

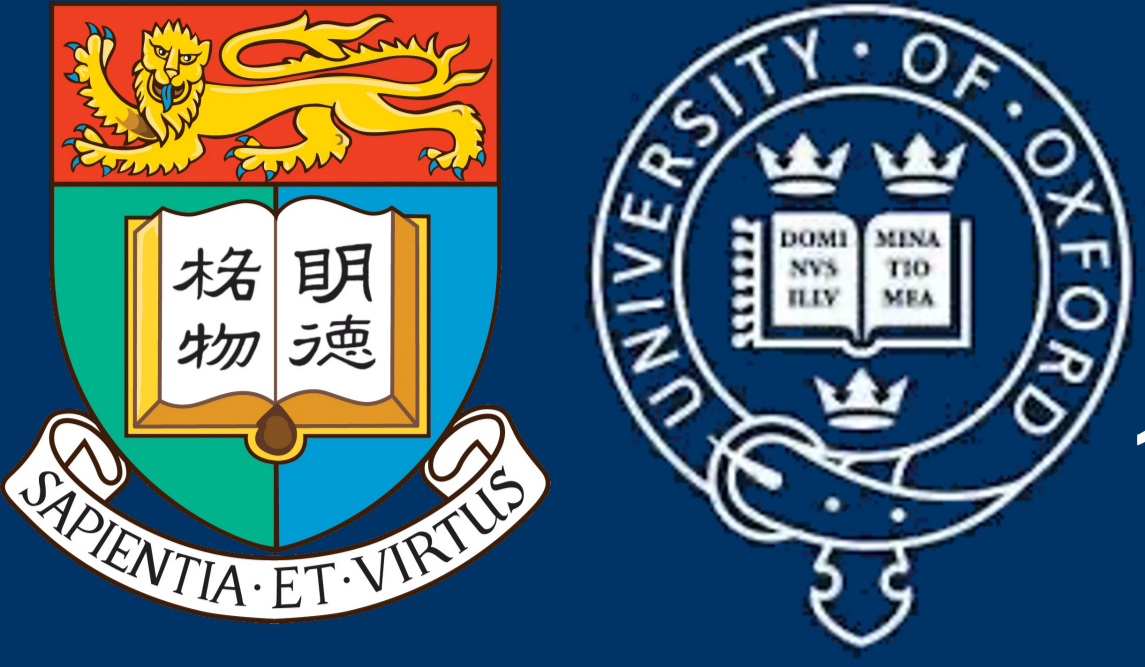
Decision-focused Learning for Local Energy Communities

Management Under Uncertainty

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Background

➤ **Local energy communities (LECs)** coordinate a large number of distributed energy resources (DERs) and achieve the on-site management of energy balance.

➤ The stochasticity and variability associated with renewable energy and loads introduce significant **uncertainty** for LECs.

Dispatch with uncertainty:

- **Stochastic optimization:** overly optimistic
- **Robust optimization:** over-conservative
- **Distributional robust optimization (DRO):** A Balanced approach by considering the worst-case distribution within a specified ambiguity set.

Probabilistic forecasting:

- **Parametric:** Based on the assumption that the data follows a specific statistical distribution.
- **Non-parametric:** Kernel density estimation or Quantile regression.
- **Scenario generation:** Diffusion or GAN.

