Solving the Problem of Large-Scale Optimal Scheduling of Distributed Energy Resources in Smart Grids Using an Improved Variable Neighborhood Search

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ABSTRACT Since the last decade, power systems have been evolving dynamically due to smart grid technologies. In this context, energy management and optimal scheduling of different resources are very important. The main objective of this paper is to study the optimal scheduling of distributed energy resources (OSDER) problem. This problem is a challenging, complex and very large-scale mixed-integer non-linear programming (MINLP) problem. Its complexity escalates with incorporation of uncertain and intermittent renewable sources, electric vehicles, variable loads and markets which makes it hard to be solved using traditional optimization algorithms and solvers. However, it can be handled efficiently and without approximation or modification of the original formulation using modern optimization algorithms such as metaheuristics. In this paper, an improved version of the variable neighborhood search (IVNS) algorithm is proposed to solve the OSDER problem. The proposed algorithm was tested on two large-scale centralized day-ahead energy resource scenarios. In the first scenario, the 12.66 kV, 33-bus test system with a total of 49,920 design variables is used whilst in the second scenario, the 30 kV, 180-bus test system is used with a total of 154,800 design variables. The optimization results using the proposed algorithm were compared with five existing optimization algorithms, i.e., chaotic biogeography-based optimization (CBBO), cross-entropy method and evolutionary PSO (CEEPSO), chaotic differential evolution with PSO (Chaotic-DEEPSO), Levy differential evolution with PSO (Levy-DEEPSO), and the variable neighborhood search (VNS). For the first test system, the IVNS has achieved a score of -5598.89 while for the second test system it has achieved a score of -3180.15. A comparative study of the results has shown that the proposed IVNS algorithm performs better than the remaining algorithms for both cases.

INDEX TERMS Distributed energy resources, large-scale optimization, smart grids, variable neighborhood search.

I. NOMENCLATURE

B_{bk}	Real part of the admittance of a line
$C_{DG(I,t)}$	Costs of generation of distributed unit (DGU) I in period t
$C_{Discharge(E,t)}$	Costs of discharging of energy storage unit (ESU) E in period t
$C_{Discharge(V,t)}$	Costs of discharging of electric vehicle (EV) V in period t
$C_{GCP(I,t)}$	Costs of curtailment of DGU I in period t
$C_{LoadDR(L,t)}$	Costs of load reduction (DR) of load L in period t
$C_{NSD(L,t)}$	Costs of non-supplied demand (NSD) of load L in period t
$C_{Supplier(S,t)}$	Costs of external supplier S in period t
$E_{BatCap(V)}$	Battery energy capacity of EV V
$E_{MinCharge(V,t)}$	Minimum stored energy to be guaranteed for the EV V at the end of period t
$E_{Stored(V,t)}$	Stored energy for the EV V at the end of period t

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$E_{Stored(V,t-1)}$	Stored energy for the EV V at the end of period $t-1$
$E_{Trip(V,t)}$	EV V energy consumption forecast in period t
G_{bk}	Imaginary part of the admittance of a line
N_{DG}	Number of DGUs
N_E	Number of ESUs
N_L	Number of loads
N_M	Number of markets
N_S	Number of external electricity suppliers
N_v	Number of EVs
$P_{Charge(E,t)}$	Active power for charge of ESU E in period t
$P_{Charge(V,t)}$	Active power for charging of EV V in period t
$P_{ChargeLimit(V,t)}$	Active power maximum limit for charging of EV V in period t
$P_{DG(I,t)}$	Active power for the generation of DGU I in period t
$P_{DGMaxLimit(I,t)}$	Active power maximum limit for the generation of DGU I in period t
$P_{DGMinLimit(I,t)}$	Active power minimum limit for the generation of DGU I in period t
$P_{Discharge(E,t)}$	Active power for discharging of ESU E in period t
$P_{Discharge(V,t)}$	Active power for discharging of EV V in period t
$P_{DischargeLimit(V,t)}$	Active power maximum limit for discharging of EV V in period t
$P_{GCP(I,t)}$	Active power for the generation curtailment power of DGU I in period t
$P_{Load(L,t)}$	Active power for the demand of load L in period t
$P_{LoadDR(L,t)}$	Active power for the reduction of load L in period t
$P_{LoadDRMaxLimit(L,t)}$	Active power maximum limit reduces allowed for load L in period t
$P_{NSD(L,t)}$	Active power for the non-supplied demand for load L in period t
$P_{Sell(M,t)}$	Active power for sale to market M in period t
$P_{Supplier(S,t)}$	Active power for the generation of the external supplier S in period t
$P_{SupplierLimit(S,t)}$	Active power maximum limit for the generation of the external supplier S in period t
$P_{TFR_{MV/LV(b\cdot t)}}$	Active power in MV/LV transformer in period t
$Q_{DG(I,t)}$	Reactive power for the generation of DGU I in period t
$Q_{DGMaxLimit(I,t)}$	Reactive power maximum limit for the generation of DGU I in period t
$Q_{DGMinLimit(I,t)}$	Reactive power minimum limit for the generation of DGU I in period t
$Q_{Load(L,t)}$	Reactive power for the demand of load L in period t,
$Q_{Supplier(S,t)}$	Reactive power for the generation of the external supplier S in period t
$Q_{SupplierLimit(S,t)}$	Reactive power maximum limit for the generation of the external supplier S in period t
$Q_{TFR_{MV/LV(b\cdot t)}}$	Reactive power in MV/LV Transformer in period t
S^{max}	Apparent power maximum limit
V^{max}	Voltage magnitude maximum limit
V^{min}	Voltage magnitude minimum limit
$X_{(E,t)}$	Binary decision variable for discharging of ESU E in period t
$X_{(V,t)}$	Binary decision variable for discharging of EV V in period t
$X_{DG(I,t)}$	Binary decision variable for the commitment status of DGU I in period t
$X_{Supplier(S,t)}$	Binary decision variable for the supplier S in period t
$Y_{(E,t)}$	Binary decision variable for power charging of ESU E in period t
$Y_{(V,t)}$	Binary decision variable for power charging of EV V in period t
y_{bk}	Admittance of a line
y_{shunt}	Shunt admittance of a line
$\mathbf{x_i}$	i^{th} design variable
$\eta_{c(V)}$	Efficiency of grid to vehicle when vehicle V is charging
$\eta_{d(V)}$	Efficiency of grid to vehicle when vehicle V is discharging
θ^{max}	Voltage angle maximum limit
θ^{min}	Voltage angle minimum limit
$h(\mathbf{x})$	Set of inequality constraints
$\mathbf{x}$	Vector of design variables
E	Index for ESUs,
I	Index of DGUs
In	Income
L	Index for loads
M	Index for market/energy buyer
$MP_{Charge(E,t)}$	Prices for the charge process of ESU E in period t
$MP_{Charge(V,t)}$	Prices for the charge process of EV V in period t
$MP_{Load(L,t)}$	Prices for load L in period t
$MP_{Sell(M,t)}$	Prices for the market M in period t
OC	Operation cost
$Profits$	Profits
V	Index for EVs,
V	Voltage magnitude
$f(\mathbf{x})$	Objective function
$g(\mathbf{x})$	Set of equality constraints
k	Number of equality constraints
m	Number of inequality constraints
n	Number of design variables
t	Index for time periods

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Δt	Duration of time period
θ	Voltage angle
$\{F_v\}$	Fibonacci sequence
$\{L_v\}$	Lucas sequence
$\{ML_v\}$	Modified Lucas sequence

II. INTRODUCTION

Development of renewable distributed energy has significantly increased around the globe by reason of reducing dependence on conventional power plants while at the same time minimizing the environmental impact of electricity generation [1]. As promising energy systems, microgrids powered by renewable energy sources are a viable solution for electricity shortages as they are close to the consumer and are economically feasible, now and into the future. Also, of considerable technical importance are the facts that many countries have outlaid high capital investment and implemented policies to integrate renewable energy sources into microgrids for sustainable energy generation, and electricity generation from renewable energy sources has received substantial consideration due to its significant benefits, such as increasing the share of renewables in the energy mix [2]–[5]. Therefore, it is necessary to apply communication and control technologies to microgrids to cope with continuously rising energy consumption and the complexity of grids.

