A study of battery SoC scheduling using machine learning with renewable sources

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Abstract

An open energy system (OES) enables the shared distribution of energy resources within a community autonomously and efficiently. For this distributed system a rooftop solar panel and a battery are installed in each house of the community. The OES system monitors the State of Charge (SoC) of each battery independently, arbitrates energy-exchange requests from each house, and physically controls peer-to-peer energy exchanges. In this study, our goal is to optimize those energy exchanges to maximize the renewable energy penetration within the community using machine learning techniques. Future household electricity consumption is predicted using machine learning from the past time series. The predicted consumption is used to determine the next energy-exchange strategy, i.e. when and how much energy should be exchanged to minimize the surplus of solar energy. The simulation results show that the proposed method can increase the amount of renewable energy penetration within the community.

1. Introduction

In recent years, improvements in the technology and reductions to the cost of distributed energy resources (DERs) have led to a rise in popularity of on-site energy sources and storage such as solar panels and batteries (Creara, 2015). To utilize the energy generated by DERs effectively, energy sharing methods between these DERs has been proposed (Zhou et al., 2021; Spasova et al., 2019; Mengelkamp et al., 2017; Wang & Huang, 2016). By sharing electricity between DERs, it is possible to minimize transmission distances, increase resilience to natural disasters, increase the amount of renewable energy penetration, and reduce greenhouse gas emissions.

For stable operation of the power system, it is necessary to maintain the balance between energy demand and supply. Researches have been conducted on forecasts of energy demand and supply in order to efficiently manage the balance of power system (Aslam et al., 2020; del Real et al., 2020; Kuo & Huang, 2018; Ruiz-Cortés et al., 2019). While accurate prediction techniques have been proposed in these studies, no concrete proposals have been made for the control of power systems using the energy prediction results. Especially in the control of DERs, batteries play an essential role for stabilizing intermittent renewable energy generation, and it is important to optimize the energy balancing between these batteries using energy prediction results.

In this paper, machine learning techniques are used to predict next-day energy consumption to make SoC forecasts of individual prosumers. Surplus energy is predicted from state-of-charge (SoC) forecasts, and an energy-exchange strategy is created to share surpluses with neighbors. The open energy system (OES) is a peer-to-peer energy-exchange technology operating in a real-world microgrid in Okinawa, Japan (Werth et al., 2018). Simulation is based on this real system and shows that the individual optimal scenario for minimizing surplus energy leads to an increase in both individual and overall renewable penetration.

2. Microgrid Architecture and battery SoC management

The OES is a bottom-up, distributed energy system that mainly uses renewable energy sources. It consists of multiple subsystems with solar panels, batteries, and DC/DC converters, which are interconnected by a communication line and DC grid, as shown on the left side of Fig. 1. Each subsystem has an energy-exchange scenario that describes the SoC targets of the day, as shown on the right side of Fig. 1. If the SoC is lower than the target, the subsystem requests energy charging. If the SoC is higher than the target, subsystem requests energy discharging. The request

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is negotiated between the subsystems, and if the negotiation succeeds, the energy exchange is executed between the concerned subsystems. Instead of a system-wide optimization, the OES uses best-effort control logic with local optimization that does not require global knowledge.

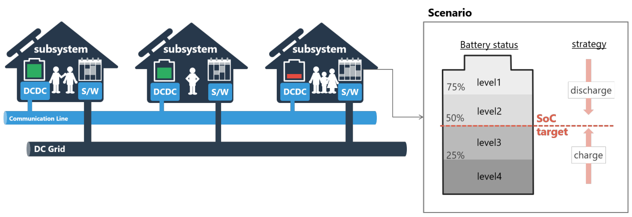

Figure 1. OES structure

3. Machine learning for future SoC target

The energy exchange among subsystems is indirectly controlled through a scenario that describes the SoC target. Currently, in the OES, SoC targets are set in accordance with the daily demand of households with a constant value for 24 hours. However, if the SoC target for each time slot can be set independently, a more flexible energy-exchange strategy could be executed in accordance with the energy conditions for each time slot. In this paper, machine learning is used to predict future surplus amounts and times of solar energy. Then, the SoC target is set to discharge the battery before the surplus occurs, and energy exchanges are executed on the basis of the SoC target. Fig, 2 shows the scenario-generation algorithm using machine learning. The scenario is generated for each subsystem using the following method.

