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Short term load forecasting based on ARIMA and ANN approaches

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Abstract

Forecasting electricity demand requires accurate and sustainable data acquisition systems which rely on smart grid systems. To predict the demand expected by the grid, many smart meters are required to collect sufficient data. However, the problem is multi-dimensional and simple power aggregation techniques may fail to capture the relational similarities between the various types of users. Therefore, accurate forecasting of energy demand plays a key role in planning, setting up, and implementing networks for the renewable energy systems, and continuously providing energy to consumers. This is also a key element for planning the requirement for storage devices and their storage capacity. Additionally, errors in hour-to-hour forecasting may cause considerable economic and consumer losses. This paper aims to address the knowledge gap in techniques based on machine learning (ML) for predicting load by using two forecasting methods: Auto Regressive Integrated Moving Average (ARIMA) and Artificial Neural Network (ANN); and compares the performance of both methods using Mean Absolute Percentage Error (MAPE). The study is based on daily real load electricity data for 709 individual households were randomly chosen over an 18-month period in Ireland. The results reveal that the (ANN) offers better results than ARIMA for the non-linear load data.

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Keywords: Artificial Neural Network (ANN); Auto Regressive Integrated Moving Average (ARIMA); Smart grid; Short time load forecasting (STLF); Storage device

1. Introduction

A smart grid is an electric grid that incorporates facilities to manage service and electricity including smart meters, smart appliances, renewable energy infrastructure, and energy conservation mechanisms. Therefore, a smart electricity sector requires methods that allow collecting significant data from generators and small measuring devices [1]. Utilizing renewable energy requires utilizing large energy storage devices which are selected based on Demand Side Management (DSM). The DSM is used to forecast the baseload regeneration and capacity of

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smart grid [2]. It is necessary to study the predictability of the electrical load by using real load data from customers under the same environmental conditions to manage demand in smart grid systems effectively [3]. Recently, machine learning approaches have been used as common forecasting techniques in the literature, where the machine learning is the study of computer algorithms that automatically improve by experience and is seen as a sub-set of artificial intelligence. STLF is defined as the prediction of the electrical load demand that the customers will need in the future. The STLF as a machine learning (ML) algorithm performs the primary role in load prediction; and is applied to consumers including residential and industrial that have an increased proportion of the total consumption. Moreover, for grid operators, STLF is important for grid formation, voltage monitoring, and controlling generation units. STLF can also allow users to reduce consumption and thus their electricity bill. Furthermore, electricity suppliers produce more accurate STLF to stimulate plans for markets and settlement [4]. The key objective of any ML algorithm is to transfer good rendering over anonymous data. The change of a minimum value in the training error is the factor that can evaluate the performance of ML method. This study proposes a framework that uses unsupervised ML and based on a comparison between Artificial Neural Network (ANN) and Auto Regressive Integrated Moving Average (ARIMA). To achieve high accuracy in the prediction of future time periods depends on several key factors including regulation, transmission, scheduling, and unit involvement of the electrical grid. Therefore, national grids are required to be up to date with new technologies and required capacity [5].

Different scoring methods can be used to study the prediction of the electrical load: Very STLF (one minute to tens of minutes) used to achieve economic control and control of load frequencies and STLF (a few minutes to one day) used to set demand and supply, medium period load forecasting (one day to a year) used to plan power cut and repair, and Long periods (more than a year) used for infrastructure planning and development [6]. STLF is an essential tool for determining and planning power in grid requirements as it can be used to predict customers' future electrical load demand. Furthermore, energy suppliers can use STLF to achieve a balance between supply and demand. Moreover, STLF ensures the reliability of a continuous power flow during power shortage or outage. Therefore, implementation of an accurate tool for load forecasting using STLF provides effective planning of energy systems which can then improve economic growth of a country [7]. The reliability of a power system is affected from sudden changes in the load demand. Each factor affecting the load demand is required to be considered to achieve the highest possible predicted results. Temperature, humidity and dew point, day of the week, holidays, and load diversity of consumers are some of the examples of these factors. At this point, storage systems can help to provide flexibility to the power system, to fulfill self-consumption and local market energy transfer. As a result, storage devices need to be configured to maximize the economic gain and reliability of the supply.

