

Electrical Load Manageability Factor Analyses by Artificial Neural Network Training

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Abstract- On typical medium voltage feeder, Load side management means power energy consumption controlling at connected loads. Each load has various amount of reaction to essential parameters variation that collection of these reactions is mentioned feeder behavior to each parameter variation. Temperature, humidity, and energy pricing variation or major event happening and power utility announcing to the customers are essential parameters that are considered at recent researches. Depends on amount of improvement that each changeable parameters effect on feeder load consumption, financial assets could be managed correctly to gain proper load side management. Collecting feeder loads behavior to all mentioned parameters will gain Load Manageability Factor (LMF) that helps power utilities to manage load side consumption. Calculating this factor needs to find out each types of load with unique inherent features behavior to each parameters variation. This paper and future works will help us to catch mentioned LMF. In this paper analysis of typical commercial feeder behavior due to temperature and humidity variation with training artificial neural network will be done. Load behavior due to other essential parameters variations like energy pricing variation, major event happening, and power utility announcing to the customers, and etc. will study in future works.

Keyword: Load sensitivity, Load side management, Manageability factor, Neural network, Soft load behavior.

1. INTRODUCTION

Dependency of load behavior to essential parameters like environmental temperature, humidity, energy pricing, major events happening and announcing TV program to the customers helps the utility companies to manage load side consumption and improve balancing between load and generation side. Collecting of one typical load behavior to each parameter variations will leads the financial assets to improve system. Due to the inherent characteristics of each customer, reaction to the parameter variations can be different. These inherent characteristics are customer welfare level and customer knowledge level. In order to have unification in our study, one types of load with the same inherent characteristics was considered in our paper and commercial load was selected. Recently load side managing is the main subject of all researches that have been published in smart grid

load managing area. In [1] a new method based on intelligent algorithm was proposed to optimal operate the demand side management in the presence of DG units and demand response. First, the best location and capacity of different technologies of DG are selected by optimizing the technical index including the active and reactive loss and the voltage profile. Second, the daily performance of multi-DG and grid is optimized with and without consideration the demand response. The economic and environmental indices are optimized in this step. In the both steps, the non-dominated sorting firefly algorithm is utilized to multi-objective optimize the objective functions and then the fuzzy decision-making method is used to select the best result from Pareto optimal solution. In our paper demand side management have studied in general condition with and without DG. All condition and parameters that had been affected in power energy consumption will study in our researches. In [2] a heuristic mathematical model for optimal decision-making of a Distribution Company (DisCo) is proposed that employs demand response (DR) programs in order to participate in a day-ahead market, taking into account elastic and inelastic load models. The proposed model is an extended responsive load modeling that is based on price elasticity and

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customers' incentives in which they participate in demand response program, voluntarily and would be paid according to their declared load curtailment amounts. It is supposed that Distribution Company has the ability to trade with the wholesale market and it can use its own distributed generation (DG), while decision-making process. In this regard, at first, DisCo's optimization frameworks in two cases, with and without elastic load modelings are acquired. Subsequently, utilizing Hessian matrix and mathematical optimality conditions, optimal aggregated load curtailment amounts are obtained and accordingly, individual customer's load reductions are calculated. In our paper the effect of multi parameters has been studied that their effect could vary transmission line loads so our study doesn't limit to distribution company. In [3] analysis of residential load behavior due to temperature variation with training artificial neural network has been done. In this paper, only the effect of temperature without humidity has been studied. In our paper temperature and humidity effect on power electric company has been studied. In [4] they estimate climate-attributable capacity reductions to transmission lines by constructing thermal models of representative conductors, then forcing these models with future temperature projections to determine the percent change in rated ampacity. Next, they assess the impact of climate change on electricity load by using historical relationships between ambient temperature and utility-scale summer time peak load to estimate the extent to which climate change will incur additional peak load increases. They find that by mid-century (2040-2060), increases in ambient air temperature may reduce average summertime transmission. This capacity by 1.9%-5.8% relative to the 1990-2010 reference period. In our paper it is not limit to conductors or other tools, and after extracting results it could be easy to study on all tools. In [5] analysis of temperature changes on electricity consumption in Fars Province has been studied. Climate change is one of the factors that effects on electricity consumption behavior and changes in load of the network. Our paper contains humidity effect in addition. In [6] their purpose is to develop a methodology to quantify the impact of climate change on electric loads in the United States. They perform simple linear regression, assisted by geospatial smoothing, on paired temperature and load time-series to estimate the heating- and cooling- induced sensitivity to

