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Article

Data-Driven Load Forecasting of Air Conditioners for Demand Response Using Levenberg–Marquardt Algorithm-Based ANN

Muhammad Waseem, Zhenzhi Lin * and Li Yang

School of Electrical Engineering, Zhejiang University, Hangzhou 310027, China
* Correspondence: linzhenzhi@zju.edu.cn; Tel.: +86-571-8795-1542

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Abstract: Air Conditioners (AC) impact in overall electricity consumption in buildings is very high. Therefore, controlling ACs power consumption is a significant factor for demand response. With the advancement in the area of demand side management techniques implementation and smart grid, precise AC load forecasting for electrical utilities and end-users is required. In this paper, big data analysis and its applications in power systems is introduced. After this, various load forecasting categories and various techniques applied for load forecasting in context of big data analysis in power systems have been explored. Then, Levenberg–Marquardt Algorithm (LMA)-based Artificial Neural Network (ANN) for residential AC short-term load forecasting is presented. This forecasting approach utilizes past hourly temperature observations and AC load as input variables for assessment. Different performance assessment indices have also been investigated. Error formulations have shown that LMA-based ANN presents better results in comparison to Scaled Conjugate Gradient (SCG) and statistical regression approach. Furthermore, information of AC load is obtainable for different time horizons like weekly, hourly, and monthly bases due to better prediction accuracy of LMA-based ANN, which is helpful for efficient demand response (DR) implementation.

Keywords: Air Conditioners (AC); Artificial Neural Network (ANN); big data analysis; cooling demand; energy consumption; Demand Response (DR); Load Forecasting (LF); Levenberg–Marquardt Algorithm (LMA)

1. Introduction

In power systems, the end-users electrical demand characteristics have the most significant role. End user's participation in DR programs can provide load reductions during peak energy use periods. Also, energy consumption can be controlled in distribution voltage level due to appliance level demand management in an intelligent manner [1,2]. Among appliances, ACs are major contributors in energy consumption at residential and commercial levels nowadays. ACs usage has been undoubtedly acknowledged as an important contributor, especially to peaks perceived during strongly intense summer. During intense summer, there is a probability of blackouts as a result of enormously rising demand together with high temperatures contributing to generation and power transmission networks. Similarly, peak electricity demands in several warmer global regions have been caused by AC usage. Only in California, commercial AC usage shows almost 45% contribution in peak demand and projected in commercial demand of about 30–40% during Australia peak demand days [3]. In addition to this, in many areas, residential ACs are also significant contributors in peak demand of power systems [4]. In South Australia, ACs play a major role in rising of electricity peak demand where almost 90% of the residences are equipped with AC due to frequent heat waves [5]. During the summer season, residential ACs contribute about 20–25% in electrical system peak demand of the Ausgrid, a largest distribution utility in the New South Wales Sydney region of Australia [6].

Nowadays the most important challenge for electricity utility is to manage electricity demand to satisfy customers. As electrical demand is totally uncertain and variable during different horizons during a complete day. Traditionally, only utility adopts different options to manage demand variations. But nowadays due to a variety of factors such as penetration of intermittent energy sources in existing power system, minimization of energy cost with less energy consumption and energy efficiency improvement create options for end customers to manage consumption of electricity. Demand side management (DSM) is commonly referred to as activities for involvement of demand side in electricity usage [7].

DR programs make available in 2016 of about total 13,036 MW peak reductions, and 26% of total peak reductions from residential energy sector according to US Energy Information Administration [8]. Residential customers had showed their significant contribution in DR manipulation in [9–11]. Among home appliances, ACs contribute more significantly in DR attainment as investigated by different researchers [12]. Residential ACs power reductions forecasts are required by both end users and electric utilities for DR programs implementation [13,14]. To achieve DR benefits and exploitation from residential appliances smart energy meters have been deployed in numerous homes as discussed in [15]. By deployment of smart home energy management systems, DR implementation from ACs become easily attainable. Residential electric appliances control in the variable electricity prices for DR implementation was also highlighted in [16].

Big data is an outcome of advanced digital technologies in human daily life. These technologies yield massive data volumes termed as big data due to rising of humans and machines intercommunication. Mainly volume, velocity, veracity, and variety are fundamental characteristics of big data. Load in power system is random and uncertain with respect to time. In power sector due to smart grid technologies volume of data generated from grid increased excessively [17]. Future energy consumptions are predictable by mean of LF-based upon information availability according to end-user's behavior. Future energy requirements have been predicted by making use of several forecasting models based upon past load, weather observations, off-weak days, economy, power tariff mode adoption, new load growth and availability of intermittent sources of energy. It is an efficient tool for power system planning, operation, load switching, infrastructure development, contracts renewal, investment/planning for new generating power units, new staff inductions, supply/demand balance and effective DSM. LF approaches may be short, medium and long-term based upon planning and operation [18]. But end-user's energy usage randomness and seasonal uncertainties has made LF more challenging. Based upon forecast error power system operational and maintenance costs may get increase [19].

Big data analysis is more effective, detailed and accurate predictions from generation of energy and its utilization by loads [20]. In [21], it has been discussed that LF can be classified as statistical, probabilistic, physical methods, artificial intelligence (AI) and hybrid approaches based upon the methods. The main contributions of this manuscript are as follows: 1) Big data analysis and its applications in power systems are discussed, and main applications of LF approaches of AC demand have been highlighted for DR accomplishment; 2) With weather information and past load data considered, a novel LMA-based ANN approach to forecast future residential AC loads is proposed, which is suitable for different time horizons like weekly, hourly and monthly basis, and could improve the accuracy of forecasting; 3) Different performance assessment indices are presented and real time hourly TMY3 data for Austin Texas is used for demonstrating the proposed LMA-based ANN approach, which show that the proposed LMA-based ANN approach is better than SCG-based ANN and conventional multiple linear regression approach.

The rest of this paper is organized in following sections.: Section 2 presents an overview of big data analysis in context of power system and its applications. In Section 3 there is discussion about increase in AC demand worldwide and LF classes, benefits, and influencing factors. Section 4 presents LMA-based ANN approach for forecasting of AC loads. There is discussion about different performance comparison parameter indices in Section 5. Section 6 highlights different forecasting results. Finally, discussion and conclusions are also given in Section 7.