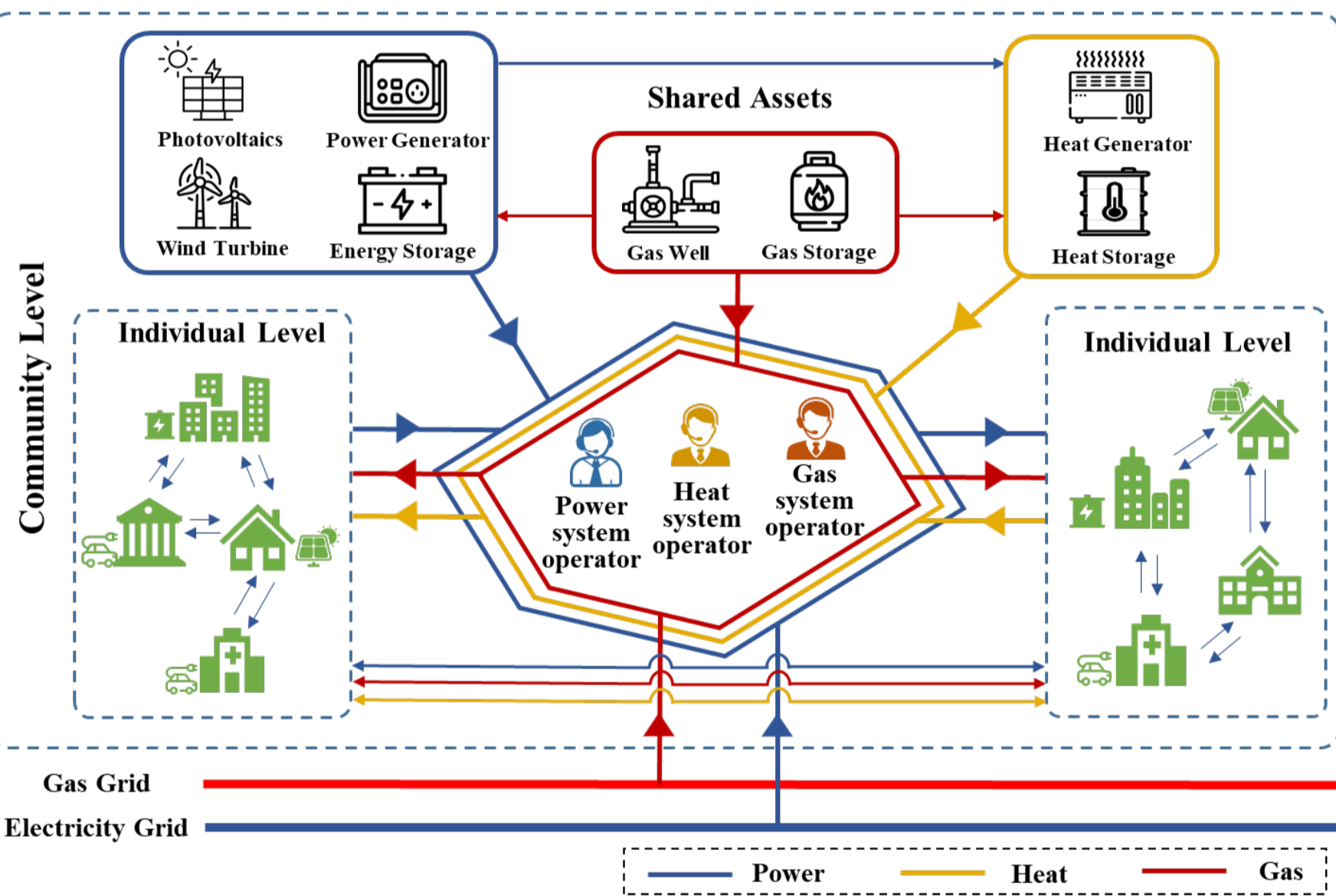
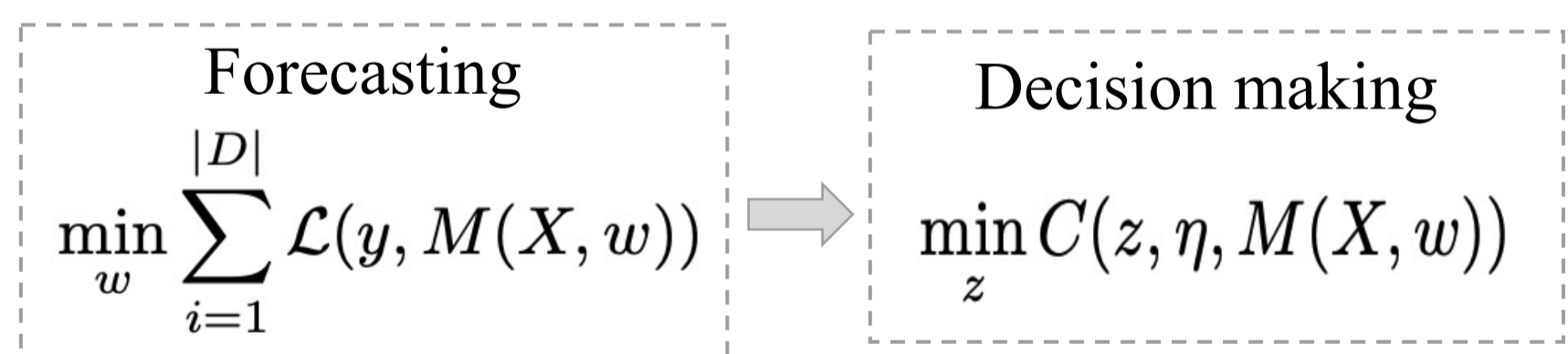


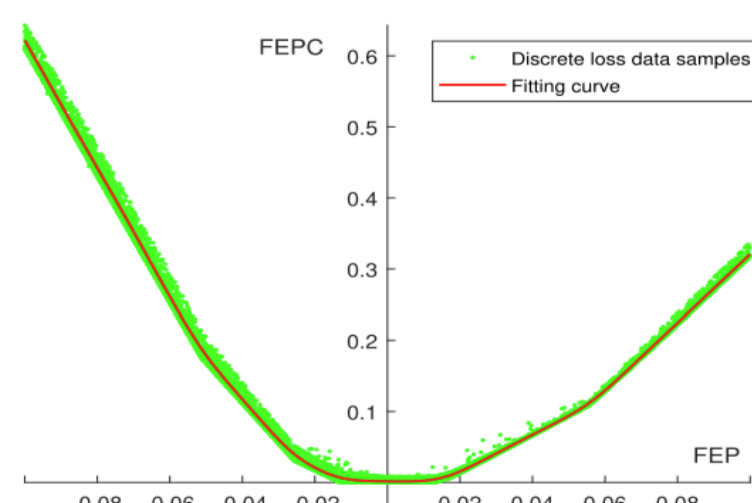
Fig. 1. Sketch of LECs

Motivation and Contribution

➤ Traditional forecasting approach: Minimizing forecasting errors.



Higher accuracy does not necessarily imply lower operation costs^[1].



➤ **Decision-focused Learning (DFL):** Optimize z and w as a whole.

