International Journal of Advanced Engineering Research and Applications (IJA-ERA) *ISSN: 2454-2377*

Volume – 6, Issue – 7, November – 2020

Forecasting and Simulation for Electrical Power System and Load Distribution in Taif – Saudi Arabia

Osman E. Taylan[1] & Zayed A. Alharthi[2*]

[1]King Abdul-Aziz University, Faculty of Engineering, Jeddah, Saudi Arabia
E-mail: *otaylan@kau.edu.sa*

[2]Taif Electricity Branch, Planning and Construction Department
Taif, Saudi Arabia, E-mail: *zayed.ayedh@gmail.com**

Abstract: Monitoring electrical power system and clarifying the way of electricity flow is a difficult task, that might cause electricity cuts because of the increasing loads of grids. In recent years, the observations showed that electric loads in Taif city have increased significantly due to the population growth and large urbanization. These causes require a good monitoring and analyzing system intensively to maintain continuity and reliability of electrical service. Machine learning and dynamic programming approaches will be employed for forecasting the distribution of power load and optimization of Electrical Power System in Taif City to avoid the unexpected problems in electrical network before they have occurred. The other goal is to facilitate monitoring of the electrical power system in Taif city and clarify the electricity flow from Makkah to Taif and then to other neighboring districts. The results and findings of the study will be evaluated using the methods of error calculation and ranking and presented in detail.

Keywords: Forecasting.; Electric Loads; Machine Learning; Dynamic Programming; Artificial Intelligence.

I. INTRODUCTION AND STATEMENT OF PROBLEM

The statement of the problem includes the difficulty of monitoring electrical power system in Taif and clarifying the way of electricity flow from Makkah to Taif and then to other neighboring districts (Ranyah, Turubah, Muwayh, Thaqif, and Khurma), as well as electrical cuts because of the increasing of loads. In recent years, it has been observed that electric loads in Taif have increased significantly, due to population growth (1,083,693 inhabitants in 2013 compared to 451,321 inhabitants in 1986) and large urbanization (13,908 ha in 2013 compared to 6,517 ha in 1986) [1]. Which required good monitoring of electrical power system and analyzing intensively to maintain continuity and reliability of electrical service.

II. GOAL

The goal of this study is to apply machine learning and dynamic programming approaches for short term load forecasting of power load and optimization of Electrical Power System in Taif City to avoid the unexpected problems in electrical network before they have occurred.

III. LITERATURE REVIEW

The literature research for this study covers the main topic of this study. Which is the avoided of the unexpected problems in electrical network before they have occurred, by choosing the optimal distribution of the electrical network and making the appropriate prediction of electrical load. As well as giving a broader perspective on the side of using Artificial Intelligence technology in the prediction of electrical loads.

Load forecasting came to life with the introduction of power systems. Samuel Insull "A pioneer of electric utility industry" was one of the first people to become involved with load forecasting. Insull figured out that certain consumers have patterns of energy consumption, e.g. commercial buildings and households use more electricity in the daytime, while street lighting and industry use it more in the night-time. With a good mix of different customer types, he figured out that more electricity could be produced from the same generating unit and, thereby, maximizing a return on investment [2].

Reyneau's paper, which was in 1918 is one of the oldest scientific paper on load forecasting. Throughout its centennial history, load forecasting matured together with the power systems [3]. Early statistical methods and then, Box-Jenkins methodology [4], in the 1970s, paved the way for new time-series approaches.

Dynamic Programming was invented by Bellman at the RAND Corporation circa 1950. The word "programming" is not used in its modern sense but in the sense of finding an optimal schedule or programmed of activities. Bellman explains the reason for this name by his saying: "The 1950s were not good years for mathematical research. We had a very interesting gentleman in Washington named Wilson. He was Secretary of Defense, and he had a pathological fear and hatred of the word, research. His face would suffuse, he would turn red, and he would get violent if people used the term, research, in his presence. You can imagine how he felt, then, about the term, mathematical. I thought Dynamic Programming was a good name. It was something not even a Congressman could object to".

Dynamic Programming (DP) [5] is an optimization strategy that provides the global minimum of a given objective function. According to Yu et al. [6], DP is more effective than linear and nonlinear programming and proves its effectiveness by solving multiple objective function problems by dividing the complex problem into interrelated subproblems [6,7]. In addition, Chen et al. [8] stated that the lack of empirical coefficients and predetermined parameters constitute one of the main advantages in using DP. Nevertheless, DP may require higher computational time than linear algorithms [9], especially if the number of variables increases [8].