The use of ML methods to predict the electrical load has given effective results, as the ML algorithm offers ability to learn from the data while various functions including sampling, classification, regression, duplication, etc. can be programmed by ML. Additionally, troubles that cannot be resolved with classic methods, can be programmed by ML algorithm in the load forecasting. The accuracy factor and the error rate are used to evaluate the performance of ML algorithm. Fig. 1 shows the relationship of ML with Artificial Intelligence (AI), Reinforcement Learning (RL) and Deep Learning (DL). The literature classifies ML algorithm into two main types: supervised and unsupervised. Supervised impart over a dataset of traits where every proof is additionally joined by a group label or target group. Linear Regression is an essential method used in supervised ML, which belongs to the first generation of ML. Different characteristics of dataset should be used in Unsupervised ML to achieve valuable links. Deep

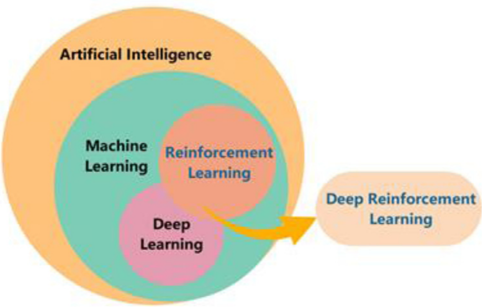


Fig. 1. Relationship of learning algorithms.

Neural network (DNN) is the essential method employed technique in Deep Learning which is considered from unsupervised machine learning. The prediction in this paper has been studied in two ways, the first method, which is based on supervised Machine Learning, consists of a classification technique that uses sensor data from the smart grid based on a regression model which belong to the first generation of STLF. The second solution depends on one type of artificial neural network ANN.

ML using time series forecasting as the first-generation load prediction methods has widely used in the literature: time series analysis, regression methods [8,9], similar day method, Wavelet Transform (WT) [10], least square estimation [11], (ARIMA, SARIMA, ARMA), Support Vector Machines (SVM), and Classification and Regression Trees (CART). These first generation load prediction methods use historical data to link energy consumption with variables as inputs. Therefore, they require a large amount of historical data set to use as statistical patterns [12]. The second-generation load prediction methods are artificial intelligence methods such as ANN [13] including deep neural networks [14], random forests, gradient boosting [15], Fuzzy logic [16],

Genetic algorithms, Particle Swarm Optimization (PSO) [17], and ant colony optimization-based methods [18]. The utilizing ANN models has several advantages: The relationship between the input and output process can be reset without making complex reliance between the inputs, ANN extracts the nonlinear relationship between input factors utilizing the network training approach, Network performance can be improved using future demand load data and reorganizing the model while training the network, Output models are learned by using the data models of the input, appropriate choice of training data, learning algorithm, Optimal network structure leads to better performance and lower complexity, and ANN has parallel processing capacity that can perform more than one task at the same time due to its numerical power. Some articles that discussed the forms of prediction such as; Abdulkarim [19], proposed a model to predict load using periodic analysis of the time series, (MLP, SVM,GP,RPF, Rep Tree), methods were used to test the proposed model and the best performance was obtained using MLP and SVM. New algorithm was designed in Oprea & Bara [20], for 6 ML algorithms (FF-ANN algorithms, NARX, DNN, GTB, NEST_BCKTR and RF). Algorithm had high prediction accuracy and the proposed method, NEST_BCKTR reduced the effect of weather and noise. The author Raza [21] evaluated the performance of prediction models and identified the benefits and drawbacks of ANN and ARIMA. Also, the Hybrid prediction gave further improvement in the accuracy of predicting. As for Ahmad [22] compared two forecasting models, FNN and ARIMA; he reported that FNN provides significantly better results than ARIMA. In B. Prabadevi's paper [23], a comprehensive survey and scheduling of demand response applications in SG has been created. The focus was on four important topics; electrical load prediction, energy theft detection, energy sharing, circulation and condition estimation. The author Cini [24], the problem of the huge data that coming from smart meters in SG has been solved. Suggested method is suitable for deep learning models and introduced a neural network. As the author's Ruluca paper [25], it has been proposed to implement solar energy systems on residential rooftops in addition to storing energy to meet demand, to reach to the best performance in the SG. The authors Ch.M. Cheung [26], two new methods have been developed in order to accurate the load aggregation for users in the network and It was concluded that the classification and grouping of users with similar electrical consumption characteristics improves the accuracy of the prediction. The author Tang [27], presented a methodology for the development of statistical load models and load characteristic profiles in distribution networks based on year-long field measurements. In Ajewole's paper [28], three methods (LM, GD and GDM) were used from NN to predict load, It was concluded that the LM method in prediction is the best performing of the two methods mentioned above. The author M. Grabner [29], the unsupervised ML was used to analyze the profiles in DR program to assess the usefulness of the future DR program. Many studies have also considered additional information including monitoring consumer behavior and weather conditions to improve the accuracy of load forecasting. However, several problems arising during the supplication of the same model to other households remains. This paper proposed a new short term load forecasting technique based on ANN and ARIMA methods. Both presented methods have an acceptable error rate on STLF.

