Transmission System and Microgrid Co-optimization Model

Nomenclature

Indices

t	a time period (time interval from the beginning through the end of a period)
g	TS network generator index

Parameters

T	length of the planning horizon
G	total number of generators in the TS
$\overline{R}_g$	TS generator upper ramp rate limit
$\underline{R}_g$	TS generator lower ramp rate limit
$\overline{P}_g$	TS generator generation upper bound
$\underline{P}_g$	TS generator generation lower bound
$Line$	TS line limit
C_g	TS generater g cost
C_g^r	TS generater g reserve cost
C_g^c	TS generator g commitment cost
GSF	TS generation shift factor matrix
W^f	forecasted wind power
W^{up}	positive wind deviation from the forecast
W^{dn}	negative wind deviation from the forecast
N_b	number of buses in the TS
L_t	TS load power vector in hour t

$\underline{L}_t^d$ MG aggregated dispatchable load lower bound in hour t

$\overline{L}_t^d$ MG aggregated dispatchable load upper bound in hour t

L_t^i MG inelastic load in time t

$\overline{B}$ MG storage energy state max level

$\underline{B}$ MG storage energy state min level

C^b MG storage energy maintenance cost

C_t^{m1} MG generation linear cost

C_t^{m2} MG generation quadratic cost

C_t^d MG utility for consuming dispatchable load in the MG in hour t

C^{dr1} MG linear demand response cost

C^{dr2} MG quadratic demand response cost

$\overline{P}^m$ MG generation upper bound

$\underline{P}^m$ MG generation lower bound

$\underline{P}^b$ MG storage discharging limit

$\overline{P}^b$ MG storage charging limit

$\overline{P}_t^d$ DR lower price cap in period t

ϵ constraint violation probability

Variables

$r_{g,t}^{up}$ TS generator g upward reserve in hour t

$r_{g,t}^{dn}$ TS generator g downward reserve in hour t

p_t^{dr} demand response price in hour t

$p_{g,t}$ TS generator g generation in hour t

b_t MG storage energy state in hour t

p_t^{ex} MG exported power in hour t

p_t^{im} MG imported power in hour t

p_t^b MG storage power output in hour t

l_t^d MG aggregated dispatchable load in hour t

dr_t^{up} MG storage power output in hour t

dr_t^{dn} MG aggregated dispatchable load in hour t

p_t^{inj} bus power injection vector in hour t

$w_{g,t}$ TS generator commitment variable in hour t for generator g

Acronyms

TS transmission system

DL dispatchable load

WP wind penetration

MG microgrid

DR demand response

DG distributed generation

1. Problem Description

1.1. Transmission System Problem

The TS has a network of transmission lines and buses. Traditional and renewable generation units, loads and MGs are connected to different buses in the network. The TS solves a day ahead market unit commitment problem, which is a co-optimization of the energy market and ancillary service market. For the energy market optimization, the TS tries to minimize the cost of meeting the system demand with its own generation or energy from MGs. For the ancillary service market optimization, the TS minimizes the cost of providing enough reserve to account for the renewable forecast uncertainty. The reserve service could either come from the TS generator's reserve or the MG's DR. The TS objective function minimizes the energy and ancillary service cost at the same time.

1.2. Microgrid Problem

The microgrid has an aggregated dispatchable load and an aggregated non-dispatchable load, an energy storage unit, and a distributed generation. In the day-ahead market, the MG solves an optimal dispatch problem. The dispatchable load is optimized at some point in between its upper and lower bound. The difference between the upper/lower bound and its set point could be used to provide upward/downward DR. The objective of the MG is to minimize the cost of meeting its demand either by its distributed generation or importing power from the TS and maximize the revenue of providing DR

1.3. Co-operation Mode

The TS and MG could work in two modes. The first mode is standalone mode, in which the two systems are totally separated from each other. In this mode, the two systems could not exchange energy and the MG could not provide DR to the TS. The second mode in co-optimization mode. Under our bilevel optimization framework, the TS decides the price of MG energy import and export as well as the price for purchasing MG DR, the MG responds to those prices by exchanging a certain amount of energy with the TS and selling a certain amount of DR to the TS.

