

Integrated vs. total approach in short-term load forecasting

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Abstract

Strategic and operative decisions in the electricity sector are mostly driven by forecasts. Electricity dispatch is one of the most important operative process in electricity sector. In electricity dispatch, short-term load forecasting (STLF) is a necessary tool to achieve an efficient decision-making process. The lack of accuracy of the STLF method causes an excessive or insufficient electric supply to the power grid. An excessive supply of electricity may cause damage to the electricity generation equipment, whereas insufficient electric supply may cause load cuts that affects directly to the electricity users. STLF methods can be trained to construct models in different levels of aggregation. In this paper, we study the effects of STLF training method in two levels of aggregation. This study is conducted in the ERCOT dataset, which is composed of 8 load zones, and the objective is to predict the load of ERCOT in a hourly manner. We train two different artificial intelligence methods in every zone: Artificial Neural Networks and Support Vector Machines. Using these methods, we compare two approaches: Total and Integrated. The integrated approach consists in training both artificial intelligence methods in every one of the load zones, so the final prediction is de addition of the prediction of every model. The total approach consists in training both artificial intelligence methods directly to the total demand of ERCOT. The results show that the integrated approach is in general more accurate than the Total approach.

Keywords: Short-term load forecasting, artificial intelligent, neural networks, support vector machines.

1. Introduction

Strategic and operative decisions in the electricity sector are mostly driven by forecasts. Among the many processes required to generate and distribute electricity, electricity dispatch is one of the most important operative process [1]. In electricity dispatch, short-term load forecasting (STLF) is a necessary tool to achieve an efficient decision-making process [2]. The lack of accuracy of the STLF method may lead to an inefficient decision-making process.

Specifically, the lack of accuracy may cause overestimation or underestimation of electricity demand [3]. The former causes that an excessive amount of electricity is purchased and supplied to the power system, which causes power balance disturbances that may damage energy generation equipment. The latter leads to a risky operation of the power system by restraining the production of electricity, which may lead to load cuts affecting directly electricity users.

STLF can be estimated in different levels of the power system, this means that the STLF methods can be trained to construct models in different levels of aggregation. These different levels of aggregation may affect the accuracy of the final model of load forecasting.

In this regard, there is plenty of research reported in the literature with different objectives. In [4], an algorithm which considers external information in related with the energy consumption profiles of different consumers, is proposed to forecast electrical load at different scales and smaller errors are shown due to clustering of consumers.

In [5], STLF techniques were implemented for a detailed comparative analysis to verify the forecasting performance and the effectiveness method is validated with numerical results.

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In [6], the data obtained through experiments were used to generate an ANN model to predict the regional peak load of Taiwan. Through the results, some changes to the power market providers were suggested.

In [7], levels of aggregation were modified to show the importance of aggregate more levels in forecasting methods, which obtained better results in forecasting than lower levels of aggregation.

In this paper, we study the effects of STLF training method in two levels of aggregation. This study is conducted in the ERCOT dataset, which is composed of 8 load zones. The objective is to predict the load of ERCOT in a hourly manner.

We train two different artificial intelligence methods in every zone: Artificial Neural Networks and Support Vector Machines. Using these methods, we compare two approaches: Total and Integrated. The integrated approach consists in training both artificial intelligence methods in every one of the load zones, so the final prediction is de addition of the prediction of every model.

The total approach consists in training both artificial intelligence methods directly to the total demand of ERCOT. The results show that the integrated approach is in general more accurate than the Total approach.

This paper is organized as follows, in section 2 the methodology is described, in section 3 the experiments and results are reported and in section 4 the conclusions of this work are described.

2. Methodology

Methodology process is described in this section. In section 2.1 the data preparation is described (data preprocessing). Then, in section 2.2 the artificial neural network method used in this work is described. Then, in section 2.3 support vector machine method used in this work is described. Finally, in section 2.4 ANN and SVM training and validation process are explained.

2.1. Data preprocessing

The dataset is obtained from the ERCOT hourly load data. ERCOT load data consist in eight load zones and the sum of them as total demander. The date range of the dataset is from 2018-01-01 to 2018-31-12. The following table illustrates the ERCOT data format:

Table 1. Load dataset from Texas state by zone.

