Transmission and Distribution Substation Energy Management Considering Large-Scale Energy Storage, Demand Side Management and Security-Constrained Unit Commitment

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ABSTRACT In this paper, a bi-level optimization model including the problem of transmission network market and energy management in the distribution substation is presented. In the proposed bi-level model, the lower level includes the demand-side management (DSM) program and the optimal charge/discharge of large-scale energy storage system (LSESS) at distribution substations to increase grid profits and send decisions to the upper-level transmission market operator. The upper level of the proposed model is a security-constrained unit commitment (SCUC) to minimize production, no-load, startup, shutdown, and active power curtailment costs, and also the unavailability of the generation units. In this paper, to solve the bi-level optimization problem, the Karush–Kuhn–Tucker (KKT) equation modeling method will be used to turn the problem into a single-level problem. One of the advantages of converting a bi-level model to a single-level model compared to the methods of the decomposition algorithms is the lack of use of iterative algorithms, which leads to an increase in problem-solving time. The proposed model is tested on standard distribution substations and transmission networks, which shows that the proposed method is more effective than decomposition algorithms in terms of problem-solving time. The simulation results showed that the proposed method can be more efficient in large optimization problems.

INDEX TERMS Bi-level optimization, demand side management, large scale storage system, unit commitment, security-constrained.

NOMENCLATURE

Index and Set

N: Set of transmission nodes.
B: Set of transmission branches.
T: Set of hours in a day.
S: Set of distribution substations.

Parameters

\( c_v^i \): The variable cost of the unit at the node \( i \).
\( c_n^i, c_{su}^i, c_{sd}^i \): The no load, startup and shutdown cost of the unit at the node \( i \), respectively.
\( c_c^m \): The active power curtailment cost at substation \( m \).

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\( \overline{R}_j, R_j \)  
Total availability and availability of the  \( j \)th unit.

\( w_1, w_2 \)  
Weights of objectives.

\( P^\text{min}, P^\text{max} \)  
The lower and upper bounds of active power generation of the  \( i \)th unit, respectively.

\( h^u_i, h^d_i \)  
The ramp up and ramp down limits of the unit at node  \( i \) and time  \( t \), respectively.

\( B_{ij} \)  
The branch series susceptance of branch  \( ij \).

\( k_g, k_b \)  
Number of unavailable generators and branches (security criterion parameter), respectively.

\( \mu_j \)  
The repair rate of committed unit at node  \( j \).

\( \lambda_j \)  
The failure rate of committed unit at node  \( j \).

\( mr_j \)  
The mean time to repair of committed unit at node  \( j \).

\( mf_j \)  
The mean time to failure of committed unit at node  \( j \).

\( p_t \)  
The price of energy at time  \( t \).

\( \Omega_{ij}, \Omega_{ma}, \Omega_{nh} \)  
The purchasing price of energy from the transmission network at low, medium and high price, respectively.

\( c^\text{diff}_m \)  
The investment of upgrading facility at substation  \( m \).

\( c^\text{in}_m \)  
The inflation rate at substation  \( m \).

\( c^\text{om}_m \)  
The discount rate at substation  \( m \).

\( X_m \)  
Capacity of the storage at substation  \( m \).

\( c^\text{p}, c^\text{w}_m \)  
The peak/energy specific cost of the storage at substation  \( m \), respectively.

\( c^\text{mf}, c^\text{mv}_m \)  
Fixed and variable operating and maintenance costs of storage at substation  \( m \), respectively.

\( \eta^\text{in}_m \)  
Storage efficiency at substation  \( m \).

\( L_{m,t}, \Gamma_{m,t} \)  
The initial load at substation  \( m \) and time  \( t \).

\( h^d_m \)  
The percentage of shiftable load at substation  \( m \).

\( \eta^\text{in}_m \)  
The number of allowed demand side management at substation  \( m \).

\( L_{\text{max}} \)  
The cut current peak load by energy storage system at substation  \( m \).

\( \tilde{c}^\text{c}, \tilde{c}^\text{d}_m \)  
The number of allowed charging/discharging storage at substation  \( m \), respectively.

\( \Delta_m \)  
The initial energy remaining of the storage at substation  \( m \).

\( M \)  
Large positive number.

\( P_{i,t} \)  
The real power output of the unit at node  \( i \) and time  \( t \).

\( r_{m,t} \)  
Active power curtailment at substation  \( m \) and time  \( t \) associated with node  \( i \) of the transmission network.

\( P_{ij,t} \)  
The real power flow on branch  \( ij \) and time  \( t \).

\( \theta_{i,t}, b_{m,t}^{\text{dis}}, b_{m,t}^{\text{ch}} \)  
The shifted load at substation  \( m \) and time  \( t \) obtained from demand side management.

\( f(x) \)  
The coefficient of the equality constraint function.

\( \lambda_j \)  
The coefficient of the inequality constraint function.

\( h_j \)  
The inequality constraint function.

\( g_i \)  
Auxiliary binary variable for linearization.

\( \tilde{z}_{m,t} \)  
Continuous variable is equivalent to binary variable  \( z_{m,t} \).

\( \tilde{\gamma}_{m,t} \)  
Continuous variable is equivalent to binary variable  \( \gamma_{m,t} \).

**Binary Variables**

\( v_{i,t}, s_{i,t}, u_{i,t} \)  
Commitment status, startup and shutdown of the generation unit at node  \( i \) and time  \( t \), respectively.

\( a_{i,t} \)  
Binary variable that is equal to 0 if unit at node  \( i \) is unavailable in the worst-contingency state of time  \( t \), being 1 otherwise.

\( a_{ij,t} \)  
Binary variable that is equal to 0 if branch  \( ij \) is unavailable in the worst-contingency state of time  \( t \), being 1 otherwise.

\( \tilde{z}_{m,t} \)  
The binary variable corresponding to the storage status at substation  \( m \) and time  \( t \),

\( \tilde{\gamma}_{m,t} \)  
The binary variable corresponding to the demand side management program at substation  \( m \) and time  \( t \).