The smart grid (SG) has been developed to answer the increasing needs of the modern electric grid and to fulfil several technological and environmental constraints. Although there is no universal definition of the SG, it can simply be an 'intelligent' grid. In contrast to traditional grids that can only transmit and distribute power, SGs can store, communicate, and make decisions [6]–[9]. Another advantage of SGs is that there is no need to build new infrastructure, rather improvements to existing setups to make them more autonomous and improve their power delivery is all that is required.

SG systems have real potential by reason that existing power grids are overly complex and overloaded, and the current infrastructure cannot be expected to handle significant increases in energy demand [10]. In worst-case scenarios, insufficient grid supplies to meet peak load demands could cause power shortages. Different problems can occur at generation, transmission, and distribution levels [11]. In addition, power grids have numerous environmental and economic problems as most of the electricity is generated by conventional power plants [12],[13]. To counter these issues, SG allows alternative resources to be connected to the grid in order to supply additional power to the main supply. However, the incorporation of such resources has increased the complexity of power systems and their planning and operation have become cumbersome tasks. This has led to the development of new algorithms to efficiently solve the so-called energy resource management (ERM) problem [14].

Aimed at reducing consumers' electricity bills and interconnecting large-scale distributed energy generation, many technical studies have investigated the problems and technical challenges of ERM in SGs. For example, Moretti *et al.* [15]

comprehensively analyzed the environmental and economic impact of SGs for variations in cost estimation and concluded that reducing the uncertainty about the environmental impacts and cost is important to achieving more accurate results. Another study [16] analyzed various models of SG for improving the power network, while Lin and Chen [17] presented an analysis of the required enhancements of distribution network automation to maintain a balance in demand and supply and lead to efficient electrical networks. In other studies, the application of digital communication and networking for SG has been evaluated [18], [19]. Research results indicated that the SG with the latest technology and advanced equipment is the best solution to overcome grid problems. In addition, the distributed optimization algorithm has been successfully used for a vast variety of SG operational problems and constraints [20]–[22].

Several optimization approaches have been proposed to optimize distributed energy resource (DER) scheduling in SGs with the application of renewable generation and electric vehicles (EVs). These include mathematical problem-based optimization with equilibrium constraints [23], optimization using exchange problems based on agent coupling constraints [24], mixed integer linear programming (MILP) with dynamic pricing and peak power limiting [25], simulation and implementation of vehicle-to-grid (V2G) and vehicle-to-home (V2H) in the distribution network [26], MILP for electricity consumption and EVs [27], and a distributed optimization algorithm with a demand respond model [28].

Over the years, some computational methods have been proposed to optimize scheduling of DER problems in SGs. In this respect, an optimization method was developed using an artificial neural network (ANN) and demand side management (DSM) for industrial peak load to optimize available energy resources, and an improvement in energy system efficiency was achieved with reference to the load factor [6]. The genetic algorithm (GA) was applied to optimally design an SG using a generalized optimization formulation of distributed generators [29]. It was found that the proposed algorithm could be an effective solution to the reactive power management problem, and its evolution process was suitable in evaluating microgrid systems based on different multi-objective functions. GA has also been used to solve the economic operation problem of SG with DER (i.e., PV generation, combined heat and power (CHP), and energy storage device) considering Demand Response (DR) [30]. Gomes *et al.* [31] managed direct load control in distribution networks using an interactive evolutionary algorithm (EA). The proposed method was effective for supplying evolutionary processes and was satisfactory for use in fitness assessment of load control strategies. In another study, Markovic *et al.* [32] analyzed integration of renewable energy sources in SGs using EAs and cloud computing and concluded that by enhancing the renewable energy use, SGs could minimize the environmental problems from power plants.

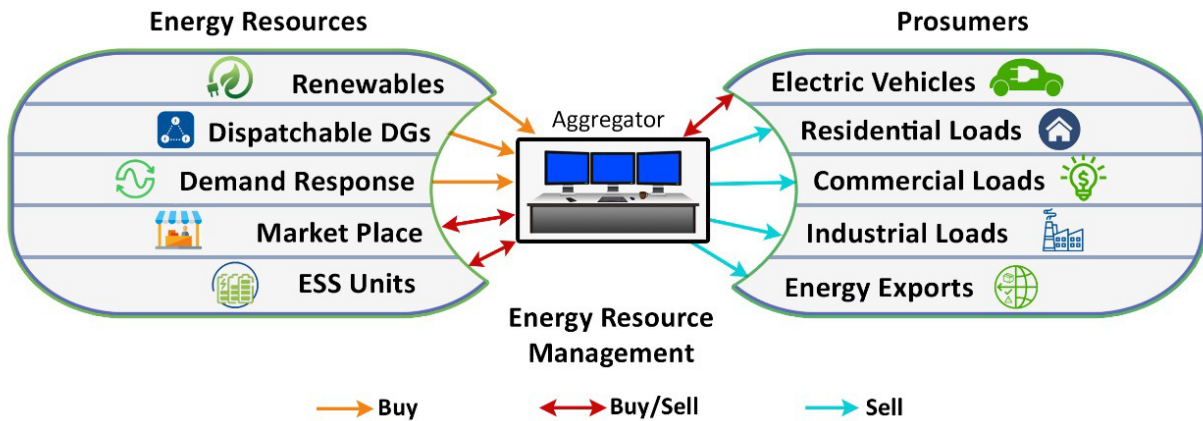Binary particle swarm optimization (IBPSO) algorithm has also been used for scheduling different interruptible

loads with multi-objective optimization problems, and the effectiveness of the method was evaluated [33]. By simplifying multi-objective functions into a single aggregate objective function, the BPSO algorithm could provide near-optimal solutions, was useful for challenging scheduling tasks, and was also effective in scheduling varied interruptible loads with complex, nonlinear and noncontinuous problems. Faria *et al.* [34] proposed a modified particle swarm optimization (PSO) with Gaussian mutation of strategic parameters to minimize operation costs and manage DER in a distribution network. They compared the solutions with PSO without mutation, evolutionary PSO, and a deterministic approach using self-parametrization. A recent study [35] applied multi-objective glow-worm swarm particle optimization to optimize SGs consisting of DER and controlled shiftable loads. In this work, the optimization algorithm was based on a new formulation that reduced the number of design variables and adopted a real-valued optimization, and its performance was compared with non-dominated sorting genetic algorithm (NSGA-II) on selected power systems.

The variable neighborhood search (VNS) algorithm is a simple and effective metaheuristic method to solve global and combinatorial optimization problems [36]. Over the years, some researches have been done using VNS technique for smart grid applications. For example, a short-term long forecasting framework for smart grid systems has been proposed to deal with the variability and nonstationary of loads [37]. This approach combines two heuristic methods, i.e. Multi-Start (MS) and General Variable Neighborhood Search (GVNS), to find solutions for the complexity problem of energy prices determination. A VNS based optimization method was successfully developed to study demand response in smart grids using a smart client model based on real-time pricing [38]. The proposed algorithm, a combination of MS and Variable Neighborhood Decent (VND), is used to minimize the total cost of the smart grid systems consists of distributed generations, energy storage, electric vehicles, and general loads. The VNS was also proposed to optimize the islanded operation of renewable energy systems by controlling the size and number of its components [39].

The application of the VNS algorithm was based on two different approaches which concern to the mutation stage, i.e. random selection of mutation parameters within the set parameters and making distinction among the parameters. In another study, differential evolutionary PSO method was combined with VNS method to optimize smart microgrids by solving multi-objective control model while maximizing profit [40]. In a recent study, this multi-objective hybrid algorithm was also used for the optimization of smart grids management by considering electricity market [41].

The aim of this paper is to develop an improved variable neighborhood search (IVNS) algorithm to solve ERM problems more efficiently. The ERM problem investigated in this work covers a huge variety of DERs, such as distributed generation units (DGUs) including renewables [42], energy storage units (ESUs), and EVs. Additionally, when demand response (DR), market bids, V2G capabilities, and external suppliers are considered along with power balance constraints of an AC power system, the entire problem becomes a mixed-integer non-linear programming (MINLP) problem [43],[44]. In this paper, this specific ERM problem is called the optimal scheduling of distributed energy resources (OSDER) problem.

