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Yield of the Hydroelectric Power Plant using Feed Forward and Recurrent Neural Networks: Hirfanlı Dam Application Example

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Abstract: The yield variety of the hydroelectric power plants according to the fall and flow changes depending on climatic conditions was investigated. For this purpose, Hirfanlı Hydroelectric Power Plant in Kaman where is the district of Kırşehir was selected as the sampling plane. The water consumption, decreased the flow of water to energy ratio, yield such data in 2008 from Hirfanlı Hydroelectric Power Plant and this data changes in the amount of precipitation, climate data were taken from the Kaman Weather Directorate and examination was performed about them. In this study, the methods to apply the feed forward and Elman's recurrent neural networks to estimate the net head according to climatic data and power plant production yield relationship. According to this data, the yield data of the hydroelectric power plants have been estimated to the system. As a result, the yield variety of hydroelectric power plants was found to be effective from all these climatic factors by using neural network structures.

Keywords: Hydroelectric Power Plants, Yield, Neural Network.

İleri Beslemeli Ağ ile Elman Ağı Kullanılarak Hidroelektrik Santralinin Verimi Hesabı: Hirfanlı Barajı Uygulama Örneği

Özet: Bu çalışmada iklim koşullarına bağlı olarak suyun düşüş ve akış değişikliklere göre hidroelektrik santrallerin verimi araştırıldı. Bu amaç için Kırşehir ilinin Kaman ilçesinde yer alan Hirfanlı Barajı örnek çalışma olarak belirlendi. Suyun tüketimi, suyun akış hızından ötürü enerji oranını azaltmaktadır. Bu konu ile ilgili Hirfanlı Hidroelektrik santralinin 2008 yılında alınmış yağış miktarları gibi iklimsel datalar ile verim hesabı araştırılmıştır. Bu çalışmada bir ileri beslemeli ağ ile elman ağı kullanılarak iklimsel etkiler ile barajın verimliliği arasındaki ilişki tahmini yapılmıştır. Sonuç olarak hidroelektrik santralinin verimlilik tahmini için iklimsel faktörlerin etkisi olduğu sonucuna varılmıştır.

Anahtar Kelimeler: Hidroelektrik Enerji Santrali, Verim, Yapay Sinir Ağları.

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1. Introduction

Energy is essential to economic and social development and improved quality of life in Turkey as in other countries [1]. Electricity supply infrastructures in Turkey as in many developing countries are being rapidly expanded as policymakers and investors around the world increasingly recognize electricity's pivotal role in improving living standards and sustaining economic growth [1]. With a young and growing population, low per capita electricity consumption, rapid urbanization, and strong economic growth, Turkey is one of the fastest growing power markets in the world, for nearly two decades [2]. The electricity demand of Turkey is expected to increase 555,7 TWh in 2020 [2]. With the increase in electricity demand per capita, electricity consumption was realized to be 1013 kWh in 1990 and will increase to 6794 kWh in 2020 [2]. The share of industrial sector energy consumption in total final consumption decreased from 62% in 1990 to 48% in 2001 [3]. On the other hand, the electricity demand increased from 29,211 to 46,989 GWh [4]. Due to the high economic development and the increase of population in Turkey, it is expected that between 2000 and 2030, it will be almost fivefold; Table 1 summarizes the sectoral distribution of general energy demand [3].

Table 1. Sectoral distribution of the general energy demand (1000 tons of oil equivalents) [3].

Year	Industry	Household	Transportation	Agriculture	Other	Total
1995	18181	17475	10827	2790	1514	50787
1997	22779	21374	12209	3120	1558	61040
1999	26576	23021	13521	3483	1604	68205
2001	30815	24708	14842	3868	1651	75883
2003	35491	26414	16146	4273	1699	84024
2005	40764	28239	17564	4721	1749	93037
2007	46863	30125	19122	5148	1800	103068
2010	57493	33193	21722	5862	1880	120174
2020	121179	50675	33049	11016	4407	200325
2030	203700	63447	36733	20036	10018	333934

Turkey's energy consumption and imports are experiencing rapid growth as is the Turkish economy. Net energy imports grew 28,5 million tons of oil equivalent (mtoe) in 1990 to 54,4 mtoe in 2000, and are expected to reach 228,2 mtoe in 2020. Net energy import, which met 54% in 1990 and 67% in 2000 of the total primary energy supply (TPES), will increase to 76% in 2020 [5].