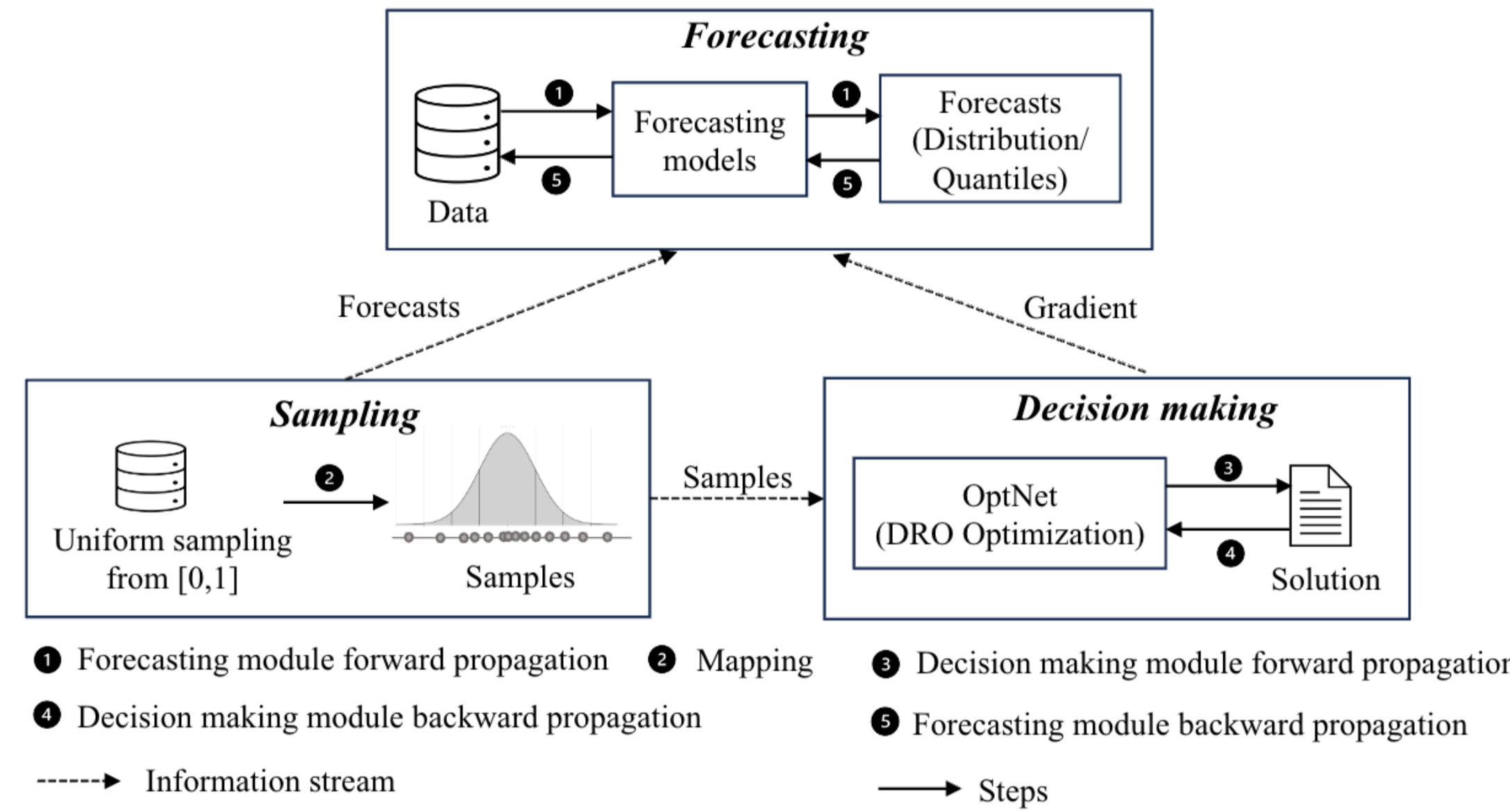
$$\min_{z, w} C(z, \eta, M(X, w))$$

➤ Two issues are neglected by existing works on DFL:

- **Probabilistic output $\hat{y} = M(X, w)$:** develop a unified framework to bridge probabilistic forecasting (parametric or non-parametric) with LECs energy management.
- **Dynamic parameter η :** develop an adaptive DFL model that can adjust to dynamically changing decision-making parameters.

Methodology

Unified DFL Framework



Sampling module

Sampling from a uniform distribution $[0,1]$ and then mapping into different scenarios (Ensures differentiability).

- Parametric: e.g., Gaussian output: $\xi_n = s_n\sigma + \mu$
- Non-parametric: e.g., Quantile Regression.