Hour	Coast	East	Fwest	North	Ncent	South	Scent	West	ERCOT
01/01/2018 01:00	11,425.98	1,852.66	2,823.41	1,135.36	18,584.34	3,831.65	9,151.19	1,762.47	50,567.07
01/01/2018 02:00	11,408.42	1,850.17	2,809.75	1,136.63	18,524.14	3,988.27	9,144.99	1,754.72	50,617.09

From the ERCOT hourly load dataset, 9 datasets were constructed (one per region plus the total demand). Every constructed dataset contains a V_t value (load value in time t) associated with its fifteen previous load values $\{V_{t-15}, V_{t-14}, \dots, V_{t-2}, V_{t-1}\}$. Each V_t value is also assigned to the corresponding period. In this paper, a period per hour is considered, so we have 24 periods. In Fig. 1, a graph of the complete data set is shown.

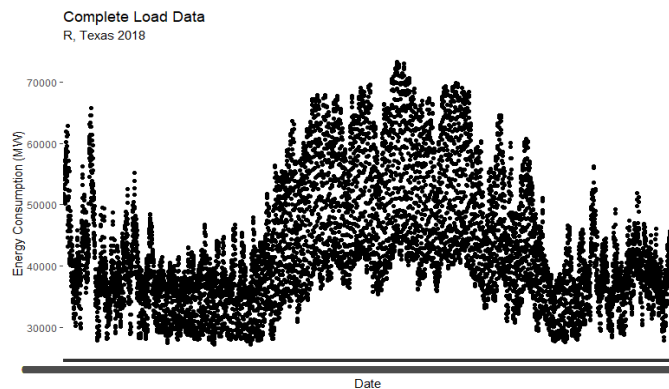


Fig. 1. Completely load data

Table 2. Constructed dataset format.

Period	Vt-15	Vt-14	...	Vt-2	Vt-1	Vt
16	50,567.06	50,617.08	...	52,638.07	51,448.20	50,789.64
17	50,517.08	50,694.30	...	51,448.20	51,352.31	50,789.64

The constructed dataset format allows the training of the artificial intelligence methods used for this work. In the following sections, the artificial neural networks and support vector machine methods are described.

2.2. Support vector machine definition

Support Vector Machines (SVM) are supervised learning models used for data prediction and classification, developed by Vapnik (1995) [8]. Even though SVM are commonly used for classification problems where training data is linearly separable, nonlinear data can be mapped into a high dimensional feature space, with help of a kernel function where linear regression can be applied (The hyperplane). Then it builds 2 parallels bounds with radius epsilon (ϵ) to the hyperplane that covers the most quantity of data, where ϵ defines a margin of tolerance where no penalty is given to errors and ξ is the distance between data not covered by support vectors and bounds [9]. In Fig. 2 a graphical representation of SVM is shown.

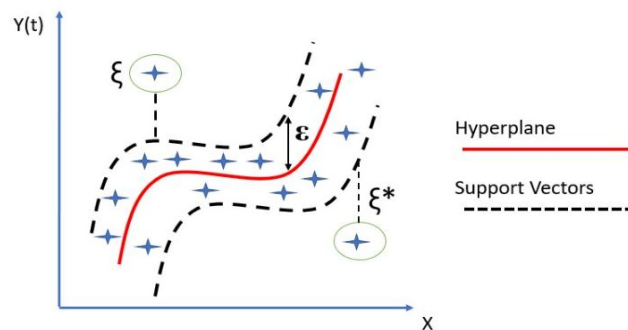


Fig. 2. Support Vector representation for regression.

The equation, transformed by means of Lagrangian multipliers represented in the original dimensional variable is:

$$f(x) = \sum_{i=1}^l (\alpha_i - \alpha_i^*) k(x_i, x) \tag{1}$$

Where, K is a kernel function, α_i and α_i^* are Lagrange multipliers, C is a constant greater than 0, represents a penalty for prediction error that is greater than ξ .

Table 3. Basic Kernel Functions.

Linear	$k(x, x') = x * x'$
Polynomial	$k(x, x') = (x' * x + c) + d$
Gaussian Radial Basis (RBF)	$k(x, x') = \exp(-\gamma \ x - x'\ d)$

For this research, a Gaussian Radial kernel is used to build the models due to it showed better results in predictions. Accuracy of SVM depends on 2 important factors: C and ϵ , which were modified with a programming function to find the combinations of these values that will deliver better results in models. Best models' parameters were saved for future predictions. For this research optimal SVM regression

parameters (C and ϵ) are estimated by using 10-fold cross-validation on training data selection.

2.3. Artificial neural network definition

The neural biological network has more than 100 billion of neurons, organized in layers, connected each for a thousand or more synapse. Artificial Neural Network (ANN) is a computational model inspired by neural brain structure with the objective of imitating brain cognitive functions like to recognize patterns to predict and classify [10]. Multilayer Perceptron (MLP) is an artificial neural network paradigm composed of three-layer types: input layer, one or more hidden layer and output layer. Input layer is connected to the hidden layers and the last hidden layer is connected to the output layer. Every neuron of the hidden layers is represented by a weight, so that the inputs are processed by the hidden layer by means of those weights and the result of the final hidden layer is then processed by the output layer by means of an activation function [11]. The training algorithm for this neural network is described in [12]. In Fig. 3, a graphical ANN representation and activation function is shown.

