Highly-accurate Short-term Forecasting Photovoltaic Output Power Architecture without Meteorological Observations in Smart Grid

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Abstract—We propose a forecasting architecture of near future photovoltaic output power based on the multipoint output power data via smart meter. The conventional forecasting methods are based on the analysis of meteorological observation data, and need the implementation of dedicated meters and the connection to them. Moreover, highly-accurate forecasting(in second-scale, or meter-scale) is difficult in the conventional methods. Our proposed method is based on not meteorological observation data but the actual measured output power data by using the solar panels connected with a smart meter as sensing units. A forecasting calculation server interpolate spatially the actual measured data collected from multipoint, and forecasts near future output power in each point using optical flow estimation. Virtual sampling technique involves the forecast performance when the sampling point is sparse. We show the forecasting method achieves high accuracy of less than 5% error rate by the computer simulation.

I. INTRODUCTION

With global greening trend, renewable energy power generation is rapidly spread. Especially, photovoltaic power generator will become one of the main renewable energy power generation in the future, since it can be implemented with low cost[1]. In Japan, grid-connected domestic photovoltaic power generator is rapidly spread over the last decade, and the efficient use of the distributed energy is main research issue of smart grid in Japan. For the efficient use of the distributed energy, there is coordinated scheduling control between generations, storages, and demands by a smart meter. For instance, the smart meter charges electric vehicle(EV) or turns a temperature of an air conditioner settings down when the amount of power generation is large or power price is cheap, and it discharges EV or turns the temperature of the air conditioner settings up when the amount of power generation is small or power price is expensive. Moreover, a stable power supply systems can be structured by coordinated operation with diesel engine generator based on forecasting photovoltaic output power in micro-grid technology[2], [3]. The accurate scheduling, however, is difficult because of the unexpected use of demand devices by users or uncontrollable renewable energy generation. While the uncertainty by the former can be eliminated partially by using advanced reservations with penalty or demand response[4], the uncertainty by the latter cannot be eliminated easily since the output power of the renewable energy generations changes intensely depending on weather conditions or geographical effects. Especially, forecasting the output power of photovoltaic generators is difficult by the weather varies from hour to hour on overcast days.

Morsy et al. [5] proposed an on-line prediction technique under skies based on artificial intelligence. They analyze the image of the cloudy sky by using fuzzy logic. The forecasting method by using measured air temperature, relative humidity and previous sunshine hours values is proposed in [6]. Oke et al. proposed a forecasting method through atmospheric pressure forecast using neural network[7].

As mentioned above, conventional forecasting methods are focused on the analysis of meteorological observation data. That is, the conventional methods need the implementation of dedicated meters and the connection to them. Moreover, highly-accurate forecasting(in second-scale, or meter-scale) is difficult in the conventional methods. We propose a forecasting architecture based on not meteorological observation data but the actual measured output power data in a number of photovoltaic power generator connected with smart meter. It needs no special meteorological observation equipment by using the solar panels connected with a smart meter as sensing units.

The paper is organized as follows. In Section II, we explain our overlay smart meter network model, and in Section III, we propose a forecasting architecture. Simulation results are provided to evaluate the performance of the proposed architecture in Section IV. In Section V, we summarize this paper.

II. OUR SMART METER NETWORK MODEL

A smart meter is an advanced meter that records power consumption and production and communicates that information via some communications network for telemetering. Moreover, scheduling management of domestic devices by smart meter gives efficient distribution and saving energy with Demand Response Program(DRP).
As shown in figure 1, we assume that smart meters in each house connect to Internet. Smart meters send photovoltaic power output data to forecasting calculation server, and receive the forecasting data from it via Internet.

III. PROPOSED METHOD

A. Overview

Figure 2 shows the general flow of the proposed method. A forecasting calculation server collects the actual measured data from multipoint. The server create a 2-Dimensional output power data map by spatial-interpolation technique, and detects the optical flow vectors between the past data map. The forecasting output power data are calculated with the output power data map and the flow vector, and are distributed to each point. We propose virtual sampling method that uses previous sampling data repeatedly, for highly accurate forecasting.

