NUS
National University of Singapore

ENERGY MANAGEMENT & ECONOMIC EVALUATION OF GRID-CONNECTED MICROGRID OPERATION

Presented by: Hau Chong Aih (A0111953L)
Supervisor: Prof. Sanjib Kumar Panda
Examiner: Prof. Dipti Srinivasan

Contents

Microgrid Architecture

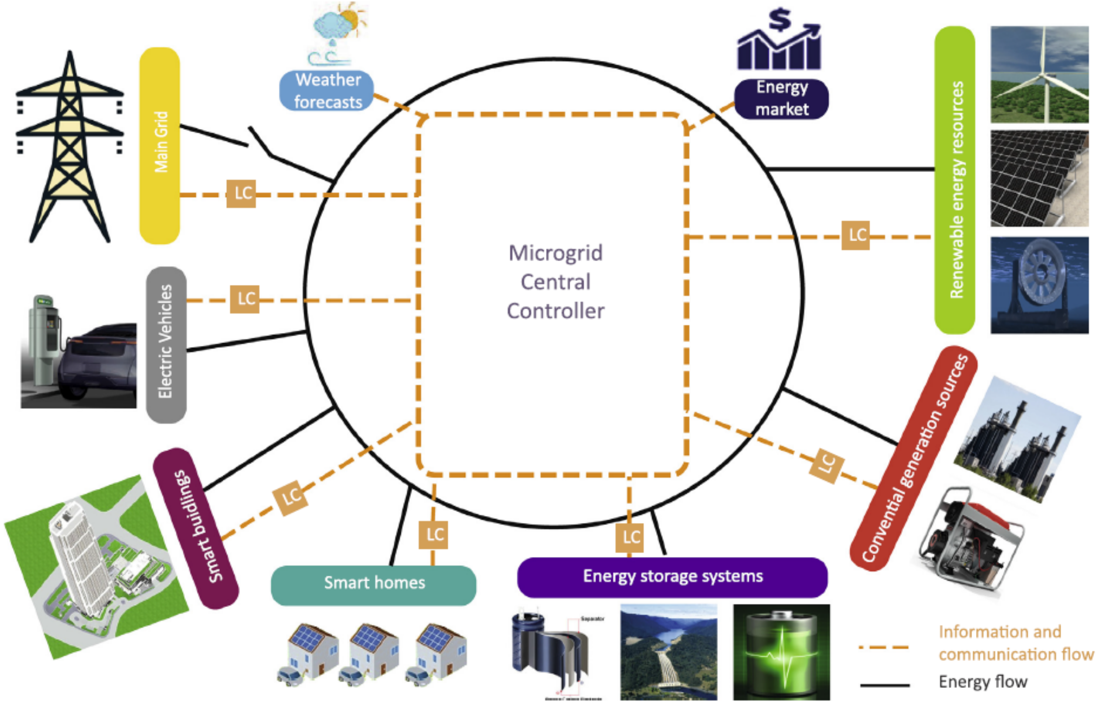


Figure 1. Microgrid Architecture

Literature Review

Objective Function — Identify the objective of microgrid energy management system

Uncertainty Management — Identify the approach of handling uncertainty result from renewable energy or load

Optimization Techniques — Identify the techniques in finding the optimal solution

Literature Review – Objective Function

GHG emission cost

[4],[5].[6],[12],[10]

Energy transaction cost

[1],[4],[7],[8],[9],[13],[14],[15]

Reliability

Physical limit of ESS

Energy balancing

Load shedding penalty

[3],[11],[16]

Demand response incentives

[2],[10]

Network loss

[12],

Operation and maintenance cost of ESS/ battery

[12],[13],[14],[16]

Operation and generation cost of generator

[3],[5],[6],[12],[15],[10]

Literature Review – Uncertainty Management

Known Forecasted

[2],[3],[4],[8],[12]

No Measurements

[13],[14]

ARMA

[11]

Neural Network

[1],[5],[6],[7],[11]

Scenario generation method

[15],[16]

Markov Chain

[9]

Literature Review – Optimization Techniques

MILP/ MINLP/ MLP
[1],[2],[3],[15],[16]

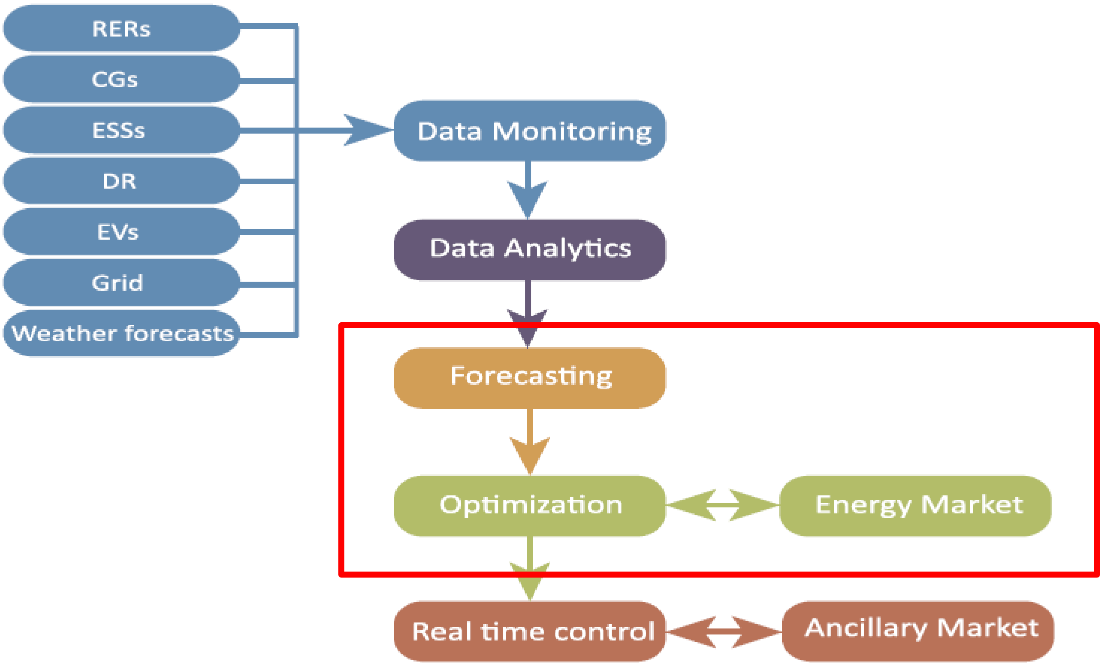
NN (Lagrange NN)/ RL
[5],[6],[7],[8],[9],[13],[14]

Rule-based
[4],[11]

Model Predictive Control (with MILP)
[10]

Meta-heuristics (GA, PSO)
[12]

Literature Review – Microgrid Energy Management Function Summary



Motivation & Research Objectives

- Study role of ESS being a source of contingency reserve on top of energy trading medium.

- Study and identify the optimal energy management algorithms to maintain microgrid's reliability (maintain critical-mission operation during outbreak of main grid) and maximize monetary benefits.
  - Formulate an objective function and constraint for model predictive control
  - Identify the optimal forecasting models used in model predictive control
  - Design a reinforcement learning based algorithm and a suitable reward function.

- Develop a graphical user interface for good visualization of algorithms' decision.

Model Predictive Control Linear Programming With Forecast Future Knowledge

- **Model predictive control (MPC)** – an advanced process control method that allows the process at the current time step to be optimized while keeping the future time steps into account.
- **Linear programming (LP)** – an optimization method solve problem with linear objective functions and constraints.
- **Forecasting models** – models to predict the consumer load, solar power and electricity price.
- **Model predictive control linear programming (MPCLP)** – to optimize the energy transaction each hour based on the current and future information.

Model Predictive Control Diagram

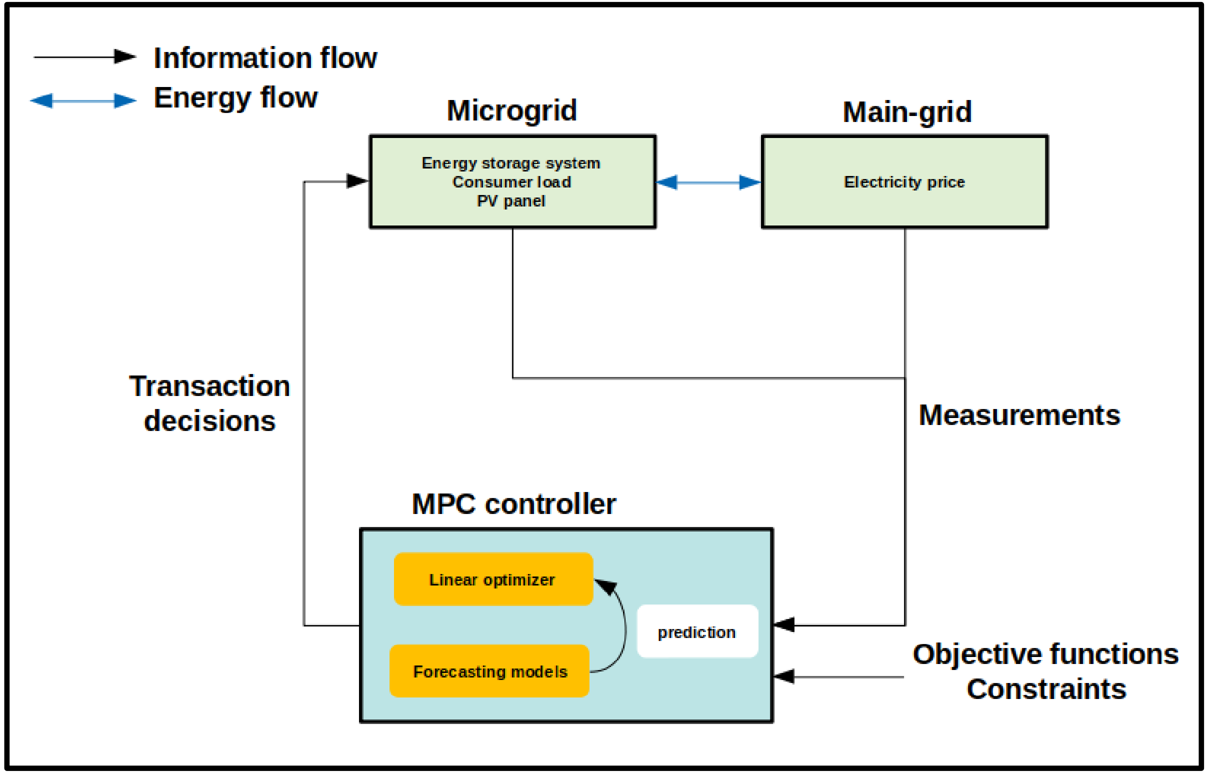


Figure 2. Model Predictive Control

Linear Programming Objective Function

- **Objective function** – minimize the cost of purchasing electricity from the main grid → when there is no solar power, ESS operation depends on the electricity price; charge (discharge) when solar power is higher (lower) than consumer load.

