determining the numerical equivalents of the parameters, a scale consisting of integers between 0-10 is used, and the highest score (10) is given to the parameter which directly affects the electricity generation in the power plant (unit shutdown). Other parameter scores are determined by considering the highest scores given between all the criteria and the scores given between each criterion.

Upon completion of this stage, the initial decision matrix which dimension is 6,111 x 9 is obtained and TOPSIS methodology is started. In order to determine the criticality levels of 6,111 equipment under 9

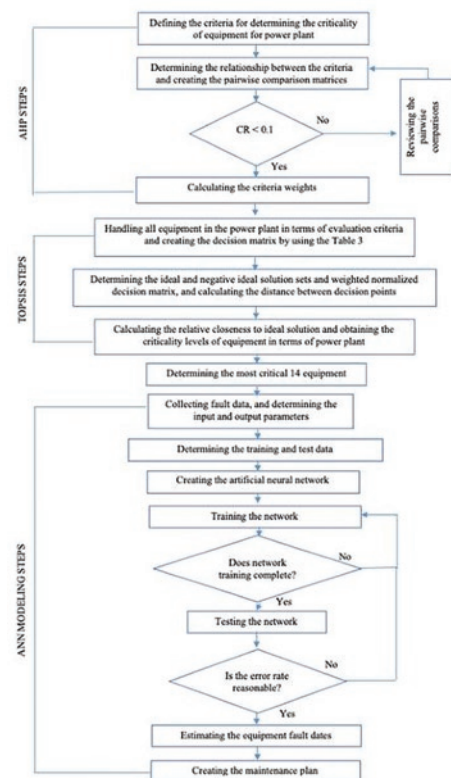


Fig. 3. Application steps

Table 3. Evaluation criteria

Criteria	Criteria Parameters	Numerical Equivalents of the Parameters
C1 Warehouse backup	Never	3
	Sometimes	2
	All the time	1
C2 Maintenance pre-conditions	Unit shutdown	7
	Shutdown by situation	6
	Shutdown by time	5
	Maintenance without back up	2
	Shutdown does not require	1
C3 Additional work requirement	Required	5
	Not required	1
C4 Failure period	Monthly	8
	Quarterly	5
	Semi - annually	3
	Annually	2
	Long term	1
	Unknown	1
C5 Possible consequences	Unit shutdown	10
	Problem in emergency situation	9
	Load reduction	8
	Running without back up	7
	Equipment shutdown	6
	Security problem	6
	Deficient function	2
	Damage in associated equipment	2
	Problem in start	1
Fluid consumption increase	1	
C6 Availability of measuring equipment	Yes	3
	No	1
C7 Static, dynamic or electrical property of equipment	Mechanical-dynamic	2
	Mechanical-static	1
	Electrical	1
	I&C	1
C8 Fault shooting time	One week	9
	More than one day	3
	Unknown	3
	2-8 hours	2
	Less than 2 hours	1
C9 Detectability of failure	Difficult	3
	Easy	1

criteria in terms of power plant, the evaluation criteria weights are calculated with AHP at first. The CR of the pairwise comparison matrix formed between the criteria is calculated as 0.051, and it means the relevant matrix is consistent. The weight of the 9 criteria as a result of the calculations made on this consistent matrix are given in Table 4.

Weighted normalized decision matrix is formed by using the criteria weights calculated with AHP and, ideal and negative ideal solution

sets are determined. Then, the separation measures are calculated for each equipment with Eq.5 and Eq.6. Finally, equipment priority levels (C_i^*), which are defined as relative closeness to ideal solution, of each equipment are found by using Eq.7.

According to the priority levels of the equipment calculated with TOPSIS, the most critical equipment in terms of power plant is found as turbines, generators and disconnectors with a value of 0.837 C_i^* .

Table 4. Criteria weights

Criteria		Weights
C1	Warehouse backup	0.051
C2	Maintenance pre-conditions	0.241
C3	Additional work requirement	0.029
C4	Failure period	0.071
C5	Possible consequences	0.400
C6	Availability of measuring equipment	0.062
C7	Static, dynamic or electrical property of equipment	0.055
C8	Fault shooting time	0.029
C9	Detectability of failure	0.062

This value is considered as 100 full score to ensure the ease of calculations and the scores of all remaining equipment are recalculated accordingly. As a result of this process, power plants experts have determined that the equipment which directly affects the sustainable power generation have 95 and more scores. In this context, the most critical 14 equipment in the power plant which determines the scope of the study are given in Table 5.

Table 5. The most critical equipment of the power plant

Rank	Equipment	Score
1	Turbine	100
2	Generator	100
3	Disconnecter	100
4	Intake structure	98
5	Butterfly valve	98
6	Main power transformer	97.5
7	Brake system	97.5
8	Compressed oil tank	96.9
9	Cooling water structure	96.9
10	Wicket gate	96.8
11	Relay	96.7
12	Excitation transformer	96.7
13	Speed governor	95.9
14	Circuit breaker	95

4.2. Failure date estimation of the critical equipment

In this study, it is focused on the MTBF which is one of the maintenance performance parameters for determining the possible breakdown dates of the 14 most critical equipment of the power plant. On the first step of the prediction stage, the input parameters affecting the breakdown are determined by 8 power plant professionals, each having 10 to 25 years of hydroelectric power plant operation and maintenance experience and their occupations are industrial, electrical, electrical-electronic and mechanical engineer. Equipment type, pressure effect, economic life of the equipment, fault repair time and predictive maintenance effect are determined as input parameters. The output parameter is determined as the number of days between two faults of each equipment based on the fault data recorded since 2005. Since the numerical use of data in the ANN models has a positive effect on the education of the network, the data obtained are converted to nu-

merical form. The data set used in the study is given in Annex-1. The process of distinguishing data is one of the factors affecting the education of the network. Because, with the application of different training and test data groupings, it has been observed that the test results have changed although the structure of the network is not changed. The success of artificial neural network application is closely related to the approaches and experiences to be applied. Determining the appropriate structure in the success of the application is another factor that greatly influences the results of the model. In this context, 80% (228 faults) of the 285 faults that occurred in 11 years were used for training in the network and the remaining part (57 faults) was used to test the performance of the network. The 228-training data are allocated with rates of 70-15-15 in MATLAB as training, validation and test data respectively. Weights are estimated during the training phase. The generalization ability of untrained data is preserved during the validation phase. In the testing phase, the error rate is calculated.

