Turkish Journal of Electromechanics and Energy
ISSN: 2547-975X
Vol:6, No:3, Page 88-95 (2021)
https://www.scienceliterature.com

Turkish Journal of Electromechanics & Energy
an international open access journal

# Artificial neural network modelling of parabolic trough types solar thermal power plant

D. Erikgenoğlu[1,*], O. Arslan[1]

[1]Department of Mechanical Engineering, Faculty of Engineering, Bilecik Seyh Edebali University, Bilecik, Turkey

**ARTICLE INFO**

***Article Type*:**
Selected Research Article [€]

***Article History:***
Received: 16 April 2021
Revised: 28 October 2021
Accepted: 31 October 2021
Published: 30 December 2021

***Editor of the Article:***
D. Rekioua

***Keywords:***
Artificial neural network
Solar thermal power plant
Parabolic trough collector
Net present value analysis

**ABSTRACT**

This study aims to determine the most appropriate design point for solar energy aided power plant system using the R-134a as a working fluid, using the Artificial neural network (*ANN*) method. A total of 900 different data, with varying fractions of solution and working parameters, were analysed utilising energy-exergy, power, and Net Present Value (*NPV*) analysis. In the training phase, 630 data were used. The remaining 270 data were reserved for testing. Levenberge Marguardt ($LM$), Pola-Ribiere Conjugate Gradient ($CGP$), and Scaled Conjugate Gradient ($SCG$), algorithms are used to find the best approximation in the network. According to the *ANN* results, the error rate of 0.013% was determined in an acceptable range for engineering applications. The best results were obtained in the training and testing stages in the $LM$-10 algorithm. The values of absolute change percentage ($R^2$), Mean Percentage Error ($MPE$), Coefficient of Variation ($CoV$) and Root Mean Square Error ($RMSE$) were determined as 0.9999, 0.5100, 0.3807, and 0.0031, respectively, for the output of $NPV$ in training steps. When the obtained results are examined, the analysis results of the most suitable system are as follows; the energy efficiency 18.4%, exergy efficiency 23.6%, and generated power of the system 281.9 $MWh$. Besides, the profitability value of the system has been determined as 1.31 million USD.

**Cite this article:** D. Erikgenoğlu, O. Arslan, "Artificial neural network modelling of parabolic trough types solar thermal power plant," *Turkish Journal of Electromechanics & Energy*, 6(3), pp.88-95, 2021.

## 1. INTRODUCTION

Rapidly growing population and technological developments in the world also bring energy demand. Today 80% of the energy demand in the world is provided by fossil fuels [1]. These sources are not inexhaustible, and the use of energy coming from fossil origin has adverse environmental effects such as climate change, greenhouse gas emission, global warming, and depletion of the ozone layer. So, clean and inexhaustible energy sources have attracted great interest in recent years, which can be an alternative to these sources. Therefore, it is worth exploring renewable energy sources that can alternative these sources. Renewable energy sources are solar, wind, geothermal, hydropower, and biomass. The utilisation of these sources is desirable because they are continuing or non-depletion sources of energy and relatively non-pollutant, a significant consideration [2]. Solar energy, which is one of the most widely used renewable energy sources, is preferred because it is a free and endless source and an easily accessible source. Various solar technologies exist to convert this energy for multiple uses, including generating electricity, heating, cooling, commercial or industrial use [3]. This study investigated a solar-based power plant used in electricity generation.

There are many studies on solar-based power plants in the literature. In some of these studies, Ferrara et al. [4] designed a system using different working fluids (R134a, R245fa, Acetone) for a small-scale solar power plant with 20 kWe. Al-Sulaiman [5] has performed an exergy analysis of parabolic trough solar collectors integrated with steam and $ORC$ cycles. Comparison was made using R134a, R152a, R290, R407c, R600, R600a and ammonia refrigerants in the power block. Boukelia et al. [6], in their study, parabolic trough types solar thermal power plant (*PTTSTPP*) have designed that with and without integrated the thermal energy storage system and fuel backup systems. Eight different configurations were created. These configurations were analysed as energy, exergy, economic and environmental. Arslan and Kilic [7] optimised a solar thermal power plant for a region with low solar radiation. As a result, the optimum design was determined as the conventional Rankine cycle with R718. Energy and exergy efficiency were reported as 11.05% and 11.86%, respectively. Thaker et al. [8] investigated different thermal energy storage systems and conducted a sensitivity analysis for solar power plants. The results indicate the investment cost for thermochemical storage is higher than other designs. Yang et al. [9] investigated solar power plants using parabolic trough

€Initial version of this article was presented in the 5th International Anatolian Energy Symposium (5th AES) proceedings held on March 24-26, 2021, in Trabzon, Turkey. It was subjected to a peer-review process before its publications.

*Corresponding author e-mail: damla.kilic@bilecik.edu.tr

collectors. They performed a thermodynamic analysis of the system using toluene as the working fluid at organic Rankine cycle (ORC). In the study, the energy efficiency was reported as 17.9%.

