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Physically Consistent Deep Learning-Based Model Predictive Control for Community Energy Management

Tianqi Xiao*, Fengqi You

Cornell University, Ithaca, NY, 14853, USA
tx72@cornell.edu

Communities are one of the essential elements of modern cities, significantly contributing to overall energy consumption and carbon emissions. To further support ongoing decarbonization initiatives, this study presents a novel Physically Consistent Deep Learning (PCDL)-based Model Predictive Control (MPC) approach for community energy management. This approach incorporates both building-to-grid interactions and on-site renewable energy resources. The PCDL model, starting with the definition of physics consistency, is constructed in line with the established physical laws that govern community thermal dynamics. Serving as a precise thermal load and indoor climate estimator, the PCDL model is then implemented in a centralized MPC to reduce the community energy cost and maintain comfortable indoor environments for buildings in the community. To verify the effectiveness and control performance of the proposed framework, we use a simulation case study of a student residential hall at Cornell University. The results demonstrate that the PCDL-based MPC is highly effective in maintaining comfortable indoor conditions and contributes to load shifting and shaving through its participation in the demand response service.

1. Introduction

Buildings, as an integral part of modern society, not only provide comfortable habitats for humans but also account for significant energy consumption. In the U.S., buildings account for 76 % of electricity use, 39 % of primary energy use, and 35 % of energy-related carbon emissions (U.S. Energy Information Administration, 2023). As a result, enhancing building energy efficiency and minimizing carbon emissions is vital to promoting societal sustainability. A promising pathway toward building decarbonization is through the adoption of distributed electricity sources (DERs) (Roberts et al., 2019). DERs encompass various energy supplies such as renewable energy sources, storage systems, electric vehicles, and other on-site electricity providers to the buildings. The smart community concept considers a combination of separate buildings (same type or different type). Smart communities have the potential to generate community-level optimum solutions that lead to deeper connections with microgrids and DERs, resulting in more significant reductions in buildings' carbon emissions and energy consumption (Liu et al., 2022).

However, these advancements introduce challenges to Building Energy Management (BEM) systems due to the associated complexity and uncertainty (Chen et al., 2022a). The boomed development of modern communities also reinforces the building-to-grid (B2G) service, which can greatly contribute to enhancing grid stability (Trigkas et al., 2022). In B2G applications, the building or community systems receive regulation information from the grid market and then alter their operation strategy to reduce or increase their grid power consumption, which is also called demand response (DR) (Nikzad and Mozafari, 2014). Compared to single buildings, communities manage to integrate more buildings and other facilities, such as district heating pumps, on-site renewable energy resources, and electric vehicles, attaining more flexibility in DR service (Salehi et al., 2022). A common DR method is to implement the grid market price, which is calculated based on predicted total energy supply and energy consumption (Nweye et al., 2023). However, a severe issue in the current literature is the lack of reliable load and indoor climate estimation methods, which could impair the DR service quality and lead to uncomfortable indoor environments. As such, there is a compelling need for an accurate and interpretable model for estimating load and indoor climate to bridge this knowledge gap. Among all control

