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Computing Technique Using ANNs for Optimal Scheduling of Hydrothermal Power Systems with Inclusion of Pump-Storage Plants

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Abstract

The paper deals with the application of the technology of the artificial neural networks (ANNs) on a power system to obtain the optimal scheduling of generation. The presented hydrothermal power system (HTPS) contains pump-storage plants (PSPs) besides the thermal plants (TPs) and hydro-plants (HPs). Given the system load in each time interval of the optimization period in addition to the decision variables (DVs) of TPs and HPs moreover of PSPs for both operation conditions (generating or pumping), the most economical generation of each power plant can be evaluated. Also, the generated power by PSPs in each generation operation or the power taken by these plants in each pump operation will be predicted. Estimation of the corresponding optimal generation cost of the TPs is occurred. The computing technique can determine the available water volume of HPs and of PSPs. ANNs have been designed and trained with patterns of input and output data at different values of training parameters. Agreeable results have been obtained and presented.

Keywords

Optimal scheduling, Short-range optimization, Optimal hydro-thermal operation, Artificial Neural Networks, Pump-storage power plants.

1. Introduction

Power systems are interconnecting for purposes of economy interchange and reduction of reserve capacity. Economic operation of power systems deals with the means and techniques for achieving minimum operating cost to supply a given predicted load. Any deviation from the optimum loading would result in an increase in fuel input and consequently in the generation cost. The optimal operation of thermal power systems has been discussed in Refs. [6], [8], [15] and [18], while it has been presented in Refs. [1-5], [11-14] for the HTPSs. DVs of the generating units must be estimated from unit commitment study taking into consideration the optimal generation costs with fullfilment of the operation constraints [7-10], [16] and [17]. To estimate DVs of PSPs in each time interval, the additional generation cost in pump operation and the costs that can be saved by setting the plants in generation operation must be evaluated and compared [14].

The maximum principle method (MPM) by Pontryagin [2], [4], [13] and [14] has a wide range of application in the area of the optimization problem side by side with the gradient methods [15], calculus variations and dynamic programming [1], [7] and [16]. The most important advantage of MPM is defining of the solution for TPs and HPs which operate at points or limits of discontinuity.

Artificial intelligence techniques and ANNs are widely used in the area of the power systems and they represent efficient alternatives for unit commitment [19], voltage stability assessment [21], [29] and for the thermal-rating computation of the transmission lines [28]. The ANNs have been applied also for the load forecasting [22], [25], contingency analysis [23] and for the optimal operation of hydro-steam power systems [30]. Using of ANNs has an increasing attention due to their gross capability, rapidity and validity for on-line operation.
MPM has been applied in Ref.[14] on a HTPS containing a PSP and the obtained results have been used in this work for training of the suggested artificial neural networks (SANNs). Feed-forward multi-layered networks with the generalized delta rule and back propagation of error will be designed to obtain continuous planning between their input and output data.

2. Economic Dispatch Of Hydrothermal Generation With PSPs

The aim of the objective function of a power system contains W TPs, M of HPs in addition to P of PSPs is to minimize the total generation cost (TGC) over the optimization time period that will be devided into N time intervals. In each time interval n, TGC is equal to the sum of the generation costs $F_{in}(P_{in})$ of each plant i

$$TGC = \sum_{n=1}^{N} \sum_{i=1}^{W} F_{in}(P_{in})\ \Delta t_n \tag{1}$$

Where P_{in} is the generated power of each thermal unit i in the interval n and Δt_n is the length of this time interval.
$F_{in}(P_{in})$ can be obtained in terms of the corresponding generation P_{in} and the cost constants A_i, B_i and C_i as follows

$$F_{in}(P_{in}) = A_i\ P_{in}^2 + B_i\ P_{in} + C_i \tag{2}$$

Till the time interval n, the thermal generation cost $FT^{(n)}$ can be predicted by

$$FT^{(n)} = FT^{(n-1)} + \sum_{i=1}^{W} F_{in}(P_{in})\ \Delta t_n \tag{3}$$

In each time interval, the sum of the output P_{in} of each plant of TPs and P_{jn} of each HP in addition to the output P_{gn} of each PSP in generating operation PG must be equal to the load demand PR_n plus the sum of the consumed power P_{pn} of each PSP in pump operation PP moreover the transmission losses of the system PL_n.