2.4. Training and validation models

To train SVM and ANN, the 8 load zones dataset and total demand of ERCOT dataset were divided in two groups: Train_Data, which constituted the 80% of the total and Test_Data with the remaining 20%. Then, Train_Data is sub divided again in the same 80%-20% format. Data was selected randomly for all models. Subdivided Train_Data was used to train 24 models, one per every period, this process is applied 9 times, because of we have 8 regions and a total load demand, obtaining 216 models. In Fig. 4, a graphical representation of the Artificial Neural Networks and Support Vector Machines models training are shown.

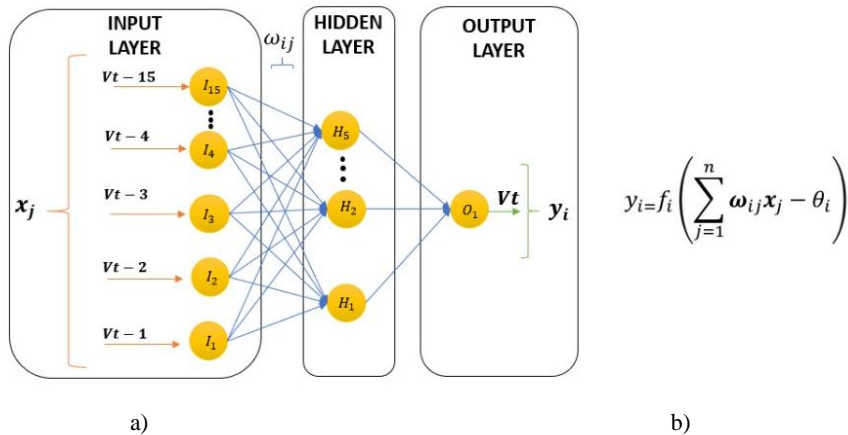
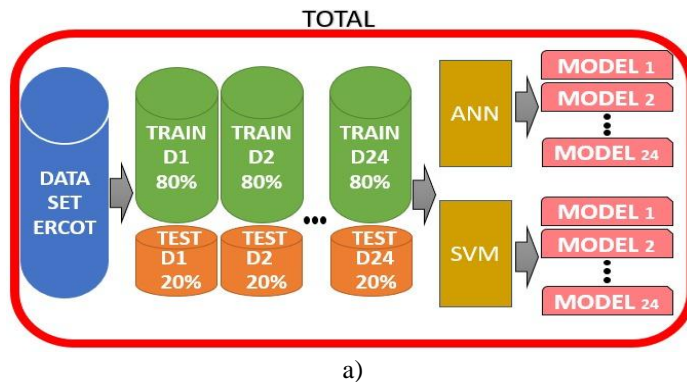


Fig. 3. a) Architecture for ANN model b) Activation Function Equation



a)

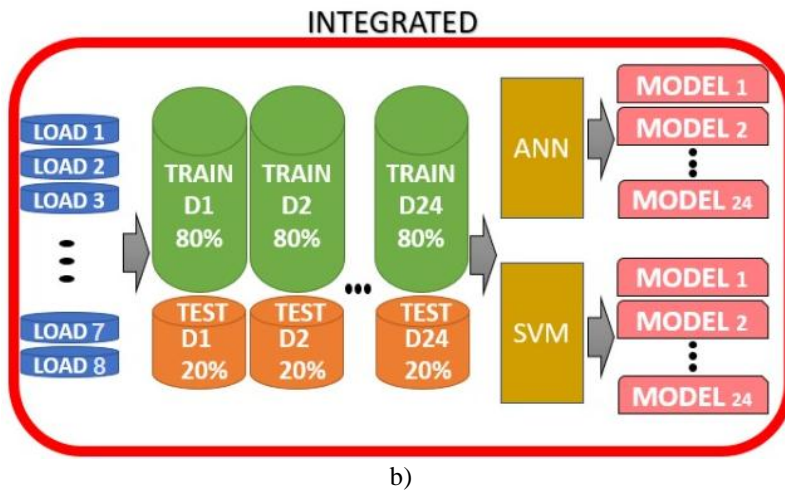


Fig. 4. Graphical representation of the ANN & SVM models training: (a) total, (b)integrated data.