Multiple attempts should be made to find the appropriate results in the network model. These trials are carried out in three stages. First, the process is continued until the learning is achieved. In other words, trials are maintained until the deviations from the target values fall below a certain rate. If the proximity to the target values is provided, the learning is stopped for the network, and the samples which are not shown in learning phase are submitted to the network, and thus, test phase is started. If the deviation between the test results and the targeted values is not acceptable, improvements are made by backing to the learning stage of the network, and this process is continued until it is close to both learning and test objectives. Therefore, the process after the completion of the data related to the study is continued by examining the ANN models. The studies on ANN models are conducted with MATLAB program and the network model and algorithm to be used are investigated [55]. The network type, number of layers in the network, number of neurons in each layer, types of learning and activation function types used in network training, learning and momentum coefficients and the number of iterations are changed separately according to the results obtained during the study. The ANN architecture proposed in this study selected by comparison of network trial results as in most studies in the literature [11,14,28,46,60,71, etc.]. The suitability of the ANN model with 285 data was examined by comparing the results of approximately 150 trials rather than the Vapnik – Chervonenkis dimension theory. Learning and generalization errors of each ANN model were observed, and the model with the lowest error rate, and no memorization in the performance graph was chosen. As a result, it was concluded that 5-20-10-1 ANN model was suitable for solving this problem with 285 fault data that occurred in the 11-year time period in the hydroelectric power plant. The network structure is given in Figure 4.

Figure 5 shows the network with the best regression graph results among the networks established by changing the above-mentioned parameters. 2 hidden layers are used in this selected network, and the

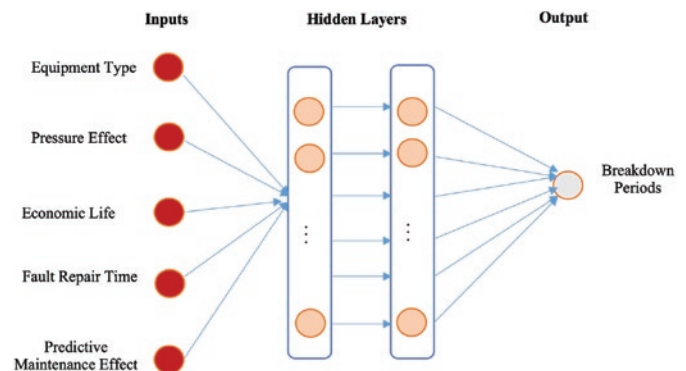


Fig. 4. Network structure

number of neurons in these layers are 20 and 10, respectively. In the network structure, purelin and tansig functions were used as transfer functions respectively, and learnqdm was used as a learning function. Moreover, Levenberg-Marquardt algorithm was used in the training of the network. “Epoch=1000”, “performance goal=0”, “learning rate=0.01”, “momentum constant=0.9” and “maximum validation failures=6” were taken as stopping criteria. These are the stopping criteria in the ANN module in the MATLAB program.

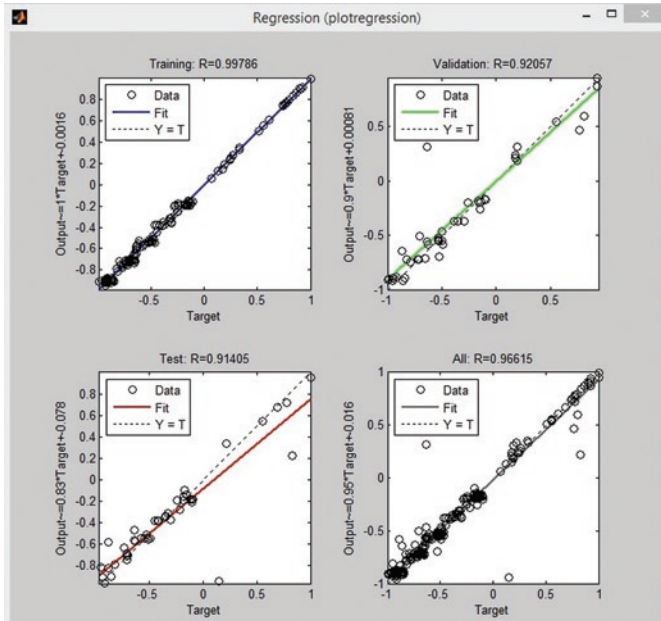


Fig. 5. Regression graphs of selected network

Table 6. Average fault periods of critical equipment

Rank	Equipment	Average Fault Period (Day)
1	Turbine	1,096
2	Generator	1,095
3	Disconnecter	733
4	Intake structure	730
5	Butterfly valve	201
6	Main power transformer	1,091
7	Brake system	731
8	Compressed oil tank	367
9	Cooling water structure	365
10	Wicket gate	1,457
11	Relay	1,461
12	Excitation transformer	722
13	Speed governor	372
14	Circuit breaker	728

The performance of the network is tested with unused data in the training of the network. The Mean Absolute Percentage Error (MAPE) and R^2 values of the performance tested network are obtained as 0.03 and 0.91, respectively. The values are consistent with the performance values of the studies examined in the literature. Therefore, this network is selected for the failure date estimation problem handled in this study. As a result of the estimation phase, the breakdown periods

are determined for each critical equipment. The average fault period for the equipment is given in Table 6. Finally, maintenance plans are applied in such a way that they will be performed before to the failure dates.

5. Conclusions and Recommendations

Electricity generation power plants are continuous production facilities focused on sustainable energy supply, which consist of continuity, reliability, efficiency, economy and environmental sensitivity. In order to achieve this comprehensive objective, it is necessary to comply with the operating rules determined by the power plant manufacturers and to implement the effectively managed maintenance processes simultaneously. In this context, it is a necessity to manage the maintenance processes to be carried out in the power plants, and the most critical and complex phase of maintenance management in electricity generation power plants, which consists of thousands of equipment, is maintenance planning. From this point of view in this study, a maintenance planning is performed with the integration of AHP-TOPSIS-ANN for 14 equipment with the highest importance in one of the large-scale hydroelectric power plants which meet about quintile of Turkey's energy demand.

