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# Short- and long-term prediction of energy to be produced in hydroelectric energy plants of Sakarya Basin in Turkey

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**ABSTRACT**

In recent years, it has been aimed to increase diversity of energy having a positive relationship with environment and minimize damage to environment and use water potential of country more effectively. Therefore, hydroelectric energy plants have become the most important sources used for energy production. In these energy plants, issues such as the amount of water used for energy and net drop, and pre-determination of energy output are very important in terms of energy planning. Moreover, approximate estimation of energy value to be generated in future by using estimation models is also very important for energy planning. Therefore, in this study is to estimate prospective energy which will be generated in two hydroelectric energy plants in Sakarya Basin of Turkey (Adasu Regulator and Hydroelectric Energy Plant and Pamukova Hydroelectric Energy Plant) in short and long term. Artificial Neural Networks Method was used to make short-term estimation analyzes and Innovative Sen Method, one of trend analysis methods was used to make long-term estimation analyzes. Data to be used in study (Daily Generated Energy, Daily Average Net Drop, and Daily Average Flow) were obtained from Hydroelectric Energy Plant Operation Directorate. As a result of study, value of energy to be generated by 2030 with Artificial Neural Networks model formed by these data was prediction with numerical data. In addition, long-term estimations were made with Innovative Sen Method, which is one of Trend Analysis Methods.

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Artificial neural networks; Innovation Sen Method; Pamukova; Adasu; hydroelectric energy plants; Sakarya Basin

## Introduction

In consequence of increase in industrialization and development of technology, energy value per capita has increased considerably. Operation of industrial facilities, communication, heating, lighting, communication, and transportation activities require a great deal of energy. Energy is considered as a potential power in development of countries. Therefore, when assessing development level of countries, energy value generated and consumed should be taken into consideration (Bozkurt 2009).

When evaluated with technological conditions of today, hydroelectric energy potential of world is 14.368.000 GWh per year. As of May 2018, approximately 19, 25% of technical hydroelectric energy potential and only 33, 82% of hydroelectric energy potential have currently been utilized. Ratio of hydroelectric energy generated on land to technically feasible potential is a determining factor for investments made or to be made in hydroelectric plants. As a matter of fact, Europe has developed 48, 39%, North and Central America 41, 84%, Australia/Oceania 22, 57%, South America 19, 81%, Asia 12, 23%, and Africa 4, 8% of this energy. As can be understood from this data, the vast majority of unused in other words wasted, hydroelectric energy potential in world is in Africa, Asia, and Latin America. (Hunutlu 2019; Sundin 2017).

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According to ten-year Development Report of International Energy Agency (IEA), in 2020, the share of energy production based on hydroelectric energy and other renewable energy sources in total energy consumption of world was prediction to increase by more than 53% compared to today. This situation is interpreted as hydroelectric energy potential of each power will become economically viable in following years and investments will increase rapidly. European Union Commission has decided for entire member states of European Union to increase share of renewable energy in total gross energy consumption to 20% by 2020 and enacted necessary legal arrangements. (Hunutlu 2019; International Energy Agency (IEA) 2016).

Electricity consumption in Turkey has been increasing approximately 8% each year over previous year. New energy projects should be developed in Turkey to meet this continuously increasing demand and it is also important to investigate energy value to be generated in future by using prospective estimation models (Turkish Electricity Transmission Company (TEIAS) 2013, Turkish Electricity Transmission Company (TEIAS) 2015). Therefore, short term and long term projections of energy which will be generated in two hydroelectric energy plants (Pamukova Hydroelectric Energy Plant (HEPP) with Adasu Regulator and HEPP) in Sakarya Basin of Turkey will be prediction. Artificial Neural Networks Method will be performed in this hydroelectric energy plants in order to make future energy estimation in short term. In long term, future estimation analyzes will be performed with Innovative Sen Method, which is one of Trend Analysis Methods. Short and long term prediction energy will play an extremely important role in energy planning of this region and would enlighten similar studies. There are many studies conducted in literature with these methods (Al-Saba and El-Amin, 1999; Ceribasi 2017, 2018a, 2018b, 2019; Dabanli et al. 2016; Dash, Satpathy, and Liew 1998; Guclu, Sisman, and Yelegen 2016; Haktanir and Citakoglu 2014; Hamzacebi and Kutay 2004; Kermanshahi and Iwamiya 2002; Kodogiannis and Anagnostakis 1999; Liang and Cheng 2002; Markus et al. 2014; Mishra and Coulibaly 2014; Ozen 2008; Padmakumari, Mohandas, and Thiruvengadam 1999; Park and Sandberg 1991; Parlos et al. 1996; Peng, Hubele, and Karady 1992; Saplioglu, Kilit, and Yavuz 2014; Sen 2014; Sonali and Kumar Nagesh 2013; Srinivisan 1998; Tamimi and Egbert 2000; Timbadiya et al. 2013; Yilmaz and Tosunoglu 2019).

## Materials and methods

### *Study areas*

In this study, two hydroelectric energy plants in Sakarya Basin of Turkey for making short and long-term future estimates of energy generated have been selected.

### *Pamukova HEPP*

Pamukova HEPP is located within boundaries of Sakarya province, south of Sakarya province; approximately 12 km south-west of Pamukova district and 50 km away from Adapazari and its location is given in Figure 1. This HEPP is 748$^{th}$ largest power plant in Turkey and 8$^{th}$ in Sakarya with an installed capacity of 9.30 MW with HEPP. The facility is also 346$^{th}$ largest Hydroelectric Energy Plant in Turkey. Pamukova HEPP meets entire electricity need of 14.955 people in daily life with an average of 49.500.000 kilowatt-hours of electricity generation. Considering electricity consumption of houses, Pamukova HEPP generates electricity that can meet electricity need of 15.714 dwellings (URL-1 2019).

The general characteristics of Pamukova Hydroelectric Energy Plant are given in Table 1.

In study, daily produced energy, daily average net drop and daily average flow data between 01/01/2007-28/02/2019 dates from Pamukova HEPP Management Directorate were used to establish Artificial Neural Networks model and to apply analyzes with Innovative Sen Method. Data graphs of these parameters are given in Figure 2 (Daily Produced Energy in Figure 2a, Daily Average Net Drop in Figure 2b and Daily Average Flow in Figure 2c).

