Optimal stochastic scheduling in microgrids under managed risk

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This paper addresses the stochastic optimal day-ahead microgrid (MG) energy resources scheduling, considering the uncertain load, price of electricity, and generated electrical power by wind and solar units. Moreover, the vehicle-to-grid (V2G) implementation, load curtailment cost, and spinning reserve requirements are modeled to make the results more practical and applicable. Furthermore, the price elasticity of supply is considered to explore the relation between V2G capability and the optimization process. The stochastic energy resources scheduling problem is formulated in a two-level optimization framework. The unit commitment of dispatchable resources is analyzed in the upper level, and the lower level is formulated as a scenario-based two-stage stochastic programming problem that minimizes the operation cost of MG considering all the constraints. The risk of attaining unfavorable high costs of MG scheduling is considered using the variance approach. The generated scenarios are reduced by using the backward reduction method for each uncertain variable at each hour, independently. The artificial intelligent-based methods, including differential evolution algorithm (DEA), particle swarm optimization (PSO), and covariance matrix adaptation evolution strategy (CMAES) are applied to solve the problem. The effectiveness of the proposed approaches is confirmed by simulations on a modified 13-bus IEEE test system, in two cases of neglecting the risk and including the managed risk by applying the real-world data. The results confirmed the better performance of CMAES for solving such optimization problems.

keywords: *Covariance matrix adaptation evolution strategy (CMAES), load curtailment cost, microgrid (MG), price, risk management, stochastic scheduling, uncertainty, vehicle-to-grid (V2G).*

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NOMENCLATURE

Indices and Sets

N_D The total number of loads

N_E The total number of energy storage systems.

N_G The total number of dispatchable generation units.

N_I The total number of non-dispatchable generation units.

N_L The total number of loads able to be curtailed.

N_S The total number of scenarios.

d The index of loads.

e The index of energy storage systems.

g The index of dispatchable generation units.

j The index of non-dispatchable generation units.

l The index of loads able to be curtailed.

S The index of scenarios.

BESS Battery energy storage system.

ESS Energy storage system.

FC Fuel-cell unit

MT Micro-turbine unit.

N The upstream/utility network.

PEV The plug-in electric vehicle fleet.

PV Photovoltaic array unit.

WT Wind turbine unit.

SR Spinning reserve.

0 The index of initial state of parameter or variable.

Parameters, Constants and Variables

b The bid/price of electricity.

E Price elasticity of power supply.

h Time period counter (24 hours).

P Active power.

P_N Exchanged power with the upstream/utility network.

SUC Start-up cost constant

SUC Shut-down cost constant

U Unit-commitment decision set

u Unit-commitment decision variable, $u \in \{0, 1\}$.

$(0)^{(s)}$ Parameter or variable (0) in scenario$s$

$\pi^{(s)}$ Occurrence probability of scenario s.

x_l Lower-level variables in two-level problem.

x_{up} Upper-level variables in two-level problem.

β Risk aversion factor.

Vectors, Matrixes, and Sets

A First-stage left-hand side matrix in the constraints.

c First-stage objective vector $(c^T x)$.

d First-stage right-hand side vector in the constraints.

m Right-hand vector in the constraints.

q Second-stage objective vector $(q^T y)$.

T Technological matrix.

W Recourse matrix.

x First-stage decision variable vector.

y Second-stage decision variable vector.

Symbols

min Minimum of the parameter

max Maximum of the parameter.

1. INTRODUCTION

A microgrid (MG) is a complex of distributed energy resources with energy storage devices and controllable loads, with the capability of operating as a self-sufficient energy network [1]. MGs help to modify reliability, resiliency, flexibility, and accessibility of safe and green energy resources with some significant abilities such as cost optimization, and implementation of demand response programs (DRP) [2]. Energy management is a critically important task in MGs [3].

Nowadays, a transition from consumption of fossil fuel to renewable and sustainable energy is occurring [4, 5]. High fuel economy and low pollution emissions of plug-in hybrid electric vehicles (PHEVs) have caused them to be more attractive [6]. Vehicle-to-grid (V2G) technology is defined as the ability of electric vehicles (EVs) to inject electrical power into the grid [7]. The applicability of assigning EVs to discharge some unused energy by V2G technology was proposed in [8]. The V2G capability helps to improve the system reliability and plays the role of a backup system for renewable power sources [9]. This technology reduces the impact of sharp fluctuations of renewable power sources, the carbon emissions, and procurement costs of the transportation section [10]. In addition, the V2G technology can provide energy storage by matching the time of supply to the time of consumption [11].

However, the advantages of this technology for the power system depend on the proper scheduling of these resources. Utilities must be assured of the reliable availability of the power of plug-in electric vehicles (PEVs) over extended periods.

Addressing the challenges of the operation of PEVs in an MG with renewable energy sources is a novel research field. Several studies have been conducted on PEVs. Investing in V2G technology in MG economics was investigated in [12]. Based on Markov chain optimization [13], it was realized that an efficient EV charging plan needs a matching degree between wind energy and EV charging demand.

Variations in operating conditions are inevitable in power systems. Contingency conditions are probable due to the sudden increase in electrical load and unscheduled outages of transmission lines or generators [14]. Spinning reserve (SR) requirements must be sufficient for network reliability, risk response, and security considerations [15, 16]. As an important subject, the authors of[15] insisted on a compromise between cost and reliability to supply the SR. In this study, the value of lost load for each prioritized customer was determined and then the SR capacity was calculated to minimize the total cost by considering the PEVs. Moreover, Wu et al. [16] suggested a deterministic two-phase mixed integer programming (TPMIP) strategy to solve the non-convex economic dispatch (ED) problem considering different constraints containing the SR requirements. It should be mentioned that the scheduled load shedding is a technique to ensure system reliability.