2. The use of ANN and ARIMA techniques

In this study, the real load electricity profile as an input for 709 individual's household level during 12 865 h from 2009 to 2010 in Ireland, was conducted and considered as a historical data. The stages of this study could be summarized as follows: the first stage is to process the data provided by Ireland was introduced to the MATLAB program; the second stage is to apply prediction using the ANN as well as ARIMA methods. At the final stage, the results were analyzed using both models, ARIMA and ANN, and these models compared through the error factors (MSE and MAPE%).

2.1. Time series forecasting based on (ARIMA)

Autoregressive ARIMA is the most common in the series family due to the adaptability of linear patterns amongst all time series strategies [30,31]. Moreover, ARIMA model has the benefits of using a simpler algorithm and being a studied technology in comparison to the second generation of forecasting methods which is the artificial neural networks.

2.1.1. Mathematical modeling of ARIMA

The mathematical model of ARIMA (p, d, q) is shown to be precise in the literature by combining AR (p) and MA (q), While Integrated (I) reflects the separation of raw observations to allow the time series to become stationary, the difference between the real data values, and the previous values are replaced with the data values. The finite distinction of the data points in ARIMA (p, d, q) are used to transform the non-stationary time series to the steady one. Eqs. (1), (2) and (3) demonstrate the mathematical formulation of ARIMA (p, d, q).

$$\varphi(L)\,(1-L)^{d}\,yt=\theta(L)\varepsilon t \tag{1}$$

$$(1-\sum_{i=0}^{p}\varphi\mathrm{i}L^{i})\,(1-L)^{d}\,\mathrm{y}_{t}=(1+\sum_{j=1}^{q}\theta\mathrm{j}L^{j})\varepsilon\mathrm{t} \tag{2}$$

$$\mathrm{Y}_{t}=\phi_{0}+\phi_{1}\mathrm{y}_{t-1}+\phi_{2}\mathrm{y}_{t-2}+\cdots+\phi_{p}\mathrm{y}_{t-p}+\varepsilon_{t}-\theta_{1}\varepsilon_{t-1}-\theta_{2}\varepsilon_{t-2}-\cdots-\theta_{p}\varepsilon_{t-p} \tag{3}$$

where y_t and ε_t are the actual value and random error at time period t, respectively; φ i (i = 1,2,.,p) and θ j (j = 0,1, 2, …,q) are model parameters; p, d and q are positive integers, referring to the order of the autoregressive, integrated, and moving average parts of the model, respectively. A typical method for identifying p and q is achieved by implementation of the Autocorrelation Function (ACF) and Partial Autocorrelation Functions (PACF) of the data. The PACF plot helps to decide if the ACF plot can classify non-stationary time series by the maximum order of AR (p).

2.1.2. Model creation and training

The creation of ARIMA model in this paper was achieved using the provided data as an input that forms some specific pattern.

2.1.3. Intuitive method

The main target is to accurately determine the values of 'p' and 'q', which are estimated from the intuitive method, as shown in Table 1.