The co-optimization between the TS and MG is illustrated in Fig. 1

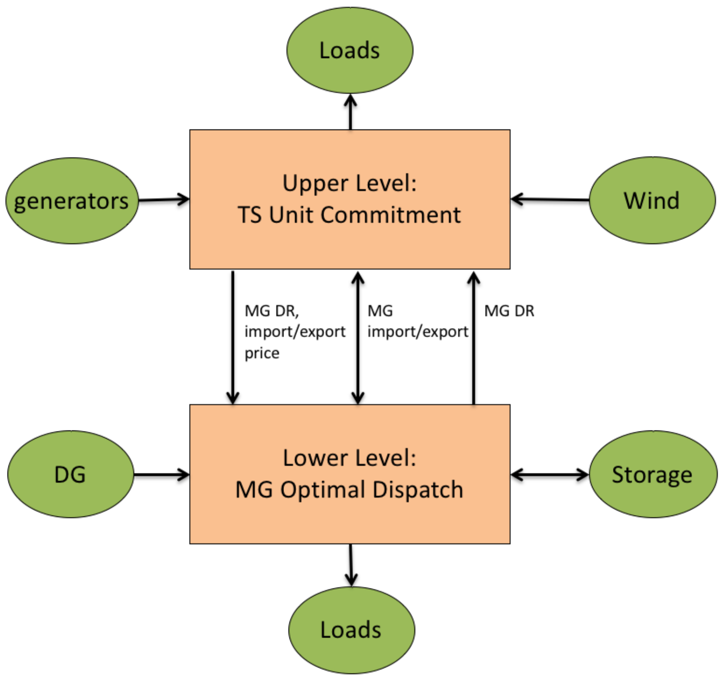

Figure 1: Co-optimization between the TS and MG

1.4. Renewable Forecast Uncertainty Management

In this work, we use a robust approach to manage the uncertainty in renewable forecast. Specifically, for a renewable generation forecast and a set of possible generation scenarios, we calculate the upward/downward forecast deviation by taking the difference of the hourly maximum/minimum generation scenario and the hourly forecast. The downward/upward TS generation reserve and upward/downward MG DR are used to account for the upward/downward renewable forecast deviation.

2. Optimization Model

In this section, the structure of the bi-level optimization problem is described. The general formulation of a bilevel optimization is given below:

$$\begin{aligned}
&\min_{x\in X, y\in Y} F\left(x,y\right) \\
\text{st: } & G_i\left(x,y\right) \leq 0, \text{for } i \in \{1,2,...,I\} \\
& H_k\left(x,y\right) = 0, \text{for } k \in \{1,2,...,K\} \\
& y \in \underset{y\in Y}{\operatorname{argmin}}\{f(x,y) : g_j(x,y) \leq 0, \text{for } j \in \{1,2,...,J\}, \\
& h_m(x,y) = 0, \text{for } m \in \{1,2,...,M\}\}
\end{aligned} \tag{1}$$

In the above formulation, $x, F(x,y), (G_i, H_k)$ are the optimization variables, objective function and constraints of the upper level problem. Whereas, $y, f(x,y), (g_i, h_m)$ are the optimization variables, objective function and constraints of the lower level problem. According to this formulation, the bilevel formulation of the TS and MG co-optimization is given in the following sections.

2.1. Upper Level Problem: TS Unit Commitment Problem

The upper level transmission day-ahead unit commitment problem seeks to compute the optimal operation schedule including the generator commitment status $w_{g,t}$, generation output $p_{g,t}$, upward and downward generator's reserve $R^{up}_{g,t}$, $R^{dn}_{g,t}$, MG DR price $P^{dr}_{g,t}$, and the MG energy import and export price c^{im}_t, c^{ex}_t to minimize the total TS operation cost. The optimization variables are denoted by the vector x_t, and include:

$$x_t = [w_{g,t}, p_{g,t}, r^{up}_{g,t}, r^{dn}_{g,t}, p^{dr}_t, c^{im}_t, c^{ex}_t]$$

The objective of the upper level optimization problem is to minimize the TS operation cost including the generator commitment cost, generation cost, reserve cost, energy exchange cost with the MG and the MG DR cost.

