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# 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. Ayodeji 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 / 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.

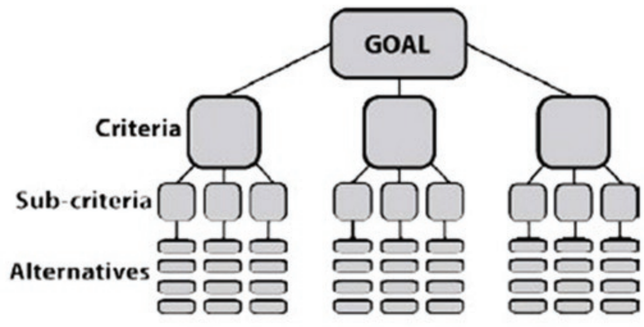


*Fig. 1. Hierarchical structure [65]*

*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 |

$$w_i = \sum_{i=1}^{n} b_{ij} / n \quad (1)$$

*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*:

$$CI = \left(\lambda_{max} - n\right) / \left(n - 1\right) \quad (2)0$$

*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:

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

*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:

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

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

*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.

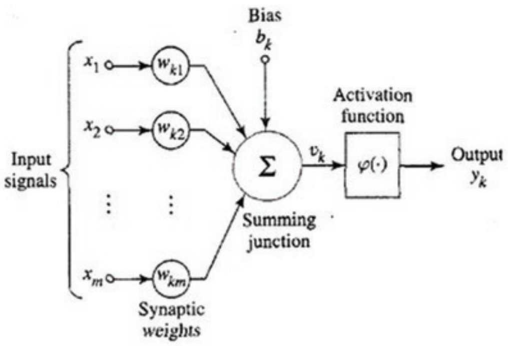


*Fig. 2. A simple ANN structure [28]*

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

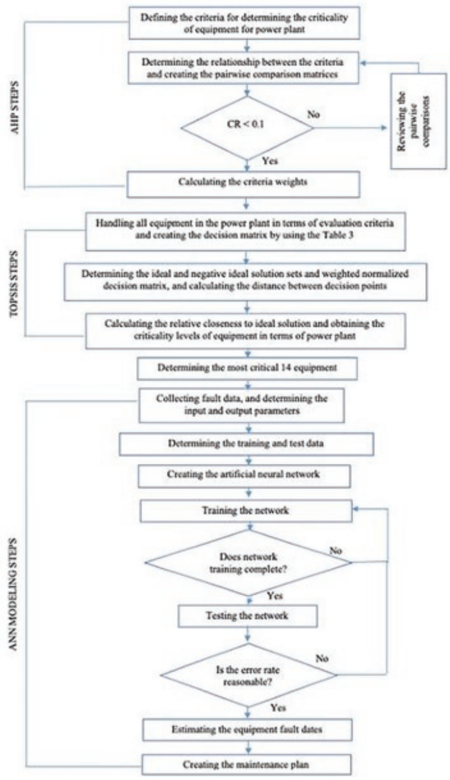


*Fig. 3. Application steps*

*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 | Disconnector | 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 numerical 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

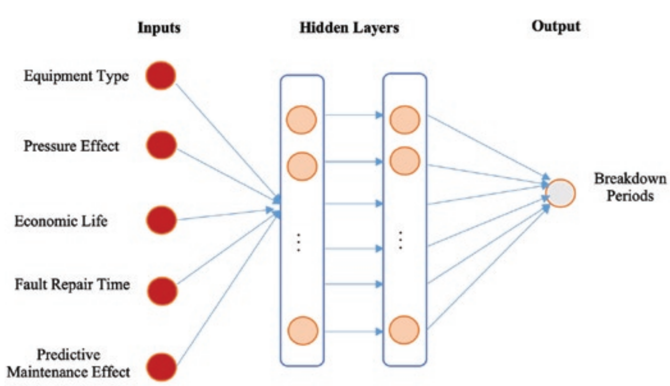


*Fig. 4. Network structure*

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 learngdm 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.

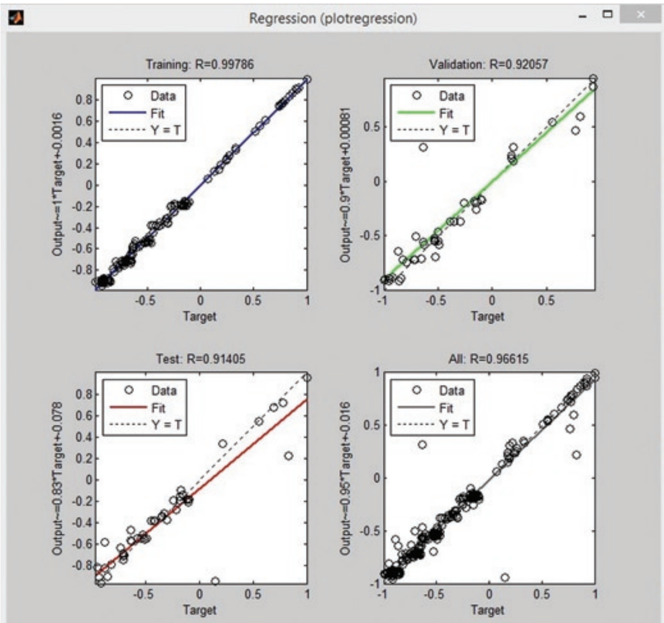


*Fig. 5. Regression graphs of selected network*

*Table 6. Average fault periods of critical equipment*

| Rank | Equipment | Average Fault Period (Day) |
|---|---|---|
| 1 | Turbine | 1,096 |
| 2 | Generator | 1,095 |
| 3 | Disconnector | 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 |
| Disconnector | 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 |
| Disconnector | 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 |
| Disconnector | 2 | 0.345 | 165 | 0 | 206 |
| Wicket gate | 12 | 4.018 | 164 | 12 | 2466 |
| Generator | 100 | 2.848 | 160 | 0 | 200 |
| Disconnector | 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 |
| Disconnector | 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 |
| Disconnector | 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 |

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|---|---|---|---|---|---|
| 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 |

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|---|---|---|---|---|---|
| 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 |

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|---|---|---|---|---|---|
| Circuit breaker | 25 | 2.668 | 7 | 0 | 0 |
| Relay | 10 | 2.343 | 7 | 0 | 70 |
| Disconnector | 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 |

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