Effective End-to-End Learning Framework for Economic Dispatch

The Problem: The pervasive intelligent smart meter devices in the electricity grid are generating huge volumes of data, which warrants using advanced AI techniques to power the grid. We explore the possibility of applying AI to conduct economic dispatch, which is a classical power system control task. Generally speaking, economic dispatch is conducted by the system operator to match the supply demand in the system subject to the physical constraints.

Challenges: Conventionally, the renewable penetration in the grid is limited. The major challenge is how to accurately characterize the non-convex physical constraints. However, with the increasing penetration of renewables, the stochastic nature in the renewable generation poses additional challenge on the effectiveness of economic dispatch.

Conventional Wisdom: The conventional wisdom identifies the key issue brought by the renewables: the integration of renewables makes the load hard to predict. As renewable generation is often regarded as negative load, this wisdom believes that more accurate load prediction leads to more effective economic dispatch. Doesn't it sound correct?

Our Idea: On further review, we realize that the goal of more accurate load prediction does not align with that of more effective economic dispatch. More precisely, to achieve accurate load prediction, mean square error (MSE) is the most widely adopted training criteria. However, the goal of economic dispatch is to minimize the operational cost or the generation cost. The misalignment comes from isolating the load prediction from the whole economic dispatch process. This inspire us to adopt the end to end machine learning framework to conduct the economic dispatch.

The most straightforward way to apply end to end machine learning is to directly learn the control policy, i.e., the final dispatch profiles [1]. However, it is not clear if the learning outcome would be valid dispatch profile as it has to satisfy all the physical constraints. Also, if not well designed, it often suffers from low data utilizing to directly learn the control policy.

Hence, we start from investigating the structure of stochastic optimization in economic dispatch and use the notion of task specific criteria to better utilize the data. Figure 1 visualizes this process.

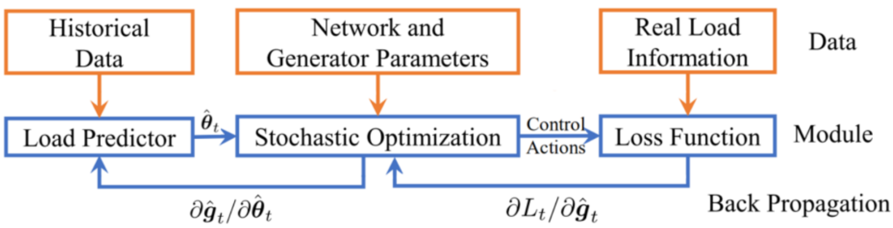

Fig. 1 Task-Specific Optimization Based Learning Process.

While it is theoretically sound, its efficiency is low. This framework requires solving the multivariate constrained stochastic optimization problem during iteration. To tackle this computational challenge, we establish the relationship between the distribution of the predicted load and the optimal total generation. Then, we use binary search to obtain the control policy efficiently.

Diving into this relationship, we submit that the knowledge of distribution is not necessary. This allows us to further improve the efficiency of end to end machine learning [2]. More importantly, we can design a model free algorithm to predict the total dispatched generation, which can be used to effectively construct the dispatch profile. Figures 2 and 3 illustrate the performance of the proposed frameworks.

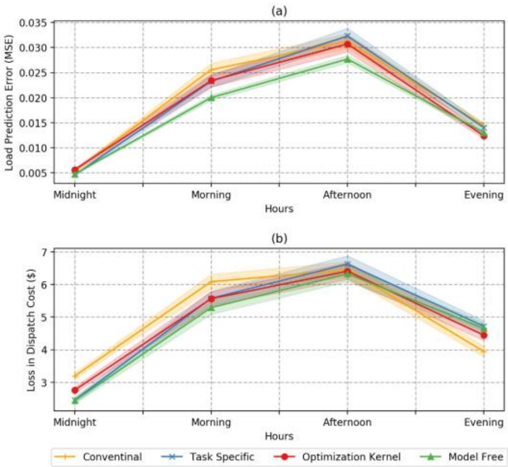

Fig. 2 Effectiveness Comparison

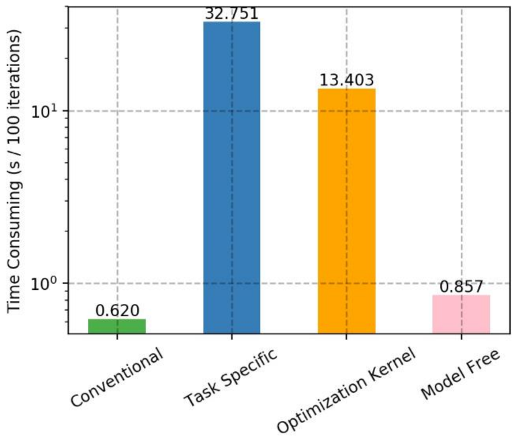

Fig. 3 Efficiency Comparison.

Future Work: There is still certain gap between theory and practice model. We haven't considered the ramping constraints and other temporal constraints. We also focus on the economic dispatch with linear cost functions. It will be interesting to see how these changes in the stochastic optimization problem will change the end to end machine learning framework design.

References

[1] Donti, P., Amos, B. and Kolter, J.Z., 2017. Task-based end-to-end model learning in stochastic optimization. In Advances in Neural Information Processing Systems (pp. 5484-5494).

[2] C. Lu, K. Wang, and C. Wu, Effective End-to-End Learning Framework for Economic Dispatch, https://arxiv.org/abs/2002.12755