2. Big Data Analysis in Power Systems

Data generation has increased tremendously in recent years. Mechanisms and tools required for extraction, conversion, and analysis of huge data volumes in order to present results for system administrator is termed as big data analysis [22]. Due to big data complexity, researchers and technologists are transforming traditional methods into advanced algorithms, frameworks, and platforms to tackle novel challenges [23,24]. Parallel and cloud computing are applied for big data analysis. Grid energy data gathered in power systems is categorized as high-volume big data collected from numerous sources of various types, locations and applications at high velocity. Power systems big data is classified as domain and off-domain data in [25]. Domain data comprises SCADA, telemetry, oscillography, synchro phasor, metadata and financial data. While off-domain power systems consist of data about social media, traffic, trade, weather, gas and water usage.

In power systems the main challenging factors handled due to big data analysis are reduction in data collection cost and data storage [26]. Big data analysis shows most promising contributions in short-term and long-term operations of power systems including theft indication, demand modelling, distribution system management and granular level load and intermittent generation sources forecasting [27]. Big data analysis supports in finding price trends of electricity and its utilization. Furthermore, utility can handle demand and supply balance. Big data analysis in power systems has been applied to indicate fault and outage, communication data management, forecasting of energy consumption and cost of electricity [28–31]. In power generation, big data analysis assists in economic dispatch, power planning, optimization, and efficiency improvement. Outage restoration, detection of power loss, fault and transformer actions can be monitored during transmission and distribution of power. Furthermore, big data analysis plays a significant role in load management. In load management, main applications of big data analysis are loads classification, DR, energy savings and theft control. Also, big data analysis plays a prominent role in LF. It can be applied to analyze different appliance level effects on power system. In this paper, appliance level AC load forecasting by using LMA-based ANN has been achieved. A big set of information indicated by different variables that effect AC energy consumption have been applied to predict future AC load, that is also a sort of big data analysis on appliance level that has been investigated in this manuscript.

3. AC Demand and Load Forecasting

Sales of ACs have blow-up worldwide over the last few years. Increase in ACs usage is dependent on several social, economic and climatic factors. Globally in 2014 AC market was increased by up to 98 billion US dollars. It represents about 58% of the world total market and nearly about 10% total increase as compared to 2013 [32]. AC demand for 2017 has increased by about 8.1% as compared to 2016. Largest AC sales were observed in China that show significant contribution of about 42% in total world AC demand. Usage of about 17.30 million ACs units with 5.4% increase was observed in Asia. Similarly, North America comprising AC demand of about 15.32 million ACs units with 4.9% increase [33]. Cooling demand that is ACs utilization will significantly rise in coming years globally especially in developing regions like Asia and Africa mainly due to climatic variation, income growth and population increase as explored in [34] and [35].

According to the latest figures globally, there are 1.6 billion ACs. International Energy Agency (IEA) has predicted about 244% increase in the number of ACs worldwide from up till 2050. Worldwide energy demand by 2050 due to AC usage has expected to reach about 6205TWh. The IEA forecasted that global energy demand could be just 3407TWh if AC efficiency will be improved so that it becomes double [36]. It has been revealed from the above observations that ACs figures are growing day by day. As AC contribute significantly in world-wide total energy demand so it is a major challenge to handle and design some demand management programs to tackle this issue. It has been investigated that LF is an efficient tool for power system planning, optimization, economic dispatch, scheduling and operation among both utilities and end-users. LF classes, prediction horizons, achievable benefits and influencing factors have been presented in Table 1 as follows.

Table 1. Comprehensive Summary of Load Forecasting (LF) classes, prediction horizons achievable benefits, and influencing factors.

<table>
<tr><th>LF Approach</th><th>Prediction Horizon</th><th>Achievable Benefits</th><th>Influencing Factors</th></tr>
<tr><td>Very Short-Term</td><td>• Few minutes
• One hour</td><td>• Security and sensitivity analysis of electric equipment
• Load shedding planning
• Matching of demand and supply</td><td rowspan="2">• Seasonal variations
• Events
• Holidays
• Festivals
• TV programs</td></tr>
<tr><td>Short-Term</td><td>• One hour
• One day
• One week</td><td>• Matching of demand and supply
• Spot power procurement
• Control and power system scheduling to minimize reduction
• Regulate voltage, unit commitment
• Utility revenues maximization [37]</td></tr>
<tr><td>Medium-Term</td><td>• Few months
• One year</td><td>• Maintenance scheduling
• Operation planning
• Energy management
• Power Procurement
• Load dispatching coordination
• Matching of demand and supply</td><td>• Seasonal variations
• Growth rate
• New customers</td></tr>
<tr><td>Long-Term</td><td>• One year
• Four to five years</td><td>• Planning of capacity expansion
• Investment for new generating units
• New staff induction</td><td rowspan="2">• Seasonal variations
• Growth rate
• New customers
• Change in lifestyle</td></tr>
<tr><td>Very Long-Term</td><td>• Greater than five Years</td><td>• Investment planning of capacity expansion
• Renewable sources integration planning
• Planning about environmental policies [38]</td></tr>
</table>

Traditionally load forecasting is based upon physical models unable to tackle uncertainties and complex interrelationships among variables. Big data analysis as a data-driven approach is not dependent upon physical models. These data-driven approaches consist of decision tree algorithm, support vector machine (SVM) and ANN [19]. In [39], it has been discussed that upon the basis of methods LF can be classified as statistical, artificial intelligence (AI)-based methods, physical and hybrid approaches. Statistical-based LF can be achieved by using autoregressive moving average (ARMA) [40], autoregressive integrated moving average (ARIMA) [41], autoregressive-moving-average model with exogenous inputs [42], time series analysis, exponential smoothing, adaptive filtering, similar day lookup approach, regression method and probabilistic methods as highlighted in [43]. Statistical methods are simple in implementation but not efficient in handling uncertainties. Therefore, nowadays AI-based forecasting approaches are preferred to handle complex, non-linear relationships and uncertainties between output and affecting variables. Furthermore, their results have fast convergence and less computational complexities [44]. AI approaches are some modern or soft computing methods may be categorized as support vector machines (SVM), fuzzy logic and genetic algorithms (GA) and ANN. Although these techniques required a huge amount of observations for training and assessment.