B. Forecasting calculation flow

1) Data collection: In a smart house, the amount of the photovoltaic output power is monitored and registered by a smart meter.

The forecast calculation server requests transmission of the present photovoltaic output power data for smart meters of each home at fixed time interval $T_{\text{timestep}}$. Then, the server discards the data the RTT of which from request to reply is exceed a fixed threshold for the correspondence of all the collected data.

The output power data are normalized based on that in a basis day (desirable in fine weather) on the smart meter side or the server side so that the data calculation is facilitated. The aging deterioration of the solar panel and great change with seasonal transition are addressed by updating the standard value at constant period (about once a month). Moreover, the server collects from not only smart meter but also the solar panel set up in the public domain (for instance, street lamp with the solar panel etc.).

2) Data map creation: A 2-Dimensional photovoltaic output power data map is created based on the actual measured output power data of multipoint as sampling data by using a scattered data interpolation technique (figure 3).

The cause of photovoltaic output power variation are cloud, aerosol distribution, obstacles such as airship and bird, and the influence of solar activities such as sunspot. In this paper, we take account of only the cloud shading as main factor of the variation. The output power data map can be viewed as a cloud distribution map.

The data map $M_t$ generated at time $t$ is given by

$$M_t = G_{IP}(S_t)$$

$$S_t = \{ q_n(t) = [x_n, y_n, z_n(t)]^T \mid n \leq N_{sampling}, n \in \mathbb{N} \}$$

where $G_{IP}$ is the data interpolation function for the map generation, $N_{sampling}$ is sampling number, and $S_t$ is the class of photovoltaic output data collected from each client. That is, the output power of the client $n$ in the positional vector $[x_n, y_n]^T$ is $z_n(t)$ at time $t$.

3) Optical flow estimation: Optical flow (motion vector) of the data map is detected by comparing a present data map with a previous data map (figure 4). In this paper, we assume that the flow vector of the data map corresponds to that of clouds, and that all the clouds move in the same direction within the range of the data map created by the forecast calculation server. The server, therefore, need not to run the optical flow estimation calculation for all the unit block, but also only for a sufficiently-reliable unit block.

The flow vector $v_t$ generated at time $t$ is given by
Fig. 4. Optical flow estimation by comparison with the previous output data map.

Fig. 5. Forecast data extraction based on the output data map and flow vector.

\[ \mathbf{v}_t = G_{OF}(M_t, M_{t_{\text{previous}}}) \]  \hspace{1cm} (3)

\[ t_{\text{previous}} = t - T_{\text{interval}} \]  \hspace{1cm} (4)

where \( t_{\text{previous}} \) is the previous run time in forecasting calculation and the data map \( M_{t_{\text{previous}}} \) was generated at the time \( t_{\text{previous}} \).

4) Forecasting data extraction: In this part, forecast output data sequence in each point is extracted with the photovoltaic output data map and the optical flow vector. In this paper, we assume that the flow vector continues in the future, and use data on the vector reverses to the flow vector as forecasting data. As shown in figure 5, the forecasting output data sequence \( f_k(t) \) in the point \( p_k \) at time \( t \) is given by

\[ f_k(t) = M_t(p_k - \frac{t}{T_{\text{interval}}} \mathbf{v}_t) \]  \hspace{1cm} (5)

where \( T_{\text{interval}} \) is the forecasting interval. More accurate forecasting data sequence can be calculated with direct-interpolation by using the function of data map creation, while we use the grid-interpolated data in this paper.

5) Forecasting data distribution: The forecasting data sequences are distributed to each client that needs the forecasting data. An actual amount of the output power data sequence is obtained by multiplication by the standard value on the server side or on each client side. The server can distribute only to the clients which need the forecasting data, since this distribution phase is independent of the data collection phase (For instance, street lamps don’t need the data.).

C. Virtual sampling

In this forecasting flow, the accuracy of the output data map is important. The accuracy, however, decreases due to increase of the difference between the data map and actual cloud distribution when the sampling point within the range of the data map is poor. We propose virtual sampling method for improvement of the accuracy by using previous sampling data virtually as present sampling data.