Although Turkey has every kind of energy resources, it is an energy importing country because these resources are limited. More than half (52%) of the Net Energy Consumption in the country is met by imports, and the share of imports continue to increase each year [6]. In spite of its natural sources, Turkey depends on other countries in terms of energy production, and a transfer from conventional fossil sources to sustainable energy sources is strongly necessary [3]. Fig 1. shows the distribution of the energy sources according to their contribution to the total energy consumption in Turkey by the year 2005.

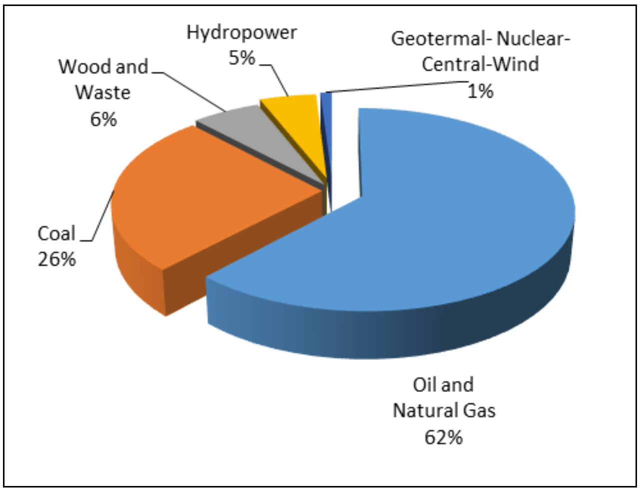

Fig. 1. Distribution of the energy sources according to their contribution to the total energy consumption in Turkey by the year 2005 [4].

Renewable energy is a significant resource considered as an alternative for fossil fuel consumption not only for Turkey but also for the world [7]. Renewables must be viewed as "alternative "only to traditional fossil fuel sources. They are, in fact, complementary to each other and can be used effectively alone or in combinations of two or more (wind and biomass, for example). Thus all renewable options should be pursued in tandem [8]. Table 2, summarizes Turkey's renewable energy potential.

Table 2. Turkey's renewable energy potential [10].

Renewable energy source	Gross (Gwh/year)	Technical (Gwh/year)	Economically available (Gwh/year)	Usage (%)
Hydropower	430-450	215	100-130	30
Geotermal	16	8*	4**	22,5
Solar	365	182*	91**	4,5
Wind	400	124	98	62
Biogas	1,58	0,79*	0,4**	16,8

* 50% of the gross value is taken
** 50% of the technical value is taken [11].

Furthermore, Turkey requires 360 billion kWh energy produced by other energy resources. Accordingly, renewable energy resources should be used until the year 2050 to respond to the requests [1]. In Turkey's renewable energy usage, hydroelectric energy has the biggest share. Then, Turkey's hydroelectric energy potential can respond 33–46% of its electric energy demand in 2020 [7].

Recently however, the unit price of energy provided to households and industries has risen up to about 0.10 $/kW h. Therefore, it has become reasonable to take the unit value of secondary hydroelectric energy produced as 0.05 $/kW h in current feasibility studies. If however, the annual irrigation demand is less than about 60% of the average annual inflow, it is physically possible to begin generating electricity in the dormant season also enabling production of firm energy to some extent [11]. As [7] says; Estimations on energy demand consider the cost of energy investment and production as well as energy potential. Whether a particular hydroelectric installation is economically competitive with a fossil fuel power plant will depend upon a number of factors, in particular fuel and construction costs. In numerous instances, a hydroelectric power plant is clearly economically superior to a comparable thermal power plant. In Turkey, most of the important water power plants have been developed, hence only amodest increase in the hydroelectric generating capability can be anticipated in the next two decades [1].

In the development of ANN modeling, two networks were tested; Feedforward Neural Network (FFNN) and Elman Network for the performance of training, validation and testing with training algorithm, Levenberg-Marquardt Back-propagation and the suitable transfer function for hidden node and output node was logsig/purelin combination. The results show the performance of Elman network was good compared to FFNN to predict the yield variety of hydroelectric power plants.