Unlike the statistical and AI-based forecasting approaches, the physical methods require detailed information for future prediction. Normally satellite is applied for short-term forecasting as explored in [45]. For long-term forecasting weather-based numerical prediction models are appropriate. In addition to physical forecasting tools, hybrid methods combine different approaches to handle challenges in standalone techniques. Several hybrid techniques comprise fuzzy neural network, fuzzy expert neural network system, neural expert systems and neural-genetic algorithm [46]. Forecast studies have been mainly focused on aggregate loads but individual residential household level and appliance level energy forecasts have not been analyzed [47]. With the recent advancement of smart grid, there is a growing interest for residential electricity analysis at individual household and appliance level for DR manipulation and optimum power system planning and operation Residential load profiles show high uncertainty and variations in comparison to commercial or larger loads. This is mostly due to random residents' behavior [48]. Hence, it is a greater challenge to forecast residential loads at individual and appliance level.

In LF, past observations have been utilized to observe different variables relationship. Numerous short time horizon load prediction approaches have been explored in literature. Regression is commonly applied in case of historic data unavailability. ANNs are preferred in case of uncertainties that are difficult to manage by conventional tools. Indonesian South Sulawesi Island's load has been predicted by regression based LF [49]. A short-term LF model was presented in [50] by applying clustering regression. A fuzzy logic-based approach was applied for short time horizon load prediction which utilizes fuzzy rules that were obtained from past weather and load. In addition to this fuzzy logic, genetic and evolutionary algorithm were applied with ANN was also investigated in [46]. In [51], an online support vector regression algorithm was presented to forecast Surrey, British Columbia residential sector. In this paper there is investigation of AC load prediction by making use of multiple linear regression, SCG and LMA-based ANN approach described as below.

4. LMA-based ANN Approach

ANN models have been applied for best execution through several small interrelated units termed as neurons. In order to achieve better results, simultaneous massive processing's have been performed by neurons that have an artificial interconnection. Numerous repetitive processing is performed by neurons that also connect input, output and hidden layers of neural network. Relationship between input and output can be mapped by neurons weights updating that is achieved by training algorithm applied in ANN. Activation function generates output by making use of weighted inputs summation. Desired and generated output error can be minimized by adjustment of weights and biases. Generally, neural network has been discussed in [52] can be represented mathematically in (1) as follows.

$$A_n = \sum_{n=1}^{k} P_n w_n \tag{1}$$

where n = 1, 2, 3, ..., k, P_n is the nth input, w_n is the allocated weight for nth input and A_n is the nth ANN output. ANN approaches have been reviewed in detail in [20]. For ANN calibration network architecture is selected and number of neurons will be selected as required. In addition, ANN training algorithm for weights updating will be decided. Speed, accuracy and complexity of load forecasting model depends upon machine learning algorithm applied for model training. In this paper, a feed forward three-layer multi perceptron neural network has been proposed. By making use of an activation function desired outcomes will be obtained by hidden neurons. Most commonly log-sigmoid mathematical function is applied for training. Transfer function for this proposed function [52] is represented as

$$F(n) = \frac{1}{1+e^{-n}} \tag{2}$$

In the proposed forecasting model, the LMA has been used to for hidden layer weights updating in order to solve nonlinear least square problems. Various algorithms applied for multi-layer perception ANN model training are LMA, gradient decent and Bayesian regularization. In the proposed forecasting approach, the LMA has been used for weights updating of hidden layers in order achieve desired outcomes. In LMA, initially random weights w_n are generated. Then sum square error E_n will be computed from initial weights by using

$$E_n = \frac{1}{2} \sum_{\substack{1 \le p \le P \\ 1 \le o \le O}} e_{p,o}^2 \tag{3}$$

where $e_{p,o}$ is training error that can be calculated from desired output $d_{p,o}$ and actual output $A_{p,o}$ as given by

$$e_{p,o} = d_{p,o} - A_{p,o} \tag{4}$$

After this LMA weights are updated by

$$w_{n+1} = w_n - (H)^{-1} J E_n \tag{5}$$

where J is Jacobian matrix and H is hessian matrix that can be computed by

$$H = J^T J + (\beta I) \tag{6}$$

where I is unity matrix and β is combination coefficient that value will be considered if updated error E_{n+1} becomes less than original E_n. If updated error E_{n+1} becomes greater than original E_n, then procedure will be again started from initial random weights generation [53–55]. LMA procedure can be observed in detail from the following flow diagram given in Figure 1.

