POWER CONSUMPTION MODEL OF A MICROGRID BASED ON UTILITY-PROVIDING HISTORY DATA

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Abstract— This paper develops an energy consumption model for a microgrid based on utility-providing records and evaluates its accuracy. Built upon a data processing framework totally consisting of free open software, the well-known auto-regressive integrated moving average method is exploited for time series tracking. The series of quarter-hourly records during 60 days are fed to the modeling process, and the consumption of thenext 1/4, 1, 2, and 3 hours is predicted. The average prediction error of 15-minute-ahead forecast remains below 3.4 *kwh*, while that of the 3-hour-ahead forecast is extended to 12.37 *kwh*. Next, day-by-day measurement shows that the 15-minute-aheadprediction has about just 1.5 % for the whole period in spite ofa significant change between weekdays and weekends. This bigdata-based prediction can allow us to build a new intelligent energy application such as battery controllers and electricity trade coordinators.

Keywords: Microgrid, Power Consumption History, ARIMA, Prediction Accuracy, Statistics Package.

I. INTRODUCTION

[*]A microgrid is a local power system with its own control capability and energy storage equipment [1]. Energy is usually provided from the main grid but recent microgrids are stuffed with renewable energy generators. In each microgrid, it is possible to monitor and accumulate the power consumption records to accelerate the development of a sophisticated prediction model and other intelligent services. By an accurate power consumption model, a microgrid can build anefficient equipment operation schedule, make an economic energy purchase plan, and call for bid from EVs (Electric Vehicles) for V2G (Vehicle-to-Grid) electricity trades [2]. In this regard, this paper develops a power consumption model for a microgrid, specifically, Jeju National University, taking advantage of energy consumption records provided by its utility company. Here, the model exploits the ARIMA (Auto Regression Integrated Moving Average) scheme and measures the accuracy of the prediction.

Figure 1 depicts the data flow in our analysis procedure. To begin with, after logging-in to the utility web site, we can download the power consumption series as a data file formatted in the HTML syntax. A file contains 96 consumption records captured for each 15 minutes during a single day. Then, our application program parses the downloaded files and converts into 2 formats, namely, one for plain texts and the other for SQL *insert* statements. While the SQL statements are run on aMySQL database server, plain text files are loaded into the Rspace, where we can apply a variety of data mining libraries[3]. This data analysis process employs freely available open software components such as the R statistics package.

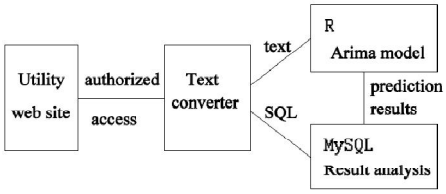

Fig. 1. Data analysis flow

In this paper, the well-known ARIMA scheme is selected due to its efficiency and computation speed [4]. ARIMA is one of the most widely used methods for the prediction of diverse time series. R also provides an easy-to-use library forit, and Figure 2 shows the pseudo code of our prediction script. Basically, the power consumption records of the previous 60days, namely, 96 × 60 values are fed to an ARIMA model, and the power demand prediction for the next 15-minute, 1-hour, 2-hour, and 3-hour periods are calculated respectively. This step is repeated 96 × 70 times, which corresponds to 70days. In the figure, the initial values of *si* and *ei* are 1 and 96× 70 to represent the target prediction interval, while *st* and *ed* represent the moving window as large as 60 days.

```
// Init si and ei to the size of learning intervals
    for ( i in si : ei) {
    st←i, ed←i + 5759
    mv←v[st:ed]
    myts←ts (mv)
    fit←auto.arima(myts)
    pr← forecast(fit, 12)
    // Store results
    }
```

Fig. 2. R pseudo code

[*]Following are results of a study on the Leaders Industry-university Cooperation Project, supported by the Ministry of Education, (MOE).

