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Adaptive robust energy management for isolated microgrids considering reactive power capabilities of distributed energy resources and reactive power costs

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ABSTRACT

This paper presents an adaptive robust Energy Management (EM) model for an isolated Microgrid (MG) to decide for the day-ahead optimal dispatch to effectively manage the MG power sources considering uncertainties in Renewable Energy Sources (RESs). The aim of this model is to minimize the operation costs, reactive power costs, spinning reserve and load shedding. Usually, fuel consumption costs of diesel generators are considered to be dependent on active power generation only. However, neglecting the related reactive power costs might result in increased operation costs and deviations from optimal dispatches. Hence, this paper optimizes the costs related to both active and reactive powers of diesel generators. Furthermore, simultaneous active/reactive power dispatch can lead to accurate operation decisions compared to separate dispatch for active or reactive power alone. In addition, this study considers the reactive power capability of inverter-interfaced Distributed Energy Resources (DERs) so that reactive powers can be supplied from inverter-interfaced DERs. Moreover, detailed models for the different resources are presented, especially for diesel generators and inverter interfaced DERs where actual capability curves are used instead of the widely used box constraints. The problem is formulated as nonlinear programming problem using GAMS program and solved by the CONOPT solver.

1. Introduction

1.1. Motivation and Incitement

Uncertainty in modern power systems has a salient bad effect on the optimal decisions not only in the planning stage but also in the operation phase. Recently, the effect of uncertainty increases with more penetrations of renewable energies and increased demands. Uncertainty in modern energy systems comes from various sources such as load variations, failure of components, intermittent behavior of renewable energy sources (RESs), and energy price changes. Classical optimization techniques that prove to be accurate under deterministic conditions become insufficient in computational ability in the microgrids (MGs) framework due to their wider range of uncertainties in the decision variables like component failures and RESs forecast errors [1]. In system operation, it is more complex to manage uncertainties than in planning stage as if the forecasts are not accurate, approximations are accepted and deviations can be rescued in the operation stage. Furthermore, the effect of uncertainties in MGs is higher than that of conventional power systems as MGs are small power systems so that even small variations would have a significant influence. Neglecting the effect of the RESs uncertainties may affect the MG operation schedule such that the final optimal decision may not be the best operating point in the practical application [2].

The classical way to handle uncertainty in power systems is considering some spinning reserve to be deployed when needed but if the reserve requirements are underestimated this leads to reliability issues and on the other hand, overestimation may result in increased costs. Stochastic optimization (SO) has a huge literature in uncertainty modeling in power systems applications. Uncertain parameters in stochastic programming are usually represented by scenarios sampled from probability distributions.

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Nomenclature

Indices and Sets

Ω_g^i	Set of generators connected to bus "i"
Ω_l^i	Set of lines connected to bus "i"
E^B	Second stage decisions
E^D	First stage decisions
$g \in G$	Diesel Generator
$i,j \in I$	Indices for buses
L	Set of lines
$t \in T$	Time periods "h"
x_i	Type of load at bus "i" that can be shed (residential and commercial)

Constants and Parameters

α	Load shedding percentage ε {0, 25, 50, 75, 100}
θ_{ij}	Phase angle of line "ij"
Δ_{ch},Δ_{dis}	Charging and discharging efficiency of BESS
Δt	Time slot "h"
∅	Rated power factor angle of generator
Φ_l	Power factor angle of different loads
μ_w, μ_{pv}	Uncertainty sets for wind and PV, respectively
ΔP_i^w, ΔP_i^{pv}	Deviations of wind, PV powers from forecast
$\Delta P_i^{w,max}$, $\Delta P_i^{pv,max}$	Max. deviations of wind, PV powers from forecast
Γ_w, Γ_{pv}	Budget of uncertainty for wind and PV, respectively
a_g, b_g, c_g	Active power cost coefficients of diesel generators
$a_g^{'}$, $b_g^{'}$, $c_g^{'}$	Reactive power cost coefficients of diesel generators
C_d	Diesel fuel cost \$/L or \$/gal
E_{max}	Max induced EMF of synchronous generator "V"
Nw, Npv	Number of wind and PV sources, respectively
$P_{g,max}$	Max active power of generator "g"
$P_{g,min}$	Min active power of generator "g"
$P_{i,max}^{ch}$, $P_{i,min}^{ch}$	Max and min charging power of BESS at bus "i"
$P_{i,max}^{dis}$,$P_{i,min}^{dis}$	Max and min discharging power of BESS at bus "i"
$P_{i,t}^{PV,forecast}$	Forecasted PV power connected to bus "i" at time "t"
$P_{i,t}^{W,forecast}$	Forecasted wind power connected to bus "i" at time "t"
$R_g^{up,max}$,$R_g^{dn,min}$	Max, min spinning reserve capacity for generator "g"
$S_{g,rating}$	VA rating of Generator "g"
$S_{ij,max}$, $S_{ij,min}$	Max and min VA rating capacity of line "ij"
$SOC_{i,max}$	Max state of charge of BESS connected to bus "i"
$SOC_{i,min}$	Min state of charge of BESS connected to bus "i"
$V_{c,max}$	Max converter voltage "V"
V_{DER}	DER voltage "V"
$V_{i,\max}$, $V_{i,\min}$	Max and min bus voltage "V"
V_t	Synchronous generator terminal voltage "V"
$VOLL_{x_i}$	Value of lost load cost "\$/kWh" for load type "x"
X	Reactance of transformers and grid filters "Ω"
X_s	Synchronous reactance of synchronous generator "Ω"
Z_{ij}	Impedance of line "ij" ,"Ω"

First Stage Variables

$\delta_{i,t}$, $\delta_{j,t}$	Voltage angle of bus "i" or "j" at time "t"
$P_{DER,t}$	DER active power scheduled dispatch at time "t" For BESS: $P_{DER} = P_{i,t}^{dis,sch} - P_{i,t}^{ch,sch}$ For RES (PV, Wind): $P_{DER} = P_{i,t}^{PV,sch}$ *or* $P_{i,t}^{W,sch}$
$P_{ij,t}$	Active power flow through line "ij" at time "t"
$P_{i,t}^{ch,sch}$	Scheduled BESS active power charging at bus "i" & time "t"
$P_{i,t}^{dis,sch}$	Scheduled BESS active power discharging at bus "i" & time "t"
$P_{i,t}^{l}$	Active load at bus "i" at time "t"
$Q_{DER,t}$	DER reactive power scheduled dispatch at time "t" For BESS: $Q_{DER} = Q_{i,t}^{BESS,sch}$ For RES (PV, Wind): $Q_{DER} = Q_{i,t}^{PV,sch}$ *or* $Q_{i,t}^{W,sch}$
$Q_{g,t}$	Scheduled Reactive power of generator "g" at time "t"
$Q_{ij,t}$	Reactive power flow through line "ij" at time "t"
$Q_{i,t}^{BESS,sch}$	Scheduled BESS reactive power at bus "i" & time "t"
$Q_{i,t}^{l}$	Reactive load at bus "i" at time "t"
$Q_{i,t}^{PV,sch}$	Scheduled PV reactive power at bus "i" and time "t"
$Q_{i,t}^{W,sch}$	Scheduled Wind reactive power at bus "i" and time "t"
$R_{g,t}^{up}$	Scheduled up spinning reserve for generator "g" at time "t"
$R_{g,t}^{dn}$	Scheduled down spinning reserve for generator "g" at time "t"
$S_{ij,t}$	Apparent power flow through line "ij" at time "t"
$SOC_{i,t}$	Scheduled State of charge of BESS at bus "i" and time "t"

Second Stage Variables

γ	Auxiliary variable represents the worst-case recourse cost
$\delta_{i,t,\ s}$, $\delta_{j,t,\ s}$	Voltage angle of bus "i" or "j" at time "t"at deviation "s"
$P_{DER,t,\ s}$	DER active power dispatch at time "t"at deviation "s" For BESS: $P_{DER} = P_{i,t,s}^{dis} - P_{i,t,s}^{ch}$ For RES (PV, Wind): $P_{DER} = P_{i,t,s}^{PV}$ *or* $P_{i,t,s}^{W}$
$P_{ij,t,\ s}$	Active power flow through line "ij" at time "t"at deviation "s"
$P_{i,t,s}^{ch}$	BESS active power charging at bus "i" & time "t" & deviation "s"
$P_{i,t,s}^{dis}$	BESS active power discharging at bus "i" & time "t" at deviation "s"
$P_{i,t,s}^{PV}$	PV active power at bus "i" and time "t" at deviation "s"
$P_{i,t,s}^{W}$	wind active power at bus "i" and time "t" at deviation "s"
$P_{i,t,s}^{lsh}$	Active load shed at bus "i" & time "t" & deviation "s" (=0 for industrial load)
$Q_{DER,t,\ s}$	DER reactive power dispatch at time "t" at deviation "s" For BESS: $Q_{DER} = Q_{i,t,s}^{BESS}$ For RES (PV, Wind): $Q_{DER} = Q_{i,t,s}^{PV}$ *or* $Q_{i,t,s}^{W}$
$Q_{g,t,\ s}$	Reactive power of generator "g" at time "t" at deviation "s"
$Q_{ij,t,\ s}$	Reactive power flow through line "ij" at time "t" at deviation "s"
$Q_{i,t,s}^{BESS}$	BESS reactive power at bus "i" & time "t" at deviation "s"
$Q_{i,t,s}^{PV}$	PV reactive power at bus "i" and time "t" at deviation "s"
$Q_{i,t,s}^{W}$	Wind reactive power at bus "i" and time "t" at deviation "s"
$Q_{i,t,s}^{lsh}$	Reactive shedding at bus "i", time "t" & deviation "s" (=0 for industrial load)
$r_{g,t,s}^{up}$	up reserve deployment for generator "g" at time "t" at deviation "s"
$r_{g,t,s}^{dn}$	down reserve deployment for generator "g" at time "t" at deviation "s"
$S_{ij,t,\ s}$	Apparent power flow through line "ij" at time "t" at deviation "s"
$SOC_{i,t,\ s}$	State of charge of BESS at bus "i" and time "t" at deviation "s"