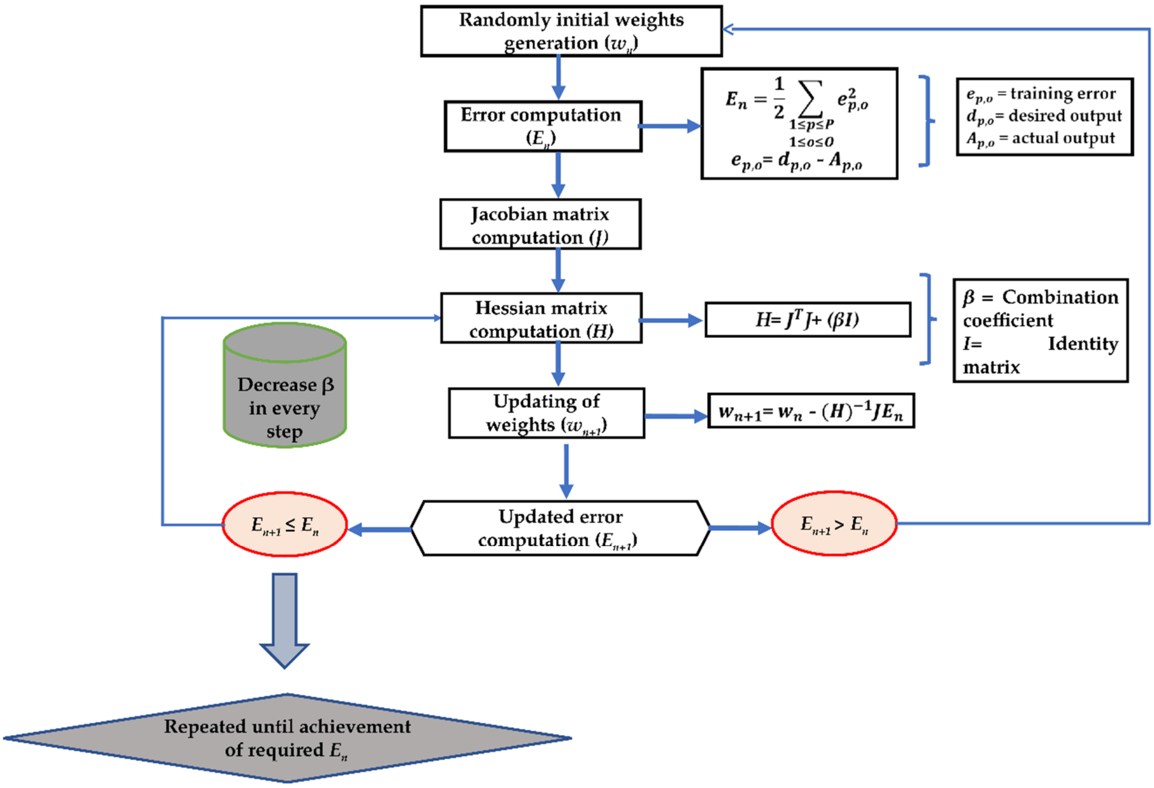

Figure 1. Flow chart for Levenberg–Marquardt Algorithm (LMA) considered in Artificial Neural Network (ANN).

5. Performance Assessment Indices

To access the fitness of LF approaches, different performance evaluation indices have been applied. Firstly, the percentage absolute error has been computed to observe accuracy of proposed approach as given in Equation (7). X_i represents actual AC load, Y_i represents AC load predictions by applied LF approach.

$$\%AE = \left| \frac{X_i - Y_i}{X_i} \right| \times 100\% \quad (7)$$

Secondly, the mean squared error *MSE* a performance assessment indicator, has been applied to observe the applied LF approach accuracy for AC load predictions. Equation (8) shows how to formulate mean squared error. E_i is difference between observed and actual load for N observations. An *MSE* value closer to zero represents that the predicted outcome is more accurate.

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (E_i)^2 = \frac{1}{N} \sum_{i=1}^{N} (X_i - Y_i)^2 \quad (8)$$

Thirdly, the mean absolute percentage error (*MAPE*) that is also a performance assessment indicator, to observe the applied LF approach accuracy for AC load predictions [56]. Equation (9) represents *MAPE* formulation as follows:

$$MAPE = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{Y_i - X_i}{Y_i} \right| \times 100\% \quad (9)$$

However, the greater variations in energy consumptions have been observed for smaller households. *MSE* and *MAPE* are not suitable accuracy predictions indicators in this case as power consumption varies greatly during peak and off-peak periods. Therefore, another performance indicator namely the mean absolute error (*MAE*) has been adopted to access accuracy of applied approach for AC load predictions that can be formulated as,

$$MAE = \frac{\sum_{i=1}^{N} (Y_i - X_i)}{N} \tag{10}$$

The whole procedure adopted for LMA-based ANN including performance assessment indices is given in the following flow chart given in Figure 2.

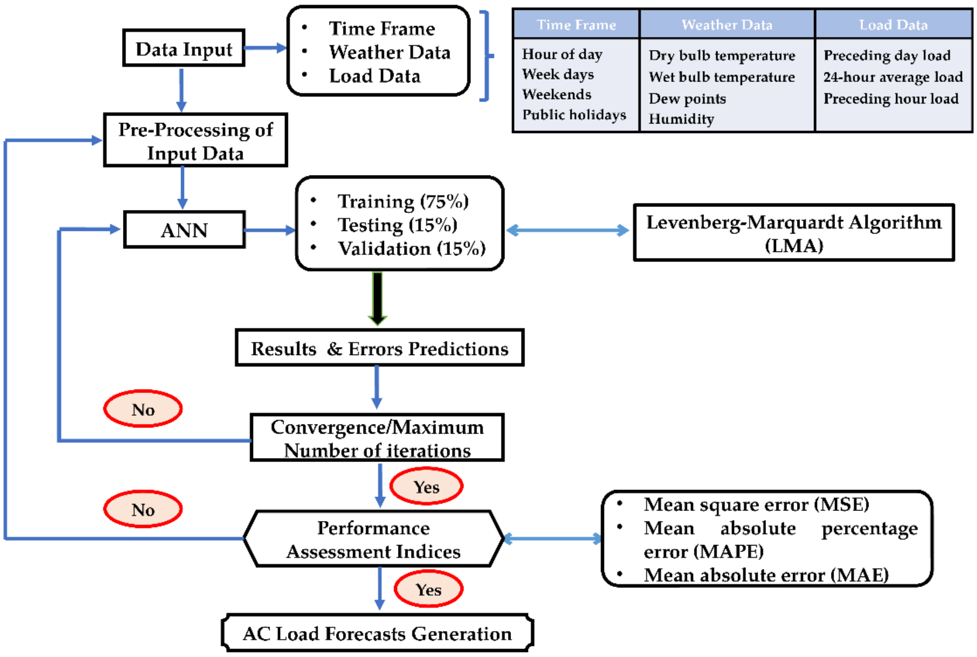

Figure 2. Flow chart for LMA-based ANN.

6. Case Studies

The residential AC real time hourly TMY3 data for Austin Texas are served for demonstrating the effectiveness of the proposed LMA-based ANN AC load forecasting approach. TMY3 represents typical metrological yearly parameters of different locations. Data collected is most accurate and recommended to forecast buildings energy consumption. It represents typical data for 1020 different regions that has been utilized nowadays, an improved version as compared to old version TMY2 and initial TMY collected information [57,58]. All forecast results have been obtained by making use of Statistics and Machine Learning and Neural Network Toolboxes in MATLAB R2016b. Accuracy of forecasting approach is affected due to numerous parameters. Figure 2. presents the input variables applied for AC load predictions. Overall accuracy and efficiency of proposed LF approach have been accessed by input variables data like time, weather and load. Large number and volume of input data is used to analyze forecasting results. AC load variations profile during complete year 2014 for Austin Texas that has been applied also as an input can be observed from the Figure 3 given below.