Even though Artificial Intelligence science is a modern science, it was used since ancient times in the year of 1956 by John McCarthy from MIT, roots of this science extend to thousands of years ago before of Messiah born, Artificial Intelligence science have been discovered by the philosophers where they define mind of human of somewhat that like a machine that knowing things by an encoded language in an internal language, and that machine can be used to reach to a correct decision. Mathematics have been interested in securing the tools that deal with logical data and proven probabilities and algorithms, psychologists confirmed that man can be regarded as a machine that process information, and languages scientists explained that the use of languages are in line with this representation. The invention of electronic calculators and their rapid evolution make a possible of processing and conversion of these theoretical ideas to practical ideas, the engineers of electronic computer provided the tools and applications that make Artificial Intelligence possible. The evolution of the fields of Artificial Intelligence can be summarized as follows; In 1950, a test was applied based on a rule that the machine performed its purpose through an intelligent role [10]. In 1960, the field of Artificial Intelligence was established as a research field, and as a result, expert systems were emerged based on knowledge base. In 1970, Artificial Intelligence began to be used, and decision-making was appeared with the support of Artificial Intelligence appeared, in 1980, the Artificial Neural Network appeared and thus the structures that like communication of cerebral nerves between each other was appeared, and in 1990, smart programs appeared, and as a result of that, software appeared, that does different tasks instead of the user himself [10].

IV. METHODOLOGY

The Electrical System in Taif City consists of three central substations (380 kV) that feed separate areas through 29 main substations (110 kV). The connection between these stations is through main lines (ground cables or overhead conductors) and there are some open lines that can be energized when a fault occurs on main lines. To achieve my search, I simplified the electrical system in Taif to be divided into three zones, according to the three central substations (380 kV) of Taif city, in the normal condition without any spare connections. My study to of Electrical System in Taif City is based on the maximum loads recorded on each main substation (110KV) per hour (STLF), for the year 2019, as registered in the control panel of load dispatch center in Taif city. In addition to that, I was taken data for hourly temperatures recorded in TAIF city for the same period of time of loads from the website [11]. I consider on my study electrical losses due to transmission on electrical lines. The losses on electrical lines depends on the parameters of the lines (types, and lengths) and to a small extent to the temperature of lines. Usually the highest specifications are used in electrical lines to reduce electricity losses and the temperature in Taif is usually moderate along the year. So, losses approximately depend on the lengths of lines. The losses of transmission lines are calculated as follows: -

$$\text{Losses} = \left(\frac{Load}{\sqrt{3}\times 110}\right)^2 * R \qquad (1)$$

Where: Load = MVA load on the line and R = resistance of the line in ohm.

The average value of resistance of our electricity network in Taif is 0.05 Ohm / km, and this is what I was used in our calculations for losses. To achieve my search, I use Dynamic Programming to find the optimizing road system of electrical loads on each zone, the formulation of Dynamic Programming is as follows: -

Let the decision variables x_n $(n = 1, 2, 3, 4, \ldots \ldots)$ be the immediate substation on stage n (the nth stagecoach run to be taken). In which, the route selected is from the main substation (110 KV) to the central substation (380 KV), so I back from the load to the source. Let $f_n(s, x_n)$ be the possible total length, from immediate substation to destination substation for the remaining stages, given that the immediate substation is in state s, ready to start stage n, and selects x_n as the destination substation. Given s and n, let $x_n{}^*$ denote any value of x_n (not necessarily unique) that minimizes $f_n(s, x_n)$, and let $f_n{}^*(s)$ be the corresponding minimum value of $f_n(s, x_n)$. Thus,

$$f_n{}^*(s) = \min_{x_n} f_n(s, x_n) = f_n(s, x_n{}^*) \qquad (2)$$

Where; $f_n(s, x_n)$ = immediate length (stage n) + minimum future length (stage $n+1$ onward)

$$= d_{sx_n} + f^*_{n+1}(x_n) \qquad (3)$$

After determining the optimal road system, the total losses load of transmission lines is calculated according to the previous equation and combined with the electrical load of each main substation (110 KV) in each zone, to obtain the total electrical load of central substation (380 KV) in each zone. After that, the total load of the three zones is collected together, to obtain the total load for Taif city.