Statistical analysis values of each energy parameter (Daily Produced Energy, Daily Average Net Drop and Daily Average Flow) data of Pamukova HEPP are given in Table 2.


Figure 1. Location of Pamukova hydroelectric energy plant.

Table 1. Pamukova HEPP Information (URL 2019).

| | |
|---|---|
| Installed Energy | 9,30 MW |
| Rate to Installed Energy | 0,0114% |
| Annual Electricity Production | 50 GWh |
| Location | Sakarya |
| License Number | EU/594-14/597 |

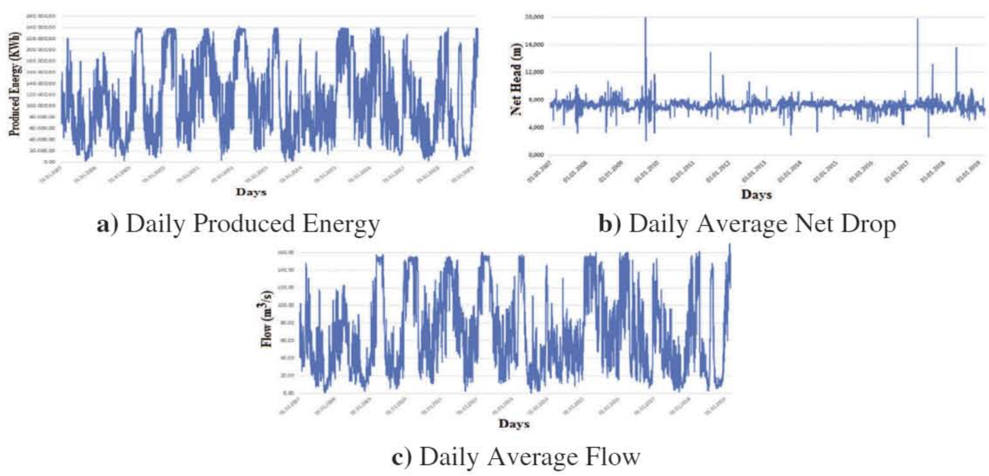



Figure 2. Data graphs of energy parameters in Pamukova HEPP (Pamukova HEPP Operating Directorate Energy Data 2019).

Table 2. Statistical analysis values of each energy parameter data of Pamukova HEPP.

| Energy Parameters | Minimum | Average | Maximum | Standard Deviation | Variation |
|---|---|---|---|---|---|
| Flow ($m^3/s$) | 0,500 | 69,0110 | 176,000 | 46,474 | 0,673 |
| Net Head (m) | 2,136 | 7,23500 | 19,9210 | 0,7190 | 0,099 |
| Produced Energy (MWh) | 0,500 | 110,467 | 242,071 | 69,576 | 0,630 |

## Adasu regulator and HEPP

Adasu Regulator and HEPP are located on the Sakarya River, in lower Sakarya Basin and just south of the Adapazari city center, in north-western of Turkey, its location is shown in Figure 3. This HEPP is the 730th largest power plant in Turkey and the 6th in Sakarya with an installed capacity of 9.60 MW. The facility is also 338th largest Hydroelectric Energy Plant in Turkey. Adasu Regulator and HEPP can meet the entire electricity need of 10.766 people in daily life with an average of 35.667.115 kilowatt-hours of electricity generation. Considering the electricity consumption of houses, Adasu Regulator and HEPP generates electricity that can meet electricity need of 11.323 dwellings (URL-1 2019).

The general characteristics of Adasu Regulator and Hydroelectric Energy Plant are given in Table 3.

In the study, daily produced energy, daily average net drop and daily average flow data between 01/01/2014-31/03/2019 dates from Adasu Regulator and HEPP Management Directorate were used to establish Artificial Neural Networks model and to apply analyzes with Innovative Sen Method. Data graphs of these parameters are given in Figure 4 (Daily Produced Energy in Figure 4a, Daily Average Net Drop in Figure 4b and Daily Average Flow in Figure 4c).

Statistical analysis values of each energy parameter (Daily Produced Energy, Daily Average Net Drop and Daily Average Flow) data of Adasu Regulator and HEPP are given in Table 4.

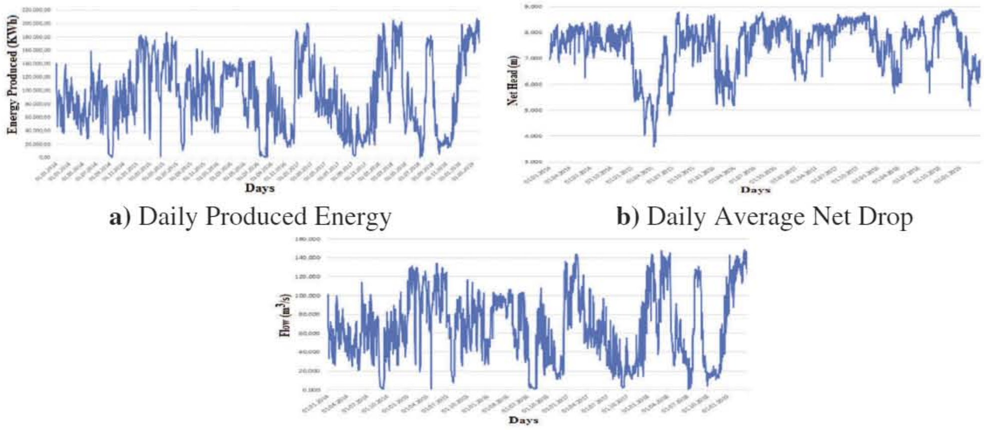
## Artificial neural networks

Having operation principle of brain nerve cells, Artificial Neural Networks (ANNs) can be defined as a system designed by modeling like brain. A network belonging to ANNs are formed


Figure 3. Location of Adasu regulator and hydroelectric energy plant.

Table 3. Adasu regulator and HEPP Information (URL-1 2019).

| | |
|---|---|
| Installed Energy | 9,60 MW |
| Rate to Installed Energy | 0,0118% |
| Annual Electricity Production | 36 GWh |
| Location | Sakarya |
| License Number | EU/1583-2/1146 |




**a)** Daily Produced Energy **b)** Daily Average Net Drop

**c)** Daily Average Flow

**Figure 4.** Data graphs of energy parameters in Adasu regulator and HEPP (Adasu Regulator and HEPP Operating Directorate Energy Data 2019).

