Project Midterm Update

Shih-Hung Chiu, Aoyu Zou, Chia-Chu Kung, Abhishek Manickam

Topic

Data-driven control of building energy usage and bidirectional EV charging using deep reinforcement learning

Description of current progress

Synthetic Building Operational Dataset

The dataset for the building energy is extracted from metadata collected by researchers in Lawrence Berkeley National Laboratory. The metadata contains 30 years of building operation information including HVAC, lighting, miscellaneous electric loads (MELs) system operating conditions, occupant counts, environmental parameters, end-use and whole-building energy consumptions at 10-minute intervals. The whole dataset is stored in amazon web service for the scope of this study, the subset of electricity time series in climate zone 3C (San Francisco) is extracted through Identity and Access Management (IAM).

	Total Occupant Count	Electricity:HVAC[J]	datetime	climate	efficiency	weekday	Interior Lighting (kWh)	MELs (kWh)	Site Electricity (kWh)	Site Gas (kWh)	Site Total Energy (kWh)	HVAC Electricity (kWh)	Outdoor Air Temperature (degC)	Operating Time	hour
2017-01-01 00:00:00	0.0	0.000000e+00	2017-01-01 00:00:00	3C	Standard	False	0.821181	2.772776	4.466209	0.212824	4.679034	0.000000	6.783333	No	0
2017-01-01 00:10:00	0.0	6.832140e+05	2017-01-01 00:10:00	3C	Standard	False	0.821181	2.772776	4.655991	0.212824	4.868815	0.189782	6.866667	No	0
2017-01-01 00:20:00	0.0	2.663367e+06	2017-01-01 00:20:00	3C	Standard	False	0.821181	2.772776	5.206033	0.212824	5.418858	0.739824	6.950000	No	0
2017-01-01 00:30:00	0.0	2.654557e+06	2017-01-01 00:30:00	3C	Standard	False	0.821181	2.772776	5.203586	0.212824	5.416410	0.737377	7.033333	No	0
2017-01-01 00:40:00	0.0	0.000000e+00	2017-01-01 00:40:00	3C	Standard	False	0.821181	2.772776	4.466209	0.212824	4.679034	0.000000	7.116667	No	0

Charging Station EV Charging Dataset

The EV Charging dataset we found was based on the CalTech EV data collection program which collected data from multiple charging stations within the Southern California region. The categories of collected data include specific user IDs for each user, station IDs for each individual charging station, and data specific to each Electric Vehicle. Some examples of individual EV data are the connection time, disconnected time, the time the EV was done charging, and kilowatt hours delivered during that time period. The dataset we collected was a year's worth of data from April 1, 2021 to April 1, 2022.

Description of attempted methods

A. Synthetic Building Operational Dataset

The aim is to predict the building energy consumption based on the given input as energy demand for reinforcement learning. Since the electricity profile is nonlinear but with strong patterns, neural networks could potentially be a suitable method especially considering the large dataset extracted. For now, training of fully connected dense layers is in progress, but other methods such as long short-term memory (LSTM) recurrent neural networks may be an alternative way of predicting time series.

B. The aim is to predict the state of charging based on the given time the EV was done charging and the kilowatt hours delivered during the charging time period. Since the state of charging is not linear while approaching the fully charged state, some non-linear regression models can be good methods to estimate the state of charging.

Preliminary results (could be theoretical or computational)

A. Synthetic Building Operational Dataset

To better understand the dataset, several parameters were plotted. In Fig. 1, the gray line records the temperature every 10 minutes within the 30 years. The orange line is the distribution of the average daily temperature and the blue line is the yearly data. The trend that the temperature is slightly rising can be observed, especially after 2013.