temperature across 300 transmission zones and 16 seasonal and diurnal time periods. This paper studied only temperature effect on load consumption, but in our paper beside temperature affection, humidity affection also have been studied. In [7] the basic objective of short term load forecasting is to predict the near future load for example next hour load prediction or next day load prediction etc. The total system load is the load seen at the generating end of the power system, which includes the sum of all types of loads connected to the system plus the losses. To design efficient and accurate forecasting model one must have good understanding of the characteristics of the system. There are various factors which influence the behavior of the consumer load and also affect the total losses in transmission lines. In this paper, short-term effect has been proposed, but in our paper, short and long-term period has been considered. [8] Presents the temperature impacts on daily peak load of commercial load in KOREA. This research focuses on the overall summer and winter peak load characteristics and the impact of temperature change on the commercial load. This paper studied only temperature effect on load consumption, but in our paper humidity effect have been added. In [9] climate change impacts on residential and commercial loads in the Western U. S. grid has been discussed. This paper presents a multidisciplinary modeling approach to quickly quantify climate change impacts on energy consumption, peak load, and load composition of residential and commercial buildings. This research focuses on addressing the impact of temperature changes on the building cooling load in ten major cities across the Western United States and Canada, but in our paper both of temperature and humidity effect have been studied. In [10] the temperature sensitivity of the residential load and commercial building load has been studied. This paper presents a building modeling approach to quickly quantify climate change impacts on energy consumption, peak load, and load composition of residential and commercial buildings. This research focuses on addressing the impact of temperature changes on the building heating and cooling load in 10 major cities across the Western United States and Canada and in our paper with considering temperature and humidity changes, the effect of them on load consumption variation was studied. In [11] they investigated climate change-driven effects on electricity demand. The research focused on the

estimating the impact of higher temperatures on electricity consumption using hourly data and annual data, but in this paper temperature and humidity effect have been studied. In [12] temperature effect to load profiles and feeder losses has been studied. A systematic procedure is proposed to study the effect of temperature change to the power system load demand by using the typical load patterns of customer classes, in this paper natural condition like humidity and temperature affect was studied and it will be easy to catch total formula after collecting our future research results. Reference [13] presents a summary of Demand Response (DR) in deregulated electricity markets. The definition and the classification of DR as well as potential benefits and associated cost components are presented. In addition, the most common indices used for DR measurement and evaluation are highlighted, and some utilities' experiences with different demand response programs are discussed, but in our paper price effect was mentioned and detail research will be done in our future work. In [14] Demand-response (DR) is regarded as a promising solution for future power grids. They used a Stackelberg game approach, and describe a novel DR model for electricity trading between one utility company and multiple users, which is aimed at balancing supply and demand, as well as smoothing the aggregated load in the system. In [15] investigations on DSM programs which are done in different countries, enlarge the view of managers for program designing. This paper reviews DSM programs of 13 countries and at the end; there are some suggestions for the case of Iran. In this article peak reduction and load shifting could be apply for DSM programs in Iran. Also unreal electricity price is known as a major problem in Iran. In our paper, energy price effect was mentioned and detail research will be done in our future work. In [16] they consider an abstract market model for demand response where a supply function bidding is applied to match power supply deficit or surplus. They characterize the resulting equilibria in competitive and oligopolistic markets and propose distributed demand response algorithms to achieve the equilibria. In addition, they further show that the equilibrium in competitive market maximizes social welfare, and the equilibrium in oligopolistic market has bounded efficiency loss under certain mild assumptions. Finally, they propose distributed demand response

algorithms to achieve the equilibria. [17] Proposes a reward based demand response algorithm for residential customers to shave network peaks. Customer survey information is used to calculate various criteria indices reflecting their priority and flexibility. Criteria indices and sensitivity based house ranking is used for appropriate load selection in the feeder for demand response. Customer Rewards (CR) are paid based on load shift and voltage improvement due to load adjustment. The proposed algorithm can be deployed in residential distribution networks using a two-level hierarchical control schemes. Realistic residential load model consisting of non-controllable and controllable appliances is considered in this study.

