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Short-term electricity load forecasting of buildings in microgrids

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ABSTRACT

Electricity load forecasting plays a key role in operation of power systems. Since the penetration of distributed and renewable generation is increasingly growing in many countries, Short-Term Load Forecast (STLF) of micro-grids is also becoming an important task. A precise STLF of the micro-grid can enhance the management of its renewable and conventional resources and improve the economics of energy trade with electricity markets. As a consequence of the highly non-smooth and volatile behavior of the load time series in a micro-grid, its STLF is even a more complex process than that of a power system. For this purpose, a new prediction method is proposed in this paper, in which a Self-Recurrent Wavelet Neural Network (SRWNN) is applied as the forecast engine. Moreover, the Levenberg–Marquardt (LM) learning algorithm is implemented and adapted to train the SRWNN. In order to demonstrate the efficiency of the proposed method, it is examined on real-world hourly data of an educational building within a micro-grid. Comparisons with other load prediction methods are provided.

1. Introduction

Micro-grids are integrated energy systems composed of distributed energy resources and multiple electrical loads operating as an autonomous grid, which can be either in parallel to or islanded from the existing power grid. A micro-grid can be considered as a small-scale version of the traditional power grid that its small scale results in far fewer line losses and lower demand on transmission infrastructure. All of these advantages are consequently motivating an increased demand for micro-grids in a variety of application areas such as campus environments, military operations, community/utility systems, and commercial and industrial markets [1].

Considering the fast and worldwide development of micro-grids, their optimal operation requires advanced tools and techniques. In particular, Short-Term Load Forecast (STLF) is an indispensable task for the operation of a micro-grid. In conventional power systems, STLF is an important tool for reliable and economic operation of power systems, as many operating decisions, such as dispatch scheduling of generating capacity, demand side management, security assessment and maintenance scheduling of generators, are based on load forecast [2–7]. Load forecasts also have significant roles in energy transactions, market shares and profits in competitive electricity markets [7,8]. Different prediction strategies have already been presented for the STLF of traditional power systems over the years. These methodologies are generally divided into two main groups: classical statistical techniques and computational intelligent techniques. Reviews on some of these strategies can be found in [2,4–8].

In a similar way, STLF is a key factor in operation of micro-grids such as energy management for optimal utilization of available resources in order to minimize the operation cost or any environmental impact of a micro-grid [9]. Moreover, STLF for a micro-grid can be used for profitable trade of electric energy within the grid. In other words, it is important for the operator of a micro-grid to determine the amount of exchanged power with a wholesale energy market so as to maximize the total benefit [10]. It has also been discussed that the forecasted loads as well as forecasted generation of renewable resources are the main inputs for optimal energy management [11,12] and generation scheduling [13] in micro-grids.

However, modeling and forecasting of micro-grids' loads can be more complex tasks than those usually applied for conventional power systems, as the load time series of micro-grids is more volatile in comparison with the load of power systems, as demonstrated later in the present paper. Since the size of a micro-grid is considerably small compared to a traditional power system, the load of a micro-grid includes more fluctuations. In other words, the inertia in small-scale systems is low and therefore, the smoothness of load time series in such systems degrades. Using a criterion to measure the volatility of a time series, it will be shown in this paper

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that the volatility of load time series for a micro-grid is considerably higher than that for a conventional power system. As a result, there is a need to adapt a suitable STLF model to volatile behavior of micro-grids load time series. Despite the importance of STLF for micro-grids there are a few works presented in this area. Authors in [14] present an on-line learning model based on Multiple Classifier Systems (MCSs) for short-term load forecasting of micro-grids, and the model was tested on real data of a micro-grid. A bi-level prediction strategy is proposed in [15] for STLF in micro-grids. This strategy is composed of a forecaster including neural network and evolutionary algorithm in the lower level and an enhanced differential evolution algorithm in the upper level for optimizing the performance of the forecaster. The proposed models in [15] is designed having the aggregated micro-grid load in mind. However, the present paper focuses on forecasting the load of the individual loads within a micro-grid, with potentially significantly higher volatility compared to the aggregated micro-grid load. Forecasting individual micro-grid load components is important for operation scheduling and determining load serving priorities at the feeder level [16].

