Reinforcement Learning Enabled Energy Optimization for Prosumers

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Data Science Capstone Project with Accenture

Overview

With net-zero targets and real-time market pricing policies, consumers are being increasingly encouraged to invest in smart automation of energy management systems. The project goal is to develop a reinforcement learning model agent for prosumers and consumers, to minimize the overall energy cost and increase the renewable energy utilization. The solution will help control the flexible load and optimize the charging and discharging schedule of energy storage.

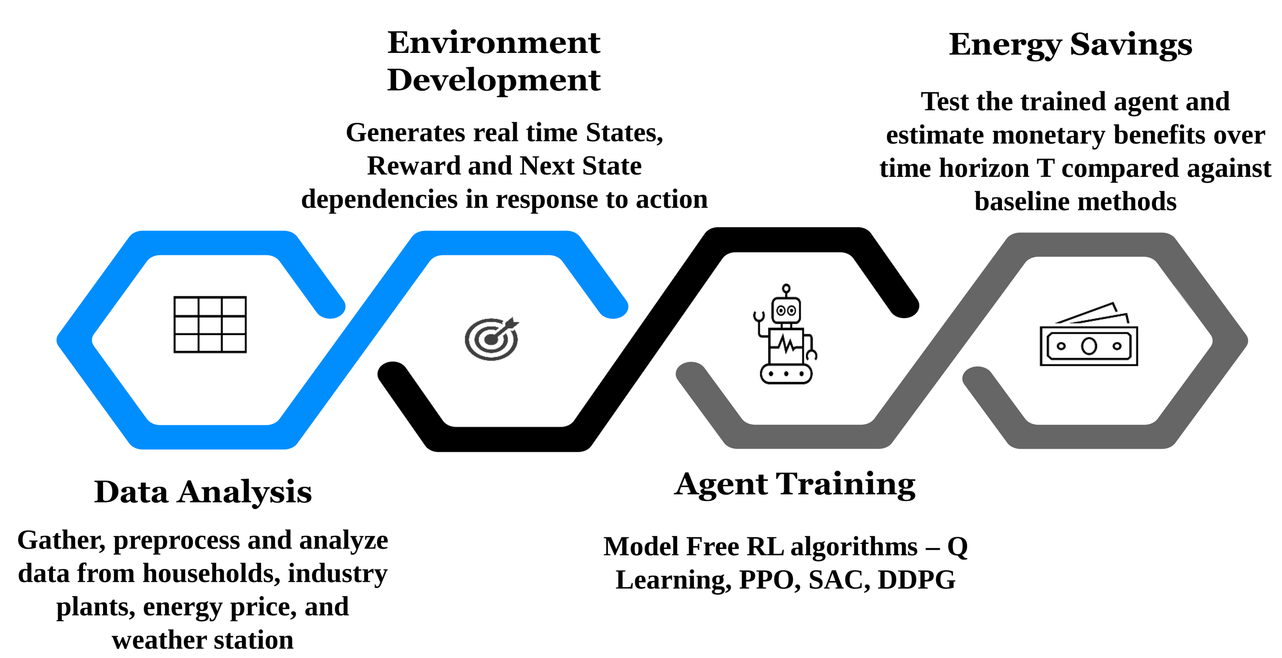

Figure 1. Project Overview

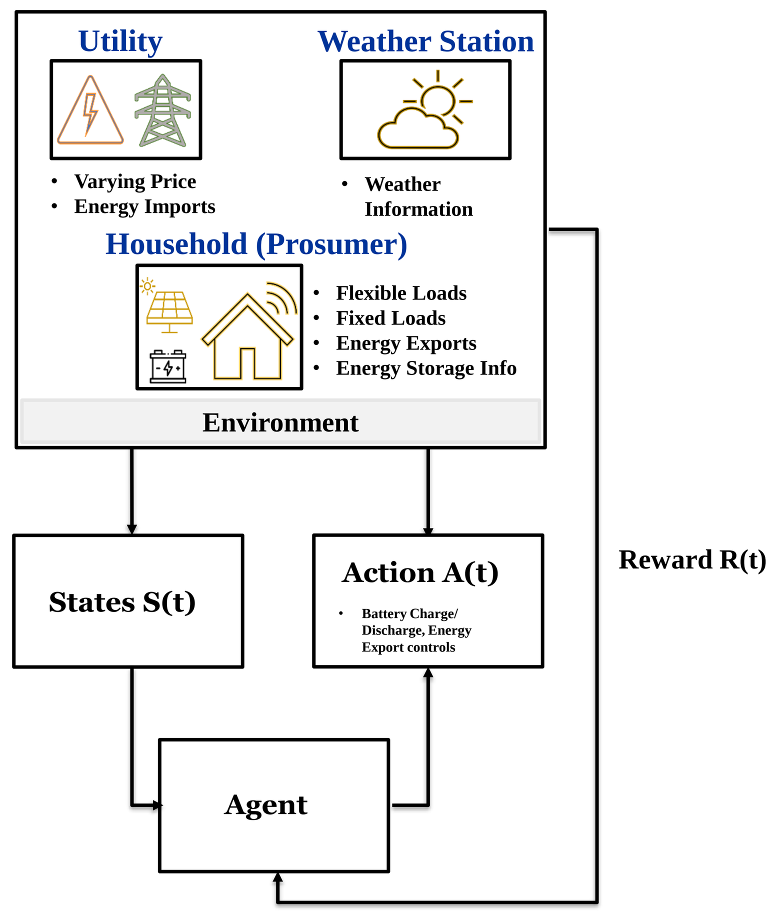

Figure 2. Reinforcement Learning

Exploratory Data Analysis

Household (Consumer) Data **- 6 residential household data is available. Different households show distinctive patterns over time; some households generate numerous amount of Photovoltaic energy, while others import from public grids.**

Timeseries Data **- The household's self pv-generation and the export to public grid is highly positively correlated with the solar generation. The household is inclined to import less from public grid when the solar generation is high and vise versa.**