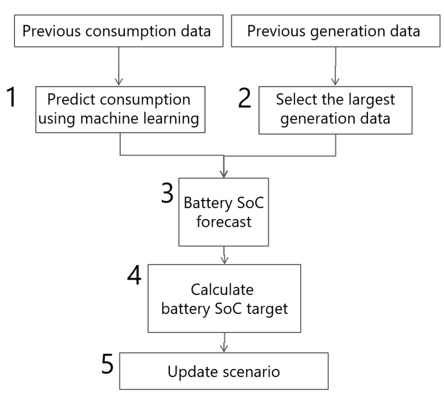

Figure 2. Scenario generation algorithm using machine learning

1. Predict the energy consumption one day in advance from the past energy-consumption data using machine learning. Each vector is composed of 24 elements.

$$\mathbf{X1_{d+1}} = X1_{d+1,0}, X1_{d+1,1}, \cdots, X1_{d+1,23} \tag{1}$$

2. Create energy generation one day ahead from the largest generation date data.

$$\mathbf{X2_{d+1}} = X2_{d+1,0}, X1_{d+1,1}, \cdots, X2_{d+1,23} \tag{2}$$

3. Predict the battery SoC one day in advance from the energy consumption forecast and generation data.

$$\mathbf{Y_{d+1}} = Y_{d+1,0}, Y_{d+1,1}, \cdots, Y_{d+1,23} \tag{3}$$

$$Y_{d+1,i} = \frac{E_0 + \sum_{i=0}^{23}(X2_{d+1,i} - X1_{d+1,i})}{E_{full}} \tag{4}$$

where E_0 is the battery remaining capacity at time $i = 0$, E_{full} is the battery full capacity.

4. Calculate the estimated surplus of solar generation from the predicted battery SoC. The value obtained by subtracting the estimated surplus from the predicted value is the target of the battery SoC.

$$E_{surplus,i} = (Y_{d+1,i} - 100) \times E_{full} \tag{5}$$

$$\mathbf{SoC_{target}} = \mathbf{Y_{d+1}} - \frac{max(E_{surplus,i})_{i=0\sim23}}{E_{full}} \tag{6}$$

5. Update the scenario and execute energy exchanges in the local community.

4. Simulation Setup and Results

4.1. Input Data and Configuration

The period of September 1 to 20, 2018 is selected for the simulation. The subsystem settings are 5.0 kWp for the solar panel, 10.0 kWh for the battery, and 2.5 kW for the DC/DC converter for energy exchange in each house. Okinawa's actual consumption data for six houses with 15-minute resolution is used as energy consumption data, and Okinawa's actual sun radiation data (15-minute resolution) is used to calculate solar generation.

4.2. Prediction by machine learning

Linear Regression, simple RNN (Elman-net), long short term memory (LSTM) are used to predict future energy consumption of each house. In this paper, GUI machine learning tool called Nearal Network Console is used for Elman-net and LSTM as shown in fig. 3, 4. Elman-net consists of one hidden layer. LSTM consists of one hidden layer and input gate, output gate, and forget gate. Original hyperparameters of Nearal Network Console is used for training.