3. Experiments and Results

Two experiments were performed, the first using Artificial Neural Networks (with 5 neurons in hidden layer) and second with Support Vector Machines. The software used for this research is R studio supporting us with libraries in R language. Neuralnet, Metrics, GGPlot2, e1071 were the basic libraries used for this research. All the experiments were carried out on a 2.8 GHz Intel Dell Inspiron 15 7000 computer with 8GB of RAM and Windows 10. To evaluate the accuracy for both experiments and to know how close predicted values are from real values, applied 2 criteria: Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). In Fig. 5 and Fig. 6. the graphs of the results of the SVM and the ANN experiments are shown respectively.

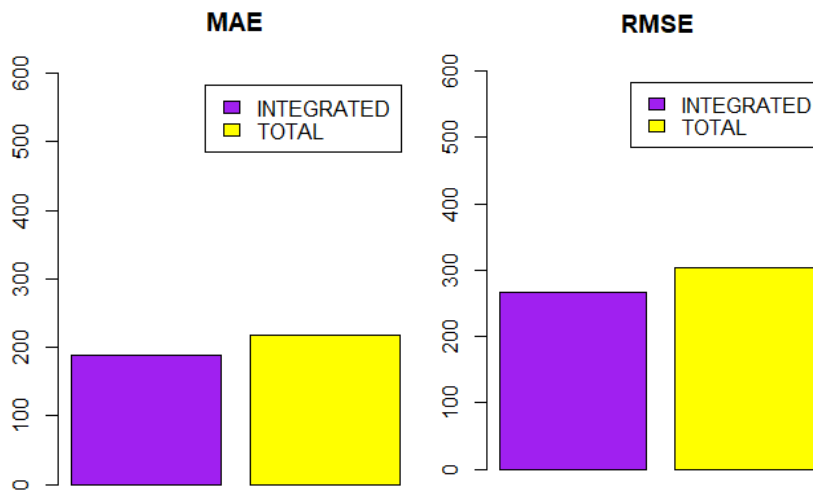


Fig. 5. Graphs of the results of the error metrics with SVM: (a) MAE (b) RMSE

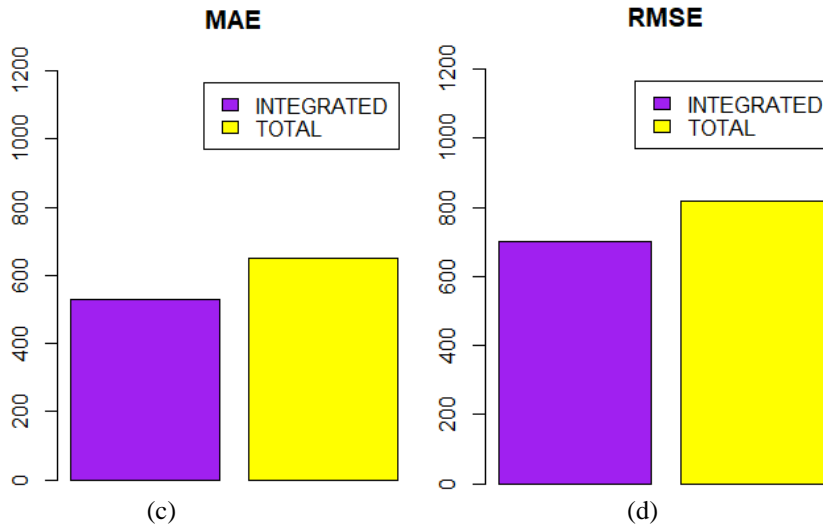


Fig. 6. Graphs of the results of the error metrics with ANN: (a) MAE (b) RMSE

4. Conclusions

The effects of STLF training method in two different levels of aggregation are studied. This study was conducted in the ERCOT dataset, which consists in hourly load data from eight load zones. Also, the ERCOT data set includes the total load of ERCOT. We compared two approaches: total and integrated. The total approach consists in creating one predictor model for the total load of ERCOT. The integrated approach consists in creating one predictor for every load zone so the final prediction will be the prediction sum of all the models. Two artificial intelligence methods to create models were used, Artificial Neural Networks and Support Vector Machines. Two error metrics were applied: MAE and RMSE. Integrated approach is more accurate when using Artificial Neural Networks or Support Vector Machines in general. As future work, statistical methods will be used to measure the error metrics for both integrated and total approach. Also, a more detailed study will be conducted so we can measure the error metrics in a period level (in this case, per hour).

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Miguel A. Zuniga-Garcia stated the methodology and supervised the research process; Katia G. Morales and Eduardo Nava Morales, conducted the research, the experiments and wrote the paper, Rafael Batres supervised the research process and helped to obtain funding; all authors had approved the final version.

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