Acronyms

BESS	Battery Energy Storage System
DER	Distributed Energy Resource
EM	Energy Management
GAMS	General Algebraic Modeling System
LV	Low Voltage
MG	Microgrid
OPF	Optimal Power Flow
PV	Photovoltaic
RES	Renewable Energy Source
SOC	State of Charge
VOLL	Value of Loss of Load
WT	Wind Turbine

Probability distributions are fitted and modeled according to the available historical data and experience which may not reflect the statistical properties of the uncertain variables accurately. Each scenario can be seen as a plausible realization of the stochastic variable. Large number of scenarios is required to perfectly model the stochastic variable but this leads to intractability and computational complexity problems. Therefore, scenario reduction is required to solve this problem in expense of some information loss [3–5].

On the other hand, robust optimization (RO) is another method for handling uncertainties that requires moderate information about the uncertain variables through uncertainty set to restrict the uncertainties within upper and lower limits to make robust decisions against worst cases. RO does not require fitting or modeling neither probability distributions nor scenario generation thus, computational complexity is reduced dramatically compared to SO. The disadvantages of RO are that its solution is conservative and considering low probability (worst) cases may result in increased costs compared to SO [2,4]. Although these disadvantages, RO can be a good uncertainty modeling technique in isolated MGs as the isolated MGs depend on their local power sources without access to the main grid, so that the operation priority is given to reliable continuity of supply rather than operation cost reduction compared to grid connected MGs that have main grid support [6,7].

1.2. Literature review

Day-ahead energy management (EM) in MGs are widely studied in the literature in order to effectively manage the local power sources to supply its load demands in the most techno-economical way over a certain time horizon to find the optimal dispatch of the different sources. In [8], EM model is proposed for an isolated MG with unbalanced conditions and a novel linearization approach is proposed. Whereas in [9], an EM model with demand response is derived with a smart load estimator in an isolated MG. While in [10], EM model is proposed to minimize the operation costs and emissions for different operating strategies. Also, in [11], EM of MGs including plug-in hybrid electric vehicles is proposed while maximizing the employment of RESs. While in [12], EM is used in a high RESs penetration MG to reduce energy cost, power fluctuations, peak load, and emissions while maximizing the reliability. Whereas in [13], EM strategy is derived with smart charging/discharging of plug-in hybrid electric vehicles while improving the lifetimes of Battery Energy Storage Systems (BESSs) and decreasing the energy drawn from the upstream utility grid. In [14], the aim is to manage an MG with RESs and BESSs for optimizing the peak load curtailment with adaptive neuro-fuzzy inference system forecasting. In [15], a multi objective particle swarm optimization is presented to reduce the MG different costs and reliability indices. While in [16], a mixed-integer linear programming model for the optimal EM of residential MGs, modeled as unbalanced, three-phase system is presented. Also, in [17], a power quality constrained optimal EM for three phases residential MG is developed in the transition mode between grid-connected and islanded operation to minimize the operation costs considering the outage of the main grid. In all the previous studies, the uncertainties from RESs are not considered which may affect the optimal dispatch and the calculated operation cost results.

Several studies have considered the RESs uncertainties using RO. For example, in [18], the mathematical formulation and architecture of a robust EM system for isolated MGs featuring RESs, energy storage, and interruptible loads is presented utilizing RO. Whereas in [19], A scenario-based robust EM method considering the worst-case conditions of RESs and load is developed in this paper. The economic and robust model is proposed to optimize the operation cost and social benefits simultaneously. While in [20], RO is utilized to effectively handle the RESs and electricity price uncertainties in an AC/DC hybrid MG. While in [7], chance constraint approximations and RO approaches are developed to face the uncertainties from RESs and heat demands. Whereas in [6], two-stage RO is used to obtain robust decisions considering the uncertain RESs, market prices, and voltage dependent loads in the day-ahead operation planning of unbalanced three phase MGs. Although in the aforementioned studies RESs uncertainties are considered using RO in the EM model but the contribution of the reactive power from Distributed Energy Resources (DERs) units or BESSs was not considered. This leads to loss the opportunity to gain benefits from the reactive power capability of DERs even with the use of power electronic converters. Moreover, the cost of reactive power of diesel generators was not considered. Therefore, optimal dispatch results may be affected and errors in the calculated total operation costs will occur. The optimization of the reactive power supplied from DERs to allow for ancillary services such as voltage support and the reduction of power losses has been considered in [21,22]. However, these studies did not consider the costs related to the reactive power. In addition, most of these studies solve the OPF problem either for the active power dispatch or the reactive power dispatch, which may result in deviations from the system optimal solutions.

Despite some studies have taken the costs of reactive power into account in the problem of reactive power dispatch [23,24] but the active power dispatch is not considered. Simultaneous active/reactive power dispatch in the EM problem can lead to accurate operation decisions compared to the separate dispatch for active power or reactive power when executed alone.

1.3. Contributions and paper organization

As shown from the previous review, RESs uncertain behavior is a critical issue in isolated MG operational planning to operate the system securely. RO is selected in this paper due to its reliable behavior in the worst-case scenario which is a major concern in isolated MGs and its lower computational complexity compared to SO. Reactive power costs from conventional generators are usually neglected for simplifications and due to their small value compared to active power costs which affects the operation cost calculations. Therefore, considering the diesel reactive power costs is concerned in this work to study their effect on the overall operation costs. Utilization of the inverter interfaced DERs reactive power capability is usually neglected although power electronic converters have high installation costs, and therefore their capacity should be fully utilized to reduce the stress on diesel generators and reduce the operation costs. Despite the possibility of managing the dispatch of both active and reactive powers of the different sources, most works have focused on one or the other although they are related and should be co-optimized so that the optimal operating decisions can be found accurately. Detailed modeling of the generators and inverter interfaced DERs through their capability curves is important to provide more accurate representations of these power sources.

Therefore, in this paper, a day-ahead adaptive (two-stage) robust EM in an isolated MG is proposed based on network-constraint multi-period AC OPF. The isolated MG has a variety of power/energy sources; including diesel generators, Wind Turbines (WTs), PhotoVoltaic (PV) systems, and BESSs. The optimization problem aim is to decide for the day-ahead optimal dispatch and the optimal worst case re-dispatch of the MG. The objective is to effectively manage the available sources such that the opertaion costs related to diesel generators and load shedding are minimized. Hence, the main contributions in this paper compared to the previous literature can be highlighted as follows:

- Reactive power costs from diesel generators are considerd. These were usually neglected or considered separately from active power costs although they are related and should be co-optimized. Neglecting diesel reactive power costs causes deviations in the optimal dispatch results and introduces errors in the calculated total operational costs.
- Utilization of the reactive power capability of the inverter-interfaced DERs like WTs, PVs, and BESSs with consideration of the capability curves of the inverters to get benefit from this ability and do not depend only on diesel generators in supplying reactive power. In

most of the previous literature, only active powers are supplied from DERs.
- Detailed modeling of the synchronous diesel generators and inverter interfaced DERs by the consideration of their capability curves not just the widely used box constraints to provide a realistic behavior of these sources.

The rest of the paper is organized as follows. Section 2 provides the detailed adaptive robust EM problem formulation. Section 3 discusses the MG test system description and Section 4 presents the results and discussions. Conclusions are outlined in Section 5.

2. Adaptive robust energy management problem formulation

RO concerns with decision making problems under uncertainty that are not characterized by probability distributions but uncertainty sets. An uncertainty set is utilized to model the possible deviations of the uncertain variables and it has a set structure. A RO problem aims to find a solution that is feasible for any realization of the uncertain variables within the uncertainty set, and optimal for the worst-case condition [25].

The problem is a two-stage optimization problem, where the here-and-now decisions contain the day-ahead active/reactive power and reserve dispatch for the different power sources while the redispatch at the balancing stage are wait-and-see decisions, which adapt to the realization of the uncertainty. The adaptation in the second stage can be carried out by a redispatch of the diesel generators and load shedding events [26].