Variables to be optimized

$$Obj_t = min \sum_{t_k=t}^{t+23} [(Pr_{t_k} + k) \times A_{t_k} \times P_{rated} \times \frac{L_{t_k}}{L_{t_k} + PV_{t_k}}]$$

This term handles
1) transaction cost
2) optimal use of ESS

This term serves as a multiplier based on the solar power and consumer load

Linear Programming Constraint

- **Constraints** – 1) ESS operates within the physical limit; 2) ESS reserves a sufficient amount of energy for critical-mission operations

Energy capacity limit

$$\begin{bmatrix} A_t & 0 & 0 & \dots & 0 \\ A_t & A_{t+1} & 0 & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots \\ A_t & \dots & \dots & A_{t+22} & 0 \\ A_t & \dots & \dots & A_{t+22} & A_{t+23} \end{bmatrix} \times \frac{Prated}{E_{rated}} <= \begin{bmatrix} 1 \\ 1 \\ \dots \\ 1 \\ 1 \end{bmatrix} \times (1 - SOC_t)$$

Energy capacity limit & contingency reserve

$$\begin{bmatrix} A_t & 0 & 0 & \dots & 0 \\ A_t & A_{t+1} & 0 & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots \\ A_t & \dots & \dots & A_{t+22} & 0 \\ A_t & \dots & \dots & A_{t+22} & A_{t+23} \end{bmatrix} \times \frac{-Prated}{E_{rated}} <= \begin{bmatrix} 1 \\ 1 \\ \dots \\ 1 \\ 1 \end{bmatrix} \times (SOC_t - SOC_{target})$$

Power operation limit

$$A_{t_k} \in [-1, 1] \, \forall t_k \in \{t, t+1, \dots t+23\}$$

Forecasting Models

- Forecasting models are used to predict the information of future time steps which is used in linear programming for optimization.
- **Models** – Long-short-term-memory (LSTM), sequence-to-sequence (Seq2Seq), attentive sequence-to-sequence (AttSeq2Seq), transformer (TX). The performance of models are compared and analysed.
- **LSTM** – a special type of neural network to capture dependencies between time steps.

Forecasting Models (Cont'd)

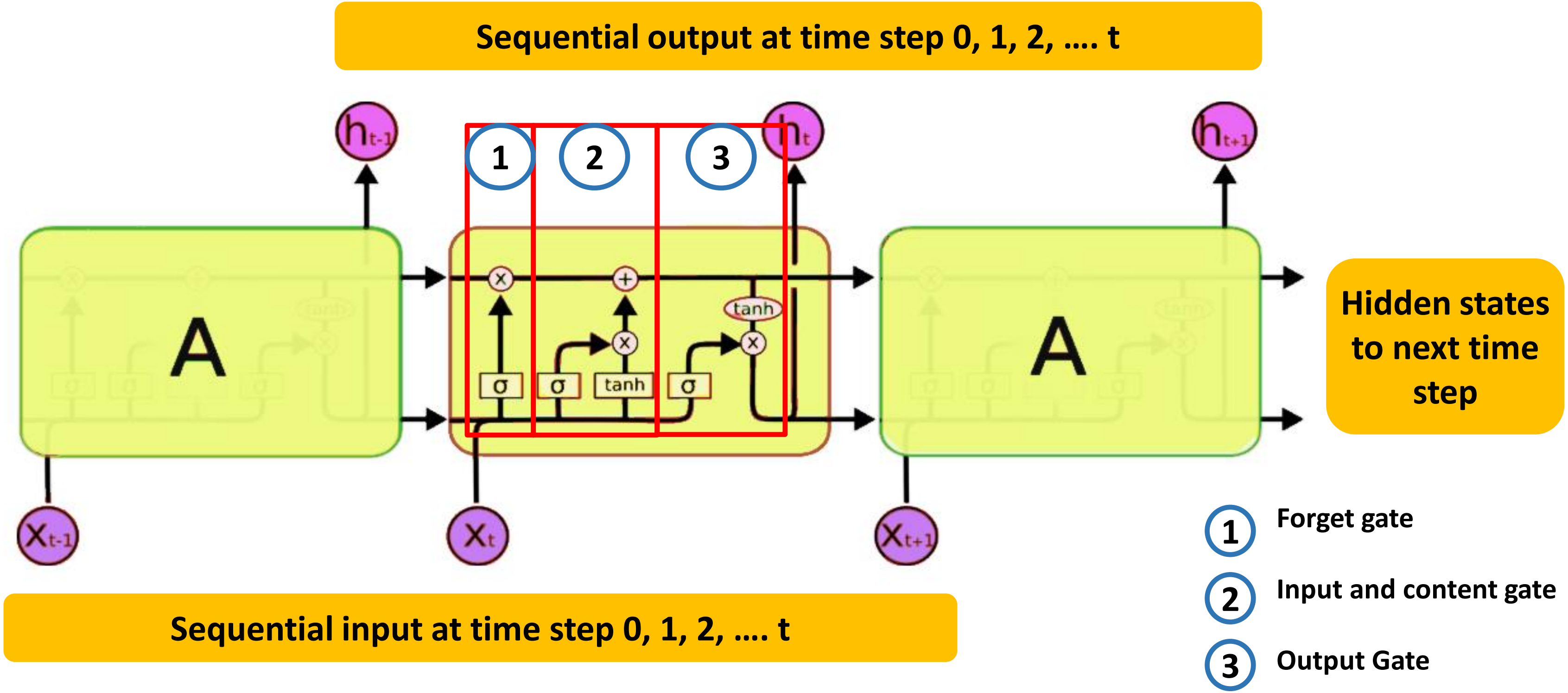


Figure 3. Architecture of LSTM

Forecasting Models (Cont'd)

- **LSTM Model** – Stacked LSTM to form LSTM model. Use the last hidden state of LSTM for prediction of outputs.

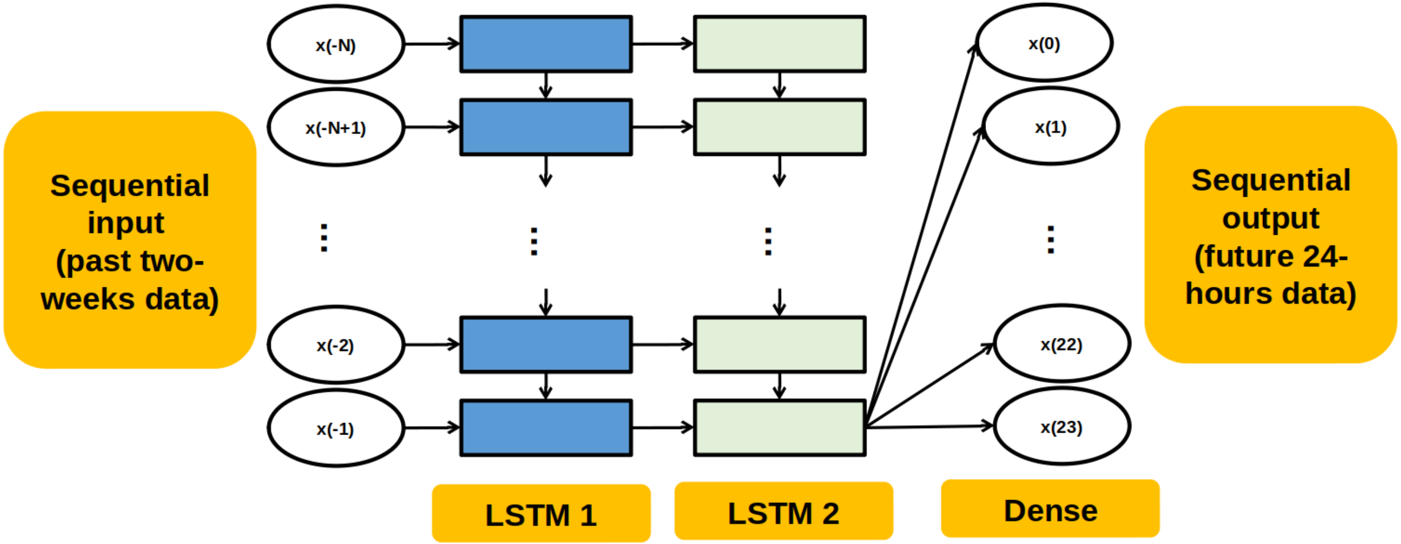


Figure 4. LSTM Model Architecture

Forecasting Models (Cont'd)

- **Seq2Seq Model** – Capture the sequential dependency of the targets when making the prediction. Comprises 2 deep LSTM layers acting as encoder and decoder.

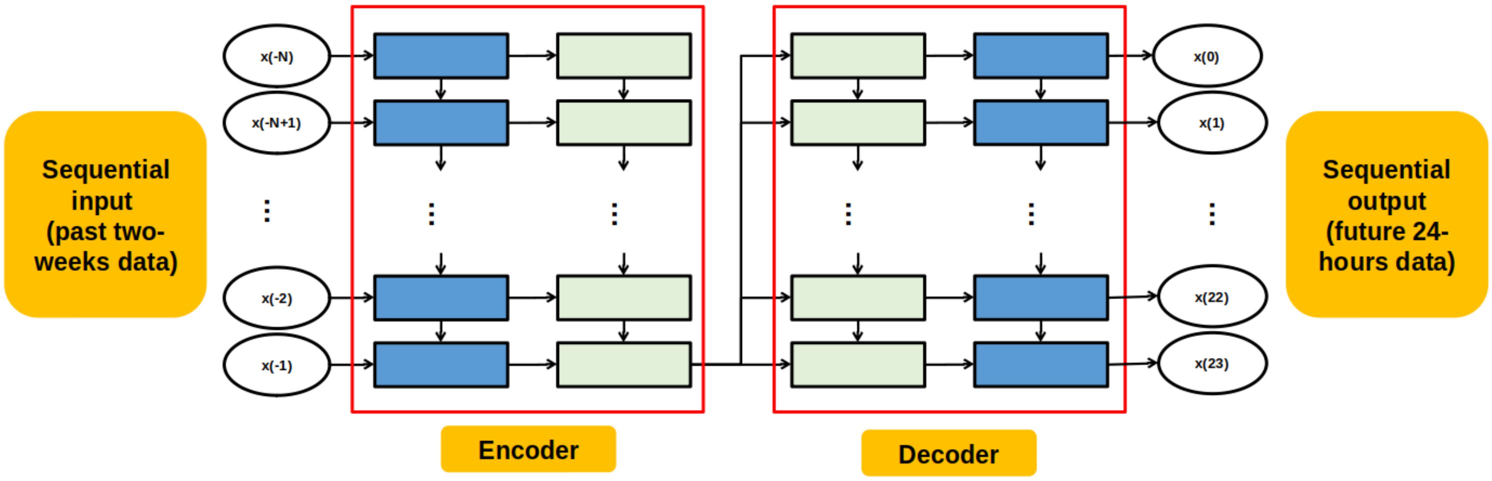


Figure 5. Seq2Seq Model Architecture

Forecasting Models (Cont'd)

- **AttSeq2Seq Model** – By having the attention layer in place, the decoder knows which hidden states of the encoder it should pay more attention in order to achieve a better result.