**Table 4.** Statistical analysis values of each energy parameter data of Adasu regulator and HEPP.

| Energy Parameters | Minimum | Average | Maximum | Standard Deviation | Variation |
|---|---|---|---|---|---|
| Flow ($m^3$/s) | 0,387 | 67,2300 | 148,487 | 37,715 | 0,561 |
| Net Head (m) | 3,577 | 7,49000 | 8,90400 | 0,9844 | 0,131 |
| Produced Energy (MWh) | 0,540 | 93,8740 | 207,342 | 52,663 | 0,561 |

by connecting neurons to each other. These links are rated with specific weights. Moreover, Network created by connections of neurons aligns in layers. A simple ANN network input layer composes of three layers; input, hidden and output layer. ANN model used in this study is shown in Figure 5.

Working in a manner like learning fundamentals of brain, ANNs can be seen as a processor with ability to compile, evaluate, deduce, produce results, and retain data given as input for entire data center (Kiki 2008). In ANN model of this study, days, daily average flow, daily average Net drop, and daily generated energy data will be used as inputs, and as output, quantities of energy to be produced prospectively will be taken numerically.

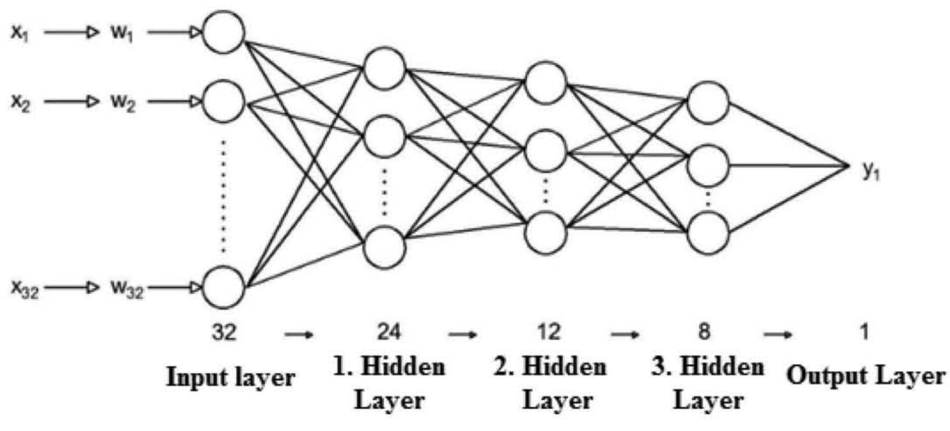



**Figure 5.** ANN model used in this study.

### Innovative Sen methods

In this method, present series of data is divided equally into two. Both series are lined up ascending. Afterward, first series ($X_i$) on X-axis and second series ($X_j$) on Y-axis, are lined up on Cartesian system of coordinates (Figure 6). If data are lined up on 1:1 line, it means there is no trend. If data are in sub triangle of 1:1 line, and are in below area, it means there is a low level of trend, if placed in middle area it means there is a medium level of trend, and if placed in high area, it means there is an increasingly decreasing trend. If data are on upper triangle of 1:1 line and are in low area, it means there is a low level of trend, if placed in middle area, it means there is a medium level of trend, if placed in high area, it means there is a highly increasing trend (Ceribasi 2017, 2018a, 2018b, 2019; Sen 2014, 2012).

## Results and discussion

In this study, artificial neural networks method has been performed to make a short term estimation analysis of energy generated in two hydroelectric energy plants in Sakarya Basin of Turkey and Innovative Sen method, one of Trend Analysis Methods, has been performed to do prospective analysis in long term.

### Results of ANNs method of Pamukova HEPP

There are 4.443 data in ANNs model of Pamukova HEPP. These data are between 01/01/2007-28/02/019. 4.019 of these data (01/01/2007-31/12/2017) were used as 70% training and as 30% test. 20% of data used for training were used as validation tests. According to analysis results of 2.813 (70%) data which are taught for train in ANNs model, $R^2$ value was calculated as 96.80%. Results are shown in Figures 7 and 8.

When training results of ANNs model of Pamukova HEPP are analyzed, it is observed that actual and prediction energy graphs are generally in consistency with each other. Moreover, when $R^2$ value of scattering diagram of ANNs model of Pamukova HEPP is analyzed, getting score of 96, 70% for

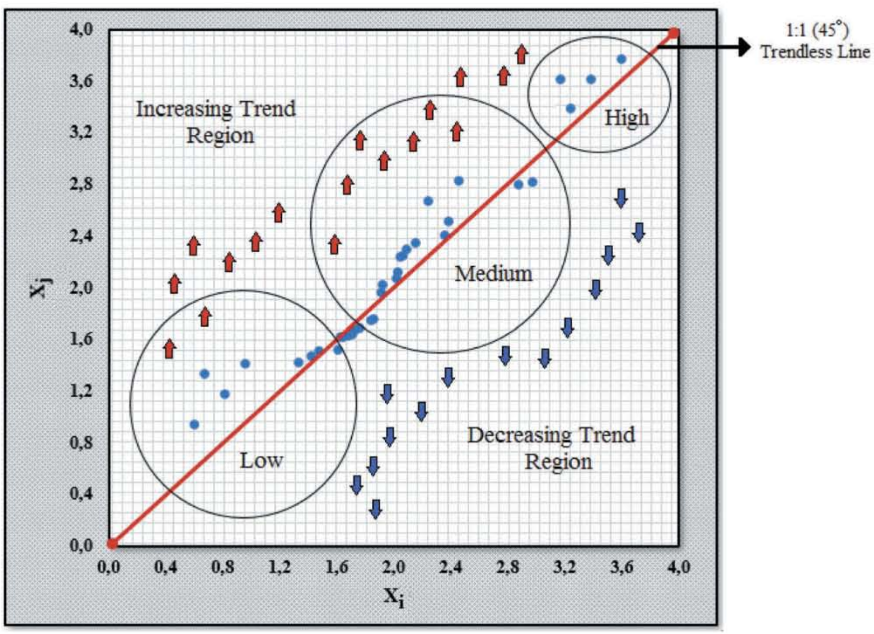



Figure 6. Illustration of the Innovative Sen Methods.