In all previous researches that were reviewed there was no inclusive information about all parameters effectiveness on load side consumption to find out which parameter has more affective and should be focused in order to improve load side managing. In this paper and our future researches, we are going to extract all parameters effectiveness on load side consumption and collect them as a Load Manageability Factor (LMF) is used to find out which parameter is more valuable for asset allocation to improve load profile curve.

2. LOAD MANAGEABILITY FACTOR ANALYSES

If there was a method to find out the amount of reactions level to each parameter variation and then collect them in a unit mathematical equation or an artificial neural network, then it will be easy to catch the amount of manageability amount of each feeder load with changing parameters that we are allowed to change them. Major and essential parameters that will consider and their changes maybe affect to power energy consumption and causes load reaction are environmental condition such as temperature and humidity variation, energy price variation at a specific period of time, major events like sport game broadcast and president lecture on TV, and power utility announcing to the own customers. These parameters respectively are shown with x_1 to x_5 in (1). In this paper environment conditions like temperature and humidity variation and their affective on load side consumption will be discussed and their role on LMF will be gained.

$$\begin{aligned} X_1 &\rightarrow \text{Environment temperature} \\ X_2 &\rightarrow \text{Environment humidity} \end{aligned} \quad (1)$$

- $X_3 \rightarrow$ Power energy price
- $X_4 \rightarrow$ major events happening
- $X_5 \rightarrow$ announcing to the customers

Each customer’s reaction to the mentioned parameters depends on inherent feature of them like customer’s welfare, customer’s knowledge, and type of loads such as residential, commercial, and industrial loads. Suppose that the parameters x_2 to x_5 are the same for definite period are shown with (2). And so on for conditions that parameters x_1 and x_3 to x_5 are the same are shown with (3). In addition, continue this situation for each parameters, thus there will be five equations that each of them will illustrate load profile with only one parameter variation effectiveness. Therefore, with combination of these five equations, the main equation will be achieved. In the main equation that shows load profile, with changing one of the essential parameters, the amount of load profile variation would be calculated. So with changing one of these parameters, the amount of manageability of load could be calculated.

$X_1 \rightarrow$ with variation
 X_2 to $X_5 \rightarrow$ without variation
 $P_1(t)$ =load profile equation with above condition (2)

$X_2 \rightarrow$ with variation
 X_1 and X_3 to $X_5 \rightarrow$ without variation
 $P_2(t)$ =load profile equation with above condition (3)

$X_3 \rightarrow$ with variation
 $X_1, X_2, X_4, X_5 \rightarrow$ without variation
 $P_3(t)$ =load profile equation with above condition (4)

$X_4 \rightarrow$ with variation
 $X_1, X_2, X_3, X_5 \rightarrow$ without variation
 $P_4(t)$ =load profile equation with above condition (5)

$X_5 \rightarrow$ with variation
 X_1 to $X_4 \rightarrow$ without variation
 $P_5(t)$ =load profile equation with above condition (6)

In this paper, the aim is using Eqs. (2) and (3) to get load manageability for temperature and humidity variation. For achieving total load manageability, it is necessary to use Eqs. (4) – (6) and combine them in a total formula that it may be the results of this paper. In the future research, we want to do that and complete this aim to gain total

load manageability factor. In total load manageability factor, the relationship between all parameters that mentioned in Eq. 1 and electric load consumption will be showed. In the other words, you could change the parameters that their changes are in your control like energy pricing, but parameters like environmental temperature and humidity are determined from environmental circumstance. Because of load variation dependency to environmental condition variation, it must be calculated. With having this total load manageability factor and parameters that you are allowed to vary them, power utility companies could manage load side energy consumption more effectively. Calculating this factor or the main artificial neural network should be done for every kind of loads with unique innate features. In this paper, calculation has been done for commercial load with average welfare and knowledge level for two parameters variation that is environmental temperature and humidity variation. Fig. 1 shows flowchart of our strategy for each parameter. In fact, for getting total load manageability factor we must repeat this flowchart for all parameters and then collect their results.