To achieve the goal of this research, I use the ANN approach to predict the total load of Taif city (STLF), considering the load of main substations (110 KV) as inputs, and the total load of Taif city that resulting from the DP approach as outputs. With the use of Levenberg-Marquardt algorithm in the training process for the Artificial Neural Network approach. After that I compare between the results of Dynamic Programming approach and Artificial Neural Network approach using the methods of error calculation and ranking. Error calculation is the important part of forecasting because it determines the way in which results are evaluated. There are numerous metrics for the error calculation. The most important metrics are: Mean Absolute Error; Mean Square Error; Root Mean Square Error; Mean Absolute Percentage Error.

They are defined as follows [12]: -

Mean Absolute Error (MAE)

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{Y}_i - Y_i\right| \quad (4)$$

Mean Square Error (MSE)

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{Y}_i - Y_i\right)^2 \quad (5)$$

Root Mean Square Error (RMSE)

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\hat{Y}_i - Y_i\right)^2} \quad (6)$$

Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{Y}_i - Y_i}{Y_i}\right| \quad (7)$$

Where $\hat{Y}i$ is the actual value, Yi is the predicted value, and n is the number of samples.

V. RESULTS AND DISCUSSIONS:

A. DYNAMIC PROGRAMING:

All possible roads for the distribution system of TAN2 network are shown in figure 1.

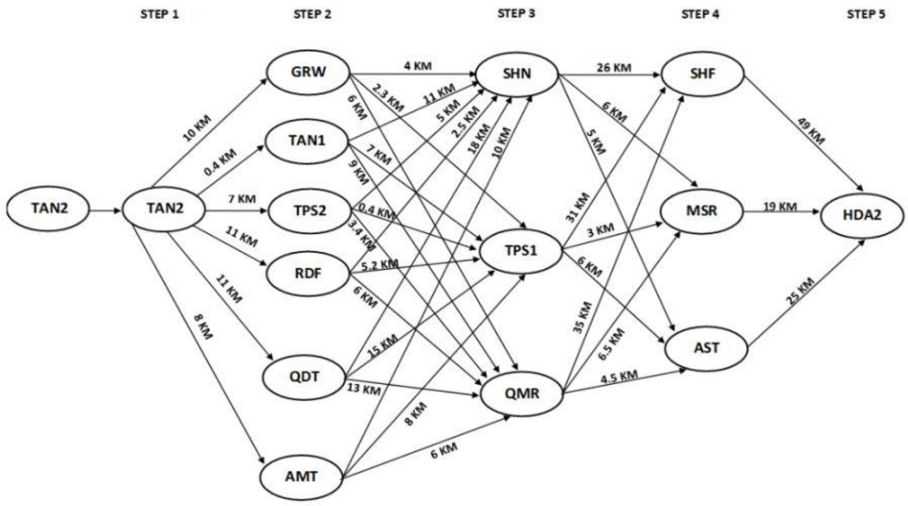

Figure .1 The Road System for TAN2 Substation (380 kV).

The calculations using this recursive relationship (using equation (2) & (3)) are summarized below in (Table .1, Table .2, and Table .3), as follows:

Table .1 Calculation for minimizing the distances of stage 5 for TAN2 zone.

s \ x_5	$f_5(s,x_5) = d_{sx_5} + f_6^*(x_5)$			$f_5^*(x_5)$	x_5^*
	SHF	***MSR***	***AST***		
HDA2	49	19	25	19	MSR

Table .2 Calculation for minimizing the distances of stage 4 for TAN2 zone.

s \ x_4	$f_4(s,x_4) = d_{sx_4} + f_5^*(x_4)$			$f_4^*(x_4)$	x_4^*
	SHN	***TPS1***	***QMR***		
SHF	26	31	35	26	SHN
MSR	25	22	25.5	22	TPS1
AST	5	6	4.5	4.5	QMR

Table .3 Calculation for minimizing the distances of stage 3 for TAN2 zone.

s \ x_3	$f_3(s,x_3) = d_{sx_3} + f_4^*(x_3)$						$f_3^*(x_3)$	x_3^*
	GRW	***TAN1***	***TPS2***	***RDF***	***QDT***	***AMT***		
SHN	30	37	31	28.5	44	36	28.5	RDF
TPS1	24.3	29	22.4	27.2	37	30	22.4	TPS2
QMR	10.5	13.5	7.9	10.5	17.5	10.5	7.9	TPS2

According to this calculation the optimizing road system of electrical loads on TAN2 zone is as shown below in (Figure .2).

