A Method To Model And Forecast Seasonal Load Duration Curve

Mahtab Kaffash, Ali darudi, Navid Yektay, Mohammad Hossein Javidi
Faculty of engineering, PSRES Lab.
Ferdowsi University of Mashhad (FUM)
Mashhad, Iran
mahtab_kaffash@yahoo.com

***Abstract*—In power system studies, seasonal load duration curve (LDC) plays an important role in medium term horizon power system planning, reliability and energy markets studies, and economic analysis of electric power systems. Therefore, finding a simple and accurate model to forecast LDC is beneficial to network operators as well as market participants. This paper proposes a new framework to forecast seasonal LDC. As there are few contributions regarding forecasting curve time series, we redefine the problem of forecasting LDCs into a vector forecasting problem. In fact, we divide LDCs into three parts, and then, artificial neural network (ANN) engines are used to forecast future values of the three parts. The load data of Alberta electricity market from 2000 to 2013 is used to verify validity of the proposed method.**

Keywords—artificial neural network (ANN); forecasting; load duration curve (LDC); modeling; seasonal load duration curve

I. INTRODUCTION

A. Motivation

During the recent decades, the structure of some electricity industries have changed from the central controlled frameworks to restructured competitive markets. In the restructured markets, achievement of market participants in reaching their goals depends on their own behavior, future conditions of the market, and the behavior of other market players. So, market participants desire to forecast certain parameters and signals of the market to manage their actions more profitably [1], [2]. The aim of this paper is to propose a framework to forecast seasonal load duration curve (LDC) which could be beneficial to different market participants.

"LDC is a series of power demands arrange decreasingly in chronological order" [3] (Fig. 1). Based on desired time horizon, LDC can be divided into annual, seasonal, monthly, weekly and even daily time intervals. In power system studies, LDC plays an important role in power system planning, particularly in medium term horizon. In order to be able to plan for power systems, future values of demand is essentially needed to know. In medium and long term studies, network demand is taken into account in terms of annual or seasonal LDCs because forecasting hourly load data with adequate accuracy for medium and long horizons is practically impossible. This paper focuses on forecasting seasonal LDC which is widely used in medium term power system planning.

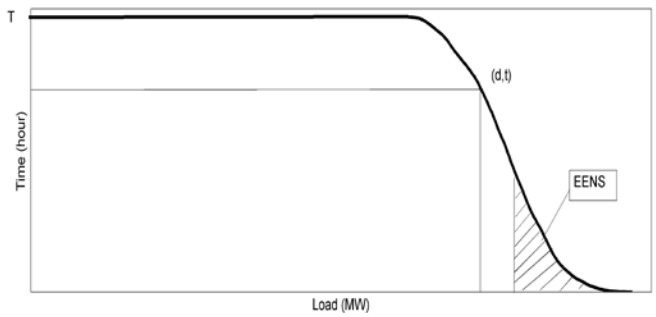

Fig. 1. Load duration curve (LDC) of Alberta in 2013.

B. Literiture Review

Many researchers have been carried out on modeling and forecasting seasonal or annual LDCs. Authors of [4] try to fit a model on seasonal LDCs using asymmetric generalized Gaussian distribution method. They model seasonal LDC of Tunisia in the summers from 2000 to 2005. In [5], four-section exponential function is used to model monthly or seasonal LDCs. The main drawback of the above-mentioned researches is that they only fit a model on previously observed LDCs and do not intend to use their model to forecast future LDCs.

On the other hand, some authors focus on forecasting LDCs. In [6], a method is developed to forecast LDCs to estimate demand growth. However, in this paper, it is assumed that the shape of LDCs remind constant and the area under them increase gradually and so, the LDCs move upward as the energy consumption increases. Nevertheless, in [7], it is shown that the shape of LDCs change during time.

C. Contribution

This paper proposes a new method to forecast year-ahead seasonal LDCs. As there are few contributions regarding forecasting curve time series, we redefine the problem of forecasting LDCs into a vector forecasting problem. In fact, we divide LDCs into three parts, and then, artificial neural network (ANN) engines are used to forecast future values of these three parts.