The remainder of this paper is organized as follows. In section II, the OSDER problem is described and mathematically formulated. In section III the proposed algorithm is explained. In section IV, the application and results are presented and discussed. Finally, the conclusions of this paper are drawn in section V.

III. PROBLEM FORMULATION
A. DESCRIPTION
The energy management aggregator (EMA) in an SG (Fig. 1) is defined as any organization or individual that uses several resources with the objective of obtaining reduced prices, better services, or more benefits when providing energy or any related services to the group of retail energy customers [45]. Furthermore, the EMA can use its own assets like ESUs to supply the required load. It sets up bilateral contracts between

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the EMA and the final-end user that can, for example, be residential or industrial customers.

Therefore, the goal of optimal scheduling is to minimize a defined objective function such as operational costs, losses, pollution, and so on, in order to determine the scheduling of different available energy resources in the day-ahead context for the 24 hours of the following day, while at the same time respecting certain technical and operational constraints.

B. MATHEMATICAL FORMULATION

The main objective of the EMA is to maximize profits. Therefore, the OSDER problem formulated as an optimization problem can be expressed by the following equations:

$$\text{Minimize } f(\mathbf{x}) \tag{1}$$

$$\text{Subject to } g_i(\mathbf{x}) = 0 \, i = 1:k \tag{2}$$

$$\text{and} \quad h_j(\mathbf{x}) \leq 0 \, j = 1:m \tag{3}$$

$$\text{where} \quad \mathbf{x} = [x_1, x_2, \ldots, x_n] \tag{4}$$

where: $f(\mathbf{x})$ represents the objective function, $\mathbf{x}$ represents the vector of design variables, $\mathbf{x_i}$ is the ith design variable, $\mathbf{n}$ represents the number of design variables, $\mathbf{g}(\mathbf{x})$ represents the set of equality constraints, $\mathbf{k}$ is the number of equality constraints, $\mathbf{h}(\mathbf{x})$ represents the set of inequality constraints, and $\mathbf{m}$ is the number of inequality constraints.

C. OBJECTIVE FUNCTION

Profits, aimed at being maximized while solving the OSDER problem, can be written in terms of the income, referred to as *In*, and the operation cost, referred to as *OC*:

$$\text{Profits} = In - OC \tag{5}$$

In equation (5), both *In* and *OC* are given in Monetary Units (m.u.).

The objective function of this problem, written to be minimized, is given by

$$OF = OC - In \tag{6}$$

If the objective function is negative it means that the system is profitable because the income is greater than the operation cost. Alternatively, if the operation cost is greater than the income it means that there are no profits.

The income can come from four sources, based on consumer demand, the charging process of ESUs, the energy sold to the electricity market, and the charging of EVs. Therefore, *In* in (m.u.) can be expressed as [46]

$$In = \sum_{t=1}^{T} \left[\left(\begin{array}{c} \sum_{L=1}^{N_L} P_{Load(L,t)} \cdot MP_{Load(L,t)} \\ + \sum_{M=1}^{N_M} P_{Sell(M,t)} \cdot MP_{Sell(M,t)} \\ + \sum_{E=1}^{N_E} P_{Charge(E,t)} \cdot MP_{Charge(E,t)} \\ + \sum_{V=1}^{N_V} P_{Charge(V,t)} \cdot MP_{Charge(V,t)} \end{array} \right) \times \Delta t \right] \tag{7}$$

where: L, M, E, V, and t are the indices of loads, market/energy buyer, ESUs, EVs, and time periods, respectively. N_L, N_M, N_E, and N_v are the number of loads, the number of markets, the number of ESUs, and the number of EVs, respectively. $P_{Load(L,t)}$, $P_{Sell(M,t)}$, $P_{Charge(E,t)}$, and $P_{Charge(V,t)}$ are the active powers in (MW) for the demand of load L in period t, for sale to market M in period t, for charge of ESU E in period t, and for charge of EV V in period t, respectively. $MP_{Load(L,t)}$, $MP_{Sell(M,t)}$, $MP_{Charge(E,t)}$, and $MP_{Charge(V,t)}$ are the prices in (m.u.) for load L in period t, for the market M in period t, for the charge process of ESU E in period t, and for the charge process of EV V in period t, respectively.

The operational cost of different DERs managed by the Virtual Power Plants (VPP) represents the OC. This cost includes the cost of DGUs, the cost from external suppliers, the cost from discharging ESUs and EVs, the cost from DR programs, the penalization with non-supplied demand, and the penalization with DGUs generation curtailment. So OC in (m.u) can be determined by [46]

$$OC = \sum_{t=1}^{T} \left[\left(\begin{array}{c} \sum_{I=1}^{N_{DG}} P_{DG(I,t)} \cdot C_{DG(I,t)} \\ + \sum_{S=1}^{N_S} P_{Supplier(S,t)} \cdot C_{Supplier(S,t)} \\ + \sum_{L=1}^{N_L} P_{LoadDR(L,t)} \cdot C_{LoadDR(L,t)} \\ + \sum_{M=1}^{N_M} P_{Buy(M,t)} \cdot MP_{Buy(M,t)} \\ + \sum_{V=1}^{N_V} P_{Discharge(V,t)} \cdot C_{Discharge(V,t)} \\ + \sum_{E=1}^{N_E} P_{Discharge(E,t)} \cdot C_{Discharge(E,t)} \\ + \sum_{L=1}^{N_L} P_{NSD(L,t)} \cdot C_{NSD(L,t)} \\ + \sum_{I=1}^{N_{DG}} P_{GCP(I,t)} \cdot C_{GCP(I,t)} \end{array} \right) \times \Delta t \right] \tag{8}$$

where: I is an index of DGUs. N_{DG} and N_S are the number of DG units, and the number of external electricity suppliers, respectively. $P_{DG(I,t)}$, $P_{Supplier(S,t)}$, $P_{LoadDR(L,t)}$, $P_{NSD(L,t)}$, and $P_{GCP(I,t)}$ are the active powers in (MW) for the generation of DGU I in period t, for the generation of the external supplier S in period t, for the reduction of load L in period t, for the non-supplied demand for load L in period t, and for the generation curtailment power of DGU I in period t. $C_{DG(I,t)}$, $C_{Supplier(S,t)}$, $C_{LoadDR(L,t)}$, $C_{Discharge(E,t)}$, $C_{Discharge(V,t)}$, $C_{NSD(L,t)}$, and $C_{GCP(I,t)}$ are the costs of: the generation of DGU I in period t, the external supplier S in period t, the load reduction due to DR of load L in period t, the discharging of ESU E in period t, the discharging of

EV V in period t, the non-supplied demand (NSD) of load L in period t, and the curtailment cost of DGU I in period t, respectively.

D. CONSTRAINTS

The energy management problem is constrained by the energy balance (i.e., the flow of active and reactive powers), the limits on voltages, the generation limits of DG and suppliers in each period, the capacity of ESUs, the limits of charge and discharge rates, the capacity of EVs, the trip requirements for EVs, and the limits of charge and discharge efficiencies and rates [43],[44],[46].