$$\sum_{i=1}^{W} P_{in} + \sum_{j=1}^{M} P_{jn} + \sum_{g=1}^{PG} P_{gn} = PR_n + PL_n + \sum_{p=1}^{PP} P_{pn} \tag{4}$$

The basic control variables (BCVs), which are P_{in}, P_{jn}, P_{gn}, P_{pn}, the water volumes V_{jn}, V_{gn} and V_{pn} of each HP and PSP in generation or pump operation, respectively, must satisfy in each time interval n the following inequality constraints. In other words, each BCVs must not violate each corresponding maximum and minimum limits ($\bar{P}$, $\bar{V}$ and $\underline{P}$, $\underline{V}$).

$$\underline{P}_i \leq P_{in} \leq \bar{P}_i \tag{5}$$

$$\underline{P}_j \leq P_{jn} \leq \bar{P}_j \tag{6}$$

$$\underline{P}_g \leq P_{gn} \leq \bar{P}_g \tag{7}$$

$$\underline{P}_p \leq P_{pn} \leq \bar{P}_p \tag{8}$$

$$\underline{V}_j \leq V_{jn} \leq \bar{V}_j \tag{9}$$

$$\underline{V}_g \leq V_{gn} \leq \bar{V}_g \tag{10}$$

$$\underline{V}_p \leq V_{pn} \leq \bar{V}_p \tag{11}$$

Where $\underline{V}_g = \underline{V}_p$ and $\bar{V}_g = \bar{V}_p$

The inequalities (5)-(11) can be converted to equality constraints by using the method of Valentine in calculus variations, [14], in terms of the additional control variables (ACVs) as given in Eq.(12), which is corresponding to the inequality (5).

$$(\bar{P}_i - P_{in})\ (P_{in} - \underline{P}_i) - X_{1in}^2 = 0 \tag{12}$$

Where X_{1in} is an additional control variable.

The water volume $V_j^{(n)}$ of HPs, in each time interval n, can be deduced from the corresponding volume to the previous interval $V_j^{(n-1)}$ as follows

$$V_j^{(n)} = V_j^{(n-1)} + AV_{jn} - Y_j\, P_{jn} \tag{13}$$

Where AV_{jn} is the additional volume of the plant j in the interval n, Y_j is a constant that relats between the drowdown volume and the generated power of that plant P_{jn}.

The water volume $V_g^{(n)}$ and $V_p^{(n)}$ of PSP for both generation or pump operation will be obtained by the following equations in terms of their constants Y_g and Y_p, respectively.

$$V_g^{(n)} = V_g^{(n-1)} - Y_g\, P_{gn} \tag{14}$$

$$V_p^{(n)} = V_p^{(n-1)} + Y_p\, P_{pn} \tag{15}$$

The Hmiltonian function $H^{(n)}$ can be constructed, in each time interval n, as

$$H^{(n)} = Z^{(n)} \; [\; FT^{(n-1)} + \sum_{i=1}^{W} F_{in}(P_{in}) \;\; \Delta t_n \;]$$

$$+ L_1^{(n)} \; [\sum_{i=1}^{W} K_{in} \, P_{in} + \sum_{j=1}^{M} K_{jn} \, P_{jn} + \sum_{g=1}^{PG} K_{gn} \, P_{gn} - PR_n - PL_n$$

$$- \sum_{p=1}^{PP} K_{pn} \, P_{pn}]$$

$$+ \sum_{i=1}^{W} K_{in} \, L_{2i}^{(n)} \; [(\bar{P}_i - P_{in}) \; (P_{in} - \underline{P}_i) - X_{1in}^{2}]$$

$$+ \sum_{j=1}^{M} K_{jn} \, L_{3j}^{(n)} \; [(\bar{P}_j - P_{jn}) \; (P_{jn} - \underline{P}_j) - X_{2jn}^{2}]$$

$$+ \sum_{j=1}^{M} K_{jn} \, L_{4j}^{(n)} \; [(\bar{V}_j - V_{jn}) \; (V_{jn} - \underline{V}_j) - X_{3jn}^{2}]$$