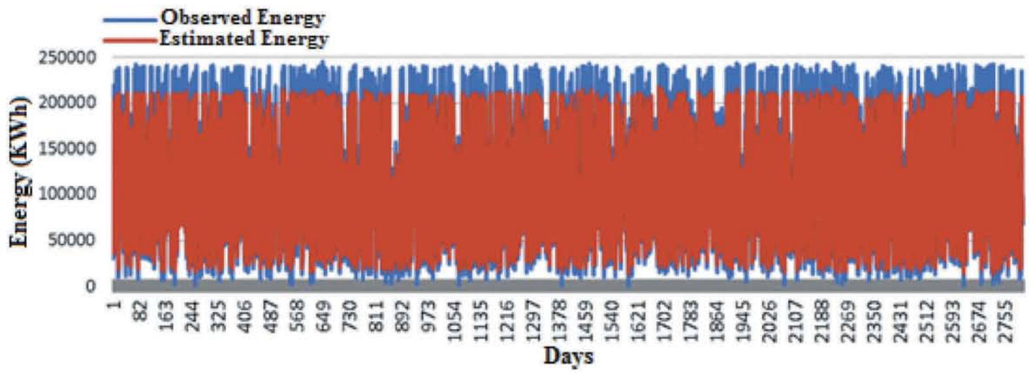



Figure 7. Training test result of ANNs model of Pamukova HEPP.

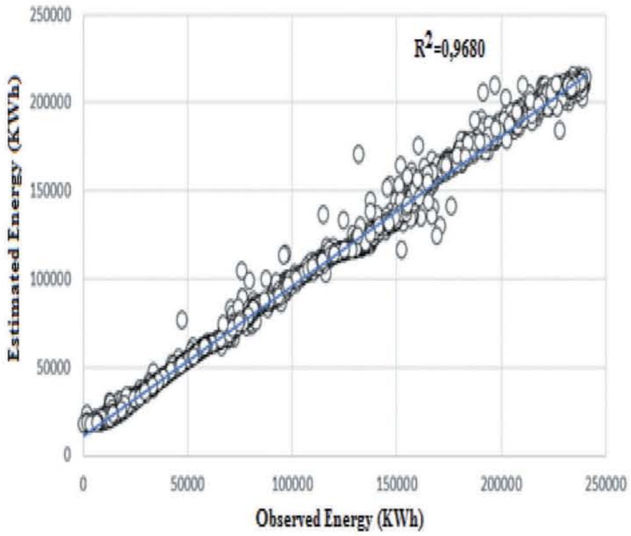



Figure 8. Scattering diagram of training test result of ANNs Model of Pamukova HEPP.

this value shows that model is very well trained. According to analysis results of 1.206 (30%) data, which were taught to be tested in ANNs model of Pamukova HEPP, $R^2$ value was calculated as 96, 70% and results are given in Figures 9 and 10.

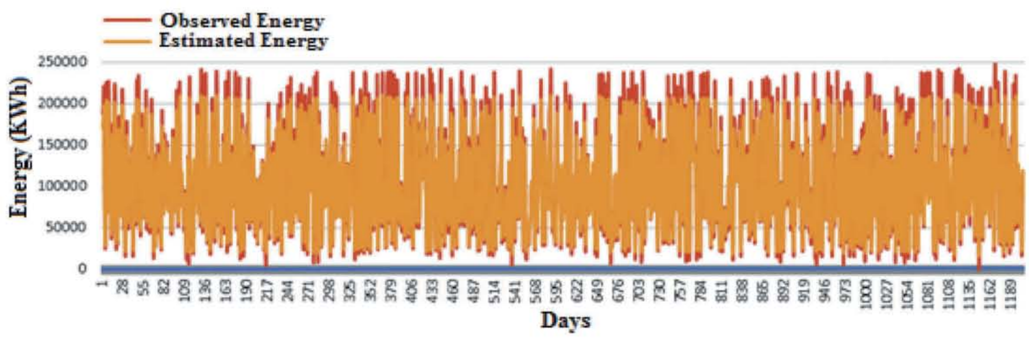



Figure 9. Test result of ANNs model of Pamukova HEPP.

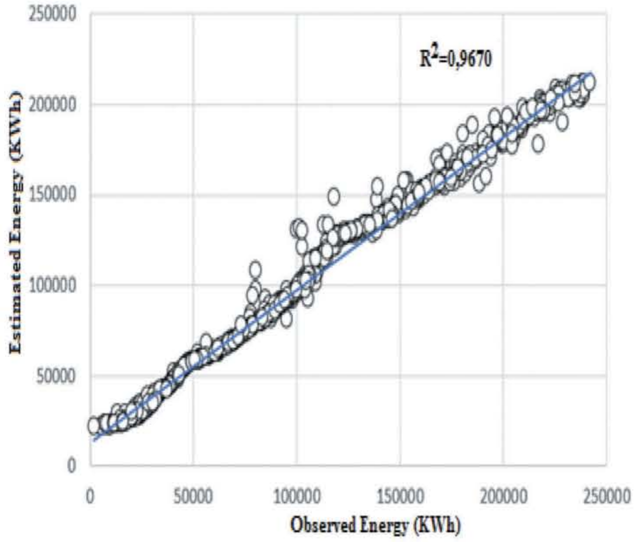



Figure 10. Scattering diagram of test result of ANNs model of Pamukova HEPP.

When test scores of ANNs model of Pamukova HEPP are analyzed, it is observed that actual and prediction energy graphs were consistent. In addition, getting a score of 96, 70% for $R^2$ of scattering diagram of ANNs model of Pamukova HEPP shows that model is very well tested. Verification test was performed according to ANNs model of 424 data, (01.01.2018–28.02.2019) which is not taken into account except for 4.019 data taught for training and testing purposes, out of 4.443 data in ANNs model of Pamukova HEPP and its comparison with actual data is given in Figure 11.