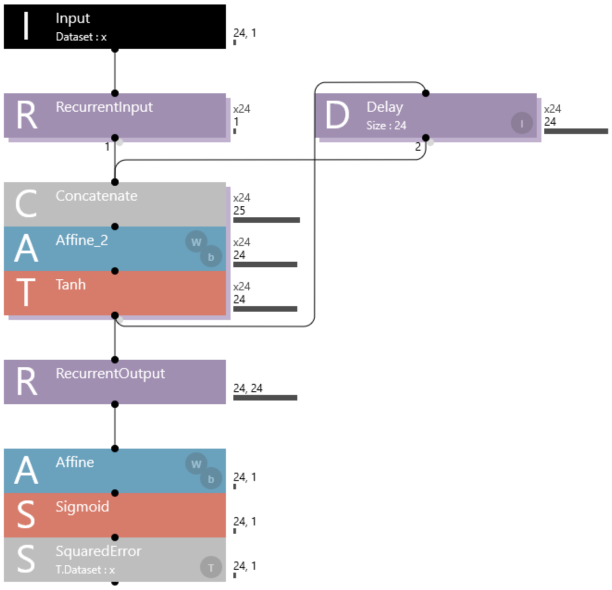

Figure 3. Model of Elman-net

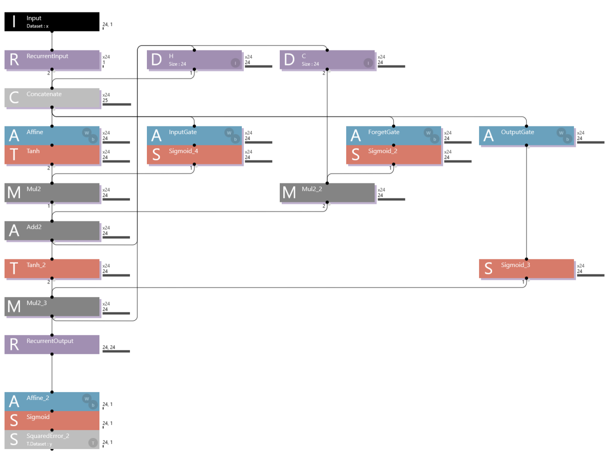

Figure 4. Model of LSTM

The forecast predicts the energy consumption and generation for the next 24 hours from the previous 24 hours. Energy-consumption data from September 1 to 20 is used as training data to predict hourly consumption of September 21 and 22. The consumption model trained each of the six houses. Fig. 5, 6 shows the consumption prediction results and Table 1, 2 shows the mean absolute percentage error (MAPE) of the consumption predictions. Regarding the errors of consumption predictions, Elman-net shows the lowest errors for both days then Elman-net prediction results are used to make the future SoC predictions in next section.

Table 1. MAPE of consumption predictions for September 21

	Linear Regression	Elman-net	LSTM
House1	17.7%	**7.0%**	14.0%
House2	5.9%	**1.9%**	3.5%
House3	20.8%	**5.0%**	12.4%
House4	**5.0%**	5.4%	16.2%
House5	13.8%	**5.5%**	12.7%
House6	31.0%	**11.5%**	38.1%

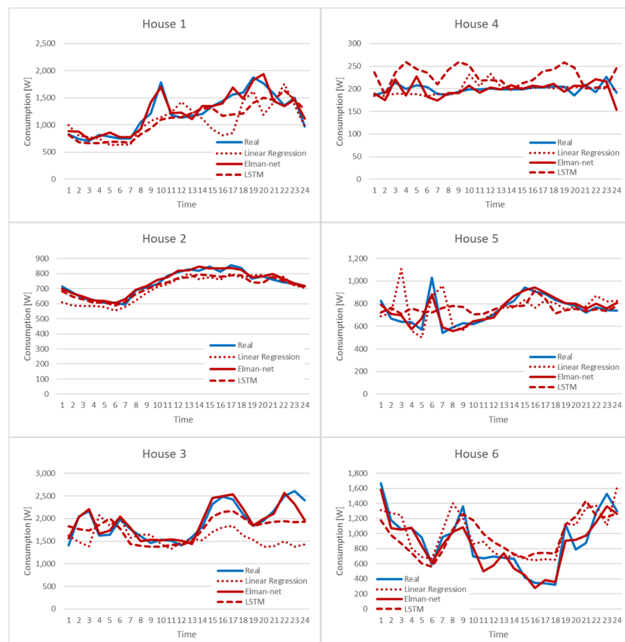

Figure 5. Consumption prediction results for Sept. 21

Table 2. MAPE of consumption predictions for September 22

	Linear Regression	Elman-net	LSTM
House1	14.9%	**5.9%**	22.5%
House2	2.1%	**1.7%**	3.4%
House3	12.2%	**4.7%**	14.9%
House4	6.0%	**5.3%**	17.5%
House5	11.1%	**5.8%**	13.6%
House6	43.8%	**13.7%**	33.4%

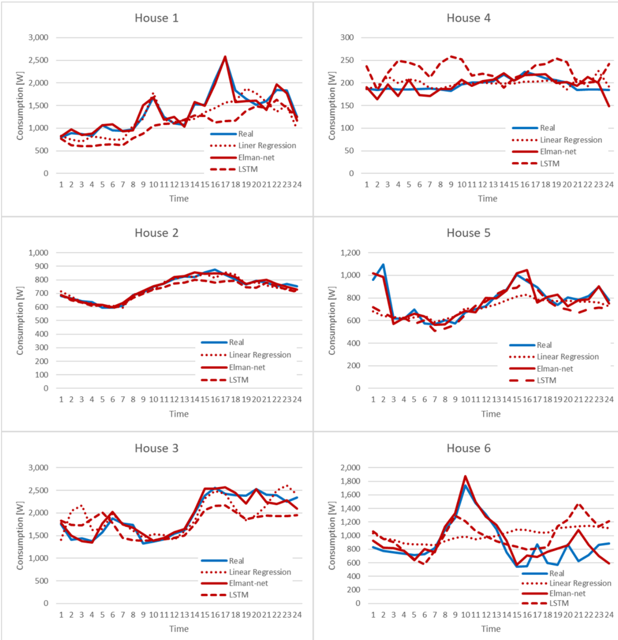

Figure 6. Consumption prediction results for Sept. 22

4.3. Scenario configurations

Simulations were performed for three types of scenario configurations. Case 1 uses the original scenario for all six houses. The original scenario is based on the current operating scenario in Okinawa, which set a fixed SoC target in accordance with the energy demand of the household. The SoC target of House 3, with high demand, is set to 70%; the SoC target of House 4, with low demand, is set to 30%; and the other SoC targets are set to 50%. Case 2 uses a new scenario for House 2 and the original scenario for the other five houses. Case 3 uses the new scenario for all six houses. The new scenario sets an hourly SoC target using Elman-net prediction results. Fig, 7 shows the new scenario of House 2. *SoC prediction* shows the future SoC predicted with Elman-net. *SoC target (new)* is a SoC target in the scenario to prevent solar surplus on the basis of the forecast.