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strategies for community energy management, model predictive control (MPC) is appealing for real application (Chen et al. 2022b). Nevertheless, obtaining an accurate prediction model for MPC in real applications can be quite challenging (Komkrajang et al., 2014). This problem becomes more critical in the community due to the complexity, varying time scale, and uncertainties of the energy systems (Ning et al., 2019).
A common method is to develop state-space models based on mass and thermal balance equations, as illustrated in previous works (Jin et al., 2021). Yet, this approach tends to oversimplify the system dynamics, leading to subpar performance when dealing with complex systems (Shang et al., 2019). Its dependency on extensive expert intervention also compromises its generality across diverse building architectures (Di Natale et al., 2022). On the other hand, data-driven approaches, like machine learning and deep learning methods, were developed in recent years and showed convincing performance in capturing system dynamics (Djenouri et al., 2019). Through the end-to-end training process, these data-driven models bypass the intricacies of traditional modeling, offering broad applicability (Sun et al., 2021). To solve the generalization and interpretation issues, researchers further developed physics-informed AI models in which physics laws are imported into the training process or model structure (Ajagekar et al., 2023). Such efforts were also completed in the building modeling field, as illustrated by the physics-constrained neural network with pre-defined parameter constraints (Drgoňa et al., 2021) and physics-consistent neural network model with specified model architecture (Di Natale et al., 2022). In our previous work (Xiao and You, 2023), we come up with a physically consistent deep learning (PCDL) method for building thermal modeling, which provides strict guarantees of following physics laws. Based on the current research, the application of a physics-informed AI model in MPC can be an appealing method for enhancing DR and community energy management performance (Hu et al., 2022). This work proposed a centralized MPC for community energy management embedding with the PCDL model, which is utilized to estimate the indoor climate and community loads. The PCDL model is developed with the presented physics consistency definitions and guarantees. Subsequently, it is integrated into the centralized MPC framework. The control objective is to reduce the total energy cost based on the real-time grid market and maintain comfortable indoor environments for each building. A test case on a student residential community at Cornell University is used to verify the performance of the proposed approach. The simulation results prove the superior performance of control-oriented generalization ability and control applications of the PCDL model compared to a long short-term memory (LSTM), a Gated Recurrent Unit (GRU), and a Gaussian Process (GP) regression model. The main contributions of this work include the following: (1) introducing a novel PCDL-based modeling and centralized MPC framework for community energy management; (2) PCDL model prediction accuracy and generalization ability validation compared to alternative AI models; (3) demonstrating the superior closed-loop performance of the PCDL model through a simulation case.

2. Physically consistent deep learning model

In this section, we will briefly present the PCDL modeling process, including the physics consistency definitions, PCDL model architecture, and the physics consistency guarantee. The PCDL model is used to predict the community thermal dynamics (including indoor temperature, indoor relative humidity, and WT temperature) based on system inputs, such as space heating power and heating pump supply power. In the context of the community, we interpret physics consistency as straightforward positive or negative associations between the system's inputs and outputs. An illustrative example is the current indoor temperature's proportional rise with an increase in the preceding indoor heating power. This relationship can be written as:

$$\frac{\partial T_k}{\partial HP_{k-i}} > 0, \ i = 1, 2, 3, \ldots k \tag{1}$$

In the above notation, T stands for the indoor temperature, while HP denotes the heating power. The subscripts i and k are indicators for time steps. This equation encapsulates the basic relationship between indoor temperature and heating power, a connection that can be readily discerned through heuristic understanding. A detailed description of the physics consistency definition can be found in our previous work (Xiao and You, 2023). In this work, we further extended the definition to the ground source heating pump (GSHP) and water tank (WT). Specifically, the water tank temperature is set as the system output with physically consistent inputs, including GSHP heating or cooling supply power and indoor heating or cooling load power.
The architecture of the PCDL model is depicted in Figure 2, which includes both a recurrent neural network (RNN) cell and an LSTM cell. These components serve to classify all inputs into two categories: physically consistent inputs and other inputs. In Figure 2, the symbols $\tilde{x}_k$, $\tilde{h}_k$, x_k, h_k, and c_k correspond to the physically consistent inputs, outputs of the RNN cell, other inputs, outputs of the LSTM cell, and the LSTM cell's memory states. By employing the proposed model structure, we effectively segregate the physically consistent inputs, which are processed within the RNN cell. The LSTM cell, on the other hand, is used to approximate other

dynamics that do not exhibit clear physics consistency. For example, parameters such as time information, the number of occupants, and solar irradiances are accounted for in the LSTM cell. The physics consistency guarantees are provided by additional parameter constraints: the state-to-state and input-to-state weighting parameters of the RNN cell are positive. Following the proof in our previous works (Xiao and You, 2023), the physics consistency guarantees can be written as

$$\frac{\partial \mathbf{Z}_k}{\partial \tilde{x}_{k-i}} = \frac{\partial \tilde{h}_k}{\partial \tilde{x}_{k-i}} + \frac{\partial h_k}{\partial \tilde{x}_{k-i}} = TD \cdot W_{hh}^{i} \cdot W_{ih} > 0, \quad \frac{\partial \mathbf{Z}_k}{\partial \mathbf{Z}_{k-i}} = TD \cdot W_{hh}^{i+1} > 0 \tag{2}$$

In the above expressions, *TD* stands for the derivatives of the tanh function. Given finite inputs, *TD* always yields positive outcomes. Up to this point, we have successfully demonstrated that all positive physics consistency can be characterized by the above expressions. To address negative physics consistency, one can simply modify the input $\tilde{x}_k$ to $-\tilde{x}_k$ and follow the same process outlined above.