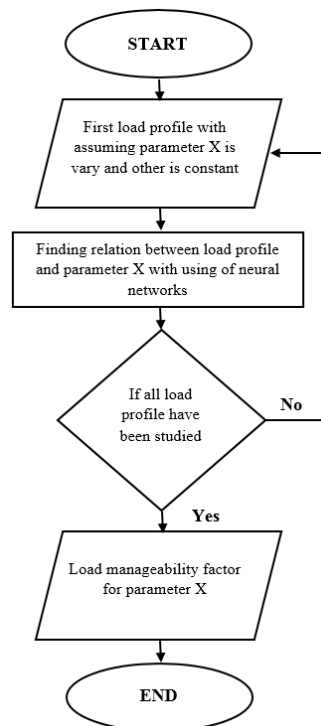


Fig. 1. Flowchart of our strategy

Suppose that there is 24-hour load profile for unique medium voltage feeder and there are basic information about that feeder for respective day. Basic information about the feeder could be the type of loads connected, knowledge level of

customers, and social welfare. Basic information about the respective day could be environment temperature, environment humidity, and some important events that have happened on typical day with large effective on energy consumption like principal football matches playing, political debates, and popular TV programs. If we have supposed feeder load profile curve with blue color on Fig. 2 (Pa), after applying affecting parameters factors we will have new load profile curve for respective day that is shown with red color (Pm). In Fig. 2, Load Manageability Factor (LMF) is defined with dividing blue curve equation (Pa) to red curve equation (Pm) that is shown with (7). This equation is the symbolic equation because of both Pa(t) and Pm(t) were defined as nonlinear equations. With having basic load profile (Pa) and LMF, it is capable to catch new load profile that is managed in a way that more effective lode side management is obtained. LMF have all affective parameters and their amount of effects. In this paper, we aim to catch commercial load behavior due to temperature and humidity variation.

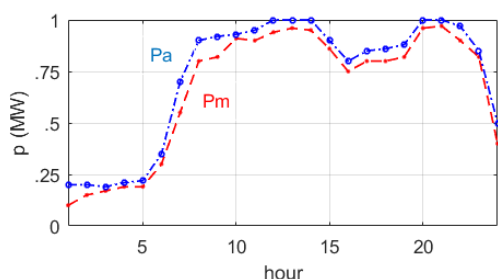


Fig. 2. Real load profile and new load profile after applying affecting parameters for typical feeder

$$\text{Load Manageability Factor} = \frac{P_a(t)}{P_m(t)} \quad (7)$$

3. THREE TYPES OF LOADS FEATURES

For measuring the real and reactive power consumption of customers within each 1-hour time interval, the intelligent meters had been installed. Statistic software is used to detect the abnormal load demand or outlier in the data set. The mean value and variance of customer power consumption in the same stratification are solved for each study hour of the weekday. Then the typical load patterns are normalized by the daily peak power demand as shown in Fig. 3. It is found that the peak loading for residential customers occurs at nighttime period when people stay at home with high loading percentage of air conditioners and other home appliances. For the commercial customers, the power loading increases dramatically during the

day time business hours. This implies that the power consumption by this customer class makes very significant contribution to the system peak loading during the summer season. For the industrial customer class, very flat load patterns have been resulted because of the continuous manufacturing process and the implementation of various load management programs. Besides, the loading percentage of air conditioners.

By plotting the active power consumption vs. the temperature in Fig. 4 for the commercial customers, the power consumption is quadratically increased with the temperature. In addition, the active power consumption vs. the humidity changes for commercial customers is shown in Fig. 5. Power consumption vs. the temperature and humidity changes for industrial and residential customers are shown in Fig. 6 to Fig. 9.