The active power balance is expressed as

$$
\sum_{I=1}^{N_{DG}} \left(P_{DG(I,t)} - P_{GCP(I,t)} \right) + \sum_{S=1}^{N_S} P_{Supplier(S,t)}
$$
$$
+ \sum_{L=1}^{N_L} \left(P_{NSD(L,t)} + P_{LoadDR(L,t)} - P_{Load(L,t)} \right)
$$
$$
+ \sum_{V=1}^{N_V} \left(P_{Discharge(V,t)} - P_{Charge(V,t)} \right)
$$
$$
+ \sum_{E=1}^{N_E} \left(P_{Discharge(E,t)} - P_{Charge(E,t)} \right) - \sum_{M=1}^{N_M} P_{Sell(M,t)}
$$
$$
= \sum_{k=1}^{N_B} V_{b(t)} \cdot V_{k(t)} \cdot \left(G_{bk} \cdot \cos \left(\theta_{b(t)} - \theta_{k(t)} \right) \right.
$$
$$
\left. + B_{bk} \cdot \sin \left(\theta_{b(t)} - \theta_{k(t)} \right) \right) \quad k \neq b \quad (9)
$$

The reactive power balance is expressed as

$$
\sum_{I=1}^{N_{DG}} Q_{DG(I,t)} + \sum_{S=1}^{N_S} Q_{Supplier(S,t)} - \sum_{L=1}^{N_L} Q_{Load(L,t)}
$$
$$
= \sum_{k=1}^{N_B} V_{b(t)} \cdot V_{k(t)} \cdot \left(G_{bk} \cdot \sin \left(\theta_{b(t)} - \theta_{k(t)} \right) + B_{bk} \right.
$$
$$
\left. \cdot \cos \left(\theta_{b(t)} - \theta_{k(t)} \right) \right) \quad k \neq b \quad (10)
$$

The voltage limits (magnitude and angle) are expressed in the following equations:

$$
V_b^{min} \leq V_{b(t)} \leq V_b^{max} \quad (11)
$$
$$
\theta_b^{min} \leq \theta_{b(t)} \leq \theta_b^{max} \quad (12)
$$

The thermal limit of lines limiting their power flows is expressed as follows:

$$
\left| V_{b(t)} \times \left(\left[(V_{b(t)} - V_{k(t)}) \, y_{bk} \right]^* + \left[V_{b(t)} \times \frac{1}{2} y_{shunt_b} \right]^* \right) \right|
$$
$$
\leq S_{bk}^{max} k \neq b \quad (13)
$$

The limits on the power of HV/MV transforms are defined as

$$
\sqrt{ \left(\sum_{S=1}^{N_S} P_{Supplier(S,t)} \right)^2 + \left(\sum_{S=1}^{N_S} Q_{Supplier(S,t)} \right)^2 }
$$
$$
\leq S_{TRF_{HV/MV(b)}}^{max} \quad (14)
$$

The limits on the power of MV/LV transforms are defined as follows:

$$
P_{TFR_{MV/LV(b\cdot t)}} = \sum_{I=1}^{N_{DG}} \left(P_{DG(I,t)} - P_{GCP(I,t)} \right)
$$
$$
+ \sum_{L=1}^{N_L} \left(P_{NSD(L,t)} + P_{LoadDR(L,t)} - P_{Load(L,t)} \right)
$$
$$
+ \sum_{V=1}^{N_V} \left(P_{Discharge(V,t)} - P_{Charge(V,t)} \right)
$$
$$
+ \sum_{E=1}^{N_E} \left(P_{Discharge(E,t)} - P_{Charge(E,t)} \right) \quad (15)
$$

$$
Q_{TFR_{MV/LV(b\cdot t)}} = \sum_{I=1}^{N_{DG}} Q_{DG(I,t)} - \sum_{L=1}^{N_L} Q_{Load(L,t)} \quad (16)
$$

$$
\sqrt{ \left(P_{TFR_{MV/LV(b\cdot t)}} \right)^2 + \left(Q_{TFR_{MV/LV(b\cdot t)}} \right)^2 }
$$
$$
\leq S_{TRF_{MV/LV(b)}}^{max} \quad (17)
$$

Constraints imposed on DG active and reactive powers during the online status are given by:

$$
X_{DG(I,t)} \cdot P_{DGMinLimit(I,t)} \leq P_{DG(I,t)}
$$
$$
\leq X_{DG(I,t)} \cdot P_{DGMaxLimit(I,t)} \quad (18)
$$
$$
X_{DG(I,t)} \cdot Q_{DGMinLimit(I,t)} \leq Q_{DG(I,t)}
$$
$$
\leq X_{DG(I,t)} \cdot Q_{DGMaxLimit(I,t)} \quad (19)
$$

The constraints imposed on the upstream supplier are defined as

$$
P_{Supplier(S,t)} \leq X_{Supplier(S,t)} \cdot P_{SupplierLimit(S,t)} \quad (20)
$$
$$
Q_{Supplier(S,t)} \leq X_{Supplier(S,t)} \cdot Q_{SupplierLimit(S,t)} \quad (21)
$$

Constraints imposed on the charging and discharging of EVs, since these two phases cannot occur at the same time, are given by

$$
X_{(V,t)} + Y_{(V,t)} \leq 1 \quad (22)
$$

The constraints imposed on the relationship between the energy stored in an EV indexed by V and the energy used during the trips and the charging/discharging power in each period are given by

$$
E_{Stored(V,t)} = E_{Stored(V,t-1)} - E_{Trip(V,t)}
$$
$$
+ \eta_{c(V)} \cdot P_{Charge(V,t)} \cdot \Delta t
$$
$$
- \frac{1}{\eta_{d(V)}} P_{Discharge(V,t)} \cdot \Delta t \quad (23)
$$

If the EV is connected to the grid, its charging and discharging power ratings are constrained as follows:

$$
P_{Charge(V,t)} \leq P_{ChargeLimit(V,t)} \cdot Y_{(V,t)} \quad (24)
$$
$$
P_{Discharge(V,t)} \leq P_{DischargeLimit(V,t)} \cdot X_{(V,t)} \quad (25)
$$

The charging capacity of an EV noted as V at t is restricted by the EV's battery and the stored energy in the battery at

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$(t - 1)$; that is,

$$\eta_{c(V)} \cdot P_{Charge(V,t)} \cdot \Delta t \leq E_{BatCap(V)} - E_{Stored(V,t-1)} \quad (26)$$

Since the EV can, in a maximum case, discharge the stored energy in the battery, the following constraints are imposed on EVs

$$\frac{1}{\eta_{d(V)}} P_{Discharge(V,t)} \cdot \Delta t \leq E_{Stored(V,t-1)} \quad (27)$$

For a given EV noted as V, the following constraint is imposed to be the maximum energy that can be stored by the battery:

$$E_{Stored(V,t)} \leq E_{BatCap(V)} \quad (28)$$

A constraint is imposed on the stored energy or reserve at each period,

$$E_{Stored(V,t)} \geq E_{MinCharge(V,t)} \quad (29)$$

The constraints imposed on ESU are similar to the ones imposed on EVs. Therefore, the following constraints are also imposed on the OSDER problem:

$$X_{(E,t)} + Y_{(E,t)} \leq 1 \quad (30)$$

$$E_{Stored(E,t)} = E_{Stored(E,t-1)} + \eta_{c(E)} \cdot P_{Charge(E,t)} \cdot \Delta t$$
$$- \frac{1}{\eta_{d(E)}} P_{Discharge(E,t)} \cdot \Delta t \quad (31)$$

$$P_{Charge(E,t)} \leq P_{ChargeLimit(E,t)} \cdot Y_{(E,t)} \quad (32)$$

$$P_{Discharge(E,t)} \leq P_{DischargeLimit(E,t)} \cdot X_{(E,t)} \quad (33)$$

$$\eta_{c(E)} \cdot P_{Charge(E,t)} \cdot \Delta t \leq E_{BatCap(E)} - E_{Stored(E,t-1)} \quad (34)$$

$$\frac{1}{\eta_{d(E)}} P_{Discharge(E,t)} \cdot \Delta t \leq E_{Stored(E,t-1)} \quad (35)$$

$$E_{Stored(E,t)} \leq E_{BatCap(E)} \quad (36)$$

$$E_{Stored(E,t)} \geq E_{MinCharge(E,t)} \quad (37)$$

Finally, constraints imposed by DR on the reduction of each load is given by

$$P_{Load(L,t)} \geq P_{LoadDRMaxLimit(L,t)} \quad (38)$$

IV. OPTIMIZATION ALGORITHMS

As aforesaid, the energy management problem investigated in this paper is an MINLP problem. There are two options to solve this kind of problems either by using traditional methods or metaheuristics. As reported in several references, without assumptions or simplification, dealing with these problems can be time consuming, whereas by using modern metaheuristics, they can be solved efficiently without simplification and with far less computational time.

The main contribution of this paper is that we have improved the initial version of VNS for solving the large-scale OSDER problem. Therefore, in the upcoming subsections, we will present the initial version of VNS and then we will detail our improved version IVNS.

Algorithm 1 Pseudocode of the VNS Algorithm Used to Solve the OSDER Problem

---

Initialization Step

　　Generate a random initial solution
　　Considering the first group of variables, adjust each group to optimize the objective function
Repeat the main step until the stopping criterion is met

Main Step

　　For $i = 1 : 2$
　　　　Optimize each group of variables for each hour of the day using the CCM
　　　　Use an intelligent strategy to transform each group of variables to individual variables → Consider the costs of generation, for example
　　End if
　　Use the CCM to optimize the variables, for each hour, according to the third type of grouping.