2.1. Adaptive robust energy management problem objective function

The objective is to minimize the day-ahead operation costs and the worst-case re-dispatch costs. The objective function is given by a min-max-min problem as following:

$$\min_{E^D}\left\{C_1 + C_2 + \max_{\Delta P_i^w, \Delta P_i^{pv} \epsilon \mu} \; \min_{E^B \epsilon B\left(E^D, \Delta P_i^w, \Delta P_i^{pv}\right)} C_3\right\} \tag{1}$$

Where:

$$C_1 = C_d\left\{\sum_{t\epsilon T}\sum_{g\epsilon G}\left[\left(a_g\, P_{g,t}^2 + b_g\, P_{g,t} + c_g\right) + b_g\left(R_{g,t}^{UP} + R_{g,t}^{DN}\right)\right]\right\},$$

$$C_2 = C_d{*}\left\{\sum_{t\epsilon T}\sum_{g\epsilon G}\left[a_g^{'}\, Q_{g,t}^2 + b_g^{'}\, Q_{g,t} + c_g^{'}\right]\right\}, \text{ and}$$

$$C_3 = C_d\sum_{t\epsilon T}\sum_{g\epsilon G} b_g\left(r_{g,t,s}^{up} - r_{g,t,s}^{dn}\right) + \sum_{t\epsilon T}\sum_{i\epsilon I}\left(VOLL_{x_i} {*}\, P_{i,t,s}^{lsh}\right)$$

The related active power fuel cost is a function of the fuel consumption and it is given by the first term in the objective function. The fuel consumption characteristics can be fitted to a quadratic function of the active power output and the cost coefficients can be obtained [20]. The scheduled reserve cost is assumed to be linear and added to the fuel costs in the first term. Moreover, the related reactive power costs of the diesel generators are given in the second term. The simplest form for the related reactive power costs from diesel generators is the triangle method where the reactive power cost coefficients are related to their corresponding active power cost coefficients, i.e., $a_g^{'} = a_g\, sin^2\varnothing$, $b_g^{'} = b_g\, sin\varnothing$, $c_g^{'} = c_g$ [23,24].

The third term (inner max-min problem) of the objective function is the second stage worst case cost and is composed of two terms; the deployed reserve costs and the load shedding related costs depending on the RESs deviations within the uncertainty set. The outer maximization problem finds the worst-case realization of the deviations ΔP_i^w and ΔP_i^{pv} of uncertain RESs production from their forecast. These deviations are to be chosen from within an uncertainty sets μ_w and μ_{pv}, which will be defined later. Once the worst-case realization of the uncertainty is fixed, the inner minimization problem determines the optimal second stage decision. These decision variables must be optimized within the feasibility set B, which relies on the first stage decision set E^D and the worst-case realizations ΔP_i^w and ΔP_i^{pv} of the uncertainty. Therefore, the feasibility set B is defined by the constraints representing the second stage (i.e., the recourse problem).

VOLL is a metric that calculates the cost per unit energy not supplied to consumers. Alternatively, this is the price consumers would pay to prevent disconnections [27]. Many studies have used arbitrary values for *VOLL*, but this may affect the accuracy of the model and the cost results [16,28,29]. Therefore, in this paper, inflation adjusted real *VOLL* values are utilized to obtain more accurate results [27].

2.2. Adaptive robust energy management problem constraints

The adaptive robust EM problem constraints are divided into first-stage constraints and second-stage constraints as follows.

2.2.1. The problem first stage (day-ahead) constraints

These are the constraints pertaining to the scheduling stage and involving first-stage variables.

2.2.1.1. The problem first stage equality constraints. These constraints include the active and reactive power balance at each bus, the active, reactive, and apparent power flow through lines, BESSs state of charge, and preventing the simultaneous charging/discharging of the BESSs for each time slot.

- Active power balance at each bus and time:

$$\sum_{g\epsilon\ \Omega_g^i} P_{g,t} + P_{i,t}^{W,forecast} + P_{i,t}^{PV,forecast} + P_{i,t}^{dis,sch} - P_{i,t}^{ch,sch} - P_{i,t}^{l} = \sum_{j\epsilon\ \Omega_l^i} P_{ij,t} \tag{2}$$

- Reactive power balance at each bus and time:

$$\sum_{g\epsilon\ \Omega_g^i} Q_{g,t} + Q_{i,t}^{W,sch} + Q_{i,t}^{PV,sch} + Q_{i,t}^{BESS,sch} - Q_{i,t}^{l} = \sum_{j\epsilon\ \Omega_l^i} Q_{ij,t} \tag{3}$$

- Active power flow through lines at each time:

$$P_{ij,t} = \frac{V_{i,t}^2}{Z_{ij}} cos\theta_{ij} - \frac{V_{i,t} {*} V_{j,t}}{Z_{ij}} cos\left(\delta_{i,t} - \delta_{j,t} + \theta_{ij}\right) \tag{4}$$

- Reactive power flow through lines at each time:

$$Q_{ij,t} = \frac{V_{i,t}^2}{Z_{ij}} \sin\theta_{ij} - \frac{V_{i,t} {*} V_{j,t}}{Z_{ij}} sin\left(\delta_{i,t} - \delta_{j,t} + \theta_{ij}\right) \tag{5}$$

- Apparent power flow through lines at each time:

$$S_{ij,t}^2 = P_{ij,t}^2 + Q_{ij,t}^2 \tag{6}$$

- Storage state of charge at each bus and time:

$$SOC_{i,t} = SOC_{i,t-1} + \left(P_{i,t}^{ch,sch^{*}}\eta_{ch} - P_{i,t}^{dis,sch} / \eta_{dis}\right){*}\Delta t \tag{7}$$

- Storage charging and discharging allowance at each bus and time: (to prevent charging and discharging simultaneously):

$$P_{i,t}^{ch,sch} * P_{i,t}^{dis,sch} = 0 \tag{8}$$

2.2.1.2. The problem first stage inequality constraints. These constraints involve the capability curves and the spinning reserve limits for diesel generators, inverter interfaced DERs capability curves, BESSs SOC limits, BESSs charging and discharging power limits, line capacity limits, and bus voltage limits for each time slot.

- Diesel Generator Active and Reactive Power Limits (Generator Capability Curves) [30,31]:
  - Prime-mover limits at each time:

  Limits on the mechanical power input from the prime-mover impose constraints on the active power generation.

$$P_{g,t} + R_{g,t}^{UP} \leq P_{g,max} \tag{9}$$

$$P_{g,t} - R_{g,t}^{DN} \geq P_{g,min} \tag{10}$$

  - Armature current limits at each time:

  The armature current results in copper losses leading to increased temperature in armature windings and the surrounding environment. This encounters a limitation on generator maximum current flowing in the armature without overheating. The apparent power rating depends on the armature current and the terminal voltage of the generator.

$$P_{g,t}{}^2 + Q_{g,t}^2 \leq S_{g,rating}^2 \tag{11}$$

  - Field current limits at each time:

  A maximum limit on the value of the field current is imposed by the heating in the field winding due to copper losses in the field circuit.

$$P_{g,t}{}^2 + \left(Q_{g,t} + \frac{V_{i,t}^2}{X_s}\right)^2 \leq \left(\frac{E_{max} * V_{i,t}}{X_s}\right)^2 \tag{12}$$

  - Diesel generators spinning reserve limits at each time:

$$0 \leq R_{g,t}^{UP} \leq R_g^{up,max} \tag{13}$$

$$0 \leq R_{g,t}^{DN} \leq R_g^{dn,max} \tag{14}$$

  - Inverter Interfaced DERs' Capability Curves:

  In this paper; WTs, PVs, and BESSs DERs are assumed to have inverter interface with the MG so that reactive power as well as active power could be supplied according to their capability curves. It is possible to represent the constraints due to the converter current and voltage limitations, analogous to the synchronous generators, by the following constraints, respectively [32,33]:

  - Inverter current limits at each time:

$$P_{DER,t}^2 + Q_{DER,t}^2 \leq \left(V_{DER,t} * I_{c,max}\right)^2 \tag{15}$$

  - Inverter voltage limits at each time:

$$P_{DER,t}^2 + \left(Q_{DER,t} + \frac{V_{DER,t}^2}{X}\right)^2 \leq \left(\frac{V_{c,max} * V_{DER,t}}{X}\right)^2 \tag{16}$$

- Storage state of charge limits at each bus and time:

$$SOC_{i,min} \leq SOC_{i,t} \leq SOC_{i,max} \tag{17}$$

- Storage charge and discharge active power limits at each bus and time:

$$P_{i,min}^{ch} \leq P_{i,t}^{ch,sch} \leq P_{i,max}^{ch} \tag{18}$$

$$P_{i,min}^{dis,sch} \leq P_{i,t}^{dis,sch} \leq P_{i,max}^{dis,sch} \tag{19}$$

- Line capacity limits at each time:

$$S_{ij,min} \leq S_{ij,t} \leq S_{ij,max} \tag{20}$$

- Bus voltages bounds at each time:

$$V_{i,min} \leq V_{i,t} \leq V_{i,max} \tag{21}$$

2.2.2. The problem second stage (balancing) constraints

These constraints define the feasibility set *B* in (1), which determines the operating region of the MG in the actual operation. Indeed, in the RO framework, it is sufficient to apply one instance of the operation constraints, valid for the worst-case condition; i.e., the deviation of the uncertain RESs generation. In contrast, in the SO technique one set of second stage constraints for each scenario should be enforced.