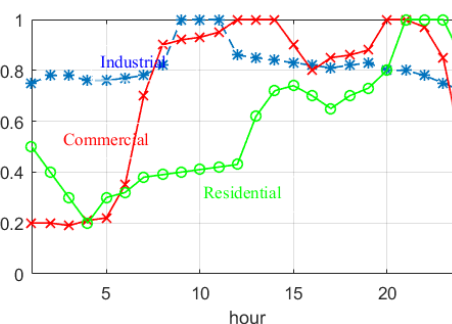


Fig. 3. The normalized load patterns of industrial commercial and residential customers

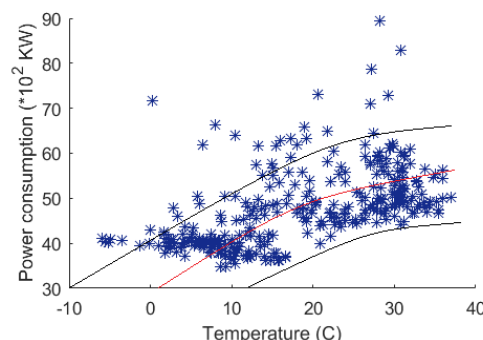


Fig. 4. The power consumption of a commercial customer vs. temperature

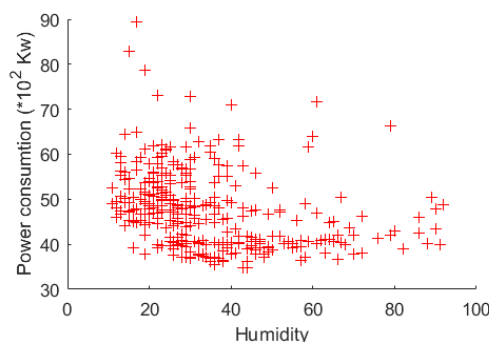


Fig. 5. The power consumption of a commercial customer vs. humidity

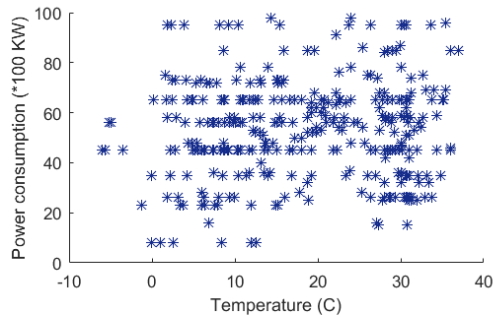


Fig. 6. The power consumption of an industrial customer vs. temperature

According to the plotting of commercial, industrial and residential customers vs. temperature and humidity changes, this fact is deducing that the commercial customer's behavior to the temperature increase is more dependence than industrial or residential.

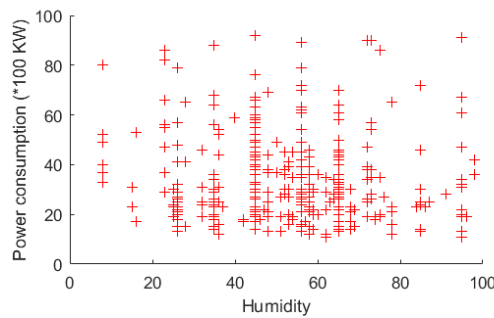


Fig. 7. The power consumption of an industrial customer vs. humidity

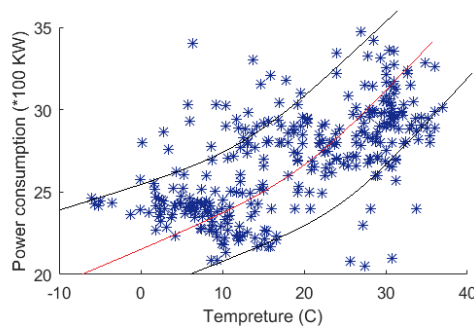


Fig. 8. The power consumption of a residential customer vs. temperature

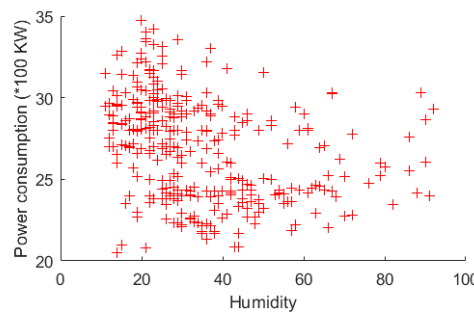


Fig. 9. The power consumption of a residential customer vs. humidity

The correlation between the power consumption and temperature is very poor for industrial

customers and the increase of temperature will has little impact to the power consumption of this customer class. All of these reasons caused that our study focus on commercial customer's behavior.