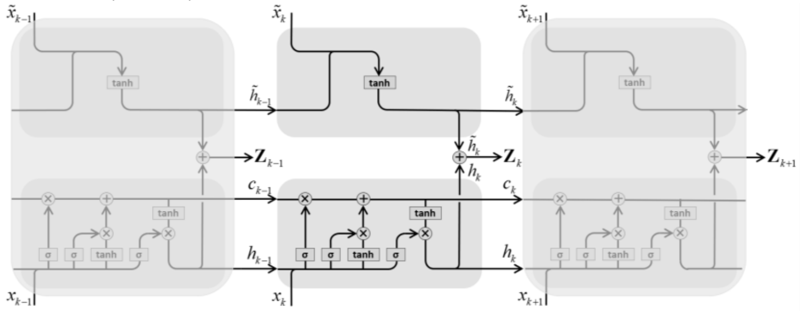

Figure 1: PCDL model architecture: the RNN cell (top)and the LSTM cell (bottom)

3. PCDL-based centralized MPC

In this section, we will present the PCDL-based centralized MPC for community energy management. The community energy facilities included in this work are depicted in Figure 2. Photovoltaic (PV) panels with battery storage are used to supply renewable energy to the community. GSHP with WTs is used to supply hot and chilled water to the heating, ventilation, and air conditioning (HVAC) system, which maintains the indoor temperature and humidity of each building. As we discussed before, the PCDL model is implemented as an estimator for indoor climate and facility loads. The aim of the real-time MPC is to reduce the total energy cost of the community based on the real-time grid market price. The indoor thermal comfort and facility constraints are also considered in the MPC framework. In Table 1, we showed the control variables for the centralized MPC. During the control process, an open-loop optimization problem will be recursively solved at each time step, and the first control action will be utilized in the community system.

$$\begin{aligned}
&\min_{\boldsymbol{u}} \ \sum_{k=1}^{K} gp_k P_{grid,k} + \sum_{k=1}^{K}\sum_{n=1}^{N} W_n \varepsilon_{n,k} \\
s.t.\ \ &\boldsymbol{x}_k = f_{pred}\left(\boldsymbol{x}_{k-1}, \boldsymbol{u}_{k-1}, \boldsymbol{z}_{k-1}\right) \\
&\boldsymbol{x}_0 = \hat{\boldsymbol{x}}_0 \\
&\boldsymbol{x}_{LB} - \boldsymbol{\varepsilon}_k \le \boldsymbol{x}_k \le \boldsymbol{x}_{UB} + \boldsymbol{\varepsilon}_k \\
&\boldsymbol{u}_{LB} \le \boldsymbol{u}_k \le \boldsymbol{u}_{UB} \\
&k \in \boldsymbol{K} = \{1, 2, \ldots, K\}
\end{aligned} \tag{3}$$

In the above expression, symbols gp, P, W, ε, f, **x**, $\hat{\mathbf{x}}$, **u**, **z**, K, and N represent the real-time grid price, power, weighting parameter, slack variable, function, system state, real-time measurement, control variable, disturbance, number of time steps, and number of slack variables (Lu et al., 2020); subscript k, grid, n, pred, LB, and UB represent the time step notation, grid, slack variable notation, prediction model, lower bound, and upper bound. The prediction function $\mathrm{f}_{\mathrm{pred}}$ includes not only the PCDL prediction process for community thermal dynamics but also the PV power generation prediction, predicted mean vote value (PMV) prediction, battery state of charge (SoC) prediction (computed based on battery charging/discharging power), and the purchased grid power prediction (computed based on power balance equation). The PV generation is predicted by an LSTM model, which is not included in this paper due to space limits (Abdel-Nasser and Mahmoud, 2019). The PMV values are computed based on indoor temperature and humidity to quantify indoor comfort (Yang et al., 2022a). The system states **x** includes the indoor temperature, indoor relative humidity, SoC states, WT temperature, and PMV values. Noted that slack variables are used to guarantee the feasibility of the problem. The control variables **u** are specified in Table 1. Their lower and upper bounds are based on facility capacities.