Objective function:

$$\begin{aligned} F(\{x_t\}_{t=1}^{T}) &= \textstyle\sum_{t=1}^{T}\sum_{g=1}^{G}(C_{g,t}^{c}w_{g,t} + C_{g,t}p_{g,t} + C_{g}^{r}(r_{g,t}^{up} + r_{g,t}^{dn}) \\ &- p_t^{im}c_t^{im} + p_t^{ex}c_t^{ex} \\ &+ p_t^{dr}(dr_t^{up} + dr_t^{dn})) \end{aligned}$$

The constraints of the TS are listed below.

Power flow constraints:

$$-Line \leq GSF * pinj_t \leq Line, t \in 1, ..., T \tag{2}$$

$$-Line \leq GSF * pinj_t^{*} \leq Line, t \in 1, ..., T \tag{3}$$

$p_{inj,t}$ is the DC net power injection vector (ie: generation + wind - demand) for all the buses in each hour. $p_{inj,t}^{*}$ incorporates the wind forecast error, generator reserve and MG DR on top of $p_{inj,t}$. Eqn (2),(3) bound the transmission line flows within the flow limits.

Generator constraints:

$$\underline{P}_g \leq p_{g,t} \leq \overline{P}_g, t \in 1, ..., T \tag{4}$$

$$(p_{g,t} + r_{g,t}^{up}) - (p_{g,t-1} - r_{g,t-1}^{dn}) \leq \overline{R}_g, t \in 2, ..., T \tag{5}$$

$$\underline{R}_g \leq (p_{g,t} - r_{g,t}^{dn}) - (p_{g,t-1} + r_{g,t-1}^{up}), t \in 2, ..., T \tag{6}$$

Eqn (4) bounds the generator generation within its capacities. Eqn (5),(6) satisfy the generator ramping capability.

Power balance constraint:

$$\sum_{g=1}^{G} p_{g,t} + \mathbf{1}_{1\times N_b} * L_t + W^f = P_t^{im} - P_t^{ex}, , t \in 1, ..., T \tag{7}$$

where $\mathbf{1}_{1\times N_b}$ is a vector of length N_b filled with 1's. The dot product $\mathbf{1}_{1\times N_b} * L_t$ gives the total load in the system. Eqn (7) balances the system power supply and demand.

Reserve constraints:

$$W_t^{up} \leq DR_t^{up} + \sum_{g=1}^{G} r_{g,t}^{dn}, t \in 1, ..., T \tag{8}$$

$$W_t^{dn} \leq Dr_t^{dn} + \sum_{g=1}^{G} r_{g,t}^{up}, t \in 1, ..., T \tag{9}$$

Eqn (8), (9) ensure enough generator reserve and MG DR to compensate the possible wind forecast deviation.

Finally, the TS unit commitment problem is formulated as:

$$\begin{aligned} &\min_{\{x_t\}_{t=1}^T} F\left(\{x_t\}_{t=1}^T\right) \\ &\text{s.t. } (1)-(10) \end{aligned} \tag{10a}$$

2.2. Lower Level Problem: MG Operation Optimization

A comprehensive MG is considered in this work. The MG consists of distributed generation (DG), a storage unit, aggregated dispatchable and non-dispatchable loads, and is able to exchange power with the main grid.

The goal of the MG optimal dispatch model is to compute the generation schedule $p_{g,t}^m$, the battery power output p_t^b, the battery charging and discharging decision p_t^b, MG energy import p_t^{im} and export p_t^{ex} schedule, dispatchable load profile l_t^d, the upward/downward DR dr_t^{up}, dr_t^{dn} provided by the dispachable load, and the storage energy state b_t. The lower level optimization variables are denoted by the vector y_t, and include:

$$y_t = [p_{g,t}^m, p_t^b, p_t^{im}, p_t^{ex}, dr_t^{up}, dr_t^{dn}, l_t^d, b_t]$$

The objective of the MG optimization is to minimize the MG operation cost including its generation cost, battery maintenance cost, energy exchange cost with the TS, and DR cost and maximize its dispatchable load utility and DR revenue.