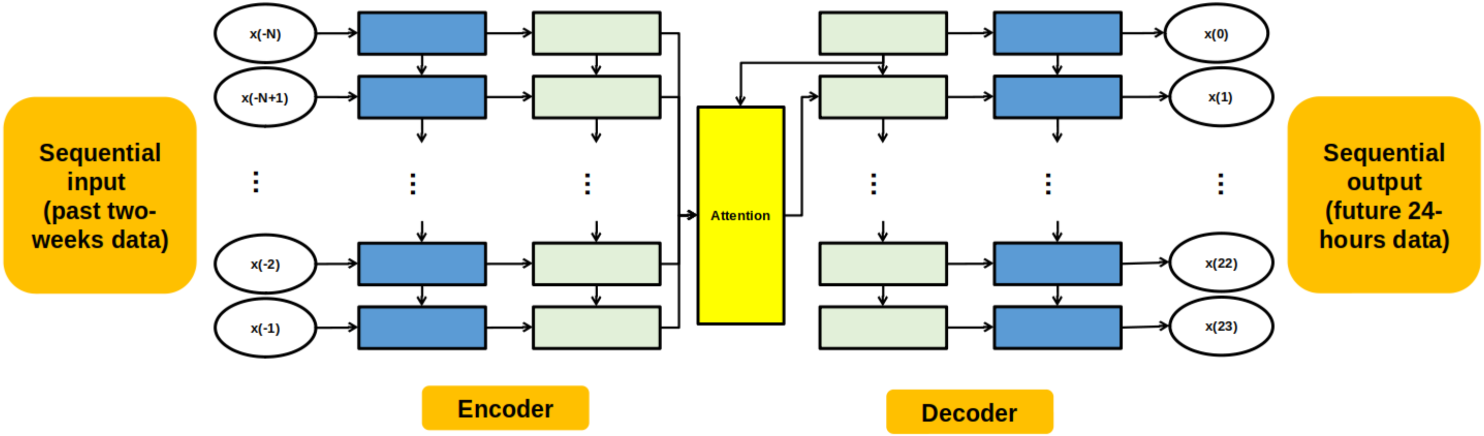


Figure 6. AttSeq2Seq Model Architecture

Forecasting Models (Cont'd)

- **Convolution neural network –** Train a convolution kernel to capture pattern presents in the data.

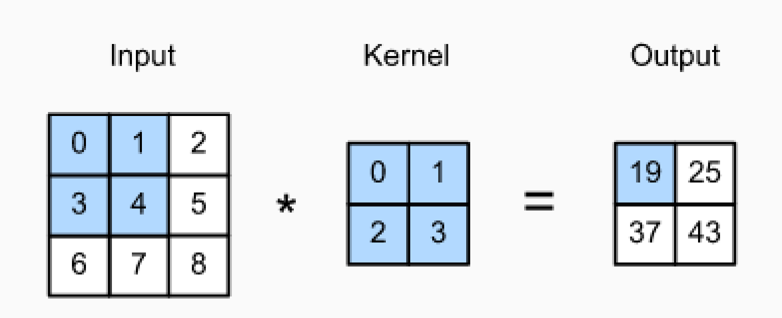


Figure 7. Example of Convolution Kernel

- **TX Model** – replacement of LSTM layer with convolution layer for faster training due to parallel computation.

Forecasting Models (Cont'd)

- **TX Model (Cont' d)** – used in Natural Language Processing (NLP) problem. Attention is found between encoder sequences and between encoder and decoder sequences.

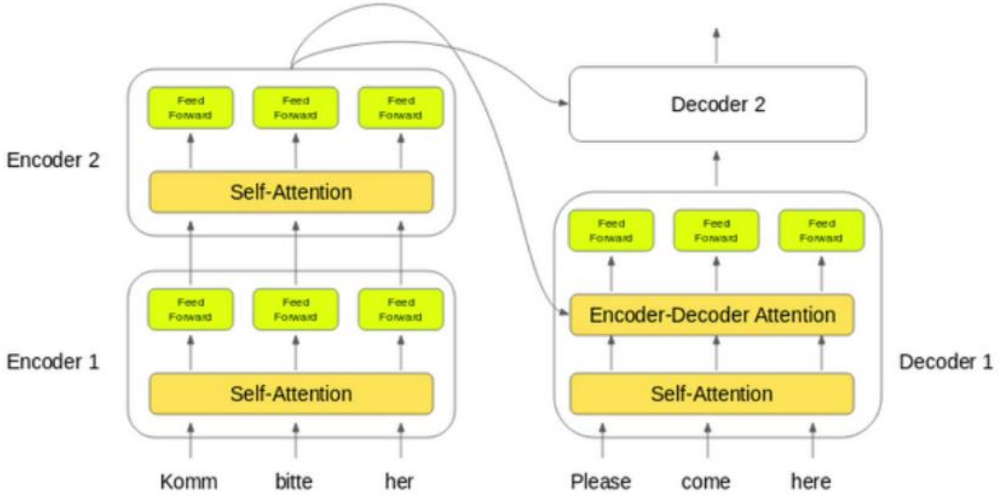


Figure 8. Example of TX Model in Translation

Forecasting Models (Cont'd)

- **TX Model** – Adapt the model to suit the forecasting requirement.

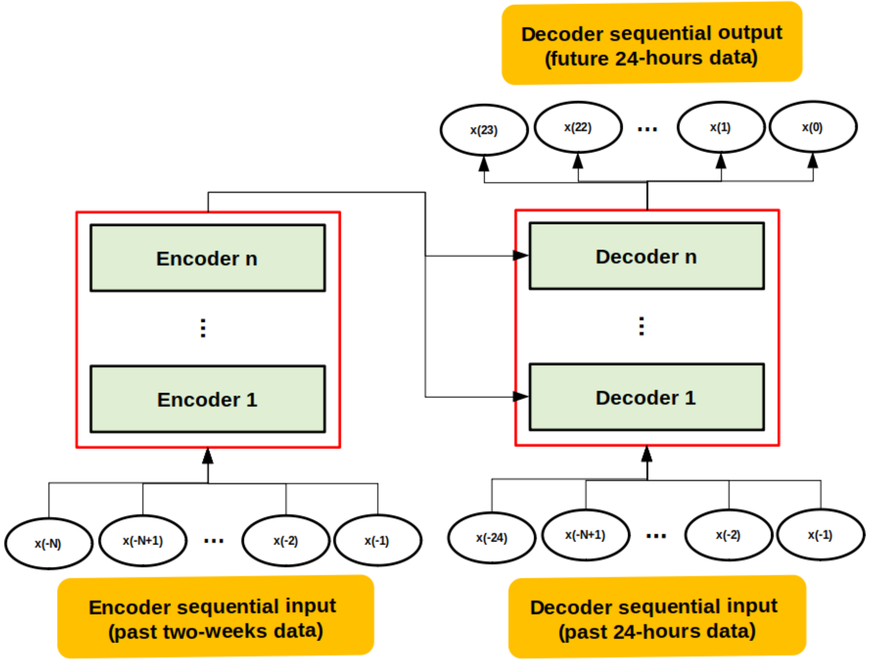


Figure 9. TX Model Architecture

Forecasting Results (Cont'd)

- 4 models are trained for consumer load, solar power and electricity price respectively.

- The performance is evaluated by computing the mean absolute error of each dataset and the optimal models with the lowest MAE are identified.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - \hat{Y}_i\right|$$

Forecasting Results (Cont'd)

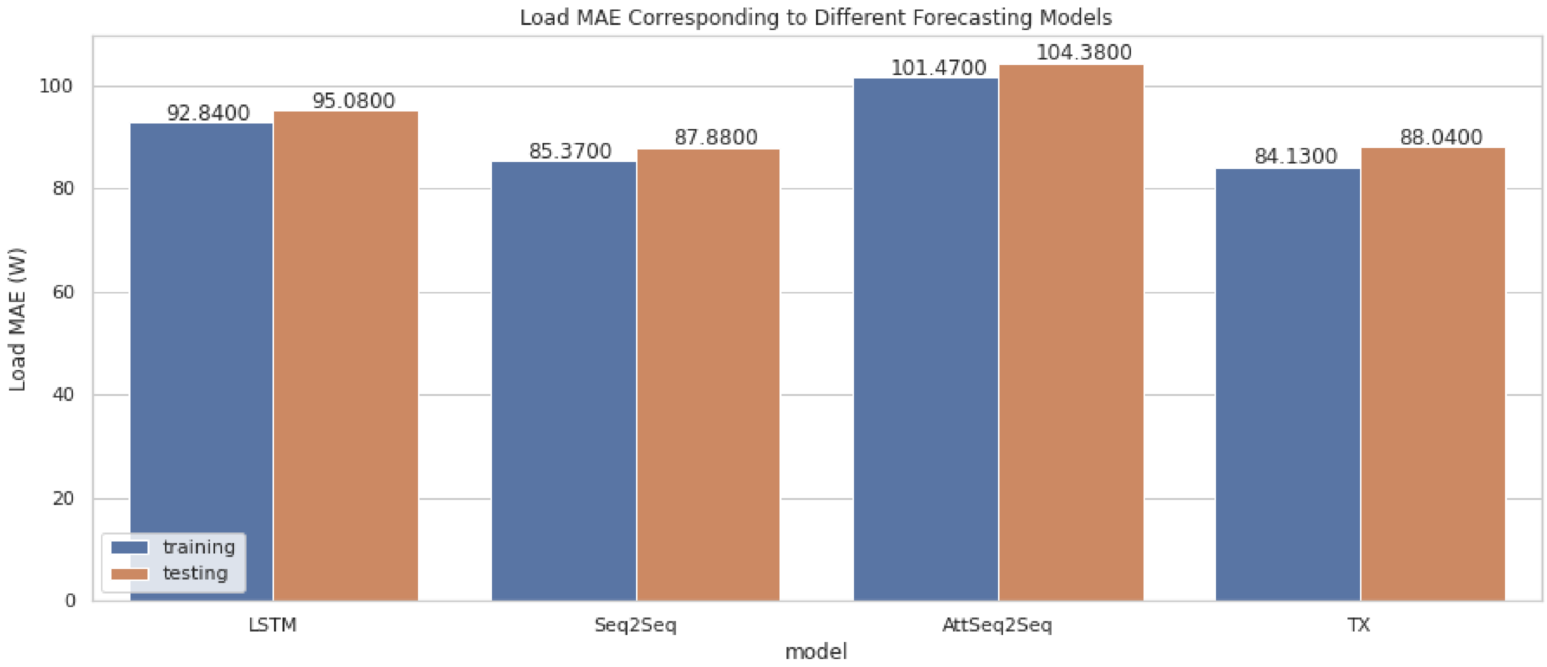


Figure 10. Consumer Load MAE Corresponding to Different Forecasting Models

Forecasting Results (Cont'd)

