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

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Latest trend in energy system

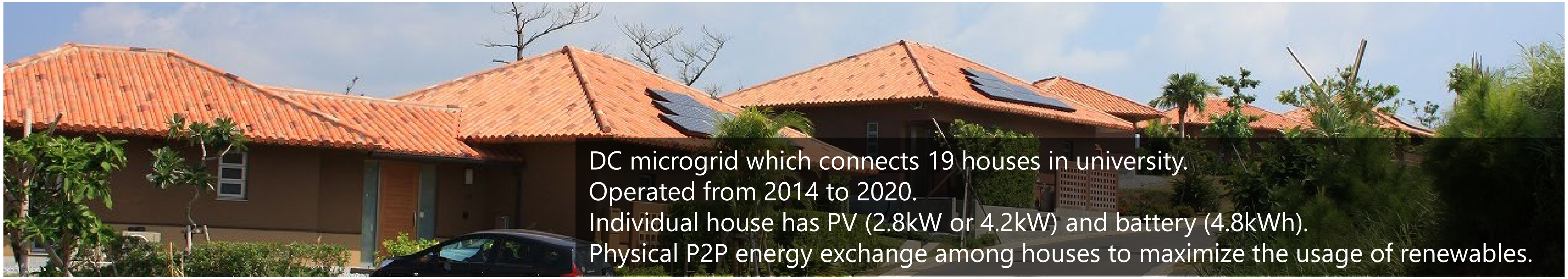
■ Distributed energy resources (DERs)

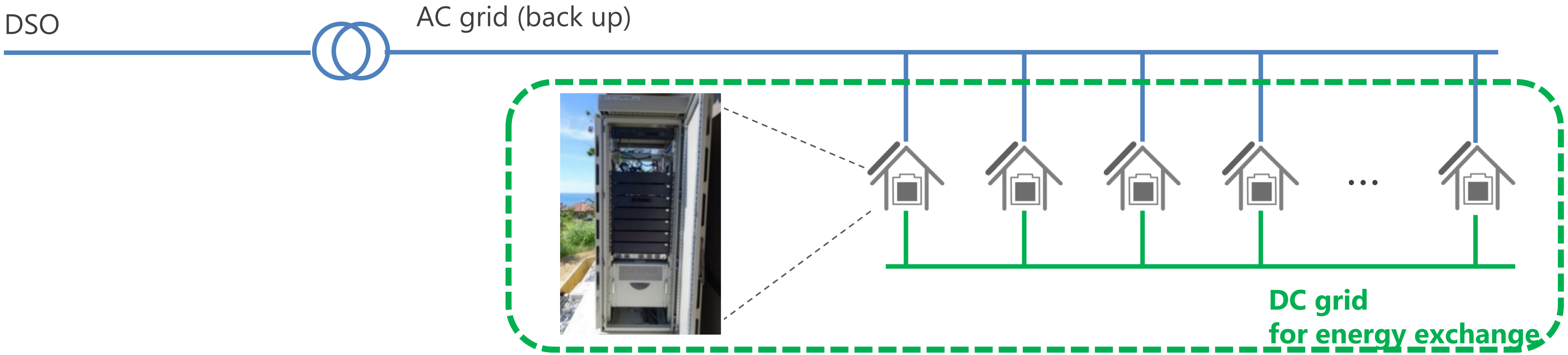
- High demand for carbon free energy (Carbon neutral, RE100, SBT etc.)
- Reductions to the cost of solar panels and batteries
- On-site renewable energy sources such as roof top solar and batteries are increasing

■ Microgrid

- Interconnecting DERs and sharing power within the community
- Efficient use of renewable energy and reduce greenhouse gas emissions
- Increase resilience to natural disasters

Open Energy System (OES)





Maximize the generation of renewable energy: 5% average, 25% max improvement
Resilient against disaster: survive AC grid blackout

The core technology is available in open source: https://github.com/SonyCSL/APIS
Open source project with LF energy: https://www.lfenergy.org/projects/hyphae/