In this paper, single parameters that had been varied are temperature and humidity ((2) and (3)). Therefore, we select load profiles that have same effective in terms of other factors except environment temperature and humidity differences. Equation (8) shows load profile curve equations for all days that have same conditions except different temperature and humidity.

$$\begin{aligned}
 P_1(t) &= \alpha_1 t^n + \alpha_2 t^{n-1} + \dots + \alpha_n t \\
 P_2(t) &= \beta_1 t^n + \beta_2 t^{n-1} + \dots + \beta_n t \\
 P_3(t) &= \gamma_1 t^n + \gamma_2 t^{n-1} + \dots + \gamma_n t \\
 &\vdots \\
 P_m(t) &= \omega_1 t^n + \omega_2 t^{n-1} + \dots + \omega_n t
 \end{aligned}
 \tag{8}$$

For all days of 1 to m, effective factors that causes load consumption variation are the same, except environmental temperature and humidity changes. All equations for these days are equations of trending applied on load profile curves. If we have temperature and humidity variation for two typical days, then it is concluded that the differences between energy consumption during the days are because of differences in environmental temperature and humidity. If we consider first day's load profile curve equation (P1(t)) as a base curve and for each day obtain relative equation with dividing respective day equation to base curve equation, we will have relative equations that are shown in (9).

$$\begin{aligned}
 \frac{P_2(t)}{P_1(t)} &= \varepsilon_1 t^n + \varepsilon_2 t^{n-1} + \dots + \varepsilon_n t \\
 \frac{P_3(t)}{P_1(t)} &= \zeta_1 t^n + \zeta_2 t^{n-1} + \dots + \zeta_n t \\
 \frac{P_4(t)}{P_1(t)} &= \eta_1 t^n + \eta_2 t^{n-1} + \dots + \eta_n t \\
 &\vdots \\
 \frac{P_m(t)}{P_1(t)} &= \theta_1 t^n + \theta_2 t^{n-1} + \dots + \theta_n t
 \end{aligned}
 \tag{9}$$

If we could train artificial neural network that its input vector is temperature and humidity of typical days and its target vector is 24 hours load profile for that typical day we will achieve relation between temperature and humidity variation to load consumption. With having this relationship, we are able to predict load profile in typical day and be

near to our main aim that is catching LMF. It is necessary to consider other parameter beside temperature-humidity information as an input vector for training network and it is load growth for relative days. It is obvious that load profile variation in two similar days depends on load growth so we consider input vector with four dimensions. In addition, load profiles that are used for training neural network must have same conditions except temperature variation. According to recent description, input vector for neural network training is like matrix A is shown at (10). Each row is relative day's temperature and humidity information and load growth. Columns 1 to 7 are minimum, average, maximum temperature, humidity, and load growth amount for respective day. Target vector for neural network training is like matrix B that is shown at (10). In this matrix, each row shows 24 load amounts at 24 hour on relative day. Columns 1 to 24 of matrix B are representative 24 hour for special day. Matrix A and B order depends on the number of days that we have same condition except temperature and humidity variation.

$$A = \begin{bmatrix} t_{\min_1} & t_{\text{avg}_1} & t_{\max_1} & h_{\min_1} & h_{\text{avg}_1} & h_{\max_1} & l_{g_1} \\ t_{\min_2} & t_{\text{avg}_2} & t_{\max_2} & h_{\min_2} & h_{\text{avg}_2} & h_{\max_2} & l_{g_2} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ t_{\min_n} & t_{\text{avg}_n} & t_{\max_n} & h_{\min_n} & h_{\text{avg}_n} & h_{\max_n} & l_{g_n} \end{bmatrix} \quad (10)$$

$$B = \begin{bmatrix} P_1 & P_2 & \dots & P_{24_1} \\ P_1 & P_2 & \dots & P_{24_2} \\ \vdots & \vdots & \dots & \vdots \\ P_1 & P_2 & \dots & P_{24_n} \end{bmatrix}$$