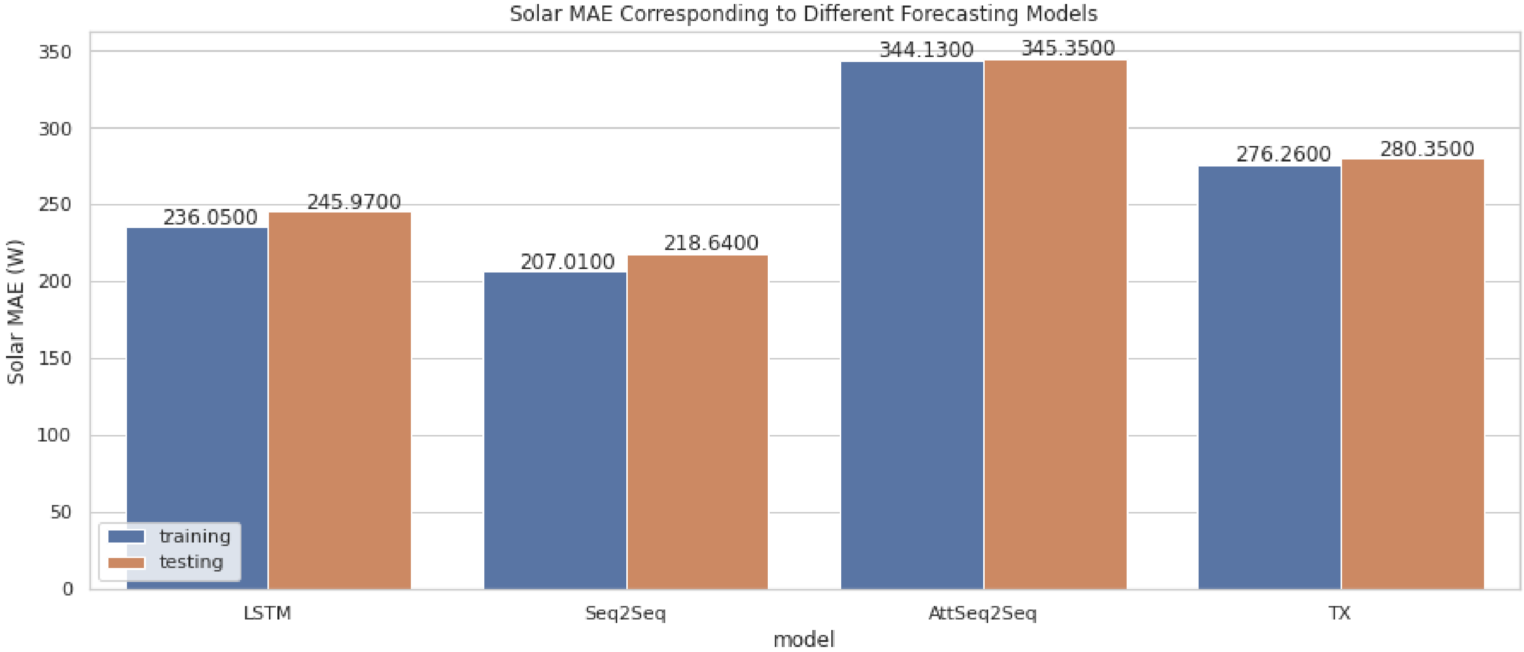


Figure 11. Solar Power MAE Corresponding to Different Forecasting Models

Forecasting Results (Cont'd)

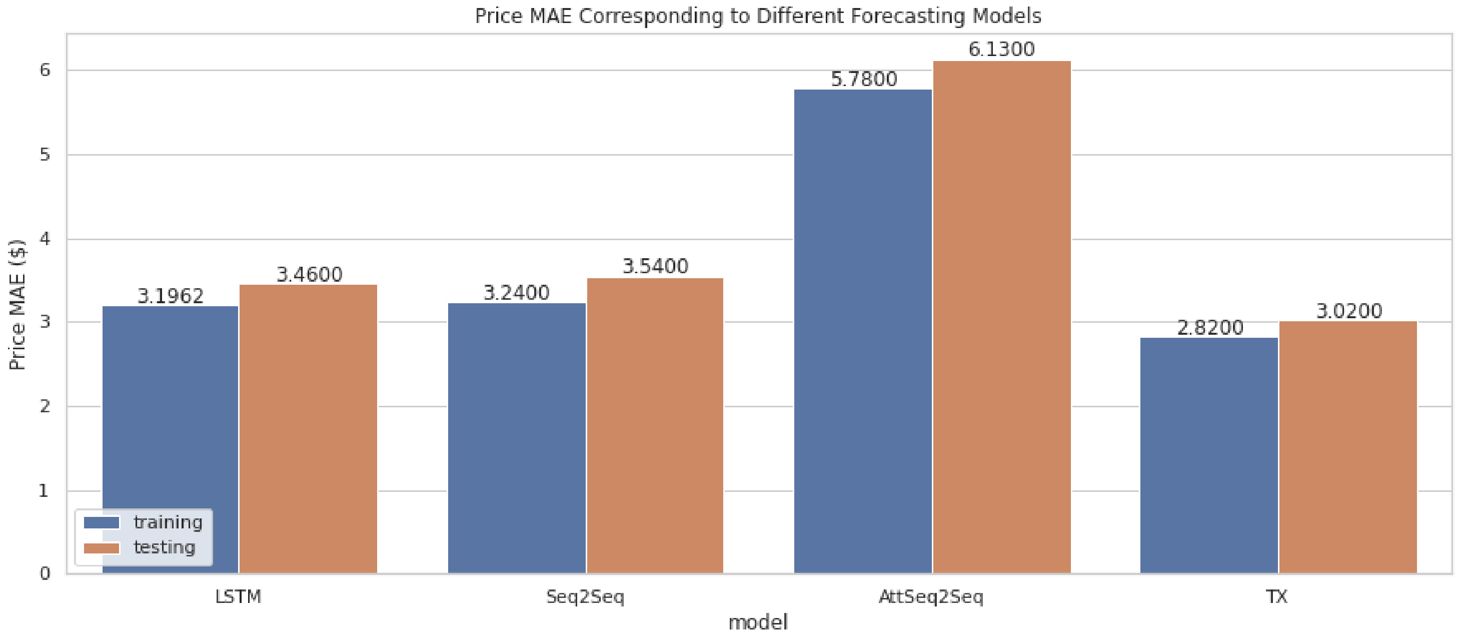


Figure 12. Price MAE Corresponding to Different Forecasting Models

Forecasting Results (Cont’d)

- Seq2Seq model performs the best in consumer load and solar power predictions while TX model has the lowest MAE in electricity price prediction.

- AttSeq2Seq model has the worst performance.

- LSTM model has the average performance.

- TX model works better in electricity price due to the vastly different pattern which makes it easier to generate accurate attention map.

Forecasting Results (Cont'd)

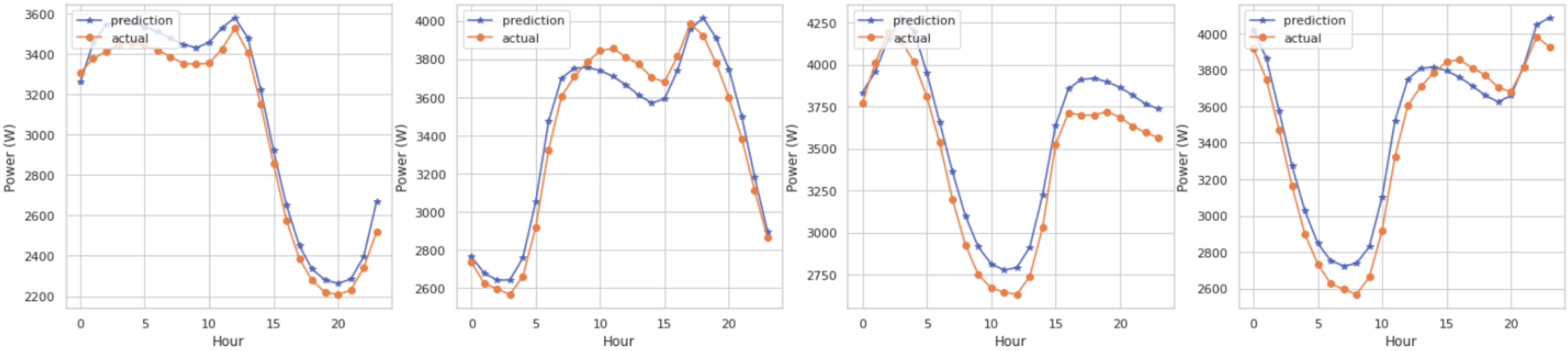


Figure 13. Consumer Load Predictions of Seq2Seq Model

Forecasting Results (Cont’d)

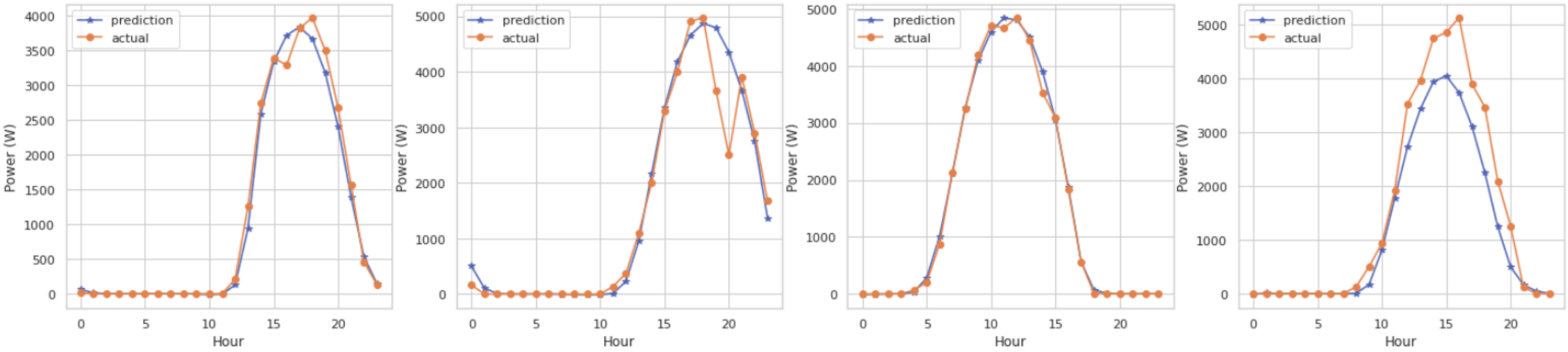


Figure 14. Solar Power Predictions of Seq2Seq Model

Forecasting Results (Cont'd)