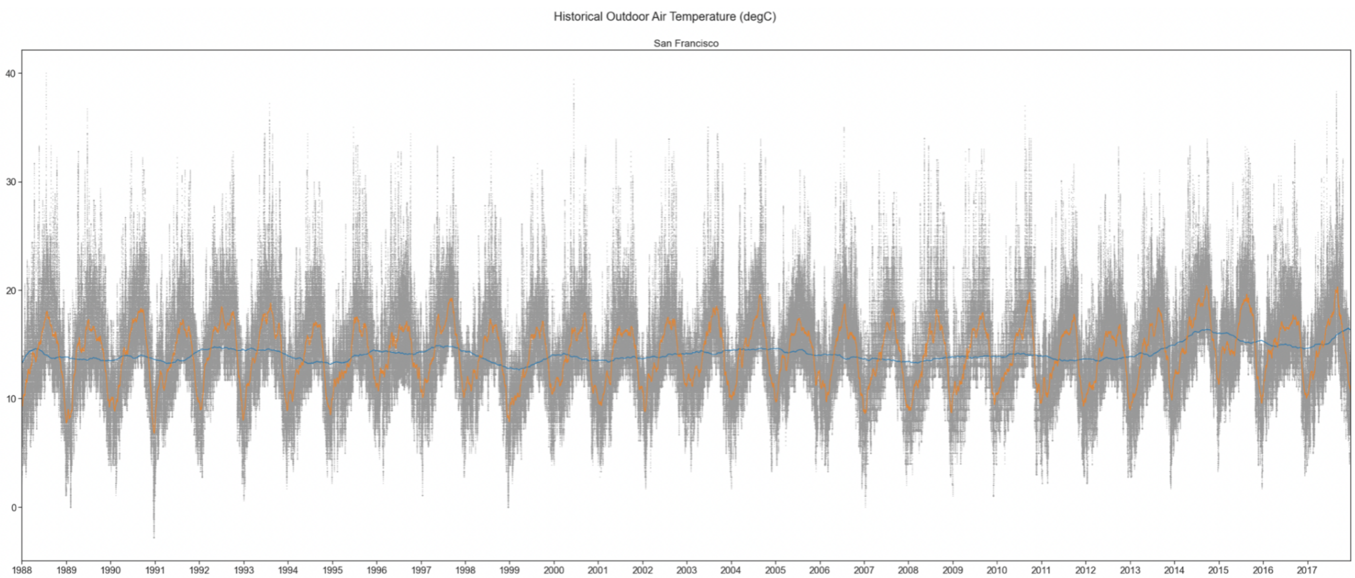

Fig. 1 Weather data of 30 years

The electricity consumption profile is the key pattern that we want to extract from the dataset. Fig 2 demonstrates the monthly total electricity consumption profile (January 2017 for example). Since the data were collected from a commercial building, it's obvious that the building consumes much more energy during the weekdays than on the weekends. To see the daily pattern, the plot is further zoomed in to the 1st week of January, 2017. The trend of electricity usage is similar for weekdays. Three repeating peaks (i.e. building opening, lunch break, building closing) can be identified.

Currently, we are working on building the fully connected dense layer Neural Networks model to model the electricity usage profile of the commercial building. However, the training result is not promising. Therefore, we are not reporting the result in this report.