Architecture of OES

SoC: State of Charge

■ bottom-up, distributed energy system

- Consists of multiple subsystems with solar panels, batteries, and DC/DC converters
- Each subsystem has an energy-exchange scenario that describes the SoC* targets of the day
- If the SoC is lower than the target, the subsystem requests energy charging.
- If the SoC is higher than the target, the subsystem requests energy discharging
- The request is negotiated between the subsystems, and if the negotiation succeeds, the energy exchange is executed between the concerned subsystems.
- OES uses best-effort control logic with local optimization that does not require global knowledge

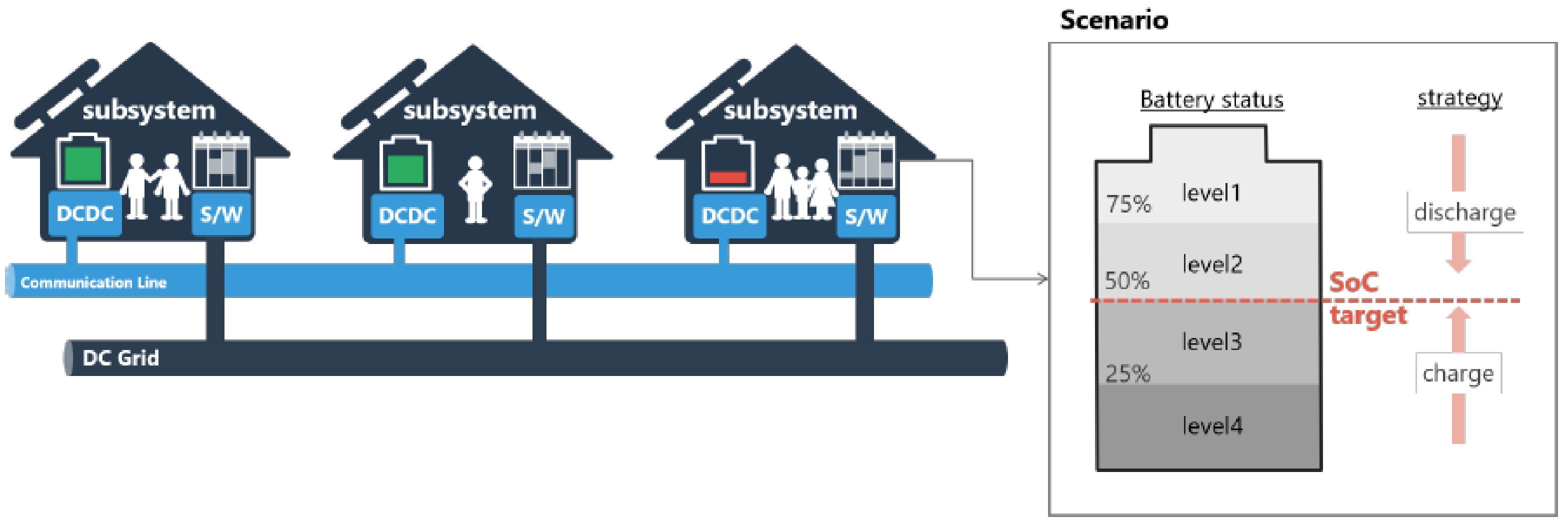


Figure 1. OES structure

Why machine learning ?

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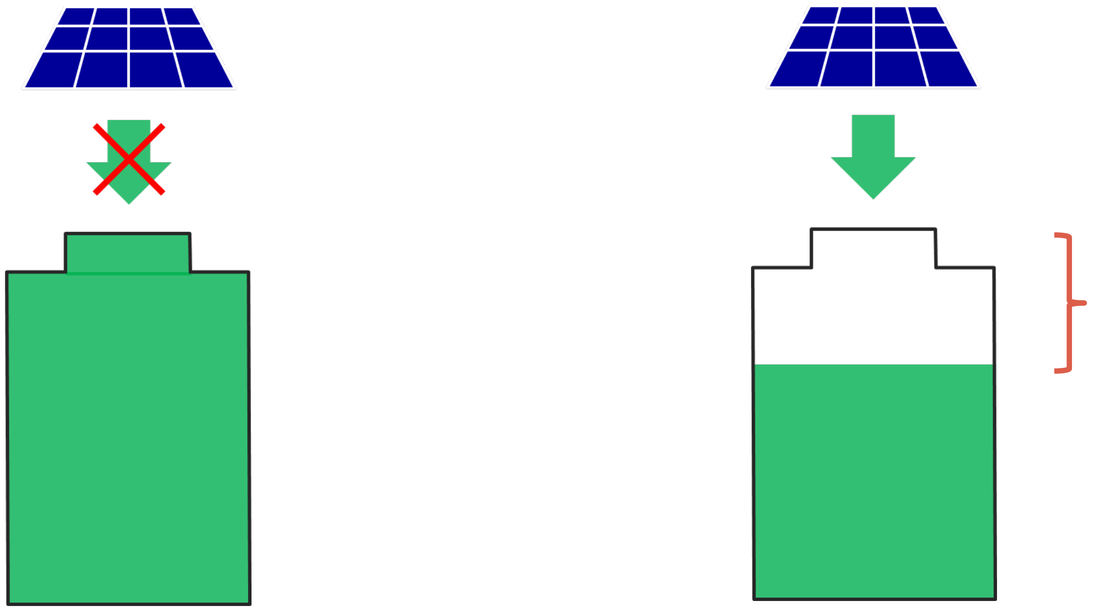
■ Optimize battery SoC target and maximize renewable energy

