**Documentation**

This study conducts a quantitative comparison of the four existing decision-focused learning methods. Overall, they can be categorized into two types: indirect and direct. They can be further divided into gradient-free and gradient-based methods. The model section includes a load forecasting model and a decision-making model (day-ahead and real-time market). IEEE 118-node system is utilized as the test system. The comparison dimensions include offline training time, online decision time, decision performance, and prediction accuracy. The way prediction and decision-making are linked varies according to the four different decision-focused learning methods, with the data parameters and indicators used uniformly, as detailed below.

**(1) Decision-making model**

**① Sets and Indices**

|  |  |
| --- | --- |
|  | Set of hours. |
|  | Set of transmission lines. |
|  | Set of conventional generation units. |
|  | Set of loads. |
|  | Set of nodes. |
|  | Day-ahead voltage angle at node *n* [rad]. |
|  | Real-time voltage angle at node *n* [rad]. |
|  | Up-/Downward reserve requirement of power system [MW]. |
|  | Up-/Downward reserve capacity of unit i [MW]. |
|  | Forecasting value of load *q* [MW]. |
|  | Actual value of load *q* [MW]. |
|  | Shedding of load *q* [MW]. |
|  | Day-ahead dispatch of conventional unit *i* [MW]. |
|  | Up-/Downward reserve provision from unit *i* [MW] |
|  | Up-/Downward reserve deployment of unit *i* [MW]. |
|  | Day-ahead price offer of unit *i* [$/MW]. |
|  | Up-/Downward reserve price offer of unit *i* [$/MWh] |
|  | Value of lost load [$/MWh]. |
|  | Punishment cost of slack variable [$/MWh]. |
|  | Capacity of transmission line (*n*, *m*) [MW]. |
|  | Maximum day-ahead quantity offer of unit *i* [MW]. |
|  | Slack variable indicating the real-time stage generator output waste [MW]. |

**② Day-ahead market**

The typical electricity market clearing model consists of the day-ahead market clearing model and the real-time market clearing model[1]. The day-ahead energy schedule can be formulated as (2). The objective (2.1) is to minimize the total cost including generation costs and reserve procurement cost. The generator constraints include reserve requirements (2.2) - (2.6) and generation limits (2.7), power balance (2.8), transmission line capacity limits (2.9).

 (2.1)

 (2.2)

 (2.3)

 (2.4)

 (2.5)

 (2.6)

 (2.7)

 (2.8)

 (2.9)

where is the set of optimization variables comprising the output power of thermal units, the upward and downward reserve schedule, and voltage angles at each node.

**③ Real-time market**

The real-time market is modelled solving the linear programming problem in (3), where indicates the optimal solution from day-ahead stage. The objective function (3.1) is to minimized is the balancing cost. Constraints (3.2) and (3.3) ensure the real-time nodal power balance and account for the power capacity of transmission lines. Constraints (3.4) limits activation of upward and downward reserves considering the procured reserve quantities. Constraints (3.5) limit load shedding actions.

 (3.1)

 (3.2)

 (3.3)

 (3.4)

 (3.5)

where is the set of re-dispatch decisions, i.e., the activation of operating reserves, load shedding and real-time voltage angles.

**(2) Forecasting model**

In load forecasting, the specific forecasting model can be freely selected based on the different decision-focused learning tasks. The datasets for training and testing, as well as the input and output, are uniformly defined as follows.

1. **Training data of load forecasting**

**The folder named “train\_data” contains two files, X\_train and Y\_train, which represent the input features for the load forecasting model and the load output value labels, respectively.** Specifically, in the X\_train file, the load input features for the whole system load are stored. The input file contains 14 types of features, including trend, day\_multiply\_hour, month, and temperature data from 11 meteorological stations, named temperature\_1 to temperature\_11. The input and output of the forecasting model are shown in Equation (4). All data comes from the Global Energy Forecasting Competition 2012[2].

 (4)

* **Trend:** Trend is used to capture the locally increasing (or decreasing) trend by assigning a natural number to each hour in ascending order. For example, the Trend variable for the first hour in 2005 is 1, the second hour in 2005 is 2, and the last hour of 2008 is 35064.
* **Day\_multiply\_hour:** The input feature includes the product of the day (1-31 of each month) and the hour (1-24 of each day) for the predicted load.
* **Month:** The input feature includes the month (January to December) of the predicted load.
* **Temperature\_1 to temperature \_11:** The input feature includes the temperature data from 11 meteorological stations, which are randomly distributed across the 118 load locations.

1. **Testing data of load forecasting**

Similarly, the file storage format in the “test\_data” folder is consistent with that of the train\_data folder. **The training data and test data are split in a 7:3 ratio.**

**(3) Test system: 118 Nodes System**

In the Excel file named “118nodes\_system,” there are two sheets.

**① Sheet 1 is named “topology,” which stores the electrical admittance parameters of the connecting lines in the 118-node system.** This topology is in a 118×118 format, with diagonal elements representing the self-admittance of the lines and off-diagonal elements representing the mutual admittance between line i and line j. The matrix is symmetric.

**② Sheet 2 is named “unit,” which stores the generator unit parameters for the 118-node system.** The columns represent Bus, Installed capacity [MW], Day-ahead price offer [$/MW], Upward reserve capacity offer [MW], Downward reserve capacity offer [MW], Upward reserve price offer [$/MWh], and Downward reserve price offer [$/MWh]. Each row represents a different node, with rows where Installed capacity is 0 indicating no generator, and rows where Installed capacity is non-zero indicating a generator is present.

**(5) Reference**

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