2.2.2.3. The problem second stage equality constraints. These constraints include the active and reactive power balance at each bus, the active, reactive, and apparent power flow through lines, BESSs SOC, preventing the simultaneous charging/discharging of the BESSs, and load shedding for each time slot and deviation.

- Active power balance at each bus, time, and deviation:

$$r_{g,t,s}^{up} - r_{g,t,s}^{dn} + \Delta P_{i,t,s}^{W} + \Delta P_{i,t,s}^{PV} + P_{i,t,s}^{dis} - P_{i,t}^{dis,sch} - P_{i,t,s}^{ch} + P_{i,t}^{ch,sch} + P_{i,t,s}^{lsh} = \sum_{j\epsilon\ \Omega_l^i} P_{ij,t,s} - \sum_{j\epsilon\ \Omega_l^i} P_{ij,t} \tag{22}$$

- Reactive power balance at each bus, time, and deviation:

$$Q_{i,t,s}^{W} - Q_{i,t}^{W,sch} + Q_{i,t,s}^{PV} - Q_{i,t}^{PV,sch} + Q_{i,t,s}^{BESS} - Q_{i,t}^{BESS,sch} + Q_{i,t,s}^{lsh} = \sum_{j\epsilon\ \Omega_l^i} Q_{ij,t,s} - \sum_{j\epsilon\ \Omega_l^i} Q_{ij,t} \tag{23}$$

- Active power flow through lines at each time and deviation:

$$P_{ij,t,s} = \frac{V_{i,t,s}^2}{Z_{ij}} \cos\theta_{ij} - \frac{V_{i,t,s} * V_{j,t,s}}{Z_{ij}} \cos\left(\delta_{i,t,s} - \delta_{j,t,s} + \theta_{ij}\right) \tag{24}$$

- Reactive power flow through lines at each time and deviation:

$$Q_{ij,t,s} = \frac{V_{i,t,s}^2}{Z_{ij}} \sin\theta_{ij} - \frac{V_{i,t,s} * V_{j,t,s}}{Z_{ij}} \sin\left(\delta_{i,t,s} - \delta_{j,t,s} + \theta_{ij}\right) \tag{25}$$

- Apparent power flow through lines at each time and deviation:

$$S_{ij,t,s}^2 = P_{ij,t,s}^2 + Q_{ij,t,s}^2 \tag{26}$$

- Storage state of charge at each bus, time and deviation:

$$SOC_{i,t,s} = SOC_{i,t-1,s} + \left(P_{i,t,s}^{ch} * \eta_{ch} - P_{i,t,s}^{dis} / \eta_{dis}\right) * \Delta t \tag{27}$$

- Storage charging and discharging allowance at each bus, time and deviation: (to prevent charging and discharging simultaneously):

$$P^{ch}_{i,t,s} * P^{dis}_{i,t,s} = 0 \tag{28}$$

- Load shedding at each bus, time and deviation:

$$P^{lsh}_{i,t,s} = \alpha P^{l}_{i,t} \tag{29}$$

$$Q^{lsh}_{i,t,s} = P^{lsh}_{i,t,s} \tan \Phi_l \tag{30}$$

2.2.2.4. The problem second stage inequality constraints. These constraints involve the capability curves and the spinning reserve limits for diesel generators, inverter interfaced DERs capability curves, BESSs SOC limits, BESSs charging and discharging power limits, line capacity limits, bus voltage limits, and load shedding limits for each time slot and deviation.

- Diesel Generator Active and Reactive Power Limits (Generator Capability Curves):
  - Prime-mover limits at each time and deviation:

$$P_{g,t} + r^{up}_{g,t,s} \le P_{g,max} \tag{31}$$

$$P_{g,t} - r^{dn}_{g,t,s} \ge P_{g,min} \tag{32}$$

  - Armature current limits at each time and deviation:

$$\left(P_{g,t} + r^{up}_{g,t,s} - r^{dn}_{g,t,s}\right)^2 + \left(Q_{g,t}\right)^2 \le S^2_{g,rating} \tag{33}$$

  - Field current limits at each time and deviation:

$$\left(P_{g,t} + r^{up}_{g,t,s} - r^{dn}_{g,t,s}\right)^2 + \left(Q_{g,t} + \frac{V^2_{i,t,s}}{X_s}\right)^2 \le \left(\frac{E_{max} * V_{i,t,s}}{X_s}\right)^2 \tag{34}$$

  - Up/Down deployment reserve limits at each time and deviation:

$$0 \le r^{up}_{g,t,s} \le R^{UP}_{g,t} \tag{35}$$

$$0 \le r^{dn}_{g,t,s} \le R^{DN}_{g,t} \tag{36}$$

Inverter Interfaced DERs' Capability Curves at each time and deviation:

  - Inverter current limits at each time and deviation:

$$P^2_{DER,t,s} + Q^2_{DER,t,s} \le \left(V_{DER,t,s} * I_{c,max}\right)^2 \tag{37}$$

  - Inverter voltage limits at each time and deviation:

$$P^2_{DER,t,s} + \left(Q_{DER,t,s} + \frac{V^2_{DER,t,s}}{X}\right)^2 \le \left(\frac{V_{c,max} * V_{DER,t,s}}{X}\right)^2 \tag{38}$$

- Storage State of Charge Limits at each bus, time and deviation:

$$SOC_{i,min} \le SOC_{i,t,s} \le SOC_{i,max} \tag{39}$$

- Storage charge and discharge active power limits at each bus, time and deviation:

$$P^{ch}_{i,min} \le P^{ch}_{i,t,s} \le P^{ch}_{i,max} \tag{40}$$

$$P^{dis}_{i,min} \le P^{dis}_{i,t,s} \le P^{dis}_{i,max} \tag{41}$$

- Load shedding limits at each bus, time and deviation:

$$0 \le P^{lsh}_{i,t,s} \le P^{l}_{i,t} \tag{42}$$

- Line capacity limits at each time and deviation:

$$S_{ij,min} \le S_{ij,t,s} \le S_{ij,max} \tag{43}$$

- Bus voltages bounds at each time and deviation:

$$V_{i,min} \le V_{i,t,s} \le V_{i,max} \tag{44}$$

2.3. Uncertainty sets definition

Polyhedral uncertainty sets are commonly utilized in the problems of adaptive RO. Considering symmetrical intervals for the deviations of both PVs and WTs power generation from their forecast, maximum deviations can be utilized to construct the uncertainty sets μ_{pv}, μ_w for PVs and WTs, respectively. Furthermore, a *budget of uncertainty* is included to limit the overall output deviations for RESs as following:

$$\mu_w\left(\Delta P^w_i, \Delta P^{w,max}_i, \Gamma_w\right) := \sum_{N_w} \frac{\left|\Delta P^w_i\right|}{\Delta P^{w,max}_i} \le \Gamma_w \tag{45}$$

$$\mu_{pv}\left(\Delta P^{pv}_i, \Delta P^{pv,max}_i, \Gamma_{pv}\right) := \sum_{N_{pv}} \frac{\left|\Delta P^{pv}_i\right|}{\Delta P^{pv,max}_i} \le \Gamma_{pv}. \tag{46}$$

The budget of uncertainty controls the level of conservatism as it can be varied from "0" to "N_w" for WTs and from "0" to "N_{pv}" for PVs. When Γ_w and $\Gamma_{pv} = 0$, the uncertainty sets become singleton equal to the RES forecast and the problem is converted to the normal deterministic case. As Γ_w and Γ_{pv} increase, the size of the uncertainty sets enlarges. This implies that larger deviations from the forecast are supposed, thus the resulting operation solutions are more conservative and the MG is protected against a higher level of uncertainty. When Γ_w and Γ_{pv} equal to N_w and N_{pv} respectively, the uncertainty sets will be defined by the whole intervals for each one of them.

The budget of uncertainty constraint ensures that the output of the two RESs cannot be at the lower or upper allowed production limits resulting from (45) and (46) at the same time. Indeed, if the production from one RES is at the lower limit then, the deviation for the other must be at most equal to 40 % of its maximum value. This represents nature's behavior and added to restrict the conservatism of the robust optimization problem and avoid less likely occurring events [25].

Furthermore, the maximum deviations from RESs power forecast can be described by the following constraints:

$$\left|\Delta P^w_i\right| \le \Delta P^{w,max}_i \tag{47}$$

$$\left|\Delta P^{pv}_i\right| \le \Delta P^{pv,max}_i \tag{48}$$

The maximum RESs forecast deviations can be extracted utilizing the predicted forecast errors in short term forecasting studies. In general, wind forecasting errors are often considered to be higher than solar ones. For 24 and 48-h-ahead horizons, wind errors become twice the solar ones. Based on various studies reviewed in [34] and [35], the maximum error bounds for the 24-h-ahead wind power forecast is ranged from 30 % to 50% and for solar is from 6 to 30 %. In this paper, the used values for maximum power deviations from forecasts for wind and solar are 40%, 20%, respectively.