2. Hydropower

According to meteorological observations, 643 mm rain fall in a year equals 501 billion m^3 of water. However, it is estimated that only 186 billion m^3 of this average value flows to seas and lakes through rivers of different sizes [8].

Hydroelectric potential in our country is nearly 1% of the world potential, 16% of the European potential. Nearly 65% of hydroelectric potential are still not converted to energy. Turkey's theoretical hydroelectric potential with available water sources is calculated as 433 milliard kWh. Turkey is using only 46 kWh part of the hydroelectric potential by 2005 [10].

The practical use of hydroelectric energy has great potential to be installed to benefit the needs of Turkey. Although a lot of effort and a lot of finance have gone toward implementation of the hydroelectric energy technology system within the country, to overcome the increasing energy problem more hydroelectric energy production will be needed [8].

The working principle of a hydropower is not complicated. Typical hydropower is consisting of a dam, water slot, a power station and an transformer station. Kinetic energy of flowing water has the ability of producing electrical energy. Hydropower is produced by a turbine which is triggered by falling water on it. The potential energy formed by the altitude level according to power station, is converted to the kinetic energy during the flow of water from higher point (dam) to the lower point (station). This kinetic energy is firstly turned into the mechanical energy to turn the shaft and then converted to electricity in a synchronous generator. The amount of the produced electricity depends on how the head pressure differantial is big and how the flow of water is strong. Exactly these rules are valid for all kinds of hydropower stations as shown in Fig. 2.

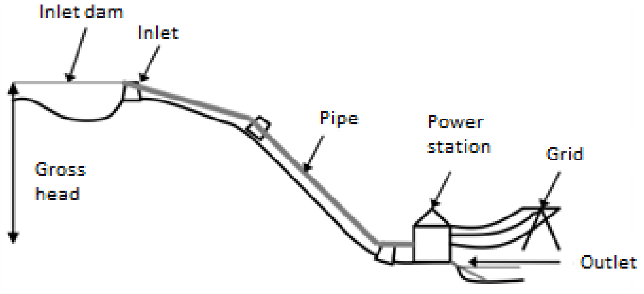

Fig. 2. Illustration of a hydropower plant [12].

Shortly the reservoir keeps and accumulates the water in order to boost potential energy of water, water slots transfer water from the reservoir to the turbine. This water actuates the turbines which prompt the generators to produce electricity.

Head is described as a vertical distance, or as a function of the characteristics of the channel or pipe. Most SHP sites are categorized as a low or high head [13].

The net head (H_0) of an SHP can be created in quite number of ways, being the most known the following two types: building a dam across a stream in order to increase the water level just above the plant; or diverting part of the stream, with a minimum of head loss, to just above the plant**.** Fig. 3 shows components of a hydropower scheme. The basic hydropower principle is based on the conversion of a large part of the gross head, H_g (m), (i.e. net head H_0 (m)) into mechanical and electrical energy [14]:

$$H_0 = H_g - \Delta H_{AB} \tag{1}$$

Being head losses along the total conversion system expressed by ΔH_{AB} (m). The hydraulic power P_0 (kW) and the corresponding energy E_0 (kWh) over an interval time Δt (h) will be, respectively:

$$P_0 = \rho g Q H_0 \tag{2}$$

$$E_0 = \rho g Q H_0 \Delta t \tag{3}$$

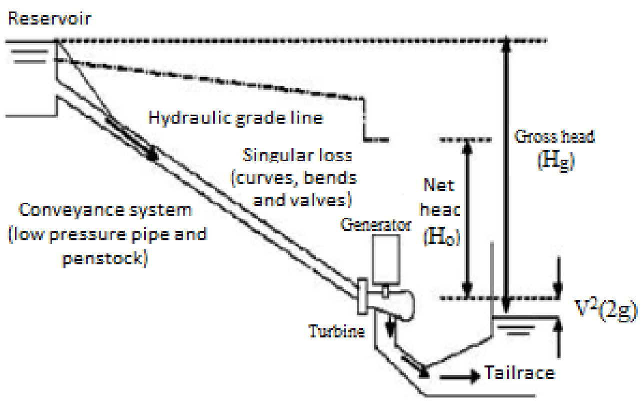

Fig 3. Components of a hydropower scheme [15].