$$+ \sum_{j=1}^{M} K_{jn} \, L_{5j}^{(n)} \; [V_j^{(n)} - V_j^{(n-1)} - AV_{jn} + Y_j \, P_{jn}]$$

$$+ \sum_{g=1}^{PG} K_{gn} \, L_{6g}^{(n)} \; [(\bar{P}_g - P_{gn}) \; (P_{gn} - \underline{P}_g) - X_{4gn}^{2}]$$

$$+ \sum_{g=1}^{PG} K_{gn} \, L_{7g}^{(n)} \; [(\bar{V}_g - V_{gn}) \; (V_{gn} - \underline{V}_g) - X_{5gn}^{2}]$$

$$+ \sum_{g=1}^{PG} K_{gn} \, L_{8g}^{(n)} \; [V_g^{(n)} - V_g^{(n-1)} + Y_g \, P_{gn}]$$

$$+ \sum_{p=1}^{PP} K_{pn} \, L_{9p}^{(n)} \; [(\bar{P}_p - P_{pn}) \; (P_{pn} - \underline{P}_p) - X_{6pn}^{2}]$$

$$+ \sum_{p=1}^{PP} K_{pn} \, L_{10p}^{(n)} \; [(\bar{V}_p - V_{pn}) \; (V_{pn} - \underline{V}_p) - X_{7pn}^{2}]$$

$$+ \sum_{p=1}^{PP} K_{pn} \, L_{11p}^{(n)} \; [V_p^{(n)} - V_p^{(n-1)} - Y_p \, P_{pn}] \qquad (16)$$

Where $Z^{(n)}$ is a variable vector, all values of L are multiplicators to include the operation constraints in $H^{(n)}$ and all values of X are ACVs; K_{in}, K_{jn}, K_{gn} and K_{pn} are DVs of TPs, HPs and of PSPs in generation or pump operation, respectively. DVs are obtained from unit commitment by ranking the plants in optimal list that fullfills requirements within given available facilities. Each variable of DVs must equal 1 when the plant is in operation and equals 0 if the plant is out of operation.

To solve the problem by using MPM by Pontryagin, $H^{(n)}$ must be maximized and their first derivatives with respect to BCVs and ACVs in addition to the variable vector and multiplicators must be equal zero. A nonlinear equations system will be resulted. Newton-Raphson method is applied to convert the nonlinear system to a linear system that can be solved by Gauss-Jordan method to obtain the control variables.

3. Neural-Network Technology

The back propagation learning algorithm will be used for feed-forward networks, in which the information passes through the intermediate layers from the input layer (IL) to the output layer (OL) using transfer functions and summation. The information will be propagated back through the network during the learning operation to update the connection weights (CWs), which are connected between the consecutive layers. All biases of the hidden layer (HL) and OL must be also updated [20], [24], [26] and [27]. The output of each neuron in IL equals to its input. But for HL and OL, the input X_j and output Y_j of each neuron can be given in terms of the biases b_j and threshold Z_j of the neurons as follows

$$X_j = \Sigma_j \; w_{ij} \, Y_i + b_j \tag{17}$$

$$Y_j = 1 \,/\, [1 + e^{-(X_j+Z_j)}] \tag{18}$$

Where w_{ij} are CWs between the neurons in a layer and the neurons in the previous layer of output Y_i.

By applying the generalized delta rule, the weights w_{ki} and w_{ji}, which are connected between OL and HL, also between HL and IL, respectively, must be modified by

$$\Delta w_{kj}(p) = \eta \, \delta_k(p) \; Y_j(p) + \alpha \, \Delta w_{kj}(p-1) \tag{19}$$

And

$$\Delta w_{ji}(p) = \eta\ \delta_j(p)\ Y_i(p) + \alpha\ \Delta w_{ji}(p-1) \tag{20}$$

Where,

$$\delta_k(p) = [Y_{kd} - Y_k(p)]\ Y_k(p)\ [1 - Y_k(p)] \tag{21}$$

$$\delta_j(p) = Y_j(p)\ [1 - Y_j(p)] \sum_{k=N_j+1}^{N_k} \delta_k(p)\ w_{kj} \tag{22}$$

Where N_j, N_k are the total number of neurons tell HL and OL, respectively, p is the pattern number, it varies between 1 and the total number of patterns N_p, Y_{kd} is the desired output of neuron k, η is the learning rate and α is the momentum constant. The values of η and α are between 0 and 1.