This study has the feature of being the first in the literature in terms of both the use of these methods in an integrated manner and creating a maintenance schedule with MTBF estimation in hydroelectric power plants. In the studies examined in the literature, condition-based fault estimations are made for a single equipment or machine system. However, in this study, a preliminary qualification is performed for all equipment in a large-scale hydroelectric power plant and the most critical equipment are selected by analytical methods in wide perspective. In hydroelectric power plants where the maintenance activities are costly in terms of material, manpower and time requirements, and generation losses, these selected equipments are directly affecting the sustainable energy generation in the power plant. In this context, only the effective maintenance planning to be applied to these equipments meet the main target of the power plant and this corresponds exactly with the real-life plant management. The selected equipment is determined not only for a single service of the plant but also for its mechanical, electrical and electronic equipment. In this context, a structure covering the entire power plant is established. In addition to this, considering the lack of measuring sensors in all of the equipment, the possibility of arriving at very close time intervals of the signals and the difficulty of interfering with the equipment, and the costs about equipping all of the equipment with measuring sensors, the occurrence of failure etc., interfering with the equipment before the failure occurrence by using the signals of the sensors called as predictive maintenance have no effective results at the power plant. Because, prolonged and unexpected faults have often occurred, and the expected output from the plant could not be obtained for the plant owner and country. However, by performing the proposed maintenance planning approach within the scope of the study, significant improvements are achieved in the power plant in terms of increasing generation efficiency, extending the economic life of the power plant, minimization of generation and maintenance costs, maximization of availability ratio and profit maximization.

Hajian and Styles stated that in this state the output trains the targets very well for training, testing and validation and the R-value is over 0.9 also in this case the test set error and the validation set error have similar characteristics, so the ANN response is satisfactory [27]. Our ANN model is also suitable for explanation in this sentence. Furthermore, in the proposed model, two-stage test application and the error rate were found to be 0.03, which is an accepted rate in the literature. In addition, the purpose of the model is to ensure energy supply security by keeping downtime caused by malfunction to a minimum. When maintenance planning is made according to the model results,

it has been observed that the stoppages caused by malfunctions are prevented and the results are effective in this sense.

In order to validate the maintenance schedule obtained as a result of this study and to determine the added-value, relevant maintenance schedule has been implemented in 1 unit of the power plant for 2 years. In this context, no unit shutdowns have occurred due to lack of maintenance in 14 selected equipment as a result of maintenance activities carried out the power plant. When the malfunction data are analyzed, it is determined that the time required to eliminate such a malfunction varies between 8 hours and 20 days. In other words, a minimum of an 8-hours shutdown has been prevented and a potential loss of 1.6 million kWh of energy has not occurred.

One of the maintenance strategies required for hydroelectric power plants is revision maintenance. This maintenance strategy needs to be implemented at an average of 2 years at the plant where the application is carried out for each unit, and an average of 110 calendar days is needed. The proposed maintenance schedule is also positively affected the revision maintenance performed. This is because only the necessary maintenance processes are carried out to include all stages of implementation in the power plant which has previously applied only the corrective maintenance strategy. Thus, the revision period is reduced to 82 days. This means a 34% improvement. Considering that the unit could not be used in electricity generation during the revision

period, a total of 134.4 million kWh energy is gained for the 28-days difference between the pre- and post- period of proposed approach. These results show that the power plant owner gains millions of liras, as well as Turkey has an important contribution to the energy supply security.

As a result of the implementation of the entire maintenance schedule, the added-value will be increased as a result of the implementation of the said plan in the other units of the plant. The above-mentioned additives of the study can be considered as important contributions to the literature when evaluated with the bullets mentioned at the end of the second section.

In addition, as a continuation of this study, the entire process of the operation should be reevaluated over the fault-free operation period of the power plant and a new network design can be made that learns the effect of maintenance on the system as well as a period that learns the faults.

Acknowledgement

This study was conducted at Kırıkkale University Projects Coordination Unit coded 2018/008 scientific research project.

Annex 1

Table 7. Data set

Equipment	Pressure effect	Economic life of the equipment	Fault repair time	Predictive maintenance effect	Breakdown periods
Intake structure	81	1.550	288	0	960
Cooling water structure	56	3.300	281	4	937
Butterfly valve	80	1.753	257	12	856
Relay	6	4.002	238	52	298
Disconnecter	3	2.675	232	0	772
Butterfly valve	80	1.341	230	0	287
Intake structure	72	1.723	228	1	761
Relay	4	3.010	226	0	282
Cooling water structure	63	3.006	214	4	268
Speed governor	81	2.941	212	4	708
Disconnecter	1	0.677	208	12	694
Cooling water structure	70	2.151	203	0	254
Cooling water structure	70	2.013	198	0	248
Butterfly valve	90	1.505	198	0	659
Excitation transformer	12	1.317	191	0	239
Cooling water structure	70	3.437	190	4	237
Turbine	80	2.871	188	4	235
Generator	90	2.687	181	0	603
Speed governor	90	2.676	179	4	596
Intake structure	81	1.293	173	0	216
Excitation transformer	16	1.342	167	0	418
Speed governor	90	3.077	165	4	413
Disconnecter	2	0.345	165	0	206
Wicket gate	12	4.018	164	12	2466
Generator	100	2.848	160	0	200
Disconnecter	2	0.183	159	0	529

Relay	6	2.675	157	0	392
Turbine	80	2.443	156	0	520
Relay	10	2.848	153	0	383
Cooling water structure	56	2.430	152	0	506
Relay	6	2.337	147	0	35
Turbine	72	1.889	146	4	486
Compressed oil tank	72	1.670	145	2	2169
Main power transformer	12	2.866	143	52	2143
Butterfly valve	100	1.259	141	0	470
Speed governor	81	2.009	141	0	197
Circuit breaker	35	2.838	140	0	35
Turbine	72	2.159	133	0	333
Wicket gate	18	2.852	133	0	186
Butterfly valve	90	1.924	132	12	441
Wicket gate	12	2.842	131	0	184
Butterfly valve	90	1.838	131	12	437
Brake system	4	2.306	130	2	1957
Turbine	80	1.205	130	0	182
Turbine	80	1.550	129	0	322
Excitation transformer	20	1.424	128	0	320
Excitation transformer	12	1.508	127	0	318
Speed governor	81	3.204	127	4	178
Turbine	64	2.730	124	4	310
Speed governor	81	1.873	124	0	99
Butterfly valve	100	1.510	123	0	172
Turbine	64	1.978	121	4	303
Excitation transformer	20	1.923	120	4	1801
Circuit breaker	30	2.850	120	0	96
Relay	8	4.010	119	52	167
Butterfly valve	100	1.925	119	12	29
Generator	100	2.838	119	0	95
Speed governor	90	2.001	118	0	71
Relay	10	2.507	117	0	164
Speed governor	81	2.405	116	0	93
Generator	90	3.677	115	4	1730
Relay	10	3.838	115	52	1725
Wicket gate	6	2.345	114	0	91
Speed governor	72	3.079	113	4	29
Speed governor	72	2.401	112	0	157
Relay	8	3.950	111	52	1661
Main power transformer	12	2.009	110	0	154
Generator	90	2.507	109	0	87
Butterfly valve	100	1.171	108	0	151
Disconnecter	1	2.338	108	0	86
Cooling water structure	63	3.444	107	4	150
Circuit breaker	25	3.010	105	0	123
Wicket gate	12	2.513	105	0	84
Wicket gate	18	2.682	104	0	146
Turbine	80	1.891	104	4	83