When test scores of ANNs model of Pamukova HEPP are analyzed, it is observed that actual and prediction energy graphs were nearly close to each other. Hence, it is observed that future estimates of ANNs model of Pamukova HEPP will very well match with real figures. According to this model, numerical estimation analysis of daily energy to be generated between 2019 and 2030 was conducted and resulting graph is shown in Figure 12.

## Innovative Sen method results of Pamukova HEPP

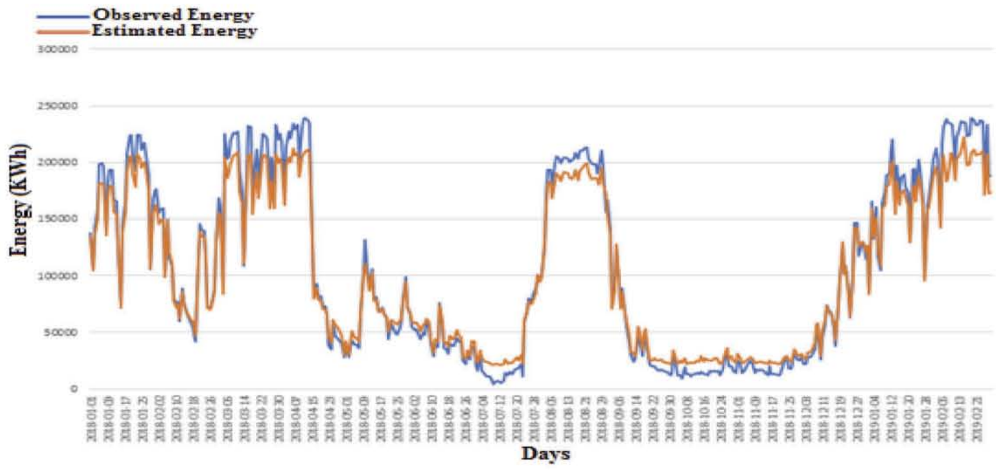
Daily average flow, daily average net drop and daily produced energy data of Pamukova HEPP were applied Innovative Sen Method and results were given in Figure 12 (Daily Average Flow in Figure 12a, Daily Average Net Drop in Figure 12b and Daily Produced Energy in Figure 12c).

General evaluation of the analysis results for energy parameters of Pamukova HEPP is given in Table 5.

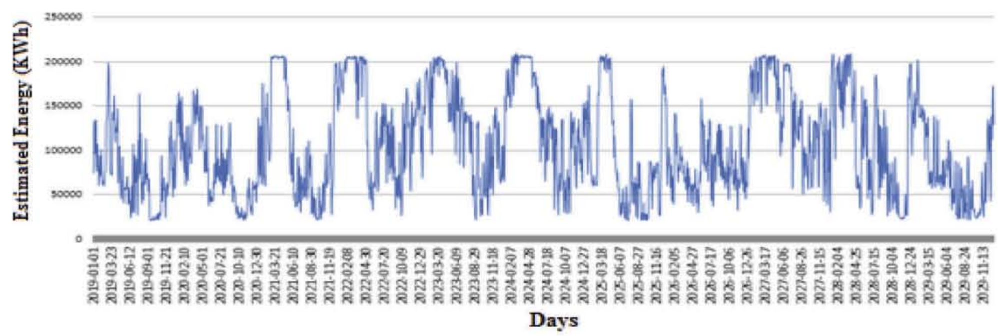
## Results of ANNs method of Adasu regulator and HEPP

There are 1.916 data in ANNs model of Adasu Regulator and HEPP. These data are between 01/01/2014-31/03/019. 1.550 of these data (01/01/2014-30/03/2018) were used as 70% training and as 30% test. 20% of data used for training were used as validation tests. According to analysis results of 1.085 (70%) data which are taught for train in ANNs model, $R^2$ value was calculated as 85.40%. Results are shown in Figures 13 and 14.

When training results of ANNs model of Adasu Regulator and HEPP are analyzed, it is observed that actual and prediction energy graphs are generally in consistency with each other. Moreover, when $R^2$ value of scattering diagram of ANNs model of Adasu Regulator and HEPP is analyzed, getting score of 85, 40% for this value shows that model is very well trained. According to analysis




(a)




(b)

**Figure 11.** (a) Validation test result of ANNs model of Pamukova HEPP. (b) Prediction energy values between 2019–2030 years of Pamukova HEPP.

results of 465 (30%) data, which were taught to be tested in ANNs model of Adasu Regulator and HEPP, $R^2$ value was calculated as 86, 70% and results are given in Figures 15 and 16.

When test scores of ANNs model of Adasu Regulator and HEPP are analyzed, it is observed that actual and prediction energy graphs were consistent. In addition, getting a score of 86, 70% for $R^2$ of scattering diagram of ANNs model of Adasu Regulator and HEPP shows that model is very well tested. Verification test was performed according to ANNs model of 366 data, (31.03.2018–31.03.2019) which is not taken into account except for 1.550 data taught for training and testing purposes, out of 1.916 data in ANNs model of Adasu Regulator and HEPP and its comparison with actual data is given in Figure 17.

When test scores of ANNs model of Adasu Regulator and HEPP are analyzed, it is observed that actual and prediction energy graphs were nearly close to each other. Hence, it is observed that future estimates of ANNs model of Adasu Regulator and HEPP will very well match with real figures. According to this model, numerical estimation analysis of daily energy to be generated between 2019 and2030 was conducted and resulting graph is shown in Figure 18.