Objective function:

$$\begin{aligned} f(\{y_t\}_{t=1}^T) = &\sum_{t=1}^{T}(C_g^{m1}p_{g,t}^m + C_g^{m2}p_{g,t}^m p_{g,t}^m + C^b b_t + p_t^{im}c_t^{im} - p_t^{ex}c_t^{ex} \\ &+C^{dr1}(DR_{g,t}^{up} + DR_{g,t}^{dn}) + C^{dr2}(DR_{g,t}^{up}DR_{g,t}^{up} + DR_{g,t}^{dn}DR_{g,t}^{dn}) \\ &-C_t^d l_t^d - p_t^{dr}(dr_t^{up} + dr_t^{dn})) \end{aligned}$$

The constraints for the MG are given below. The λ and μ variables next to the constraints are the dual variables associated with the corresponding inequality and equality constraints.

Generator constraints:

$$\underline{P}^m \leq p_{g,t}^m \leq \overline{P}^m, \lambda_{1,t}, \lambda_{2,t}, t \in 1, ..., T \tag{11}$$

Eq (11) limits the generator's output within the upper and lower bound.

Dispatchable load constraint:

$$\underline{L}_t^d \leq l_t^d \leq \overline{L}_t^d, \lambda_{3,t}, \lambda_{4,t}, t \in 1, ..., T \tag{12}$$

Eq (12) constrains the dispatchable loads within predefined bounds.

DR constraints:

$$l_t^d + dr_t^{up} \leq \overline{L}_t^d, \lambda_{5,t}, t \in 1, ..., T \tag{13}$$

$$l_t^d - dr_t^{dn} \geq \underline{L}_t^d, \lambda_{6,t}, t \in 1, ..., T \tag{14}$$

$$0 \leq dr_t^{up} \leq W^{up}, \lambda_{7,t}, \lambda_{8,t}, t \in 1, ..., T \tag{15}$$

$$0 \leq dr_t^{dn} \leq W^{dn}, \lambda_{9,t}, \lambda_{10,t} t \in 1, ..., T \tag{16}$$

Eq (13), (14) limit the DR of dispatchable load within the dispatachable load bounds. Also the amount of DR could not exceed the wind forecast deviation, which is reflected in Eq (15), (16).

Storage constraints:

$$\underline{P}^b \leq p_t^b \leq \overline{P}^b, \lambda_{11,t} \lambda_{12,t}, t \in 1, ..., T \tag{17}$$

$$\underline{B} \leq b_t \leq \overline{B}, \lambda_{13,t}, \lambda_{14,t}, t \in 1, ..., T \tag{18}$$

$$b_t = B_{t-1} + p_{t-1}^b, \mu_{1,t}, t \in 1, ..., T \tag{19}$$

Eq (17) and (18) restrict the storage's output power and the energy state to their upper and lower bounds. Equation (19) shows the transition of the storage energy state from one period to the next. A positive/negative p_t^b value corresponds to charging/discharging of the battery.

Import and Export constraints:

$$0 \leq p_t^{im}, \lambda_{15,t}, t \in 1, ..., T \tag{20}$$

$$0 \leq p_t^{ex}, \lambda_{16,t}, t \in 1, ..., T \tag{21}$$

The MG import and export power is defined to be non-negative as shown in Eqn (20), (21).

Power balance constraint:

$$p_t^m - p_t^b - L_t^i - l_t^d = p_t^{ex} - p_t^{im}, \mu_{2,t}, t \in 1, ..., T \tag{22}$$

Eq (22) ensures the power balance within the MG system.

Finally, the MG optimal dispatch can be formulated as:

$$\begin{aligned} \min_{\{y_t\}_{t=1}^T} f\left(\{y_t\}_{t=1}^T\right) \\ \text{s.t. } (12)-(25) \end{aligned}$$

2.3. Reformulation to a Single Level Problem

If the lower level problem is convex and satisfies certain regularity conditions [33], it can be replaced by its Karush-Kuhn-Tucker(KKT) conditions [19], the formulation in (1) becomes a single -level problem reformulation as follows:

$$\begin{aligned} & \min_{x\in X, y\in Y} F\left(x,y\right) \\ \text{st: } & G_i\left(x,y\right)\leq 0, \text{for } i\in\{1,2,...,I\} \\ & H_k\left(x,y\right)=0, \text{for } k\in\{1,2,...,K\} \\ & g_i\left(x,y\right)\leq 0, \text{for } j\in\{1,2,...,j\} \\ & h_m\left(x,y\right)\leq 0, \text{for } m\in\{1,2,...,M\} \\ & \text{dual feasibility: } \lambda_i\geq 0, \text{for } i\in\{1,2,...,i\} \\ & \text{complementary slackness: } \lambda_i * g_i\left(x,y\right)=0, \text{for } i\in\{1,2,...,i\} \\ & \text{stationarity: } \nabla L(x,y,\lambda,\mu)=0 \\ & where: \\ & L(x,y,\lambda)=f(x,y)+\sum_{i=1}^{J}\lambda_i g_i(x,y)+\sum_{m=1}^{M}\mu_m h_m(x,y) \end{aligned}$$