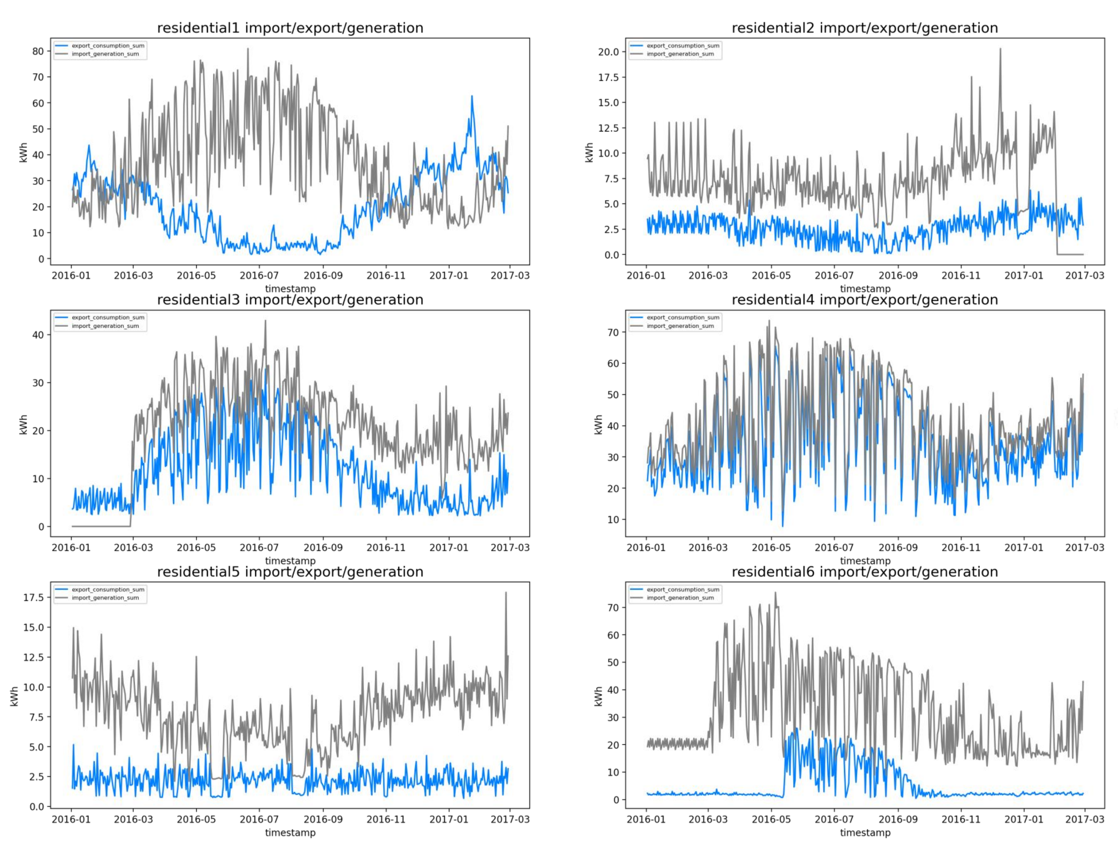

Figure 3. Consumer (Household) Energy Metrics

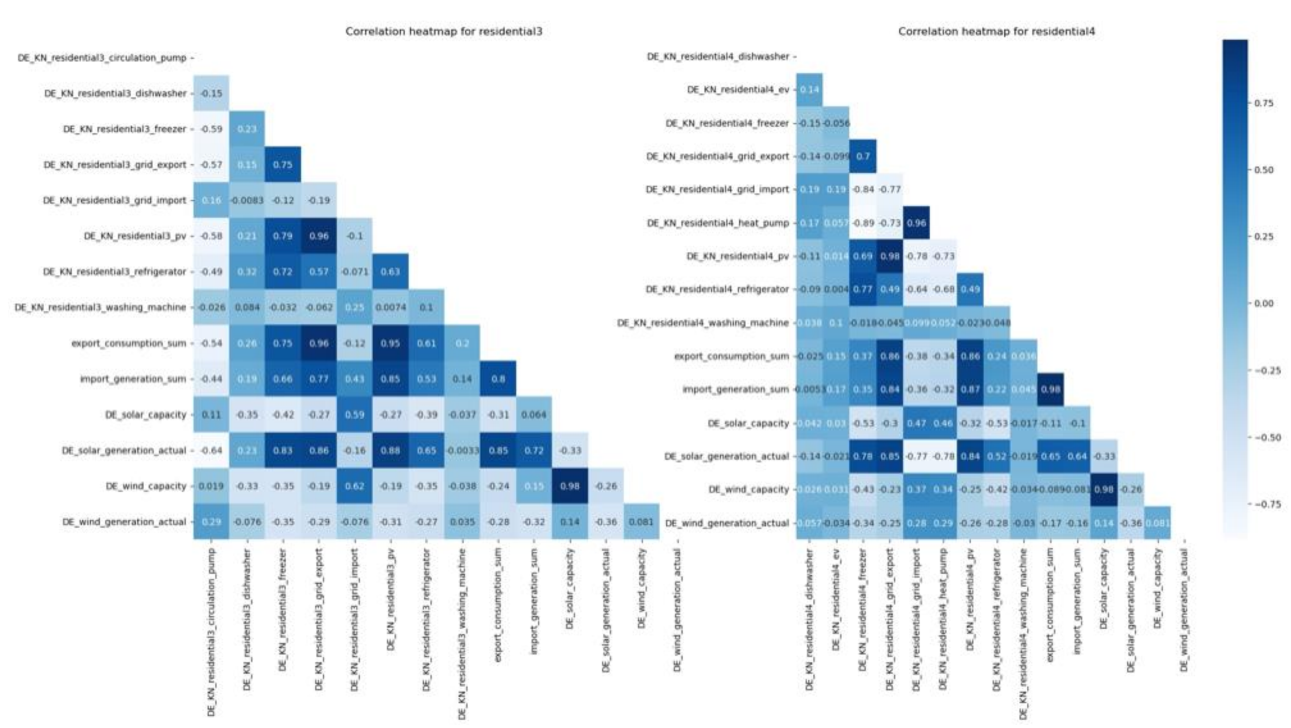

Figure 4. Correlations between Timeseries and Households

Reinforcement Learning With Q-Learning

For the agent training, Offline learning policy is applied including three main algorithms: Tabular Q-learning, Deep Q-learning, and PPO2. Three different agents are trained for each kind of appliance and let them to interact with the environment created. Below are the graphs which show the agents states at each different time intervals during a random day. Agents behave in a reasonable situation under some constraints that are set in the MDP Formulation process.