The Artificial Neural Network (*ANN*) is a good option for modelling energy systems. *ANN* is quicker and more practical than other traditional methods. Many researchers have used this method. Kumar and Kaur [10] determined the solar radiation values using the $ANN$ model for a region in India. Arslan and Yetik [11] designed a system for the Simav region in Kütahya based on the $ORC - Binary$ geothermal power plant. They used the *ANN* model to determine the most appropriate design, which includes the life cycle cost. Three different algorithms, $LM$, $CGP$ and $SCG$, were used to find the best approach in the network. As a result of the study, the most suitable algorithm was $LM$-16 for designed cycles. Sencan et al. [12] used $ANN$ to determine the thermodynamic properties of Li-Br water and Li-Clewater fluid pairs in an absorption heat pump system. Boukelia et al. [13] used the *ANN* model to design and optimise the solar thermal power plant. Sözen et al. [14] investigated solar energy potential using $ANN$ methods for 17 different cities in Turkey. $LM$, $CGP$, and $SCG$ learning algorithms and logistic sigmoid transfer functions were used in the network. Arslan [15] examined the electricity production in the Simav geothermal field using the Kalina Cycle. The optimisation of the system was realised with the $ANN$ model. In this study, three different types of back-propagation learning algorithms, $LM$, $CGP$ and $SCG$, have been tried to find the best approach in the network. As a result, the most suitable algorithm was *LM* with seven neurons. Yilmaz and Koyuncu [2] determined the optimum plant capacity for the geothermal power plant using the *ANN* model. The plant's energy and exergy efficiencies are calculated as 10.4% and 29.7%. The optimised simple payback period and exergy cost of the electricity generated in the plant is calculated as 2.87 years and 0.0176 $/kWh, respectively. Senkal [16], using $the\ ANN$ method, Turkey's solar radiation values have been determined by selecting 19 different regions. Boukelia et al. [17], in their study, the level of electricity cost of the power plant using parabolic trough type solar collectors was determined using the $ANN$ model. Kalogirou [18], using the TRNSYS program, modelled the solar energy system according to the meteorological values of Cyprus. To determine the most economical value of the solar energy system, the design has been optimised by using $ANN$. Ighravwe and Mashao [19] used the *ANN* models for generated power prediction by Energy Storage System. Tuğcu and Arslan [20] optimised the geothermal energy aided absorption cooling system with the *ANN* method. *LM*, *SCG*, and *CGP* variants were used to determine the best *ANN* model. As a result, error rates for engineering applications have been reported to be in an acceptable range between 0.07% and 6%.

A literature review shows that most studies on the design of parabolic trough power plants are based on analytical models. In contrast, machine learning models such as *ANN* models are rarely used. In addition, as a result of the examinations in the literature, it has been shown that the *ANN* model has a negligible error rate. The design of a parabolic trough type solar thermal power plant (*PTTSTPP*) requires many calculations and data analysis. From this point of view, the *ANN* model is a preferable option in this regard. Therefore, this study compares the accuracy in estimating electricity production, energy efficiency, exergy efficiency, and payback cost of a *PTTSTPP* using analytical and *ANN* methods.

The *PTTSTPP* was analysed according to the first and second laws of thermodynamics by considering different parametric values. The economic analysis of this system was made using the $NPV$ method. Then, the analysis result and the results obtained by $ANN$ were compared. Many values such as system parameters, solar radiation values, and ambient temperatures were used to train and validate the $ANN$ model. Various analysis was performed to select the best *ANN* model by changing the number of neurons in the hidden layer. Three different back-propagation algorithms were used to find the best approach in the network. These are Levenberge Marguardt ($LM$), Pola- Ribiere Conjugate Gradient ($CGP$), and Scaled Conjugate Gradient ($SCG$), respectively. The accuracy rate of $ANN$ in applications was discussed by determining the error rate between $ANN$ results and analysis results.

## 2. MATERIAL AND METHOD

Turkey has the average solar radiation values. In this paper, Bilecik is determined as the study area. Bilecik is located between 40.1° latitude and 29.9° longitude. In Figure 1 shows the average solar radiation values, monthly average temperature values and sunshine times for Bilecik city of Turkey.

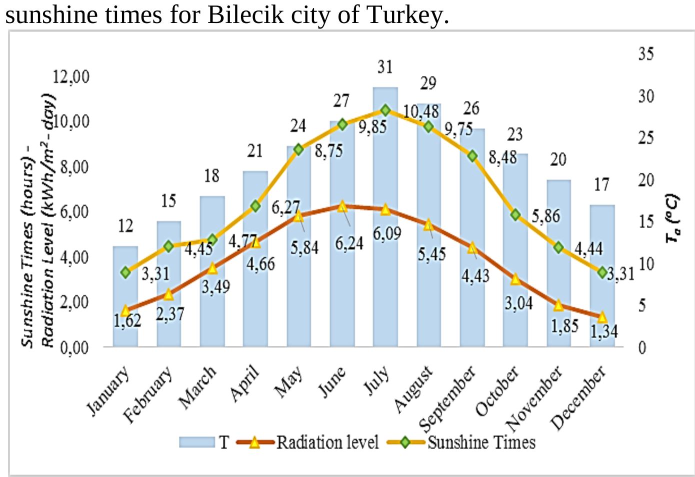


Fig. 1. Monthly average solar radiation, temperature and sunshine times of Bilecik [21].

When Figure 1 is examined, Bilecik has a radiation range between 1.34-6.24 kWh/m$^2$-day. The solar radiation value is highest in June and the lowest in December. Similarly, the weakest times were observed in January and December as 3.31 hours, and the highest sunshine time was observed in July as 10.48 hours. The temperature values shown in the graph belong to by 2018. These values are taken for Bilecik from Meteorology General Directorate [21]. The highest temperature value is 31 °C in July, and the lowest temperature is 17 °C in January. Considering these values, a solar power plant was designed according to Bilecik conditions. Figure 2 shows the flow diagram of the planned solar power plant.

