A novel risk-based operational model for an islanded microgrid with electric vehicle parking lots, energy storage devices and flexible demand

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In traditional networks, power transmission from production centers to consumption centers causes many issues such as energy losses, decreased reliability, and low power quality. These issues have given rise to a new trend in electricity networks known as microgrids. This paper presents a new hybrid two-stage operational model based on the information gap decision theory (IGDT)/stochastic method for optimum energy management of an islanded microgrid under uncertainties. The suggested model investigates the uncertainty associated with wind energy using the IGDT method without using a probability distribution function or scenario creation. Uncertainties in electricity demand and vehicle owners behavior are also examined using a two-stage stochastic method. The suggested hybrid method, which is described as a bi-level two-stage optimization framework, benefits from both IGDT and scenario-based stochastic programming methods. Furthermore, the proposed microgrid includes new energy sources such as intelligent electric vehicle parking lots, energy storage devices, and demand response programs, all of which work together to decrease the cost of daily operation. According to numerical findings, the optimum utilization of new energy sources under the suggested hybrid approach lowers operational costs by 4.8%.

keywords: *Islanded microgrid, hybrid optimization, risk-based model, electric vehicles, demand response, emerging energy resources.*

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NOMENCLATURE

Sets

b Bus index
g DGUs index
es EES index
el Power load index
pl EVPL index
t Time index
wp Wind turbine index
s Scenario index
p_s Scenario probability
β_g, c_g Cost factor of DGUs
C_{pl}^{evpl} Cost of EVPL in V2G mode
C_{es}^{bes} Cost of ESS in discharge mode
C_{el}^{edr} Cost of applying DR
$su_{g,t}, sd_{g,t}$ Cost of startup and shutdown
R_g^{up} / R_g^{dn} Up/down ramp rate of DGUs
MDT_g / MUT_g Minimum down/up time of DGUs
$P_{es}^{dis,\min} / P_{es}^{dis,\max}$ Minimum/maximum discharge rate of EES
$P_{es}^{ch,\min} / P_{es}^{ch,\max}$ Minimum/maximum charge rate of EES
$DR_{el,t}^{up\_\max} / DR_{el,t}^{dn\_\max}$ Maximum participation rate in DRPs
$N_{pl,t,s} / Cap_{pl,t,s}$ Number/capacity of EVs in EVPL
$P_{g,t,s} / Q_{g,t,s}$ Active/reactive power generated by DGUs
$I_{g,t}$ State of DGUs in network
$P_{pl,t,s}^{dis\_evpl}, P_{pl,t,s}^{ch\_evpl}$ Power dispatch of EVPL in discharge/charge mode
$P_{es,t,s}^{dis\_es}, P_{es,t,s}^{ch\_es}$ Power dispatch of EES in discharge/charge mode
$DR_{el,t,s}^{dn}, DR_{el,t,s}^{up}$ Downward/upward changes of power demand

$x^{ch}_{es,t,s}, x^{dis}_{es,t,s}$ Binary variables related to charge/discharge of EES

$SOC_{es,t,s}, SOE_{pl,t,s}$ State of charge of EES and EVPL

$d^{DR}_{el,t,s}, d_{el,t,s}$ Power demand after and before DR

$P_{wp,t,s}$ Wind power generation

$U^{PL2G}_{pl,t,s}, U^{G2PL}_{pl,t,s}$ Binary variables related to charge/discharge of EVPL

$PF_{b,b',t,s}, QF_{b,b',t,s}$ Active and reactive power flow

$\delta_{b,t,s}, V_{b,t,s}$ Angle and voltage of buses

1. INTRODUCTION

In recent years, the growing trend of energy consumption and the constraints, economic and environmental problems caused by fossil fuel sources have made the issue of energy management one of the most important issues. The concept of microgrids (MGs) has become very important due to goals such as the development of renewable energy sources (RESs), technological advances and government policies to reduce fossil fuel consumption and the deprivation of some areas of energy distribution networks. The MG is a part of the electricity generation and distribution network that consists of a number of distributed generation units (DGUs), energy storage systems, loads and protection equipment and can operate in two modes: connected to the grid or independent of the national grid [1]. The advantages of MGs include reducing energy and fuel costs, increasing system reliability, increasing power system flexibility, improving the quality of services for consumers, and improving the management of renewable resources uncertainty [2]. Furthermore, as the use of RESs has increased, new difficulties in the operation of power networks have emerged owing to the uncertain nature of these resources. To meet these challenges, it is necessary to increase flexibility in the operation of power systems. Operational flexibility in the power grid means creating a balance between production and consumption with the lowest operating costs. Various solutions have been proposed to enhance the flexibility of electrical networks, such as using modern approaches to uncertainty management [3], using resources with fast startup [4], improving network infrastructure and efficiency, and applying emerging resources [5].The presence of emerging flexible sources such as intelligent electric vehicle parking lots (EVPL), energy storage devices (EES) and demand response programs (DRPs) are good options to decrease the impact of uncertainty on the output power of RESs and create. Also, with the enhancing penetration of EVPLs and RESs in power systems, the need to provide a modern uncertainty management approach has become very important. Therefore, this paper proposes a new two-stage optimization problem to manage uncertainties related to RESs, power demand, and the behavior of EV owners in an islanded MG integrated with emerging energy sources.