The lower level problem in this study is a convex optimization problem and satisfies Slater's condition, which is one of the sufficient conditions for strong duality theorem [33]. Therefore, the lower level problem could be replaced by its KKT conditions. The KKT conditions are given below:

Stationarity:

For stationarity, the derivative of the lagrangian function $L(x,y,\lambda)$ is taken with respect to each optimization variable. For example, eq(24) is the derivative of the lagrangian function with respect to p_t^m.

$$C^m+\lambda_{2,t}-\lambda_{1,t}+\mu_{2,t}=0, t\in 1,...,T \tag{24}$$

$$-C^d-\lambda_{4,t}+\lambda_{3,t}-\mu_{2,t}=0, t\in 1,...,T \tag{25}$$

$$C^b+\lambda_{13,t}-\lambda_{14,t}+\mu_{1,t}=0, t\in 1,...,T \tag{26}$$

$$c_t^{im}-\lambda_{14,t}-\mu_{2,t}=0, t\in 1,...,T \tag{27}$$

$$- c_t^{ex} - \lambda_{15,t} + \mu_{2,t} = 0, t \in 1, ..., T \tag{28}$$

$$\lambda_{8,t} - \lambda_{11,t} - \mu_{1,t} - \mu_{2,t} = 0, t \in 1, ..., T \tag{29}$$

$$- P_t^{dr} - \lambda_{8,t} - \lambda_{7,t} + \lambda_{5,t} = 0, t \in 1, ..., T \tag{30}$$

$$- P_t^{dr} - \lambda_{10,t} - \lambda_{9,t} + \lambda_{6,t} = 0, t \in 1, ..., T \tag{31}$$

Dual feasibility:

For dual feasibility, all dual variables need to be non-negative.

$$\lambda_{1,t} ... \lambda_{16,t}, t \in 1, ..., T \geq 0 \tag{32}$$

Complementary slackness:

For complementary slackness, the product of the dual variables and their corresponding inequalities need to be zero.

$$\lambda_{1,t} * (P_t^m - \underline{P}^m) = 0, t \in 1, ..., T \tag{33}$$

$$\lambda_{2,t} * (P_t^m - \overline{P}^m) = 0, t \in 1, ..., T \tag{34}$$

$$\lambda_{3,t} * (l_t^d - \overline{L}_t^d) = 0, t \in 1, ..., T \tag{35}$$

$$\lambda_{4,t} * (l_t^d - \underline{L}_t^d) = 0, t \in 1, ..., T \tag{36}$$

$$\lambda_{5,t} * (dr_t^{up} + l_t^d - \overline{l}_t^d) = 0, t \in 1, ..., T \tag{37}$$

$$\lambda_{6,t} * (-dr_t^{dn} - l_t^d + \underline{l}_t^d) = 0, t \in 1, ..., T \tag{38}$$

$$\lambda_{7,t} * (dr_t^{up}) = 0, t \in 1, ..., T \tag{39}$$

$$\lambda_{8,t} * (dr_t^{up} - W^{up}) = 0, t \in 1, ..., T \tag{40}$$

$$\lambda_{9,t} * (dr_t^{dn}) = 0, t \in 1, ..., T \tag{41}$$

$$\lambda_{10,t} * (dr_t^{dn} - W^{dn}) = 0, t \in 1, ..., T \tag{42}$$

$$\lambda_{11,t} * (p_t^b - \overline{p}_t^b) = 0, t \in 1, ..., T \tag{43}$$

$$\lambda_{12,t} * (p_t^b - \underline{p}_t^b) = 0, t \in 1, ..., T \tag{44}$$

$$\lambda_{13,t} * (b_t - \overline{B}) = 0, t \in 1, ..., T \tag{45}$$

$$\lambda_{14,t} * (b_t - \underline{B}) = 0, t \in 1, ..., T \tag{46}$$

$$\lambda_{15,t} * (b_t) = 0, t \in 1, ..., T \tag{47}$$

$$\lambda_{16,t} * (b_t) = 0, t \in 1, ..., T \tag{48}$$

This reformulation is not easy to solve mainly due to the non-convexity in the complementary slackness and bilinear terms in the objective function. The big-M reformulation is used to transform the complementary conditions to mixed integer constraints. The technical details of the Big-M method is given in the appendix.