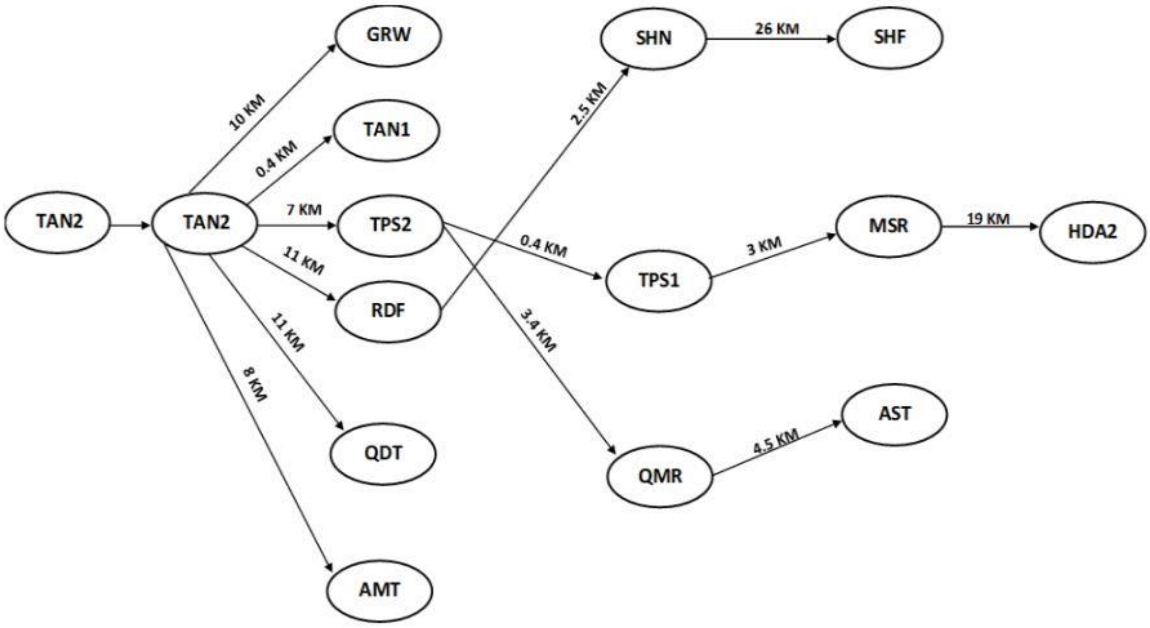

Figure .2 The Optimizing Road System for TAN2 Substation (380 kV).

Now, I can calculate the losses (using equation (1)) on the optimizing electrical networks of TAN2 zone, as follows: -

$$\text{Losses} = \left(\frac{GRW_L}{\sqrt{3}\times 110}\right)^2 \ast 10 \ast 0.05 + \left(\frac{TAN1}{\sqrt{3}\times 110}\right)^2 \ast 0.4 \ast 0.05 + \left(\frac{HDA2_L}{\sqrt{3}\times 110}\right)^2 \ast 19 \ast 0.05 + \left[\left(\frac{HDA2_L}{\sqrt{3}\times 110}\right)^2 + \left(\frac{MSR_L}{\sqrt{3}\times 110}\right)^2\right] \ast 3 \ast 0.05 + \left[\left(\frac{HDA2_L}{\sqrt{3}\times 110}\right)^2 + \left(\frac{MSR_L}{\sqrt{3}\times 110}\right)^2 + \left(\frac{TPS1_L}{\sqrt{3}\times 110}\right)^2\right] \ast 0.4 \ast 0.05 + \left(\frac{AST_L}{\sqrt{3}\times 110}\right)^2 \ast 4.5 \ast 0.05 + \left[\left(\frac{AST_L}{\sqrt{3}\times 110}\right)^2 + \left(\frac{QMR_L}{\sqrt{3}\times 110}\right)^2\right] \ast 3.4 \ast 0.05 + \left[\left(\frac{HDA2_L}{\sqrt{3}\times 110}\right)^2 + \left(\frac{MSR_L}{\sqrt{3}\times 110}\right)^2 + \left(\frac{TPS1_L}{\sqrt{3}\times 110}\right)^2 + \left(\frac{AST_L}{\sqrt{3}\times 110}\right)^2 + \left(\frac{QMR_L}{\sqrt{3}\times 110}\right)^2 + \left(\frac{TPS2_L}{\sqrt{3}\times 110}\right)^2\right] \ast 7 \ast 0.05 + \left(\frac{SHF_L}{\sqrt{3}\times 110}\right)^2 \ast 26 \ast 0.05 + \left[\left(\frac{SHF_L}{\sqrt{3}\times 110}\right)^2 + \left(\frac{SHN_L}{\sqrt{3}\times 110}\right)^2\right] \ast 2.5 \ast 0.05 + \left[\left(\frac{SHF_L}{\sqrt{3}\times 110}\right)^2 + \left(\frac{SHN_L}{\sqrt{3}\times 110}\right)^2 + \left(\frac{RDF_L}{\sqrt{3}\times 110}\right)^2\right] \ast 11 \ast 0.05 + \left(\frac{QDT_L}{\sqrt{3}\times 110}\right)^2 \ast 11 \ast 0.05 + \left(\frac{AMT_L}{\sqrt{3}\times 110}\right)^2 \ast 8 \ast 0.05$$