End Main Step

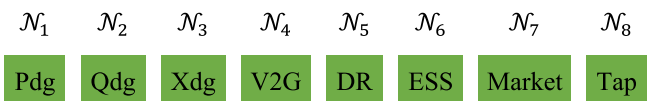| $\mathcal{N}_1$	$\mathcal{N}_2$	$\mathcal{N}_3$	$\mathcal{N}_4$	$\mathcal{N}_5$	$\mathcal{N}_6$	$\mathcal{N}_7$	$\mathcal{N}_8$
Pdg	Qdg	Xdg	V2G	DR	ESS	Market	Tap

FIGURE 2. First form of grouping of variables.

A. VARIABLE NEIGHBORHOOD SEARCH (VNS)

Based on metaheuristics, VNS is a global optimization algorithm that systematically explores the concept of neighborhood change, not only in descending to the local minima but also by escaping the valleys which contain them [47],[48]. In most cases, VNS and its extensions need few parameters, or often no parameters at all, to be tuned [37].

The pseudo code of the VNS algorithm used in [42] and reproduced in this paper is given in Algorithm 1.

The proposed approach starts first by randomly generating an initial solution in the search space. Since the OSDER issue is a very large-scale problem, using local search strategies will not produce a good result. Therefore, in the initial version of VNS, the authors proposed a procedure of grouping variables [42]. The grouping step is made in three different forms for each hour of the day:

First Form: Illustrated in Fig. 2, the first form of grouping aims to substitute all the variables with eight variables $(\mathcal{N}_1, \mathcal{N}_2, \ldots \mathcal{N}_8)$.

$$\mathcal{N}_1 \quad \mathcal{N}_2 \quad \mathcal{N}_3 \quad \mathcal{N}_4 \quad \mathcal{N}_5 \quad \mathcal{N}_6 \quad \mathcal{N}_7 \quad \mathcal{N}_8$$

Second Form: Eight variables are used for each hour of the day.

Third Form: In this form of grouping, variables are taken separately, only the V2G is considered: one variable of each node per hour of the system.

After the grouping phase and the number of variables is reduced, the Cyclic Coordinate Method (CCM) is used,

Algorithm 2 Pseudocode of the CCM Used in the VNS Algorithm to Solve the OSDER Problem

Initialization Step

Choose a scalar $\varepsilon > 0$ to be used for terminating the algorithm.

Let $d_1, d_2, \ldots d_n$, be the coordinate directions

Initialize point x_1

$y_1 = x_1$

$k = j = 1$

go to the Main Step

Main Step

Let λ_j be an optimal solution to the problem to minimize $f(y_j + \lambda d_j)$ subject to $\lambda \in R$

Let $y_{j+1} = y_j + \lambda_j d_j$

Step 1   **If** $j < n$

$j = j + 1$

repeat Step 1

Otherwise, if $j = n$

go to Step 2.

End if

Step 2 $x_{k+1} = y_{n+1}$

If $\|x_{k+1} - x_k\| < \varepsilon$

Stop

Otherwise

$y_1 = x_{k+1}$

$j = 1$

$k = k + 1$

go to step 1

End If

End Main Step

Algorithm 3 Pseudocode of Fibonacci Line Search Method Used by the CCM

Initialization Step

Select an allowable final length of uncertainty $\ell > 0$

Select a scalar $\varepsilon > 0$

Let $[a_1, b_1]$ be the initial interval of uncertainty

Select the number of observations n to be taken such that $F_n > \frac{(b_1 - a_1)}{l}$

Calculate $\lambda_1 = a_1 + \left(\frac{F_{n-2}}{F_n}\right)(b_1 - a_1)$ and evaluate $F(\lambda_1)$

Calculate $\mu_1 = a_1 + \left(\frac{F_{n-1}}{F_n}\right)(b_1 - a_1)$ and evaluate $F(\mu_1)$

$k = 1$

Go to main step

Main Step

Step 1   **If** $\mu F(\lambda_k) > F(k)$

go to step 2

Otherwise, if $\mu F(\lambda_k) < F(k)$

go to step 3

End if

$a_{k+1} = \lambda_k, b_{k+1} = b_k, \lambda_{k+1} = \mu_k$

$\mu_{k+1} = a_{k+1} + \left(\frac{F_{n-k-1}}{F_{n-k}}\right)(b_{k+1} - a_{k+1})$

Step 2   **If** $k = n - 2$

Go to step 5

Otherwise

Evaluate $F(\mu_{k+1})$

go to step 4

End If

$a_{k+1} = a_k, b_{k+1} = \mu_k, \mu_{k+1} = \lambda_k$

$\lambda_{k+1} = a_{k+1} + \left(\frac{F_{n-k-2}}{F_{n-k}}\right)(b_{k+1} - a_{k+1})$

Step 3   **If** $k = n - 2$

Go to step 5

Otherwise

Evaluate $F(\lambda_{k+1})$

go to step 4

End If

Step 4 $k = k + 1$

Go to step 1

$\lambda_n = \lambda_{n-1}$

$\mu_n = \lambda_{n-1} + \varepsilon$

If $F(\lambda_n) > F(\mu_n)$

Step 5 $a_n = \lambda_n$

$b_n = b_{n-1}$

Otherwise, if $F(\lambda_n) \leq F(\mu_n)$

$a_n = a_{n-1}$

$b_n = \lambda_n$

Stop (the optimal solution is between $[a_n, b_n]$
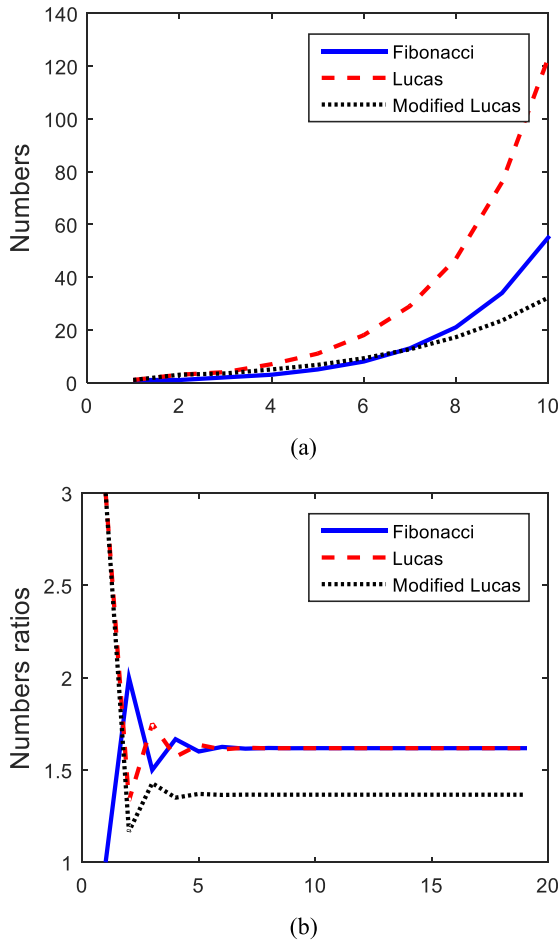
End if

End Main Step

---

employing a Fibonacci algorithm to explore each neighborhood.

The idea behind the CCM is conceptually simple. It states that the initial problem with n-dimensions can be decomposed into n-single-dimensional sub-problems. The variables are treated one-by-one while the remaining variables remain fixed. This step is achieved by solving a one-dimensional optimization sub-problem using any suitable one-dimensional optimization algorithms available in the literature [49].

The CCM method uses the coordinate axes as the search directions. In other words, it searches along the directions $d_1, d_2, \ldots d_n$, where d is a vector of zeros except for a 1 at the jth position. Therefore, only x_j changes along d_j and the remaining variables remain fixed [50]. The pseudocode of the CCM is explained in Algorithm 2.

The Fibonacci line search method used by the CCM is given in Algorithm 3. This method is a line search algorithm for minimizing a strictly quasi-convex bounded objective function. It makes two evaluations of the objective function

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FIGURE 3. Comparison between Fibonacci, Lucas and Modified Lucas sequences.