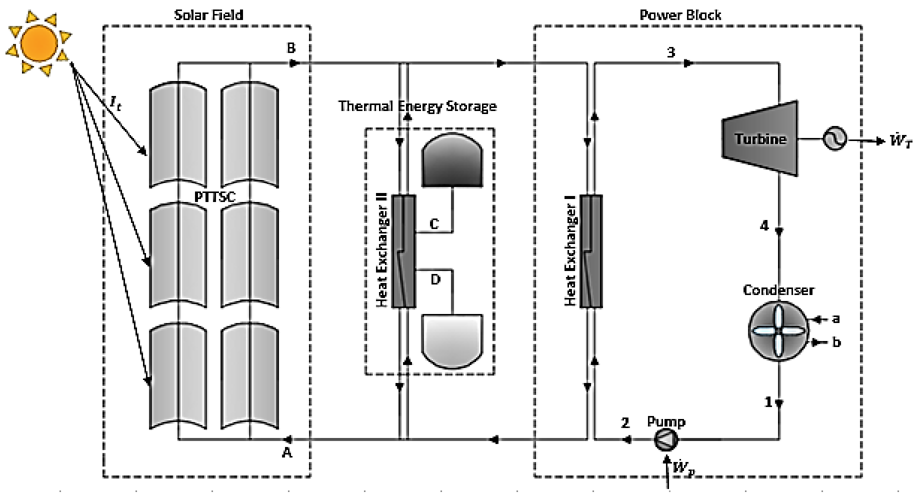

Fig. 2. Flow diagram of the *PTTSTPP* system.

The *PTTSTPP* system consists of three main sections: solar field, thermal energy storage and power block. The most commonly used among the concentrator systems is parabolic trough type solar collectors have selected in the Solar field. In these systems, the sun rays coming to the surface of the parabolic collectors reflect the receiving pipe in the centre of the collector. In this way, the fluid in the solar field becomes the heat source. Then, this fluid is transferred to the power cycle to obtain steam. The technical details of the parabolic trough type solar collectors used in system design are given in Table 1.

Table 1. Technical details of parabolic collectors [22].

| *Parabolic Collectors* | *Values* |
|---|---|
| Receiver outside diameter ($D_{o,r}$) | 0.07 m |
| Receiver inside diameter ($D_{o,i}$) | 0.066 m |
| Heat transfer coefficient inside the receiver ($h_{fi}$) | 300 W/m$^2$ |
| Thermal conductivity of the receiver ($\kappa$) | 16 W/m °C |
| Transmissivity of the cover glazing ($\tau_{cover}$) | 0.90 |
| Effective transmissivity of PTC ($\tau_{PTC}$) | 0.94 |
| Absorptivity of the receiver ($\alpha_r$) | 0.87 |
| Correction factor for diffuse radiation ($\gamma$) | 0.95 |
| Single collector width ($W$) | 1.5 |
| Single collector length ($L$) | 5 |

The Thermal Energy Storage (TES) system stores hot or cold fluid for use when necessary. These systems feed the turbine during cloudy or stormy weather without the sun and during the night. Thus, it ensures the operation of the power plant and prevents the decrease in inefficiency. Thanks to the TES systems, it is possible to increase the working time of solar power plants up to 24 hours. This study considers the TES system with hot and cold storage tanks.

The heat obtained from the solar energy is transferred to the refrigerant fluid by the heat exchanger in the $ORC$. The refrigerant fluid exiting the heat exchanger operates the turbine at high temperatures and pressure to generate electrical energy. The expanding fluid in the turbine is converted to liquid in the condenser. Then, the pressure of the fluid entering the pump increase. The fluid exiting the pump is sent to the heat exchanger and completes the cycle.

The therminol VP-1, molten salt and R-134a have been used as a working fluid in the solar field, thermal energy storage, and power block, respectively. The properties of the juices are given in Table 2.

Table 2. The properties of the working fluids [23, 24, 25].

| *Properties* | *Therminol VP-1* | *Molten Salt* | *R-134a* |
|---|---|---|---|
| Boiling point (°C) | 257 | - | -26.074 |
| Freezing point (°C) | 12 | 221.85 | -103.3 |
| Critical Temp. (°C) | 400 | - | 101.06 |
| Critical Pres. (MPa) | - | - | 4.059 |
| Density (kg/m$^3$) | 1068 | 1840 | 511.9 |
| $c_p$ (kJ/kg.K) | 1.53 | 1.56 | 1.5 |

While determining the system parameters, both the studies in the literature have been examined, and the values suitable for the properties of the fluid have been selected. Accordingly, different parameters for collector inlet and outlet temperatures, hot and cold storage tank temperatures have been determined. Different parametric values have been specified for refrigerant fluids for the pump inlet and outlet pressures and the steam temperature suitable for operating the turbine. The main parameters of the *PTTSTPP* are given in Table 3.

Table 3. The main parameters of the *PTTSTPP*.

| *Parameters* | *Values* |
|---|---|
| Number of collectors | 2531 |
| $T_A$ (°C) | 290-310 |
| $T_B$ (°C) | 390-410 |
| $T_C$ (°C) | 380-400 |
| $T_D$ (°C) | 280-300 |
| $P_1$ $(kPa)$ | 610-1045 |
| $P_2$ $(kPa)$ | 2000-3000 |
| $T_3$ (°C) | 100-120 |
| $\eta_{th}$ | 0.88 |
| $\eta_P$ | 0.8 |

### 2.1. Energy and Exergy Analysis

The system was analysed according to the first and second laws of thermodynamics. Thermodynamic analysis of the system was carried out for steady regime conditions, and the pressure losses in the system were neglected. For a continuous flow system, the mass balance is expressed in the mass flow rate entering and exiting the system as shown in Equation (1) [26];

$$\Sigma \dot{m}_i = \Sigma \dot{m}_o \tag{1}$$

For continuous flow systems, the conservation of energy in terms of energy entering and exiting the system as shown in Equation (2);

$$\sum \dot{E}_i - \sum \dot{E}_o = 0 \tag{2}$$

In a continuous flow system, the energy conservation equation for the energy transmitted by heat, work and mass is written as shown in Equation (3);

$$\dot{Q} + \dot{W} = \Sigma \dot{m}_o h_o - \Sigma \dot{m}_i h_i \tag{3}$$

Enegy efficiency is as shown in Equation (4);

$$\eta = \frac{\dot{W}_{net}}{\dot{Q}_i} \tag{4}$$

General exergy balance is shown in Equations (5) and (6),

$$\Sigma \dot{E}x_i - \Sigma \dot{E}x_o = \Sigma \dot{E}x_d \tag{5}$$

$$\dot{E}x_{heat} + \dot{E}x_{work} + \dot{E}x_{mass,i} - \dot{E}x_{mass,o} = \dot{E}x_d \tag{6}$$