- Keep charge space in the battery to prevent the surplus of renewable energy
- Predict the future battery state of charge (SoC) level and discharge battery energy before it becomes full
- Battery SoC could be predicted from the amount of energy generation and consumption forecast.



Use ML to predict future battery SoC and prepare charge space for renewable generation

Fully charged -> surplus

Charge space -> introduce renewable energies

Proposed algorithm

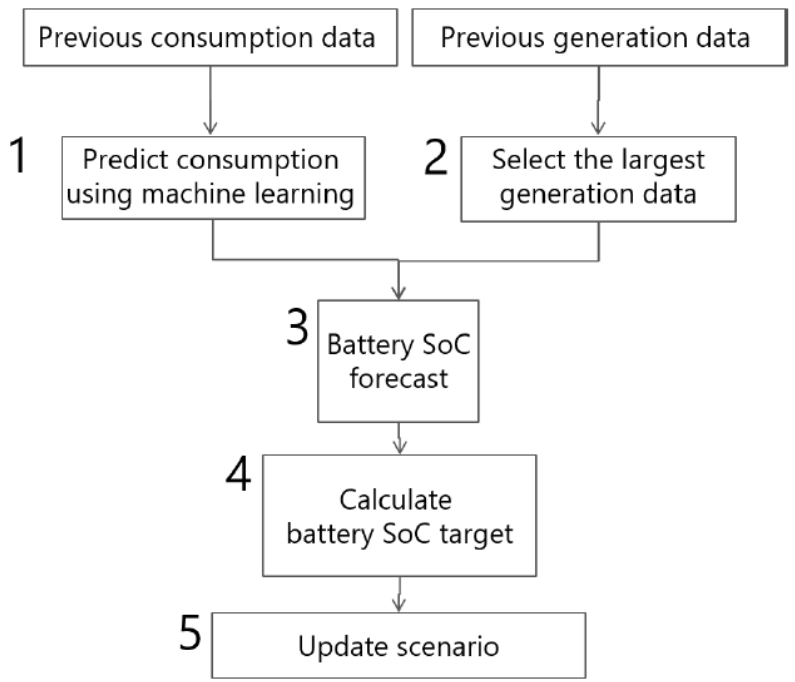


Figure 2. Scenario generation algorithm using machine learning

1. Predict consumption

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

2. Select generation data

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

3. Battery SoC forecast

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

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

4. SoC target

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

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

Prediction by machine learning

Conditions

- Input data
  - September 1 to 20, 2018
  - Okinawa's actual consumption data for six houses with 15-minute resolution and sun radiation data
- System configuration
  - 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.
- Models
  - Linear Regression, simple RNN (Elman-net), long short term memory (LSTM)