A hydropower plant can be characterized by its input–output curves. The input is in terms of water discharge (Q). The output is in terms of power generation (P). The net hydraulic head (H) is defined as the difference between the level of the reservoir and the tail water. The power generated by a hydropower plant depends on the characteristics of the net hydraulic head (or the volume of reservoir V) and water discharge. The hydro plant generation characteristics can be transformed into a characteristic surface where power generation is a function of the water release through the turbine and the net head. The general form is expressed by [16].

$$P = f(Q, H) \tag{4}$$

It is proved up to the hilt by (2), (3) and (4) that the yield of hydropower plant according to power or energy is linear with the head.

When constructing a hydropower plant the goal is to transform the potential energy into electrical energy as efficiently as possible, to the lowest costs possible. Finding the optimal choice is not simple [12].

The water inflow through the year and from one year to another is uncertain in addition to the uncertain electricity price [12].

Although many of the systems are constituted to large areas some of them has hydrometric data collection network. Because of this reasons the available hydrologic information is not accurate completely and lack. Additionally there is a nonlinear relation between the variables which produce water-flow, accordingly forecasting the water-flow is complicated further. As seen forecasting techniques for hydrologic should be advanced. Available techniques which used in modelling suppose linear relation between the variables and generating synthetic water-flows.

The annual per capita water potential is at present 1700 m^3 but expected to be reduced to 1000 m^3 in the year 2020. Thus Turkey cannot be considered a `water-rich' country, and its per capita potential is nearly the same as that of its neighbors such as Iraq (2000 m^3/yr) and Syria (1400 /yr). Precipitation differs considerably both from year to year and among the river basins [17].

Local hydrology of every river in the word is likely to be affected by climate change in some way [18]. For long-term planning and management of water resources, future change of the pattern of land use, water demand and water availability should be analyzed well in advance. Understanding how a water resources system responds to changing trends and variability requires knowledge of how it is affected by those conditions today and how it might respond in the future if those conditions change. Assessment of climate change helps to build resilience to the possible impacts of climate change through enhanced institutional flexibility and consideration of climate-related risks in the planning process [18]. The impact of climate change on water resources depends not only on changes in the volume , timing and quality of stream flow and recharge but also on system characteristics, changing pressures on the system evolves, and what adaptations to climate change are implemented [19]. The changed scenario of water availability needs to be properly taken into account for the long-term basin scale water management. There would be change in hydroelectric power generation capacity of the power plants, change in the water quality and change in the water availability for agricultural, residential, and industrial uses. It is becoming more and more urgent for developing better ways to manage the water in the face of changing climate to meet the competing needs of hydropower, water supply, irrigation and environmental quality. This will give an idea of the possible changes in the magnitude of discharge and corresponding changing pattern in the hydropower production and agricultural yield [18].

The impression of the climatic changes can be particular on a local districts compare to large scale areas involved. Because of this reason considerations should be done for local changes instead of large scale areas.

3. Previous Study

Neural Networks (NN) have been successfully applied in water resources. In the hydrological forecasting context, recent experiments have reported that artificial neural Networks (ANNs) may offer a promising alternative for rainfall – runoff modelling [20,21], stream flow prediction [9,22,25], reservoir inflow forecasting [26,27] and suspended sediment estimation [28,29,34]. Ref [29] used a single ANN approach to establish daily sediment–discharge relationship and found that the ANN model could perform better than threating curve. In the hydrological forecasting context, recent experiments have reported than ANNs may offer a promising alternative for R-R modeling [35,20], stream flow prediction [22,23,36,38] and reservoir inflow forecasting [14,39]. Recently, Ref [40] reviewed the ANN based modeling in hydrology over the last years, and reported that about 90% of experiments make extensive use of the multi-layer feed-forwards neural networks (FNN) trained by the standard back propagation (BP) algorithm [41]. Very few studies have been conducted on climate change impacts on water resources in South Asia [42] and there exists only limited knowledge concerning impact of climate change on water resources in the foothills and mountains of Nepal.