The expression on the right side of equality refers to exergy destruction. The terms on the left side of the same Equation, exergy generated by the heat interaction ($\dot{E}x_{heat}$), exergy caused by the interaction of the work ($\dot{E}x_{-work}$) and exergy entering ($\dot{E}x_{mass,i}$) and exiting ($\dot{E}x_{mass,o}$) the mass due to the mass flow are defined in Equations (7-10) [26];

$$\dot{E}x_{heat} = \Sigma\left(1 - \frac{T_0}{T}\right)\dot{Q} \tag{7}$$

$$\dot{E}x_{work} = \Sigma \dot{W} \tag{8}$$

$$\dot{E}x_{mass,i} = \Sigma \dot{m}_i \psi_i \tag{9}$$

$$\dot{E}x_{mass,o} = \Sigma \dot{m}_o \psi_o \tag{10}$$

Specific exergy is calculated as shown Equation (11);

$$\psi = (h - h_0) - T(s - s_0) \tag{11}$$

where $h_0$ ve $s_0$ refers to the fluid's enthalpy and entropy values at the dead state pressure and temperature, respectively.

Exergy efficiency can be defined as shown Equation (12) [26];

$$\varepsilon = \frac{\dot{E}x_ç}{\dot{E}x_g} = 1 - \frac{\dot{E}x_d}{\dot{E}x_g} \tag{12}$$

### 2.2. Economic Evaluation

The Net Present Value $(NPV)$ method is used in the economic analysis of the system. In this method, the cash flows of the project to be invested are determined according to the time value of money. Investments incurred due to cash outflow are considered unfavourable, and earnings are taken as positive, and a net result is obtained. If the result is negative, the investment project cannot be done, and if it is positive, the decision to make is correct. $NPV$ method can be expressed mathematically as in Equation (13);

$$NPV = \sum_{t=0}^{n} \frac{B_t}{(1+r)^t} \tag{13}$$

where $n$; the project's useful life, $B_t$; cash flow in $t$ year, $r$; discount rate. The following Equation (14) calculates the $B_t$ value;

$$B_t = -C_{mr} - C_r - C_p + C_e \tag{14}$$

Cash flow contains the cost of maintenance and repair, the cost of refrigerant, the total annual personnel expenses, and the cost of electricity. Cost data for the economic model is given in Table 4.

Table 4. Cost data for the economic model [18].

| *Parameters* | *Values* |
|---|---|
| Solar field | 270.00 $\$/m^2$ |
| Thermal energy storage system | 80.00 $\$/kWh$ |
| Power block | 830.00 $\$/kWe$ |
| Minimum wage | 485.46 $ |
| Electricity unit cost | 0.13 $\$/kWh$ |
| Discount rate | 13% |

Maintenance and repair costs are included in the calculations as 2% of the initial investment cost. Initial investment cost consists of total cost and assembly cost. The total cost consists of the solar field cost, thermal energy storage system cost, and power block cost given in Table 5. The assembly cost is 10% of the total cost. Refrigerant cost constitutes 10% of the power block cost. Personnel expenses were calculated using Equation (15). The labour force requirement of the power plant has been included in the calculations by considering a manager, an engineer, and nine workers to meet the system operation. The minimum wage average of 2019 is based on [27].

$$C_p = 485.46 \cdot 12 \cdot (5 \cdot 1 + 3 \cdot 1 + 1.5 \cdot 9) \tag{15}$$

While calculating the cost of electricity for the system, the unit cost of electricity was included in accounts as 0.13 $\$/kWh$ [28]. Accordingly, the cost of electricity;

$$C_e = \dot{W}_p \cdot 0.13 \cdot 24 \cdot 300 \tag{16}$$

The useful life of the *PTTSTPP* has been determined as 20 years, and the cost of the system was investigated by the $NPV$ method.

### 2.3. Artificial Neural Network Modeling

The $ANN$ model, which generally mimics the human brain, is inspired by biological neurons. It has emerged as a result of artificially simulating the work system of the human brain. Various learning algorithms are available to obtain the relationships between inputs and outputs. The most widely used algorithm is the forward feedback propagation learning algorithm. The most common variants to be adapted for this algorithm in energy systems are $LM$, $SCG$ and $CGP$. With the feedback propagation algorithm, $ANN$ learns by changing link weights, and these changes are stored as information [18].

Various learning algorithms are available to obtain the relationships between inputs and outputs. The most widely used algorithm is the forward feedback propagation learning algorithm. The most common variants to be adapted for this algorithm in energy systems are $LM$, $SCG$ and $CGP$. With the feedback propagation algorithm, $ANN$ learns by changing link weights, and these changes are stored as information [18].