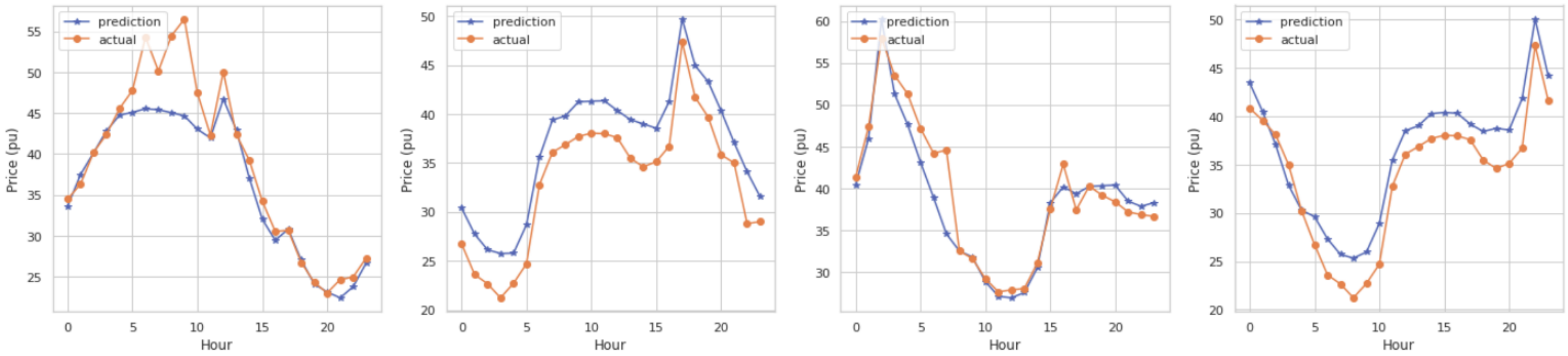


Figure 15. Electricity Price Predictions of TX Model

Reinforcement Learning With No Future Knowledge

- **S_t - States**
  Load (P_t), real time price (Pr_t), average real time price (${Pr_t}^{avg}$), state of charge (SOC_t)

- **A_t - Actions**
  (Dis)charging action ϵ [-1,1] with interval of 0.2 (multiplied with the ESS rated power)

- **r_t or u_t - Reward**
  Reward received after each action at certain state

- **R_t or Q_t - Return or Q-value**
  Expected sum of discounted reward following certain policy

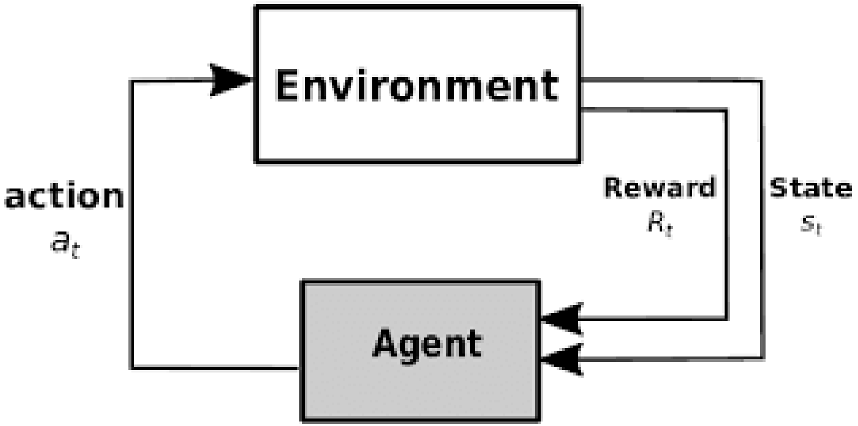


Figure 16. Reinforcement Learning

Objective is to find the optimal policy results in the best return after training

Reward Design

- **Transaction cost**
  To maximize the monetary benefit by comparing how much cheaper (more expensive) to buy at real time price as relative to past-24 hour real time price.

- **ESS wear and tear cost**
  To avoid unnecessary action to prolong the lifetime of ESS.

- **Microgrid reliability**
  To maintain microgrid's reliability, the amount of contingency reserve (ESS target SOC) for the critical device operation during a power outage of main grid should be maintained.

- **Maximal storage of renewable energy**
  To store renewable energy as much as possible when there is surplus.

Reward Design (Cont’d)

- **Optimal use of ESS**
  To adjust ESS operation power to optimally use the ESS capacity.

  - Below the target SOC
    ESS must charge as soon as possible regardless of the price. Similarly, the price must be high enough for the ESS to discharge below the target SOC.

  - Beyond the target SOC
    The closer the SOC is to the full SOC, lower the price should be to charge the ESS to make better use of remaining storing capacity. In contrast to the former case, the price should be higher to discharge the ESS to fully utilize the remaining available energy in the case where the SOC is closer to the target SOC.

Reward Design (Cont'd)

M serves as a multiplier which affects the behavior of agent (risk seeking or risk averse)

This term handles
1) transaction cost
2) microgrid's stability
3) optimal use of ESS

k is ESS wear and tear cost

$$k = \frac{C_i}{\eta_d * E_{rated} * \delta * N_c}$$

$$u(Pr_t, Pr_t^{avg}, SOC_t | A_t) = (M \times Pr_t^{avg} - (Pr_t + k)) \times (SOC_{t+1} - SOC_t) \times E_{rated} - Pnt_t^{ESS} - Pnt_t^{PV}$$

This term handles
1) violation of operation limit of ESS
2) event surplus solar energy is not stored when there is spared ESS capacity

Reward Design (Cont'd)

- **PV Penalty**
  The penalty is high with the SOC is close to 0 and decreases exponentially when the SOC is close to 1.

$$Pnt_t^{PV} = \begin{cases} 0 \text{ if } PV_t \leq (L_t + A_t \times P_{rated}) \\ exp\left(2.5 \times (1 - SOC_{t+1})\right) - 1 \text{ if } PV_t > (L_t + A_t \times P_{rated}) \end{cases}$$

- **ESS Penalty**
  The penalty is assigned if ESS violates the operation limit.

$$Pnt_t^{ESS} = \begin{cases} 0 \quad \text{if } SOC_t + A_t \leq 1 \; or \; SOC_t - A_t \geq 0 \\ 10 \quad \text{otherwise} \end{cases}$$

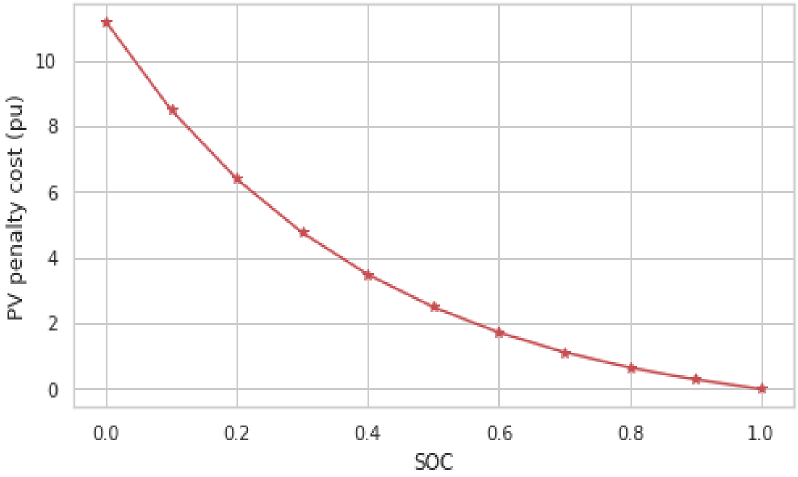


Figure 17. PV penalty assigned when the surplus solar energy is not stored

Reward Design (Cont’d)

- **M – Multiplier**

  - **Depending on the microgrid operator’s behavior**
    Risk seeking → Trade off reliability with monetary benefit more
    Risk averse → Trade off reliability with monetary benefit less

  - **To maintain microgrid’s reliability, the amount of target contingency reserve (ESS target SOC) for the operation of critical devices during a power outage of the maingrid is computed and should be maintained.**

Reward Design (Cont'd)

- **M – Multiplier (Cont'd)**
  (Below the contingency level (target SOC=0.5))

  ➢Microgrid operator will trade to buy more from main grid. The aggressiveness depends on the multiplier constant.

  ➢The further from the target SOC, it is more beneficial to buy than sell a unit of energy.

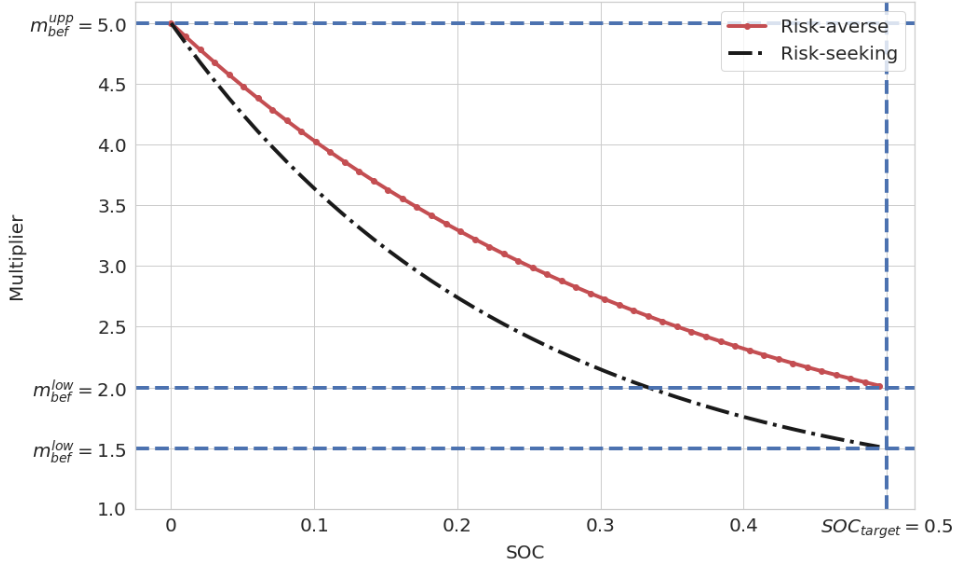


Figure 18. Multiplier below the target SOC corresponding to risk-averse and risk-seeking behaviour

Reward Design (Cont’d)

- **M – Multiplier (Cont’d)**
  (Beyond the contingency level (target SOC=0.5))

  ➢Microgrid operator will react more based on SOC.

  ➢During charging, the closer the SOC to 1, it seeks to find a much lower price to better use of remaining capacity. Vice versa for discharging.