2.4. Problem reformulation as a single minimization problem

A non-physical auxiliary variable γ representing the worst-case cost can be introduced, which is the optimal objective function value of the internal ***max-min*** problem in (1). Then the problem could be solved as a single minimization problem after including the following constraint:

$$\gamma \geq \left\{ C_d \sum_{t \epsilon T} \sum_{g \epsilon G} b_g \left(r^{up}_{g,t}\left(\Delta P^{w}_{i}, \Delta P^{pv}_{i}\right) - r^{dn}_{g,t}\left(\Delta P^{w}_{i}, \Delta P^{pv}_{i}\right) \right) + \sum_{t \epsilon T} \sum_{i \epsilon I} \left(VOLL_{x_i} \; P^{lsh}_{i,t}\left(\Delta P^{w}_{i}, \Delta P^{pv}_{i}\right) \right) \right\},$$
$$\forall \; \Delta P^{w}_{i} \in \mu_w \;, \Delta P^{pv}_{i} \in \mu_{pv} \tag{49}$$

Where the optimal redispatch decisions are written as a function of the deviations of RESs output. However, recalling that the uncertainty sets μ_w and μ_{pv}, defined by (45)–(48) represent polyhedrons that contain an infinite number of points. Then, there is an instance of each second stage variable and constraint for each ($\Delta P^{w}_{i} \in \mu_w$, $\Delta P^{pv}_{i} \in \mu_{pv}$). Since the sets μ_w and μ_{pv} are uncountable, the reformulation proposed above would lead to a problem with an infinite number of constraints and variables for the second stage. In practice, for linear problems it is shown that only the vertices of the polyhedral uncertainty set are part of the solution to the internal max-min problem [26]. However, in the proposed nonlinear problem, simple division (sampling) of the uncertainty sets (polyhedrons) into large number of points can be achieved to get rid of this problem in a simple way. The uncertainty sets for PVs and WTs are shown in Fig. 1 after sampling to a certain number of points.

Therefore, the problem objective function (1) can be reformulated as follows:

$$\min_{E^D} (C_1 + C_2 \; + \gamma) \tag{50}$$

With the constraints from (2) to (21) are applied and (22) to (49) for all "s" are also applied where the subscript "s" refers to the considered deviation points from the uncertainty sets (after sampling) which represent the RESs deviations. γ is the auxiliary variable defined in (49).

3. Test system description

The low voltage MG shown in Fig. 2 is used in this paper to implement the proposed EM strategy [32,36]. An 80-kW diesel generator is connected to Bus 1 to represent the slack bus for this isolated MG. The total active and reactive powers for the loads are presented in Fig. 3. The available active power profiles for wind and PV are displayed in Fig. 4. The cost parameters for diesel generators are obtained using the curve fitting MATLAB tool "*cftool*" to fit the fuel consumption data to a second order polynomial function. The specification data for the diesel generators are shown in Table 1 while the inverter interfaced DERs data are given in Table 2. The charging/discharging efficiencies of the BESS are assumed to be 77% [37]. The maximum and minimum bus voltages are supposed to be 1.05 and 0.95 p.u., respectively.

Three types of loads are considered in this system; residential, commercial and industrial with their profiles taken from [32,36]. It is assumed that load shedding can be done for 0, 25%, 50%, 75% or 100% of the commercial and residential loads at any bus. The cost of load shedding compensation is included utilizing real cost data from [27] and after inflation adjustment, the *VOLL* for residential and commercial loads are obtained. In addition, the price of the diesel fuel is averaged and inflation adjusted as obtained from [38,39]. These data are presented in Table 3.

4. Results and discussion

The day-ahead EM problem based adaptive robust optimization is modeled as a nonlinear programing (NLP) problem in the General Algebraic Modeling System (GAMS) environment [40] and is solved using the CONOPT solver. The CONOPT solver is a feasible path solver based on the generalized reduced gradient algorithm. The general framework of the proposed problem formulation and solution procedure is presented in Fig. 5. First, the optimization problem is solved with considering/neglecting the reactive power costs of diesel generators while considering/neglecting the reactive power capabilities from inverter interfaced DERs to investigate their impact on the MG operation while considering RESs uncertainty. Furthermore, the effect of the number of deviation points in the uncertainty sets on the accuracy of the uncertainty modeling and MG operation is analyzed. Moreover, the impact of budget of uncertainty on the total operation

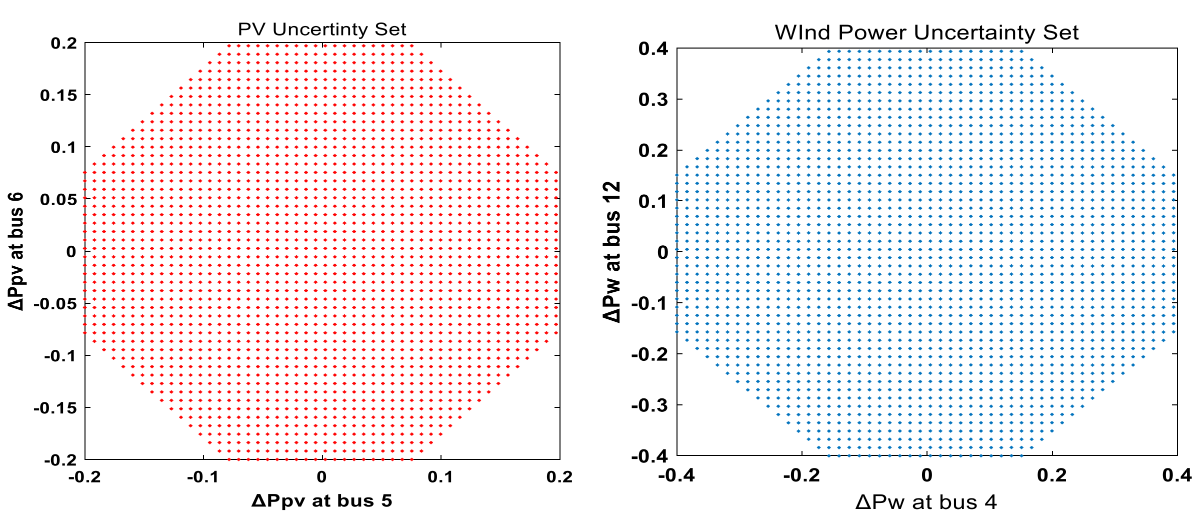

Fig. 1. Uncertainty sets for PV and wind.

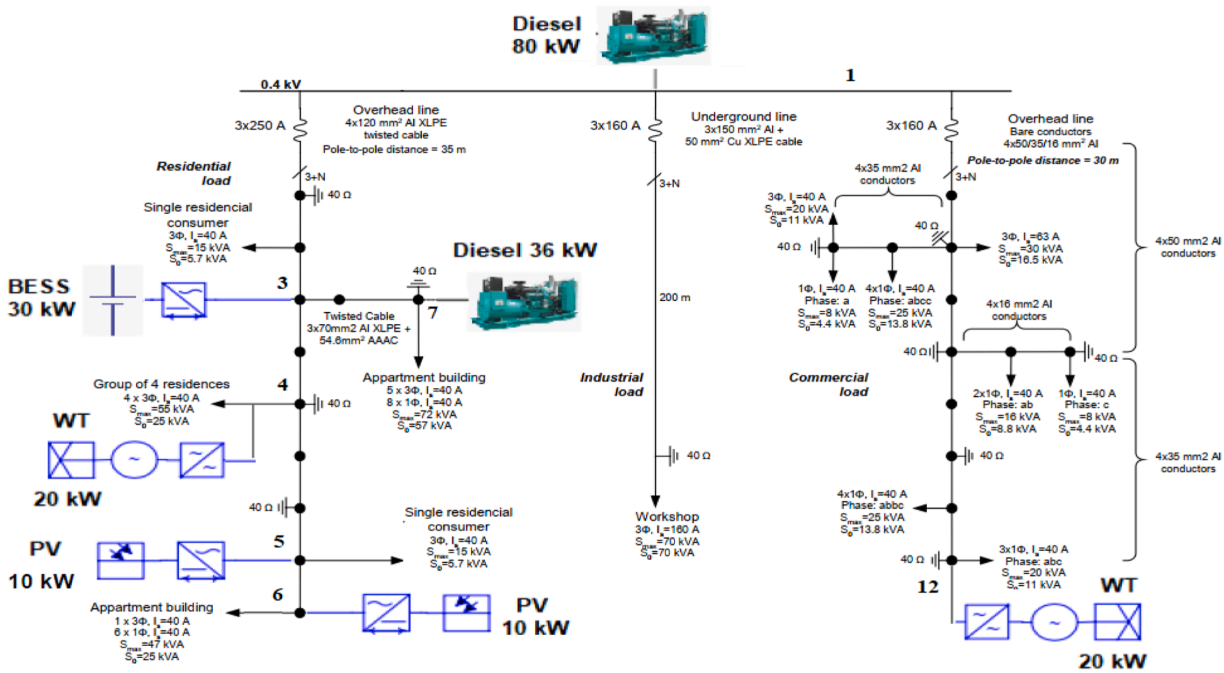

Fig. 2. The benchmark Microgrid [32,36].