Table 1. Estimation of p and q values.

p	q											
	1	2	3	4	5	6	7	8	9	10	11	12
1	10 632	10 651	10 651	10 660	10 656	10 655	10 664	10 668	10 684	10 684	10 717	10 696
2	10 646	11 199	11 211	11 224	11 207	11 225	11 202	11 227	11 277	11 253	11 254	11 258
3	11 085	11 335	11 495	11 522	11 497	11 472	11 504	11 508	11 538	11 597	11 596	11 597
4	11 097	11 228	11 575	11 724	11 685	11 682	11 696	11 708	11 744	11 761	11 814	11 765
5	11 273	11 481	11 574	11 842	11 829	11 798	11 809	11 841	11 877	11 899	11 900	11 903
6	11 290	11 575	11 527	11 814	11 960	11 830	11 911	11 925	11 952	12 030	12 048	11 991
7	11 338	11 565	11 621	11 802	11 960	12 001	11 922	11 941	11 992	12 033	12 039	12 043
8	11 363	11 517	11 673	11 747	12 975	12 037	12 006	11 947	11 999	12 053	12 066	12 071
9	11 347	11 577	11 686	11 771	11 949	12 060	12 054	12 010	11 937	12 027	12 080	12 097
10	11 387	11 605	11 674	11 787	11 899	12 013	12 051	12 057	12 021	11 966	12 043	12 066
11	11 351	11 577	11 634	11 791	11 853	11 974	12 032	12 064	12 059	11 989	11 940	12 010
12	11 388	11 549	11 606	11 819	11 850	11 933	12 022	12 074	12 076	12 032	11 968	11 925

Table 1 shows that cell one provides the best of corresponding values for both p and q parameters and thus, that is used as the intuitive approach for p and q values.

2.2. Artificial Neural Network (ANN)

ANN is commonly used for prediction due to its self-learning capabilities and high predicting accuracy. In this work, the customers' power consumption profile will be predicted using ANN. The reason why ANN used in this work for forecasting is because ANN is to be standard solution with it is high accuracy rate when the non-linearity in the input data is identified. Parallel processing of input data and model building methods, which do not rely on any previous assumptions, are the reasons behind the high accuracy rate. Additionally, the ANN output is based on the aggregation of the neurons in the input and hidden layers. In this study, the data has been split into three sets to support: planning, testing, and validation.

2.2.1. Mathematical modeling of ANN

The functionality of ANN is represented mathematically as:

$$y_j = \mathrm{f}(\sum_{i=1}^{n} W_{ij} X_i + b_j) \tag{4}$$

where nodal values from the previous layer i are defined as Xi; and the output from the current layer j as y_j; Wij and bj are the weights and bias for this neuron in the network; and n is the number of nodal values received from the previous layer.

The purpose of this study is to compare the two models ANN and ARIMA for daily load forecasting where the error rate (MSE) and mean absolute percentage error (MAPE) are used in this study to find the degree of the accuracy of these models (5), (6). Where Ý is a vector of n predictions, and Y is the vector of the real values.

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

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{\acute{Y} - Y_i}{Yi} \right| \tag{6}$$

3. Simulation results

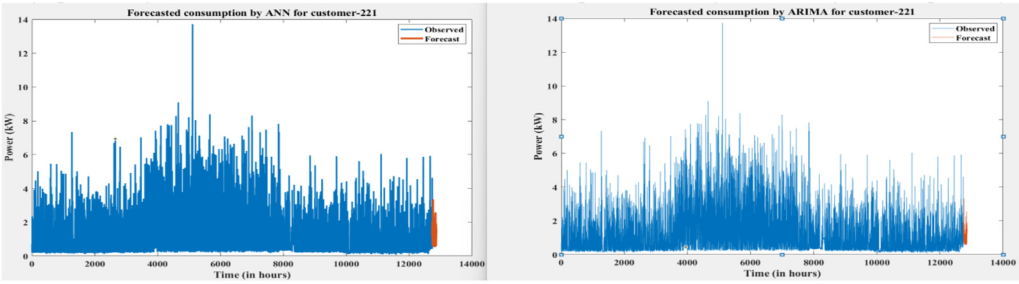
MATLAB™ was used to investigate the proposed load forecasting approach in this work. The investigation was achieved in two stages: (1) model assessment and (2) use-case demonstration of forecasting efficiency. Real consumption data set has been taken from Irish Social Science Data Archive (ISSDA) (Commission for Energy Regulation (CER), 2022) for 709 households in Ireland for 12 865 h as inputs to MATLAB in which 90% of the data was tested, and 10% of tested data was used to train the model. Several model parameters were used in MATLAB during the modeling are given as: Inputs = 709, one hidden layer, iteration value = 250, Epoch with all training data for one cycle was set to 250 with one iteration per epoch, the initial learn rate = 0.005 and learn rate drop factor = 0.2. In addition to those model parameters, the trained network was tested by predicting multiple time steps into the future. 10 graphs were generated. The results for ANN and ARIMA are presented in Fig. 2(a) and (b), respectively.