**Abbreviations:**

SDR  
Semi-Definite Relaxation.

GA  
Genetic Algorithm.

DNLP  
Discontinuous nonlinear program.

DM  
Dynamic Model.

DA  
Decomposition Algorithm.

SHT  
Sequential hypothesis testing.

PATC  
Probabilistic analytical target cascading.

DP  
Dynamic programming.

GPC  
Giza Pyramids Construction.
I. INTRODUCTION

The use of energy storage systems and demand-side management programs, despite increasing network flexibility, results in optimal management between distribution substations and transmission networks. One of the main challenges to improving system accuracy is to integrate energy management programs into active distribution substations in market-clearing programs. The present study tries to use an integrated model of demand-side management program and large-scale energy storage system as distribution systems at the transmission level.

One of the challenges for the accuracy of market operations is to reflect the real physics of the network and achieve accurate pictures of the system, using the integration of load management programs and active distribution networks in market settlement programs, with sufficient physical detail to reflect the impact and dependence of market outcomes on emerging technologies on the demand side. In fact, the decision making procedure of any autonomous smart grid is a complex optimization problem with continuous and discrete decisions. Hence, an effective energy management tool, taking into account those critical factors and interactions, is definitely needed to support the generation of optimal scheduling and operational plan of an active distribution network in modern electricity markets. Here, the goal of the market operator is to balance supply and demand, while the goal of smart grids or demand response aggregators and large energy storage systems, which act as profit-seeking intermediaries between the market and consumers, is the combination of cost and profit achieved. To address the operational challenges of active distribution networks in modern electricity markets, many advanced decision support models and sophisticated computational methods have been developed and studied. Some programs and related works are reviewed below.

In [1], the authors have proposed a three-level algorithm for the optimal management of energy storage systems based on AC optimal power flow (ACOPF) in large transmission power systems. In [2], an economic model for a large energy storage power plant has been proposed to increase the profitability of smart distribution substations in the electricity market using an evolutionary algorithm. In [3], the authors have proposed a bi-level model to reduce the costs of sharing distributed energy resources in the electricity market through demand-side management programs. Reference [4] has proposed an optimization method based on blockchain technology to increase social welfare considering the decision-making processes of a large number of consumers in the smart grid. In [5], a two-stage mixed-integer linear programming model for smart grid pricing with a demand-side management program has been proposed, which acts as an intermediary between the energy wholesale market and end consumers. In [6] a bi-level stochastic model for an independent system operator (ISO) has been proposed considering wind power and demand-side management programs to reduce the load shedding by operational constraints. Reference [7] has presented a dynamic mechanism for increasing social welfare in response to changeable demand through a negotiation process between key market players. In [8], the authors have proposed an approach based on a bi-level conic model to integrate the distribution and transmission system to reduce the power purchased from the transmission network at the distribution level and reduce production costs at the transmission level. The authors in [9] have proposed an algorithm based on decomposition and reformulation to solve the bi-level problem of transmission network planning along with the gas network to improve these two networks. Reference [10] has presented a management model for hybrid microgrids with cyber-attacks, in which lower and upper-level models minimize user costs and microgrid operating costs under cyber threats conditions. Reference [11] has proposed a bi-level model of energy management in the transmission network and distribution substations of the electricity network to increase the profit of the distribution network and reduce the operating costs of the transmission network using the decomposition algorithm. In [12], a transmission and distribution systems coordination (TSDS) model has been proposed to solve the problem of unit commitment with security constraints. A cascading algorithm based on mean matching and standard deviation was used to evaluate the TSDS decision. Instead of solving each scenario as an issue, the proposed algorithm considers a single issue of coordination with possible features as common factors, which leads to a faster solution. In [13], an approach for smoothing large-scale wind power fluctuations using vehicle-to-grid (V2G) systems has been investigated. First, the energy management and optimization system are designed and modeled, then the wave power connected to the target network, the required electric vehicle (EV) power, and the supercapacitor power is determined using the wavelet packet decomposition method. In addition, an optimal distribution strategy for EV and wind power is proposed using a dynamic programming method. In [14], voltage security-constrained stochastic programming model for day-ahead battery energy storage system schedule in co-optimization of transmission and distribution systems has been proposed. Reference [15] has proposed a combined strategy for energy management in the electric vehicle charging station (EVCS) and distribution system (DS) with grid constraints, renewable energy resources, and the random nature of EV and local weather conditions. In [16] stochastic optimal energy management and pricing model for a load-serving entity with aggregated thermostatically controlled loads and energy storage based on the Stackelberg game and stochastic programming has been proposed. The authors in [17] have proposed a hierarchical decision-making strategy based on a bi-level programming model that integrates several local decision-making units, each focusing on the energy retrofit optimization of a specific urban subsystem.

GTDA  Game theoretic distributed algorithm.
BD  Benders decomposition.
BC  Backstepping controller.
LO  Lyapunov optimization.
for the energy management of a smart city. In [18] a hierarchical decentralized System of Systems (SoS) architecture for the energy management of a multi-microgrid system is proposed and, accordingly, it is formulated as a bi-level optimization problem. In [19] the authors have proposed an adaptive backstepping controller to stabilize voltage and frequency in a smart grid and also to control current to share power between renewable energy resources in a smart island. Reference [20] has proposed an energy management strategy based on a novel bi-level stochastic multiobjective optimization model to maximize the utility of the consumed power, simultaneously with the cost minimization. Authors in [21] have proposed a new approach for the optimal energy management of a hybrid electric vehicle considering traffic conditions based on a bi-level decomposition. In [22] an energy management methodology of an active distribution network with multi-microgrids connected to the upstream high voltage grid has been proposed based on a two-stage stochastic bi-level model that is converted into a MILP model through Karush-Kuhn-Tucker conditions. In [23], the transcendental optimization algorithm according to the evolutionary optimization method to reduce the probability of locating optimal local points as well as finding the optimal values of general variables has been proposed. Table (1) is provided to better investigate the differences between this article and previous studies. As can be seen, comparisons have been made between the model and the problem-solving approach. In the proposed study, optimal coordination of distribution and transmission network has been done considering security constraints for line and power plants considering the improvement of reliability objective function and demand side management problem and large-scale batteries. For example, in reference [3] optimal demand and large-scale battery management have been done, but optimal coordination of the transmission and distribution network is not taken into account. Or [10] which considers optimal coordination of the transmission and distribution network with large-scale batteries, but has not taken into account the problem of demand-side management and security constraints. Table (1) shows the modeling gap in the optimal coordination problem of distribution and transmission networks, which has been tried in this study. Also, the proposed bi-level problem-solving approach in this study is different from most existing methods.