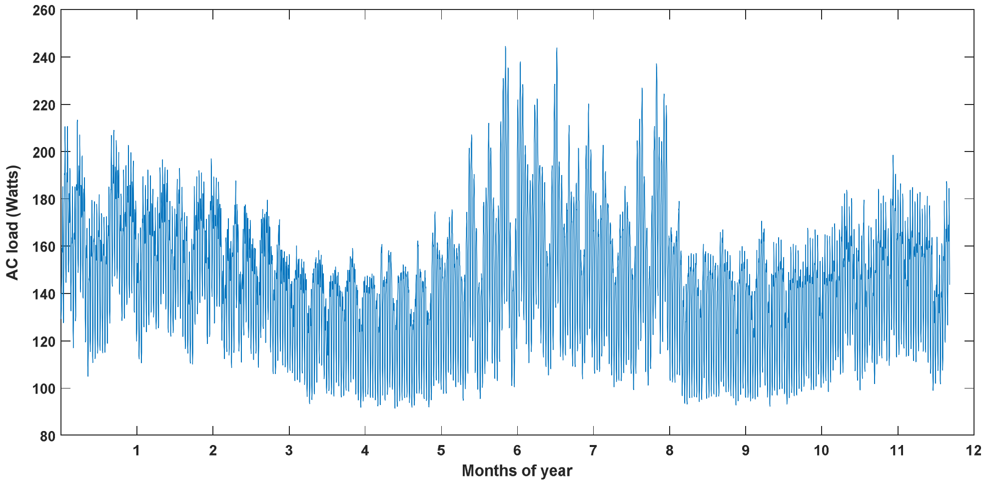

Figure 3. Air Conditioner (AC) Load variations during complete year.

Number of input variables have been applied to predict AC load. Some relationships are mentioned here to show the big data involvement in power systems nowadays. Huge amount of data is applied to check accuracy of LMA-based ANN approach. In other words, big data analysis has been performed for AC load prediction. Meanwhile, the effect of Dew Point and Dry Bulb temperature over AC loads can be visualized from Figure 4.

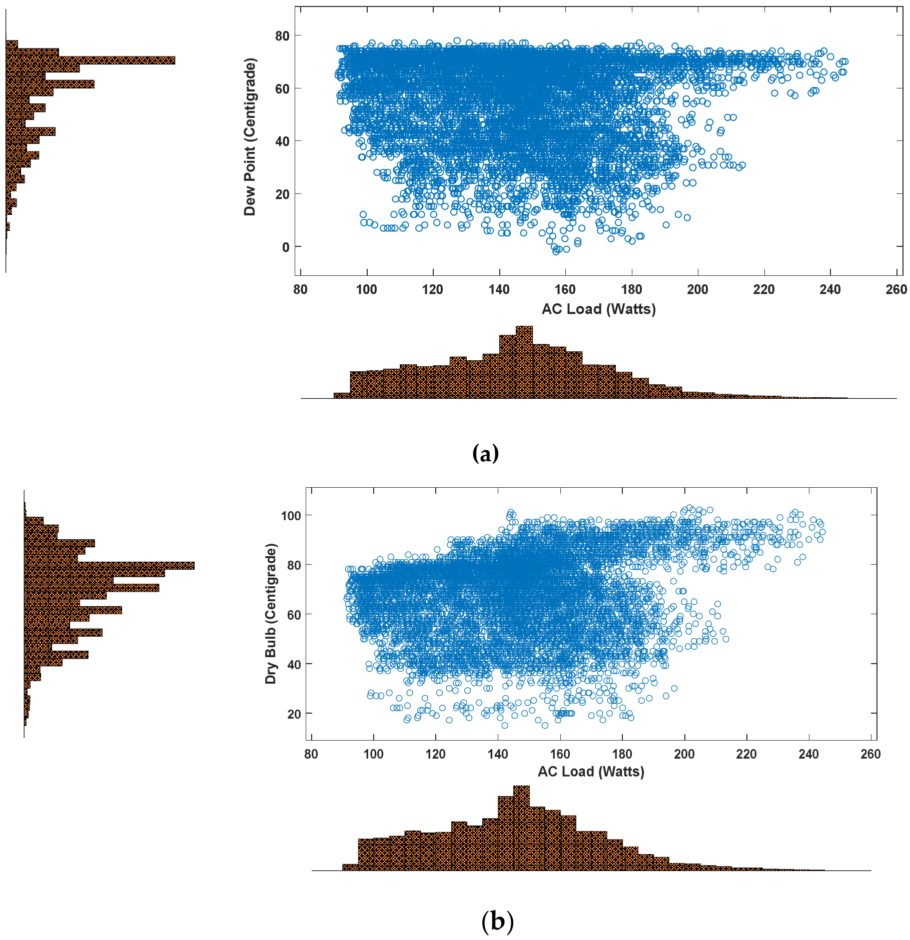

Figure 4. AC Load variations due to (**a**) Dew Point Temperature (**b**) Dry Bulb Temperature.

Both statistical and ANN based models have been validated for residential AC real time hourly TMY3 data for Austin Texas. The actual and forecasted residential AC load by applying conventional statistical multiple linear regression approach can be observed in Figure 5.

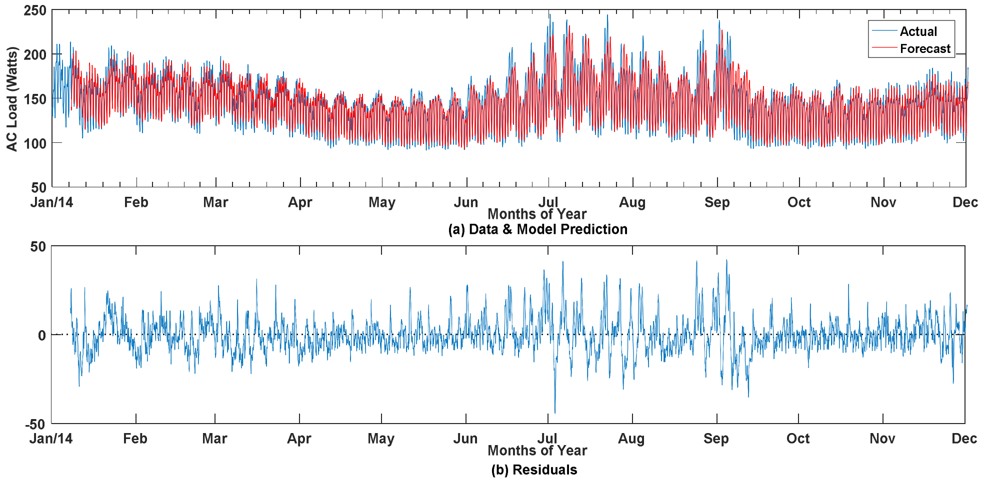

Figure 5. Actual and forecasted AC loads by multiple linear regression approach.