The range of the input and output of ANNs must be within 0 and 1 to avoid saturation caused by the sigmoidal function. Therefore, before the starting of the training, the data must be normalized.

4. Application of Neural-Network Technology on the optimal Scheduling of HTPSs

The presented power system consists of 4 TPs, one HP and one PSP. MPM was applied to obtain BCVs of the optimal scheduling of the system in Ref.[14] and the obtained results will be used to train the suggested artificial networks (SANN1) and (SANN2).

4.1 Topolpgy of SANN1

Fig.(1) illustrates the first network SANN1. Number of neurons of IL is NI = 8, number of neurons of HL is NJJ = 9, number of neurons of OL is NKK = 10, the total number of connection weights NW = 162 and the total number of biases NB = 19.

4.2 Input and output data of SANN1

Number of the variables which are used as input data of the network is 8 inputs, which are DVs of the four TPs, K1-K4, and of the hydro plant, KS, besides of PSP for generating operation, KG, or for pump operation, KP, in addition to the received power by the system load PL. The network is trained to give 10 outputs :-

- Powers of TPs, P1-P4, - Power of the hydroplant, PS,
- Power of PSP in generating or pump operation, PG or PP,
- Water volumes of the hydro plant, WS, and of PSP, WP, and
- The total generation cost TGC.