This review shows that compared to the literature on smart grid optimization and operation studies, there is limited research on models that consider the autonomy of smart grids and the distributed nature of demand-side components along with large-scale storage systems in market operations. In fact, the distribution system is a key component that connects storage devices and responsive loads in the region to meet the electricity needs of a group of consumers. Hence, an analytical method that considers all those critical factors and interactions should be employed to determine the actual operational policy of smart grids.

### A. CONTRIBUTION

In this study, a bi-level model for the integration of distribution substations and transmission networks has been proposed. Distribution substation modeling is considered as a large-scale energy storage system and demand response program, and transmission system modeling has been considered as a DC power flow problem with a security-constrained unit commitment. The main contributions of this study are as follows:
1) From a modeling point of view, we present a bi-level mixed-integer linear programming (BL-MILP) for the day-ahead market clearing integrated with the management of the distribution substation. In the upper level, we consider multi-objective function with reduced unavailability index and operation costs in security-constrained unit commitment considering DC load flow and in the lower level consider management of large scale storage and demand-side management program at distribution substations to increase their profits.

2) From a method solution point of view, we use the Karush–Kuhn–Tucker (KKT) conditions for converting the bi-level model to a single-level optimization model. It can be said that one of the advantages of converting a bi-level model to a single-level model compared to algorithm-based methods is the lack of need for repetition and convergence in the algorithm, which leads to an increase in problem-solving time.

**B. PAPER ORGANIZATION**

The rest of the paper has been organized as follows: it begins with the problem statement in Section II, where we describe lower and upper levels. Solving bi-level model has been presented in Section III, experimental results have been presented in Section IV and the concluding remarks have been provided in Section V.

**II. PROPOSED BI-LEVEL MODEL**

In this section, the proposed bi-level MILP modeling, including lower-level and upper-level problems, is presented. Figure (1) demonstrates the basic idea of integrating each distribution substation at transmission node \(i\). In general, the proposed bi-level optimization problem includes an upper-level model and a lower-level model, which is the upper-level model for transmission network modeling and the lower-level model for distribution network modeling. The upper-level model and the lower-level model are introduced and described separately in the following sections.

This figure shows the location of each distribution substation along with the storage and demand-side management at each node of the transmission network. In this model, the problem of unit commitment with security constraints is considered as upper level and the problem of optimal large-scale storage management and demand-side management in each substation is considered as lower levels. In the proposed model, distribution substations are part of the main transmission network and are related to it, and their real power exchanges are used as dependent variables, the exact values of which are calculated using lower-level (distribution substations) problems with the independent system operator (ISO).

Note that distribution substations will therefore have an effect on market effects through adjusting their operating plan and dispatch decisions. They play games in the market and their interactions are modeled with the help of bi-level optimization. This is the same old argument on the back of a Stackelberg leader-follower game formulation. Eventually, power demand calculated from the lower-level problem (each distribution substation) will enter the upper-level problem (at the transmission node). In this part, the distribution substation with the large-scale storage and the demand response to maximize its benefit as the lower-level and the transmission system with security-constrained unit commitment and DC load flow to minimize operation costs and unavailability index as the upper-level are presented.

**A. UPPER-LEVEL MODEL**

In this section, the equations dependent to the upper-level model are presented. In the upper-level model, Equations (1a) - (1p) are a security-constrained unit commitment (SCUC) with multi-objective DCOPF problem. Equation (1a) is a multi-objective function considering costs of the variable, no-load, startup/shutdown, and demand curtailment as a cost function and unavailability of the units as a reliability function. (1b) performs an acceptable bound of the units, the nonlinear term in (1b) can be easily linearized by introducing binary variable \(\bar{z}_{i,t}\) [24]. Thus, \(\bar{z}_{i,t} = v_{i,t}a_{i,t}\), and (1b) can be equivalently remodeled by \(-\bar{z}_{i,t} + v_{i,t} + a_{i,t} \leq 1, 2\bar{z}_{i,t} - v_{i,t} - a_{i,t} \leq 0, \bar{z}_{i,t}, v_{i,t}, a_{i,t} \in \{0, 1\}\), and \(P_{i,t}^{\text{min}} \leq P_{i,t} \leq P_{i,t}^{\text{max}}\). Note that the linearization of Equation (1b) is for use in mathematical programming optimization packages or solvers that cannot solve the multiplication of two binary variables, such as CVX [25]. (1c) expresses the logical relationships between the binary commitment variable, the ramp up/down rate bounds are performed by (1d), the minimum up/down time limits of the units are given in (1e) - (1f), and (1g) is the active power balance for each transmission node. (1h) is active power flow restriction on branch \(ij\). The nonlinear term in (1h) can be easily linearized by introducing a continuous variable \(\bar{x}_{i,t}\), through \(\bar{x}_{i,t} = a_{ij,t}\theta_{ij,t}\), \(\bar{x}_{i,t} \leq M\theta_{ij,t}\), \(\bar{x}_{i,t} \leq \theta_{ij,t} - (1 - a_{ij,t})M\), and \(\bar{x}_{i,t} \geq 0\), where \(M\) is a large positive number [24]. (1i) and (1j) are the voltage angle restriction for each node at time \(t\) and the reference node angle, respectively. (1k) is related to the