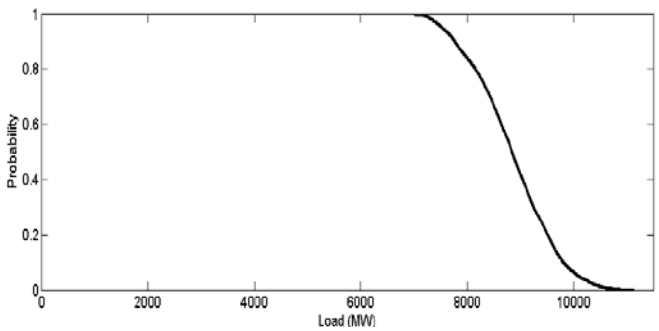

Fig. 2. Interval LDC (ILDC) of Alberta in 2013.

D. Paper Organization

The rest of this paper is organized as follows. Section II explains about LDC and its application. Section III describes proposed method. This section is divided into two sub-sections. The first part is about the proposed forecasting method and the second one demonstrates the utilized forecasting engine. Section IV presents numerical results, and finally, in section V, the paper is summarized and concluded.

II. LOAD DURATION CURVE

Fig. 1 shows a typical annual LDC in Alberta electricity market taken from [8]. According to the [9], the horizontal axis represents the system load and the vertical axis illustrates the duration time. In Fig. 1, T is a determined period, which could be a year, a season, a month, a week, a day, etc. Each point on the LDC like (d, t) indicates the system load is greater than or equal to d in duration t. The area under the LDC expresses energy demanded by the system.

Inverted load duration curve (ILDC) is obtained by dividing the vertical axis by the period T.

$$p=t/T \tag{1}$$

In (1), p can be considered as the probability of being the system load greater than or equal to d. Fig. 2 shows the ILDC derived from Fig. 1. It is simple to convert LDC to ILDC and vice versa by normalizing the time factor [4].

LDC is utilized in various applications. According to the [9], [10], medium term planning and profit maximization in liberalized market require load and generation balance. To obtain this balance, load uncertainty and the randomness in generation unit outages should be considered. Balancing load and generation over medium term is not practical due to the fact that there are many different uncertain variables. By subdividing LDC into weekly, monthly or seasonal, it is possible to calculate the probability of load uncertainty. Moreover, LDC is used in other studies such as researches done in [3], [7], [11- 13]:

- Reliability study: evaluating power system reliability indices, for instance, expected energy not served (EENS) and loss of load probability (LOLP) (Fig. 1).
- Economic analysis of electric power systems: economic dispatching.
- Power system planning: analyzing the feasibility of a generation expansion scheme.
- Energy market: determine the rate of progress of a power system energy source going into operation.
- Power system operation: according to [3], LDC assists to lay out the optimal power plants generation.

III. PROPOSED METHOD

A. Forecasting Model

This paper implements a new method to forecast year-ahead seasonal LDCs. As there are few contributions regarding forecasting curve time series, we redefine the problem of forecasting LDCs into a vector forecasting problem. In other words, the LDC is quantized into a vector of variables. As the size of the quantized vector increases, we can obtain LDC forecasts with higher resolutions. However, selecting high size for the quantized vector not only results in raising the computational burden of forecasting procedure, but also may cause complexity of the variables to increase excessively. In other words, there is a trade-off between the resolution of the LDC forecasting and computational burden of forecasting procedure. By redefinition of LDCs prediction into vector forecasting, scalar methods could be used.