The output loads for TAN2 zone is getting by adding losses to the load of all main substations (110 kV) in TAN2 zone, and the results is as shown below in (Figure .3).

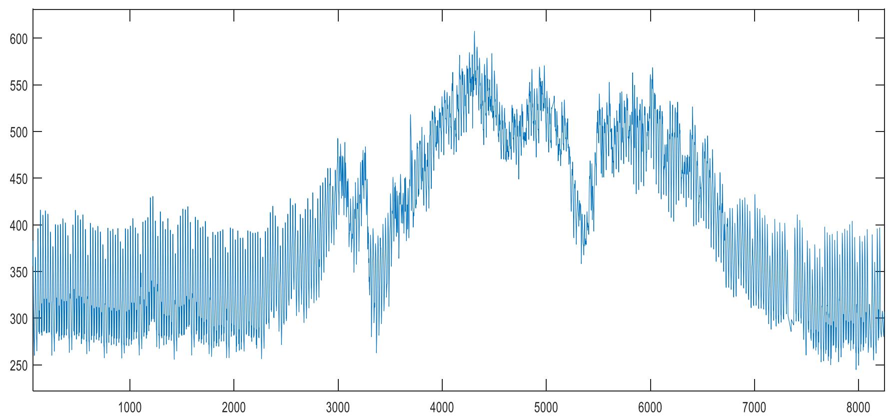

Figure .3 Output Load for TAN2 Zone.

Now, I can do the same processes to the other substations (SISED zone, and TEGO zone), then the total loads for Taif are getting by adding output loads for HVT zone, to SISED zone, and TEGO zone. The results are as shown below in (Figure .4).

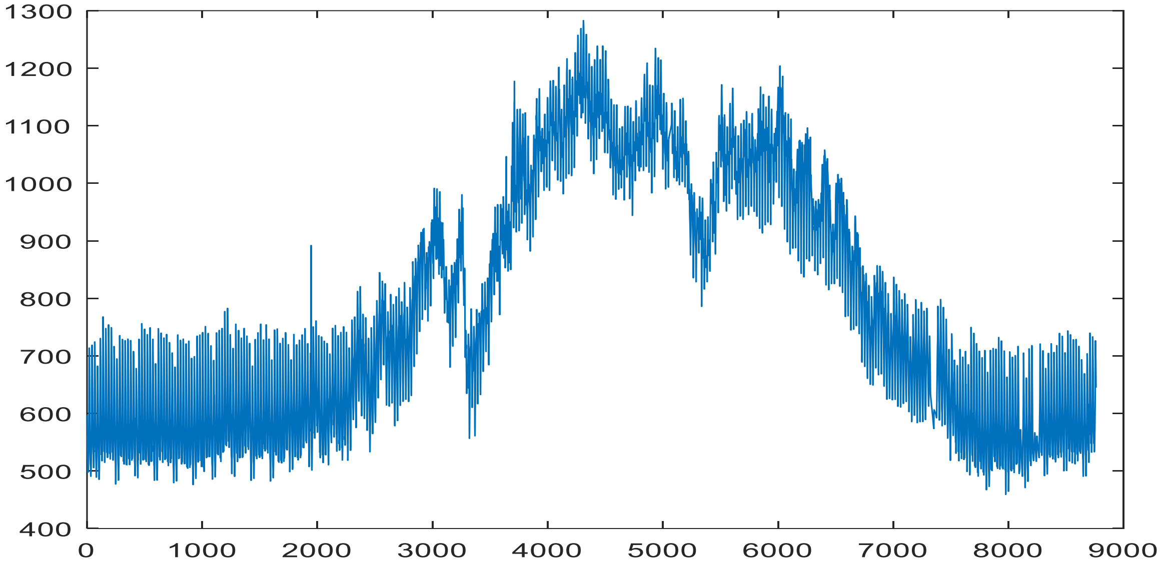

Figure .4 Output Loads for Taif Using DP.