Neglecting the intermittency of renewable energy and the uncertainty of electricity market prices as well as the load, brings a high risk to the power system. Stochastic programming is necessary to cope with the uncertainties involved in obtaining a realistic solution. To deal with uncertainties in a stochastic framework, some approaches including chance-constrained programming [17] and a variety of scenario-based methods are applied. The scenarios are all the discrete probable states of the problem, considering all the uncertain variables. In [18], the impacts of uncertainties of market price, the error of forecasted load, photovoltaic (PV), and wind turbine (WT) generation on the optimal operation management of MGs were investigated in a stochastic framework. By using scenario generation and reducing them to some deterministic problems with different probabilities, the problem was solved using the adaptive modified firefly algorithm (AMFA). In addition, a fuzzy multi-objective (MO) optimization model considering the uncontrollable sources as the negative loads was proposed in [19]. The stochastic optimal management problem was solved by chaotic binary particle swarm optimization (CBPSO). The stochastic optimal operation of an MG consisting of the fuel cell units with proton exchange membrane for generating power and heat simultaneously (PEMFC-CHP), PV, and WT was suggested in [20], by considering the uncertainties of market prices, solar radiation, and wind speed. The mixed-integer nonlinear programming (MINP) framework was considered for storing hydrogen strategy and the modified teaching-learning-based optimization (MTLBO) algorithm was applied to solve the optimal management problem on a modified 33-bus test case. Moreover, an MO day-ahead energy management was suggested in [21] to minimize the operation cost and maximize the reliability in an MG, considering renewable energy resources, micro-CHP units, energy storage system, and auxiliary boiler. The DR requirements were modeled by load shifting contracts, and the problem was solved by particle swarm optimization (PSO) algorithm.

However, in these studies, the results were obtained separately for each possible scenario and were eventually aggregated. This aggregation approach was utilized in [22] as well. Such a solution is not an optimal and realistic solution for the stochastic problem. Optimal scheduling of an energy storage system (ESS) and loss minimization were realized in day-ahead scenario-based stochastic scheduling frameworks which were presented in [23], and [24], respectively. This concept was modeled in [23] as an MO optimization problem in a MILP framework, by modeling the load curtailment in unscheduled islanding conditions. For solving the mentioned problem, the non-dominated sorting genetic algorithm II (NSGA-II) was implemented. Moreover, an MG containing WT, PV, controllable loads, distributed generators, and distributed energy storage devices (DESDs) were investigated in [24] by using a modified IEEE 37-bus test feeder in an MINLP framework and implementing CPLEX Optimizer 12.2.

By applying the proposed formulations in the mentioned studies, the problem constraints are simultaneously considered for all the scenarios. Nevertheless, a day-ahead decision about the generation amounts of dispatchable distributed energy resources is not made in the relevant formulations.

In [23], a scenario generation and a reduction technique for uncertain variables were implemented for the next 24 hours. Moreover, in [25], each probable scenario for each uncertain variable including the relevant status of that variable at all the hours of the next day was investigated.

A scenario-based approach was presented in [26] to cope with uncertainties in PV cell power generations. This approach utilized the previous year's historically recorded irradiance data to generate describing scenarios based on autoregressive and moving average methods. An MO stochastic programming approach for MG was presented in [27] to decrease environmental emissions generated by power resources, in addition to the unit's operation cost. The ε-constraint method was utilized to solve the MO optimization problem. In [28], a linear programming-based stochastic approach for MGs under uncertainties was presented. In [28], the MG itself was considered a responsible load for the upstream network. The corresponding demand response (DR) formulations and approaches were described.

Even in diverse scenario-based probabilistic techniques, especially in those presented in recent years, the obtained results are subject to risk. Hence, MG stochastic scheduling must be equipped with a risk management scheme.

The main disadvantage of ignoring risks in the optimal management of MGs is that the optimal solutions may lead to the maximum expected value of the objective function (cost or profit) and experiencing very low values in some unfavorable scenarios [29]. To obtain results close to real-world conditions, the risk should be modeled in the problem. There are some usual risk measures that can be applied to stochastic programming problems in power systems. The most important risk measures addressed in the literature include variance, shortfall probability, expected shortage, value-at-risk (VaR), and conditional value-at-risk (CVaR) [29]. Moreover, the set of properties that risk measures should fulfill are translation invariance, subadditivity, positive homogeneity, and monotonicity [30].

Risk measures have been extensively investigated and some properties for each one are addressed in the literature. VaR is one of the most popular measures for risk management, but it has a few undesirable mathematical properties such as a lack of sub-additivity and convexity. Moreover, this measure is difficult to optimize when it is calculated from scenarios. CVaR has some advantages over VaR. For instance, it is transition-equivariant, convex, positively homogeneous, and has a stochastic dominance of order 1 [31]. In addition, one of the drawbacks of the variance method when applied as a risk measure is its symmetric nature which weighs over- and under-performance equally [32].

A. Motivation and the main technical contributions of this work

The main motivations and innovations of this work can be categorized as follows:

1) There is a need for a comprehensive stochastic programming approach considering all the dispatchable and non-dispatchable resources available to simultaneously solve the unit commitment (UC) and economic dispatch (ED) problems. In this study, the day-ahead stochastic scheduling problem in an MG with uncertain load, fluctuating electricity power price, and intermittent renewable energy sources, considering V2G technology, load curtailment cost, and SR requirements is investigated to improve the MG reliability. This problem contains the UC problem in addition to the ED of resources while considering all the governing uncertainties. A mixed-integer non-linear programming (MINLP) scenario-based stochastic problem is employed in this work. To break down this structure, the optimal decisions are made on two different levels. Stochastic optimal dispatch of resources is a separate sub-problem.

2) The scenarios are generated independently and screened for each variable in each hour of the day, which makes them more reliable and precise.

3) The Latin hypercube sampling (LHS) method is utilized to generate the scenarios. This method takes less CPU time. Moreover, by taking samples from entire distributions of random variables, it produces more precise and reliable estimates than those produced by Monte-Carlo simulation with the same size [33]. In addition, the backward reduction tech-

nique is utilized to eliminate similar and low-probability scenarios.

4) The high performance of covariance matrix adaptation evolution strategy (CMAES) as a powerful optimization approach is applied to such a large-scale, non-linear, and non-convex problem.

5) To control the risk of obtaining non-desirable results, decision-making under managed risk is implemented and the results are described.