Main power transformer	6	2.870	103	52	82
Speed governor	81	2.144	100	0	140
Speed governor	90	2.277	96	0	77
Speed governor	90	1.868	96	0	26
Wicket gate	18	2.508	96	0	134
Cooling water structure	56	2.014	93	0	30
Excitation transformer	16	1.927	93	4	130
Circuit breaker	35	3.015	93	0	74
Relay	8	2.345	93	0	25
Wicket gate	12	2.673	91	0	128
Speed governor	81	2.271	90	0	126
Disconnecter	1	0.678	90	12	29
Main power transformer	12	2.873	89	52	71
Compressed oil tank	80	1.171	88	0	123
Speed governor	81	2.273	88	0	70
Speed governor	90	2.412	87	0	31
Main power transformer	6	3.004	86	52	121
Intake structure	90	1.295	84	0	117
Turbine	64	3.157	84	4	117
Circuit breaker	35	2.505	83	0	99
Cooling water structure	63	2.866	82	4	1224
Speed governor	72	2.145	80	0	32
Turbine	64	2.293	79	0	111
Relay	10	2.352	79	0	110
Circuit breaker	25	2.517	78	0	29
Wicket gate	12	3.003	77	0	108
Main power transformer	6	3.436	77	52	1152
Speed governor	72	2.136	76	0	107
Circuit breaker	20	3.018	71	0	27
Wicket gate	6	2.518	70	0	84
Relay	6	2.680	70	0	24
Circuit breaker	30	2.675	68	0	82
Circuit breaker	25	3.020	65	0	15
Circuit breaker	25	2.520	60	0	29
Relay	6	2.682	60	0	31
Wicket gate	12	2.345	56	0	15
Circuit breaker	20	3.015	55	0	13
Intake structure	72	1.551	51	0	6
Intake structure	81	1.372	50	0	6
Intake structure	90	1.372	50	0	5
Cooling water structure	56	3.301	49	4	8
Circuit breaker	25	2.838	49	0	6
Relay	8	2.352	49	0	5
Circuit breaker	30	3.003	48	0	7
Circuit breaker	30	2.843	47	0	5
Circuit breaker	25	2.680	47	0	6
Circuit breaker	25	3.018	47	0	8
Circuit breaker	30	3.017	47	0	15
Circuit breaker	30	2.520	47	0	7

Circuit breaker	35	2.682	47	0	35
Circuit breaker	30	2.680	47	0	5
Circuit breaker	35	2.342	46	0	6
Circuit breaker	30	2.838	46	0	4
Circuit breaker	30	3.003	46	0	8
Circuit breaker	20	2.505	46	0	5
Circuit breaker	20	2.517	45	0	7
Circuit breaker	25	2.835	45	0	4
Wicket gate	18	2.520	45	0	21
Circuit breaker	25	2.340	45	0	6
Butterfly valve	80	1.924	45	12	5
Circuit breaker	25	2.683	44	0	4
Wicket gate	12	2.350	44	0	7
Speed governor	81	2.409	44	0	21
Circuit breaker	20	2.512	44	0	8
Butterfly valve	80	1.173	44	0	6
Circuit breaker	20	2.670	44	0	4
Speed governor	81	2.011	44	0	5
Speed governor	90	2.147	43	0	23
Speed governor	90	1.879	43	0	15
Circuit breaker	25	2.668	43	0	4
Speed governor	72	2.411	43	0	6
Speed governor	72	2.409	42	0	8
Circuit breaker	25	2.342	42	0	4
Speed governor	72	2.011	41	0	4
Circuit breaker	35	2.687	41	0	27
Speed governor	72	1.880	41	0	8
Intake structure	90	1.551	41	0	9
Speed governor	90	1.868	40	0	4
Circuit breaker	20	3.003	40	0	3
Circuit breaker	20	2.835	39	0	3
Speed governor	72	1.876	39	0	8
Circuit breaker	25	2.687	39	0	3
Circuit breaker	30	3.020	39	0	9
Circuit breaker	35	2.683	38	0	3
Circuit breaker	30	2.835	38	0	24
Circuit breaker	20	2.670	38	0	15
Cooling water structure	70	2.151	38	0	1
Main power transformer	9	3.436	38	52	8
Circuit breaker	35	2.342	38	0	3
Circuit breaker	20	2.352	37	0	27
Speed governor	81	2.409	37	0	3
Circuit breaker	30	2.845	37	0	9
Speed governor	81	2.011	36	0	3
Circuit breaker	25	2.852	36	0	18
Speed governor	72	2.009	36	0	3
Circuit breaker	30	2.683	35	0	9
Speed governor	90	1.876	35	0	3
Circuit breaker	20	3.018	35	0	1

Circuit breaker	20	2.843	35	0	28
Relay	6	2.345	35	0	10
Intake structure	72	1.296	34	0	14
Wicket gate	6	2.502	33	0	9
Circuit breaker	25	3.017	33	0	10
Circuit breaker	30	2.672	33	0	28
Circuit breaker	25	2.853	32	0	12
Circuit breaker	35	2.852	32	0	2
Speed governor	90	2.411	32	0	20
Circuit breaker	25	3.010	32	0	1
Circuit breaker	25	2.842	32	0	15
Circuit breaker	35	2.685	32	0	2
Circuit breaker	30	2.668	31	0	2
Circuit breaker	35	2.345	31	0	13
Circuit breaker	30	3.012	31	0	10
Circuit breaker	35	2.520	31	0	2
Circuit breaker	30	2.505	31	0	2
Circuit breaker	25	2.505	30	0	2
Speed governor	90	2.012	30	0	24
Circuit breaker	25	2.352	30	0	2
Speed governor	90	2.405	30	0	11
Circuit breaker	35	2.350	29	0	2
Speed governor	72	2.941	29	4	2
Circuit breaker	35	2.520	29	0	1
Speed governor	90	2.411	29	0	2
Speed governor	72	2.325	20	0	2
Circuit breaker	20	2.342	28	0	23
Speed governor	81	2.144	28	0	2
Speed governor	63	2.011	28	0	12
Speed governor	72	2.144	27	0	2
Brake system	3	1.802	27	0	2
Relay	8	3.950	27	52	19
Intake structure	90	1.296	27	0	17
Circuit breaker	20	2.853	26	0	2
Circuit breaker	25	2.345	26	0	1
Speed governor	72	2.409	25	0	1
Circuit breaker	20	2.348	25	0	28
Circuit breaker	25	2.342	25	0	18
Cooling water structure	63	2.013	25	0	13
Speed governor	90	2.277	23	0	1
Circuit breaker	30	2.343	23	0	1
Circuit breaker	20	2.345	23	0	10
Generator	100	2.502	21	0	19
Speed governor	72	2.273	21	0	1
Relay	4	2.682	21	0	0
Circuit breaker	30	3.003	20	0	60
Circuit breaker	20	2.668	20	0	28
Compressed oil tank	80	1.672	19	2	58
Relay	8	2.340	19	0	58