Result

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%

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%

Machine learning models

- **Neural Network Console is used for machine learning**

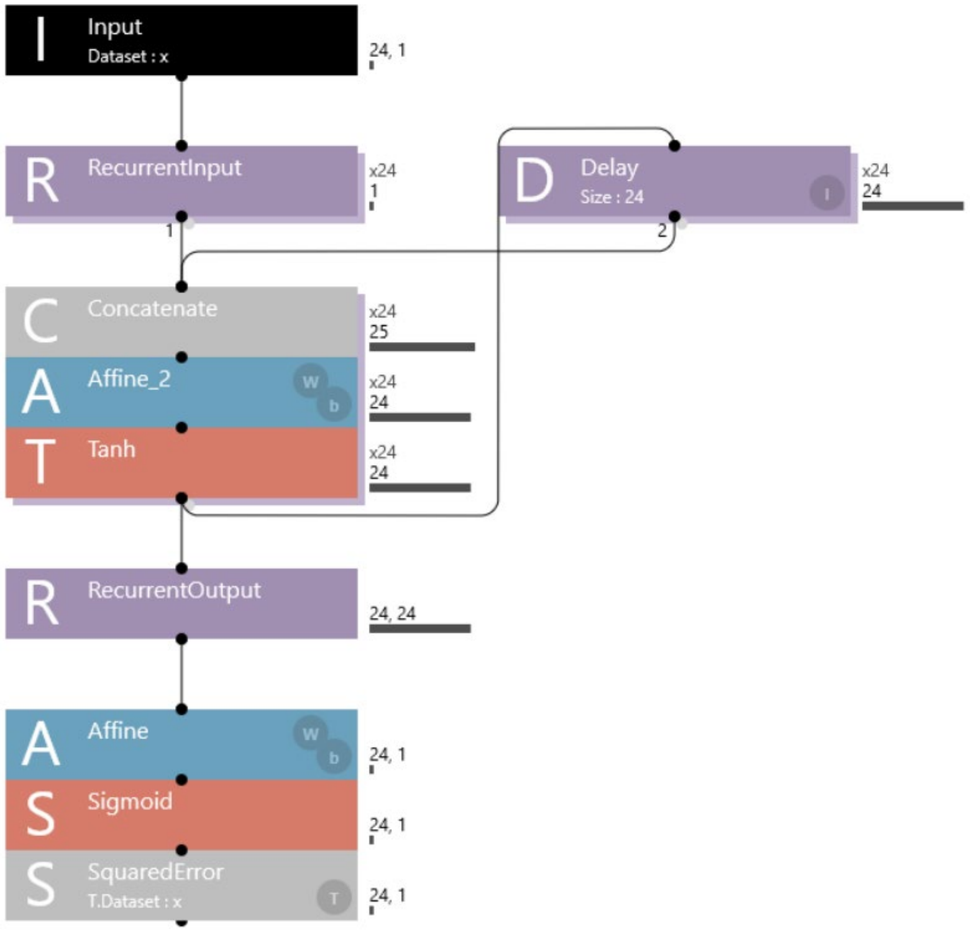