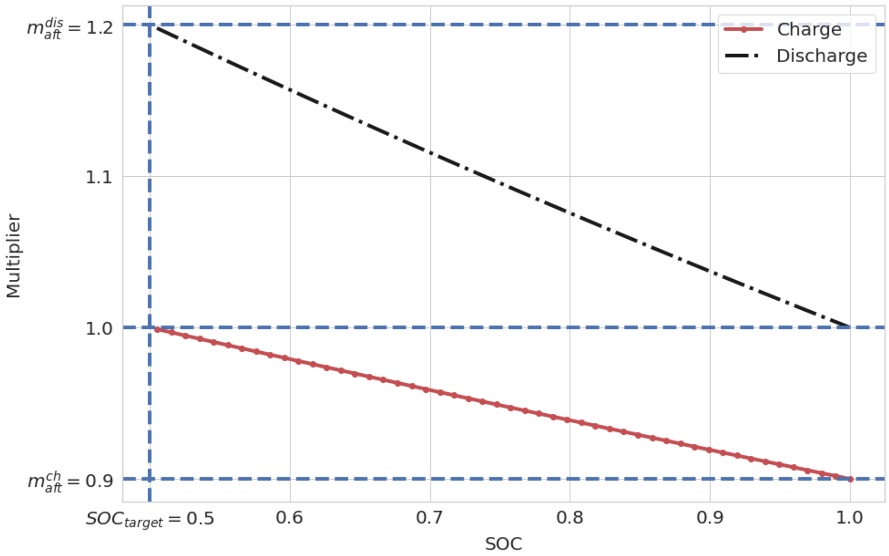


Figure 19. Multiplier beyond the target SOC corresponding to charge and discharge scenario

Optimal Policy

- **Bellman Equation**
  Bellman equation describes the recursive relationship between Q-value of consecutive time steps. It allows Q-learning to converge through dynamic programming.

Q-value (iteration k+1)

discount rate

reward

$$Q_{k+1}(s_k, a_k) = Q_k(s_k, a_k) + \alpha_k \left(\underbrace{r_{k+1} + \gamma \max_{a'} Q_k(s_{k+1}, a')}_{\text{Estimate of } Q^*(s_k, a_k)} - Q_k(s_k, a_k) \right)$$

Q-value (iteration k)

maximum q-value of next step

learning rate

- α ϵ [0, 1] - update the q-value with new q-value (rate of replacing old memory)
- γ ϵ [0, 1] - importance of the future reward

Optimal Policy (Cont'd)

- **Q-learning (Not feasible)**
  - Create a q-table storing the q-value of all state-action pair and update iteratively until it converges. Based on the q-table, the agent will select the optimal action based on the state
  - Not feasible in our case since the states are continuous which make the computation of q-table intractable.

States/ Actions	A_1	…	…	A_{11}
S_1				
…				
…				
…				
S_∞				

Figure 20. Q-table example

Optimal Policy (Cont'd)

- **DQN - Deep-Q-Network**
  - ➢ Train the network to predict the q-value of each action.
  - ➢ Once the network is trained, the agent will take the action with the greatest q-value (deterministic action).

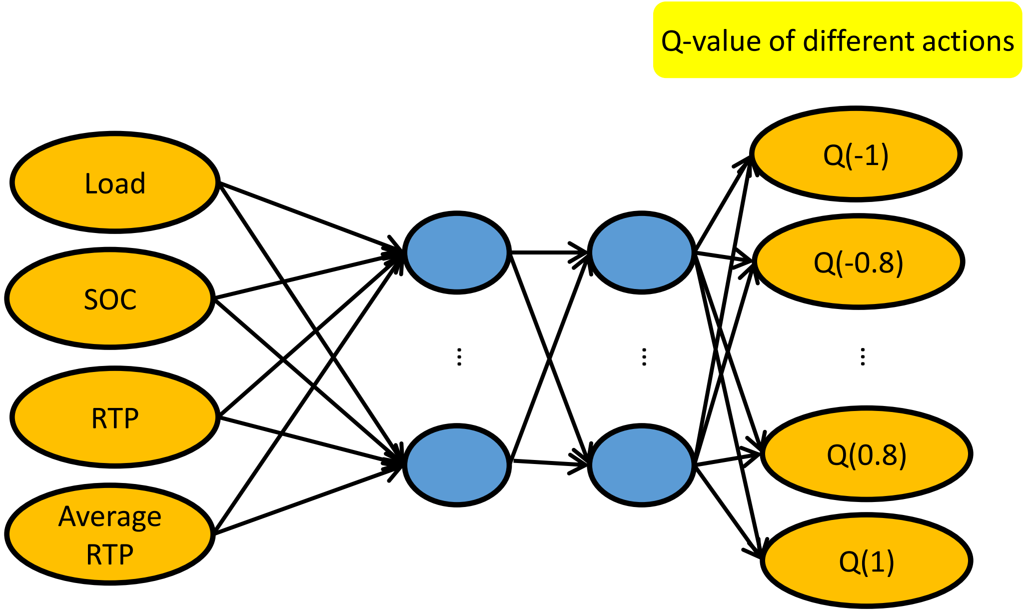


Figure 21. Deep-Q-Network replacing Q-table

Prioritized Experience Replay

- DQN is trained after each decision making. With such a training method, DQN tends to forget its previous experience due to overwriting of the new experience.

- S, A, r and err are saved in the memory after each decision making and a batch is sampled from the memory during the training. PER places more priority on those experiences with high error.

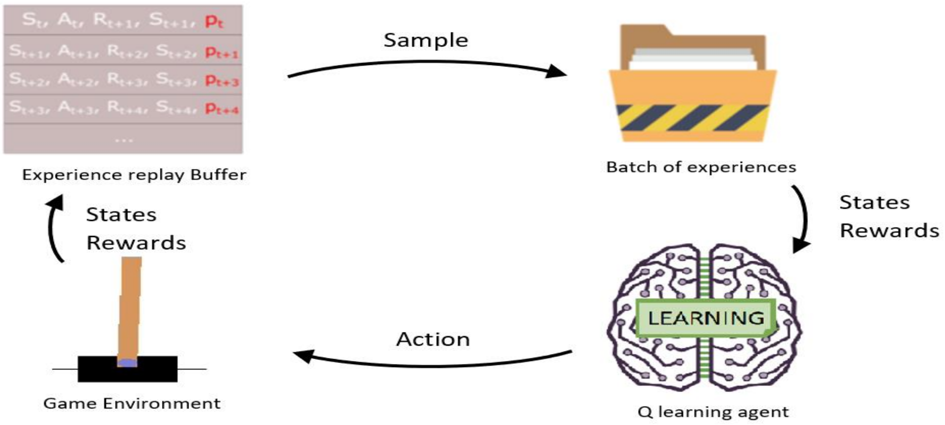


Figure 22. Prioritized Experience Replay.

Simulations Setting

- Recall that we have two energy management algorithms: 1) Model predictive control linear programming with forecast knowledge (MPCLCF). 2) reinforcement learning with no forecast knowledge – risk seeking (RSRL) and risk averse (RARL). **Our goal is to identify the optimal energy management algorithms.**

- The performance of the algorithms are evaluated with:
  - Its ability to maintain sufficient energy for critical-mission operation.
  - Its ability to maximize the monetary benefit.

- To have a good comparison, the model predictive control linear programming is performed with perfect knowledge (full knowledge of future information) (MPCLCP).

Simulations Setting (Cont'd)

- Consumer load, solar power and electricity price obtained from REFCom2014.
- Lithium-ion battery ESS information:
  - P_{rated} = 1000kW,
  - E_{rated} = 5000 kWh
  - N_c = 4996
  - δ = 1
  - $\eta_c = \eta_d = 90\%$
  - C_i= 171 $/kWh
- Contingency reserve/ SOC_{target} = 0.5 = 2500kWh.

Result & Analysis

Model	Daily average monetary benefit ($)	P(SOC < target SOC) (%)
MPCLPP	70.54	0
MPCLPF	65.93	0
RARL	37.01	0.55
RSRL	77.14	20.15

Table 1. Simulation Result Corresponding to Different Algorithms.

Result & Analysis (Cont'd)

- **System reliability** – MPCLPP and MPCLPF always maintains sufficient reserved energy for critical-mission operations. It is due to the constraint imposed on linear programming optimizer. For **0.55%** and **20.15%** of the time, RARL and RSRL do not have sufficient reserved energy for critical-mission operations. RARL is more conservative than RSRL.

- **Monetary benefit** – MPCLPP and MPCLPF obtains a daily average monetary benefit of **$70.54** and **$65.93**. MPCLP performs better with perfect knowledge but the results are still comparable in both perfect and forecast knowledge. RARL and RSRL obtains a daily average monetary benefit of **$37.01** and **$77.14**. With the risk averse perspective, the microgrid does not trade energy aggressively as compared to that with risk seeking.

- MPCLPF outperforms PARL and RSRL but it is more complex as forecasting models are needed.

Result & Analysis (Cont'd)

- **Case 1: Day with Surplus Solar Power & Spared ESS Capacity**.

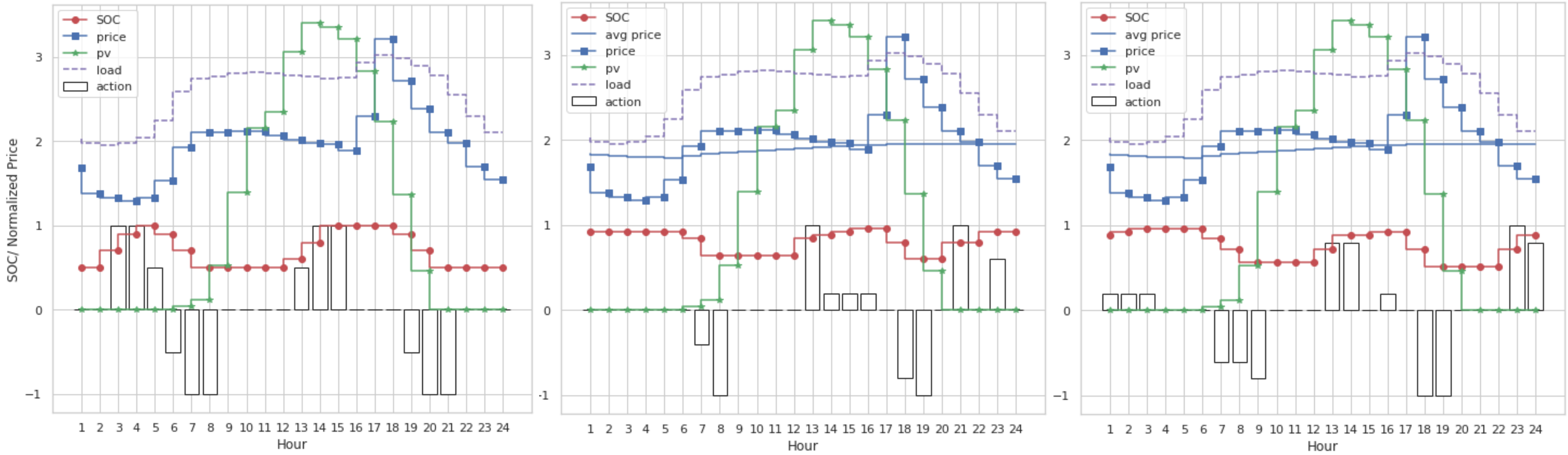


Figure 23. Actions of MPCLPF, RARL, RSRL in Case 1

Result & Analysis (Cont’d)

- **Case 1: Day with Surplus Solar Power & Spared ESS Capacity (Cont’d)**
  - **MPCLPF is more far-sighted in making decision by observing the number of charging and discharging cycles**. MPCLPF is able to identify the trough and peak with relative to the other hour and makes the best decision throughout a day. Besides, it never goes below the target SOC level.
  - Both **RARL and RSRL can charge and discharge at the appropriate timings**. However, there is a **ramp in charging and discharging power** as compared to MPCLPF which is not a healthy operation habit for the machine.
  - All three algorithms make the correct decision in storing the surplus solar power with the spared ESS capacity to maximize the monetary benefits.