Intake structure	81	1.372	19	0	1
Speed governor	72	2.011	19	0	1
Circuit breaker	35	3.015	19	0	0
Circuit breaker	35	2.340	19	0	56
Cooling water structure	56	2.156	19	0	15
Wicket gate	12	2.337	18	0	54
Excitation transformer	12	1.923	18	4	1
Circuit breaker	20	2.508	18	0	54
Circuit breaker	30	2.337	18	0	54
Relay	4	4.010	18	52	0
Wicket gate	18	2.352	18	0	53
Cooling water structure	63	2.154	18	0	53
Turbine	80	1.717	18	4	53
Circuit breaker	35	2.683	17	0	14
Relay	8	2.678	20	0	52
Speed governor	63	2.011	15	0	1
Circuit breaker	30	2.838	17	0	51
Circuit breaker	35	2.510	17	0	51
Excitation transformer	16	1.425	17	0	50
Circuit breaker	35	2.347	16	0	13
Circuit breaker	35	2.680	16	0	21
Intake structure	72	1.372	16	0	0
Generator	90	3.677	15	4	1
Speed governor	90	2.148	15	0	20
Speed governor	81	1.880	15	0	45
Speed governor	90	1.869	15	0	22
Circuit breaker	30	2.685	15	0	23
Circuit breaker	20	2.340	15	0	0
Circuit breaker	25	2.350	15	0	12
Speed governor	90	2.013	15	0	44
Turbine	72	2.874	15	4	44
Turbine	72	1.372	15	0	44
Wicket gate	18	2.340	14	0	43
Circuit breaker	30	2.350	14	0	41
Circuit breaker	20	2.345	14	0	11
Wicket gate	6	2.502	13	0	40
Brake system	4	1.802	13	0	40
Speed governor	81	2.411	13	0	1
Cooling water structure	70	2.867	13	4	38
Speed governor	90	2.144	12	0	10
Speed governor	90	2.137	12	0	37
Circuit breaker	25	2.845	12	0	37
Speed governor	72	1.876	12	0	36
Circuit breaker	30	2.668	12	0	0
Circuit breaker	20	2.518	12	0	21
Speed governor	63	1.877	12	0	35
Circuit breaker	30	2.352	11	0	0
Circuit breaker	35	2.518	9	0	0
Circuit breaker	30	2.342	9	0	0

Circuit breaker	25	2.668	7	0	0
Relay	10	2.343	7	0	70
Disconnecter	3	0.187	7	0	68
Circuit breaker	25	2.515	7	0	68
Wicket gate	18	2.348	7	0	66
Turbine	64	1.715	6	4	64
Wicket gate	6	2.685	6	0	62
Speed governor	72	2.415	6	0	62
Main power transformer	9	2.011	6	0	61
Speed governor	81	2.408	6	0	61
Butterfly valve	90	1.173	6	0	61
Circuit breaker	30	2.342	6	0	0
Speed governor	81	1.876	5	0	0

References

- Adoghe AU, Awosope COA, Ekeh JC. Asset maintenance planning in electric power distribution network using statistical analysis of outage data. *International Journal of Electrical Power & Energy Systems* 2013; 47: 424-35, <https://doi.org/10.1016/j.ijepes.2012.10.061>.
- Adya M, Collopy F. How effective are neural networks at forecasting and prediction? A review and evaluation. *Journal of Forecasting* 1998; 17: 481-95, [https://doi.org/10.1002/\(SICI\)1099-131X\(199809\)17:5/6<481::AID-FOR709>3.0.CO;2-Q](https://doi.org/10.1002/(SICI)1099-131X(199809)17:5/6<481::AID-FOR709>3.0.CO;2-Q).
- Al-Shayea QK. Artificial neural networks in medical diagnosis. *International Journal of Computer Science Issues* 2011; 8: 150-154.
- Aly MF, El-hameed HMA. Integrating AHP and genetic algorithm model adopted for personal selection. *International Journal of Engineering Trends and Technology (IJETT)* 2013; 6.
- Arıbaş M, Özcan U. Akademik araştırma projelerinin AHP ve TOPSIS yöntemleri kullanılarak değerlendirilmesi. *Politeknik Dergisi* 2016; 19: 163-173.
- Ayodeji A, Liu Y kuo, Xia H. Knowledge base operator support system for nuclear power plant fault diagnosis. *Progress in Nuclear Energy* 2018; 105: 42-50, <https://doi.org/10.1016/j.pnucene.2017.12.013>.
- Bangalore P, Patriksson M. Analysis of SCADA data for early fault detection, with application to the maintenance management of wind turbines. *Renewable Energy* 2018; 115: 521-532, <https://doi.org/10.1016/j.renene.2017.08.073>.