FIGURE 4. Single-line diagram of the 33-bus network.

TABLE 1. Test systems overview.

Data	33-bus test system	180-bus test system
Voltage level	12.66 kV	30 kV
DGUs	67 (with a large wind unit)	116
External Suppliers	10	1
ESUs	15	7
EVs (V2G)	1800	6000
Market	1	1
Various loads involved in DR	32	90
Number of design variables	49,920	154,800

at the first iteration, and only one evaluation at each of the remaining iterations [50].

B. IMPROVED VARIABLE NEIGHBORHOOD SEARCH (IVNS)

The initial version of the VNS is demonstrably competitive; it won first place in the "Evaluating the Performance of Modern Heuristic Optimizers on Smart Grid Operation Problems" competition held at the 2017 IEEE PES General Meeting. In this paper, an improved version of the VNS algorithm (IVNS) was developed based on three main modifications, described below.

Modification #1: The first modification incorporated in the VNS was the normalization of continuous variables. The aim was to transform all variables from their respective ranges to a uniform range inside the interval [0, 1] using the following expression:

$$x_i = \frac{x_i - \min(x)}{\max(x) - \min(x)} \quad (39)$$

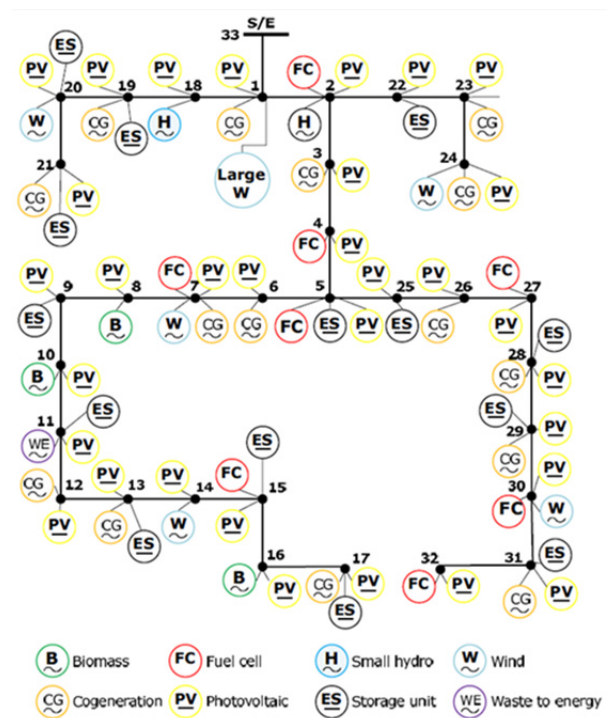This step was very important, because by restricting all the variables between 0 and 1, the same importance or weight was given to them. This was truer in the grouping phase, where summing variables with different ranges could favorize certain variables over others, based on their initial range.

Modification #2: The second modification or improvement to the VNS algorithm was to reduce the number of variables by removing the fixed ones. This allowed the reduction of the size of the problem.

Modification #3: The third improvement incorporated in the VNS was the modification of the Fibonacci line search method based on the Fibonacci sequence, with a new method based on a modified Lucas sequence.

Recalling that the Fibonacci sequence $\{F_v\}$, is defined as follows [51]:

$$F_{v+1} = F_v + F_{v-1} \quad v = 1, 2, \ldots$$
$$F_0 = 0$$
$$F_1 = 1 \quad (40)$$

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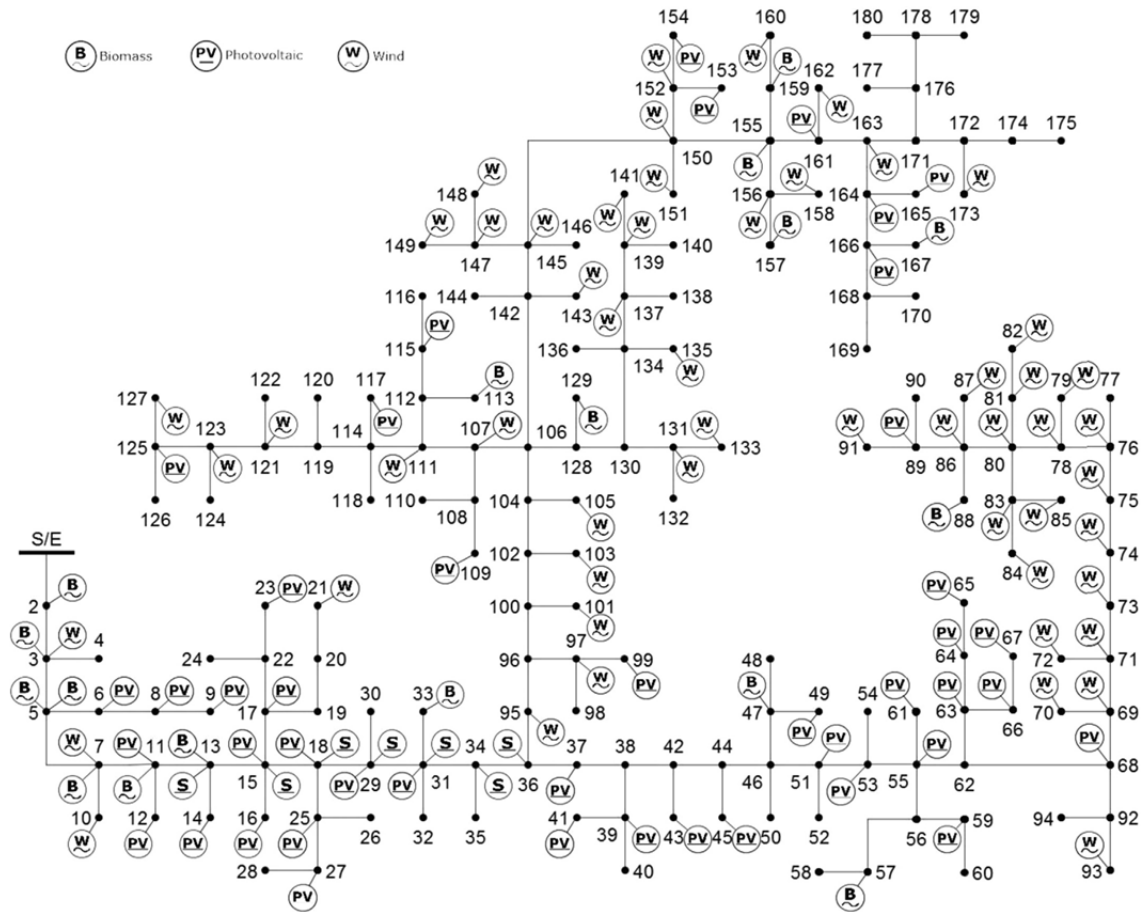
FIGURE 5. Single-line diagram of the 180-bus network.

In the Lucas sequence, the Fibonacci rule of adding the latest two terms to get the next term was applied, but here the sequence started with 2 and 1 (in this order) instead of 0 and 1 for the Fibonacci sequence.

Therefore, the Lucas sequence $\{L_v\}$ is defined as follows [51]:

$$L_{v+1} = L_v + L_{v-1} \quad v = 1, 2, \ldots$$
$$L_0 = 2$$
$$L_1 = 1 \tag{41}$$

In order to improve the VNS, a modified Lucas sequence was proposed where the new rule consisted of adding the latest two numbers while multiplying the last one by 1/2 to get the next term. The modified Lucas sequence $\{ML_v\}$ is defined as follows:

$$ML_{v+1} = ML_v + \frac{ML_{v-1}}{2} \quad v = 1, 2, \ldots$$
$$ML_0 = 2$$
$$ML_1 = 1 \tag{42}$$

A comparison between the Fibonacci, Lucas, and Modified Lucas sequences is plotted in Fig. 3. In Fig. 3-a, the generated numbers (10 first ones) are plotted while in Fig. 3-b, the number ratios between two successive numbers (20 first ones)

are plotted. Noticeably, the Fibonacci and Lucas sequences converge at 1.618 while the Modified Lucas sequence converges at 1.366.

V. APPLICATION AND RESULTS
A. CASE STUDIES
The developed approach for energy management was applied to two test systems, the 33-bus and the 180-bus test systems. Details of these two systems are given below.