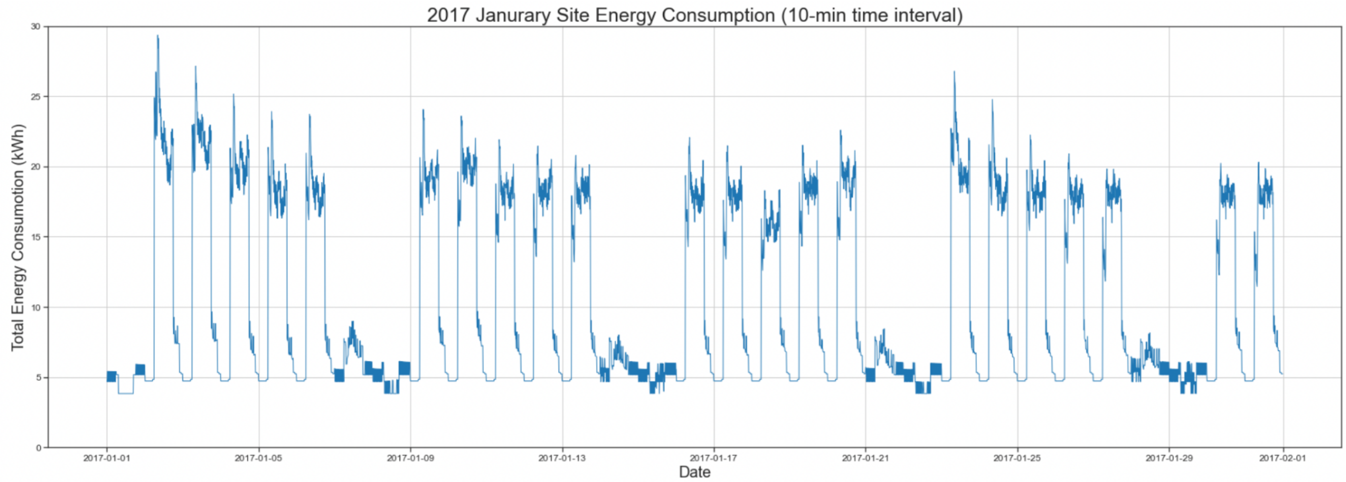

Fig. 2 Monthly data of Site Total Energy Consumption

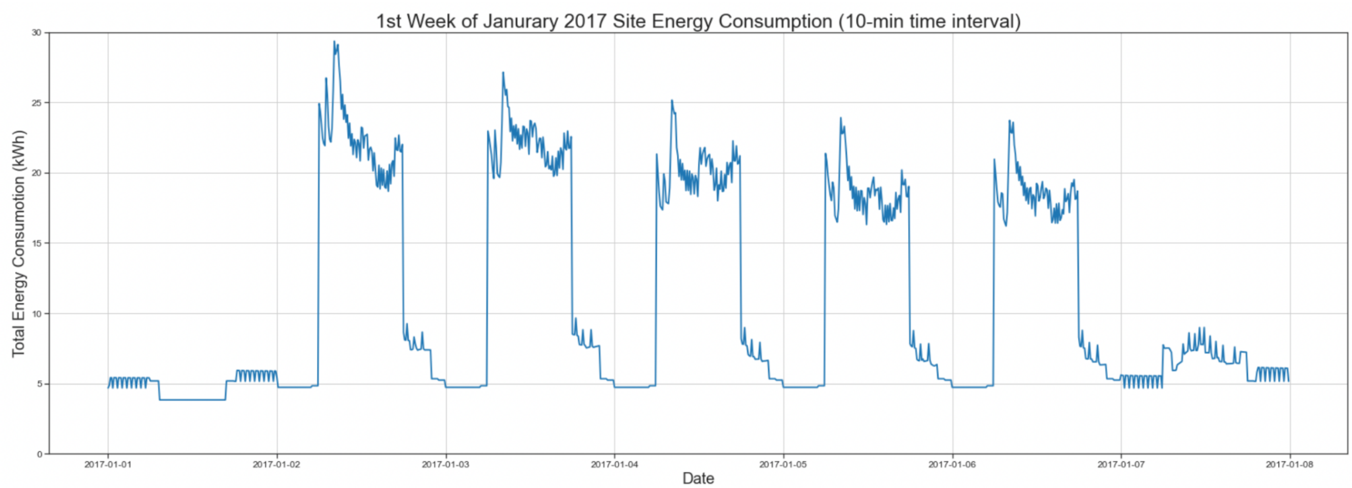

Fig. 3 Daily data of Site Total Energy Consumption

B. Charging Station EV Charging Dataset

Current problems that you are experiencing

With regards to this EV Charging dataset, the most pressing issues come from the fact that it does not have the initial state of charge data for each vehicle. Ideally this data would have been extracted to see how much energy can be supplied from the EV to the building. Given the information that is available from the data, i.e. connection time, disconnect time, done charging time, and KWh delivered, the option to work backwards exists but then involves making a series of assumptions that could inevitably render this research unviable.

Outline of your plans for the rest of the work

The next step would be combining the EV and predicted building energy profile as a sequence and constructing reinforcement learning to train the model based on the sequence. Hopefully the model would provide reasonable optimal control policies for the proposed problem. In addition, proposing a validation process for the data driven model is also required.

Reference

[1] Aswani, A., Gonzalez, H., Sastry, S. S., & Tomlin, C. (2013). Provably safe and robust learning-based model predictive control. *Automatica*, *49*(5), 1216-1226.
[2] Wang, Z., & Hong, T. (2020). Reinforcement learning for building controls: The opportunities and challenges. *Applied Energy*, *269*, 115036.
[3] Mason, K., & Grijalva, S. (2019). A review of reinforcement learning for autonomous building energy management. *Computers & Electrical Engineering*, *78*, 300-312.
[4] Svetozarevic, B., Baumann, C., Muntwiler, S., Di Natale, L., Zeilinger, M. N., & Heer, P. (2022). Data-driven control of room temperature and bidirectional EV charging using deep reinforcement learning: simulations and experiments. *Applied Energy*, *307*, 118127.