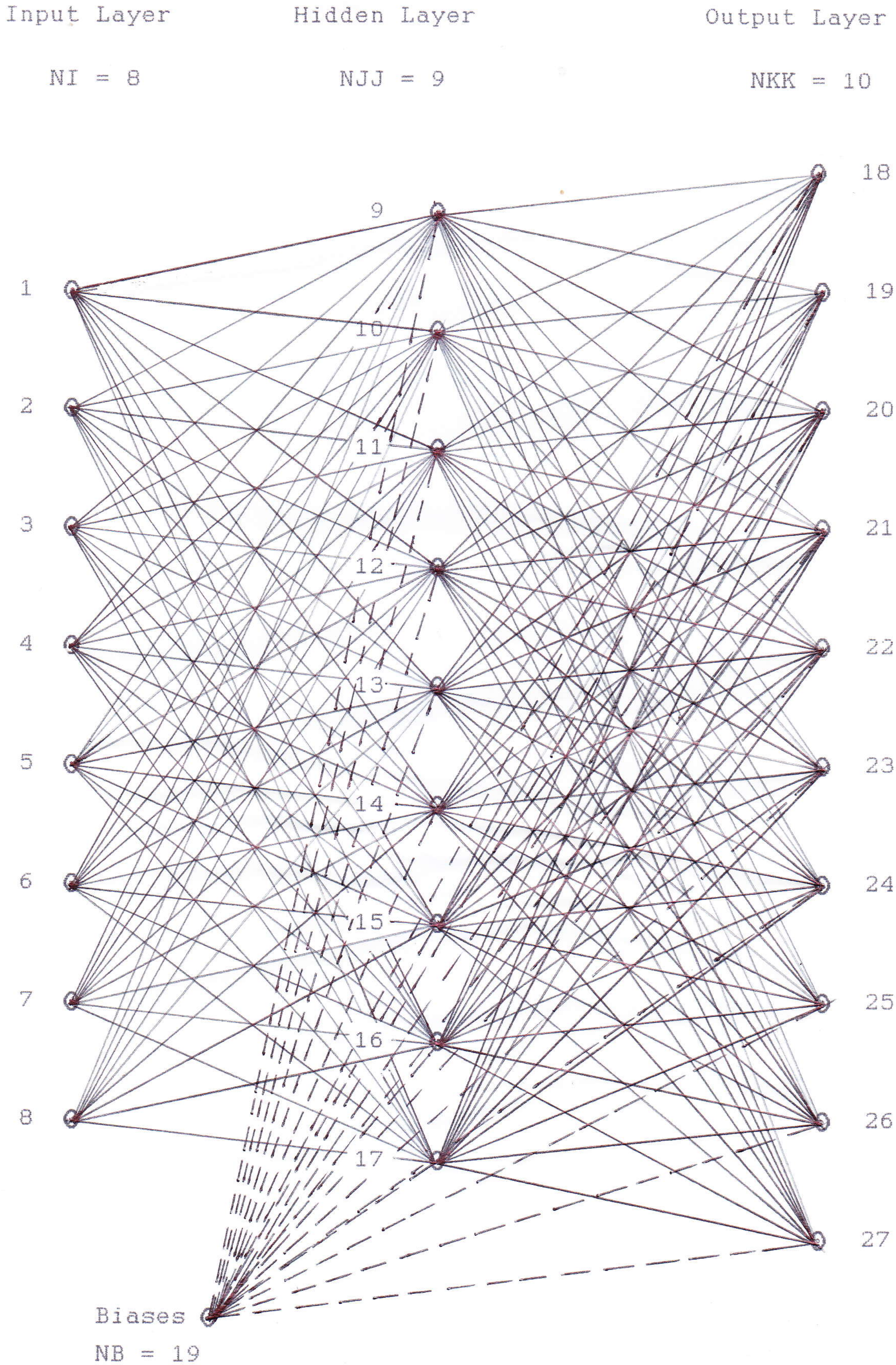

Fig.(1) The first suggested artificial neural network SANN1

Number of the used trainin-patterns (NP) for the input and output data is 45 pattern and the number of the test patterns (NT) is 5.

4.3 Initialization of the input and output data

DVs of all plants are already initialized because their values are equal 1 or 0. The other input and output variables are initialized by division of each value by the corresponding maximum value as indicated afterwards in the presented tabels.

4.4 Topology of SANN2 with removal of PSP

When PSP is removed from the system, a new network will be designed and trained by corresponding results after removing the plant data. Then, NI = 6, NJJ = 6 , NKK = 7 , NW = 78 , NB = 13.

5. Results

The training patterns of the input and output data for SANN1 are given in Table 1 and Table 2, respectively. Table 3 and Table 4 show the test patterns of the input and output data of that network.

Table 1 The training patterns of the input data for SANN1

n	K1	K2	K3	K4	KS	KP	KG	PL
Max. value	1	1	1	1	1	1	1	800 Mw
1 - 4	1	1	1	0	0	1	0	0.2500
5 - 8	1	1	1	1	0	1	0	0.3500
9 - 11	1	1	1	1	0	1	0	0.4750
12	1	1	1	1	0	0	1	0.7125
13 - 15	1	1	1	1	0	0	0	0.7125
16 - 19	1	1	1	1	1	0	1	0.8750
20 - 27	1	1	1	1	1	0	1	1.0000
28	1	1	1	1	1	1	0	0.7500
29	1	1	1	1	1	0	0	0.7500
30	1	1	1	1	1	1	0	0.7500
31 -35	1	1	1	1	0	0	1	0.7500
36 - 38	1	1	1	1	1	0	1	0.9500
39 - 42	1	1	1	1	0	1	0	0.4625
43 - 45	1	1	1	1	0	1	0	0.3500

The obtained values of CWs between IL and HL are given in the following matrix.

$$\begin{bmatrix} 0.17 & 0.17 & 0.17 & 0.17 & 0.17 & 0.17 & 0.17 & 0.17 & 0.17 \\ 0.02 & 0.02 & 0.02 & 0.02 & 0.02 & 0.02 & 0.02 & 0.02 & 0.02 \\ -0.13 & -0.13 & -0.13 & -0.13 & -0.13 & -0.13 & -0.13 & -0.13 & -0.13 \\ 1.39 & 1.39 & 1.39 & 1.39 & 1.39 & 1.39 & 1.39 & 1.39 & 1.39 \\ -0.98 & -0.98 & -0.98 & -0.98 & -0.98 & -0.98 & -0.98 & -0.98 & -0.98 \\ 1.66 & 1.66 & 1.66 & 1.66 & 1.66 & 1.66 & 1.66 & 1.66 & 1.66 \\ -0.44 & -0.44 & -0.44 & -0.44 & -0.44 & -0.44 & -0.44 & -0.44 & -0.44 \\ -3.83 & -3.83 & -3.83 & -3.83 & -3.83 & -3.83 & -3.83 & -3.83 & -3.83 \end{bmatrix}$$