To the knowledge of the authors, no work has been reported in the literature that investigates the accuracy of adaptive neural network models in power plant production yield according to the variation of the net head, using hydro-meteorological data.

4. Data and Study Area

From the tables and the figures above, it is clear that Turkey needs to start to use its sustainable energy sources immediately as previously stated [3]. As Ref [7] suggests that the survey in the energy field showed that no study has been performed about the production of hydroelectric energy although it is shown to be one of the most important renewable resources in Turkey.

Hydro contributes to electricity generation in 160 countries and the least-cost way to increase hydro generating capacity is almost always to modernize and expand existing plants [8]. Most of the hydro plant presently in operation will require modernization by 2030 [43]. Fortunately, research and development studies on design of hydroelectric power plants should be supported [8].

This study indicates the ability of the neural network models to estimate the net head increasing according to climatic data and power plant production yield relationship, so the yield variety of the hydroelectric power plants according to the fall and flow changes depending on climatic conditions, was investigated. For this reason, Hirfanlı Hydroelectric Power Plant in Kaman where is the district of Kırşehir was selected as the sampling plane. Fig. 4 shows the location of the Hirfanlı Hydroelectric Power Plant. The water consumption, decreased the flow of water to energy ratio, yield such data in 2008 from Hirfanlı Hydroelectric Power Plant.

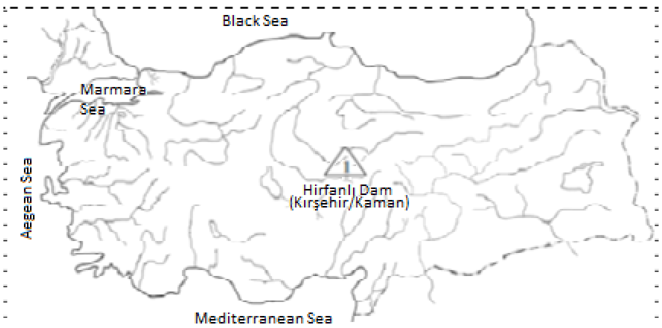

Fig. 4. Location of the Hirfanlı Hydroelectric Power Plant in Turkey.

In the development of ANN modeling, two networks were tested; FFNN and Elman Neural Network for the performance of training and testing with training algorithm, Levenberg-Marquardt Back-propagation was used for the training of the neural networks. The unipolar sigmoid and pure linear transfer functions for hidden and output nodes respectively. For this purpose, 366 data samples obtained from the operation simulation model are used for training and testing of network models. The available data set are divided into two groups as training and testing data sets which consist of 244 and 122 data samples, respectively. All samples have twelve features. These features are rainfall, in the amount of precipitation, the open surface evaporation amount, sunshine duration, mean air temperature, maximum and minimum air temperature, average wind speed, average wind directional, maximum and minimum wind directional, the time of the maximum wind and average moisture. This climate data were taken from the Kaman Weather Directorate in 2008.

5. Feed forward neural network for the yield variety of hydroelectric power plants.

At the first step we used the feed forward neural networks. Three layer feed-forward ANN are commonly encountered models found in the literature [44-45,49-55]. These networks are multilayer networks (input layer, hidden layer, and output layer). Computation nodes are arranged in layers and information feeds forward from layer to layer via weighted connections as illustrated in Fig.5. Circles represent computation nodes (transfer functions), and lines represent weighted connections. The bias thresholding nodes are represented by squares [45]. Equations used in the neural network models are given in Eq. (5)–(7) [46].