- Barros CP, Wanke P. An analysis of African airlines efficiency with two-stage TOPSIS and neural networks. *Journal of Air Transport Management* 2015; 44-45: 90-102, <https://doi.org/10.1016/j.jairtraman.2015.03.002>.
- Behzadian M, Kazemzadeh RB, Albadvi A, Aghdasi M. PROMETHEE: A comprehensive literature review on methodologies and applications. *European Journal of Operational Research* 2010; 200: 198-215, <https://doi.org/10.1016/j.ejor.2009.01.021>.
- Behzadian M, Khanmohammadi Otahsara S, Yazdani M, Ignatius J. A state-of-the-art survey of TOPSIS applications. *Expert Systems with Applications* 2012; 39: 13051-13069, <https://doi.org/10.1016/j.eswa.2012.05.056>.
- Bevilacqua M, Braglia M. Analytic hierarchy process applied to maintenance strategy selection. *Reliability Engineering & System Safety* 2000; 70: 71-83, [https://doi.org/10.1016/S0951-8320\(00\)00047-8](https://doi.org/10.1016/S0951-8320(00)00047-8).
- Bi R, Zhou C, Hepburn DM. Detection and classification of faults in pitch-regulated wind turbine generators using normal behaviour models based on performance curves. *Renewable Energy* 2017; 105: 674-688, <https://doi.org/10.1016/j.renene.2016.12.075>.
- Box GEP, Jenkins GM, Reinsel GC, Ljung GM. *Time series analysis: forecasting and control*. John Wiley & Sons; 2015.
- Braglia M, Carmignani G, Frosolini M, Zammori F. Data classification and MTBF prediction with a multivariate analysis approach. *Reliability Engineering & System Safety* 2012; 97: 27-35, <https://doi.org/10.1016/j.ress.2011.09.010>.
- Chang P-L, Chen Y-C. A fuzzy multi-criteria decision making method for technology transfer strategy selection in biotechnology. *Fuzzy Sets and Systems* 1994; 63: 131-139, [https://doi.org/10.1016/0165-0114\(94\)90344-1](https://doi.org/10.1016/0165-0114(94)90344-1).
- Chen B, Matthews PC, Tavner PJ. Wind turbine pitch faults prognosis using a-priori knowledge-based ANFIS. *Expert Systems with Applications* 2013; 40: 6863-6876, <https://doi.org/10.1016/j.eswa.2013.06.018>.
- Chen D, Fang Z, Wu L, Zhu X. Study on the Prediction of Complex Equipment El MTBF DGMW (p/q)(1, 1) Model Based on the Small Sample. *Journal of Grey System* 2013; 25.
- Cheng B, Titterington DM. Neural networks: A review from a statistical perspective. *Statistical Science* 1994; 2-30, <https://doi.org/10.1214/ss/1177010638>.
- Çamkoru AM, Sayın VO. Bakım maliyeti yönetimi, *Mühendis ve Makine* 2012; 53(635): 16-20.
- Dougherty M. A review of neural networks applied to transport. *Transportation Research Part C: Emerging Technologies* 1995; 3: 247-260, [https://doi.org/10.1016/0968-090X\(95\)00009-8](https://doi.org/10.1016/0968-090X(95)00009-8).
- Energy statistics. UCTEA. The Chamber of Electrical Engineers (www.emo.org.tr/ekler/5aa1f79e3852d94_ek.pdf).
- Fernandez C, Soria E, Martin JD, Serrano AJ. Neural networks for animal science applications: Two case studies. *Expert Systems with Applications* 2006; 31:444-450, <https://doi.org/10.1016/j.eswa.2005.09.086>.
- Gardner MW, Dorling SR. Artificial neural networks (the multilayer perceptron)-a review of applications in the atmospheric sciences. *Atmospheric Environment* 1998; 32: 2627-2636, [https://doi.org/10.1016/S1352-2310\(97\)00447-0](https://doi.org/10.1016/S1352-2310(97)00447-0).
- Govindan K, Jepsen MB. ELECTRE: A comprehensive literature review on methodologies and applications. *European Journal of Operational*