Our proposed method models LDC by using just three points. These three points are demand related to the following probabilities in the ILDC: zero, 0.05 and 0.95. As mentioned in section II, it is simple to convert ILDC to LDC, at first, we forecast ILDC and then we change it to LDC. The probability of zero in ILDC illustrates the peak load. The probability of 0.05 which is near peak load, is chosen as one of the quantization points because, as shown in Fig. 2, around the peak load, LDC changes rapidly. Another reason to choose such point is that in medium term power system planning, forecasting the peak load and medium load are very important e.g. calculating EENS depends on a range of load which is located near peak load. So forecasting ILDC in peak load and around it are momentous. Moreover, it might inferred from Fig. 2 that ILDC varies linearly in probability ranges between about 0.05 and 0.95. We do not choose a quantization point greater 0.95 since ILDC varies only slightly for probabilities over 0.95.

After the quantization step, three time series are emerged. We feed these three time series into an ANN forecasting engines to forecast future values of them. In other words, ANN forecasts future values regarding to probability of 0, 0.05 and 0.95 of the future ILDC. Final forecasted ILDC can be simply obtained by connecting these three points.

The main goal of this paper is to forecast seasonal LDCs of four different seasons of the next year, at the end of the current year. Therefore, there are four different forecasting horizons in our forecasting procedure. For instance, forecasting horizon for forecasting winter and summer seasons are 1 and 3 season-ahead, respectively. To improve accuracy of the forecasts, instead of using a general ANN with four-season-ahead horizon, we used four forecasting engines that are specialized

in forecasting different horizons ranging from one to four seasons ahead. Each of these forecasting engines are trained separately to forecast one season of the year (Fig. 3).

One of the factors that greatly affects accuracy of ANN forecasts is the set of input variables. In this paper, we have selected previous lags of the quantized ILDC as the input variables. Mainly, the following lags are chosen as the input variables for all four forecasting engines: 12, 8, and 4. However, depending on the forecasting horizon of each forecaster, we have added additional input variables, if possible. For instance, in one-season ahead forecasting ANN, the forecasting horizon allows us to consider the additional following lags: 3, 2 and 1. Details are shown in Fig. 4.

B. *Forecasting engine*

Artificial intelligence (AI) is the intelligence exhibited by machines or software. The goal of AI is: learning, perception, deduction, reasoning, problem solving, etc. AI has a wide range of tools, such as: logic, classifiers and statistical learning methods, neural network, control theory, etc. In this paper, neural network is used as the forecasting tool. Neural network consists of nodes and some ways connecting these nodes. Nowadays Neural Networks are used to model a wide range of cases [7].

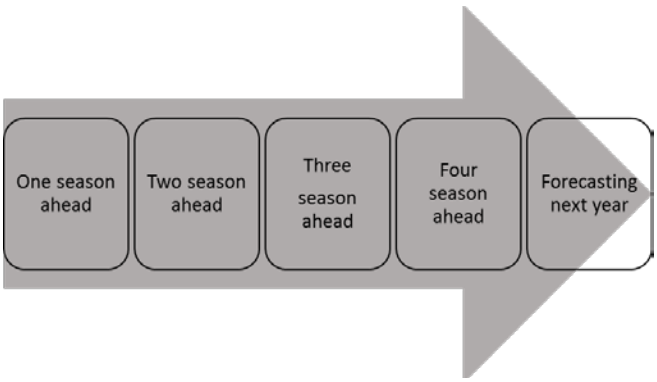

Fig. 3. Forecasting engines.

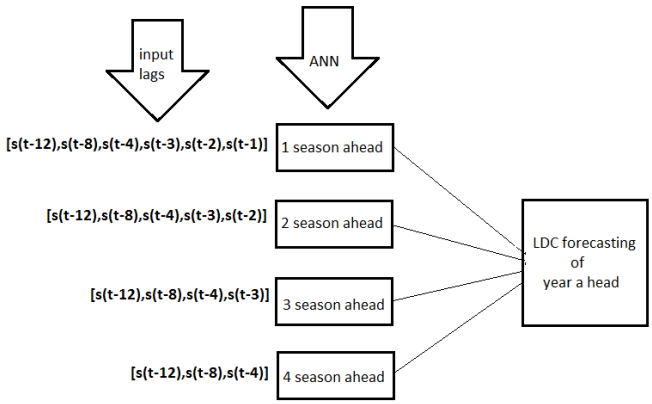

Fig. 4. Feedback delays.

