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Data-Driven Restoration Model in Wind Power Penetrated System with Parallel Decomposition

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Background

The penetration level of wind energy sources has increased significantly in modern power grid over past several years due to economical and environmental considerations. The units driven by wind energy require less cranking power and regulate outputs more flexibly, which is beneficial for fast restoration after a blackout. However, the inherent uncertainty of wind energy poses a threat for its secure utilization for restoration and should be handled carefully.

Motivation

There are mainly two prevalent methods for dealing with the wind power uncertainty, i.e., the robust optimization (RO) and stochastic optimization (SO) based methods. But both methods have the following drawbacks.

1) RO based method ignores the probability distribution (PD) information and is often criticized for its conservatism.

2) SO based method employs plenty of sample scenarios to represent the underlying PD of wind power, which results in a heavy computation burden.

3) Recently, a novel method termed as distributionally robust optimization (DRO) is proposed by remedying the RO's ignorance and specification of probability information, and it has been applied in the economic dispatch, optimal plow, and unit commitment problems.

The power system restoration is a large-scale combinatorial optimization problem, which imposes a heavy computation burden. Thus, we develop a decomposition algorithm in the Benders decomposition framework. In addition, in the proposed solution algorithm, the Benders sub-problem is decoupled in the temporal dimension and these decoupled sub-problems can be calculated in parallel for each restoration period.

Method

In our work, the ambiguity and uncertainty sets are constructed directly by the sample data set available at hand under the Wasserstein metric $\mathrm{d_W}(\mathbb{P}_1,\mathbb{P}_2):\psi(\Xi)\times\psi(\Xi)\rightarrow\mathbb{R}$. Several key aspects on modelling and solving are summarized in the following.

1) The data-driven ambiguity set $\mathbf{\Omega}$ is constructed as below.

$$\mathrm{d_W}(\mathbb{P}_1,\mathbb{P}_2)=\inf\left\{\int_{\Xi\times\Xi}\|w_1-w_2\|\Pi(d_{w1},d_{w2})\right\}$$

$$\mathbf{\Omega}=\left\{\mathbb{P}\in\mathcal{M}(\Xi):\mathrm{d_W}(\mathbb{P},\mathbb{P}_\mathrm{S})\le\rho\right\}$$

It can be viewed as a Wasserstein ball of radius ρ with the empirical PD as the center, and the radius ρ is obtained by solving the following optimization problem.

$$\rho=C\sqrt{\frac{2}{\mathrm{S}}\ln(\frac{1}{1-\Gamma})}$$

$$C=\min_{y\ge0}\ 2\sqrt{\frac{1}{2y}(1+\ln(\frac{1}{\mathrm{S}}\sum_{s=1}^{\mathrm{S}}e^{y\|w_s-\mu\|}))}$$

2) The uncertainty set $\mathbf{\Xi}$ can be calculated as follows.

$$\theta_s=\Sigma^{-(1/2)}(w_s-\mu),\quad\forall s=1,2...\mathrm{S}$$

$$\min\ l$$

$$st.\ \ \kappa\rho+\frac{1}{\mathrm{S}}\sum_{s=1}^{\mathrm{S}}(1-\kappa(l-\|\theta_s\|)^+)^+\le1-\tau$$

$$\mathbf{\Xi}=\Sigma^{1/2}\Theta+\mu$$

3) The temporal-coupled constraints such as generator ramping and maximum load pickup are considered in the Benders master problem, and thus the sub-problem can be decoupled in the temporal dimension.

Results

Simulations are conducted on IEEE 39-bus system for the validation of the proposed restoration model and solution algorithm. The system generation capacity and restored loads during the recovery process are shown in the Fig. 1 and Fig. 2.

