**Ph.D. DISSERTATION DEFENSE**

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**Title: Boosting Power System Operation Economics via Closed-Loop Predict-and-Optimize**

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**ABSTRACT**

Typically, operation tasks within the power system field follow a predict-then-optimize framework, in which machine learning (ML) methods are first trained to predict key parameters and then optimization models use these predictions as inputs to determine optimal operational decisions. For instance, renewable energy availability is predicted to serve as inputs for day-ahead operation models. The ultimate goal of such a predict-then-optimize process is to achieve the best operation economics associated with the optimal operation tasks, e.g., minimum operation cost or maximum operation revenue.

However, the predict-then-optimize framework has a critical flaw: it is an open-loop process where the prediction task prioritizes minimizing immediate statistical errors (i.e., accuracy-oriented) over maximizing ultimate operation economics. This flaw may affect operation economics adversely.

To this end, this dissertation presents a closed-loop predict-and-optimize (C-PO) framework to improve operation economics. The C-PO feeds the operation economics back to the prediction phase and evaluates prediction quality in terms of its effects in leading to good economics (i.e., cost-oriented). In this way, the goals of the prediction task and the operation task are aligned closely, thus enhancing operation economics.

To evaluate the effectiveness of the C-PO framework, this dissertation specifies the C-PO framework using different ML methods for two power systems operation tasks, i.e., unit commitment and cascaded hydropower scheduling. Case studies on real-world data demonstrate the effectiveness of the proposed C-PO framework designs.