- Research 2016; 250: 1-29, <https://doi.org/10.1016/j.ejor.2015.07.019>.
25. Granger CWJ, Terasvirta T. Modelling non-linear economic relationships. OUP Cat 1993.
 26. Gul M, Celik E, Aydin N, Taskin Gumus A, Guneri AF. A state of the art literature review of VIKOR and its fuzzy extensions on applications. *Applied Soft Computing* 2016; 46: 60-89, <https://doi.org/10.1016/j.asoc.2016.04.040>.
 27. Hajian A, Styles P. Application of soft computing and intelligent methods in geophysics. Springer International Publishing 2018, <https://doi.org/10.1007/978-3-319-66532-0>.
 28. Haykin S. Neural networks: a comprehensive foundation. Prentice Hall PTR; 1994.
 29. Hebb DO. The Organizations of Behavior: a Neuropsychological Theory. Lawrence Erlbaum; 1963.
 30. Hebb DG. The organization of behavior. Wiley Sons, New York, NY, USA 1949.
 31. Hwang C-L, Yoon K. Methods for multiple attribute decision making. *Multiple Attribute Decision Making* 1981: 58-191, https://doi.org/10.1007/978-3-642-48318-9_3.
 32. Illias HA, Chai XR, Bakar AHA, Mokhlis H. Transformer incipient fault prediction using combined artificial neural network and various particle swarm optimisation techniques. *PLoS One* 2015; 10: 1-17, <https://doi.org/10.1371/journal.pone.0129363>.
 33. Ishizaka A, Labib A. Review of the main developments in the analytic hierarchy process. *Expert Systems with Applications* 2011; 38: 14336-14345, <https://doi.org/10.1016/j.eswa.2011.04.143>.
 34. Jiang R, Huang R, Huang C. Modeling the effect of environmental conditions on reliability of wind turbines. *Journal of Shanghai Jiaotong University (Science)* 2016; 21: 462-466, <https://doi.org/10.1007/s12204-016-1747-7>.
 35. Jones B, Jenkinson I, Yang Z, Wang J. The use of Bayesian network modelling for maintenance planning in a manufacturing industry. *Reliability Engineering & System Safety* 2010; 95: 267-277, <https://doi.org/10.1016/j.res.2009.10.007>.
 36. Kahraman C, Ruan D, Doğan I. Fuzzy group decision-making for facility location selection. *Information Sciences* 2003; 157: 135-153, [https://doi.org/10.1016/S0020-0255\(03\)00183-X](https://doi.org/10.1016/S0020-0255(03)00183-X).
 37. Kalogirou SA. Artificial neural networks in renewable energy systems applications: a review. *Renewable and Sustainable Energy Reviews* 2001; 5: 373-401, [https://doi.org/10.1016/S1364-0321\(01\)00006-5](https://doi.org/10.1016/S1364-0321(01)00006-5).
 38. Komal S, Sharma SP. Fuzzy reliability analysis of repairable industrial systems using soft-computing based hybridized techniques. *Applied Soft Computing* 2014; 24: 264-276, <https://doi.org/10.1016/j.asoc.2014.06.054>.
 39. Kubler S, Robert J, Derigent W, Voisin A, Le Traon Y. A state-of-the-art survey & testbed of fuzzy AHP (FAHP) applications. *Expert Systems with Applications* 2016; 65: 398-422, <https://doi.org/10.1016/j.eswa.2016.08.064>.
 40. Kumar A, Sah B, Singh AR, Deng Y, He X, Kumar P, et al. A review of multi criteria decision making (MCDM) towards sustainable renewable energy development. *Renewable and Sustainable Energy Reviews* 2017; 69: 596-609, <https://doi.org/10.1016/j.rser.2016.11.191>.
 41. Kumar R, Singal SK. Penstock material selection in small hydropower plants using MADM methods. *Renewable and Sustainable Energy Reviews* 2015; 52: 240-255, <https://doi.org/10.1016/j.rser.2015.07.018>.
 42. Kuo RJ, Chi SC, Kao SS. A decision support system for selecting convenience store location through integration of fuzzy AHP and artificial neural network. *Computers in Industry* 2002; 47: 199-214, [https://doi.org/10.1016/S0166-3615\(01\)00147-6](https://doi.org/10.1016/S0166-3615(01)00147-6).
 43. Kusiak A, Li W. The prediction and diagnosis of wind turbine faults. *Renewable Energy* 2011; 36:16-23, <https://doi.org/10.1016/j.renene.2010.05.014>.
 44. Lee JW, Kim SH. Using analytic network process and goal programming for interdependent information system project selection. *Computers & Operations Research* 2000; 27: 367-382, [https://doi.org/10.1016/S0305-0548\(99\)00057-X](https://doi.org/10.1016/S0305-0548(99)00057-X).
 45. Liang R-H, Hsu Y-Y. Scheduling of hydroelectric generations using artificial neural networks. *IEE Proceedings-Generation, Transmission and Distribution* 1994;141: 452-458, <https://doi.org/10.1049/ip-gtd:19941156>.
 46. Liao S-H, Wen C-H. Artificial neural networks classification and clustering of methodologies and applications-literature analysis from 1995 to 2005 *Expert Systems with Applications* 2007; 32: 1-11, <https://doi.org/10.1016/j.eswa.2005.11.014>.
 47. Liberatore MJ, Nydick RL. The analytic hierarchy process in medical and health care decision making: A literature review. *European Journal of Operational Research* 2008; 189: 194-207, <https://doi.org/10.1016/j.ejor.2007.05.001>.
 48. Liu Y, Fan J, Li Y. One system reliability assessment method for CNC grynder. *Eksplotacja i Niezawodnosc - Maintenance and Reliability* 2014; 16(1): 97-104.
 49. Lu Y, Sun L, Zhang X, Feng F, Kang J, Fu G. Condition based maintenance optimization for offshore wind turbine considering opportunities based on neural network approach. *Applied Ocean Research* 2018; 74: 69-79, <https://doi.org/10.1016/j.apor.2018.02.016>.
 50. Mardani A, Zavadskas EK, Khalifah Z, Zakuan N, Jusoh A, Nor KM, et al. A review of multi-criteria decision-making applications to solve energy management problems: Two decades from 1995 to 2015. *Renewable and Sustainable Energy Reviews* 2017; 71: 216-256, <https://doi.org/10.1016/j.rser.2016.12.053>.
 51. Mayadevi N, Vinodchandra S S, Ushakumari S. A review on expert system applications in power plants. *International Journal of Electrical and Computer Engineering* 2014; 4(1): 116.
 52. McCulloch WS, Pitts W. A logical calculus of the ideas immanent in nervous activity. *Bull Math Biophys* 1943; 5: 115-133, <https://doi.org/10.1007/BF02478259>.
 53. Messai A, Mellit A, Abdellani I, Massi Pavan A. On-line fault detection of a fuel rod temperature measurement sensor in a nuclear reactor core using ANNs. *Progress in Nuclear Energy* 2015; 79: 8-21, <https://doi.org/10.1016/j.pnucene.2014.10.013>.
 54. Minsky M, Paper S. Perceptrons. MIT Press, Cambridge MA, USA 1969.
 55. Mohd Ali J, Hussain MA, Tade MO, Zhang J. Artificial Intelligence techniques applied as estimator in chemical process systems - A literature survey. *Expert Systems with Applications* 2015; 42: 5915-5931, <https://doi.org/10.1016/j.eswa.2015.03.023>.
 56. Nasiri S, Khosravani MR, Weinberg K. Fracture mechanics and mechanical fault detection by artificial intelligence methods: A review. *Engineering Failure Analysis* 2017; 81: 270-293, <https://doi.org/10.1016/j.engfailanal.2017.07.011>.
 57. Polo FAO, Ferrero Bermejo J, Gómez Fernández JF, Crespo Márquez A. Failure mode prediction and energy forecasting of PV plants to assist dynamic maintenance tasks by ANN based models. *Renewable Energy* 2015; 81: 227-238, <https://doi.org/10.1016/j.renene.2015.03.023>.
 58. Özcan EC, Ünlüsoy S, Eren T. A combined goal programming - AHP approach supported with TOPSIS for maintenance strategy selection in hydroelectric power plants. *Renewable and Sustainable Energy Reviews* 2017; 78: 1410-1423, <https://doi.org/10.1016/j.rser.2017.04.039>.