![FIGURE 1. Scheme of the proposed approach: integrating each distribution substation at transmission node \(i\).](image-url)
outage of the units and branches. (1) is the total availability amount of the units, and (1m) - (1o) are the availability, repair rate and failure rate of the units, respectively.

\[
\begin{align*}
\text{min} & \quad \sum_{i,j \in \mathcal{N}} \sum_{t \in \mathcal{T}} w_i \left( c_i^t P_{i,t}^t + c_i^{\text{V}l} \psi_i^t + c_i^{\text{sl}} s_{i,t} + c_i^{\text{ud}} u_{i,t} \\
+ c_i^{\text{vt}} v_{i,t} \right) + w_2 \left( 1 - \bar{R}_j \right) \\
\text{s.t.} & \quad P_{i,t}^t + P_{i,t}^{\text{lx}} \leq P_{i,t}^{\text{max}} \quad \forall i \in \mathcal{N}, \quad t \in \mathcal{T}, \quad v_{i,t}, \quad a_{i,t} \in \{0,1\} \\
& \quad s_{i,t+1} = s_{i,t} + u_{i,t+1} - v_{i,t} \quad \forall i \in \mathcal{N}, \quad t \in \mathcal{T}, \quad v_{i,t}, \quad u_{i,t}, \quad s_{i,t} \in \{0,1\} \\
& \quad P_{i,t}^t = \Psi_t^i - P_{i,t}^{\text{ch}} \leq h_i^t \quad \forall i \in \mathcal{N}, \quad t \in \mathcal{T} \\
& \quad \sum_{i \in \mathcal{N}, \, t \in \mathcal{T}} P_{i,t} + \sum_{b \in \mathcal{B}, \, t \in \mathcal{T}} P_{b,t} - \sum_{b \in \mathcal{B}, \, t \in \mathcal{T}} \Psi_t^b = \Delta_{i,t} \\
& \quad \left| P_{i,t} - \Psi_t^i \right| \leq a_{i,t} \quad \forall i \in \mathcal{I}, \quad t \in \mathcal{T} \\
& \quad \theta_{i,t}^l = 0 \quad \forall i \in \mathcal{N}, \quad t \in \mathcal{T} \\
& \quad \sum_{i \in \mathcal{I}, \, t \in \mathcal{T}} \left( 1 - a_{i,t} \right) = k_g \\
& \quad \sum_{i \in \mathcal{I}, \, t \in \mathcal{T}} \left( 1 - a_{i,t} \right) = k_b \\
& \quad \bar{R}_j = \prod_{i \in \mathcal{N}} R_{i,j} \\
& \quad \mu_j = \frac{\mu_{j}}{\lambda_{j} + \mu_{j}} \quad \forall j \in \mathcal{N} \\
& \quad \mu_j = \frac{8760}{m_{j}} \quad \forall j \in \mathcal{N} \\
& \quad \lambda_j = \frac{8760}{m_{j}} \quad \forall j \in \mathcal{N}
\end{align*}
\] 

\( B. \text{LOWER LEVEL MODEL} \)

The lower level model is the distribution substation with large-scale storage and demand-side management to maximize the benefits of each substation at transmission node \( i \).

The multi-objective function of the proposed model has been demonstrated in (2a). Large-scale storage at each substation is used to charge at the lower electricity prices and discharge at peak load times to increase the capacity. As can be seen, the objective function consists of five terms containing three benefits and two costs.

The first benefit term is the profit of the energy price arbitrage, which is obtained by \( \sum_{m \in \mathcal{S}, \, t \in \mathcal{T}} \theta_1 \left( \psi_m^{\text{ss}} - \psi_m^{\text{ch}} \right) \).

The large scale energy storage system is charged when the energy price is low, and discharged when it is high. Since the transmission access costs are always positive relative to the energy prices, the adoption of the large scale energy storage system can also reduce the transmission access cost [2], so, due to the second profit from the transmission access cost reduction, which is obtained by \( \sum_{m \in \mathcal{S}, \, t \in \mathcal{T}} \Omega_t (h_m^{\text{ch}} - b_m^{\text{ch}}) + \sum_{m \in \mathcal{S}, \, t \in \mathcal{T}} \Omega_t (h_m^{\text{dis}} - b_m^{\text{dis}}) \) at different time, and the last benefit from the deferring facility investment, the large scale energy storage system is charged when the demand is low and discharged when it is high. Under this operation, it can cut the peak demand and defer the upgrade of equipment, which is obtained by \( \sum_{m \in \mathcal{S}} c_m \left( 1 - \left( 1 + \frac{\Delta_{m, t}}{1 + \omega_m} \right) \right) \).

Besides, the investment cost of storage, which is obtained by \( \sum_{m \in \mathcal{S}} \left( c_m^0 + c_m^1 \right) \), and the maintenance and operation cost of the storage can be obtained by \( \sum_{m \in \mathcal{S}} \left( \frac{m_{f}}{m_{a}} \left( X_m + c_m \right) \right) \). The objective function is a set of constraints (2b) - (2o).

In (2b) the power balance between the discharge and charge power of each storage at substation \( m \) and the time \( t \) is illustrated depending on the efficiency of each of them. Inequalities (2c) and (2d) guarantee the charging and discharging power to be less than or equal to their capacity, respectively. The energy level of each storage at the time \((t+1)\) is represented by a difference equation in (2e), the initial energy level of storage is shown in (2f).

In (2g), the operation limit of the state of energy (SOE) for each of the energy storage levels at substation \( m \) and time \( t \) has been shown. At each operation hour, the permissible amount of demand flexibility has been bounded in (2h). Equality (2i) determines the allowable amount of shiftable demand per hour at substation \( m \). The number of allowed demand side management times is determined by (2j).