The performance of $PTTSTPP$ was calculated using four average statistical parameters; Root Mean Square Error ($RMSE$), Mean Percentage Error ($MPE$), Coefficient of Variation ($CoV$) and absolute change percentage ($R^2$) [18]. These statistical parameters were calculated using Equations (17-20);

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_{output} - y_{actual})^2} \quad (17)$$

$$MPE = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_{output}-y_{actual}}{y_{output}}\right) \quad (18)$$

$$CoV = \frac{\sum_{i=1}^{n}(y_{output}-\bar{y}_{output})(y_{actual}-\bar{y}_{actual})}{n}\cdot 100 \quad (19)$$

$$R^2 = \left[\frac{\sum_{i=1}^{n}(y_{output}-\bar{y}_{output})(y_{actual}-\bar{y}_{actual})}{\sum_{i=1}^{n}(y_{output}-\bar{y}_{output})^2\sum_{i=1}^{n}(y_{actual}-\bar{y}_{actual})^2}\right]^2 \quad (20)$$

$LM$, $SCG$ and $CGP$ variants of the feed-forward back-propagation algorithm were applied, and logarithmic sigmoid (logsig) was used;

$$f(ze) = \frac{1}{1+e^{-ze_j}} \quad (21)$$

$$ze_j = \sum_{i=1}^{n} w_{ij}y_i + b_j \quad (22)$$

Although the ideal values of statistical tests such as $RMSE, MPE$ and $CoV$ are close to zero or zero, the value of $R^2$ should be close to one or one [18]. The general $ANN$ model is as shown in Figure 3.

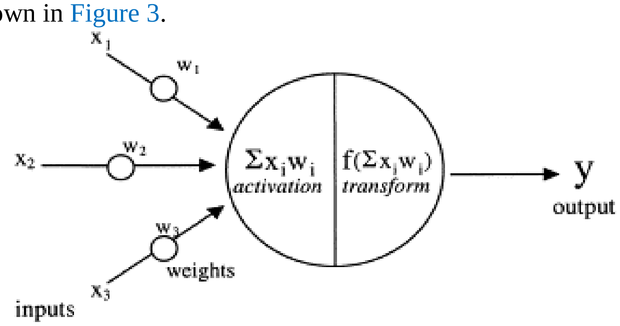


Fig. 3. Model of the Artificial Neural Network neuron. [23].

## 3. RESULTS

The $PTTSTPP$ system was designed by considering Bilecik state conditions. Thermodynamic analysis of this system was made according to different parametric values. In this context, this system's energy and exergy efficiencies were calculated between 13.14-20.34 %, 16.83-23.88 %, respectively. In addition, the generated power of the system was determined to change between 78.1-281.9 $MWh$. The maximum generated power was observed when $T_B$ is 390 ℃, $T_A$ is 290 ℃, $P_1$ is 865 $kPa$, $P_2$ is 3 $MPa$, and $T_3$ is 100 ℃. The energy and exergy efficiencies of the system in these conditions are 18.4 % and 23.6 %, respectively. The $NPV$ values of the system, designed according to different parameters, have changed between 38 million USD and 1.317 million USD.

In the $ANN$ modelling of the $PTTSTPP$, the number of 10 ınputs; solar radiations ($I_t$), ambient temperatures ($T_0$), inlet and outlet temperatures of the parabolic collector ($T_A$ and $T_B$), temperatures of storage tanks ($T_C$ and $T_D$), inlet and outlet pressures of the pump ($P_1$ and $P_2$), inlet temperatures of the turbine ($T_3$) and sunshine times ($\Delta t$) were used. $\eta$, $\varepsilon$, $W$ and $NPV$ were obtained as the output. The $ANN$ model of the system is given in Figure 4.

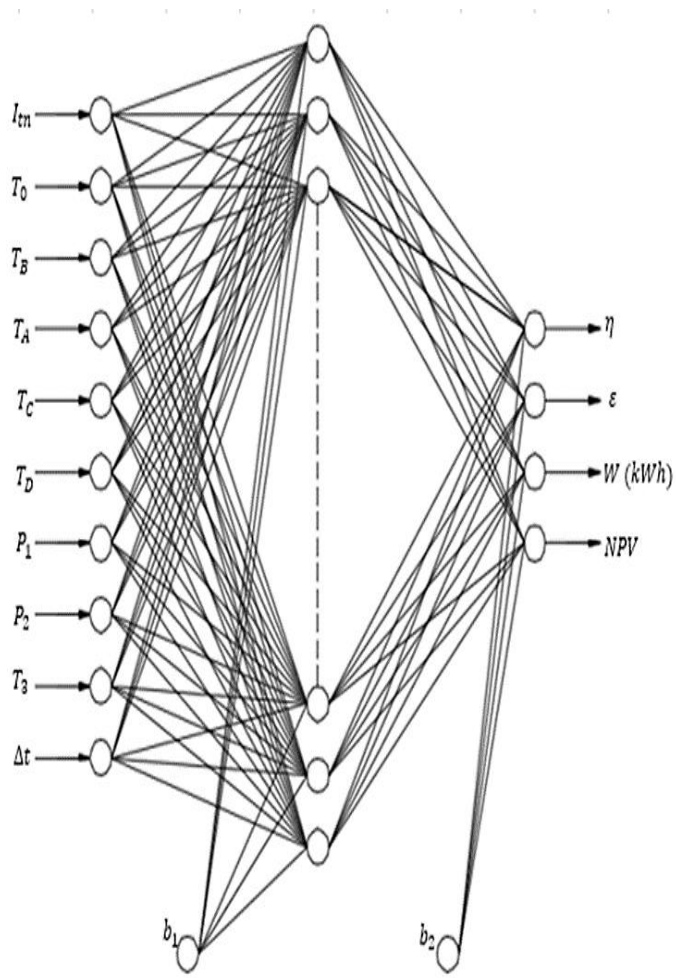


Fig. 4. The $ANN$ model of the $PTTSTPP$ system.