Linear interpolation: $\xi_n = \frac{\hat{y}_{[s_n]} - \hat{y}_{\lfloor s_n \rfloor}}{[s_n] - \lfloor s_n \rfloor} (s_n - \lfloor s_n \rfloor) + \hat{y}_{\lfloor s_n \rfloor}$

Decision-making module

General Form of two-stage DRO with Wasserstein distance

$$\min \{ \mathcal{G}(z_f) + \sup_{\mathbb{P} \in \mathcal{D}_\epsilon} \mathbb{E}_{\mathbb{P}} \{ Q^*(z_f, \xi) \} \}$$

$$\text{s.t. } \mathcal{F}_{\text{eq}}(z_f, \hat{y}) = 0, \mathcal{F}_{\text{iq}}(z_f, \hat{y}) \leq 0$$

$$Q^*(z_f, \xi) = \min_{z_s} Q(z_f, z_s, \xi)$$

$$\mathcal{H}_{\text{eq}}(z_f, z_s, \xi) = 0$$

$$\mathcal{H}_{\text{iq}}(z_f, z_s, \xi) \leq 0$$

Strong duality

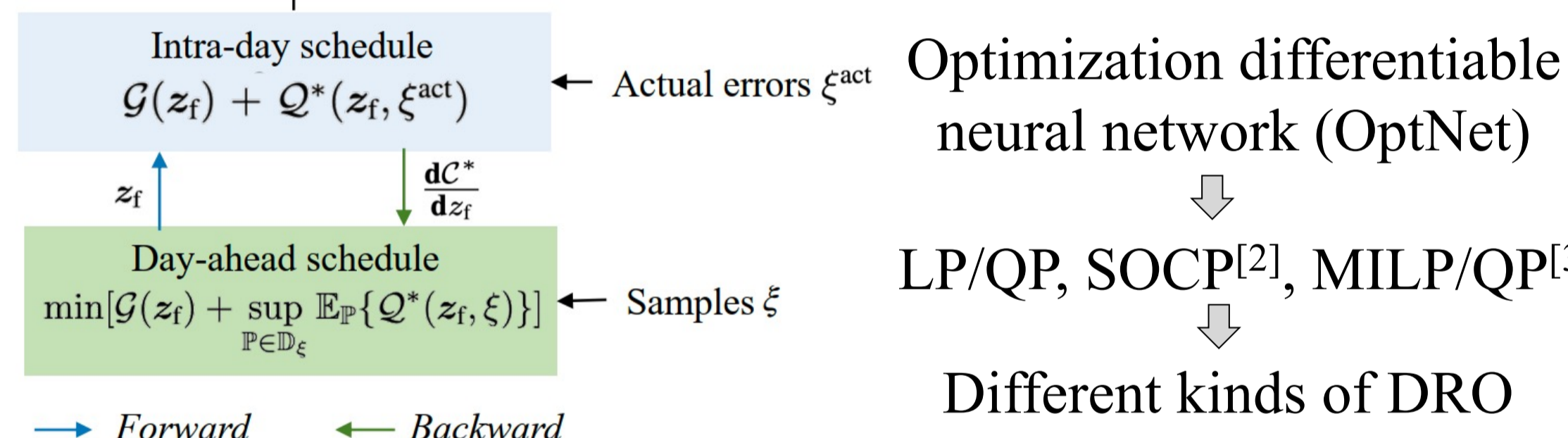
$$d_w(\mathbb{P}_\xi, \mathbb{P}_\xi) = \inf \int_{\mathbb{R}^2} \|\hat{\xi} - \xi\| \Pi(d\hat{\xi}, d\xi)$$

$$\inf_{\gamma \geq 0} \gamma \epsilon + \frac{1}{N} \sum_n \phi_n$$

$$Q^*(z_f, \hat{\xi}_n) - \|\hat{\xi}_n - \xi\| \gamma \leq \phi_n, n \in [1, N]$$

$$Q^*(z_f, \hat{\xi}_n) - \|\hat{\xi}_n - \xi\| \gamma \leq \phi_n, n \in [1, N]$$

$$Q^*(z_f, \xi) \leq \phi_n, n \in [1, N]$$



Continual DFL Approach

- Traditional load forecasting focuses on learning the distribution of the inputs to model X and its outputs Y
- **Covariate shift:** $P(X)$ changes, but $P(Y|X)$ remains the same.
- **Label shift:** $P(Y)$ changes, but $P(X|Y)$ remains the same.
- **Concept shift:** $P(Y|X)$ changes, but $P(X)$ remains the same.

These aspects do not consider the **impact of data distribution shifts on downstream tasks.**