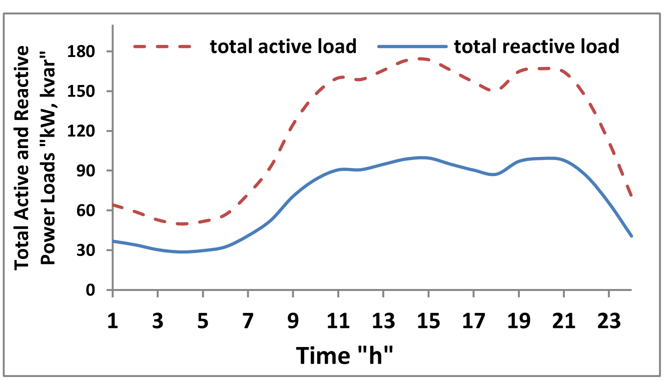

Fig. 3. Total active and reactive power loads.

Table 1
Specification data for diesel generators.

Bus	Diesel generator specifications Rated power “kW”	Min power “kW”	Fuel consumption coefficients a_g	b_g	c_g	Type used
1	80	40	0.5149	4.474	0.7389	Caterpillar DE110E2
7	36	18	0.7485	1.473	0.5761	Caterpillar DE50E0

Table 2
Inverter Interfaced Distributed Energy Resources (DERs) data.

Bus	Type	DER rated power “kW”	Inverter type used
3	BESS	30	Delta M30A/M50A
4	WT	20	TRIO-30.0-TL-OUTD-W
5	PV	10	ABB–PVI
6	PV	10	ABB–PVI
12	WT	20	TRIO-20.0-TL-OUTD-W

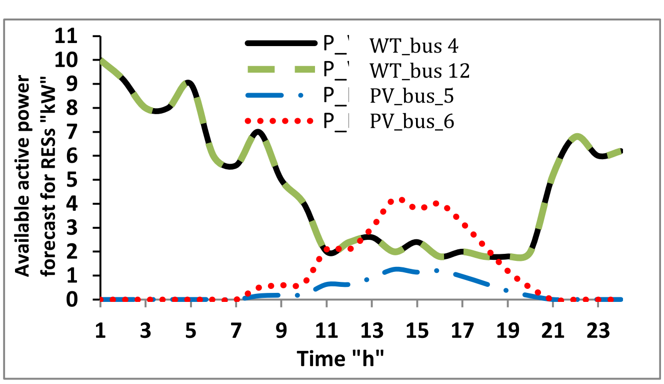

Fig. 4. Available active power forecast for RESs.

Table 3
Further system data.

Load shedding costs (VOLL) “$/kWh”	
Commercial Loads	55.88
Residential Loads	2.39

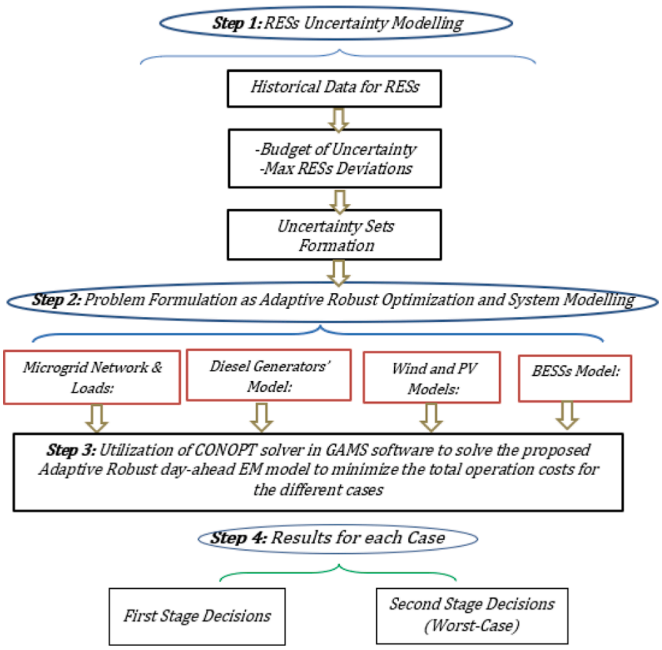

Fig. 5. Framework of the proposed adaptive robust energy management model and solution procedure.

cost is studied. Finally, the effect of changing the RESs penetration level on the system performance is studied.

4.1. Impact of considering/neglecting the reactive power capabilities and costs

In this section the optimization problem is solved with considering/neglecting the reactive power costs of diesel generators while considering/neglecting the reactive power capabilities from inverter interfaced DERs to investigate their impact on the MG operation while considering RESs uncertainty in the problem formulation.

4.1.1. Case (1) Neglecting reactive power costs and reactive power support from inverter interfaced DERs

In this case, the diesel reactive power costs are not considered and there is no reactive power support from inverter interfaced DERs. In other words, the term related to reactive power costs from diesel generators is omitted from the objective function and both RESs and BESS are able to provide active powers only. The optimized total operation costs in this case, where the diesel reactive power costs are not accounted, are 270,237 $/day. However, the actual total operation costs should be 317,413 $/day as there are 47,176 $/day (reactive power costs) not added. The neglected reactive power costs are calculated as follows; after the optimization is executed, the non-optimized reactive power costs from the dispatched diesel reactive power, Fig. 6, are calculated using the relevant terms of Eq. (1). The generators active power dispatched are shown in Fig. 7.

4.1.2. Case (2): Neglecting reactive power costs while considering reactive power support from inverter interfaced DERs

In this case, the diesel reactive power costs are neglected while inverter interfaced DERs are assumed to supply reactive power. The reactive powers produced from diesel generators are slightly decreased compared to Case 1, Fig. 8. This is because the reactive power costs were not optimized in both cases while in case 2 some reactive power is supplied from inverter interfaced DERs. Hence, in this case, both diesel generators and inverter based DERs are treated similarly regarding the reactive power injection.

In this case, diesel generators can supply active power at a given cost and reactive power at no cost while inverter interfaced DERs can supply

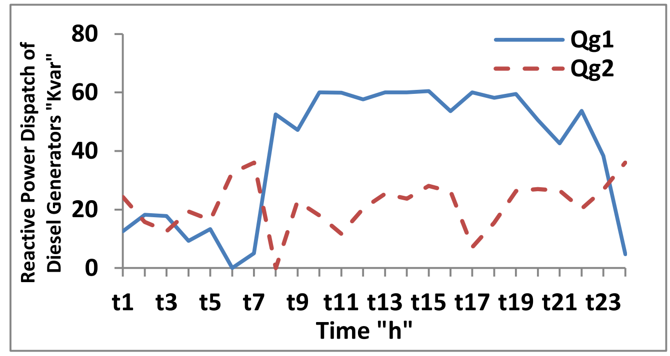

Fig. 6. Reactive power dispatch of diesel generators (Case 1).

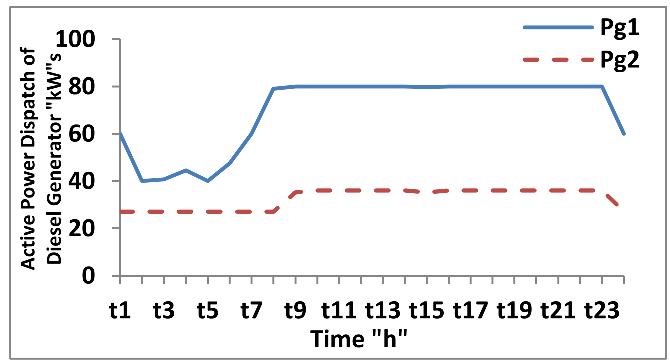

Fig. 7. Active power dispatch of diesel generators (Case 1).

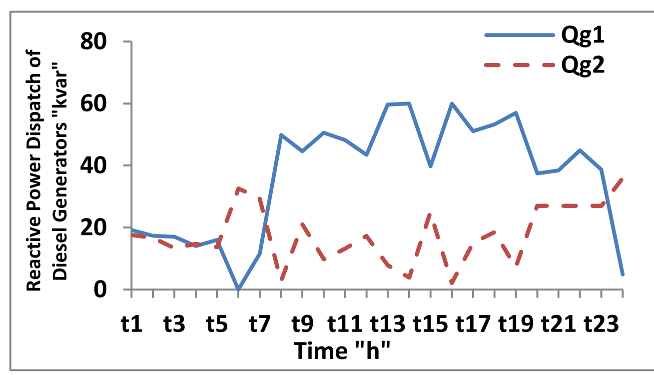

Fig. 8. Reactive power dispatch of diesel generators (Case 2).

both active and reactive powers at no cost. Therefore, the reactive power loads are supplied mainly from diesel generators while the active power loads are mainly supplied from DERs. The generators active power dispatched are nearly the same as case 1 and shown in Fig. 9.

The optimized total operation costs per day in this case are 262,312 $ without considering the reactive power costs (38,440 $). This makes the actual total operation costs to be 300,752 $. The diesel reactive power costs in this case are less than the previous case because some of the reactive powers are provided from DERs as shown in Fig. 10.