Furthermore, both actual and forecasted residential AC loads by applying SCG-based ANN can be observed in Figure 6. For ANN architecture, eight variables have been applied as input. Each input variable comprises yearly observations as input. The number of neurons is set to 10 with sigmoid transfer function in hidden layer. A single output will be achieved that represent predicted AC load. This method makes use of about 70% input data for training and 15% input data for testing and 15% of input data for validation of SCG-based ANN.

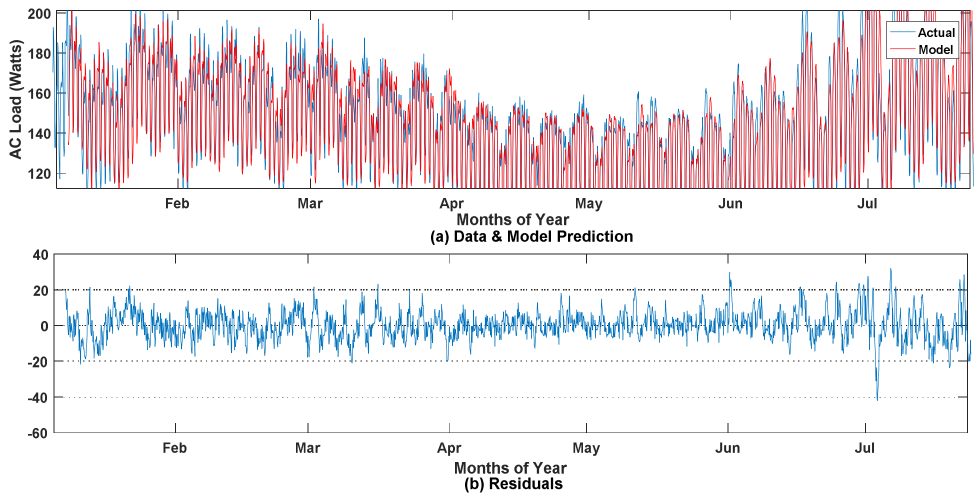

Figure 6. Actual and forecasted AC load by Scaled Conjugate Gradient (SCG)-based ANN approach.

Similarly, both actual and forecasted residential AC loads by applying proposed LMA-based ANN approach as discussed in Section 4 can be observed in Figure 7. For ANN architecture, eight variables have been applied as input. Each input variable comprises yearly 8760 observations as input. The number of neurons is set to an optimal value of 10 with sigmoid transfer function in hidden layer. A single output of predicted AC load will be achieved. This method makes use of 70% input data for training and 15% input data for testing and 15% of input data for LMA-based ANN validation.

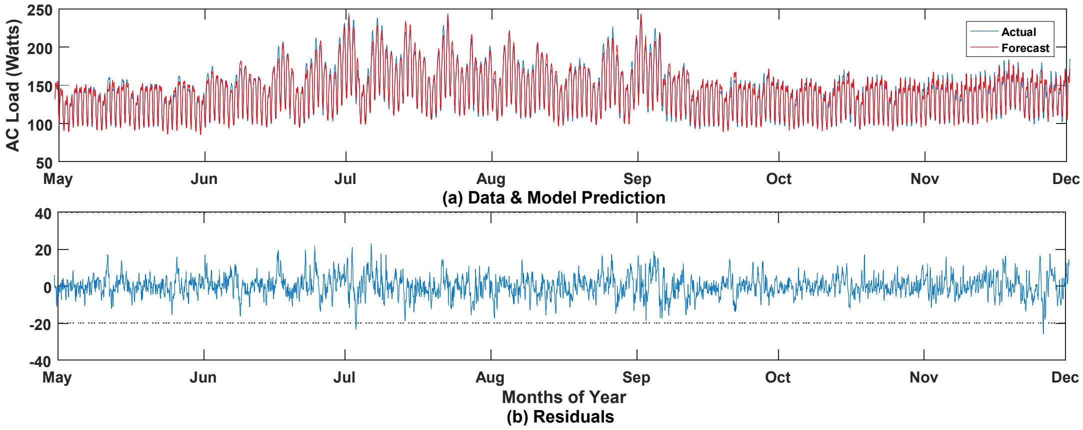

Figure 7. Actual and forecasted AC load by LMA-based ANN approach.

The performance comparisons of multiple linear regression, SCG and LMA-based ANN approach for AC load forecast by making use of performance assessment indices as discussed in Section 5 shown in Table 2.

Table 2. Comparisons of performance assessment indices for multiple linear regression SCG and LMA-based ANN approach.