The remainder of this paper is organized as follows: the formulation of the problem and concepts of the proposed approaches are presented in section 2. Section 3 details the solution methods, as well as the case study simulation results. Finally, Section 4 presents the main findings of this paper.

2. MATHEMATICAL FORMULATIONS AND METHODS

In this section, the basic formulation of the proposed methods is described in detail.

A. Two-stage stochastic programming

The extensive form of the two-stage stochastic programming formulation is a linear problem as follows [29]:

$$textmin \left[c^T x + \sum_{s=1}^{n_S} \pi^{(s)} \left(q^{(s)}\right)^T y^{(s)} \right] \tag{1}$$

S.T.:

$$\begin{aligned} &Ax = d, \\ &T^{(s)}x + Wy^{(s)} = m^{(s)}, \forall s \\ &x \geq 0, y^{(s)} \geq 0, \forall s. \end{aligned} \tag{2}$$

where is the vector of first-stage deterministic decision variables and is the vector of second-stage uncertain decision variables. As expressed by (1), the constraints are considered for all possible scenarios.

B. Risk-neutral problem description for MG

The optimal schedule of dispatchable and non-dispatchable power generation units in MG should minimize the power production cost while satisfying the load, SR requirements, and physical constraints of each generation unit considering all the uncertainties.

All market agents must cope with non-dispatchable power producers such as solar or wind power plants with intermittency and a time-dependent nature [29]. Therefore,P_{WT} and P_{PV} are received by MG completely. Hence, they are not decision variables and are considered in the problem constraints.

The planning period is divided into hourly intervals, and the optimization problem formulation is written for only a one-hour period. Hence, power and energy values are similar for all intervals.

For each time period (h), the MG optimization problem considering constraints is as follows:

$$\min \left\{ \begin{array}{l} \sum_{g=1}^{N_G} \left[\begin{array}{l} SUC_g \cdot u_g(h) \cdot (1 - u_g(h-1)) \\ +SDC_g \cdot (1 - u_g(h)) \cdot u_g(h-1) \\ +u_g(h) \cdot b_g(h) \cdot P_g(h) \end{array} \right] + \\ \sum_{e=1}^{N_E} [b_e(h) \cdot P_e(h)] + b_{PEV}(h) \cdot P_{PEV}(h) + \\ \sum_{s=1}^{n_S} \left[\pi^{(s)} \cdot \left(\begin{array}{l} b_N(h)^{(s)} \cdot P_N(h)^{(s)} \\ + \sum_{l=1}^{N_L} b_l(h) \cdot P_l(h)^{(s)} \end{array} \right) \right] \end{array} \right\} \tag{3}$$

S.T.: (eqs. (4) to (9)).
1) Power Balance:

$$\begin{aligned} &\sum_{g=1}^{N_G} u_g(h) \cdot P_g(h) + \sum_{e=1}^{N_E} P_e(h) + P_N(h)^{(s)} + \sum_{l}^{N_L} P_l(h)^{(s)} = \\ &\sum_{d}^{N_D} P_d(h)^{(s)} - \sum_{j=1}^{N_J} P_j(h)^{(s)} + P_{SR}(h), \forall s. \end{aligned} \tag{4}$$

Realizing reliability aspects entails considering the ability of the operating units to generate more power than the demanded value. Therefore, the SR power, $P_{SR}(h)$, is considered a constant percentage of the sum of the power at each period (h) .
2) Generation Constraints:

$$P_g^{\min} \cdot u_g(h) \leq P_g(h) \leq P_g^{\max} \cdot u_g(h), g = 1, ..., N_G. \tag{5}$$

3) ESS Constraints:

$$P_e^{\min} \leq P_e(h) \leq P_e^{\max}, l = 1, ..., N_E. \tag{6}$$

Positive P_e denotes discharging state and its negative value shows charging state of ESS.
4) PEV Constraints:

$$P_{PEV}^{\min} \leq P_{PEV}(h) \leq P_{PEV}^{\max}. \tag{7}$$

5) Network Power Exchange:

$$P_N^{\min} \leq P_N(h)^{(s)} \leq P_N^{\max}, \forall s. \tag{8}$$

6) Load Curtailment Cost and Constraints:

$$\begin{aligned} LCC(h) &= bP_{lS}(h) \\ 0 \leq P_{ls}(h) &\leq P_l^{\max}(h), l = 1, \ldots, N_L \end{aligned} \tag{9}$$

LCC describes the load curtailment cost which was identified as a demand response program in [14]. This capability could improve MGs' reliability.

C. The price elasticity of supply

Price elasticity of supply is defined as the supply sensitivity concerning the price [34]. It simply clarifies how responsive the quantity supplied to a given change in the price is. At the hth time period, that is:

$$E(h) = \frac{b_0(h)}{P_0(h)} \cdot \frac{\Delta P(h)}{\Delta b(h)}. \tag{10}$$

Price elasticity always has a positive value, because a price increase encourages the supply to generate and offer more electricity to consumers.

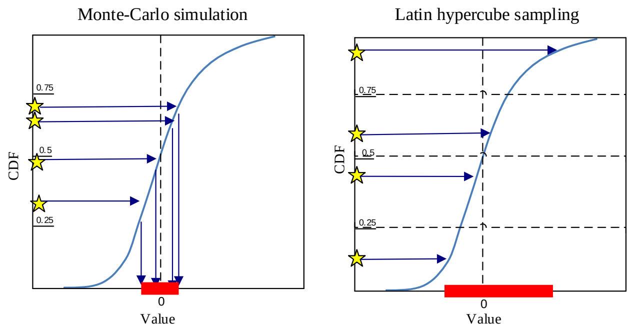

Fig. 1. Monte-carlo simulation vs. LHS

Based on the price elasticity of supply, an economic model of the pre-studied responsive fleet of EVs capable of operating in the V2G mode operation is derived in this paper. Considering a change in b_{PEV}, E_q. (10) will be:

$$E(h) = \frac{b_{PEV_0}(h)}{P_{PEV_0}(h)} \cdot \frac{P_{PEV}(h) - P_{PEV_0}(h)}{b_{PEV}(h) - b_{PEV_0}(h)}. \quad \textbf{(11)}$$

For a given elasticity value and the initial state of b_{PEV_0} and P_{PEV_0}, E_q. (11) can be used to find P_{PEV} for a presented price, b_{PEV} , according to (12):

$$P_{PEV}(h) = P_{PEV_0}(h)\{1 + E(h) \cdot \frac{b_{PEV}(h) - b_{PEV_0}(h)}{b_{PEV_0}(h)}\}. \quad \textbf{(12)}$$

Moreover, it could be used to find the correct offered price to lead PEVs, as a power supply, to provide the needed power accessed for the MG.

$$b_{PEV}(h) = b_{PEV_0}(h)\{1 + \frac{P_{PEV}(h) - P_{PEV_0}(h)}{E(h) \cdot P_{PEV_0}(h)}\}. \quad \textbf{(13)}$$

By combining (13) with the cost function in (3), could be considered a decision variable. The function thereupon will be non-linear.