The obtained values of CWs between HL and OL are given by

$$\begin{bmatrix} 0.2 & -2.6 & -1.82 & -0.12 & -5.97 & 4.16 & -5.66 & 0.0 & -0.4 & -0.24 \\ 0.2 & -2.6 & -1.82 & -0.12 & -5.97 & 4.16 & -5.66 & 0.0 & -0.4 & -0.24 \\ 0.2 & -2.6 & -1.82 & -0.12 & -5.97 & 4.16 & -5.66 & 0.0 & -0.4 & -0.24 \\ 0.2 & -2.6 & -1.82 & -0.12 & -5.97 & 4.16 & -5.66 & 0.0 & -0.4 & -0.24 \\ 0.2 & -2.6 & -1.82 & -0.12 & -5.97 & 4.16 & -5.66 & 0.0 & -0.4 & -0.24 \\ 0.2 & -2.6 & -1.82 & -0.12 & -5.97 & 4.16 & -5.66 & 0.0 & -0.4 & -0.24 \\ 0.2 & -2.6 & -1.82 & -0.12 & -5.97 & 4.16 & -5.66 & 0.0 & -0.4 & -0.24 \\ 0.2 & -2.6 & -1.82 & -0.12 & -5.97 & 4.16 & -5.66 & 0.0 & -0.4 & -0.24 \\ 0.2 & -2.6 & -1.82 & -0.12 & -5.97 & 4.16 & -5.66 & 0.0 & -0.4 & -0.24 \end{bmatrix}$$

The obtained values of the biases of HL are [0.72 0.72 0.72 0.72 0.72 0.72 0.72 0.72 0.72], and of the OL are [5.59 21.39 14.26 0.98 8.94 -14.32 14.10 3.04 7.23 1.02].

The obtained results of the output data are tabulated in Table 5 with percentage mean absolute error (%MAS) = 6.154 number of required iterations for the network convergence is IN = 2319 and training rate $\eta = 0.4$ and momentum constant $\alpha = 0.4$.

The obtained reslts of the output data by SANN2, after training it by the corresponding data after removal of PSP for the same values of the system load PL, are given in Table 6 with %MAS = 9.387, IN = 2548 , $\eta = 0.1$ and $\alpha = 0.8$.

When PSP is removed, it can be suggested that, the required data of the system can be obtained by training SANN1 after substitution zeros for all values of the corresponding data of PSP. The obtained data are illustrated in Table 7 with %MAS = 6.173, IN = 922 , $\eta = 0.8$ and $\alpha = 0.2$.

Table 8 shows %MAS and IN, which are obtained by SANN1 with including PSP in the hydrothermal power system and when it will be removed by the two networks SANN1 and SANN2 at different values of the training parameters η and α with accuracy tolerance $\varepsilon = 10^{-3}$.

Table 2 Training patterns of the output data for SANN1.