59. Pankratz A. Forecasting with univariate Box-Jenkins models: Concepts and cases. vol. 224. John Wiley & Sons; 2009.
60. Ramadevi R, Sheela Rani B, Prakash V. Role of hidden neurons in an elman recurrent neural network in classification of cavitation signals. *Int J Comput Appl* 2012; 37(7): 9-13, <https://doi.org/10.5120/4618-6626>.
61. Ravi D, Wong C, Deligianni F, Berthelot M, Andreu-Perez J, Lo B, Yang GZ. Deep learning for health informatics. *IEEE journal of biomedical and health informatics* 2016; 21(1): 4-21, <https://doi.org/10.1109/JBHI.2016.2636665>.
62. Ripley BD. Statistical aspects of neural networks. *Networks and Chaos-Statistical and Probabilistic Aspects* 1993; 50: 40-123, https://doi.org/10.1007/978-1-4899-3099-6_2.
63. Rosenblatt F. The perceptron: a probabilistic model for information storage and organization in the brain. *Psychological Review* 1958; 65: 386, <https://doi.org/10.1037/h0042519>.
64. Rumelhart DE, Hinton GE, Williams RJ. Learning internal representation by backpropagating errors. DE Rumelhart, & JL McClelland *Parallel Distributed Processing: Explorations in the Microstructure of Cognition* 1986; 1, <https://doi.org/10.7551/mitpress/5236.001.0001>.
65. Saaty TL. The analytic hierarchy process: planning, priority setting, resource allocation. McGraw-Hill International Book Company; 1980.
66. San Cristóbal JR. Multi-criteria decision-making in the selection of a renewable energy project in spain: The Vikor method. *Renewable Energy* 2011; 36: 498-502, <https://doi.org/10.1016/j.renene.2010.07.031>.
67. Schlechtingen M, Ferreira Santos I. Comparative analysis of neural network and regression based condition monitoring approaches for wind turbine fault detection. *Mechanical Systems and Signal Processing* 2011; 25: 1849-1875, <https://doi.org/10.1016/j.ymssp.2010.12.007>.
68. Schlechtingen M, Santos IF. Wind turbine condition monitoring based on SCADA data using normal behavior models. Part 2: Application examples. *Applied Soft Computing* 2014; 14: 447-460, <https://doi.org/10.1016/j.asoc.2013.09.016>.
69. Shankaracharya DO, Samanta S, Vidyarthi AS. Computational intelligence in early diabetes diagnosis: A review. *The Review of Diabetic Studies: RDS* 2010; 7: 252-261, <https://doi.org/10.1900/RDS.2010.7.252>.
70. Sharda R. Neural networks for the MS/OR analyst: An application bibliography. *Interfaces (Providence)* 1994; 24: 116-130, <https://doi.org/10.1287/inte.24.2.116>.
71. Sheela K G, Deepa S. N. Review on methods to fix number of hidden neurons in neural networks. *Mathematical Problems in Engineering* 2013, <https://doi.org/10.1155/2013/425740>
72. Sindhu S, Nehra V, Luthra S. Investigation of feasibility study of solar farms deployment using hybrid AHP-TOPSIS analysis: Case study of India. *Renewable and Sustainable Energy Reviews* 2017; 73: 496-511, <https://doi.org/10.1016/j.rser.2017.01.135>.
73. Sipahi S, Timor M. The analytic hierarchy process and analytic network process: an overview of applications. *Management Decision* 2010; 48: 775-808, <https://doi.org/10.1108/00251741011043920>.
74. Suganthi L, Samuel AA. Energy models for demand forecasting - A review. *Renewable and Sustainable Energy Reviews* 2012; 16:1223-1240, <https://doi.org/10.1016/j.rser.2011.08.014>.
75. Sun P, Li J, Wang C, Lei X. A generalized model for wind turbine anomaly identification based on SCADA data. *Applied Energy* 2016; 168: 550-567, <https://doi.org/10.1016/j.apenergy.2016.01.133>.
76. Taha Z, Rostam S. A fuzzy AHP-ANN-based decision support system for machine tool selection in a flexible manufacturing cell. *The International Journal of Advanced Manufacturing Technology* 2011; 57: 719-733, <https://doi.org/10.1007/s00170-011-3323-5>.
77. Vaidya OS, Kumar S. Analytic hierarchy process: An overview of applications. *European Journal of Operational Research* 2006; 169: 1-29, <https://doi.org/10.1016/j.ejor.2004.04.028>.
78. Vedachalam N, Ramadass GA. Reliability assessment of multi-megawatt capacity offshore dynamic positioning systems. *Applied Ocean Research* 2017; 63: 251-261, <https://doi.org/10.1016/j.apor.2017.02.001>.
79. Velasquez M, Hester PT. An analysis of multi-criteria decision making methods. *International Journal of Operations Research* 2013;10: 56-66.
80. Voyant C, Notton G, Kalogirou S, Nivet M-L, Paoli C, Motte F, et al. Machine learning methods for solar radiation forecasting: A review. *Renewable Energy* 2017; 105: 569-582, <https://doi.org/10.1016/j.renene.2016.12.095>.
81. Wang G, Huang SH, Dismukes JP. Product-driven supply chain selection using integrated multi-criteria decision-making methodology. *International Journal of Production Economics* 2004; 91: 1-15, [https://doi.org/10.1016/S0925-5273\(03\)00221-4](https://doi.org/10.1016/S0925-5273(03)00221-4).
82. Wang JJ, Jing YY, Zhang CF, Zhao JH. Review on multi-criteria decision analysis aid in sustainable energy decision-making. *Renewable and Sustainable Energy Reviews* 2009; 13: 2263-2278, <https://doi.org/10.1016/j.rser.2009.06.021>.
83. Wang Z, Srinivasan RS. A review of artificial intelligence based building energy use prediction: Contrasting the capabilities of single and ensemble prediction models. *Renewable and Sustainable Energy Reviews* 2017; 75: 796-808, <https://doi.org/10.1016/j.rser.2016.10.079>.
84. Wanke P, Azad MAK, Barros CP, Hassan MK. Predicting efficiency in Islamic banks: An integrated multicriteria decision making (MCDM) approach. *Journal of International Financial Markets, Institutions and Money* 2016; 45: 126-141, <https://doi.org/10.1016/j.intfin.2016.07.004>.
85. Weron R. Electricity price forecasting: A review of the state-of-the-art with a look into the future. *International Journal of Forecasting* 2014; 30: 1030-1081, <https://doi.org/10.1016/j.ijforecast.2014.08.008>.
86. White H. Learning in artificial neural networks: A statistical perspective. *Neural Computation* 1989; 1: 425-464, <https://doi.org/10.1162/neco.1989.1.4.425>.
87. Wong BK, Selvi Y. Neural network applications in finance: a review and analysis of literature (1990-1996). *Information & Management* 1998; 34:129-139, [https://doi.org/10.1016/S0378-7206\(98\)00050-0](https://doi.org/10.1016/S0378-7206(98)00050-0).
88. Yang Y, Lu Z, Luo X, Ge Z, Qian Y. Mean failure mass and mean failure repair time: parameters linking reliability, maintainability and supportability. *Eksplotacja i Niezawodność - Maintenance and Reliability* 2014;16(2): 307-312.
89. Zhang G, Patuwo BE, Hu MY. Forecasting with artificial neural networks: The state of the art. *International Journal of Forecasting* 1998; 14: 35-62, [https://doi.org/10.1016/S0169-2070\(97\)00044-7](https://doi.org/10.1016/S0169-2070(97)00044-7).
90. Zhang GP. Neural networks for classification: a survey. *IEEE Transactions on Systems, Man, and Cybernetics, Cybern Part C (Applications and Reviews)* 2000; 30: 451-462, <https://doi.org/10.1109/5326.897072>.
91. Zhang Y, Ding X, Liu Y, Griffin PJ. An artificial neural network approach to transformer fault diagnosis. *IEEE Transactions on Power Delivery* 1996; 16: 55, <https://doi.org/10.1109/MPER.1996.4311026>.

92. Zyoud SH, Fuchs-Hanusch D. A bibliometric-based survey on AHP and TOPSIS techniques. *Expert Systems with Applications* 2017; 78:158-181, <https://doi.org/10.1016/j.eswa.2017.02.016>.

Evrencan ÖZCAN

Tuğba DANIŞAN

Rabia YUMUŞAK

Tamer EREN

Industrial Engineering Department

Kırıkkale University

71451, Kırıkkale, Turkey

E-mails: evrencan.ozcan@kku.edu.tr, tugbadanisan@gmail.com,
rabiayumusak95@gmail.com, teren@kku.edu.tr