## *Innovative Sen method results of Adasu regulator and HEPP*

Daily average flow, daily average net drop, and daily produced energy data of Adasu Regulator and HEPP were applied Innovative Sen Methods and results are given in Figure 19 (Daily

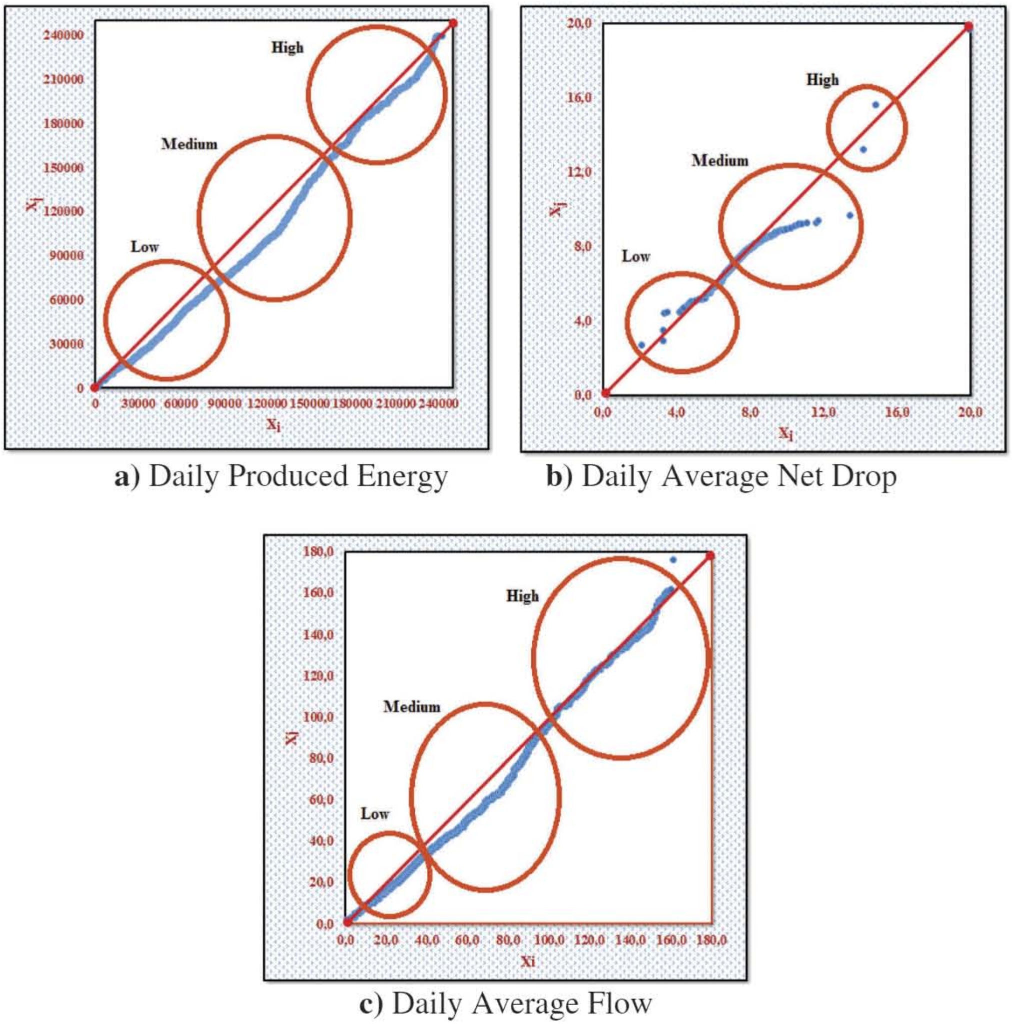



**Figure 12.** Innovative Sen Method results of energy parameters in Pamukova HEPP.

**Table 5.** General evaluation of energy parameters analysis results of Pamukova HEPP.

| Energy Parameters | Low | Medium | High |
|---|---|---|---|
| Flow ($m^3/s$) | **0-90(x10³)** — | **90-180(x10³)** ▼ | **180-240(x10³)** — |
| Net Head (m) | **0-4** ▲ | **4-15** ▼ | **15-16** — |
| Produced Energy (KWh) | **0-40** — | **40-100** ▼ | **100-160** — |

Average Flow in Figure 19a, Daily Average Net Drop in Figure 19b and Daily Produced Energy in Figure 19c).

General evaluation of the analysis results for energy parameters of Adasu Regulator and HEPP is given in Table 6.

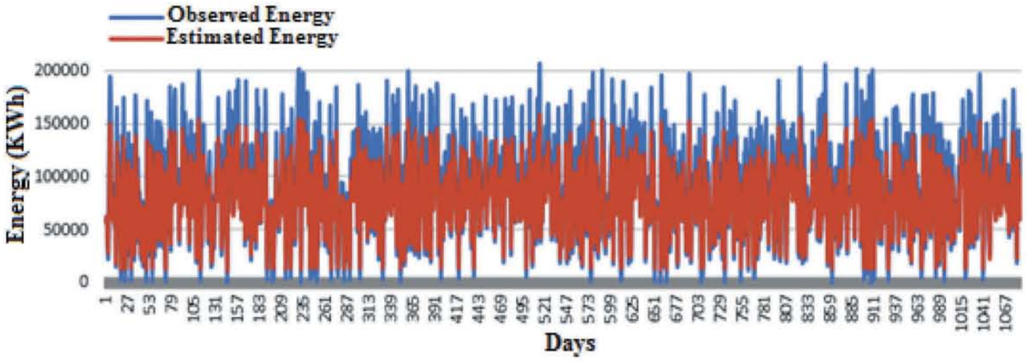



Figure 13. Training test result of ANNs model of Adasu regulator and HEPP.

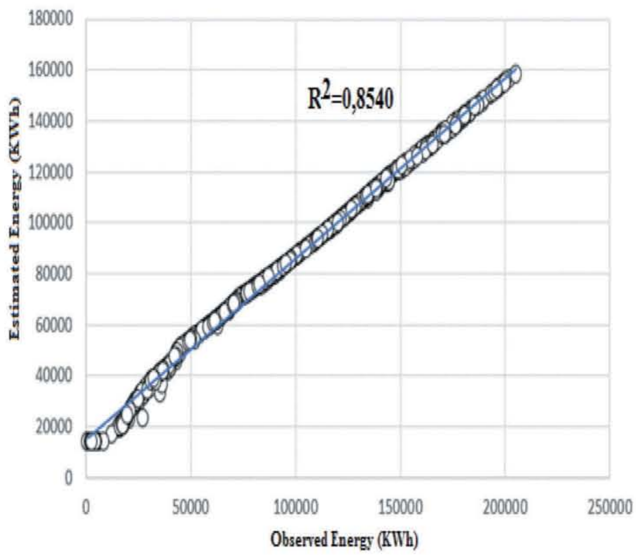



Figure 14. Scattering diagram of training test result of ANNs model of Adasu Regulator and HEPP.