In the demand-side management plan, we adopt a demand shifting method in which the demand changes from one hour to another during the 24-hour operating period. Hence, in Equation (2j), the lower limit is assumed to be 2 to guarantee at least one demand-side management implementation. This demand-side management model considering variables is sufficiently able to provide the operator the possibility to cut off any hours in a day from the set of allowed demand-side management hours (SA-DSMH); to reach this aim, \((\gamma_m,t)\) can be equal to 0 for each load at substation \( m \) and time \( t \). Equality (2k) demonstrates that the amount of total load demand in 24-hours remains equal before and after performing the demand-side management program. The inequality (2l) imposes another limitation to reduce the peak load; this limitation is realized by selecting the suitable amount of \( \alpha_m \). For instance, if parameter \( \alpha_m \) is set to 0.1, the demand-side management program is allowed to reduce the peak load by 10%. Inequality (2m) preserves the allowed discharging and charging actions within their bounds \((\psi_m^{\text{ch}}, \psi_m^{\text{dis}})\), such limitations are generally appointed based on the characteristic of the storage type. Equality (2n) illustrates demand at substation \( m \) and time \( t \) after deciding at the lower-level, which is located at transmission node \( i \), and finally (2o)
is load curtailment bound. Thus, relationships (2a) to (2o) represent lower-level optimization models that include large-scale storage management with demand-side management in the distribution substations.

The decision variables in the upper level are equal to \( \{P_{t,i}, r_{t,i}, P_{d,i}, D_{t,i}^d, \theta_{t,i}, v_{t,i}, s_{t,i}, a_{t,i}, a_{ij,t}\} \) and the decision variable in the lower-level model is \( \{D_{t,i}^m, b_{t,i}^{dis}, b_{t,i}^{ch}\} \) and the variable \( \{D_{t,i}^c, \nu_{t,i}^{sc}, \nu_{t,i}^{dc}\} \) in Equation (1g) and Equation (2n) is the shared variable of our problem. Hence, the variable \( L_{t,i} \), which is the ultimate demand in the distribution substation \( m \), is taken from the demand difference in the optimal charge and discharge of the storage and the demand-side management program and load curtailment, which should be seen in node \( i \) of the transmission network as a demand. Thus, the new demand obtained in the distribution substation of the lower-level model is seen in the upper-level problem. Also, the cost of load shedding in the lower level will be seen in the upper-level model in the market clearing. Figure 2 demonstrates the framework of the proposed bi-level model.

### III. PROPOSED SOLUTION METHOD

As can be seen from Formulations (1) and (2), the proposed bi-level optimization has a mixed-integer linear programming (MILP) structure at both the upper and lower levels. This study uses the modeling of the Karush–Kuhn–Tucker (KKT) conditions to solve this challenging computational problem and convert the bi-level model into a single-level model. In this paper, to convert the bi-level model into a single-level model, the lower level model should be converted into KKT equations and then added to the upper problem. As can be seen, the lower level model (2) is a mixed integer linear programming model for which there are no KKT equations. To solve this challenging problem, we convert the binary variables in the lower-level problem to continuous variables and then add two constraints (3a) and (3b) to the lower-level problem so that the binary characteristics of the variables do not change. These two constraints guarantee that the two continuous variables (\( \tilde{y}_{m,t} \)) and (\( \tilde{z}_{m,t} \)) that replaced the two binary variables (\( y_{m,t} \)) and (\( z_{m,t} \)) are always either zero or one.

\[
\begin{align*}
\tilde{z}_{m,t} - \tilde{z}_{m,t}^2 &= 0 \\
\tilde{y}_{m,t} - \tilde{y}_{m,t}^2 &= 0
\end{align*}
\]

Therefore, with this variable change and the addition of two constraints (3), the lower-level problem is transformed from a MILP model to a non-convex quadratic model, whose global optimal solutions are guaranteed by the Gurobi solver.

Finally, the proposed general bi-level model with new constraints is in the form of relations (4).

\[
\begin{align*}
\min & \sum_{i,j \in N} \sum_{t \in T} w_{ij} \left( c_i^y v_{t,i} + c_i^t u_{t,i} + c_{i,t}^{sc} s_{t,i} + c_{i,t}^{dc} d_{t,i} + c_{t,i}^r f_{t,i} \right) \\
& + w_t \left( 1 - \tilde{R} \right) \\
\text{s.t.} & \quad (1b) - (1o) \\
\max & \sum_{m \in S_i \subseteq T} \rho_m \left( b_{m,t}^{dis} - b_{m,t}^{ch} \right)
\end{align*}
\]
\[ + \sum_{m \in S, t \in T} \left\{ \Omega_t \left( b_{m, t}^{\text{dis}} - b_m^c \right) \right\} \\
+ \Omega_{m_t} \left( b_{m, t}^{\text{dis}} - b_m^c \right) + \Omega_{m_t} \left( b_{m, t}^{\text{dis}} - b_m^c \right) \}
+ \sum_{m \in S} c_{m}^d \left( 1 - \left( \frac{1 + \varrho_m}{1 + \omega_m} \right) \right) \]
\[ - \left[ \sum_{m \in S} \left\{ X_m \left( e_m^w + c_m^w \right) \right\} - \sum_{m \in S} \left\{ c_m^{m_f} \left( X_m \right) + c_m^{m_v} \left( e_m^d \right) \right\} \right] \]
\[ = \left( 2b \right) - \left( 2a \right) \]
\[ \hat{z}_{m, t} - \hat{y}_{m, t}^2 = 0 \]
\[ \hat{y}_{m, t} - \hat{y}_{m, t}^2 = 0 \]

Equations (5a)-(5g) are the KKT conditions model for the reformulation of the lower level (4c-4f). The equations below represent the standard form of KKT conditions with linearizing constraints using big-M method:

\[ L(x, \lambda, \mu) = f(x) - \sum_{j=1}^{k} \lambda_j (0 - h_j(x)) - \sum_{i=1}^{m} \mu_i (0 - g_i(x)) \]
\[ \nabla f(x) - \sum_{j=1}^{k} \lambda_j \nabla h_j(x) - \sum_{i=1}^{m} \mu_i \nabla g_i(x) = 0 \]
\[ h_j(x) = 0 \]
\[ g_i(x) \geq 0 \]
\[ \mu_i(x) \geq 0 \]
\[ \mu_i \leq M (1 - \alpha_i) \]
\[ g_i \leq M (\alpha_i) \]