Result & Analysis (Cont'd)

- **Case 2: Day with Extremely High Electricity Price.**

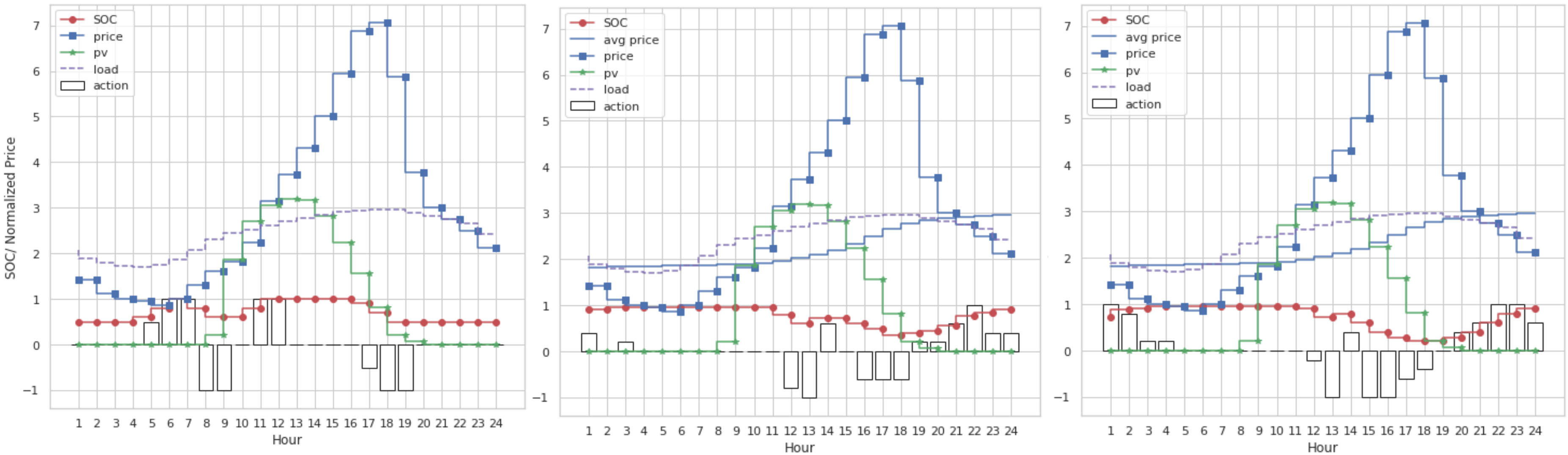


Figure 24. Actions of MPCLPF, RARL, RSRL in Case 2

Result & Analysis (Cont'd)

- **Case 2: Day with Extremely High Electricity Price (Cont'd).**

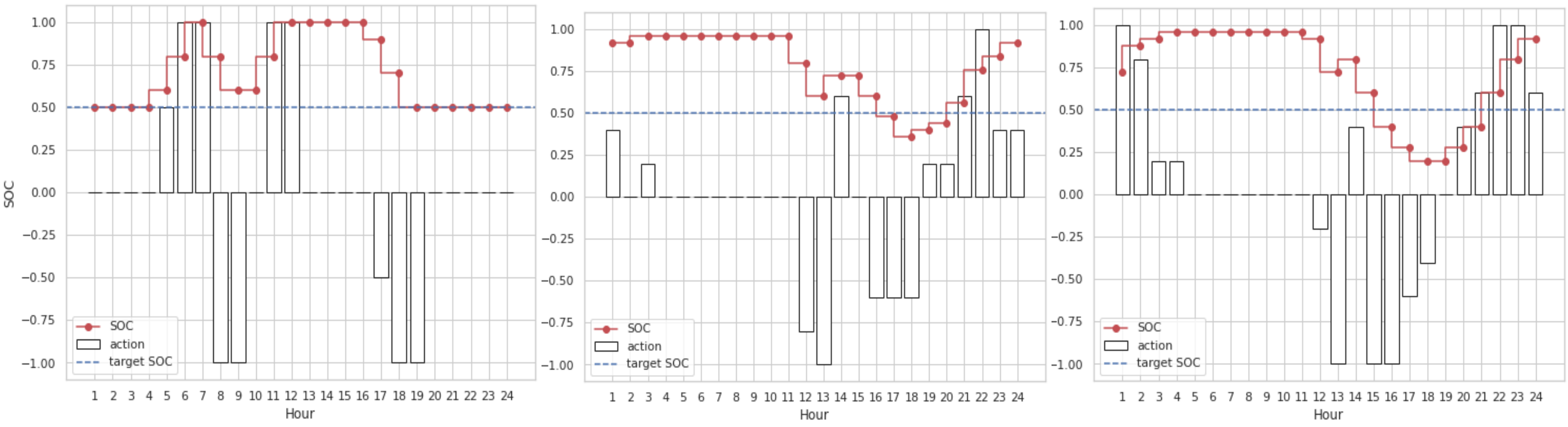


Figure 25. SOC Zoom of MPCLPF, RARL, RSRL in Case 2

Result & Analysis (Cont’d)

- **Case 2: Day with Extremely High Electricity Price (Cont’d).**
  - **MPCLPF discharges during hours with the highest electricity price** to maximize the possible monetary return. MPCLPF **operates strictly above the target SOC even when the electricity price is extremely high.**
  - **RARL and RSRL are more flexible in handling the extreme scenario with the high dynamic electricity price**. Higher monetary benefit → higher risk.
  - The case study proves the **effectiveness of the utility function of reinforcement learning**. Recalls that the piecewise utility function is designed to better utilize the remaining energy during discharging and the remaining spare capacity during charging, ESS discharges (charges) in a more meticulous way when the ESS capacity is lower during the hour 11th to 17th (the ESS capacity is higher during the hour 18th to 24th).

Graphical User Interface

- Deployment of the algorithms and create a graphical user interface to provide any user with good visualization of the algorithm's decision. The graphical user interface is an integration of software: 1) InfluxDB - open-source time-series database; 2) Grafana - multi-platform open-source interactive visualization webpage.

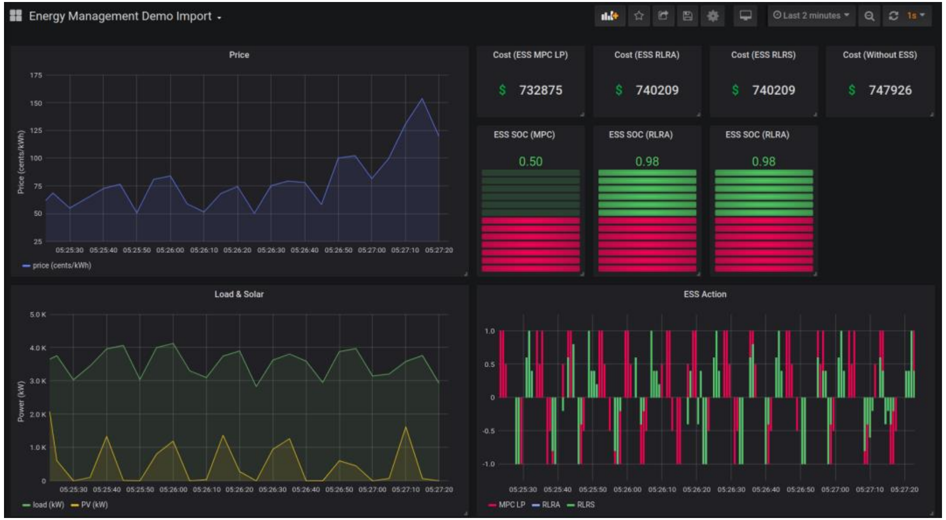


Figure 26. Graphical User Interface of Energy Management Algorithm

Conclusion

- We **studied 4 time series forecasting models** – long-short-term-memory (LSTM), sequence-to-sequence (Seq2Seq), attentive-sequence-to-sequence (AttSeq2Seq), transformer (TX). We analysed and **identified the optimal forecasting models for consumer load (Seq2Seq), solar power (Seq2Seq) and electricity price (TX) predictions**.

- We **presented two energy management algorithms** – model predictive control linear programming with forecast knowledge (**MPCLPF**), reinforcement learning with no future knowledge with risk averse (**RARL**) and risk seeking (**RSRL**) behaviour. We formulated and designed the objective or rewards and constraints for both algorithms. We showed that **MPCLPF performs the best in maintaining system reliability and gaining monetary benefit.**

- We developed a **graphical user interface** for the energy management algorithms.