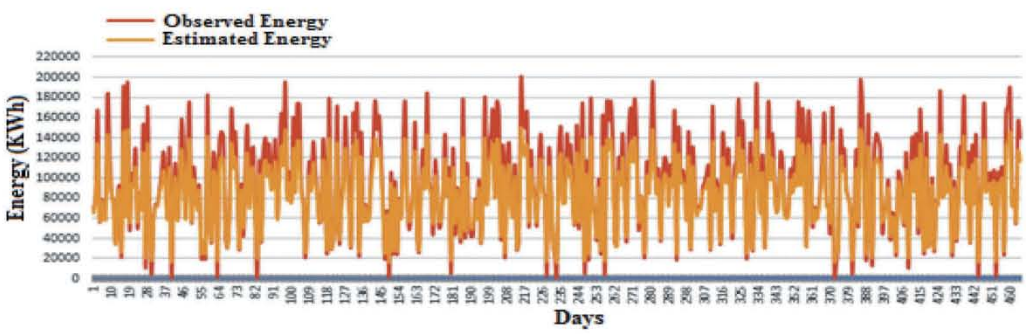



Figure 15. Test result of ANNs model of Adasu regulator and HEPP.

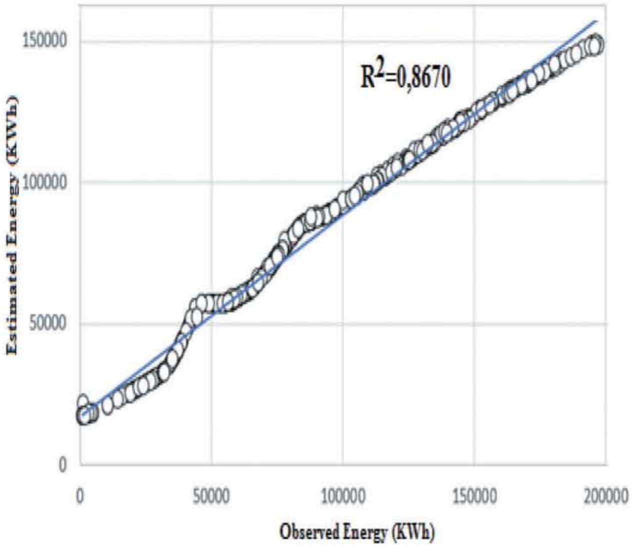



Figure 16. Scattering diagram of test result of ANNs model of Adasu regulator and HEPP.

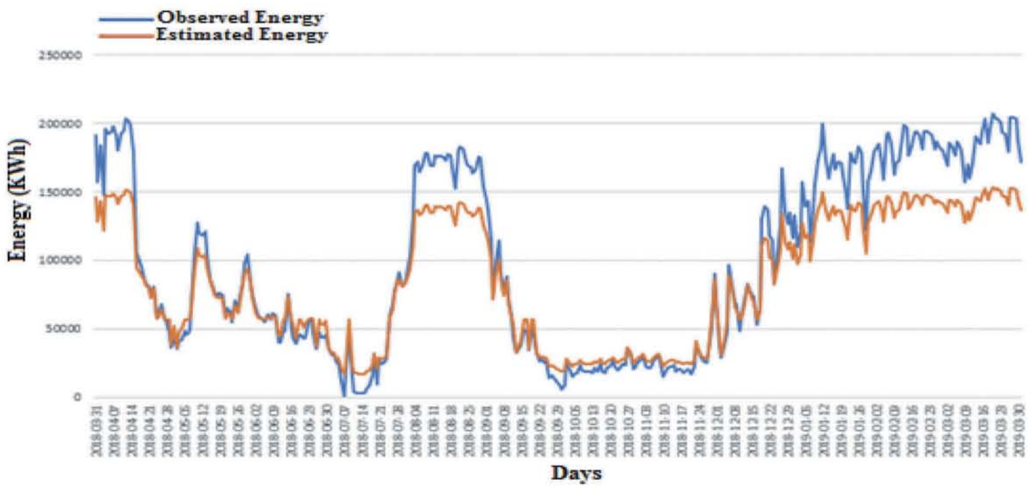



Figure 17. Validation test result of ANNs model of Adasu regulator and HEPP.

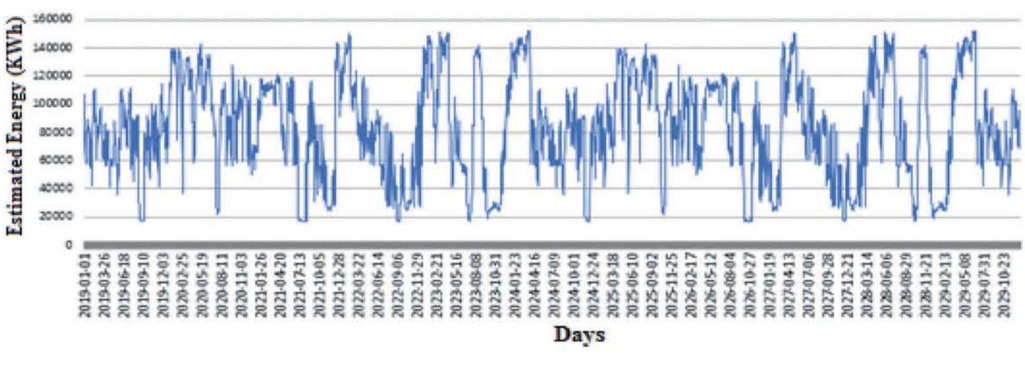



Figure 18. Prediction energy values between 2019–2030 years of Adasu regulator and HEPP.