B. Artificial Neural Networks:

I used, the loads of the 29 main substations (110 kV) in the Taif city as the input, which are a 8760×29 matrix, representing 8760 samples of 29 elements, and the total output loads for Taif that resulting from Dynamic Programming as the output, which are a 8760×1 matrix, representing 8760 samples of 1 element.

The data are randomly divided up inside the MATLAB to 70% for training, 15% for validation, and 15% for testing. I was defined a fitted neural network for number of hidden layers to be 1 hidden layer, as shown below in (Figure .5).

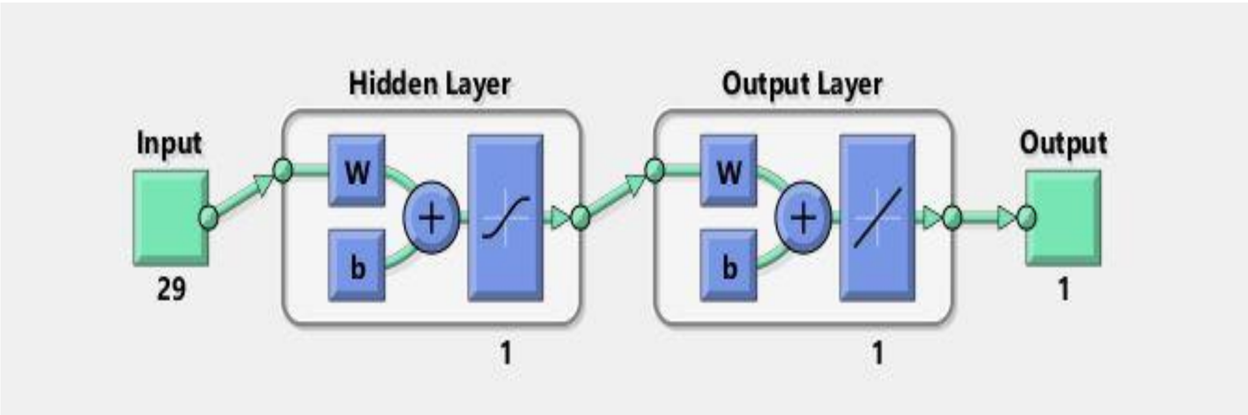

Figure .5 Modeling of ANN According to Loads of Each Substation.

I found that Levenberg-Marquardt algorithm is the best algorithm for training this network. The MATLAB trains data using (LM) approach in several steps to reaching the best performance. The performance was as shown below in (Figure .6).

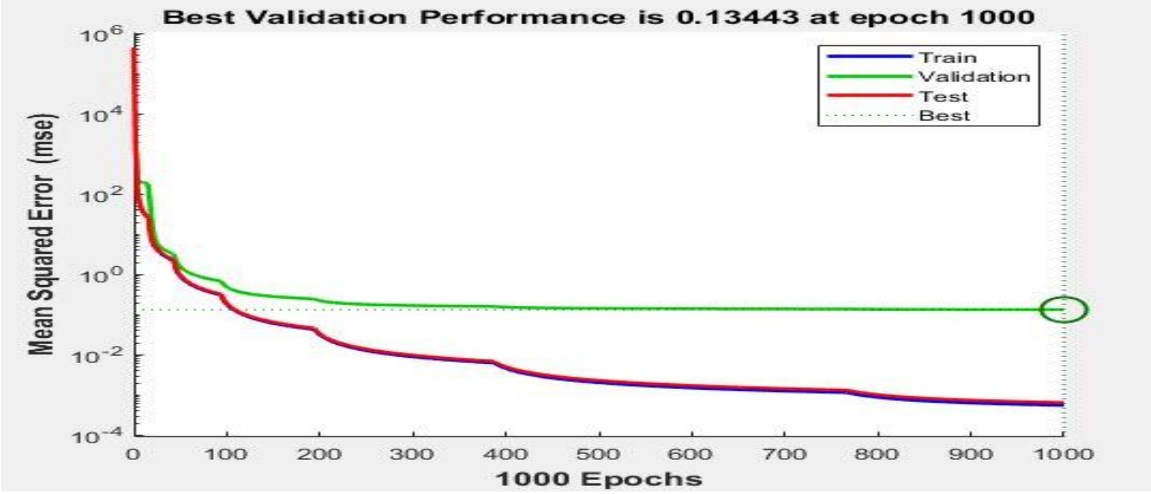

Figure .6 Performance of training ANN according to loads of each substation.