Figure 3. Model of Elman-net

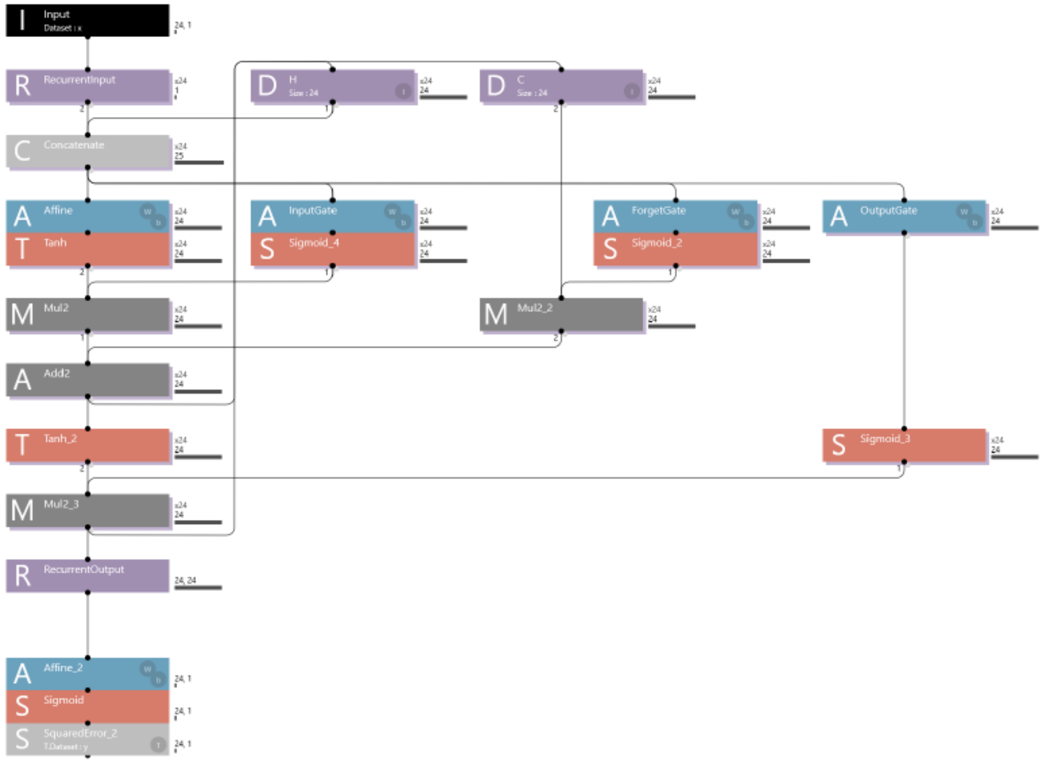


Figure 4. Model of LSTM

Consumption predictions

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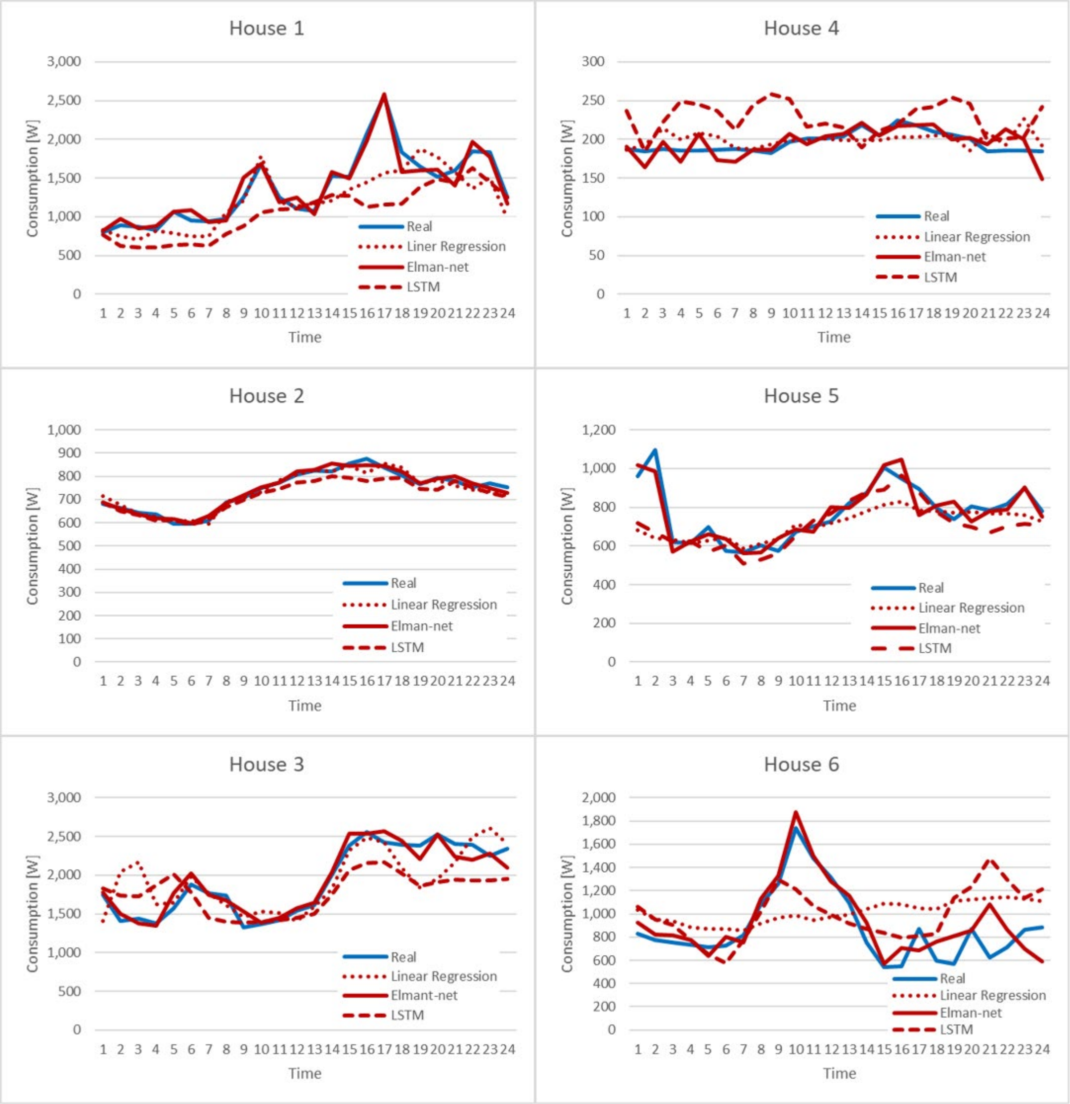