This idea could be utilized for specific hours of the day based on network policies (e.g., at peak hours). A central system operator as an interface between the suppliers and the customers is responsible for the decisions about all the resources and loads in MG.

D. Scenario generation

LHS is utilized to generate scenarios. The main difference between this method and the Monte-Carlo simulation is in the sampling method. The first method divides the probability space into equal parts as the number of samples, and then takes one random sample from each part. The second method searches all the probability space as the same and takes the needed samples. As shown in Fig. 1, LHS leads to better sampling and more realistic results, by better covering the probabilities. The star sign shows random samples. The error from the forecast values is considered a normal distribution with a mean equal to 0 and predefined variances. These scenarios are generated in MATLAB using the 'lhsnorm' function based on historically recorded data for uncertain variables.

E. Scenario reduction

A backward reduction algorithm by the Kantorovich distance (KD) [35] is utilized for scenario reduction. We assume that all scenarios have a common root in a one-stage tree if the branching occurs only after the root node. This procedure is applied iteratively by deleting a single scenario in each step and then changing the probabilities of the other ones until a decided number of scenarios remain. Let $n_T$denotes the number of stages of the optimization problem and $n_S$describe the number of scenarios. It is assumed that all scenarios have a common root in a one-stage tree where branching occurs only after the root node. Scenario $\xi^{(i)}, i \in \{1, ..., n_S\}$ is defined as a sequence of nodes of the tree.

$$\xi^{(i)} = (\eta_0, \eta_1^{(i)}, ..., \eta_{n_T}^{(i)}), i = 1, ..., n_S \quad \textbf{(14)}$$

$\eta_0 = \eta_0^{(i)}, \forall i$ denotes the root of all scenarios, and η_j^i denotes the leaf of scenario i within the scenario tree on stage j, $j \in \{1, ..., n_T\}$. For each node$\eta_j^{(i)}$, a vector $P_j^{(i)} \in R^{n_j^p}$ of parameters is given. Each node on stage j has n_j^p parameters. The probability to get from stage j to stage $j+1$ within scenario i , from $\eta_j^{(i)}$to $\eta_{j+1}^{(i)}$, is denoted by $\pi_{j,j+1}^{(i)}$. Thus, the probability for all scenarios $\xi^{(i)}$ is given by:

$$\pi^{(i)} = \prod_{j=0}^{n_T-1} \pi_{j,j+1}^{(i)} = \pi_{0,1}^{(i)} \quad \textbf{(15)}$$

The distance between the two scenarios $\xi^{(i)}$ and $\xi^{(j)}$ is defined as:

$$d(\xi^{(i)}, \xi^{(j)}) = \left(\sum_{k=0}^{n_T} (P_k^{(i)} - P_k^{(j)})^2 \right)^{1/2} \quad \textbf{(16)}$$

The algorithm for deleting scenarios is described in the following. This procedure is applied iteratively, deleting one scenario in each step and consequently changing the probabilities of other scenarios, until a given number of scenarios remains.

a) Determine the number of scenarios to be deleted: Remove scenario ξ^{s^*}, $s \in 1, ..., n_s$ satisfying:

$$\pi^{(s^*)} \cdot \min_{s \neq s^*}\{d(\xi^{(s)}, \xi^{(s^*)})\} = \min_{m \in \{1,...,n_S\}} \{\pi^{(m)} \cdot \min_{n \neq m}[d(\xi^{(n)}, \xi^{(m)})]\} \quad \textbf{(17)}$$

According to the defined distance, scenarios that are near to the others will be deleted. In addition, scenarios that have a small probability are more likely to be deleted than others.

b) Change the number of scenarios: $n_S = n_S - 1$
c) Change the probability of the scenario$\xi^{(\hat{s})}$, that is the nearest to $\xi^{(s^*)}$:

$$d\left(\xi^{(\hat{s})}, \xi^{(s^*)}\right) = \min_{s \neq s^*} d\left(\xi^{(s)}, \xi^{(s^*)}\right) \quad \textbf{(18)}$$

set $\pi_{0,1}^{(\hat{s})} := \pi_{0,1}^{(\hat{s})} + \pi_{0,1}^{(s^*)}$
This has to be done, as the sum of all the probabilities of the remained scenarios should equal 1, and the only branching occurs at stage 0 at the root node.
d) Continue with step a) as long as $n_S > N$. Otherwise, STOP.

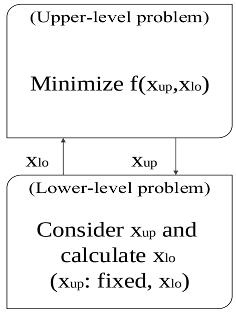

Fig. 2. Two-level problem structure.

F. Two-level optimization framework

A two-level optimization problem is expressed as follows:

$$\begin{aligned} & \min f(xup, xlo) \\ & \text{S.T. :} \\ & (xup, xlo) \in \text{X}, \\ & xlo \in S(xup). \end{aligned} \tag{19}$$

As Fig. 2 illustrates, $f(x_{up}, x_{lo})$ is the upper-level objective function,X is the feasible joint region between these sets of variables, $S(x_{up})$ and is the set of a lower-level problem [36].