1) CASES STUDY #1: THE 33-BUS TEST SYSTEM
The first test system investigated in this paper was the 12.66 kV, 33-bus MV distribution network adopted from [52] (Fig. 4). A summary of the data of this test system is summarized in Table 1. More details are given in [42].

2) CASES STUDY #2: THE 180-BUS TEST SYSTEM
The second test system considered a 30 kV, 180-bus MV distribution network (Fig. 5). Data of this test system is summarized in Table 1. More details can be found in [42].

B. RESULTS AND DISCUSSION
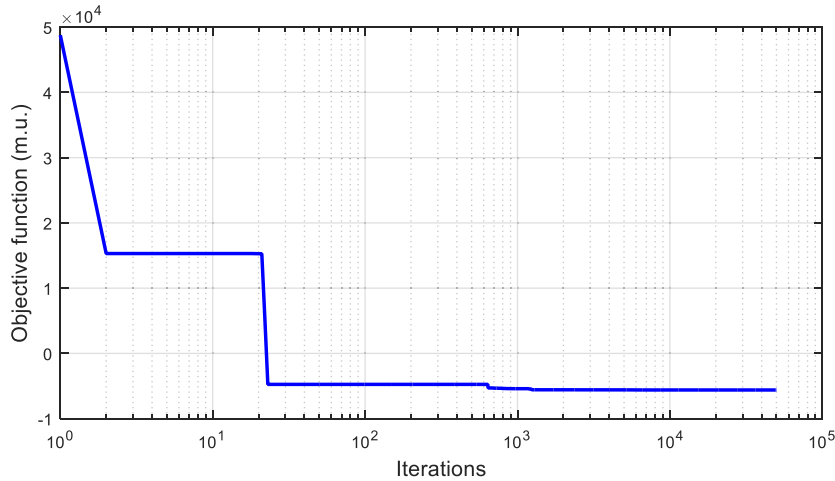The developed algorithm was run for both test systems and the results are detailed and discussed in the following

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FIGURE 6. Evolution of the objective function versus iterations for the 33-bus test system.
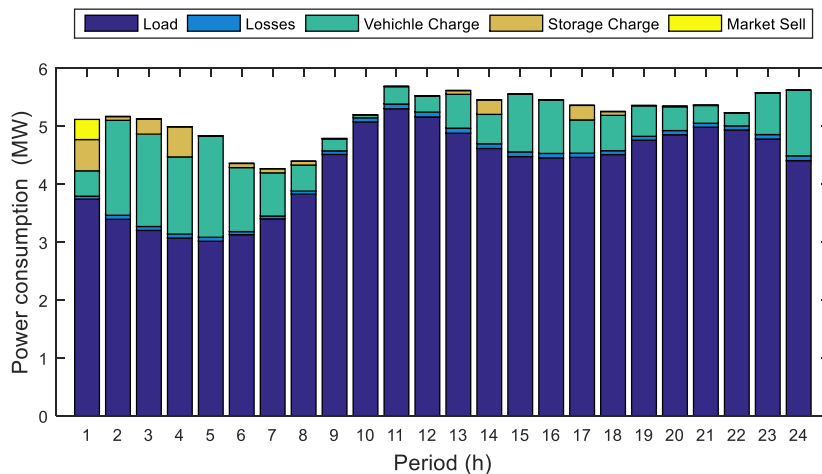

FIGURE 7. Load scheduling for the 33-bus test system.

subsections. It is worth mentioning that, for both the VNS and the IVNS the number of trials is 31 for each case study.

1) CASE STUDY #1: THE 33-BUS TEST SYSTEM

For the first test system, the curve of convergence (or the evolution of the objective function versus iterations) is shown in Fig. 6. It is worth recalling that negative values of the objective function correspond to positive profits when the problem is treated as a minimization one (minimization of the negative value of the objective function) is in fact a maximization problem.

Fig. 7 and Fig. 8 sketch the one-day load and generation scheduling, respectively, for the 33-bus test system. Several things can be seen from Fig. 7. The proposed algorithm scheduled a load of 102.966 MWh which consequently induced a total active loss of 1.682 MWh; the charge of EVs was scheduled as 17.427 MWh; the ESUs charging process was scheduled as 2.251 MWh, and the energy market selling

was scheduled as 0.348 MWh. It can also be seen that the peak load was at hour=11 with a value of 5.303 MW, the peak of losses was at hour=13 with a value of 0.087 MW, the peak of EVs charging 1.753 MW occurred at hour=5, the peak of ESUs charging, 0.540 MW, occurred at hour=1, and the energy market selling was only scheduled in the first hour.

Fig. 8 shows that the total DG scheduled was 94.799 MWh, the total external supplier scheduled was 29.245 MWh, the total DR scheduled was 0.104 MWh, the discharge of EVs was not scheduled and the storage scheduled was 0.183 MWh. Form the same figure we can also make the following remarks: the DGU generation peak (4.405MW) and the external supplier peak (1.267 MW) were recorded at hour=11 at the same time as the load peak; the DR was scheduled only in hours 9, 10, and 21 with values of 0.013 MW, 0.079 MW, and 0.012 MW, respectively, and the discharge of ESUs was only scheduled in hours 5 and 10 with values of 0.013 MW and 0.170 MW, respectively.
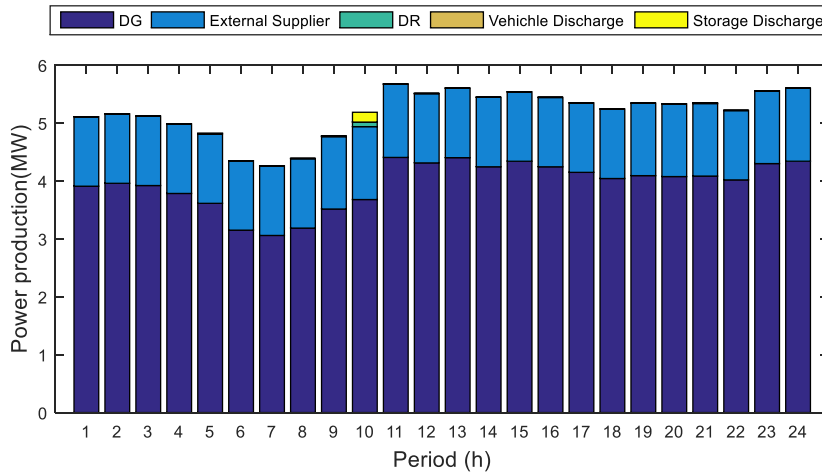
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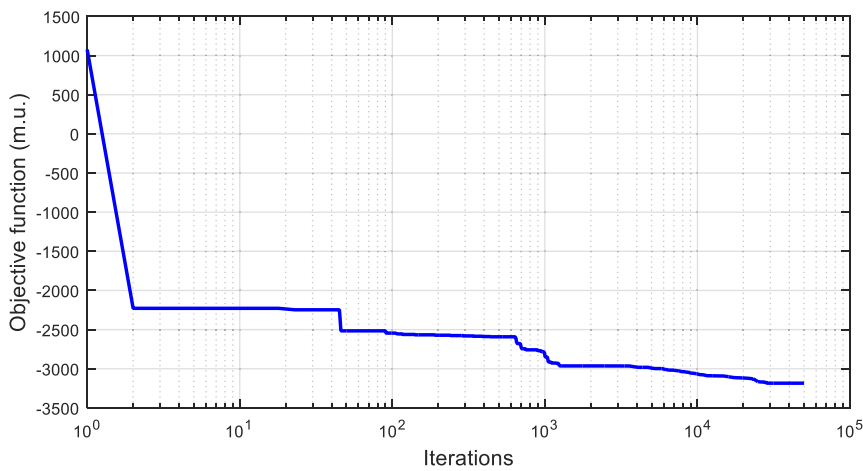**FIGURE 8.** Generation scheduling for the 33-bus test system.

FIGURE 9. Evolution of the objective function versus iterations for the 180-bus test system.