The prediction line in Fig. 2(a) approximates with the real value (kW) of the consumer with peak value less than the real load value where the error factor MAPE% was 173.65% (see Table 2). Fig. 2(b) shows that more deviation from the real value is observed when ARIMA method was used due to the more non-linear and irregular values which results in the error factor of MAPE% to reach the high values (689.21), see Table 2.

From Table 2, it is observed that the rate of MAPE of the ANN achieved to 1.80% but in the ARIMA model which lied at approximately 2.61% MAPE. However, the ANN was found to have better performance in most of

Table 2. Comparison between ARIMA and ANN forecasting methods for costumer no: 221 in terms of the error factors: R, MSE, MAPE%.

Error factor for costumer 221	R	MSE	MAPE%
ANN	0.045	174.4178	173.6596
ARIMA	0.00905	658.23	689.21



(a) (b)

Fig. 2. (a). STLF for costumer.221 using ARIMA during 24 h, (b). STLF for costumer.221 using ARIMA during 24 h.

the cases. Therefore, to achieve a clearer result with high accuracy in prediction, future research may focus on the hybrid model based on both ARIMA and ANN models.

In this study, it can be observed that the performance of both models ARIMA and ANN was entirely dependent on the seasons, the average error of forecasting for both the models was smaller in winters than that of summers. Additionally, the empirical cumulative distribution function is used for comparison of error distribution for both models, and the results: ANN produced less error than ARIMA based on most test weeks data, the cumulative error generated by ANN was less generally less than 5%. ANN has the advantage of recovering more rapidly after the gaps between the data analysis. ARIMA method needs adequate historical load data in training to reach higher accuracy of forecasting while output models are learned by using the data models of the input when training the network in the ANN method. ANN has given a better performance in terms of accuracy factor than the ARIMA method in forecasting.

The presented results show consistency with the rest of the studies presented in the literature. However, it is important to notice that if the studied area differs in the type of consumption (residential, industrial, mixed) or in the weather and seasonal conditions, the previous points may affect the accuracy of the predicted results. Overall, this paper could also predict future load which help in identifying the requested future SG to develop a smart city and to find better forecasting solution for the future expected load and using the new ANN approach which has advantages including extracting the nonlinear relationship between input factors utilizing the network training approach, the relationship between the input and output process can be reset without making complex reliance between the inputs, and obtaining parallel processing capacity that can perform more than one task at the same time.

4. Conclusion

Determining the electricity consumption profile of a single household over a given period is not difficult in modern networks. There can be great variability caused by multiple influences as consumers do not behave in the same way every day due to many factors such as weather, holidays, and seasons. This paper shows that ANN method has better and more accurate results than ARIMA. Additionally, ANN was able to predict the trends in the electricity consumption profile, although often ignoring the peaks of consumption. The key differences between ARIMA and ANN as models for the daily electricity consumption profile at the individual household level have been described in this paper. ANN had a lower error than ARIMA, seen in MSE and MAPE, and as shown by the regression factor (R) being closer to 1. The general form of the electricity consumption profile was predicted, but it was not possible to predict the size of the peaks. The results suggest that both ANN and ARIMA have the potential to predict consumption but ANN better copes with non-linear data whereas ARIMA only manages linear data structure. Moreover, ANN provides better performance in terms of tackling more than one task at the same time. Neural networks are the preferred tool for the prediction because of their simplicity, efficiency, and ease of use for many predictive data mining applications. The future research will be focusing on constructing a hybrid model to generate more accurate load prediction based on the conducted analysis in this paper. Furthermore, the output of this system will be used as an input to a short-term electricity load forecaster.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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