The training regression was as shown below in (Figure .7).

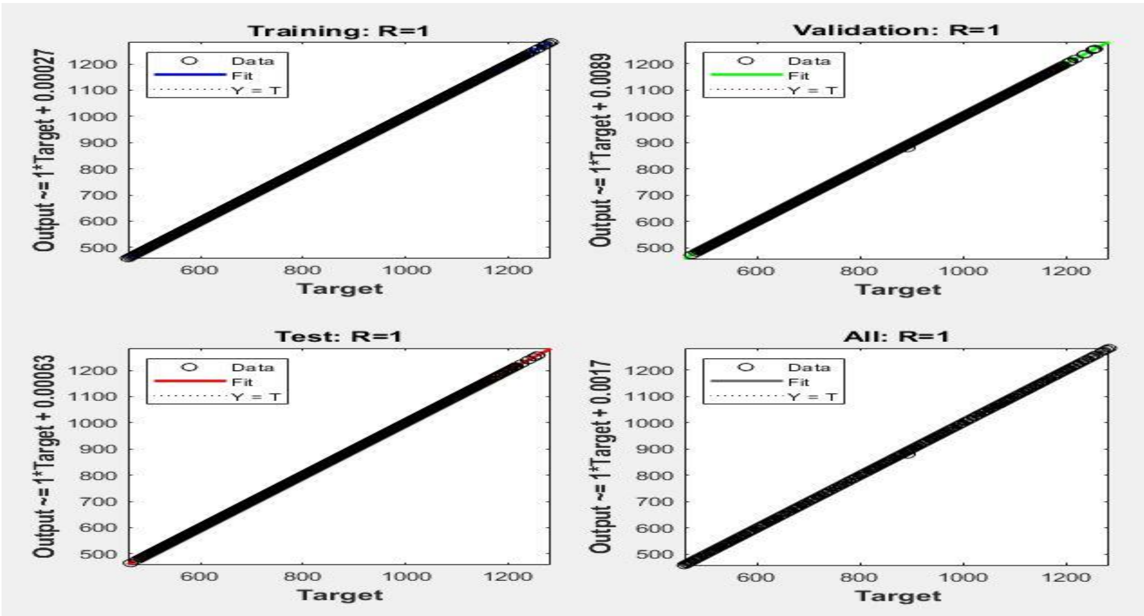

Figure .7 Training Regression ANN According to Loads of Each Substation.

The result for total loads of Taif was gotten by MATLAB using Artificial Neural Network approach (LM algorithm), as shown below in (Figure .8).

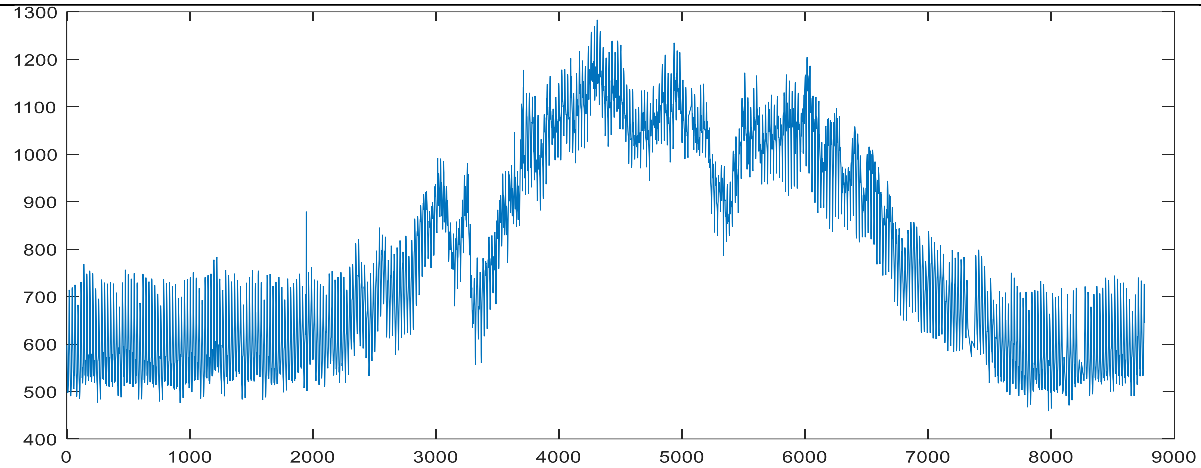

Figure .8 Output Loads for Taif Using ANN, according to the Load of Each Substation to Fit the Output of DP.