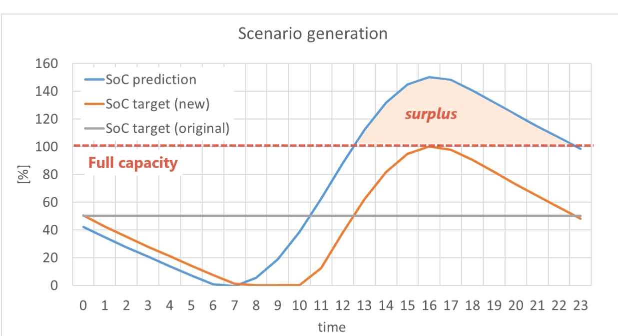

Figure 7. New scenario

4.4. Renewable usage

Solar generation is used to measure how much solar energy could be generate and consume for each case. Table 3 shows the simulation results. In Case 2, House 2 uses the new scenario, and solar generation increases 2.8 kWh from Case 1. As shown in Fig. 8, by discharging from 7:00 to 12:00, it is possible to maintain charging space for the battery and delay the time that the battery is fully charged from after 13:00 to after 15:00. In Case 3, all houses use the new scenario. There was an overall increase of 2.5 kWh in solar generation compared with Case 1. This system does not use global parameters and only optimizes the individual subsystems, but these results show that individual optimization is also effective for community-wide optimization.

Table 3. Solar generation [kWh]

	Case1	Case2	Case3
Community all	**119.4**	119.5	**121.9**
House1	22.8	22.3	22.2
House2	**19.1**	**21.9**	21.0
House3	22.8	22.8	22.0
House4	17.0	15.7	17.4
House5	20.2	20.0	20.4
House6	17.4	16.9	19.0

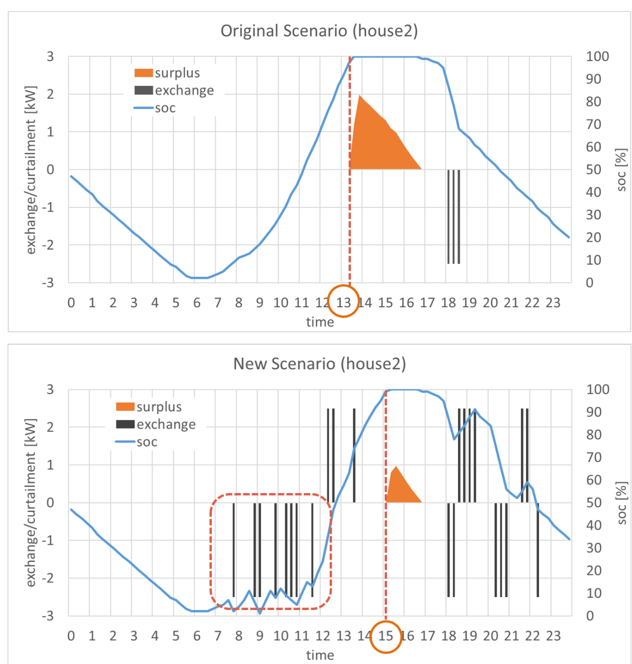

Figure 8. simulation result of house2

5. Conclusion

We conducted a simulation to see if optimizing the energy-exchange scenario with machine learning would lead to an increase in the amount of renewable energy generation based on an OES that accommodates electricity using individually optimized scenarios. Elman-net showed the best accuracy in demand prediction. This simulation was done with a simple machine learning model and limited number of data, but the accuracy can be further improved by using long-term data, variables such as temperature, and fine tune the hyperparameters. The demand forecasting results are used to make energy-exchange strategies and the energy-exchange simulation results showed that by optimizing the scenario of individual subsystems, we could increase the amount of renewable energy generated in that subsystem. In addition, by individually optimizing all subsystems in the community, the community-wide amount of renewable energy generated can be increased. This shows that individual optimization also leads to global optimization. For House1 and House2, the amount of solar generation decreased compared to the original scenario because the battery was charged with more energy than necessary. This could be amended by improving the prediction accuracy and giving a margin to the SoC target so that a surplus does not occur when prediction error occurs.

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