Table 1: Control variables of the PCDL-based centralized MPC

Control Variable	Descriptions
$P_{Heat,GSHP}$	GSHP Heating Power (W)
$P_{Cool,GSHP}$	GSHP Cooling Power (W)
$P_{Battery}$	Battery Charging/Discharging Power (W)
P_{Hum}	Humidification Power (W)
P_{Dehum}	Dehumidification Power (W)
Q_{Heat}	Space Heating Load (W)
Q_{Cool}	Space Cooling Load (W)

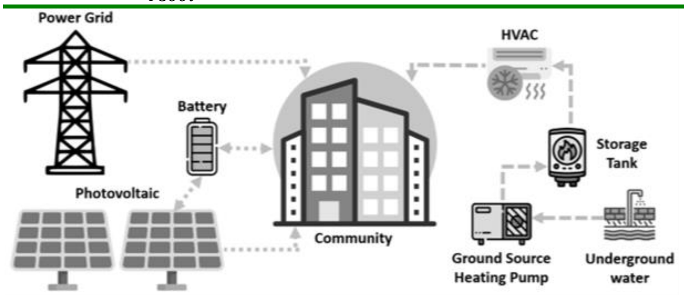

Figure 2: Community energy facilities included in this work. The PV panels with battery storage are used to supply renewable energy to the community. GSHP with WTs is used to supply hot and chilled water to the HVAC system, which maintains the indoor temperature and humidity of each building

Table 2: Loss values of the PCDL, LSTM, GRU, GP models on the training, validation, and test datasets

Dataset	Winter Case				Summer Case			
	PCDL	LSTM	GRU	GP	PCDL	LSTM	GRU	GP
Training Dataset	0.000354	0.000318	0.000294	0.000282	0.000166	0.000126	0.000145	0.000118
Validation Dataset	0.000356	0.000318	0.000290	0.000224	0.000170	0.000125	0.000148	0.000112
Test Dataset	0.0146	0.0235	0.0181	0.0179	0.0104	0.0110	0.0161	0.0243

4. Simulation results

The Townhouse Community, a student living community at Cornell University, comprises five similar two-story buildings, each with a basement. These buildings also feature an attic space. Each building covers a total area of 1,057.9 m^2 and encapsulates a volume of 3,224.5 m^3. Each floor, treated as a separate thermal zone, is served by a single HVAC system equipped with water coils and humidifiers. All buildings are supplied with hot and chilled water via a GSHP that includes storage tanks. The simulation models for this setup are created using EnergyPlus software and the Building Controls Virtual Test Bed (BCVTB) toolbox. In this process, individual buildings are defined within EnergyPlus, and the interconnections between the individual buildings are set up in the BCVTB toolbox (Yang et al., 2022b). The training and validation datasets were produced from the simulation model in an 80/20 ratio, with data recorded at 10 min intervals. More specifically, the dataset spanning from January 1st to January 14th (winter) and from July 1st to 14th (summer) in 2022 was employed for training the PCDL, LSTM, GRU, and GP model, the latter three serving as a basis for comparison. The data on January 15th (winter) and July 15th (summer) with a larger system state range was also generated as the test dataset to validate the generalization ability of all data-driven models. From Table 2, we can find that all the models present sufficient performance in both the training and validation dataset. However, The PCDL model presents smaller loss values in the test dataset, which demonstrates its generalization ability compared to other data-driven models. The physics consistency guarantees were validated through Figure 3, which is the indoor temperature simulation results of one typical thermal zone on January 15th. The PCDL model manages to generate physically feasible solutions, as inequality (1) shows and presents similar prediction results compared to the EnergyPlus model. The above feature of the PCDL model is also called control-oriented generalization ability due to the system’s physically consistent response to modified inputs.