Figure 5. Consumption prediction results for Sept. 21

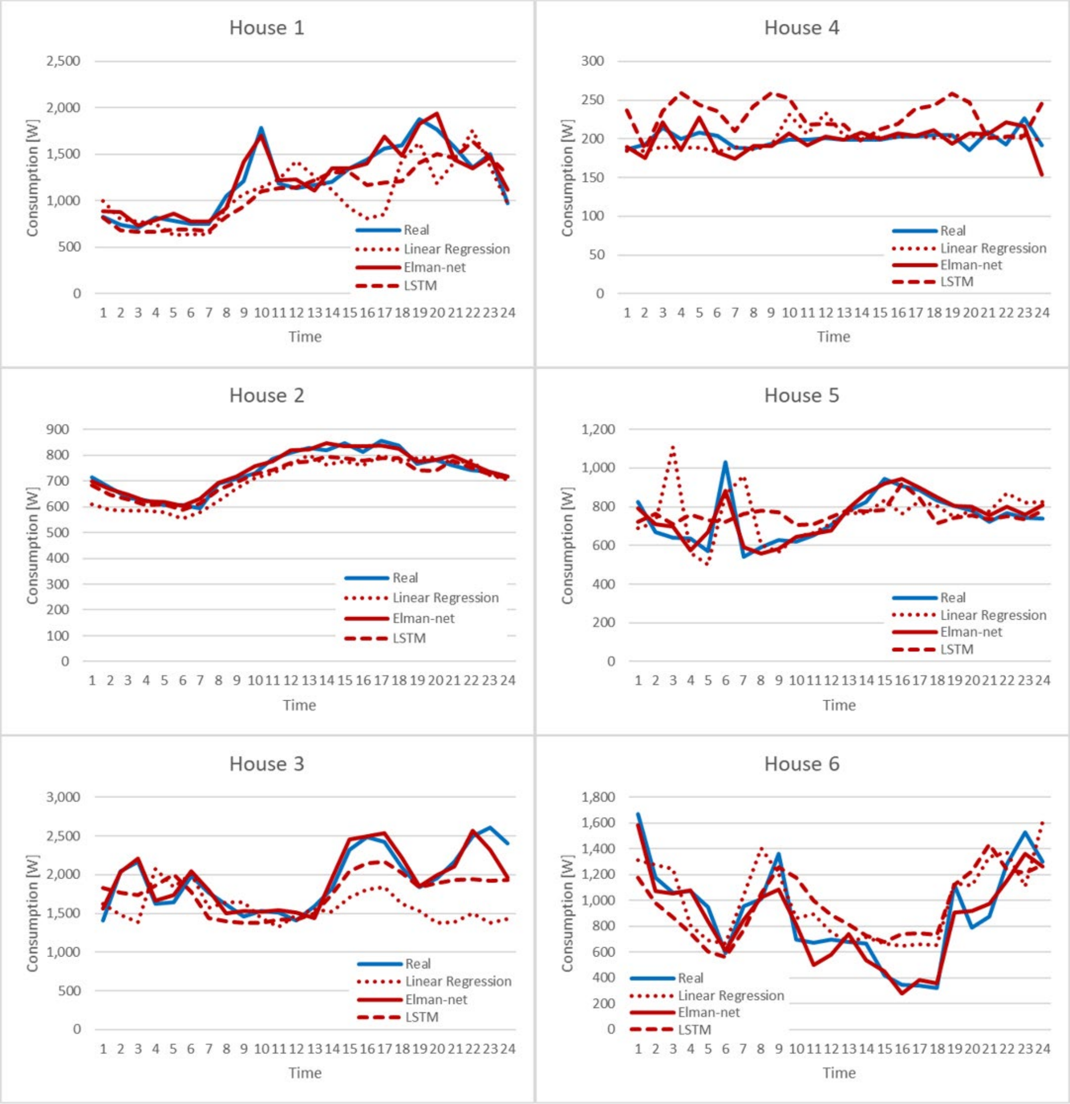

Figure 6. Consumption prediction results for Sept. 22

Scenario configurations

■ SoC target for the Scenario

- SoC prediction: future SoC predicted with Elman-net
- SoC target (new): SoC target to prevent solar surplus on the basis of the forecast