4.1.3. Case (3): Considering reactive power costs without reactive power support from inverter interfaced DERs

In this case, there is no capability for inverter interfaced DERs to generate reactive power while considering the diesel reactive power costs. The diesel generators' active power dispatches are as the previous cases. The diesel reactive power dispatches are shown in Fig. 11 which indicates a reduction in the dispatch compared to the previous cases.

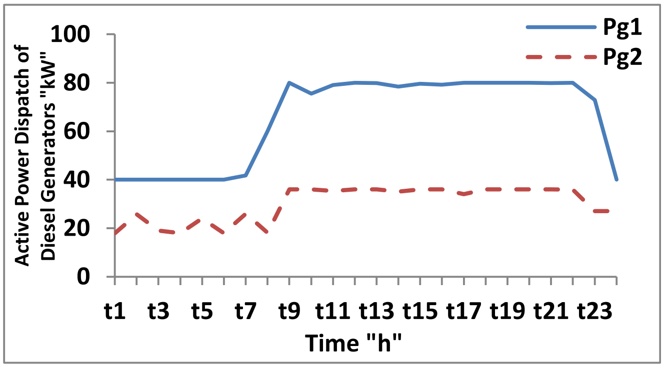

Fig. 9. Active power dispatch of diesel generators (Case 2).

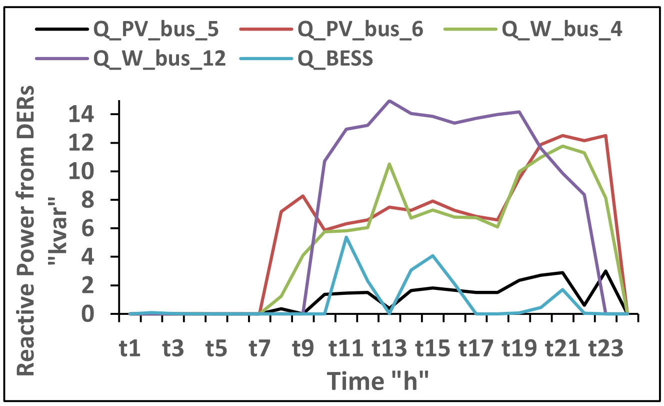

Fig. 10. Reactive power dispatch from DERs (Case 2).

This is because the reactive power costs are considered in the optimization objective. The active powers supplied from diesels are presented in Fig. 12.

The optimized (actual) total operation costs are 298,085 $/day which are less than cases (1) and (2) due to the consideration of the diesel reactive power costs in the optimization. The reactive power cost from diesel generators in this case is 35,288 $/day, which is less than the previous cases.

4.1.4. Case (4): Considering reactive power costs and reactive power support from inverter interfaced DERs

This case verifies the impact of utilizing the reactive power capability of inverter interfaced DERs in reducing the operation costs while taking the reactive power costs from diesel generators into account. In this case, the optimized (actual) total operation costs per day are 294,263 $, which is the lowest as compared to all the previous cases. The reactive power costs are 31,894 $/day in this case, the lowest reactive power costs in all cases due to taking the reactive power costs from diesel generators into account and the reactive power support from DERs. The reactive power dispatched from diesel generators are reduced compared to the previous cases and shown in Fig. 13 as more reactive powers are supplied from the DERs, Fig. 14. The generators active power dispatched are displayed in Fig. 15. The different costs for all cases are tabulated in Table 4.

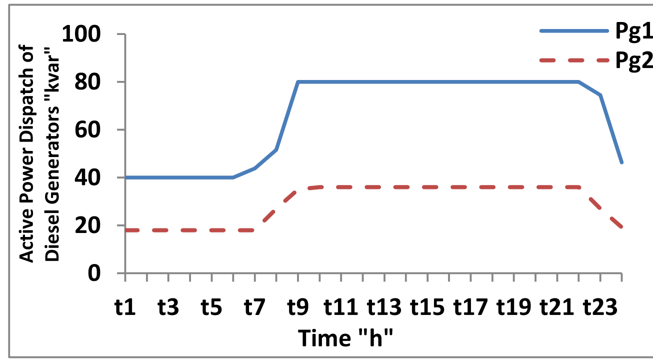

Fig. 12. Active power dispatch of diesel generators (Case 3).

4.2. Impact of the selected number of points in the uncertainty sets

The number of selected points should be large enough in order to represent the whole situations within the uncertainty sets but this affects the computational burden and execution time badly. Thus, the number of points affects the accuracy of the solution and a tradeoff between the number of points and the accuracy of the solution should be considered.

The operation costs are shown in Fig. 16 versus the selected number of points within the uncertainty sets. As shown from this figure, as the number of points is increased, the operation costs are increases due to the increased uncertainties that could be considered till roughly being constant after 40 points which may be acceptable at representing the whole deviations.

Furthermore, the computation performance of the robust EM model is evaluated through Fig. 17. In this figure, as the number of points within the uncertainty set increases, the execution time as well as the number of iterations are increased as expected but they seem not to be settled at certain values as the optimization takes some time searching for the worst-case solutions when the number of points is increased.

4.3. Impact of the budget of uncertainty

As the budget of uncertainty increases, the size of the RESs deviations from forecast increases so that the size of the uncertainty set increases which results in scheduling more reserves to face these increased uncertainties which finally increase the total operation costs. Fig. 18 shows

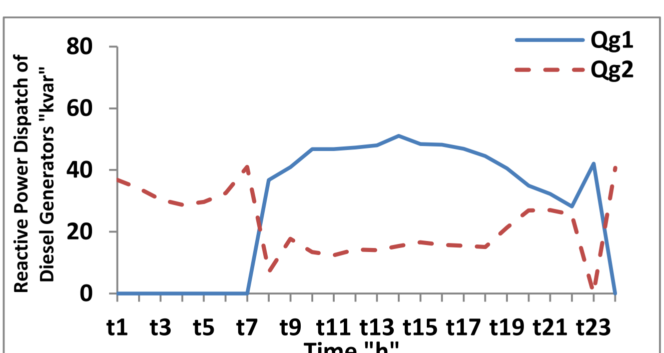

Fig. 11. Reactive power dispatch of diesel generators (Case 3).

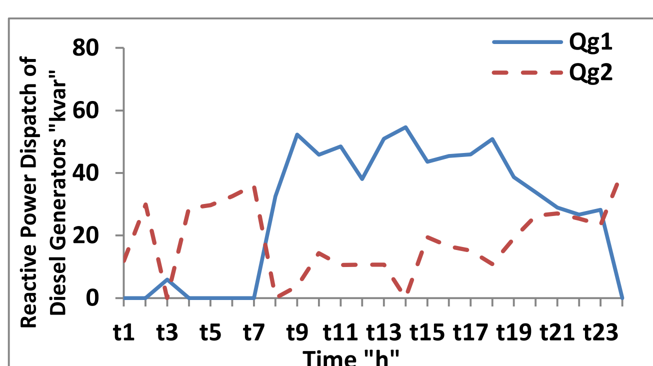

Fig. 13. Reactive power dispatch of diesel generators (Case 4).

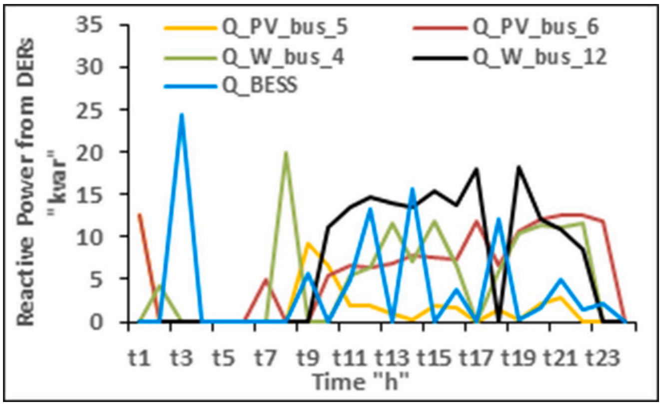

Fig. 14. Reactive power dispatch from DERs (Case 4).

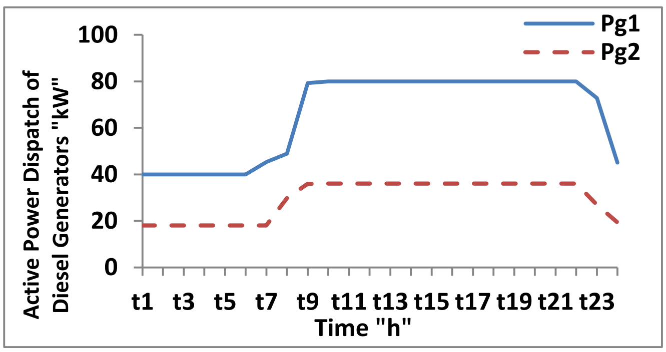

Fig. 15. Active power dispatch of diesel generators (Case 4).

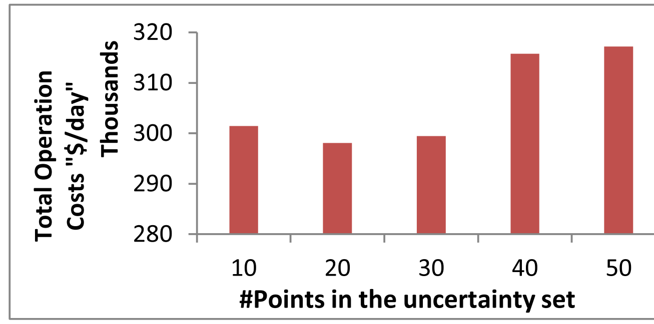

Fig. 16. Operation costs versus number of points within the uncertainty set.