II. PREDICTION RESULTS

The prediction model yields the power demand forecast after a specific time unit. Each energy application can take the forecast appropriate for its goal. For example, the battery controller may decide whether to store or discharge electricity according to the quarter hour forecast. Moreover, a V2Gscheduler prefers the 2 or 3-hour forecast to contact with as many EVs as possible. The first experiment predicts the power consumption during a single day while the records of the previous 60 days are given to the ARIMA model. That is, 96predictions are conducted. The results are shown from Figure3 to Figure 6. In all figures, solid curves track the predicted consumption while dotted curves actual consumption. As can be seen in the figures, the shorter the prediction distance, the more accurate the prediction. The maximum errors for the 4cases are 12.37 *kwh*, 49.6 *kwh*, 73.6 *kwh*, and 91.8 *kwh*, respectively. Moreover, the average errors are 3.4 *kwh*, 15.1*kwh*, 20.2 *kwh*, and 26.3 *kwh*, respectively. However, even though the error gets larger, the prediction chases the actual consumption in most cases.

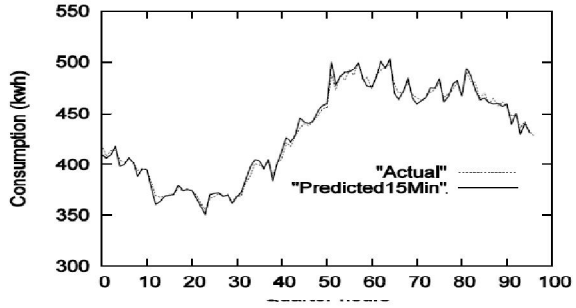

Fig. 3. Quarter-hour-ahead prediction

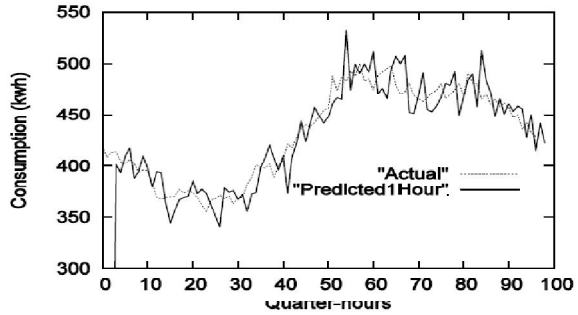

Fig. 4. One-hour-ahead prediction

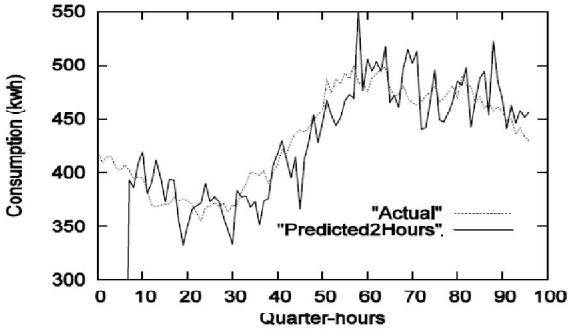

Fig. 5. Two-hour-ahead prediction

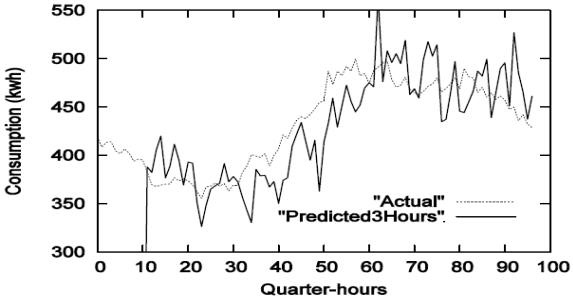

Fig. 6. Three-hour-ahead prediction

III. DAILY PREDICTION BEHAVIOR

Extending the experiment on quarter-hour level prediction, this section measures the daily prediction error for 70 days, and the results are shown from Figure 7 to Figure 10. During the period, some days have invalid consumption records from the utility web site. As the comparison with those records is meaningless, the experiment excludes them. Moreover, for the first 12 15-minute intervals, not all 4 predictions are generated. These are also excluded for a fair comparison.

First, Figure 7 plots the maximum error, while the error is calculated as follows:

$$prediction\ error = \frac{|actual\ value - predicted\ value|}{actual\ value} \quad (1)$$

This figure indicates that the 15-minute-ahead prediction error is at most 16.2 %, which corresponds 162 *kwh*. Additionally, in the case of 3-hour-ahead prediction, the error reaches 57.4%, while this situation stems from the time lag in chasing the actual curve. In addition, Figure 8 plots the day-by-day average error. The 15-minute-ahead prediction has about just1.5 % for the whole period. As the prediction distance gets larger, the prediction error increases almost linearly.