In conformity with the two-level problem depicted in Fig. 2, x_{up} decision variables are $u_g(h), g = 1, ..., N_g$. Moreover, x_{lo} decision variables are $P_g(h), g = 1, ..., N_G; P_e(h), e = 1, ..., N_E; P_N(h)^{(s)}, s = 1, ..., n_s; P_1(h)^{(s)}, l = 1, ..., N_L, s = 1, ..., n_s$.

In the following, the lower-level problem is described as a two-stage stochastic model. Here, the decision variables are:

1) The first-stage (here-and-now) decision variables, i.e., x vectors, include $P_g(h), g = 1, ..., N_g$ and $P_e(h), e = 1, ..., N_E$. The moment of making the first-stage decisions is one day ahead.

2) The second-stage (wait-and-see) decision variables, uncertainty vectors, contain $P_N(h)$ and $P_1(h), l = 1, ..., N_L$.

The UC decisions, $u_g(h), g = 1, ..., N_G$ are made one day ahead, similar to the first-stage decision variables. It should be noted that deciding about second-stage variables in practice is delayed up to the next day when uncertainties are disclosed. Moreover, when making a decision about the first-stage variables and UC, all the possible states of second-stage variables are considered with related probabilities.

It should be mentioned that $f(x_{up}, x_{lo})$ is a upper-level objective function. In the lower-level optimization problem,x_{up} is considered as a fixed variable (for a feasible case) and the problem is solved once. By solving the problem,x_{lo} is obtained and its value enters the upper-level problem, which is solved once. This procedure continued for all possible x_{up} values. For the case in which the upper-level optimization problem has the lowest value among all feasible scenarios,x_{lo} and x_{up}will be the solutions of problem.

G. Solving algorithm

In this paper, the differential evolution algorithm (DEA) [37], PSO algorithm [38], and CMAES [39] (as powerful and robust evolutionary algorithms) are applied to optimize the cost function considering all the constraints. Simplicity and fast convergence are the reasons for selecting these algorithms. In the following, a brief description regarding each of the above-mentioned algorithms is presented.

G.1. DEA

The DEA includes five main steps known as initialization, mutation, recombination, crossover, and selection [40]. In the initialization step, the initial values are randomly defined in deterministic regions, confined by the upper and lower limits. In both the recombination and mutation steps, a population of the number of population (NP) vector trail is generated. In the crossover phase, a crossover vector of the parameter value will be organized, which is regenerated on two vectors including the initial and the mutation vectors. Finally, in the selection stage, the vectors are distinguished such that they can be used as the appropriate population for the next iterations [41].

G.2. PSO

PSO is based on the simulation of the natural movement of fishes and birds to search for food [42]. Two significant parameters of PSO are the position and velocity updating rules, which are given by:

$$\begin{aligned} & x(i+1) = x(i) + v(i+1) \\ & v(i+1) = w(i) * v(i) + C_1 * rand_1 * (x(i) - P_{best}) + \\ & C_2 * rand_2 * (x(i) - G_{best}) \end{aligned} \tag{20}$$

Where, $x(i)$ and $v(i)$ are the location and velocity of ith particle, and $W(i)$ describes the inertia weight factor. C_1 and C_2 are the exploration and exploitation coefficients in the searching process, and they are normally selected in the range of [0-4].$rand_1$ and $rand_2$are the random numbers at the range $(0, 1)$.P_{best} and G_{best} are the best location of each particle, and the best location of P_{best}, respectively.

G.3. CMAES

CMAES [39] is a stochastic method for the optimization of non-linear and non-convex functions. It is an efficient solution for problems in which applying derivative-based methods is unsuccessful due to rugged search space with multiple discontinuities, sharp bends, and local optima. That is the state of the edge of estimation of distribution algorithms (EDA). In these algorithms, after sampling from the feasible space, a probability function is generated using the extracted samples, and by sampling from this probability function and replacing these samples with previous ones, the initial sampling space is upgraded. This procedure is performed iteratively to improve the solving procedure. It adapts two unique principles, maximum likelihood principle, and two evolution paths by covariance matrix adaptation and step-size adaptation, and thus is different from the other optimizers.

H. Risk management

The risk-neutral formulation of the proposed stochastic optimization model minimizes the expected value of the cost, corresponding to all the data of the remained scenarios. Decisions in this approach may encounter unanticipated or low probability scenarios in reality that could cause vast unexpected changes in the predicted state. The way of managing risk for this problem is to formulate the problem using a term measuring the risk associated with the cost optimization process. Variance, VaR, and CVaR are examples of risk measures. The mean-variance model assumes that a decision can be characterized by two parameters: The expected cost and the variance of this return which, as a dispersion measure, is used to model the risk faced by the decision-maker. Therefore, a large variance indicates that there exists a high risk of experiencing a profit different from the expected one [29]. In this paper, since risk minimization is related to the expected cost, the variance model for (1) is utilized as follows:

$$\min \left\{ \begin{array}{l} (1-\beta)\left[c^T x + \sum\limits_{s=1}^{n_S} \pi^{(s)} \left(q^{(s)}\right)^T y^{(s)}\right] \\ +\beta \sum\limits_{s'=1}^{n_S} \pi^{(s)} \left(\left(q^{(s)}\right)^T y^{(s)} - \sum\limits_{s'=1}^{n_S} \pi^{(s')} \left(q^{(s')}\right)^T y^{(s')} \right)^2 \end{array} \right\} \tag{21}$$

The weighting parameter called the risk aversion factor (β) lies within the interval [0, 1]. If $\beta = 0$, the variance is neglected and if $\beta = 1$, the expected cost is neglected. Application of the expected cost variance as a risk measure and its applicability is presented in case study 2. This risk management process eliminates the concern for high costs resulted from the adverse effect of unfavorable scenarios. Reliability increase is the result of reducing the probability of underperforming.

3. SIMULATION RESULTS

A. Case study 1; risk-neutral

In this study, a modified IEEE 13-bus distribution test feeder [43] (Fig. 3) is used to verify the proposed stochastic MG scheduling approach. The MG consists of micro turbine (MT), fuel cell (FC,) WT, PV, battery energy storage system (BESS), two loads, and a PEV power station connected to 646, 645, 652, 680, 650, 611, 634, and 675 nodes, respectively. Power losses caused by line impedance are ignored.