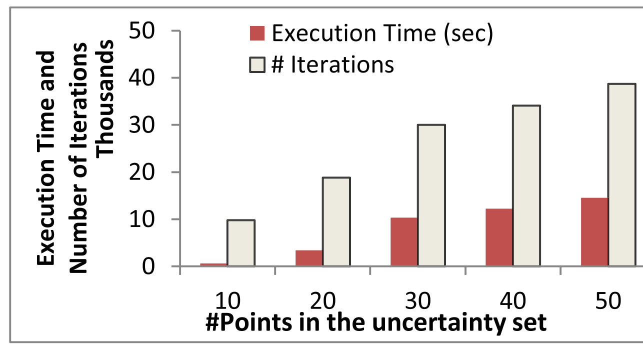

Fig. 17. Execution time and number of iterations versus number of points in the uncertainty set.

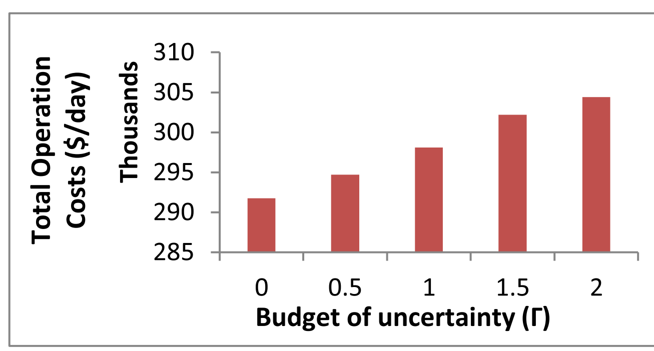

Fig. 18. Operation costs versus budget of uncertainty.

the total operation costs as the budget of uncertainty increases to interpret its effect. As shown from this figure, the budget of uncertainty can be utilized as a parameter for deciding the conservatism of the robust optimization model. Indeed, when the budget of uncertainty equals zero, the EM problem is reduced to the deterministic one with the RESs are modeled with their forecasted values, thus there is no uncertainty in this case which gives the least operation costs which is the least conservative case.

As the budget of uncertainty increases, the operation costs also increase as the uncertainty increases which adds more conservatism to the solutions against uncertainties. Additionally, as the size of the uncertainty sets increases, the execution time and the number of the iterations increase as shown in Fig. 19. Therefore, a tradeoff between the conservatism and computational complexity should be done according to the operator preferences to compromise between the operation reliability and security from one hand and economics and computations on the other hand.

Table 4
Break down of the different costs for the different cases.

Costs ($/day) Case number	Diesel active power dispatch and reserve cost	Diesel reactive power costs	Diesel active power re-dispatch costs	Load shedding costs	Optimized total operation costs (1)	Diesel reactive power costs (not accounted) (2)	Total operation costs (actual costs) (1) + (2)
Case (1)	256,704	Not considered	1,264	12,269	270,237	47,176	317,413
Case (2)	250,505	Not considered	1,085	10,718	262,312	38,440	300,752
Case (3)	250,709	35,288	1,024	11,065	298,085	Already accounted	298,085
Case (4)	250,090	31,894	1,204	11,075	294,263	Already accounted	294,263

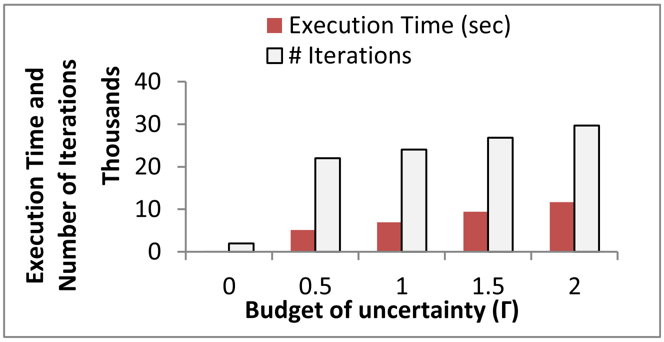

Fig. 19. Execution time and number of iterations versus budget of uncertainty.

4.4. *Effect of the RESs penetration level*

In this section, the effect of the RESs penetration level is studied by changing the size and the number of RESs units connected to the MG network. As shown from Figs. 20 and 21, the effect of changing the size and the number of RESs is similar. As the number and size of RESs increase, the execution time and the number of iterations are increased. In addition, the increase in RESs penetration level decreases the operation costs. This is due to the dependence on the diesel generators will be reduced. However, increasing the RESs penetration level increases the capital costs paid in purchasing the additional RESs units. Additionally, network congestion might occur with the increasing RESs penetration level that might lead to RESs power curtailments.

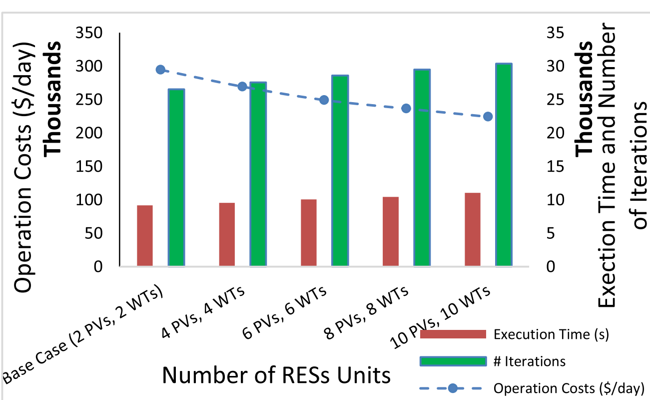

Fig. 20. EM Performance with changing the number of RESs.

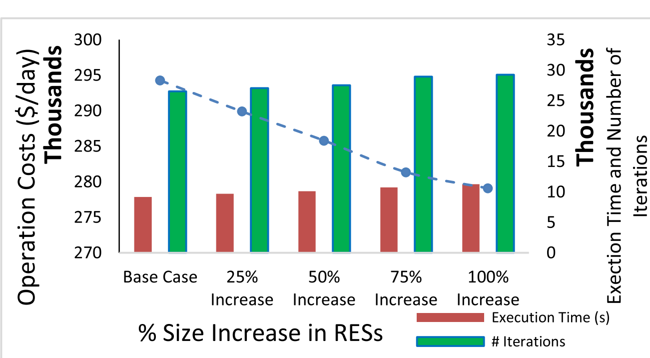

Fig. 21. EM performance with changing the RESs size.

5. Conclusions

The EM problem in isolated MGs requires reliable operation strategy to make robust operation decisions in the existence of intermittent and uncertain RESs with no support from the external grid. In this paper, the adaptive robust optimization is utilized in the EM of isolated MGs to minimize the worst-case operation costs to give more reliable solutions while considering the RESs uncertainties. Furthermore, the reactive power capabilities from inverter interfaced DERs are utilized to reduce the stress on diesel generators in supplying reactive power with no additional costs. Moreover, the reactive power related fuel costs of diesel generators are considered which are usually neglected for simplifications which results in errors in the calculated operational costs. Additionally, active and reactive power dispatches are optimized simultaneously in the proposed EM formulation which gives a more accurate results compared to active or reactive power dispatch when executed alone as in the previous literature. Accurate representation of the diesel generators as well as the inverter interfaced DERs is given through their capability curves to better model their behaviors instead of the widely used box constraints. In addition, realistic values of the costs for fuel, load shedding and all other parameters of the MG components were used to provide meaningful economic insights.

The EM problem was formulated as an adaptive (two stage) robust optimization problem and was solved via the GAMS environment using the CONOPT solver. The results showed the usefulness of the adaptive robust optimization in modeling the uncertainties of RESs to minimize the worst-case operation costs in isolated MGs and give optimal active and reactive power dispatches for the different power sources. The effect of the size of uncertainty sets and the budget of uncertainty on the total operation costs and computation burden is discussed through various simulation analyses. A tradeoff between the conservatism and computational complexity should be done according to the operator preferences to compromise between the operation reliability and security from one hand and economics and computations on the other hand.

Furthermore, the results presented in the paper showed the possible deviations of the optimal dispatch results and erroneous operation costs when neglecting the reactive power fuel costs related to diesel generators. Accordingly, combined active/reactive power dispatch is essential in the EM of isolated MGs to provide more accurate results. Moreover, utilizing the reactive power capabilities of the inverter interfaced DERs can significantly reduce the operating costs of the isolated MGs.

CRediT authorship contribution statement

Shady M. Sadek: Conceptualization, Methodology, Software, Writing – original draft. **Walid A. Omran:** Visualization, Investigation, Writing – review & editing. **M.A. Moustafa Hassan:** Supervision, Writing – review & editing, Validation. **Hossam E.A. Talaat:** Supervision, Writing – review & editing, Validation.

Declaration of Competing Interest

None.

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