Outputs of hidden layer neurons are

$$Xj(n) = \frac{1}{\left(1+exp\left(\left(b_j^h(n)+\sum_{i=1}^{N} W_{ji}^{ih}(n)u_i(n)\right)\right)\right)} \qquad (5)$$

Sigmoid activation function outputs are

$$Y_l(n) = \frac{1}{\left(1+exp\left(b_l^o(n)+\sum_{j=1}^{N1} W_{jl}^{ho}(n)x_j(n)\right)\right)} \qquad (6)$$

and linear activation function outputs are

$$Y_l(n) = b_l^o(n) + \sum_{j=1}^{N1} W_{jl}^{ho}(n)X_j(n) \qquad (7)$$

where j is 1–$N1$, and $N1$ is the number of hidden layer nodes, ℓ is 1–$N2$, and $N2$ is the number of output layer nodes, $b_j^h(n)$ are the biases of the hidden layer neurons, $b_l^o(n)$ are the biases of the output layer neurons, $W_{ij}^{ih}(n)$ are the weights from input to hidden layer, $W_{jl}^{ho}(n)$ are the weights from hidden layer to output layer, $U_j(n)$, *i* is 1–*N* are the data inputs, and $Y_l(n)$, *l* is 1–*N*2 are outputs for the yield variety of hydroelectric power plants. In this study, 366 is used as *N*, 5 is used as *N*2, and five different values, 5, 10, 15, 20, and 25 are used as *N*1.

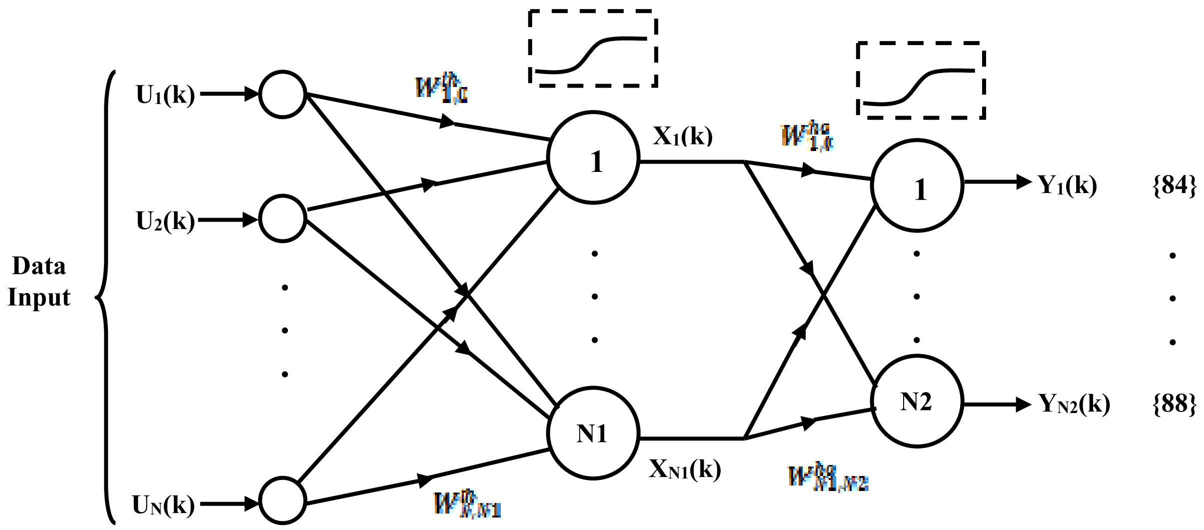

Fig. 5. FFNN structures for the yield variety of hydroelectric power plants [46].

Back propagation learning algorithm is one of the earliest and the most common method for training multilayer feed forward neural networks. Development of this learning algorithm was one of the main reasons for renewed interest in this area and this learning rule has become central to many current works on learning in ANN. It is used to train nonlinear, multilayered networks to successfully solve difficult and diverse problems [45].

6. Elman's recurrent neural network for the yield variety of hydroelectric power plants.

At the second step we proposed Elman's recurrent neural networks [47] for the yield variety of hydroelectric power plants as seen in Fig. 6. These networks are also multilayer networks (input layer, recurrent hidden layer, and output layer). While the hidden layer neurons use nonlinear sigmoid activation functions, two type activation functions (nonlinear sigmoid and linear) are used for the output layer neurons. Equations used in the neural network model are shown in Eq. (8)–(10) [46].