- SoC target (original): Original SoC target which sets to 50% for 24 hours

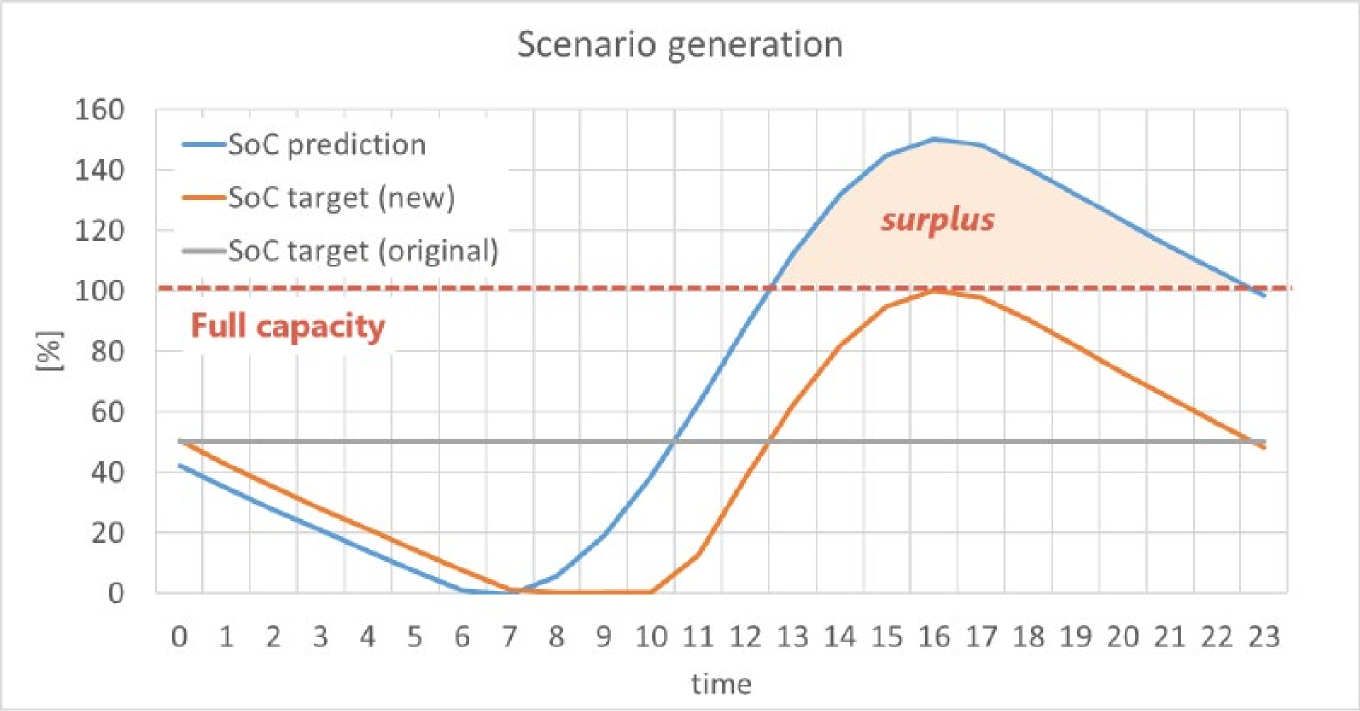

Figure 7. New scenario

Renewable usage

Solar generation

- Case 1: All houses use the original battery SoC target
- Case 2: House 2 uses the new battery SoC target
- Case 3: All houses use the new battery SoC target