Appendix

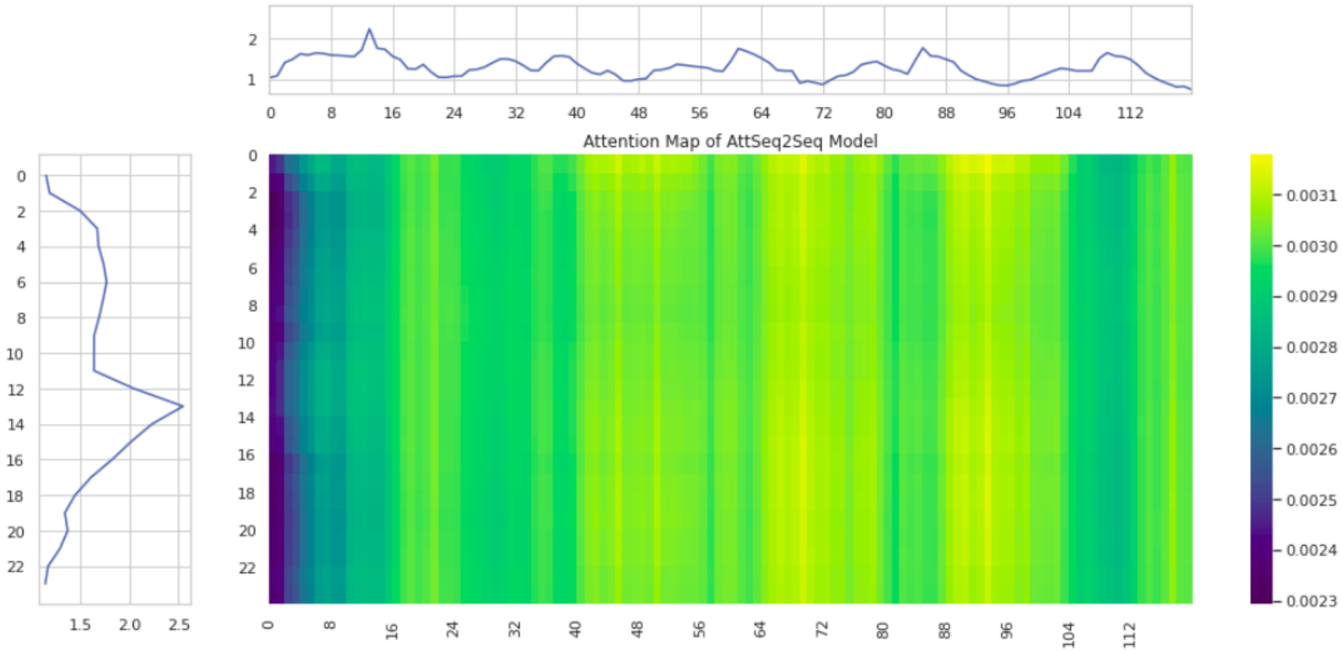


Figure 27. Price Attention Map of AttSeq2Seq Model
(Decoder Input to Encoder Output)

Appendix

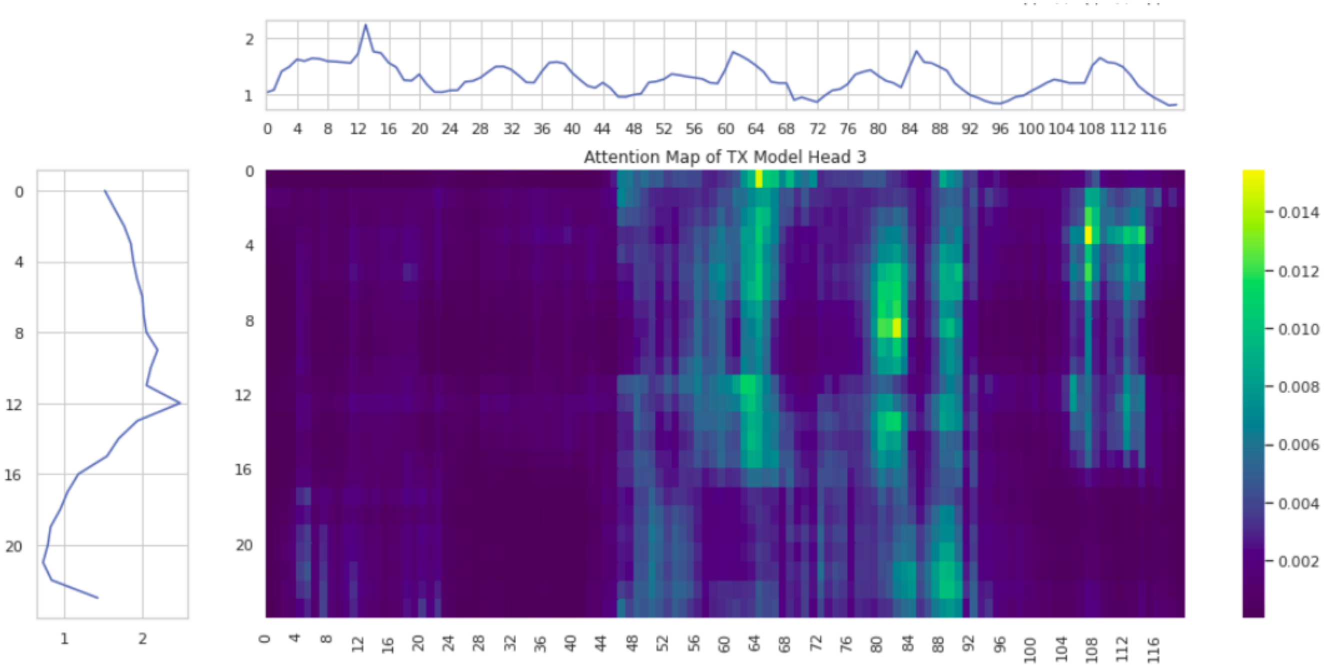


Figure 28. Price Attention Map of TX Model
(Decoder Input to Encoder Input)

Appendix

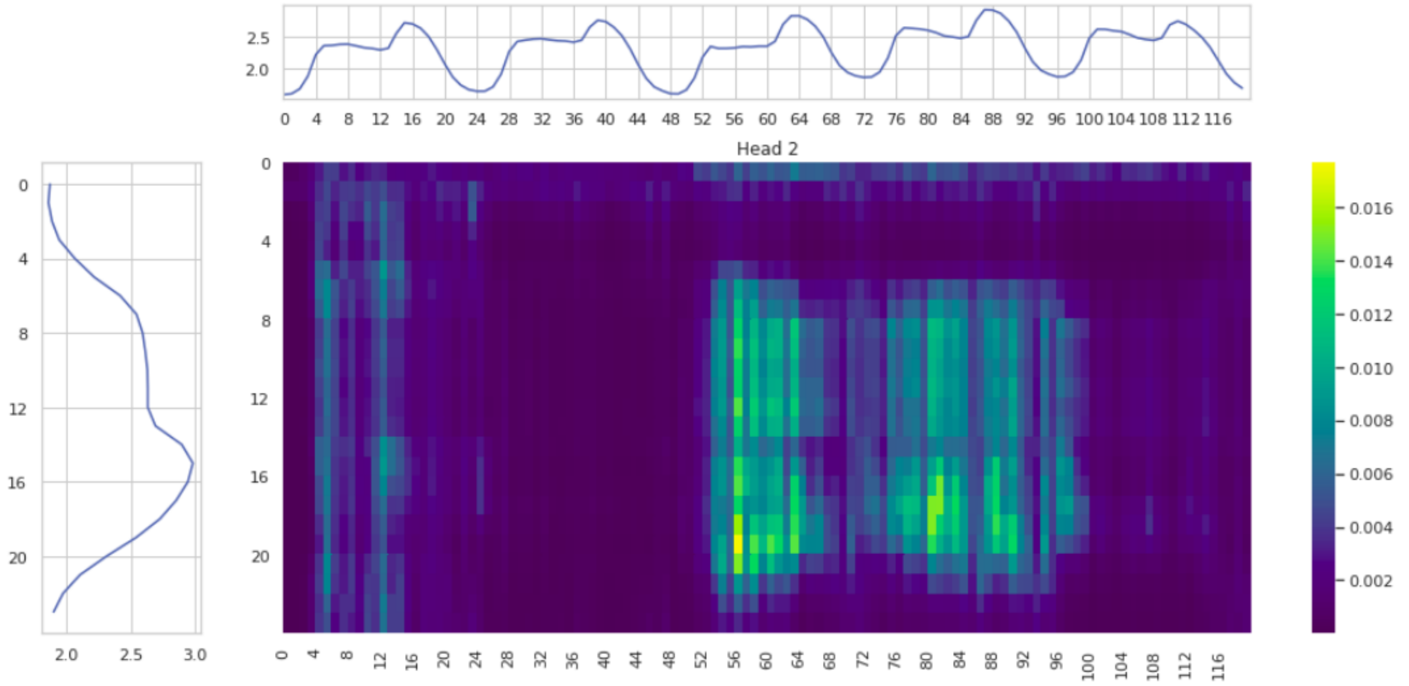


Figure 29. Load Attention Map of TX Model
(Decoder Input to Encoder Input)

REFERENCE

1. Comodi G, Giantomassi A, Severini M, Squartini S, Ferracuti F, Fonti A, et al. Multi-apartment residential microgrid with electrical and thermal storage devices: Experimental analysis and simulation of energy management strategies. Appl Energy 2015;137:854–66.
2. Shen J, Jiang C, Liu Y, Qian J. A microgrid energy management system with demand response for providing grid peak shaving. Electr Power Compon Syst 2016;44(8):843–52.
3. Luna AC, Meng L, Diaz NL, Graells M, Vasquez JC, Guerrero JM. Online energy management systems for microgrids: experimental validation and assessment framework. IEEE Trans Power Electron 2018;33(3):2201–15.
4. Kanchev H, Lu D, Colas F, Lazarov V, Francois B. Energy management and operational planning of a microgrid with a PV-based active generator for smart grid applications. IEEE Trans Industr Electron 2011;58(10):4583–92.
5. Chaouachi A, Kamel RM, Andoulsi R, Nagasaka K. Multiobjective intelligent energy management for a microgrid. IEEE Trans Industr Electron 2013;60(4):1688–99.
6. Wang T, He X, Deng T. Neural networks for power management optimal strategy in hybrid microgrid. Neural Comput Appl 2017:1–13.
7. Urias MEG, Sanchez EN, Ricalde LJ. Electrical microgrid optimization via a new recurrent neural network. IEEE Syst J 2015;9(3):945–53.
8. Venayagamoorthy GK, Sharma RK, Gautam PK, Ahmadi A. Dynamic energy management system for a smart microgrid. IEEE Trans Neural Netw Learn Syst 2016;27(8):1643–56.

REFERENCE

9. Kuznetsova E, Li Y-F, Ruiz C, Zio E, Ault G, Bell K. Reinforcement learning for microgrid energy management. Energy 2013;59:133–46.
10. Solanki BV, Bhattacharya K, Cañizares CA. A sustainable energy management system for isolated microgrids. IEEE Trans Sustain Energy 2017;8(4):1507–17.
11. Bogaraj T, Kanakaraj J. Intelligent energy management control for independent microgrid. Sādhanā 2016;41(7):755–69.
12. Dou C-X, Liu B. Multi-agent based hierarchical hybrid control for smart microgrid.IEEE Trans Smart Grid 2013;4(2):771–8.
13. H. Wang, T. Huang, X. Liao, H. Abu-Rub and G. Chen, "Reinforcement Learning in Energy Trading Game Among Smart Microgrids," in *IEEE Transactions on Industrial Electronics*, vol. 63, no. 8, pp. 5109-5119, Aug. 2016.
14. L. Xiao, X. Xiao, C. Dai, M. Peng, L. Wang, and H. V. Poor, “Reinforcement learning-basedenergy trading for microgrids,”CoRR, vol. abs/1801.06285, 2018. [Online]. Available:http://arxiv.org/abs/1801.06285
15. Ghasemi A. Coordination of pumped-storage unit and irrigation system with intermittent wind generation for intelligent energy management of an agricultural
16. Cau G, Cocco D, Petrollese M, Kær SK, Milan C. Energy management strategy based on short-term generation scheduling for a renewable microgrid using a hydrogen storage system. Energy Convers Manage 2014;87:820–31.

Q&A

Thank You