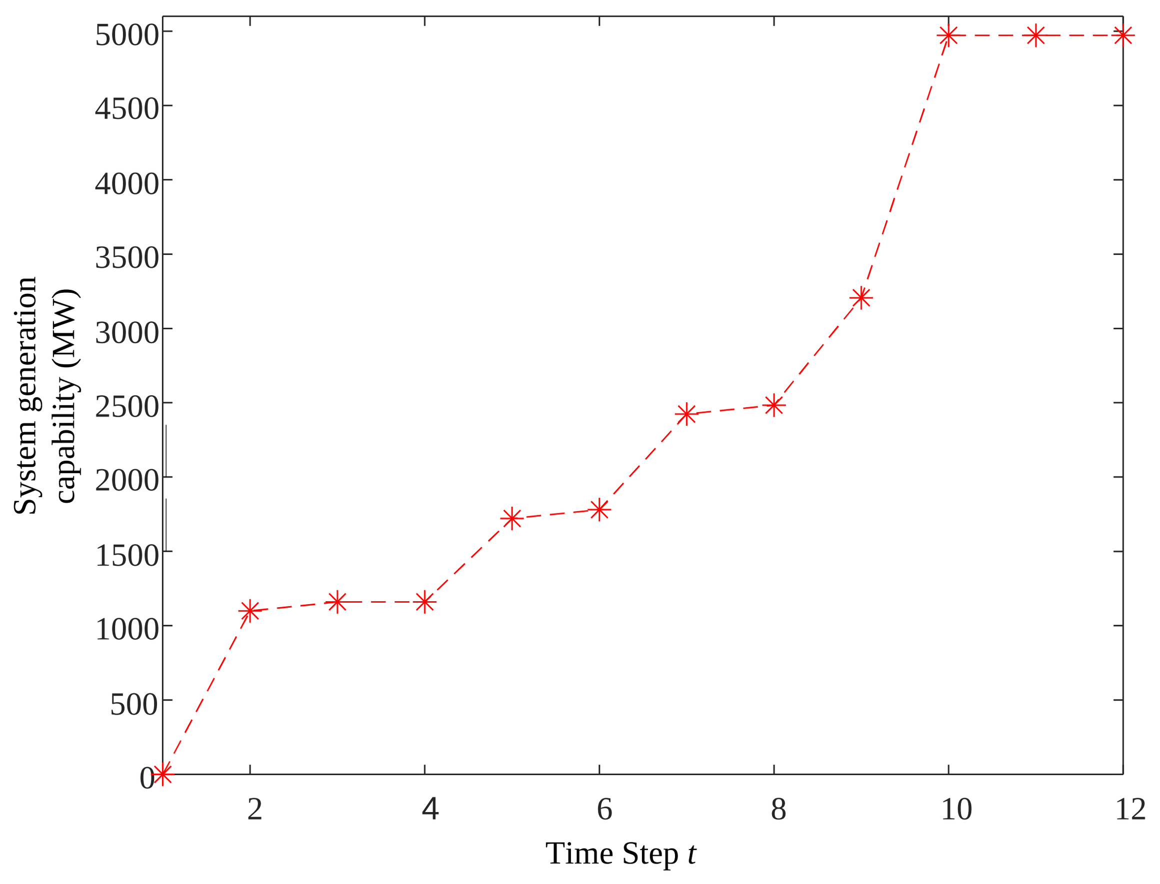

Fig.1 System generation capability at each restoration period.