FC and MT are dispatchable power sources, and WT and PV are non-dispatchable power sources. PEV power station prepares PEV power exchange with the MG. Load 1 is a complex of industrial uncertain loads and load 2 is a commercial constant certain load. This MG is considered in the network-connected mode and can receive power from the upstream network or send power to it. More details in this regard are presented in Table 1.

It has been assumed that the MG control center keeps BESS fully charged as a power security option. The control center ensures having BESS charged in the upstream network off-peak periods while the network electricity price is low. The cost of having BESS fully charged is embedded in b_{BESS} for receiving P_{BESS}.

It is supposed that for the pre-studied existing fleet of PEVs for the MG, $E(h) = 1.5$, and P_{PEV0} values for $b_{PEV0} = 0.7(\$/kWh)$ are based on Table 2.

Moreover, the penalty costs of load curtailment for load 1 and load 2 ($b_{l1}$and b_{l2}, respectively) are presented in Fig. 4.
$P_{SR}(h)$ is considered equal to 10% of the load after curtailment:
$\mathrm{P_{SR}}\ (\mathrm{h}) = 0.1 \left\{ \sum_{d=1}^{2} \mathrm{P_d}\ (\mathrm{h}) - \sum_{l=1}^{2} \mathrm{P_l}\ (\mathrm{h}) \right\}$

The electricity price and load vary with the day of the week. Therefore, as shown in Table 3, actual historically recorded network electricity prices and load 1 power were extracted from [44], and [45], respectively. Ten recorded historical data for these uncertain variables are considered as the ten input scenarios for

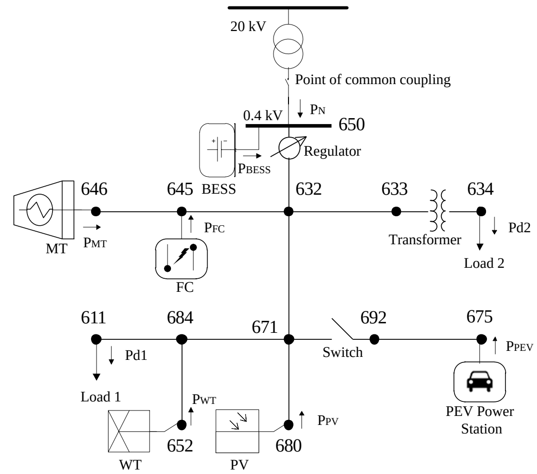

Fig. 3. Single line diagram of the MG.

Table 1. Details of the MG.

Source/Demand	Bid ($/kWh)	SUC SDC ($)	Min power (kW)	Max power (kW)
MT	0.5	1.5	40	400
FC	0.3	2	10	300
BESS	0.4	0	0	300
PEV	B_PEV	—	0	400
Utility network	0.14<Uncertain<0.77	—	-300	300
P_{WT}(Uncertain)	—	—	0	700
P_{PV}(Uncertain)	—	—	0	1400
P_{d1}(Uncertain)	—	—	0	900
P_{l1}	b_{l1}	—	0	400
P_{d2}	—	—	1000	
P_{l2}	b_{l2}	—	0	300

Table 2. The values of P_{PEV0} for b_{PEV0} equal to 0.7 ($\$/kWh$).

hour	1	2	3	4	5	6	7	8	9	10	11	12
P_{PEV0}(kW)	95	85	80	80	90	110	160	150	280	310	380	370
hour	13	14	15	16	17	18	19	20	21	22	23	24
P_{PEV0}(kW)	400	360	380	390	400	370	375	340	270	190	150	120

them.

The day-ahead forecasted values of wind and solar power for March 20, 2019 were extracted from [45]. Real values for four uncertain variables on the forecast date were extracted as well. All these data were extracted every 24 h of the day. Day-ahead forecasted values of wind and solar power generation for each hour are considered to follow normal distribution with a mean equal to the forecasted values and 20% and 10% standard deviations, respectively. Scenario generation and reduction order of uncertain variables' input data are presented in Fig. 5. The 81 resulted scenarios were utilized in the stochastic programming process. The generated scenarios are shown in Fig. 6. Moreover, the extracted reduced scenarios for each uncertain variable with values that happened on the next day are shown in one frame in

Table 3. Date of extracting historically recorded data for uncertain electricity price and load.

Forecast date	Wednesday, March 20, 2019				
Recorded data from	Wednesday Jan 09, 2019	Wednesday Jan 16, 2019	Wednesday Jan 23, 2019	Wednesday Jan 30, 2019	Wednesday Feb 06, 2019
	Wednesday Feb 13, 2019	Wednesday Feb 20, 2019	Wednesday Feb 27, 2019	Wednesday March 06, 2019	Wednesday March 13, 2019

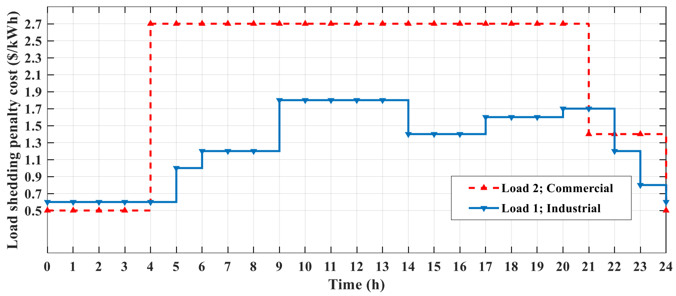

Fig. 4. Penalty cost of load curtailment

Table 4. Optimization variables in two levels and two stages.

Optimization levels and stages			**Variables**	**Decision Time**
Upper-level optimization:			U_{MT}, U_{FC}	Day-ahead
	Lower-level optimization:	First-stage:	$P_{MT}, P_{FC}, P_{BESS}, P_{PEV}$	Day-ahead
		Second-stage:	P_{Ns}, P_l; l=1,2.	Real-time

Fig. 7.
Decision variables in two levels and stages are classified in Table 4. It is supposed that, at the beginning of the scheduling period, both MT and FC are in the ON status of generation. Table 5 shows the details of the proposed approach and results.
If instead of P_{PEV} is considered a decision variable in the cost function (3), by substituting (12) in (3), the same results are obtained (Table 5).