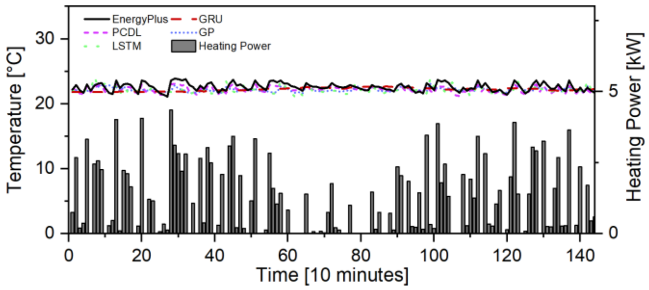

Figure 3: The indoor temperature simulation results of one typical thermal zone on January 15th

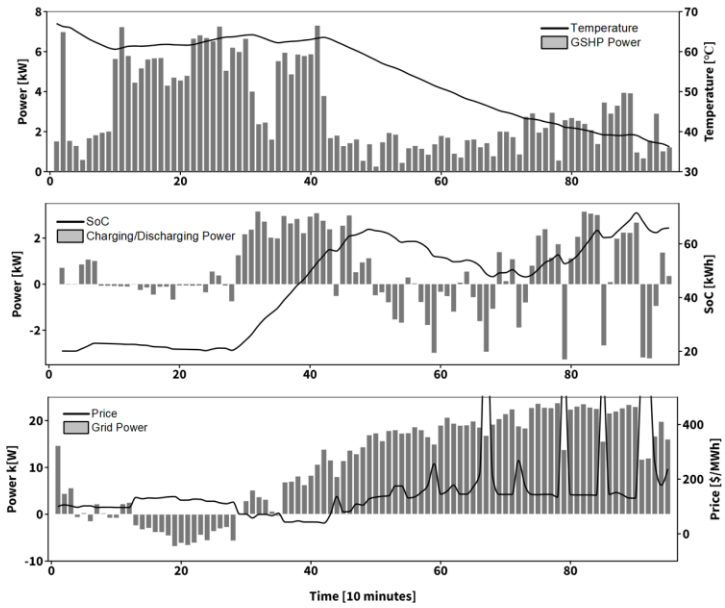

Figure 4: The closed-loop simulation results for community energy dispatching by using the PCDL-based MPC

The closed-loop simulations were conducted from 8 a.m. to 24 p.m. on January 15th in 2022 with a 10 min control interval and 6 h prediction horizon. Besides the PCDL-based MPC, LSTM-based, GRU-based, and GP-based MPC frameworks were also developed for comparison. The indoor thermal constraints were set as: (20.28 °C, 23.89 °C) for indoor temperature, (30 %, 60 %) for indoor temperature, and (- 0.5, 0.5) for PMV index. From the simulation, the indoor thermal constraint violations for the PCDL-based, LSTM-based, GRU-based, and GP-based MPC are 5.15 %, 49.35 %, 51.25 %, and 62.89 %. The PCDL model stands out in thermal comfort control results from its control-oriented generalization ability. In contrast, the other controllers struggled to uphold comfortable indoor climates, mainly due to their lackluster performance when dealing with scenarios outside of the training dataset. Figure 4 shows the energy dispatching simulation results obtained using the PCDL-based MPC. By capitalizing on the flexibilities offered by the GSHP, WTs, and battery systems, load-shaving and shifting behaviors can be observed in the simulation results. These behaviors contribute positively to grid stability and energy cost reduction for consumers.

5. Conclusion

In this study, we have proposed a centralized MPC framework for community energy management. This framework employs a novel PCDL model designed to strictly comply with physical consistency by utilizing a unique model structure and imposing parameter constraints. Serving as a reliable predictor for load and indoor climate, the PCDL model was integrated into a centralized MPC framework. The aim was to optimize community energy distribution based on current measurements and real-time grid market conditions. We used a residential community at Cornell University as a simulation case to test the efficacy of the proposed control framework. The simulation results highlighted the control-oriented generalization ability of the PCDL model compared to the LSTM, GRU, and GP models. Additionally, the closed-loop simulation revealed significant indoor thermal comfort improvements of 89.56 %, 89.95 %, and 91.81 % when employing the PCDL-based MPC, as compared to the other three data-driven MPC controllers.

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