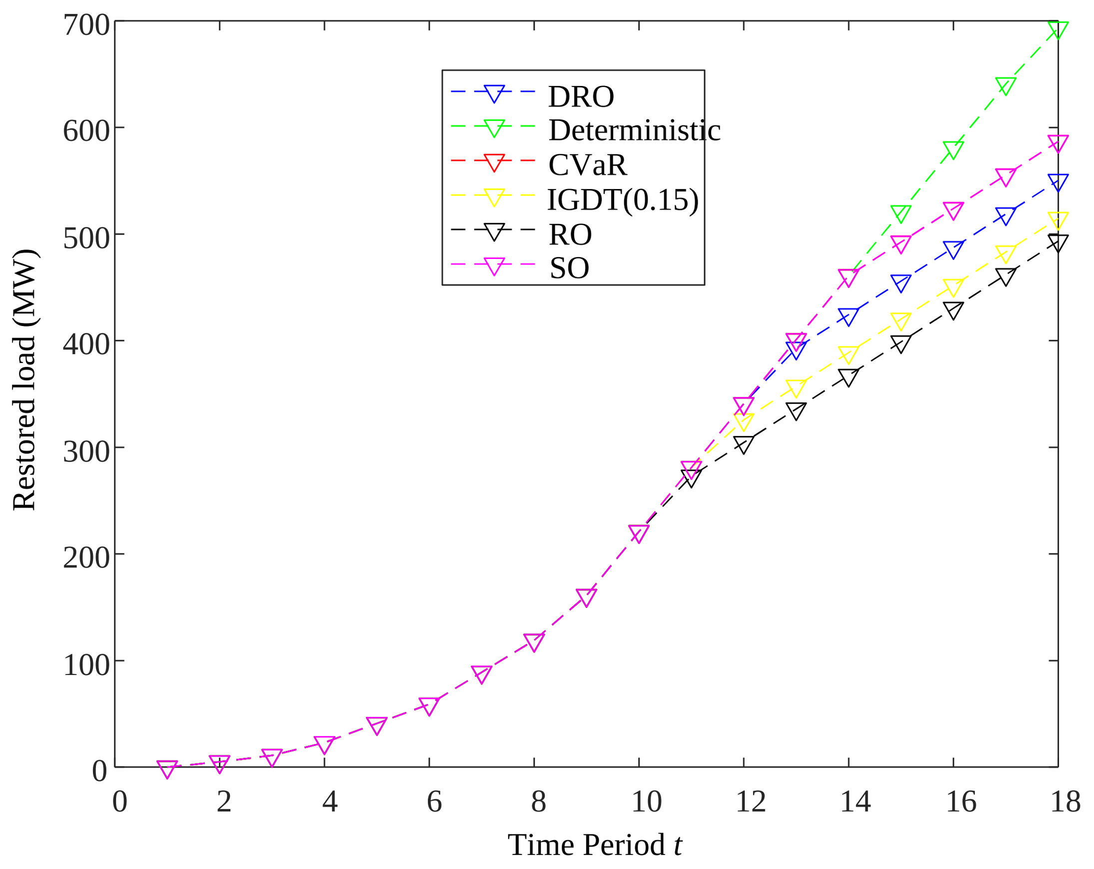

Fig. 2 Restored load under the proposed, deterministic, CvaR, IGDT (0.15), RO, and SO based restoration model at each period.

The proposed restoration model is compared with the deterministic, CvaR, IGDT (0.15), RO, and SO based model. The results of CvaR and SO are almost the same because both directly employ plenty of samples to replace the unknown PD. The RO method attains the least load pickup due to its robustness against all realizations in the pre-defined uncertainty set. The amount of the restored loads under the proposed model is intermediates between the SO (CVaR) and RO, indicating it can meet a better balance between the security and rapidity of the recovery process. In addition, it can be noted that the restored load power under above six models is the same before the 11th restoration period, because the wind power output must be increased progressively, matching the sequential load pickup to maintain the power balance. The scheduled wind power output is below the lower bound of the available wind power at those periods.

The following table reports the restored load, wind power lower bound, and radius of ambiguity set under different sizes of sample set. As the more data are exploited and employed, more probability information of uncertain wind power can be discovered, and thus the ambiguity set can be made narrower and the lower bound of available wind power can also be improved, contributing to more load pickup.

Sample size	Restored load (MW)	Lower bound	radius
1000	4196	41.3	0.3780
1500	4161	42.4	0.3750
2000	4139	43.7	0.3652
3000	4097	44.4	0.3613

Conclusions

The DRO-based restoration scheme can meet a better balance between rapidity and security in restoration process. The more sample data is incorporated, the smaller the radius of ambiguity set is, the more load power can be restored. Additionally, the proposed decomposition algorithm also enjoys superior computational performance, where the power flow solutions can be conducted parallelly for each period.