According to Table 5, Error = (Total cost in reality–The anticipated total cost)/Total cost in reality = 7.4%. In addition, the total cost values are the upper-level results shown in Fig. 8.

B. Case study 2; under managed risk

In this case study, risk management is implemented for the previous one. With the increasing complexity of the cost function, while risk management is considered according to (21), CMAES is utilized to solve the problem. Applicability and great performance of CMAES compared with DEA and PSO are shown in Fig. 9. The expected cost and variance changes with a change in risk aversion factor (β) for $h = 12$ are exhibited in Fig. 10.

As illustrated in Fig. 10, the reduction of variance as risk aversion increases confirms the effectiveness of the proposed model. Based on Table 5, for $h = 12$, there is a 46% difference between the total cost in real-time and the day-ahead expected cost.

This difference can be attributed to the unpredicted inevitable issues occurring in real-time. To better understand the results of risk management, the optimization problem with risk factor $\beta = 0.01$ is run. As a result, for $h = 12$, the expected total cost is \$121.8605, while in real-time the total cost as the result of implementing decisions is \$108.4213. This cost is less than the one in real-time in case study 1. In addition, this risk aversion approach takes \$17685.5339 total cost for the next day. The efficient proposed risk management approach, appropriately discards unscheduled system states due to unpredicted scenarios; however, it results in higher costs, as well. It is worth mentioning that risk management, despite the increase in total cost, increases system reliability with the flexibility of the resultant schedule to accept a wider range of unpredictable changes.

4. CONCLUSIONS

In this paper, a stochastic programming approach was presented for the day-ahead resources optimal scheduling in MG. This method provides a sketch of reliable and economic utilization of V2G technology along with load curtailment cost and SR requirements. The wind and solar power intermittency, as well as load and electricity market price uncertainties are modeled in the problem. In addition, the generated scenarios were reduced for each uncertain variable at each hour, independently. Utilizing the price elasticity of supply to introduce V2G technology to the cost optimization process is a novel issue presented in this paper. Moreover, load curtailment as a decision variable in the cost function was considered to help the reliable operation of MG. Finally, risk management for removing the unfavorable results of the unanticipated system state was implemented based on the variance model. The presented model in this work can be generalized to any number of dispatchable and non-dispatchable sources and any number of uncertain variables. The results showed the high efficiency of CMAES in such optimization problems, where better results were obtained by one-sixth of the number of iterations, in comparison with the DEA and PSO. The proposed comprehensive approach was validated by numerical simulations with real-world data collected for different variables. Moreover, it was shown that the risk management approach, appropriately discards unscheduled system states due to unpredicted scenarios. In the proposed approach, real historically recorded data and day-ahead forecast values were used as input data for MG. Day-ahead decisions considering all uncertainties were implemented the next day. The high performance of MG with realistic variables in the next day proved the effectiveness of the proposed approach.

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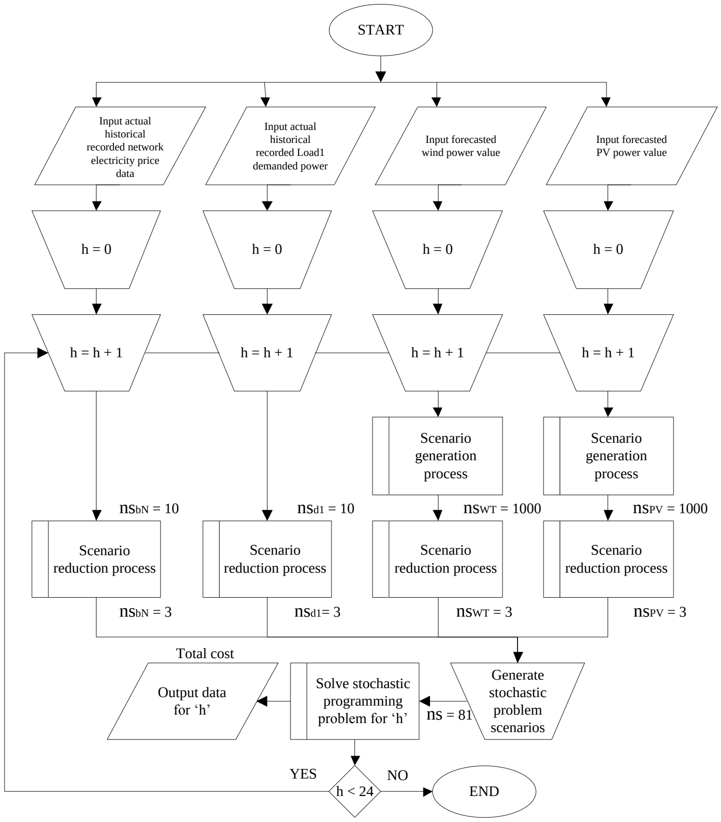

Fig. 5. Input data scenario generation and reduction sequence.

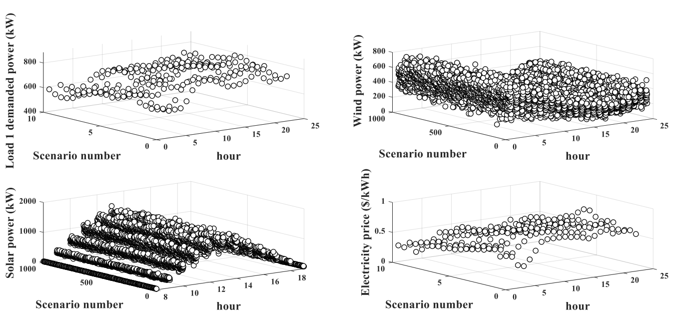

Fig. 6. The generated scenarios for March, 20, 2019.