By converting the lower-level model (4c-4f) to model (5), Equations (6) are obtained, which can be added to the model (4c-4f) as a set of constraints.

\[ L(x, \lambda, \mu) = \left[ \begin{array}{c} \rho_t \left( b_{m, t}^{\text{dis}} - b_m^c \right) \\
+ \sum_{m \in S, t \in T} \left\{ \Omega_t \left( b_{m, t}^{\text{dis}} - b_m^c \right) \right\} \\
+ \sum_{m \in S, t \in T} \left\{ \Omega_{m_t} \left( b_{m, t}^{\text{dis}} - b_m^c \right) \right\} \\
+ \sum_{m \in S} \left( 1 - \left( \frac{1 + \varrho_m}{1 + \omega_m} \right) \right) \]
\[ - \left( \sum_{m \in S} \left\{ X_m \left( e_m^w + c_m^w \right) \right\} - \sum_{m \in S} \left\{ c_m^{m_f} \left( X_m \right) + c_m^{m_v} \left( e_m^d \right) \right\} \right] \]
\[ - \lambda_4 \left( \hat{z}_{m, t} - \hat{y}_{m, t}^2 \right) \]
\[ - \lambda_5 \left( \hat{y}_{m, t} - \hat{y}_{m, t}^2 \right) - \mu_4 \left( -\hat{y}_{m, t} + X_m \left( 1 - \hat{z}_{m, t} \right) \right) \]
\[ - \mu_1 \left( -b_{m, t}^{\text{dis}} \right) - \mu_2 \left( -b_{m, t}^{\text{dis}} + X_m \left( \hat{z}_{m, t} \right) \right) - \mu_3 \left( -b_m^c \right) \]
\[ - \mu_5 \left( -D_{m, t}^{\text{dis}} + L_{m, t} + \Gamma_{m, t} \hat{y}_{m, t} \right) \]
\[ - \mu_6 \left( -P_{m, t}^{\text{ch}, \text{dis}} - L_{m, t} + \Gamma_{m, t} \hat{y}_{m, t} \right) - \mu_7 (e_{m, t}) \]
\[ - \mu_8 \left( -e_{m, t} + X_m \right) \]
\[ - \mu_9 \left( -\sum_{t \in T} \hat{y}_{m, t} + \varrho_m \right) - \mu_{10} \left( -b_{m, t}^{\text{dis}} + e_{m, t} \right) \]
\[ - \mu_{11} \left( -P_{m, t}^{\text{dis}} + \Gamma_{m, t} \hat{y}_{m, t} \right) - \mu_{12} \left( -P_{m, t}^{\text{ch}, \text{dis}} - \Gamma_{m, t} \hat{y}_{m, t} \right) \]
\[ \frac{\partial f(x)}{\partial b_{m, t}^{\text{dis}}} = \sum_{t \in T} \rho_t + \sum_{t \in T} \left( \Omega_t + \Omega_{m_t} + \Omega_{m_t} \right) \]
\[ - \sum_{m \in S} \left\{ c_m^{m_f} + c_m^{m_v} - \lambda_1 + \lambda_2 + \lambda_4 + \mu_1 \right\} \]
\[ - \mu_4 \left( \hat{z}_{m, t} \right) + \mu_{10} - \mu_{11} = 0 \]
\[ \frac{\partial f(x)}{\partial b_{m, t}^{\text{ch}}} = \sum_{t \in T} \rho_t - \sum_{t \in T} \left( \Omega_t + \Omega_{m_t} + \Omega_{m_t} \right) \]
\[ - \sum_{m \in S} \left\{ c_m^{m_f} + c_m^{m_v} + \lambda_1 (\eta_m) - \lambda_2 - \lambda_4 \right\} \]
\[ + \mu_3 + \mu_4 \left( \hat{z}_{m, t} \right) + \mu_{11} = 0 \]
\[ \frac{\partial f(x)}{\partial e_{m, t}} = - \sum_{m \in S} c_m^{m_v} - \lambda_2 \]
\[ - \mu_7 \left( -e_{m, t} + X_m \right) - \mu_4 \left( X_m \right) = 0 \]
\[ \frac{\partial f(x)}{\partial \hat{y}_{m, t}} = - \mu_9 = 0 \]
\[ \sum_{t \in T} b_{m, t}^{\text{dis}} - b_{m, t}^{\text{ch}} \eta_m = 0 \]
\[ -e_{m, t} + e_{m, t} + b_{m, t}^{\text{ch}} + b_{m, t}^{\text{dis}} = 0 \]
\[ \sum_{t \in T} D_{m, t} - L_{m, t} = 0 \]
\[ -D_{m, t}^{\text{dis}} + D_{m, t}^{\text{ch}, \text{dis}} + \Gamma_{m, t} \hat{y}_{m, t} \]
\[ b_{m, t}^{\text{ch}} \geq 0, b_{m, t}^{\text{ch}} - X_m \left( \hat{z}_{m, t} \right) \geq 0 \]
\[ D_{m, t}^{\text{dis}} - L_{m, t} - \Gamma_{m, t} \hat{y}_{m, t} \geq 0 \]
\[ \hat{y}_{m, t} - \hat{y}_{m, t}^2 \geq 0 \]
\[ \hat{z}_{m, t} + \varrho_m - \mu_4 \left( -e_{m, t} + X_m \right) \geq 0 \]
\[ \hat{y}_{m, t} - \hat{y}_{m, t}^2 \geq 0 \]
\[ \mu_1 \geq 0, \mu_2 \geq 0, \mu_3 \geq 0, \mu_4 \geq 0 \]
\[ \mu_5 \geq 0, \mu_6 \geq 0, \mu_7 \geq 0, \mu_8 \geq 0 \]
\[ \mu_9 \geq 0, \mu_{10} \geq 0, \mu_{11} \geq 0 \]
FIGURE 3. Algorithm of the proposed method.