Figure 6 shows overview of the virtual sampling method. The photovoltaic output power \( z_k(t - T_{\text{interval}}) \) of the client \( n \) in the positional vector \( [x_n, y_n]^T \) at previous run time \( t - T_{\text{interval}} \) can be viewed as the output data in positional vector \( [x_k, y_k]^T + \mathbf{v}_t \) at time \( t \). The server, therefore, can generate a highly-accurate data map with double sampling points. In the same way, the server uses \( d \) times data in the previous for data map creation, and we define it virtual sampling with depth \( d \).

Virtual sampling with depth \( d \) satisfies

\[ M_t = G_{IP}(S_t) \]  \hspace{1cm} (6)

\[ S_t = \{ S^a_{t}\}_{a = 0, \ldots, d} \]  \hspace{1cm} (7)

\[ S^b_t = \{ q_n^{(t_{\text{previous}})} + [v_x(t), v_y(t), 0]^T \}_{[q_n^{(t_{\text{previous}})}] \in S^{b-1}_{t_{\text{previous}}}, b = 1, \ldots, d} \]  \hspace{1cm} (8)

\[ S^0_t = \{ q_n(t) = [x_n, y_n, z_n(t)]^T \}_{n \leq N_{\text{sampling}}, n \in \mathbb{N}} \]  \hspace{1cm} (9)

\[ \mathbf{v}_t = G_{OF}(M_t, M_{t_{\text{previous}}}) \]  \hspace{1cm} (10)

\[ t_{\text{previous}} = t - T_{\text{interval}} \]  \hspace{1cm} (11)
IV. PERFORMANCE EVALUATION

A. Simulation model

To evaluate the practicality of our proposed forecasting architecture, we carried out computer simulations. The experiments are conducted using a discrete-event simulator implemented in Java environment.

The range of data map is 1.0[km$^2$], the node number is 64 or 144, simulation time is 1800[s], and the forecasting calculation interval $T_{\text{interval}}$ is 60[s]. The cloud were created by Perlin noise[10] used for 3D modeling. For the cloud motion, initial wind velocity is 3.00[m/s], variation of the velocity is -0.01~0.01[m/s$^2$], and variation of the direction is -0.001~0.001[rad/s]. We measured the error rates between the forecasting data and the actual measured data for each second, and evaluate the average values normalized by the power output range.

We use Triangulation with Linear Interpolation[8] as scattered data interpolation, and use Block Matching as optical flow estimation.

B. Simulation result

In figure 7 and 8, we show the simulation result of error rate between the forecasting data and actual measured data for each forecasting time. Depth 0 indicates the case in forecasting calculation without virtual sampling. These results show that the forecasting performance is improved as depth $d$ increases.

It is assumed that the cause of error rate reversion as the forecasting time changes in Fig.7 is by characteristic of Triangulation with Linear Interpolation method. In this method, the closer to center of the triangle consists of nearest three sampling points as vertices the forecasting point is, the higher the error rate in this point is. The tendency is remarkable when the sampling density is sparse. We assume that the reason why the tendency decreases as depth $d$ increases is that the sampling number increases by virtual sampling.

Moreover, the improvement of forecasting performance is remarkable when node number is large by comparison between Fig. 7 and 8. Note that there is a limit in the improvement by increase in the sampling number, because there is no substantial change with depth $d \geq 2$. These results show that the forecasting error rate can be decrease to about 60 % by virtual sampling.

V. CONCLUSION AND FUTURE WORK

We propose a forecasting architecture of near future photovoltaic output power based on the multipoint output power data via smart meter. Our proposed method needs no special meteorological observation equipment by using the solar panels connected with a smart meter as sensing units. We show the efficacy of the proposed architecture by the computer simulation.

In the future, we need to compare or propose scattered data interpolation methods suited to forecasting, and evaluate them by actual measured values.

ACKNOWLEDGMENT

This work is supported by PREDICT program of the Ministry of Internal Affairs and Communications (MIC) of Japan.
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