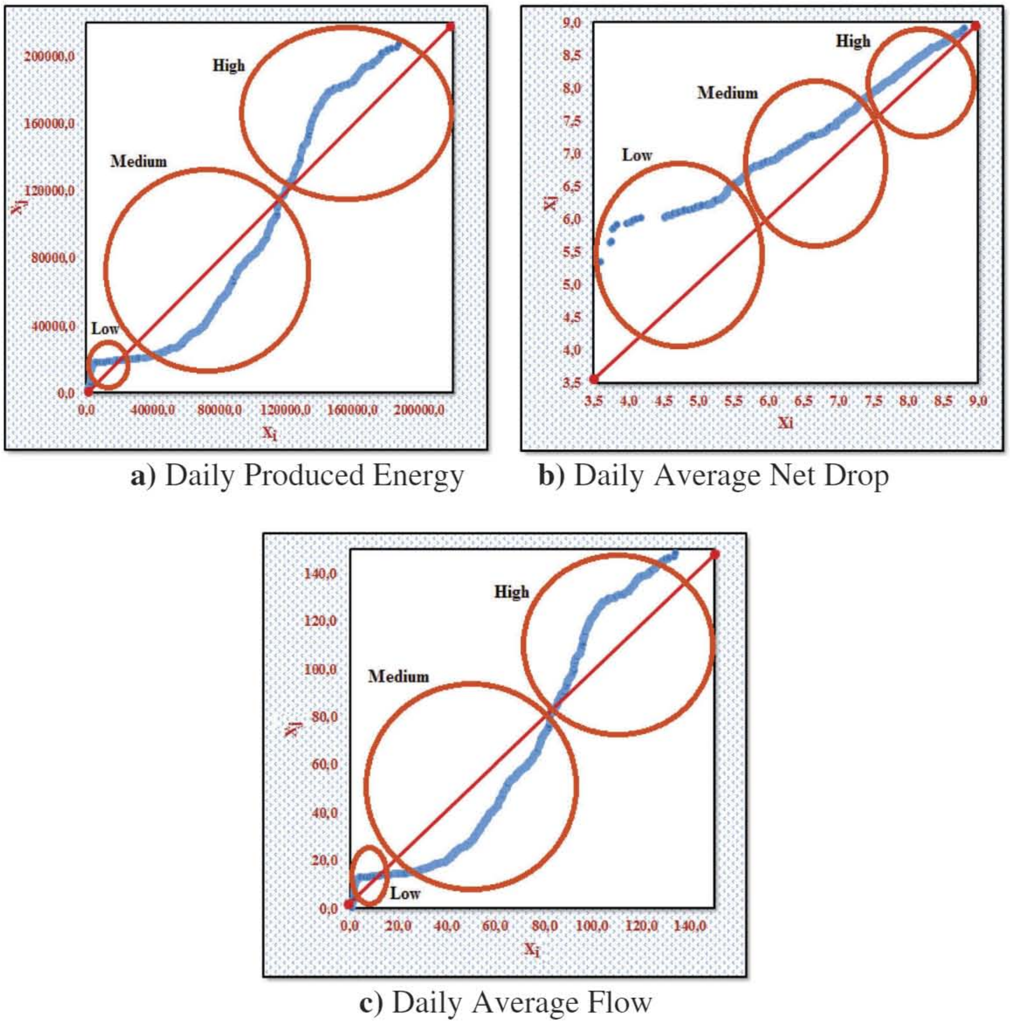



**Figure 19.** Innovative Sen Method results of energy parameters in Adasu regulator and HEPP.

**Table 6.** General evaluation of energy parameters analysis results of Adasu regulator and HEPP.

| Energy Parameters | Low | Medium | High |
|---|---|---|---|
| Flow ($m^3/s$) | **0-20(x10$^3$)** ▲ | **20-120(x10$^3$)** ▼ | **120-200(x10$^3$)** ▲ |
| Net Head (m) | **5-6,5** ▲ | **6,5-8** ▲ | **8-9** ▲ |
| Produced Energy (KWh) | **0-10** ▲ | **10-80** ▼ | **80-140** ▲ |

## Conclusion

In this study, a short- and long-term estimates of energy to be generated in two hydroelectric energy plants (Pamukova Hydroelectric Energy Plant and Adasu Regulator and Hydroelectric Energy Plant) in Sakarya Basin of Turkey were made. Artificial Neural Networks Method was used to make estimation analyzes in short-term and Innovative Sen Method was used to make estimation analyzes in long term. Data to be used in study (Daily Generated Energy, Daily Average Net Drop and Daily Average Flow) were obtained from Hydroelectric Energy Plant Operation Directorate. ANNs model formed in both HEPPs consists of three layers. These are input layer, hidden layer, and output layer. There are 32 neurons in input layer. Hidden layer was formed in three layers within itself. Their neuron numbers are 24, 12 and 8, respectively. Output layer is formed as a single layer.

In addition, when the studies in literature are examined; When the studies with ANNs were examined, only ANNs model was created and $R^2$ values were examined and reliability of model was investigated. When the studies with trend analysis methods are examined, it is seen that there is no joint study with trend analysis and ANNs. However, in this study, both ANNs and trend analysis method were used together, and forward forecasts were obtained numerically with ANNs.

As a result of this study, it is observed that $R^2$ values of modeling created for Pamukova HEPP give very good results. Therefore, these results revealed that estimations with ANNs model would give reliable results and energy to be produced by 2030 was prediction. When results of Innovative Sen Method of Pamukova HEPP are analyzed, it is observed that there is no trend in lower region of flow parameter and there is a decreasing trend in middle region and there is no trend in high region. It is observed that there is a decreasing trend in lower area of Net drop parameter, decreasing trend in middle region and there is no trend in high region. It is seen that there is no trend in lower area of the produced energy parameter, there is a decreasing trend in middle region, and there is no trend in high region. Therefore, when analysis results of both methods are examined; According to trend analysis method (in long term), three parameters will decrease in middle region and in other two regions will not trend. When results of ANNs (in short term) are analyzed, it is observed that there is no general change in energy value to be produced between 2015 and 2030.

For Adasu Regulator and HEPP, another hydroelectric energy plant, it is observed that $R^2$ values of generated modeling give also very good results. Therefore, these results revealed that estimations with ANNs model would give reliable results and energy to be generated by 2030 was prediction. When results of Sen Innovative Method of Adasu Regulator and HEPP are analyzed, it is seen that there is an increasing trend in low and high region of flow parameter and decreasing trend in middle region. An increasing trend has been observed in all three regions of Net Drop Parameter. It is observed that there is an increasing trend in low and high regions of produced Energy Parameter and a decreasing trend in middle region. Therefore, when analysis results of both methods are examined; According to trend analysis method (in long term), three parameters will increase in low and high regions and decrease in middle region. When results of ANNs (in short term) are analyzed, it is observed that there is no general change in energy value to be produced between 2015 and 2030.

Short and long term predictions made as a result of study will play a very important role in energy planning of this region and will guide to similar studies.

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