In matrix A, t_{\min_1} is the minimum temperature on first day, t_{avg_1} is the average temperature on first day, t_{\max_1} is maximum temperature on first day, h_{\min_1} is the minimum humidity on first day, h_{avg_1} is the average humidity on first day, h_{\max_1} is the maximum humidity on first day and finally l_{g_1} is load growth on first day. (n) Is number of days that have same condition except temperature and humidity variation. In matrix B, P_1 to P_{24} is active power in 24 hour on special day. After training neural network we have pattern that enables having 24-hour load profile with having temperature information and load growth. With having this pattern and predicting temperature and humidity information and load growth for typical day it will be easy to understand amount of energy consumption and manage load side consumption to

having balance between energy generation and consumption in system.

4. PRACTICAL STUDY

We collect all 20 kV feeders energy consumption of Alborz Province Power Electric Distribution Company for 4 years. In addition, temperature and humidity information of 4 years have been collected. All our study is based on collected information. This company has 309 medium voltage feeders that smart meters record energy consumption in 1-hour step. Due to importance and effectiveness of commercial loads, we concentrate this type of load behavior. Feeders that feed the large number of commercial type of loads are selected for our study. In order to ignore commercial load behavior caused by knowledge level of costumers, and social welfare, feeders that feed the part of city with the same knowledge level and social welfare with the average level have been noticed. In addition, feeders that 95% of connected loads are commercial are used for our study. Feeders do not have any load displacement for our study. Fig. 10 shows load profile curve of typical commercial feeder for typical day.

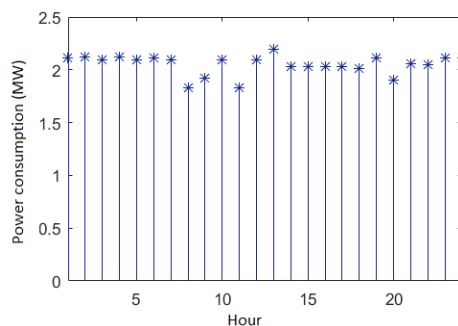


Fig. 10. Load profile curve of typical commercial feeder for typical day

There are three steps to getting proper results: training neural network, getting results, and analyzing results.

4.1. Training Neural Network

As mentioned, Alborz Province Power Electric Distribution Company (APPEDC) has 309 medium voltage feeders that 20 numbers of them have proper conditions that are noted in previous paragraph. There are 73 days with same conditions except temperature and humidity variation and load growth in collected data (4 years data). So in matrix A and B, $n=73$. With having 20 feeders and 73 days load profiles, 1460 load profile with various temperature and humidity information and load growth will exist for training neural network.

Matrix A order is 73 rows and 7 columns and matrix B order is 73 rows and 24 columns. For each

feeder, one unique neural network was trained. Neural network with two layers was used to mapping between a data set of numeric inputs (matrix A) and set of numeric targets (matrix B). 73 samples of 4 elements are considered as input vector and 73 samples of 24 elements are considered as target vector. 80% of samples are used for training and 10% of them for validation and 10% of samples are used as testing network. Number of hidden neurons is set to 10 neurons. Data division for algorithm of network was random. Levenberg-Marquardt was selected as training algorithm. Number of epoch for iteration was 1000 and number of validation checks was 6. Fig. 11 illustrated performance of training after 10 iterations for feeder 1. Improvement after second iteration for six iterations does not have acceptable amount for continuing calculation.

