**Quantify the impact of prediction error on predictive control performance**

Lunlong Li1,**#**, Yi Ju2,**#**, Zhe Wang1,3,*\**

1 Department of Civil and Environmental Engineering, The Hong Kong University of Science and Technology, Hong Kong, China

2 Department of Civil and Environmental Engineering, University of California, Berkeley, CA, 94720, USA

3 Shenzhen-Hong Kong Collaborative Innovation Research Institute, Futian, Shenzhen, China

# These two authors contribute equally to this paper

*\** *Corresponding author: cezhewang@ust.hk*

# ABSTRACT

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**KEYWORDS**

Prediction uncertainty; Predictive control; Smart grid operation

# 1. Introduction

Load prediction is a hot research topic.

The ultimate goal of load prediction is serve downstream tasks, such as predictive control.

Existing work evaluate load prediction methods based on its prediction error, very few focus on the performance of downstream tasks. This study plans to fill in this research gap under the context of smart grid operation.

## **1.1 Existing work**

*1.1.1. Building load prediction*

Problem: too slow, cannot be used for real time optimization

*1.1.2. Predictive control*

MPC and others (RL)

*1.1.3. Smart grid operation*

## **1.2 Scope and objectives**

In this study, we quantify the impact of prediction error on predictive control performance under the context of campus-level smart grid operation. We will consider two scenarios: with demand charge and without demand charge.

The key hypothesis to be tested here is whether prediction with high accuracy will lead to good control performance.

The remaining of this paper is organized as follows: we first introduced the workflow we proposed in Section 2, including... Next, we presented the results: including … (Section 3.1), … (Section 3.2), … (Section 3.3). We then discussed our contribution and limitation in Section 4, before we concluded in Section 5.

# 2. Method

## **2.1 Workflow**

*2.1.1 Load prediction*

Model, architecture, hyper-parameter tuning

*2.1.2 Model predictive control*

Decision variables

Problem formulation, control horizon, and other details

## **2.2 Test case**

UCSD campus, operational data, load characteristics

# 3. Result

## **3.1 Scenario: without demand charge**

Optimized decision variable give Time-of-Use utility price

A figure to show the impact (x: prediction error, y: control performance)

## **3.2 Scenario: demand charge**

Optimized decision variable give Time-of-Use utility price

A figure to show the impact (x: prediction error, y: control performance)

Lunlong: Several error metrics will be calculated and we may find that some of them imply more impact on the control performance. (e.g. CV, MSE, MAPE)

## **3.3 Anything else?**

Other interesting results

Lunlong: What if we concatenate predictions of different accuracies on the time scale for MPC. For example, when prediction K is set as 96, feed ground truth of [1:m] and some kind of prediction [m+1:K] to MPC, to observe whether a threshold exist at which the control performance badly deteriorated.

# 4. Discussion

## **4.1 Contribution**

This studies examines how model accuracy would impact the downstream control performance under the context of smart grid operation. This is important because at the end of the day, what matters is the control performance rather than the prediction accuracy. We found this impact has the following two characteristics:

* With and without demand charge
* With demand charge, this impact is non-linear or whatever

## **4.2 Limitation and the next step**

RMSE is a lumped parameter to characterize the prediction error, which ignores the temporal correlations. Explain why it matters.

There are couples of solutions how to handle prediction uncertainty: robust MPC, stochastic MPC. We will test their performance as the next step

# 5. Conclusion

In this paper,

# 6. Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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# 8. Reference