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

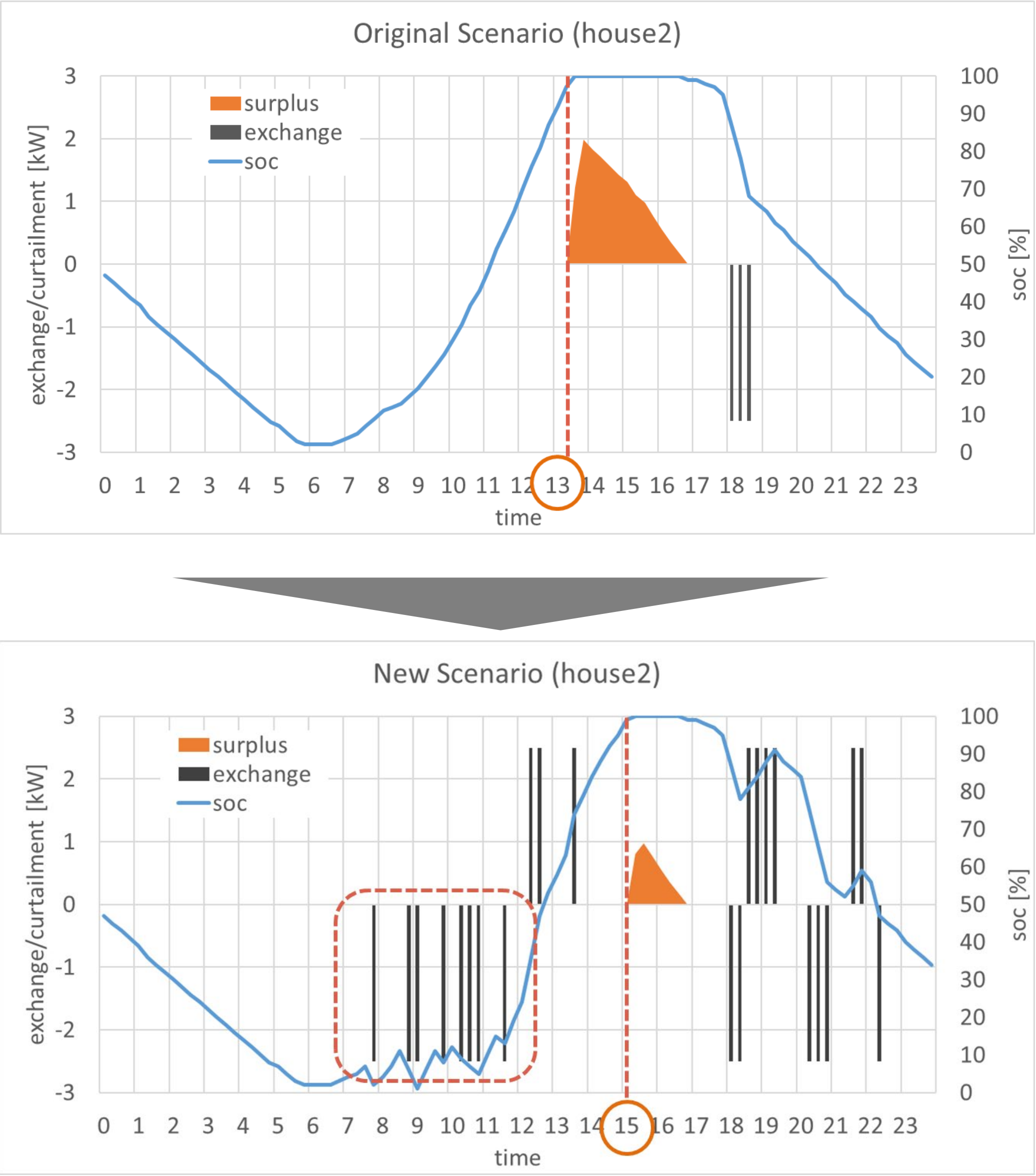

Figure 8. simulation result of house2

Conclusion / Future directions

Conclusion

- Elman-net showed the best accuracy in demand prediction
- Renewable energy generated in the can be increased by using the energy-exchange strategies based on demand forecasting results.

Future directions

- Improve accuracy of prediction by using long term demand data, adding external input variables such as weather.
- Study for the prediction time resolution which best match to the battery charge / discharge control.

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