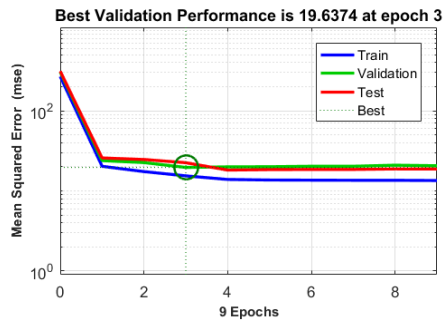


Fig. 11. Performance of training after 10 iterations

Fig. 12 and 13 displays error histogram and regression for training feeder's one data respectively. Decision base to select best training among 20 feeder's data neural network training is regression chart. This chart shows linear regression at training, validation, test, and all data and being 1 illustrate best fitting on input data and output target. Fig. 13 illustrated 0.61829 for training, 0.64065 for validation, 0.5356 for test, and 0.60631 for all. With training several neural networks for 20 different feeders and having regression chart for all of them, it will be gentle to find proper and best fitting network. In following section, it is intended to make decision for selecting best neural network training and finally catching proper mapping between inputs and targets.

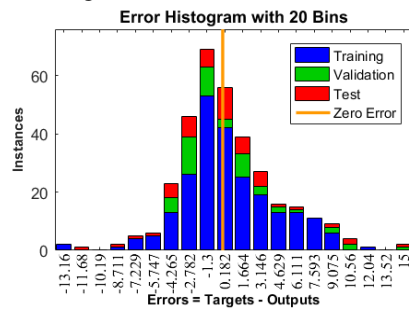


Fig 12. Error histogram for feeder's 1

4.2. Getting Results

This section is devoted to comparison between results and selected best item to illustrate existing mapping among inputs (temperature and humidity information and load growth) and targets (24 hour load profile in medium voltage feeder). The excellent tool for choosing proper-trained neural network is regression comparison of each network. Table I illustrates regression amounts at 20 trained networks.

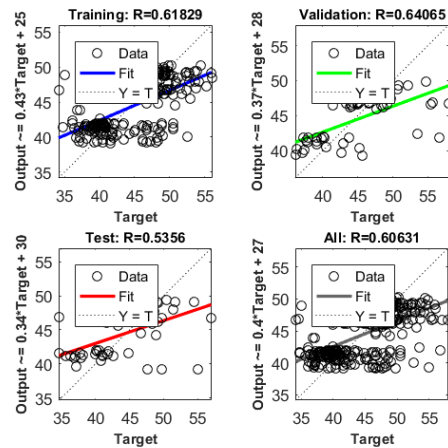


Fig. 13. Regression chart for feeder's 1

Table 1. Regression Amounts for 20 Trained Networks

Network	Training	Validation	Test	all
1	0.94934	0.81747	0.91243	0.91542
2	0.92491	0.91817	0.95279	0.91142
3	0.64690	0.85945	0.87635	0.65007
4	0.92214	0.84310	0.96501	0.92605
5	0.93669	0.95677	0.84908	0.92928
6	0.96898	0.92368	0.75027	0.95305
7	0.92511	0.93302	0.95453	0.93358
8	0.94843	0.90290	0.94750	0.94202
8	0.91406	0.92386	0.89004	0.93562
9	0.93565	0.76792	0.86905	0.92625
10	0.91576	0.97385	0.95244	0.92535
11	0.92332	0.92456	0.91996	0.93786
12	0.93385	0.94834	0.95256	0.93630
13	0.91862	0.84884	0.91570	0.91198
14	0.94342	0.91627	0.81629	0.93011
15	0.93741	0.92912	0.95219	0.93436
16	0.93909	0.92686	0.93842	0.93785
17	0.95334	0.91493	0.89227	0.94154
18	0.86994	0.89543	0.91942	0.88041
19	0.95363	0.93556	0.98162	0.91911
20	0.90952	0.94275	0.79451	0.91251

4.3. Analyzing results

With considering regression amounts in Table 1, neural networks training for feeder 6 have been fine results then it was selected as a base neural network to have proper connection between inputs and targets. With these calculation and simulation, load profile curve could be available with having environmental temperature and load growth index.

5. CONCLUSIONS

In this article, we concentrate on commercial load to find load reaction in the medium voltage feeder due to temperature and humidity variation to get the LMF. With using of neural network analyze the correlation between commercial load consumption and temperature variation and humidity change has been found. Collecting other parameters effective on load profile to finding final LMF will be done. Using final LMF more effective management in load side will be done and balancing load side and generation side in power system will be obtained.

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