Using the MATLAB software the $ANN$ model was created. Parameter settings for the $ANN$ model in MATLAB software are given in Table 5. The $ANN$ model of the designed system was normalised between 0.3-0.7. A total of 900 different data were used. In the training phase, 630 data were used. The remaining 270 data were reserved for testing. The choice of the number of hidden neurons is a parameter of great importance in determining the performance of an $ANN$ [1]. Therefore, several numerical experiments were carried out by gradually varying the number of neurons in the hidden layer from 6 to 14 to determine the most performant structure of $ANN$. The results obtained from MATLAB software were transferred to Excel tables for additional calculations and evaluations. Three different back-propagation algorithms were used to find the best approach in the network. These are Levenberge Marguardt ($LM$), Pola- Ribiere Conjugate Gradient ($CGP$), and Scaled Conjugate Gradient ($SCG$), respectively. The statistical results obtained are given in Table 6.

Table 5. Parameter settings of the $ANN$ model.

| *Parameters* | *Values* |
|---|---|
| Number of hidden layers | 1 |
| Number of epochs | 1000 |
| Train function | trainlm |
| Hidden layer function | logsig |
| Output layer function | tansig |

As shown in Table 5, obtained the statistical results are highly satisfactory. The best results were obtained in the training and testing stages in the $LM$-10 algorithm. The values of $R^2$, $MPE$, $CoV$ and $RMSE$ were determined as 0.9999, 0.5100, 0.3807, and 0.0031, respectively, for the output of $NPV$ in training steps. In the testing step, these values were 0.9996, 0.5602, 0.3114, and 0.0030, respectively. The comparison of the analysis and $ANN$ values of the energy efficiency ($\eta$), exergy efficiency ($\varepsilon$), power ($W$) and $NPV$ are given in Figures 5-8.

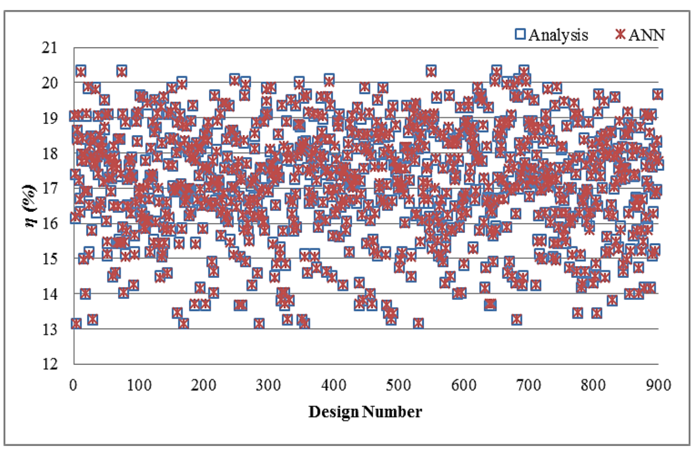


Fig. 5. The comparison of the analysis and $ANN$ values of the $\eta$.

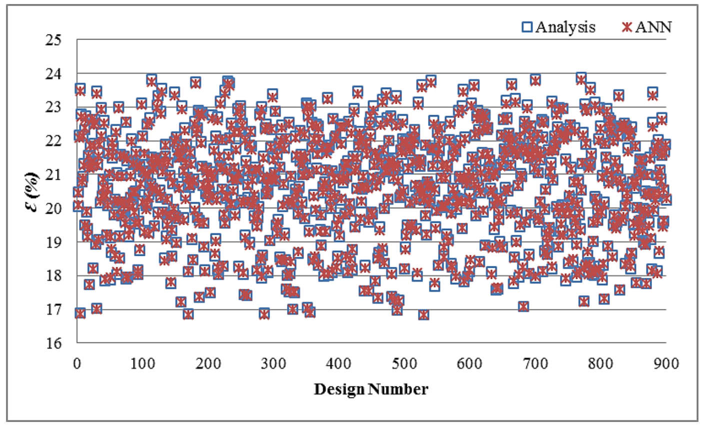


Fig. 6. The comparison of the analysis and $ANN$ values of the $\varepsilon$.

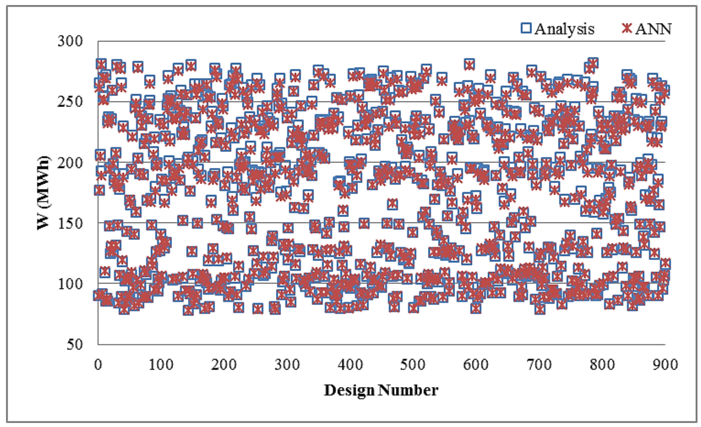


Fig. 7. The comparison of the analysis and $ANN$ values of the $W$

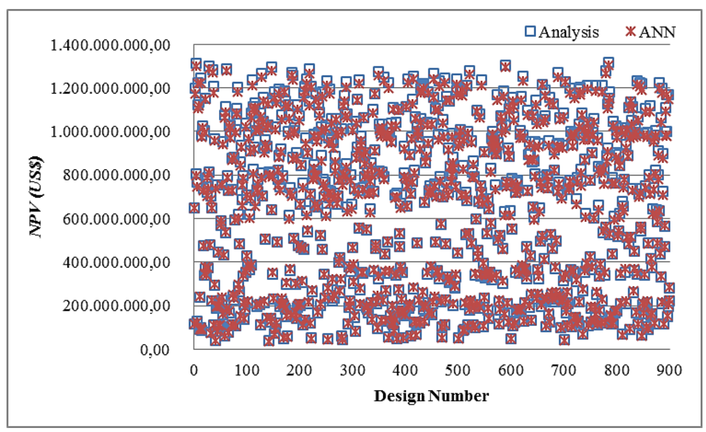


Fig. 8. The comparison of the analysis and $ANN$ values of the $NPV$.