The performance of an intelligent system improves thorough experiencing, i.e., the system learns by training. Neural Networks have been used in various applications such as pattern recognition, forecasting, identification, data compression.

ANN has many different types, such as:

- Diabolo network is used for learning efficient coding [14].
- Deep learning attempts to model high-level abstractions in data by using model architectures composed of multiple non-linear transformations [15].
- Multilayer perceptron (MLP) is a feed forward model that maps sets of input data onto a set of appropriate outputs.
- Recurrent neural network (RNN) is a class of artificial neural network where connections between units form a directed cycle.
- Restricted Boltzmann machine (RBM) is a generative stochastic artificial neural network that can learn a probability distribution over its set of inputs.
- A self-organizing map (SOM) is trained using unsupervised learning to produce a low-dimensional, discretized representation of the input space of the training samples, called a map.
- A convolutional neural network is a type of feed-forward artificial neural network where the individual neurons are tiled in such a way that they respond to overlapping regions in the visual field [16].

In this paper MLP is used which includes one input layer, one (or more) hidden layer(s) and one output layer. Fig. 5 illustrates a four layers perceptron. In this figure, neuron and weights are denoted by circles and lines, respectively.

IV. NUMERICAL RESULT

In this section, the performance of the proposed algorithms is evaluated on Alberta's electricity market. Alberta's electricity market is an energy-only, real-time market with uniform clearing mechanism. Hourly load demand from 2000 to 2013 is used as input data [17]. The data is divided into three sets: The data of 2000 to 2011 are the training data. 2012 is the validation period, and finally, the year 2013 is the test period.

Matlab software version R2013b is used in data implementing and management the ANN. Based on trial and error, the structure of the selected MLP-ANN is selected as follows: The hidden layer has three neurons and the output layer has three

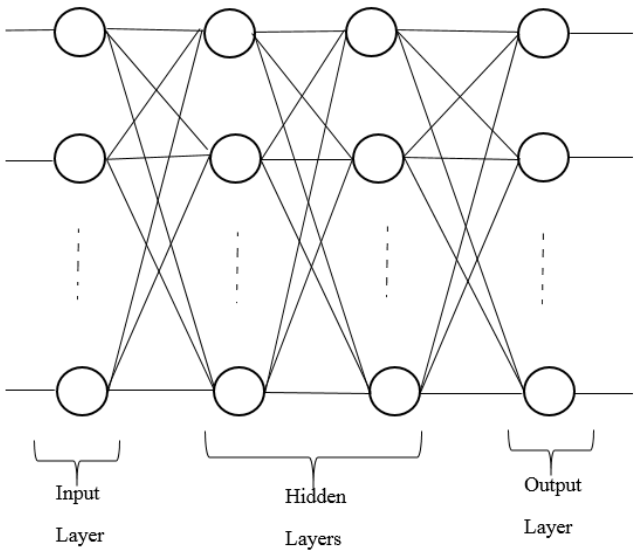

Fig. 5. Four layers perceptron.

neurons (Fig. 6) corresponding to the load related to zero, 0.05 and 0.95 in ILDC.

Seasonal ILDC forecasted curves regarding to four different seasons of the year 2013 are shown in Fig. 7 to Fig. 10. We compared our results with naïve one-year-ahead forecasting method. As shown in Fig.7 to Fig. 10 the proposed method outperforms naïve in all seasons, particularly, for the peak and near-peak load which, as mentioned earlier, are important parts of ILDC.

V. CONCOLUSION

This paper proposes a new framework to forecast seasonal LDC. We redefine the problem of forecasting LDCs into a vector forecasting problem. In fact, we divide LDCs into three parts, and then, artificial neural network (ANN) engines are used to forecast future values of these three parts. As an advantage over previous works, we do not suppose any limitation on LDC shape. Results indicate that the proposed method is able to provide accurate forecasts. Forecasting procedure is fairly easy-to-implement and computational burden is trivial.