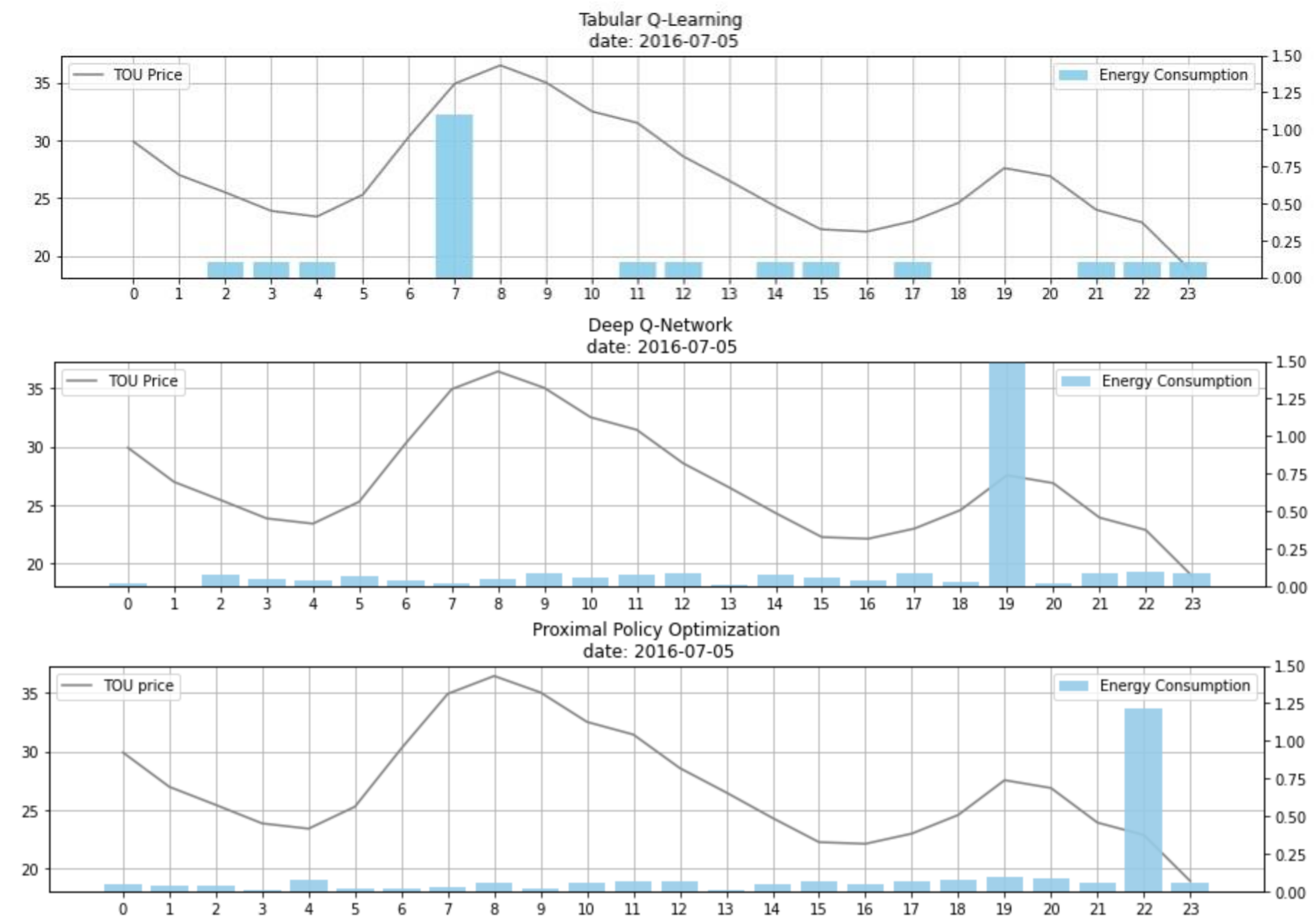

Figure 5. Output of different Reinforcement Learning methods.

Conclusion

A reinforcement learning based smart home energy management is proposed which could minimize the electricity bill through managing two controllable home appliances, and assuming fixed load for uncontrollable appliances. Among three algorithms, the Deep Q-learning performs best by learning the actions through interaction with environment to maximize the rewards. In the future work, we are considering adding the consumer comfort level into the optimization formula. We could do this either finding specific dataset with relevant information or using ANN to predict the indoor temperature directly. In addition, if possible, we also considering develop a multi-agent that scheduled actions for multiple smart homes with distributed energy resources and appliances.

Acknowledgments

Thank you to the Accenture mentors Bhushan Jagyasi, Bolaka Mukherjee, Anandu Balachandran, and faculty mentor Adam S. Kelleher; and to the data provider Jonathan Muehlenpfordt.

References

Lee, S., & Choi, D.-H. (2019). Reinforcement learning-based energy management of smart home with rooftop solar photovoltaic system, Energy Storage System, and home appliances. Sensors, 19(18), 3937. https://doi.org/10.3390/s19183937