I	P1	P2	P3	P4	PS	PP	PG	WS	WP	TGC
1	1.0	1.00	0.71	0.00	0.0	1.0	0.0	0.953	0.981	0.179
2	1.0	1.00	0.71	0.00	0.0	1.0	0.0	0.956	0.983	0.179
3	1.0	1.00	0.71	0.00	0.0	1.0	0.0	0.959	0.985	0.179
4	1.0	1.00	0.71	0.00	0.0	1.0	0.0	0.962	0.989	0.179
5	1.0	0.43	0.26	0.51	0.0	1.0	0.0	0.965	0.988	0.262
6	1.0	0.39	0.26	0.51	0.0	1.0	0.0	0.968	0.990	0.262
7	1.0	0.43	0.26	0.51	0.0	1.0	0.0	0.972	0.992	0.263
8	1.0	0.43	0.26	0.51	0.0	1.0	0.0	0.975	0.993	0.263
9	1.0	1.00	0.49	0.51	0.0	1.0	0.0	0.978	0.995	0.357
10	1.0	1.00	0.49	0.51	0.0	1.0	0.0	0.984	0.998	0.357
11	1.0	1.00	0.49	0.51	0.0	1.0	0.0	0.987	1.000	0.357
12	1.0	1.00	0.89	0.51	0.0	0.0	1.0	0.991	0.998	0.456
13	1.0	1.00	1.00	0.60	0.0	0.0	0.0	0.994	0.998	0.585
14	1.0	1.00	1.00	0.60	0.0	0.0	0.0	0.997	0.998	0.585
15	1.0	1.00	1.00	0.60	0.0	0.0	0.0	1.000	0.998	0.585
16	1.0	1.00	1.00	0.57	1.0	0.0	1.0	0.995	0.996	0.549
17	1.0	1.00	1.00	0.57	1.0	0.0	1.0	0.990	0.994	0.549
18	1.0	1.00	1.00	0.57	1.0	0.0	1.0	0.984	0.993	0.549
19	1.0	1.00	1.00	0.57	1.0	0.0	1.0	0.979	0.991	0.549
20	1.0	1.00	1.00	0.80	1.0	0.0	1.0	0.974	0.989	0.825
21	1.0	1.00	1.00	0.80	1.0	0.0	1.0	0.969	0.987	0.825
22	1.0	1.00	0.51	1.00	1.0	0.0	1.0	0.963	0.985	1.000
23	1.0	1.00	1.00	0.80	1.0	0.0	1.0	0.958	0.983	0.825
24	1.0	1.00	0.51	1.00	1.0	0.0	1.0	0.953	0.982	1.000
25	1.0	1.00	1.00	0.80	1.0	0.0	1.0	0.948	0.980	0.825
26	1.0	1.00	0.51	1.00	1.0	0.0	1.0	0.942	0.978	1.000
27	1.0	1.00	1.00	0.80	1.0	0.0	1.0	0.937	0.976	0.825
28	1.0	1.00	1.00	0.62	1.0	1.0	0.0	0.932	0.978	0.597
29	1.0	1.00	0.51	0.67	1.0	0.0	0.0	0.927	0.978	0.529
30	1.0	1.00	1.00	0.62	1.0	1.0	0.0	0.921	0.979	0.597
31	1.0	1.00	1.00	0.53	0.0	0.0	1.0	0.925	0.978	0.516
32	1.0	1.00	1.00	0.53	0.0	0.0	1.0	0.928	0.976	0.516
33	1.0	1.00	1.00	0.58	0.0	0.0	1.0	0.931	0.974	0.516
34	1.0	1.00	1.00	0.53	0.0	0.0	1.0	0.934	0.972	0.516
35	1.0	1.00	1.00	0.53	0.0	0.0	1.0	0.937	0.970	0.516
36	1.0	1.00	1.00	0.71	1.0	0.0	1.0	0.932	0.968	0.704
37	1.0	1.00	1.00	0.71	1.0	0.0	1.0	0.927	0.967	0.704
38	1.0	1.00	1.00	0.71	1.0	0.0	1.0	0.916	0.963	0.704
39	1.0	0.78	0.77	0.51	0.0	1.0	0.0	0.919	0.965	0.358
40	1.0	0.78	0.56	0.51	0.0	1.0	0.0	0.923	0.966	0.341
41	1.0	0.78	0.56	0.51	0.0	1.0	0.0	0.926	0.968	0.341
42	1.0	0.78	0.56	0.51	0.0	1.0	0.0	0.929	0.970	0.341
43	1.0	0.39	0.28	0.51	0.0	1.0	0.0	0.932	0.971	0.262
44	1.0	0.39	0.28	0.51	0.0	1.0	0.0	0.938	0.975	0.262
45	1.0	0.39	0.28	0.51	0.0	1.0	0.0	0.942	0.976	0.262

Table 3 Test patterns of the input data for SANN1.

I	K1T	K2T	K3T	K4T	KST	KPT	KGT	PLT
1	1	1	1	0	0	1	0	0.250
2	1	1	1	1	0	1	0	0.475
3	1	1	1	1	1	0	1	0.875
4	1	1	1	1	1	0	1	0.950
5	1	1	1	1	0	1	0	0.350

Table 4 Test patterns of the output data for SANN1.