According to strong duality theorem, the optimal objective function value of the lower level optimization dual problem equals the optimal objective function value of the lower level optimization primal problem. As a result, the bilinear terms $-p_t^{im}c_t^{im} + p_t^{ex}c_t^{ex} + p_t^{dr}(dr_t^{up} + dr_t^{dn})$ in the lower level objective function, which also appear in the upper level objective function, could be expressed as linear terms using the objective function of the dual problem. The lower level dual problem objective function is as follow:

$$
\begin{aligned}
D(\{\lambda_t, \mu_t\}_{t=1}^T) \quad = \quad & \textstyle\sum_{t=1}^T(-C^{dr2}dr_t^{dn}dr_t^{dn} - C^{dr2}dr_t^{up}dr_t^{up} - C_g^{m2}p_{g,t}^m p_{g,t}^m \\
- \quad & \mu_{2,t}L_t^i + \lambda 1_t\underline{P}^m - \lambda_{2,t}\overline{P}^m - \lambda_{3,t} underline L_t^d + \lambda_{4,t}\overline{L}_t^d - \lambda_{5,t}\underline{L}_t^d + \lambda_{6,t}\overline{L}_t^d \\
- \quad & \lambda_{8,t}\overline{W}^{up} + \lambda_{10,t}\overline{W}^{dn} - \lambda_{11,t}\overline{P}_t^b + \lambda_{12,t}\underline{P}_t^b - \lambda_{13,t}\overline{B} + \lambda_{14,t}\underline{B})
\end{aligned}
$$

The bilinear terms $-p_t^{im}c_t^{im} + p_t^{ex}c_t^{ex} + p_t^{dr}(dr_t^{up} + dr_t^{dn}$ in the upper level objective function are represented as:

$$
\begin{aligned}
& \sum_{t=1}^{T}(C_g^{m1}p_{g,t}^m + C_g^{m2}p_{g,t}^m p_{g,t}^m + C^b b_t + C^{dr1}dr_{g,t}^{up} + dr_{g,t}^{dn} + \\
& + C^{dr2}(dr_{g,t}^{up}dr_{g,t}^{up} + dr_{g,t}^{dn}dr_{g,t}^{dn}) - C_t^d l_t^d) - D(\{\lambda_t, \mu_t\}_{t=1}^T)
\end{aligned}
$$

The reformulated upper level objective function is as follow:

$$
\begin{aligned}
F\left(\{x_t, y_t, \lambda_t, \mu_t\}_{t=1}^T\right) \quad = \quad & \textstyle\sum_{t=1}^T \sum_{g=1}^G (C_{g,t}^c w_{g,t} + C_{g,t}p_{g,t} + C_g^r(r_{g,t}^{up} + r_{g,t}^{dn}) \\
+ \quad & C_g^{m1}p_{g,t}^m + C_g^{m2}p_{g,t}^m p_{g,t}^m + C^b b_t + C^{dr1}dr_{g,t}^{up} + dr_{g,t}^{dn} \\
+ \quad & C^{dr2}(dr_{g,t}^{up}dr_{g,t}^{up} + dr_{g,t}^{dn}dr_{g,t}^{dn}) - C_t^d l_t^d) - D(\{\lambda_t, \mu_t\}_{t=1}^T)
\end{aligned}
$$

The reformulated single level problem has the following format:

$$
\begin{gathered}
\min_{\{x_t, y_t, \lambda_t, \mu_t\}_{t=1}^T} F\left(\{x_t, y_t, \lambda_t, \mu_t\}_{t=1}^T\right) \\
\text{st: } (1) - (50)
\end{gathered}
$$

With the big-M reformulation, a set of binary variables and additional constants are introduced. The bilevel problem becomes a single level mixed integer linear problem and could thus be solved with a wide range of commercial solvers such as Cplex and Gurobi.

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