Outputs of hidden layer neurons are

$$X_j(n) = \frac{1}{\left(1+\exp\left(b_j^h(n)+\sum_{i=1}^{N} W_{ji}^{ih}(n)U_i(n)+\sum_{i=N+1}^{N+N1} W_{ji}^{ih}(n)X_i(n-1)\right)\right)} \tag{8}$$

Sigmoid activation function outputs are

$$Y_l(n) = \frac{1}{\left(1+\exp\left(b_l^o(n)+\sum_{j=1}^{N} W_{lj}^{ho}(n)X_j(n)\right)\right)} \tag{9}$$

and linear activation function outputs are

$$Y_l(n) = b_l^o(n) + \sum_{j=1}^{N1} W_{lj}^{ho}(n)X_j(n) \tag{10}$$

where j is 1–$N1$ and $N1$ is the number of hidden layer nodes, l is 1–$N2$ and $N2$ is the number of output layer nodes, $b_j^h(n)$ are the biases of the hidden layer neurons, $b_l^o(n)$ are the biases of the output layer neurons, $W_{ij}^{ih}(n)$ are the weights from input to hidden layer, $W_{jl}^{ho}(n)$ are the weights from hidden layer to output layer, $U_j(n)$, *i* is 1–*N* are the distorted wave inputs, $X_j(n-1)$, *i* is 1–*N*1 are the time delayed outputs of the hidden layer nodes which are measured at a previous time step (n − 1), and $Y_l(n)$, *l* is 1–*N*2 are outputs for the yield variety of hydroelectric power plants. In this study, 366 is used as *N*, 5 is used as *N*2, and two different values, 5,10,15,20 and 25 are used as *N*1.

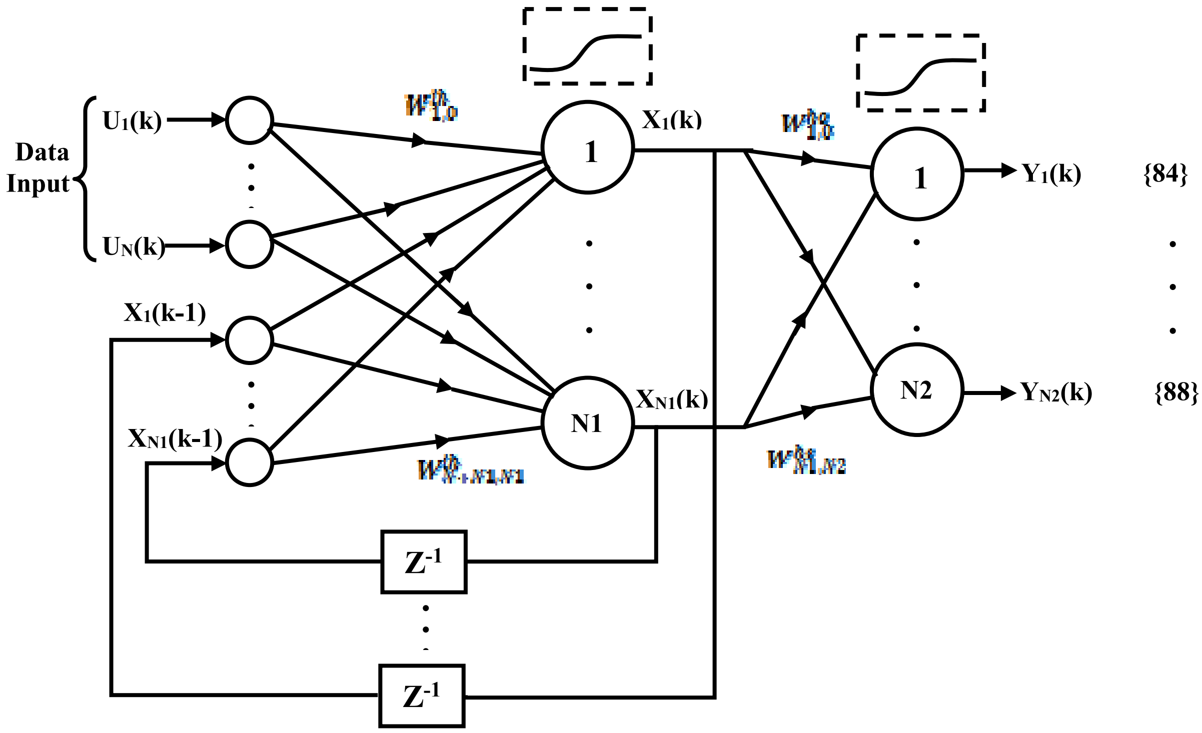

Fig. 6. Elman's recurrent neural network structures for the yield variety of hydroelectric power plants [46].