As shown in the Figures 5-8, the results of the analysis and $ANN$ values are very close to each other. Similarly, excellent results were obtained even with unspecified test values. Therefore, it was concluded that these values were statistically acceptable. According to the results obtained, the error percentage of the analysis results and the $ANN$ results were found to be 0.013%.

Table 6. The statistical results of the training and test data are according to the $NPV$ values.

| *Algorithm* | *Training* | | | | *Test* | | | |
|---|---|---|---|---|---|---|---|---|
| | *$R^2$* | *MPE* | *CoV* | *RMSE* | *$R^2$* | *MPE* | *CoV* | *RMSE* |
| LM-6 | 0.9994 | 0.5414 | 0.3874 | 0.0037 | 0.9993 | 0.6220 | 0.3231 | 0.0040 |
| LM-8 | 0.9995 | 0.5911 | 0.3843 | 0.0037 | 0.9995 | 0.6313 | 0.3192 | 0.0039 |
| **LM-10** | **0.9999** | **0.5100** | **0.3807** | **0.0031** | **0.9996** | **0.5602** | **0.3114** | **0.0030** |
| LM-12 | 0.9983 | 0.7255 | 0.4130 | 0.0053 | 0.9983 | 0.7182 | 0.3520 | 0.0052 |
| LM-14 | 0.9996 | 0.4860 | 0.3975 | 0.0027 | 0.9996 | 0.5060 | 0.3322 | 0.0028 |
| CGP-10 | 0.9985 | 0.7916 | 0.4065 | 0.0050 | 0.9981 | 0.8606 | 0.3440 | 0.0053 |
| SCG-10 | 0.9978 | 0.0104 | 0.4053 | 0.0058 | 0.9973 | 0.0702 | 0.3435 | 0.0061 |

## 4. CONCLUSION

The *ANN* model and the analytical model have different advantages and disadvantages. The solution is reached more slowly in analytical models, but it is explanatory. On the other hand, the *ANN* model provides fast solutions based on prediction. The artificial neural network model is based on the principle of teaching information to the system, and accordingly, it processes similar information and reaches a conclusion. It is not capable of predicting data other than this information. It is advantageous as it gives quicker and more practical results in changing situations.

In this study, a solar-based power plant design was made. The thermodynamic and economic analysis of the designed system was carried out. The article's primary purpose is to examine the accuracy of the analytically obtained values with the *ANN* model, taking into account the variable parameters. The $ANN$ algorithm with feed-forward back-propagation learning algorithm and $LM$, $CGP$, $SCG$ variants were used to predict the $NPV$. These algorithms were evaluated by statistical methods, such as $R^2$, $MPE$, $CoV$, and $RMSE$. The best results were obtained in the $LM$-10 algorithm during the training and testing steps. The values of $R^2$, $MPE$, $CoV$ and $RMSE$ were determined as 0.9999, 0.5100, 0.3807, and 0.0031, respectively, for the output of $NPV$ in training steps. In the testing step, these values were 0.9996, 0.5602, 0.3114, and 0.0030, respectively. When the analysis and $ANN$ results were compared, the error percentage was 0.013%. This value is an acceptable error rate. As a result, $ANN$ has given acceptable results in the solution of power plants.

Future studies aim to apply this method in more complex power plant solutions, taking into account the percent error obtained as a result of *ANN* analysis. In addition, it is predicted that the *ANN* model will be used in system optimisation and will provide convenience in many engineering applications.

## Nomenclature

$B_t$ = Cash flow ($)
$C$ = Cost ($)
$D$ = Diameter ($m$)
$E$ = Energy ($kW$)
$Ex$ = Exergy ($kW$)
$h$ = Enthalpy ($kj/kg$)
$I_t$ =Solar radiation ($kWh/m^2 - day$)
$L$ = Length ($m$)
$\dot{m}$ = Mass flow ($kg/s$)
$P$ = Pressure ($kPa$)
$\dot{Q}$ = Heat Energy ($kW$)
$r$ = Discount rate
$s$ = Entropy ($kj/kg.K$)
$T$ = Temperature (°C)
$W$ = Width ($m$)
$\dot{W}$ = Power ($kW$)

## References

**[1]** D. Guler, A Mutlu, E. Guney, B. Caglar, A. Hepbaslı and M. Araz, “Design and thermodynamic analysis of a 1 MW solar thermal power plant,” *13. National Plumbing Engineering Congress, 13-27 April 2017, İzmir*, pp, 345-359.

**[2]** C. Yilmaz, I. Koyuncu, “Thermoeconomic modelling and artificial neural network optimisation of Afyon geothermal power plant,” *Renewable Energy*, vol. 163, pp. 1166-1181, 2021.

**[3]** A. Zaaoumi, A. Bah, M. Ciocan, P. Sebastian, M.C. Balan, A. Mechaqrane, M. Alaoui, “Estimation of the energy production of a parabolic trough solar thermal power plant using analytical and artificial neural networks models,” *Renewable Energy*, vol. 170, pp. 620-638, 2021.

**[4]** F. Ferrara, A. Gimelli, A. Luongo, “Small-scale concentrated solar power (CSP) plant: ORCs comparison for different organic fluids,” *Energy Procedia*, 45(68th), pp. 217-226, 2014.

**[5]** F. A. Al-Sulaiman, “Exergy analysis of parabolic trough solar collectors integrated with combined steam and organic Rankine cycles,” *Energy Conversion and Management*, vol. 77, pp. 441-449, 2014.