Some research works have also been presented regarding electricity load prediction for residential areas and buildings [17–19]. The proper consumption of electricity in buildings leads to lower operational costs. If the facility manager could predict the electricity demand of the building, actions could consequently be taken to reduce the amount of energy and therefore, reduce the operational cost of the building [19]. A few works have been published very recently in the area of energy prediction of buildings. For instance, long-term energy consumption of a residential area in South West China has been studied in [20]. In this reference, an Artificial Neural Network (ANN) model is compared with some other prediction models, including Grey model, regression model, polynomial model and polynomial regression model, to forecast the total energy consumption of the residential area, and it is shown that ANN model outperforms the other models. Having access to detailed data of a six-story multi-family residential building located on the Columbia University campus in New York City, the authors in [21] were able to conduct a comparative spatial analysis to forecast the energy consumptions of units, floors and the whole building for different temporal intervals (e.g., 10-min, hourly and daily). The results indicate that the most effective models are built with hourly consumption at the floor level providing that high resolution and granular data is available via advanced smart metering devices. In [22], a Case-Based Reasoning (CBR) model, categorized as a machine-learning artificial intelligence technique, is proposed to forecast energy demand in an office building located in Verennes, Quebec, Canada. Three forecasting horizons of 3-hour, 6-hour and 24-hour ahead have been simulated with hourly prediction resolution, and the results demonstrate that the prediction capability of the model is improved when the horizon is reduced to 3-hour ahead. Authors in [23] have proposed a new methodology for electrical consumption forecasting based on end-use decomposition and similar days. Total consumption forecast is also obtained from end-use consumptions and the data of selected days. In [24], a building-level neural network-based ensemble model is presented for day-ahead electricity load forecasting, and it is shown that the presented model outperforms SARIMA (Seasonal Auto Regressive Moving Average) by up to 50%. However, the comparisons are made only with SARIMA model, which is a linear statistical model, which may not be capable of capturing high nonlinearity of the building-level electricity load.

To summarize the main points, micro-grids can bring considerable benefits to power systems, such as supplying loads in remote areas, reducing total system expansion planning cost, reducing carbon emission through coordinated utilization of Renewable Energy Sources (RESs), providing cheaper electricity through proper energy management of available resources and energy trade with the main grid, and improving system reliability resiliency by providing dispatchable power for use during peak power conditions or emergency situations. Moreover, it was discussed that short-term load forecasting tool is of high importance in optimal energy management and secure operation of micro-grids. In this way, some research works have been conducted to develop load forecasting models with higher accuracy. However, as discussed above, a few works have focused on day-ahead load consumption prediction of buildings in micro-grids and consequently, improvement of forecast accuracy is still needed in this area. In the present paper, a forecast method is proposed for the STLF of micro-grids with the focus of electricity load prediction for individual buildings. The main contribution of this paper is applying a Self-Recurrent Wavelet Neural Network (SRWNN) forecasting engine for electricity load prediction of micro-grids. Moreover, the Levenberg-Marquardt (LM) learning algorithm is implemented to train the SRWNN. The proposed method improves the forecast accuracy for highly volatile and non-smooth time series of micro-grid electricity load. The higher the forecast accuracy of electricity load, the more efficient energy management can be achieved in a micro-grid.

The remaining parts of the paper are organized as follows. Section 2 provides a data analysis on different electricity load time series to draw a distinction between the load of a micro-grid and a power system. The proposed forecasting method consists of the SRWNN as the forecasting engine and LM as the training algorithm, and is presented in Section 3. The proposed load forecasting method is tested on real-world test cases and the results are compared with the results of some other prediction approaches in Section 4. Finally, Section 5 concludes the paper.

2. Data analysis

A data analysis is presented in this section so as to compare the characteristics of a micro-grid load time series and electricity load in power systems. The British Columbia Institute of Technology (BCIT) in Vancouver, the Province of British Columbia (BC), Canada, is considered as the micro-grid test case studied in this paper. BCIT's Burnaby campus is Canada's first Smart Power Micro-grid comprised of power plants (including renewable resources of wind and photovoltaic modules), campus loads, command and control (including substation automation, micro-grid control center and distributed energy management), and communication network [25]. The load data used in this work is from one building with a peak value of 694 kW from March 2012 to March 2013, within the BCIT micro-grid. Hereafter, we refer to this load as BCIT. To draw a comparison between the characteristics of a micro-grid load and power system load level, the load time series of two power systems, i.e., British Columbia where BCIT micro-grid is located, and California, are analyzed.

Electricity load follows daily and weekly periodicities. In this way, we consider two measures for volatility analysis, i.e., daily volatility and weekly volatility. These measures are based on the standard deviation of logarithmic returns over a time window. In general, daily volatility quantifies the overall change in hourly electricity load from one day to another, and weekly volatility measures the load changes in subsequent weeks. For more details regarding aforementioned volatility indices, see [26].

One year hourly load data has been considered for British Columbia's and California's power systems for the same period, i.e., from March 2012 to March 2013. Observe from Table 1 that both daily and weekly volatility indices for a micro-grid are considerably higher than those for power systems, which demonstrate low smoothness of micro-grid load time series. For instance, daily