Algorithm 1: End-to-end continual learning algorithm

Input: Initial model parameters w , Testing dataset D_{test}

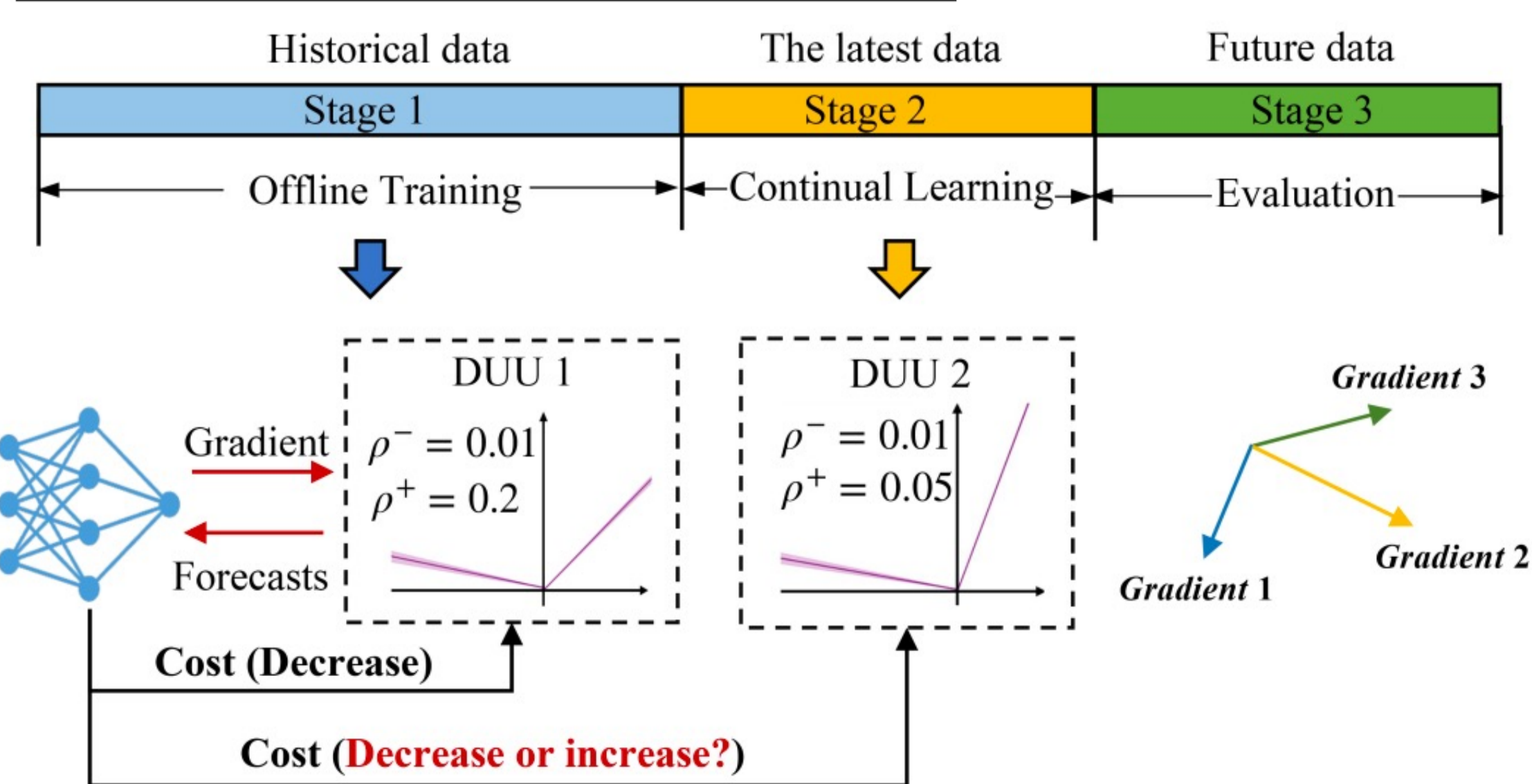
Output: Updated model parameters w_{update}

- for $t \in [1, 2, \dots, |D_{\text{test}}|]$ do
- Read latest data (X_t, y_t) and decision-making parameters p_t ;
- Forward forecasting model $\hat{y}_t = M(X_t, w_t)$;
- Sample scenarios $\xi_n, n \in [1, N]$;
- Forward OptNet with p_t and $\xi_n, n \in [1, N]$;
- Calculate operation costs C^* ;
- Update model parameter and obtain w_{t+1} ;

8 **Return** $w_{|D_{\text{test}}|}$

Task shift: The parameters involved in decision-making may change dynamically.

Equipment updates
Electricity price fluctuations
unforeseen events...