I	P1T	P2T	P3T	P4T	PST	PPT	PGT	WST	WPT	TGCT
1	1.0	1.00	0.71	0.00	0.0	1.0	0.0	0.959	0.985	0.179
2	1.0	1.00	0.49	0.51	0.0	1.0	0.0	0.981	0.997	0.357
3	1.0	1.00	1.00	0.57	1.0	0.0	1.0	0.995	0.996	0.549
4	1.0	1.00	1.00	0.71	1.0	0.0	1.0	0.921	0.965	0.704
5	1.0	0.39	0.28	0.51	0.0	1.0	0.0	0.935	0.973	0.704

Table 5 The obtained results for the test patterns of the output data by SANN1.

I	P1	P2	P3	P4	PS	PP	PG	WS	WP	TGC
1	1.0	0.91	0.72	0.53	0.00	1.0	0.0	0.953	0.986	0.330
2	1.0	0.68	0.46	0.52	0.00	1.0	0.0	0.953	0.983	0.299
3	1.0	1.00	1.00	0.71	0.99	0.0	1.0	0.954	0.999	0.705
4	1.0	1.00	1.00	0.72	1.00	0.0	1.0	0.954	0.999	0.712
5	1.0	0.44	0.30	0.51	0.00	1.0	0.0	0.953	0.980	0.281

Table 6 The obtained results for the test patterns of the output data by SANN2.

I	P1	P2	P3	P4	PS	WS	TGC
1	1.0	0.61	0.43	0.19	0.00	0.957	0.183
2	1.0	0.60	0.43	0.19	0.00	0.957	0.183
3	1.0	1.00	1.00	0.87	1.00	0.959	0.818
4	1.0	1.00	1.00	0.90	1.00	0.959	0.851
5	1.0	0.92	0.81	0.30	0.00	0.957	0.271

Table 7 The obtained results for the test patterns of the output data by SANN1 after removal of PSP.

I	P1	P2	P3	P4	PS	PP	PG	WS	WP	TGC
1	1.0	0.89	0.67	0.55	0.00	0.0	0.0	0.954	0.0	0.344
2	1.0	0.78	0.54	0.54	0.00	0.0	0.0	0.954	0.0	0.318
3	1.0	1.00	1.00	0.73	0.99	0.0	0.0	0.952	0.0	0.710
4	1.0	1.00	1.00	0.75	1.00	0.0	0.0	0.952	0.0	0.733
5	1.0	0.39	0.27	0.50	0.00	0.0	0.0	0.955	0.0	0.268

Table 8 Comparison between %MAS and number of iterations NI by the two suggested networks with accuracy limit $\varepsilon = 10^{-3}$

I	η	α	SANN1				SANN2	
			With PSP		Without PSP			
			NI	%MAS	NI	%MAS	NI	%MAS
1	0.9	0.6	3807	7.039	1241	7.196	2035	10.396
2	0.8	0.6	2947	7.754	1009	7.034	2223	10.254
3	0.6	0.5	1852	7.220	630	6.579	2828	9.682
4	0.5	0.7	2682	8.640	1076	6.302	3183	9.954
5	0.4	0.4	2319	<u>6.154</u>	495	6.762	2760	9.507
6	0.2	0.6	2218	6.639	513	7.108	2651	9.486
7	0.3	0.5	2252	6.234	492	6.911	2735	9.494
8	0.7	0.4	631	7.711	802	6.348	2468	9.657
9	0.8	0.2	592	7.537	922	<u>6.173</u>	2761	9.524
10	0.1	0.8	2249	6.956	502	7.294	2548	<u>9.387</u>

6. Conclusions

Agreeable output data for the optimal operation of hydrothermal power system can be obtained by using the neural-network technology. ANNs are valid for the on-line operation and have the capability to give the required data once these networks have been trained regardless of the solution method which has been applied.

The learning parameters have a significant influence on the obtained results and computation time, therefore, several different parameters must be taken into account to obtain satisfied results. Suggested artificial neural networks SANNs have been designed to obtain the required output data of the optimal scheduling of the hydrothermal generation by introducing of the decision variables of each plant and the load power in each time interval. The data of the optimal operation of a hydrothermal power system including or excluding a pump storage plant can be obtained from the same suggested network with acceptable values of mean absolute error. The network must be trained by the corresponding data for both situations.

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