		Multiple Linear Regression		SCG-Based ANN		LMA-Based ANN	
Hour	**Actual**	**Predicted**	**%AE**	**Predicted**	**%AE**	**Predicted**	**%AE**
1	129.60	144.31	5.26	131.49	1.46	136.41	5.26
2	124.27	141.02	5.65	131.29	5.65	131.29	5.65
3	120.89	139.27	6.12	131.78	9.01	128.29	6.12
4	119.48	139.07	7.13	133.15	11.44	128.00	7.13
5	119.96	141.09	8.98	135.88	13.27	130.73	8.98
6	123.18	147.60	11.51	141.03	14.49	137.35	11.51
7	129.91	159.20	13.14	148.64	14.42	146.98	13.14
8	138.11	166.99	10.66	154.49	11.86	152.84	10.66
9	147.38	170.49	5.74	158.07	7.25	155.85	5.74
10	155.07	172.81	1.25	160.52	3.52	157.01	1.25
11	159.14	173.72	1.54	161.90	1.73	156.69	1.54
12	160.29	172.65	2.66	162.31	1.26	156.02	2.66
13	159.40	170.55	2.62	162.10	1.69	155.23	2.62
14	157.09	168.46	1.39	161.77	2.98	154.90	1.39
15	154.99	165.95	0.28	161.18	3.99	155.43	0.28
16	155.96	165.71	1.54	161.07	3.27	158.36	1.54
17	162.86	172.54	1.09	163.30	0.27	164.64	1.09
18	167.66	180.35	0.07	165.67	1.19	167.78	0.07
19	164.53	178.28	1.89	164.33	0.12	167.64	1.89
20	158.47	173.62	3.92	162.05	2.26	164.68	3.92
21	152.15	168.57	4.23	159.26	4.67	158.59	4.23
22	143.47	161.65	4.97	154.34	7.58	150.60	4.97
23	134.31	152.91	5.01	147.31	9.68	141.04	5.01
24	124.61	143.29	4.73	138.69	11.30	130.50	4.73
Maximum		180.35	22.54	165.67	14.49	167.78	13.14
MSE %			9.68		8.30		5.57
MAPE %			4.9529		4.2782		2.9221
MAE(Wh)			7.2294		6.2456		4.2371
Daily MAPE %			4.3743		4.1249		2.5348

The *MSE* and *MAPE* are performance assessment indicators that have been formulated by (7) and (8) respectively. Difference between desired and actual output can be shown by error performance output from these indicators. LMA-based ANN for AC demand LF is showing error performance of 94.43% and 97.00% by *MSE* and *MAPE* respectively that is bitter higher than SCG-based ANN and statistical multiple linear regression-based approach.

Furthermore, *MAE* can be computed from (9) that represents mean absolute error. Figure 8 represents error distribution for LMA-based ANN approach. Most samples are in the positive region, which shows better results. Also, *MAE* can be observed from red line in error histogram that is about 4.2371Wh. In addition to this *MAPE* can be observed for LMA-based ANN approach that is approximately about 2.9221% as indicated by red line. It has been observed that in addition to error performance improvement LMA-based ANN has highest computation speed in contrast to SCG-based ANN for big data analysis. Performance indices values indicate more accurate value for proposed LMA-based ANN as observed from Table 2. It can be applied to predict appliance level loads like AC with more accuracy as compared to SCG-based ANN and conventional multiple linear regression-based approach.

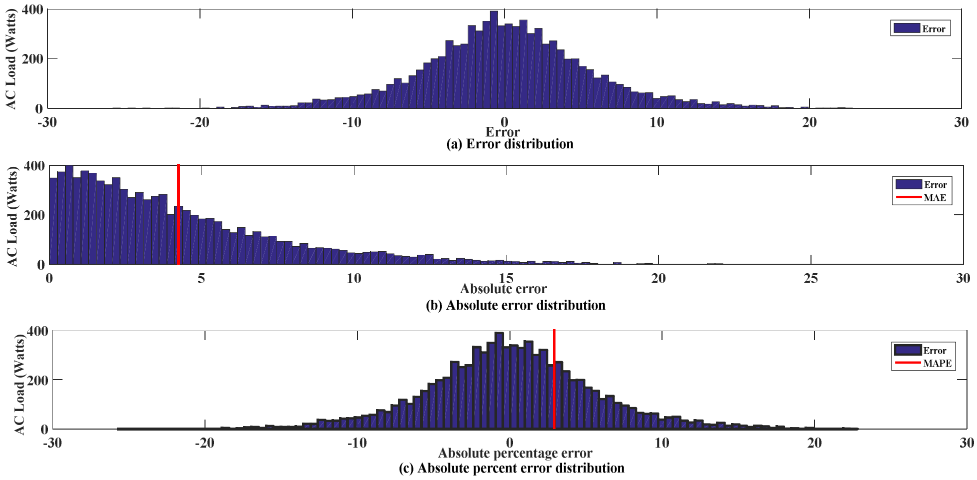

Figure 8. Error distribution histogram.

Furthermore, AC load prediction by utilizing LMA-based ANN approach for some weeks can be shown in Figure 9. It can be depicted that load predictions shows little difference from the actual one. Also, MAPE gives a less error value of 6.16% for selected weeks with prediction performance accuracy of 93.84%.

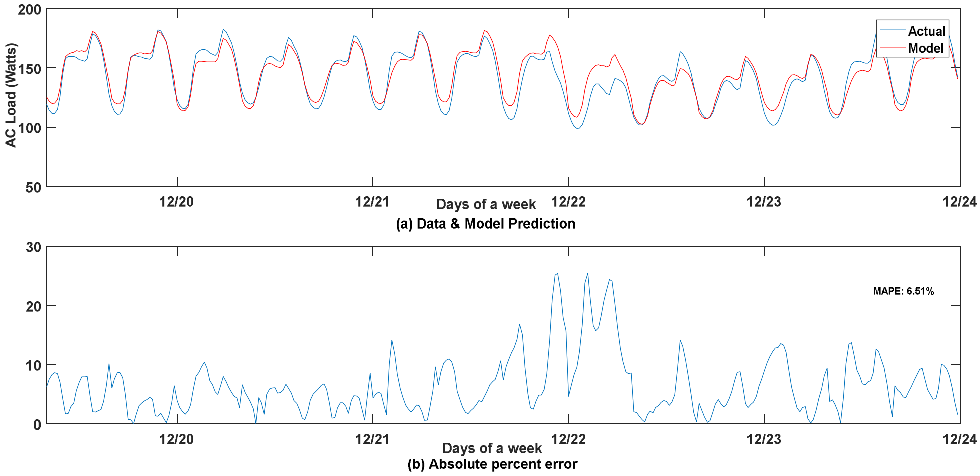

Figure 9. Comparison of forecast and actual load for every week.

In addition, it is possible to obtain AC load forecast results for different time horizons like hourly, weekly and monthly basis by making use of LMA-based ANN approach more accurately. Breakdown of error statistics by using LMA-based ANN approach for AC load predictions can be observed visually on hourly, weekly and monthly basis by each box in Figure 10. It can be seen from Figure 10 that that median forecast percent is almost zero as observed from central line of boxes in boxplots at different hours, days and months of year. The maximum value of forecast percent error is less than about 5% during different time horizons. The bottom line of the boxes indicates that 25% of AC load predicted values have about zero percent error while from top line of boxes it can be extracted that 75% of AC load predicted values have percent error of about less than 5%. From boxplot observations, it can also be visualized that due to increase in time span to predict load more values falls out of range showed using +. Furthermore, interquartile range of percent error of AC predicted loads can be observed from difference between top and bottom of boxes in box plots that presents accurate and considerable value of about less than 5% by making use of LMA-based ANN.