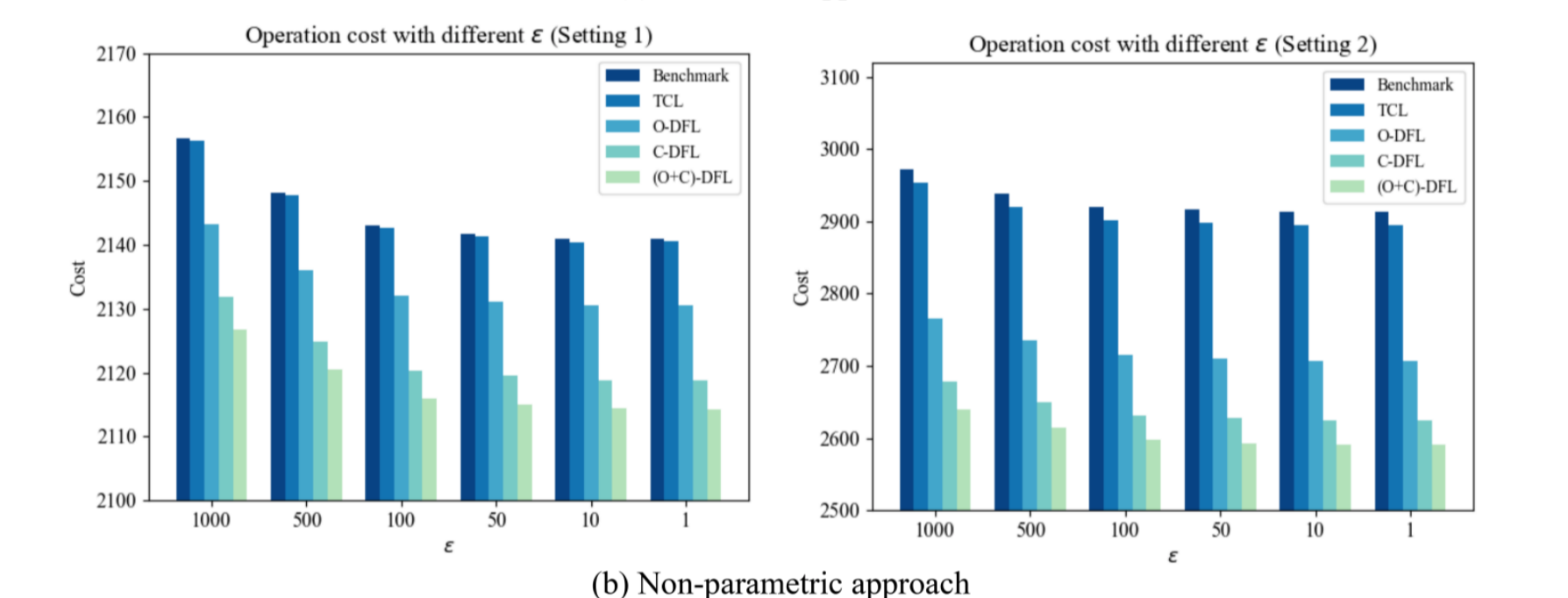
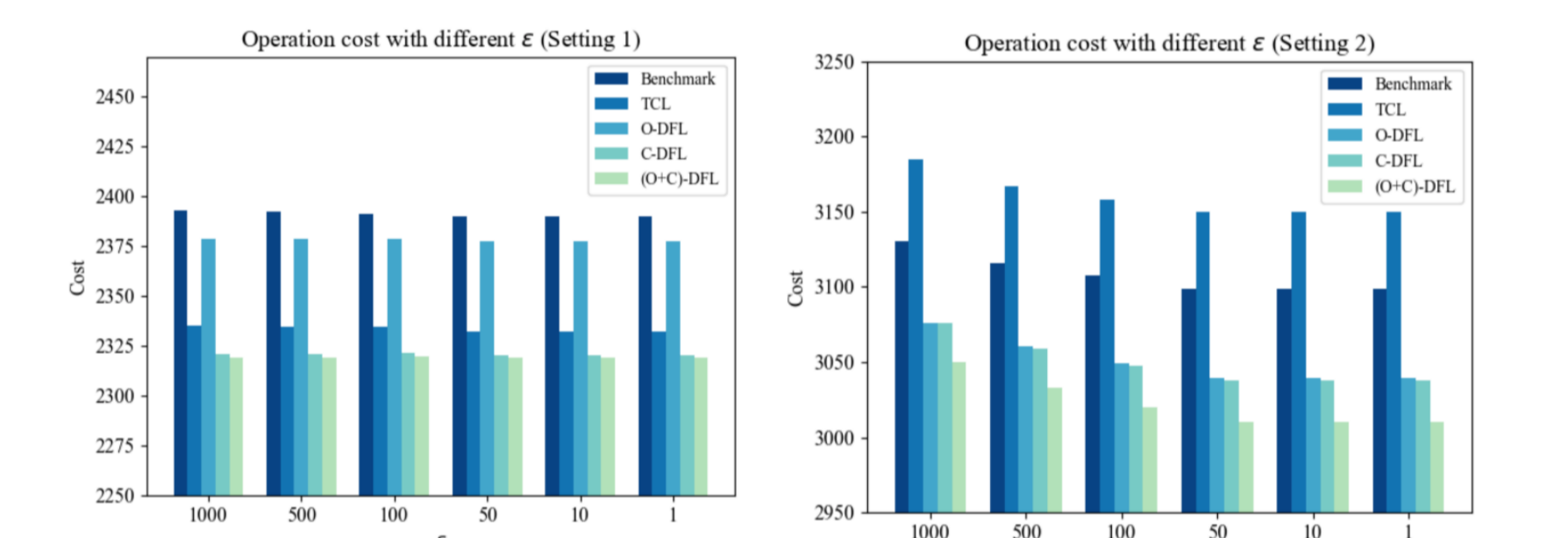
