Supplementary material for: Winning the 2023 CityLearn Challenge: a Community-based Hierarchical Energy Systems Coordination Algorithm

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1 Full Description of Observations

We report in Table 1 the full list of observations. The environment allows to select which observations the user wants to pass to the control agent, and in particular, it also allows for both centralized and decentralized control. In practice this entails that it was possible to obtain a vector of observations for each building, or a single vector with all the information shared.

Choosing to subdivide the information between buildings still allowed to control all the buildings at once with a single agent, the division is purely practical.

Table 1. Observations in the CityLearn environment.

Observation Type	Description
Time Data	Hour, Week day
Outdoor Temperature	Current Outdoor Drybulb Temperature, with predictions for next 6, 12, 24 hours
Solar Irradiance	Diffuse and Direct Solar Irradiance, with predictions for next 6, 12, 24 hours
Carbon Intensity	-
Indoor Temperature	-
Non-Shiftable Load appliances in the building	Power needed for general
Solar Generation	Generation from PV panels
DHW Storage SOC storage state of charge	Domestic Hot Water
Electrical Storage SOC	Battery State of Charge
Electricity Consumption	-
Electricity Price for next 6,12,24 hours	Price and prediction
Cooling demand	-
DHW demand	-
Occupancy	Number of people in the building
Temperature Setpoint	-
Power Outage	Signal to indicate outages in the grid

2 Further details about the forecasting ensemble model

The XGBoost models are trained using the following observations for the predicted variables:

- **Outdoor temperature**: hour, week day, direct solar irradiance, diffuse solar irradiance, expected outdoor temperature.
- **Solar generation**: hour, direct solar irradiance, diffuse solar irradiance, expected direct solar irradiance to 6-12-24h, expected diffuse solar irradiance to 6-12-24h, expected solar generation.
- **Hot water demand**: hour, weekday, occupancy, annual hot water demand estimate, hot water storage action.
- **Non-shiftable load**: hour, weekday, occupancy, annual non-shiftable load estimate, non-shiftable load estimate.

3 Model Hyperparameters

This section details the specific hyperparameter values employed in the implementation of the winning algorithm.

General Configuration

- The algorithm incorporates a single feedback loop between building-level and community-level systems. This was done to reduce the computational cost, since the online evaluation script was limited by time.
- The initial action vector at time t, denoted as $\tilde{\boldsymbol{a}}_t$, is set to zero (no action).

Forecast Module

- The forecast module predicts outcomes one simulation step ahead, with τ set to 1, again to minimize the computational cost. It is important to note that we did not find significant improvements when increasing τ.
- The online XGBoost model is retrained daily, $T_{retrain} = 24h$.
- Initial ensemble weights for various predictive factors are defined in Table 2.

Table 2. Initial Weights of the Ensemble for Various Predictive Factors

Factor	Pretrain XGB	Online XGB	Historical
Outdoor temp.	1.0	0.0	0.0
Solar generation	0.0	0.1	0.4
Hot water demand	1.0	0.0	0.0
Non-shiftable load	1.0	0.0	0.0

Temperature Module

- We report with higher precision the optimal value obtained by Bayesian Optimization for the PID controller in Equations (6), $k_p = -0.288074675781558$, $k_i = -2.489908316536426$, and $k_d = 0.009479951268930725$.

Hot Water Module

- We set the power given to the hot-water heater in each hour were the heating is allowed by the heuristic to $p_{hw} = 0.25$.

Electricity storage control

- The discretization granularity in the tree search is set to $g = 0.05$.
- The Lower Bound ($\mathrm{LB}(h)$) ensures that there is always a minimum amount of energy in case an outage happens. An Upper Bound ($\mathrm{UB}(h)$) is also critical since the battery efficiency degrades when the battery is charged close to maximum capacity. We define a constant $\mathrm{UB} = 0.95$ and the values of $\mathrm{LB}(h)$ for each hour are given by Table 3.

Table 3. Hourly Lower Bounds for Energy Storage

Hour	LB	Hour	LB	Hour	LB
0	0.60	8	0.70	16	0.70
1	0.65	9	0.60	17	0.65
2	0.72	10	0.50	18	0.70
3	0.78	11	0.60	19	0.60
4	0.80	12	0.65	20	0.60
5	0.85	13	0.65	21	0.60
6	0.80	14	0.70	22	0.60
7	0.75	15	0.70	23	0.55

Consumption Smoothing

- Consumption smoothing parameters are set to maintain the standard deviation of consumption within predefined bounds: the upper bound is set at $B_{up} = 1.00$ and the lower bound at $B_{low} = 1.18$.
- The maximum reduction in cooling capacity is set to $\Theta_{max} = 20\%$.