Note that the Elman network differs from conventional two-layer networks in that the first layer has a recurrent connection. The delay in this connection stores values from previous time step, which can be used in the current time step [48]. Because the network can store information for future reference, it is able to learn temporal patterns as well as spatial patterns. The Elman network can be trained to respond to, and to generate, both kinds of patterns [45].

Elman network is preferred because it exhibits dynamic behavior. In order to select an optimum network it can be chosen by trial and error, started with on two hidden nodes until twenty hidden nodes together with and Elman Network until the optimum network obtained. The selection corresponds based on the smallest cross-validation errors produced [45].

7. Results and conclusions

In order to choose the most appropriate network for the modeling process the network was tested depending on how efficient this network respond to any change in the modeling process. Thus, the performance of network was compared. The hidden layer and nodes were significant to the network. Therefore, the number of hidden layer used was one and the number of hidden nodes was chosen by trial and error because in most situations, there were no ways to define the number of hidden nodes without trying out several networks. In this study, the performance of various network models with different hidden layer neuron numbers was examined to choose an appropriate number of hidden layer neurons. Hence, one neuron was used in the hidden layer at the beginning of the process, and then the neuron number was increased step-by-step adding one more neuron until no significant improvement is noted.

Typically, mean square error (MSE) was used to present the network performance in order to define the best network [44,45]. The equation is shown as below;

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2 \tag{11}$$

where e_i is error, t_i is desired value, a_i is actual value and N is number of data.

The performance of an optimum network was done by trial and error, starting with two hidden nodes until twenty hidden nodes together with both networks (FFNN and Elman Network). Optimum network was selected among the networks based on the smallest cross-validation errors.

For the first step, a feed-forward back-propagation has been used. The network consisted of 5,10,15,20 and 25 hidden nodes in the hidden layer. The weights and bias values have been updated according to Levenberg–Marquardt (LM) optimization method [48]. Detailed computational issues about the application of the training algorithms to LM structures can be found in references [46,48-55]. The training samples have been processed to provide twelve parallel inputs to the NNs, which mentioned previously. The second step consisted of Elman NNs. This network consisted of 5,10,15,20 and 25 hidden nodes in the hidden layer. A data line of twelve slots has been inserted in the input layer. The traingdx function has been used for updating the weights and biases.

Table 3. Performance of training, validation and testing by using Elman network and FFNN.

Number of hidden nodes	Feedforward Network (newff)		Elman Network (newelm)	
	training	**testing**	**training**	**testing**
5	0.0204	0.0327	0.0327	0.0983
10	***0.0163***	***0.0245***	0.0245	0.0163
15	0.0286	0.0409	0.0163	0.0245
20	0.0327	0.0655	***0.0122***	***0.0081***
25	0.0573	0.0819	0.0204	0.0245

Table 3 shows the training and test performance for both networks that have been done. The result shows that the mean square error between the FFNN and Elman networks. The FFNN's training error for this result was 0.0163 with testing error of 0.0245 by 10 hidden nodes. Thus, this network was selected as an optimum network for FFNN. Meanwhile, the minimum training error for Elman Network's was 0.0122 with testing error of 0.0081 by hidden nodes of 20. Therefore this network was selected as the optimum network for Elman Network.

The differences of training error between these two networks were only 0.0041 and the training error for Elman Network was less than FFNN. The Elman Network produced testing error of

0.0081 compared to FFNN of 0.0245. The difference between them was 0.0164. Therefore, the performance of FFNN testing get worst compared to the performance of Elman Network.

As the result, the possibility of the FFNN and Elman's recurrent neural networks for the yield variety of hydroelectric power plants and it can be said that FFNN and Elman's recurrent neural networks are effective to use found the some parameter of hydroelectric power plants. In terms of greater efficiency from hydropower plants, in the feasibility studies which will consider the climatic data, the neural network models thought would be useful.

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