\[
\begin{align*}
\mu_1 & \leq M(1 - \vartheta_1), \quad \mu_2 \leq M(1 - \vartheta_2), \quad \mu_3 \leq M(1 - \vartheta_3) \\
\mu_4 & \leq M(1 - \vartheta_4), \quad \mu_5 \leq M(1 - \vartheta_5), \quad \mu_6 \leq M(1 - \vartheta_6) \\
\mu_7 & \leq M(1 - \vartheta_7), \quad \mu_8 \leq M(1 - \vartheta_8), \quad \mu_9 \leq M(1 - \vartheta_9) \\
\mu_{10} & \leq M(1 - \vartheta_{10}), \quad \mu_{11} \leq M(1 - \vartheta_{11}) \\
b_{\text{dis}, m, t} & \leq M(\vartheta_1) - \kappa_{\text{dis}, m, t} \leq M(\vartheta_2) - \kappa_{\text{dis}, m, t} \leq M(\vartheta_3) \\
b_{\text{ch}, m, t} & - X_m \left(1 - \mu_1 \right) \leq M(\vartheta_4), \quad \gamma_{\text{dis}, m, t} - \kappa_{\text{dis}, m, t} \leq m(\vartheta_5) \\
- \gamma_{\text{ch}, m, t} & - \mu_1 \leq M(\vartheta_6), \quad -X_m + X_m \leq M(\vartheta_7) \\
X_m & - X_m \leq M(\vartheta_8), \quad \sum_{t \in T} \gamma_{\text{ch}, m, t} \leq \vartheta_9 \leq M(\vartheta_9) \\
b_{\text{dis}, m, t} - e_{\text{ch}, m, t} & \leq M(\vartheta_{10}), \quad \gamma_{\text{dis}, m, t} - \kappa_{\text{dis}, m, t} \\
+ b_{\text{ch}, m, t} - X_m \left(1 - \alpha_m \right) L_{\text{max}} & \leq m(\vartheta_{11}) 
\end{align*}
\]

As can be seen, Equations (6) are equivalent to the lower-level model (4c-4f) in the form of KKT equations. By locating model (6) as constraints in the bi-level model (4), the problem becomes a single-level form:

\[
\begin{align*}
\min & \sum_{i,j \in N} \sum_{t \in T} w_1 \left( c_i^t P_{i,t} + c_j^t S_{j,t} + c_i^t u_{i,t} + c_j^t r_{j,t} \right) \\
& + w_2 \left(1 - \bar{R}_i \right) \\
\text{s.t.} & \quad (1b) - (1o), \quad (6a) - (6o)
\end{align*}
\]

IV. NUMERICAL RESULTS

A. INTRODUCTION OF SYSTEMS

In this section, the analysis of the results obtained from the simulations is presented. To test the accuracy and precision of the proposed method and model, two IEEE 6-bus and 118-bus networks, which are modeled with standard distribution substations, have been considered. In the comparison section, the superiority of the proposed method over the decomposition methods is shown. Numerical tests were performed by MATLAB and Gurobi 9 on an Intel Core i7 processor, 2.2 GHz with 8 GB of RAM. Below are the 6-bus and 118 bus networks.

B. 6-BUS SYSTEM

The first test system is made of two-generation units, three independent substations, and eight lines. The diagram of this system is illustrated in Fig. (4). In this system, the first independent substation is connected to transmission node 3, the second independent substation is connected to node 4 and the last independent substation has been connected to transmission node 6. Three different demand profiles have been used for these substations at 24-hours, and similar large-scale energy storage systems are provided for each independent substation. The considered parameters are taken from [26].

To implement the worst-contingency for branches and units in a 6-bus system, \( k \) is considered in Equation (1k) one. Based on the results of Table 2, in the 6-bus network, \( k_0 \) is supposed equal to one. Notice that because of the low number of generation units and to prevent the infeasibility of optimizing the problem, the value of \( k_0 \) is considered equal to zero. According to the Table 2, the objective function for the upper-level problem, which is a unit commitment problem, is equal to 273880US$, and the objective function for the lower-level, which is distribution branch energy management along with demand-side management, is equal to 58033US$. Considering the worst-contingency, line 3 at hours 11, 14 and 16, line 4 at hour 19, line 7 at hours 1, 2, 13, and 21, line 8 at hours 3-10, 12, 15, 17, 18, 20, 22-24, have been disconnected. It can be seen that the problem solving time is equal to 6.52 seconds. This high speed and convergence shows the superiority of the proposed method.

Table (3) demonstrates a comparison between the impact of considering or ignoring the demand side management on the costs of the problem. The percentage change of the permissible load per hour is equal to 5% of the load of the
TABLE 2. The results of the 6-bus system under contingency.

| Upper level cost ($) | Lower level benefit ($) | Total availability | Contingency | CPU Time ($) |
|----------------------|-------------------------|-------------------|-------------|--------------|
| 273880               | 58033                   | 0.802             | l_1:1,14,16 | 6.52         |
| l_4:19               |                         |                   | l_2:12,13,21|              |
| l_7:3                |                         |                   | 10,12,15,17,18,20 |          |
| 22-24                |                         |                   |             |              |

TABLE 3. Impact of demand side management on the costs in the 6-bus system.

| Start-up/Shutdown cost ($) | No-load cost ($) | Production cost ($) | Upper level cost ($) | Lower level benefit ($) |
|---------------------------|------------------|---------------------|----------------------|-------------------------|
| With DR                   | 2700             | 65700               | 205480               | 273880                  |
| Without DR                | 3500             | 66700               | 206083               | 58033                   |

same hour. As can be seen, the demand-side management program was able to reduce transmission network costs by about $2,400 and add about $2,500 to the distribution network profit by considering a maximum of 5% load change.