**[6]** T. E. Boukelia, M. S. Mecibah, B. N. Kumar, K. S. Reddy, “Investigation of solar parabolic trough power plants with and without integrated TES (thermal energy storage) and FBS (fuel backup system) using thermic oil and solar sal,” *Energy*, vol. 88, pp. 292-303, 2015.

**[7]** O. Arslan, D. Kilic, “Concurrent optimisation and 4E analysis of organic Rankine cycle power plant driven by parabolic trough collector for low-solar radiation zone,” *Sustainable Energy Technologies and Assessments*, vol. 46, 101230, 2021.

**[8]** S. Thaker, A. O. Oni, A. Kumar, “Techno-economic evaluation of solar-based thermal energy storage systems,” *Energy Conversion and Management*, vol.153, pp.423-434, 2017.

**[9]** J. Yang, J. Li, Z. Yang, Y. Duan, “Thermodynamic analysis and optimisation of a solar organic Rankine cycle operating with stable output,” *Energy Conversion and Management*, vol. 187, pp. 459-471, 2019.

**[10]** S. Kumar, T. Kaur, T. "Development of ANN based model for solar potential assessment using various meteorological parameters," *Energy Procedia*, vol. 90, pp. 587-592, 2016.
**[11]** O. Arslan, O. Yetik, "ANN-based optimisation of supercritical ORC-Binary geothermal power plant: Simav case study," *Applied Thermal Engineering*, 31(17-18), pp. 3922-3928, 2011.
**[12]** A. Sencan, K. A. Yakut, S. A. Kalogirou, "Thermodynamic analysis of absorption systems using artificial neural network," *Renewable Energy*, 31(1), pp. 29-43, 2006.
**[13]** T. E. Boukelia, O. Arslan, M. S. Mecibah, "ANN-based optimisation of a parabolic trough solar thermal power plant," *Applied Thermal Engineering*, vol. 107, pp. 1210-1218, 2016.
**[14]** A. Sozen, M. Ozalp, E. Arcaklioglu, E. Galip Kanit, "A study for estimating solar resources in Turkey using artificial neural networks," *Energy Sources*, 26(14), pp. 1369-1378, 2004.
**[15]** O. Arslan, "Power generation from medium temperature geothermal resources: ANN-based optimisation of Kalina cycle system-34," *Energy*, 36(5), pp. 2528-2534, 2011.
**[16]** O. Senkal, "Modeling of solar radiation using remote sensing and artificial neural network in Turkey," *Energy*, 35(12), pp. 4795-4801, 2010.
**[17]** T. E. Boukelia, O. Arslan, M. S. Mecibah, "Potential assessment of a parabolic trough solar thermal power plant considering hourly analysis: ANN-based approach," *Renewable Energy*, vol. 105, pp. 324-333, 2017.
**[18]** S. A. Kalogirou, "Optimisation of solar systems using artificial neural networks and genetic algorithms," *Applied Energy*, 77(4), pp. 383-405, 2004.
**[19]** D. E. Ighravwe, D. Mashao, "Development of artificial neural networks for an energy storage system generated power prediction," *Energy Reports*, 6, pp. 674-679, 2020.
**[20]** A. Tugcu, O. Arslan, "Optimisation of geothermal energy aided absorption refrigeration system—GAARS: A novel ANN-based approach," *Geothermics*, vol. 65, pp. 210-221, 2017.
**[21]** General directorate of renewable energy. https://gepa.enerji.gov.tr/MyCalculator/pages/11.aspx (date of access 10.06.2019), in Turkey.
**[22]** Y. E. Yüksel, "Thermodynamic assessment of modified Organic Rankine Cycle integrated with parabolic trough collector for hydrogen production," *International Journal of Hydrogen Energy*, 43(11), pp. 5832-5841, 2018.
**[23]** Therminol VP1 http://twt.mpei.ac.ru/tthb/hedh/htf-vp1.pdf (date of access 10.09.2018)
**[24]** M. S. Sohal, M. A. Ebner, P. Sabharwall, P. Sharpe, "*Engineering Database of Liquid Salt Thermophysical and Thermochemical Properties*", No. INL/EXT-10-18297, Idaho National Laboratory, 2010.
**[25]** Refprop. Reference Fluid Thermodynamic and Transport Properties. NIST Reference Database. Version 9.0. *National Institute of Standards and Technology*, NIST, USA, 2010.
**[26]** Y. Cengel, M. Boles, *Thermodynamics with Engineering Approach.* (Translation: T. Derbentli). Istanbul: McGraw-Hill-Literature Publishing, 1996.
**[27]** Ministry of Labor and Social Security Turkish Republic. https://www.csgb.gov.tr/media/1236/2018_onikiay.pdf (date of access 2018, January).
**[28]** S. Agatonovic-Kustrin, R. Beresford, "Basic concepts of artificial neural network (ANN) modeling and its application in pharmaceutical research," *Journal of Pharmaceutical and Biomedical Analysis*, 22(5), pp. 717-727, 2000.

## Biographies

**Damla Erikgenoğlu** is a research assistant in the Department of Mechanical Engineering, Bilecik Seyh Edebali University, Turkey. She received an M.S. degree in Energy Systems Engineering from Bilecik Şeyh Edebali University in 2019. She is continuing Ph.D. degree in Mechanical Engineering. Her research interests cover solar energy applications, renewable energy systems, thermodynamic cycle analysis and exergy analysis.
**E-mail:** damla.kilic@bilecik.edu.tr

**Oğuz Arslan** is a professor in the Department of Mechanical Engineering, Bilecik Seyh Edebali University, Turkey. His specific interest in renewable energy applications, heat transfer, thermodynamic cycle analysis, exergy analysis, and environmental analysis. He has published many research papers in international journals and conference proceedings.
**E-mail:** oguz.arslan@bilecik.edu.tr