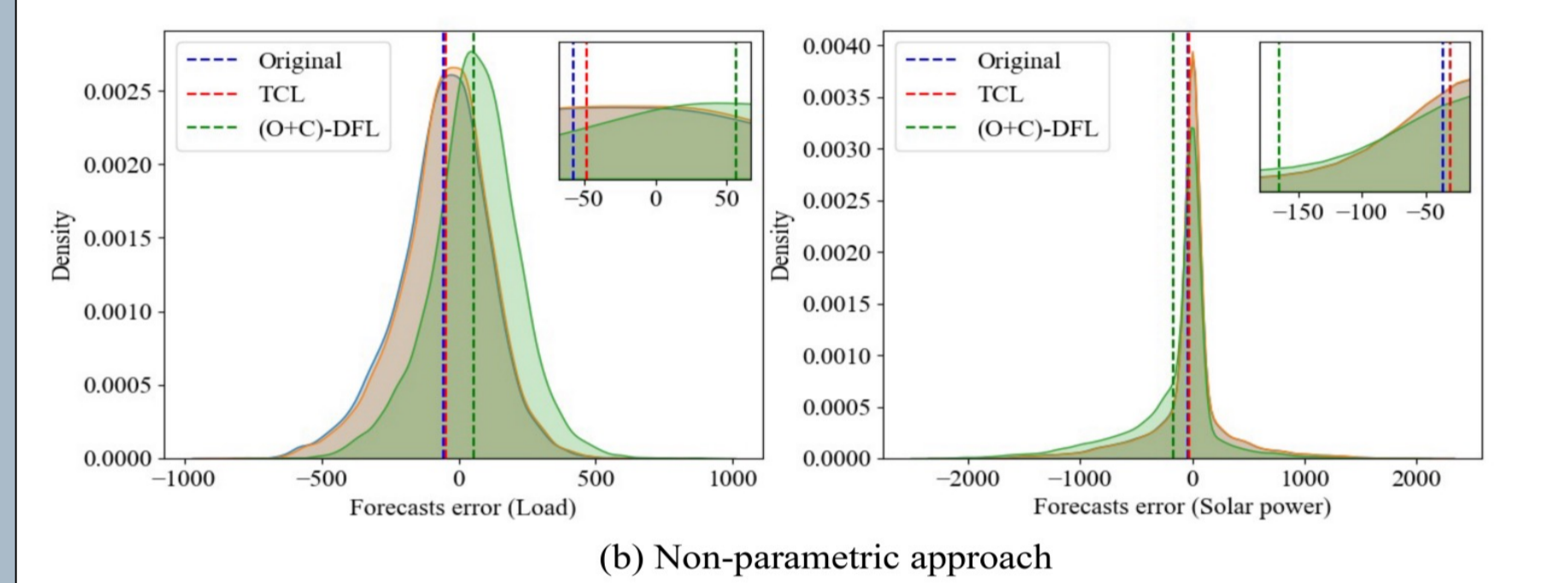
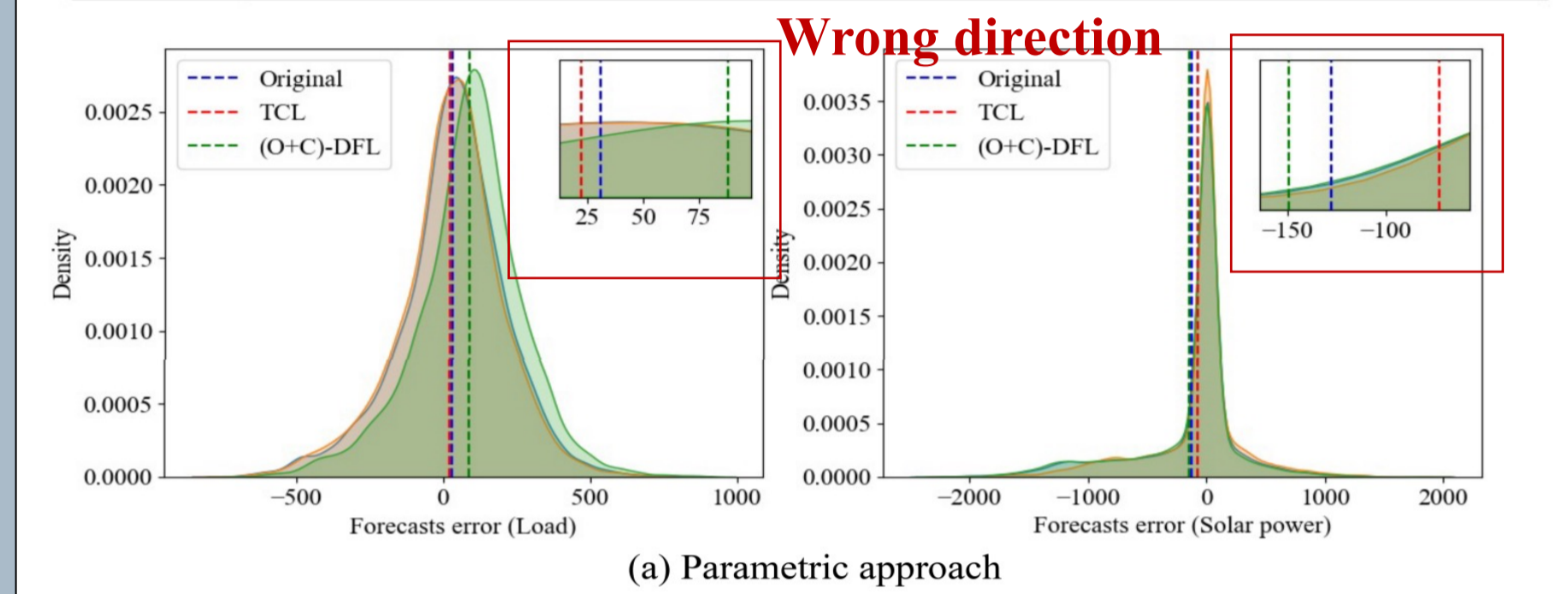