Figure (5) is given to exhibit the precise efficiency of the demand-side management program model in the worst-contingency conditions. Figure (5) illustrates a comparison of the unchanged and the changed load in the 6-bus network at three substations connected to the transmission node under the worst-contingency, where SD is equal to substation demand. Figure (6) indicates the optimal charging/discharging power of storage at independent substations considering the worst-contingency condition. The largest charge/discharge power belongs to storage 2, and the lowest power is related to storage 3. The state of energy (SOE) in the storage is illustrated in Fig. (7). It is observed that the highest capacity is related to storage 2, 1, and 3, respectively. Figure (8) indicates the units’ production in the intended 24-hour period. In this case, unit 2 generates power all over the day. The results of Table 2, as well as Figs. 5 to 8, represent the correct accuracy and performance of the model and the proposed method under worst-contingency.

C. 118-BUS SYSTEM

The second case study is made of 54 units, 186 lines, and 10 independent substations. In this case, substations are placed on buses No. 4, 6, 11, 12, 15, 62, 70, 80, 107, and 118, respectively. The considered parameters are taken from [26]. Based on the results of Table (4), the objective function for the upper-level problem, which is a security-constrained unit commitment problem, is equal to 740386US$, and the objective function for the lower-level, which is distribution substation energy management along with demand-side management, is equal to 79131US$. Considering the worst-contingency, unit 1 at hours 1-24, line 1 at hour 15, line 5 at hours 13, 20, and 23, line 10 at hour 19, line 11 at hours 9 and 14, line 19 at hours 10 and 18, line 34 at hour 22, line 36 at hour 11, line 37 at hour 1-8, 12, 16, 21, and 24, line 81 at hour 17, have been disconnected. The problem-solving time in this system is equal to 371 seconds. This short time to solve the problem shows the superiority of the proposed method.

As can be seen in Table (5), the demand side management program, like the 6-bus network, has had a significant impact
on the 118-bus network. As in the previous network, in this network, the maximum load change per hour is equal to 5%. Similarly, the demand-side management program has been able to reduce transmission network costs by about $12,000 and increase distribution network profits by nearly $17,000.

Table 4 demonstrates that the proposed method is more efficient for use in large-scale networks and online optimizations. As can be seen, the proposed method has provided more optimal solutions than the method in [8] because by using the proposed method, we have been able to reduce the cost of

### TABLE 4. Comparison of the results in the IEEE-118 bus system under contingency.

| Upper level cost ($) | Lower level benefit ($) | Total availability | Contingency | CPU Time ($) |
|----------------------|-------------------------|--------------------|-------------|--------------|
| 740386               | 79131                   | 0.627              | $G_{1}=1-24$ | 371          |
| $l_{1}=15$           | $l_{2}=13,20,23$        |                    | $l_{3}=19$  |              |
| $l_{4}=9,14$         | $l_{5}=10,18$           |                    | $l_{6}=11$  |              |
|                      | $l_{7}=1$               |                    | $l_{8}=17$  |              |
|                      |                         |                    | $l_{9}=12,16,21,24$ |            |

### TABLE 5. Impact of demand side management on the costs in the 118-bus system.

| Start-up/Shutdown cost ($) | No-load cost ($) | Production cost ($) | Upper level cost ($) | Lower level benefit ($) |
|---------------------------|-----------------|--------------------|----------------------|-------------------------|
| With DR                   | 2275            | 54603              | 683510               | 740386                  |
| Without DR                | 3100            | 56328              | 693212               | 752640                  |

### TABLE 6. Comparison of the results in problem-solving time.

|               | CPU Time (S) | Cost ($) |
|---------------|--------------|----------|
| Proposed method | 6.52         | 371      |
| Ref. [8]      | 30           | 1800     |

### D. COMPARISON

The comparisons in this paper are on problem solving time and objective function. As we know, with the increase in the modeling of distribution networks in transmission networks, the number of variables and parameters increases, therefore, it is of great importance to provide a method that can reach global optimal solutions in the shortest time compared to other methods.

To show the superiority of the proposed method in the problem-solving time, in this section the results are compared with the reformulation and decomposition technique in [8]. For this purpose, the reformulation and decomposition technique according to [8] is performed under equal conditions such as parameters and data and similar computer system.

As can be seen from Table 6, the proposed method in both 6 and 118-bus networks has solved the problem in less time, which illustrates the advantage of the proposed method. Note that the objective function and the decision variables have been equalized in both methods. The proposed method is almost 5x faster than the decomposition algorithm in the 6-bus system and nearly 4.5x faster in the 118-bus system. Table 6 demonstrates that the proposed method is more efficient for use in large-scale networks and online optimizations.

As can be seen, the proposed method has provided more optimal solutions than the method in [8] because by using the proposed method, we have been able to reduce the cost of
the 6-bus system by about 3,000 dollars and the 118-bus system by about 11,000 dollars compared to the decomposition method in [8].

V. CONCLUSION

This study proposed a bi-level model to connect autonomous substations considering the large-scale storage and demand-side management at each bus of the transmission system. The model proposed in this study was separated into bi-levels, upper and lower. The upper level consists of a MILP model of security-constrained unit commitment considering DCOPF to reduce costs and unavailability of the units. The lower level consists of a MILP model for energy management of autonomous substations considering demand-side management with large-scale energy storage with perfect control of the number of demand management and charge/discharge actions. The objective at the lower level is to increase the profits of substations by reducing energy purchases from the transmission system. To illustrate the performance of the proposed model and method, two different systems 6 and the IEEE-118 bus systems were considered. The simulation results with the Gurobi solver obtained from different networks demonstrated that the proposed approach can be properly applied to any system and provides more realistic and pragmatic results. Comparing the proposed method with the decomposition algorithm method, it was observed that the proposed method is several times faster in each system, so this method is more suitable for implementation in large systems and online optimizations. Finally, because of the proposed mathematical model and its solution with powerful commercial software such as Gurobi, optimal global solutions can be guaranteed. To continue this paper, several suggestions are presented as follows:

- Modeling the natural gas network in the proposed model and investigating its effect on the gas-fired units of the electricity network.
- Providing a robust model to investigate uncertainty in load and costs.

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