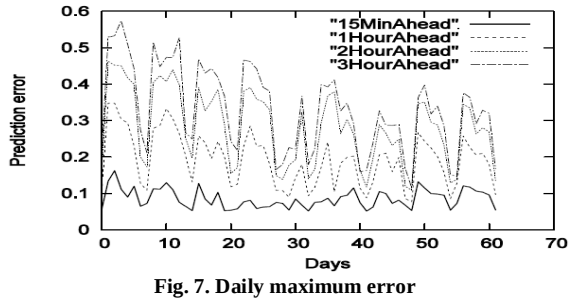

Fig. 7. Daily maximum error

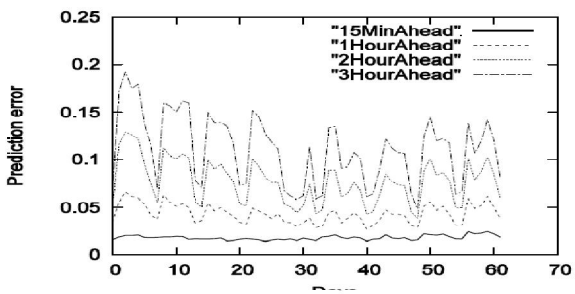

Fig. 8. Daily average error

According to Figure 7 and Figure 8, a periodic pattern can be easily recognized. As the target microgrid is a university, there is a significant behavior change between weekdays and weekends. Figure 9 and Figure 10 plot both the daily maximum and the daily average according to day-of-week. In capturing the sharp change, the ARIMA model cannot avoid time lag errors. The effect is magnified when the amount of power consumption gets larger. Hence, it is necessary to analyze week-by-week dynamics for a same week day.

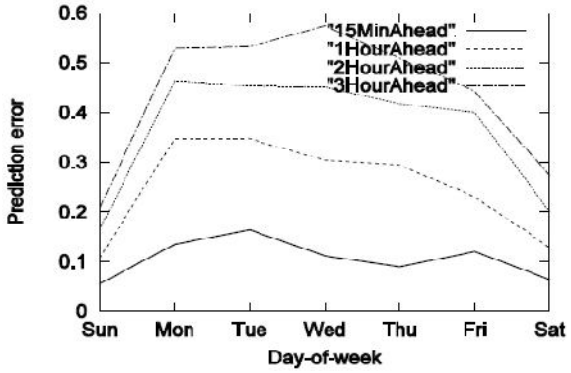

Fig. 9. Daily maximum error vs. day-of-week

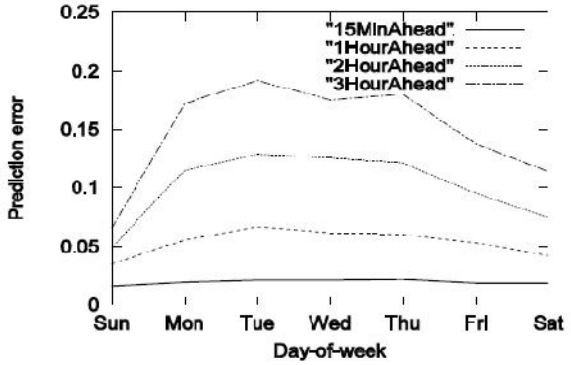

Fig. 10. Daily average error vs. day-of-week

CONCLUSIONS

In modern power systems, microgrids have their own control strategy and make operation plans. In their decision making, the availability of past data is critical [5]. In this paper, we have developed a prediction model for energy consumption in a microgrid, taking advantage of history records being accumulated in the utility company. An ARIMA model learns quarter-hourly records of past 60 days and predicts the next consumption. According to the comparison between actual and predicted values, the 15-minute-ahead forecast has about just1.5 % prediction error.

As future work, we will combine the prediction scheme with a V2G power trade coordinator, which builds an energy purchase plan interacting with a fleet of EVs. Its goal is to reduce the peak load of the microgrid and enhance the economic benefit in energy consumption.

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