Case Studies

Experiment setting

Setting 1 and 2: The variation in cost related to up and down reserve is relatively small/large in both the training and testing phases. **-No task shifts**

	Setting 1		Setting 2	
	Non-parametric	Parametric	Non-parametric	Parametric
Ground Truth	1890.71	1890.71	1890.71	1890.71
Deterministic	2298.29	2451.76	3415.61	3100.42
Original	2140.94	2390.07	2912.68	3098.98
TCL	2140.44	2332.43	2894.68	3149.68
O-DFL	2130.54	2377.65	2706.17	3039.62
C-DFL	2118.74	2320.29	2625.04	3037.80
(O+C)-DFL	2114.34	2319.02	2591.01	3010.14
(Best-Original)/Ground Truth	1.41%	3.76%	17.01%	4.70%

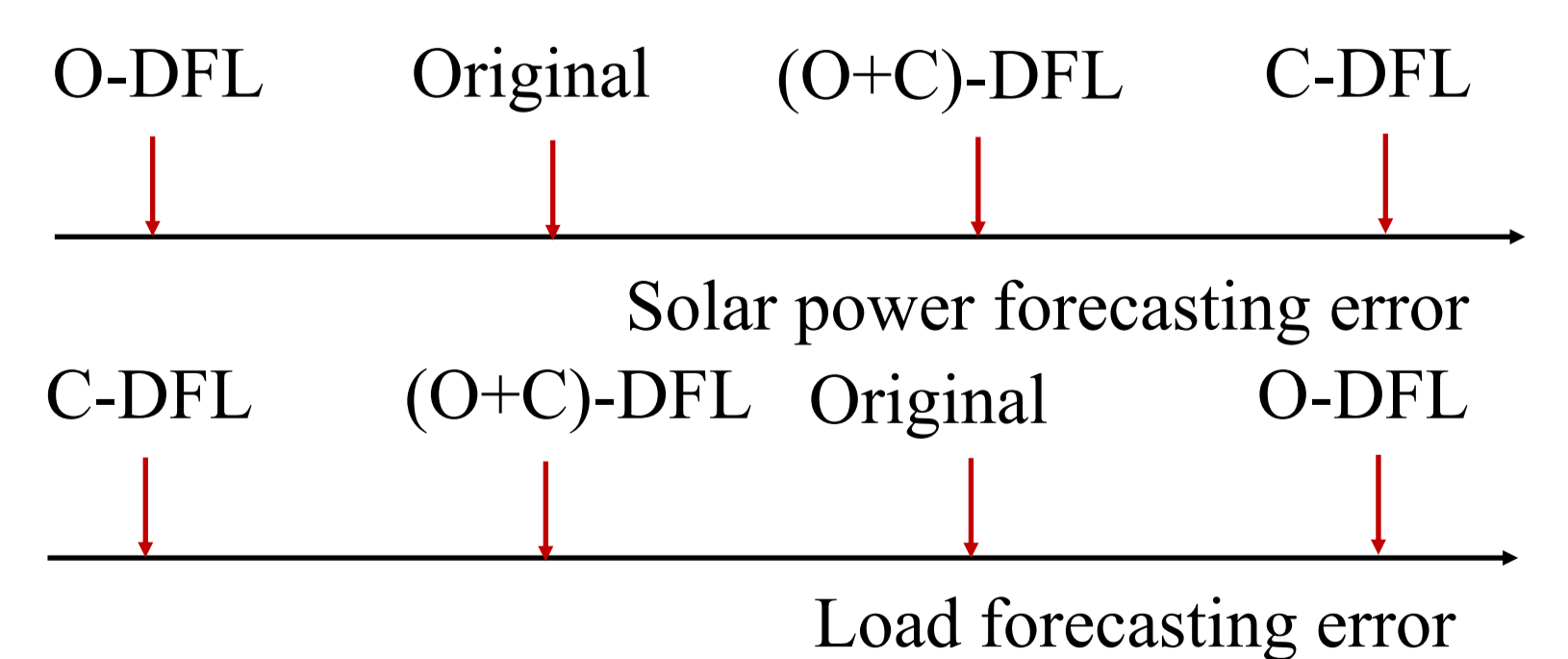


When ϵ decreases, DRO degrades to SO.

Setting 3 and 4: Costs related to up/down reserve are large/small in the training phase, while small/large in the testing phase - **task shifts**

	Setting 3		Setting 4	
	Non-parametric	Parametric	Non-parametric	Parametric
Ideal	1890.71	1890.71	1890.71	1890.71
Deterministic	2298.29	2451.76	3415.61	3100.42
Original	2140.94	2390.07	2912.71	3098.98
TCL	2140.44	2332.43	2894.71	3149.68
O-DFL	2178.31	2418.45	3008.70	3153.32
C-DFL	2118.74	2320.35	2624.74	3037.70
(O+C)-DFL	2119.73	2325.38	2632.99	3058.09
(Original-Best)/Ground Truth	1.17%	3.69%	15.23%	3.24%

	Non-parametric		Parametric	
	Solar power	Load	Solar power	Load
Original	-36.70	-57.58	-127.59	31.19
TCL	-30.93	-47.73	-72.69	22.51
O-DFL	-108.45	-3.74	-141.35	62.58
C-DFL	9.23	-83.31	-69.84	-37.15
(O+C)-DFL	0.82	-78.40	-77.15	-28.97



References

- [1] J. Zhang, Y. Wang, and G. Hug, "Cost-oriented load forecasting," *Electric Power Systems Research*, vol. 205, p. 107723, 2022.
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- [3] Zhou Y, Wen Q, Song J, et al. Load data valuation in multi-energy systems: An end-to-end approach[J]. *IEEE Transactions on Smart Grid*, 2024.