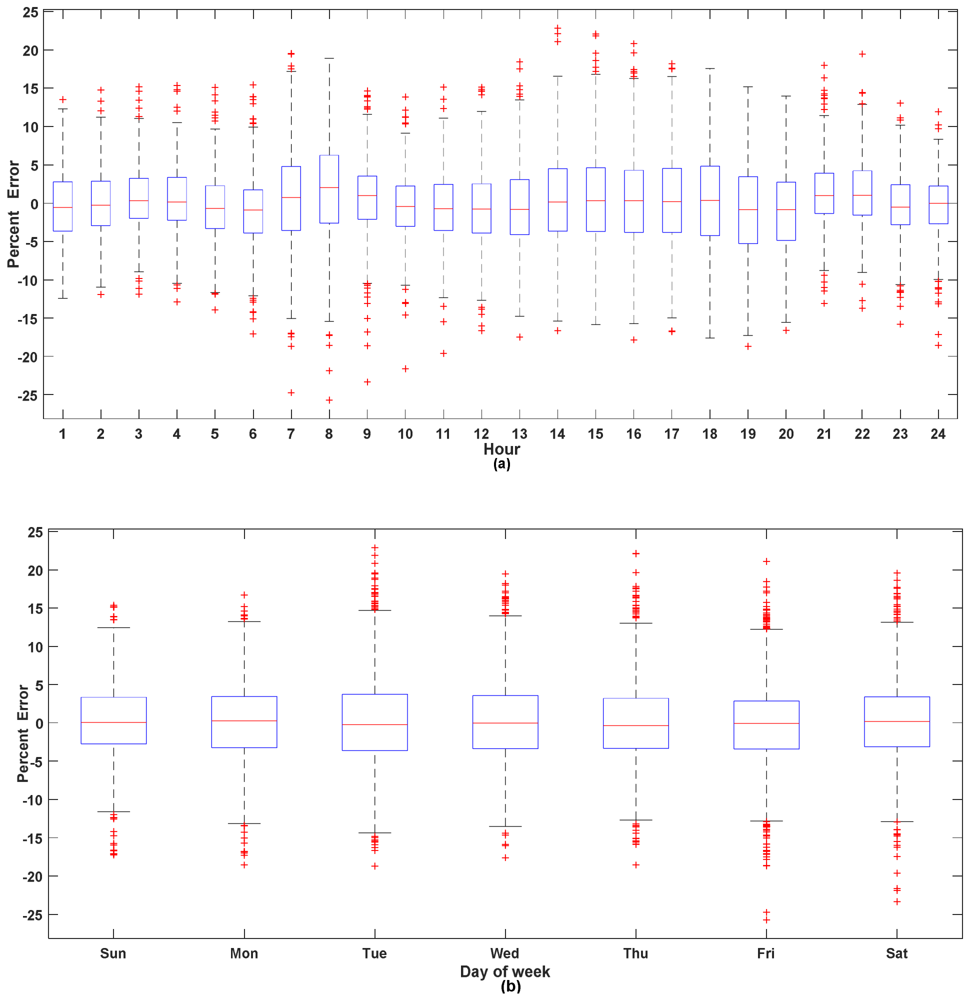

Figure 10. *Cont.*

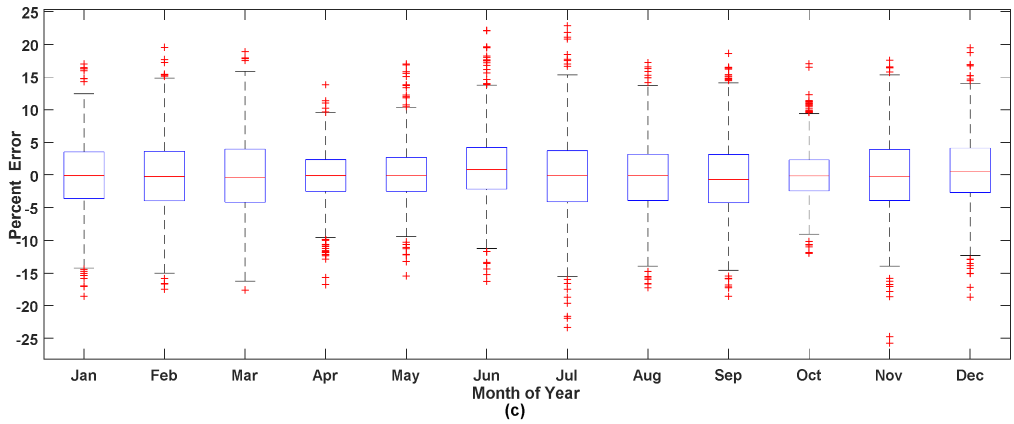

Figure 10. Breakdown of error statistics for load predictions (**a**) hourly, (**b**) weekly and (**c**) monthly.

7. Conclusions

In this paper, it has been investigated that AC impact in overall electricity consumption in buildings is very high. Therefore, controlling ACs power consumption is a significant factor for DR programs. Different evidence regarding AC load increase has been investigated worldwide. In addition to this, various big data analysis applications in power systems and load forecasting categories have been explored. Furthermore, this paper presents LMA-based ANN approach for residential AC load forecasting. Different performance assessment indices have also been investigated. Error formulations have shown that LMA-based ANN approach for residential AC load forecasting presents better results in comparison to SCG-based ANN and conventional multiple linear regression approach. It has been observed that, in addition to error performance improvement, LMA-based ANN has the highest computation speed in contrast to SCG-based ANN for big sets of input data samples. Furthermore, information of AC load is obtainable for different time horizons like weekly, hourly, and monthly bases most accurately due to better LMA-based ANN prediction accuracy. It can be applied to predict appliance level loads like AC with more accuracy as compared to SCG-based ANN and conventional regression-based approaches.

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