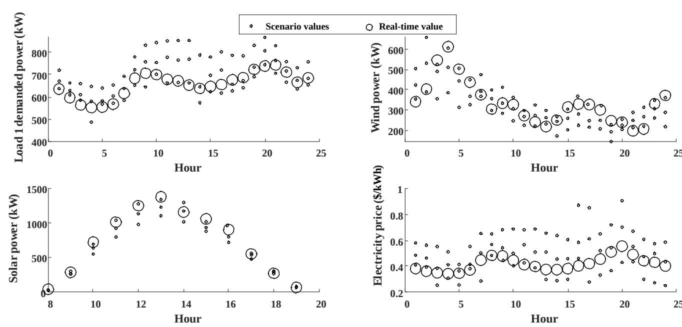

Fig. 7. Scenario values after the scenario generation and reduction process versus real-time values on March 20, 2019.

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Table 5. The solution results of case study 1

Column	1	2	3	4	5	6	7	8	9	10	11	12
h	Stochastic Programming Solution (Day-Ahead)								Stochastic Approach Results in the Next Day			
	Decided						b ($/kWh)	Expected Total Cost ($)	P (kW)	P (kW)		Real-Time Total Cost ($)
	U	U	P (kW)	P (kW)	P (kW)	P (kW)				l=1	l=2	
1	1	1	399	300	286	13	0.29	549.8535	300	0	34	
2	1	1	320	293	291	16	0.32	379.89	300	0	118	538.4063
3	1	1	393	300	300	58	0.57	454.1025	122	0	0	483.1331
4	1	1	350	288	300	12	0.3	393.6121	143	0	0	434.9556
5	1	1	400	300	300	220	1.37	727.1362	-12	0	0	710.0827
6	1	1	397	300	299	227	1.19	685.0363	62	0	0	703.6382
7	1	1	400	300	293	127	0.6	486.8802	280	0	0	610.436
8	1	1	400	295	300	254	1.02	678.1627	252	0	0	792.4235
9	1	0	398	0	298	355	0.82	642.2253	200	0	0	710.826
10	1	1	197	295	298	74	0.34	336.2864	-46	0	0	313.5158
11	0	1	0	296	114	69	0.31	159.6335	81	0	0	191.6886
12	0	1	0	237	0	19	0.25	77.1348	92	0	0	112.9721
13	0	0	0	0	135	50	0.29	72.0964	36	0	0	84.8333
14	0	1	0	300	0	59	0.31	111.3895	34	0	0	123.2354
15	0	1	0	283	224	58	0.3	193.8172	-127	0	0	143.9786
16	0	1	0	300	243	62	0.3	207.9913	-21	0	0	197.9962
17	1	1	309	296	294	92	0.34	396.3375	-30	0	0	381.6849
18	1	1	398	300	297	147	0.41	471.9596	135	0	0	531.6319
19	1	1	398	298	299	400	0.73	1254.8845	178	0	0	792.3544
20	1	1	399	300	298	400	0.78	1269.1575	273	0	0	873.9337
21	1	1	398	299	299	397	0.92	1332.6338	300	22	0	961.3489
22	1	1	400	297	297	382	1.17	1228.0544	298	0	0	987.8362
23	1	1	399	300	298	328	1.25	877.8689	174	0	0	895.744
24	0	0	398	300	299	346	1.58	1247.1226	137	0	0	1016.2733
Sum	—	—	—	—	—	—	—	14233.2667	—	—	—	13248.3475

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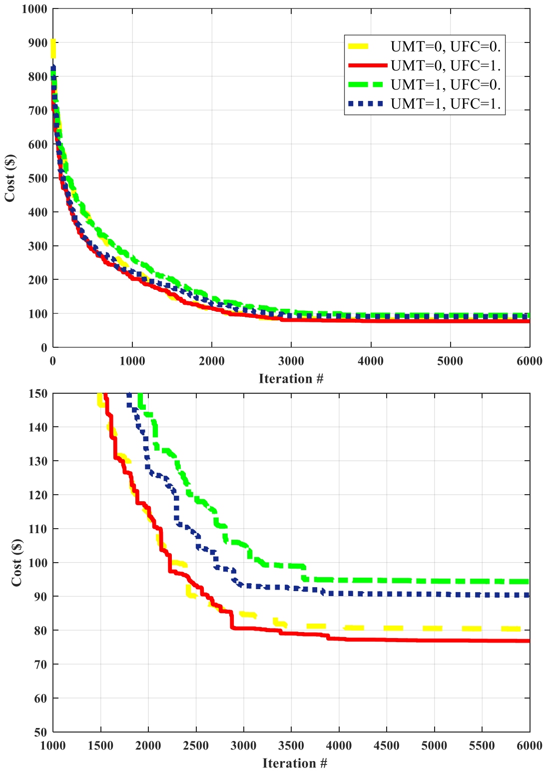

Fig. 8. The anticipated total cost of operation for h=12.

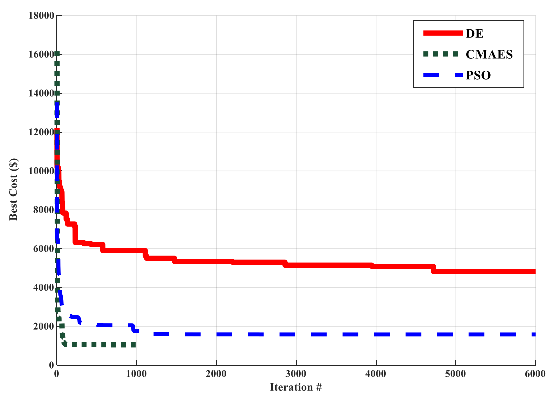

Fig. 9. CMAES optimization process in comparison with DEA, and PSO for $\beta = 0.2$, h=12.

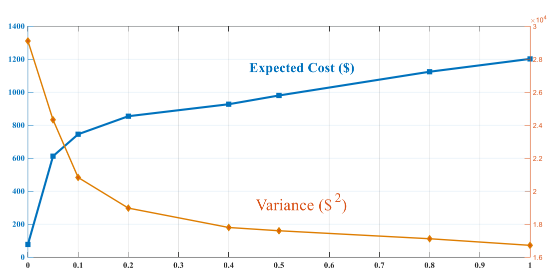

Fig. 10. The expected cost and variance changes for h=12.

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