2) CASE STUDY #2: THE 180-BUS TEST SYSTEM
For this test system, the evolution of the objective function versus iterations is shown in Fig. 9. Fig. 10, and Fig. 11 sketch the one-day load and generation scheduling, respectively, for the 180-bus test system. It can be seen from Fig. 10 that the proposed algorithm scheduled a load of 243.360 MWh; the total active losses of the system were found to be 3.068 MWh; the charge of EVs was scheduled as 49.224 MWh; the ESUs charging process was scheduled as 1.704 MWh; and the energy market selling was scheduled as 0.348 MWh. It can also be seen that the peak load (12.484 MW) was recorded at hour=12; the peak of loss (0.205 MW) was recorded at hour=23; the peak of EVs charging (5.788 MW) occurred at hour=4; the peak of ESUs charging (1.148 MW) was recorded at hour=1; and the energy market selling was only scheduled in the first hour.

Fig. 11 shows that the total DG scheduled was 251.395 MWh; the total external supplier scheduled was 0.584 MWh; the total DR scheduled was 29.985 MWh; the discharge of EVs scheduled was 13.643 MWh; and the ESUs

discharge scheduled was 0.930 MWh. Furthermore, the DG generation peak (13.360 MW) was recorded at hour=6; the external supplier peak (0.032 MW) was recorded at hour=16; the DR peak (4.189 MW) was recoded at hour=16; the discharge of EVs was scheduled only four times; and the discharge of ESUs was only scheduled in hours 12 and 13 with values of 0.783 MW and 0.147 MW, respectively.

C. COMPARATIVE STUDY
In order to assess the competitiveness and efficiency of the proposed algorithm, it was compared with the algorithms participating in the above-mentioned competition of SG operation problems [42]. These algorithms are: chaotic biogeography-based optimization (CBBO), cross-entropy method and evolutionary PSO (CEEPSO), chaotic differential eolution with PSO (Chaotic-DEEPSO), Levy differential evolution with PSO (Levy-DEEPSO), and the VNS.

The ranking process (to rank different algorithms) used here is the same as that used for the 2017 competition,
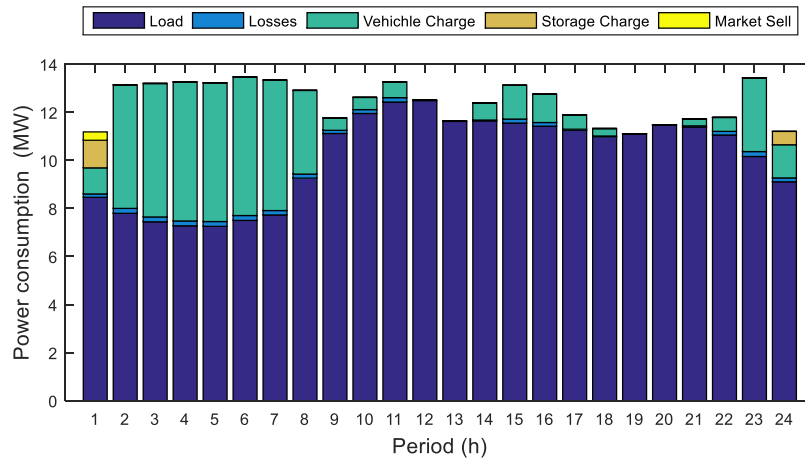
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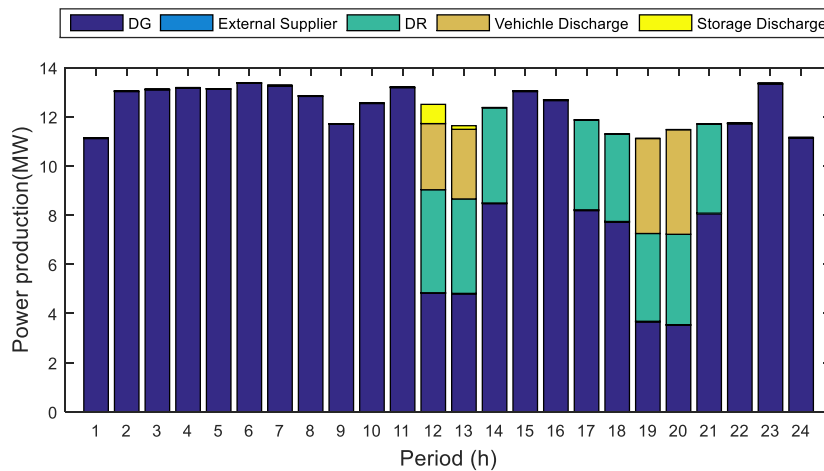**FIGURE 10.** Load scheduling for the 180-bus test system.

FIGURE 11. Generation scheduling for the 180-bus test system.

TABLE 2. Computed scores for the two investigated cases studies.

Rank	Algorithm	Case study 1 (33-bus)				Case study 2 (180-bus)				Total score
		Score	Best Fitness	Worst Fitness	Standard Deviation	Score	Best Fitness	Worst Fitness	Standard Deviation	
1	IVNS	-5598.89	-5603.19	-5596.16	1.80	-3180.15	-3184.35	-3175.84	2.48	-8779.04
2	VNS [42]	-5595.98	-5597.27	-5594.51	0.86	-3054.00	-3060.56	-3045.90	3.68	-8649.99
3	CBBO [42]	-5387.60	-5399.60	-5378.53	4.96	-2652.86	-2680.75	-2640.87	9.89	-8040.46
4	CEEPSO [42]	-5185.26	-5216.82	-5128.71	20.48	-2550.12	-2566.78	-2519.15	17.08	-7735.38
5	Chaotic-DEEPSO [42]	-4655.81	-5015.34	-3993.63	205.71	-2500.55	-2558.72	-2480.92	22.86	-7156.36
6	LEVY-DEEPSO [42]	-4538.08	-4986.48	-4191.09	204.58	-2494.26	-2554.99	-2478.44	20.31	-7032.34

given by:

$$TotalScore = \sum_{i=1}^{N_{CaseStudies}} Score_i \qquad (43)$$

where: $N_{CaseStudies}$ is the number of case studies investigated and is equal to 2 and $Score_i$ is defined in eq. (44).

$$Score_i = mean(f_{best-i}) \qquad (44)$$

In other words, the score is calculated as the mean value of the objective function found over the 31 trials for each test system.

Table 2 summarizes the final ranking for the compared algorithms. It can be seen from this table that the proposed IVNS is the best algorithm among the compared algorithms. The total score of the IVNS is -8779.04, which is better than that of the VNS (-8649.99) that ranked number one in the 2017 competition. It can also be seen that the IVNS is better than all the algorithms for both case studies and

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for all the compared performances. For example, the IVNS's score for the first case study is -5598.89 which is better than the second algorithm, VNS (-5595.98), and the third algorithm, CBBO (-5387.60). Likewise, the best and worst fitness values achieved by the IVNS for the first case studies (-5603.19 and -5596.16) are better than all the remaining algorithms. The same analysis can be made for the second case studies where the superiority of the IVNS is far more evident than the first case study. For example, the score obtained for the IVNS (-3180.15) is better than that of the VNS (-3060.56) and the CBBO (-2652.86), ranked first and second at the 2017 competition, respectively.

It is worth mentioning that many other methods were tested on the investigated cases, but the results are not worthy of presentation here because they failed to solve the problem compared to the presented algorithms in Table 2.

VI. CONCLUSION

In this paper, an efficient algorithm was proposed, implemented, and applied to solve a very large-scale OSDER problem. This algorithm was based on a simple and effective algorithm called the variable neighborhood search (VNS) algorithm. Three main improvements and modifications were incorporated to the initial VNS: 1) normalization of variables, 2) removal of fixed variables and 3) replacement of the Fibonacci sequence with a one based on a modified Lucas sequence in the Fibonacci line search method.

The OSDER problem solved in this paper considers different recourses like DG units, EVs, ESUs, and DR programs. Therefore, the treated problem is a very large-scale mixed-integer non-linear programming (MINLP) problem. Furthermore, two test systems (or scenarios) were investigated–the 30-bus and the 180-bus test systems. The results showed that the proposed algorithm is better than several other algorithms used to solve the same problem. For both test systems and for all the statistical measurement indices, the IVNS is better than the remaining five algorithms.

As future works, more scenarios can be investigated using other modern metaheuristics. Multi-objective scenarios can also be an interesting axis for future research.

ACKNOWLEDGMENT

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