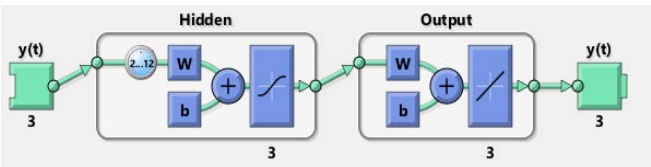

Fig. 6. The ANN of proposed mathod.

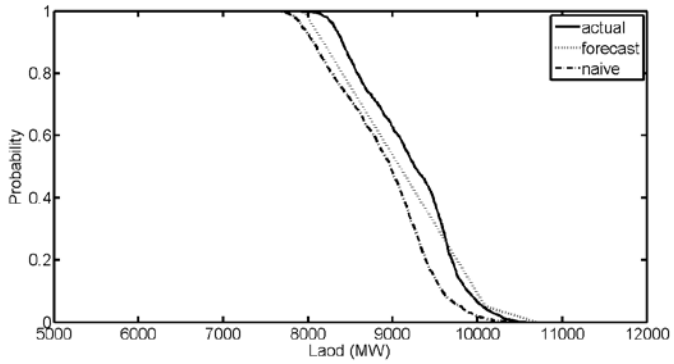

Fig. 7. First season 2013.

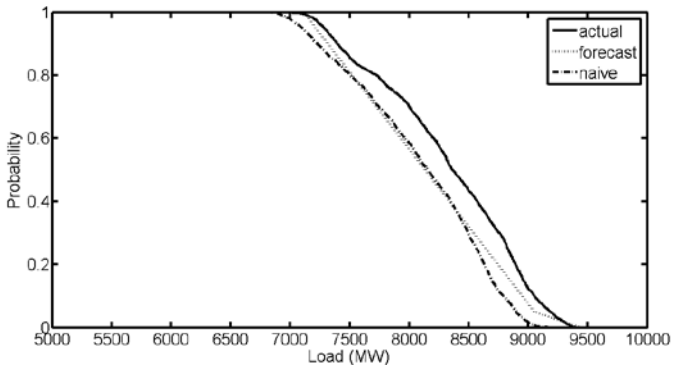

Fig. 8. Second season 2013.

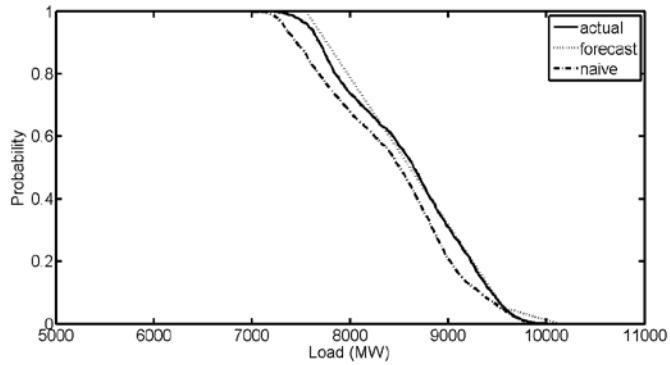

Fig. 9. Third season 2013.

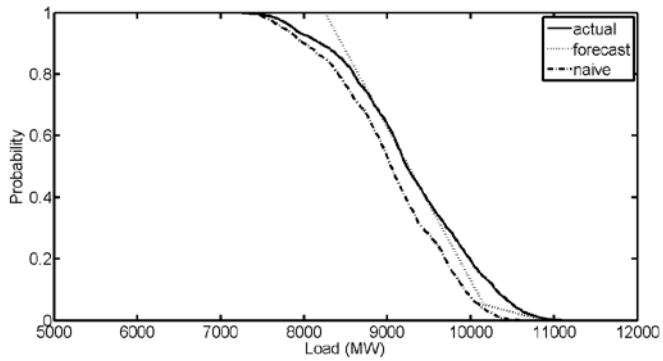

Fig. 10. Fourth season 2013.

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