C. Error and Ranking:

The results obtained from ANN, according to the load of each substation to fit the output of the DP, as mentioned previously, are very close to the results of DP, and the error percentage of this result (MAPE) is (0.000030). The full results for error rates between the two approaches (using equations from (4) to (7)) was as follows in (Table .4): -

Table .4 Comparing of results of ANN according to loads of each substation and with DP.

Ranking	***MAE***	***MSE***	***RMSE***	***MAPE***
Error	0.017055962	0.000562248	0.023711776	0.000030009

D. Discussions:

The study indicated that the structure of the electrical network in Taif is not based on choosing the shortest distances of transmission lines between the main substations (110 kV) and are not based on achieving the least amount of losses in the transmission lines.

The study also showed that electricity consumption in Taif reaches its highest levels during summer period. This is due to the increase in residential activity in summer period. Which happen due to the fact that Taif is a tourist place in summer for most people in Saudi Arabia, and also because of the increase in temperatures in the summer period, and because of the school exams, which usually happens in summer.

VI. CONCLUSIONS

In this work results were obtained by using DP technique for optimizing distances of transmission lines of the networks, and by using the ANN technique for short-term load forecasting. The most widely used techniques in ANN are Levenberg-Marquardt (LM) algorithm, Bayesian Regularization (BR) algorithm, and Scaled Conjugate Gradient (SCG) algorithm. The forecasting has been evaluated on the basis of calculating MAE, MSE, RMSE, and MAPE between the actual value and forecasted value. The effect of change in number of hidden neurons and number of hidden layers is also studied. The following observations are made:

- LM algorithm results in lower error compared to other algorithms for the same input.
- In the case of studying the flow of all loads, one hidden layer is sufficient for the formulation of the load forecasting problem, but when studying the correlation of total loads for substations to cumulative hours and temperatures, 500 hidden layers or more is sufficient for formulating the problem.
- The increase in hidden layers and neurons increases the complexity of the problem.
- The result of expecting the loads from the beginning (load sources) and branching nervously to the central substation (380 KV) gives accurate results that are almost closer to the truth.

Conflict of interest: The authors declare that they have no conflict of interest.

Ethical statement: The authors declare that they have followed ethical responsibilities.

REFERENCES

[1] B. Kermanshahi (1998). Recurrent neural network for forecasting next 10 years loads of nine Japanese utilities. Neurocomputing, pp. 125-133.
[2] S. Butler (1918). UK Electricity Networks. A report submitted in partial fulfilment of the requirements for the MSc.
[3] P. Reyneau (1918). Predicting load on residence circuits. Electrical World, vol. 19, pp. 969–971.
[4] G. Box, and G. Jenkins (1970). Time Series Analysis: Forecasting and Control. San Francisco: Prentice Hall.
[5] R. Bellman (1957). Dynamic Programming. University Press: Princeton, NJ, USA.
[6] S. Yu, S. Gao, and H. Sun (2016). A Dynamic Programming model for environmental investment decision-making in coal mining. Appl. Energy, vol. 166, pp. 273–281.
[7] S. Seijo, I. Campo, J. Echanobe, and J. García (2016). Modeling and multi-objective optimization of a complex CHP process. Appl. Energy, vol. 161, pp. 309–319.
[8] X. Chen, N. Hewitt, Z. Li, Q. Wu, X. Yuan, and T. Roskilly (2017). Dynamic Programming for optimal operation of a biofuel micro CHP-HES system. Appl. Energy, vol. 208, pp. 132–141.
[9] A. Berrueta, M. Heck, M. Jantsch, A. Ursúa, and P. Sanchis (2018). Combined Dynamic Programming and region-elimination technique algorithm for optimal sizing and management of lithium-ion batteries for photovoltaic plants. Appl. Energy, vol. 228, pp. 1–11.
[10] H. Drucker, C. Burges, L. Kaufman, A. Smola, and V. Vapnik (1997). Support vector regression machines. Advances in Neural Information Processing Systems, vol. 9, , pp. 155–161.
[11] Weather Underground. Ta'if, Weather History, [Accessed Online 24.09.2020], available:https://www.wunderground.com/history/daily/sa/ta'if/OETF/date/2019-7-31.
[12] R. Hyndman, and A. Koehler (2006). Another look at measures of forecast accuracy. International Journal of Forecasting, vol. 22, pp. 679–688.