A. Literature review

Several studies on MG energy management have been conducted in recent years. In [6], an optimum pricing approach for a MG in the energy markets utilizing the MG reconfiguration, which is stated as a two-stage optimization scheme with the AC power model in consideration. As mentioned in [**?**]one of the distinguishing features of MGs is their capacity to operate in an islanding mode, which may offer many advantages to both customers and energy providers. This literature offers a novel optimum approach for configurable MGs that seeks to minimize the overall cost of operation in terms of reliability cost, fuel cost, and the cost of buying energy from the upstream network. Due to the existing uncertainties and limitations of AC power flow, in [7], The authors of [7],presents a comprehensive optimization framework for scheduling an MG including RESs, microturbine generators, as well as batteries. In [8], an optimum scheduling model for an MG's involvement in the energy distribution market is given in conjunction with a distribution market operator. The authors of [9] propose a stochastic model for assessing economic-environmental problems in a reconfigurable MG integrated with combined heat and power, with the goal of minimizing the overall operating cost of a power and heat-based MG.

The authors of [9] examined energy management and operation from the fundamental elements of industrial performance, where intelligent systems and MGs are presented as the next step for industrial facilities to utilize and manage energy usage. The authors of [10] propose a stochastic structure for optimal planning and operation of long-term development of heat and power-based MGs as part of an active distribution network, wherein the optimal location and capacity of thermal and electrical facilities, as well as the effect of RESs and DRP, are determined. In [11], information gap decision theory (IGDT) was utilized to describe load uncertainty in order to achieve optimum MG scheduling in the short term. To offer a thorough analysis of load uncertainty, the best and worst conceivable circumstances are assessed using the robustness and opportunity functions of IGDT, resulting in risk-averse and risk-seeker models. In [12], a methodology for power management of a multi-MG system with the objective of decreasing emissions as well as other financial goals is given as a stochastic programming model in an unpredictable environment, in accordance with worldwide legislation to decrease pollutants. In [13], a stochastic technique to address uncertainties in MGs is studied by considering carbon emissions and energy costs as objective functions, focusing on the role of DRPs and EESs on the mentioned objective functions. In [14], a robust model for optimal management of multi-MGs in the presence of power-to-X technologies and EVPLs is proposed, in which a decentralized technique is employed to solve the model by considering their private information. A multi-objective IGDT model is proposed in [15] to control uncertainties linked to renewable energy resources in hydrogen-based MGs, where the influence of EVPLs on the energy cost of MGs is also studied.

The authors of [16] developed a robust-stochastic hybrid approach to find the optimum MG scheduling without taking into account the network's technological constraints. In [17], an IGDT-stochastic programming technique was assessed for the optimum performance of an energy hub, in which wind unit uncertainty is controlled using a probabilistic strategy and power price uncertainty is addressed using the IGDT method. A hybrid stochastic-IGDT approach for simultaneous optimization of gas and electricity providers in the presence of electricity to gas conversion units is also presented in [18], at which uncertainties related to wind energy are modelled using a stochastic approach and uncertainties related to gas demand are modelled using an IGDT approach. In [19], a hybrid two-stage hybrid-IGDT technique is suggested to address the electricity and heat markets, wherein the uncertainty related to wind power production is modelled using the IGDT approach and the uncertainty related to electricity demand and heat is modelled using the stochastic approach. In [20], the linked scheduling of electricity, gas, and heating networks is addressed using a combination stochastic-robust method, wherein wind energy uncertainty is represented using a robust solution while electricity, heat, and gas demand uncertainty is managed using a stochastic approach. In [21], a mixed robust-stochastic model is introduced to consider uncertainties linked to wind and energy price in multiple energy systems.

B. Contributions

In the reviewed studies, the authors focused mainly on stochastic, robust, and IGDT approaches to managing uncertainties in islanded MGs, ignoring the role of hybrid approaches in addressing uncertainties in islanded MGs. In addition, the role of emerging energy sources under a coordinated plan to decrease the cost of operating an islanded MG has not been comprehensively studied in the reviewed articles. According to Table 1 and reviewed studies, in this paper, a new two-stage hybrid stochastic-IGDT approach for optimal management of power sources in an islanded MG in the presence of EVPL, DRP, and EES is evaluated. The main contributions to this paper are as follows:

- Presenting a hybrid two-stage stochastic-IGDT approach to managing wind energy uncertainties, power load, and the behavior of electric vehicle owners in an islanded MG. In the introduced model, the uncertainty in wind power generation is modeled under an IGDT-based robust approach and the uncertainties related to power load and electric vehicles are modeled under the stochastic programming.
- Evaluating the effect of the DRP and EES on the optimum operation of an islanded MG, taking into account the technical limitations of the MG.
- Investigating the effect of the vehicle-to-grid (V2G) capability of EVPL on the optimal scheduling of the islanded MG and the daily operating cost, taking into account the uncertainties related to the time of entry and exit of EVs from the parking lot, as well as the state of charge (SoC) of vehicles when entering and leaving the parking lot.

Table 1. Comparison between the proposed model and previous works

Refs	Islanded MG	EVPL	EES	DRP	Uncertainty modeling
[?]	✓	×	✓	×	Chance-constrained stochastic
[11]	×	×	✓	✓	IGDT
[13]	×	×	✓	✓	Stochastic
[14]	×	✓	✓	✓	Robust
[15]	×	✓	✓	✓	IGDT
Proposed model	✓	✓	✓	✓	Hybrid IGDT/stochastic

2. PROBLEM FORMULATION UNDER THE STOCHASTIC MODEL

A. Objective function

The suggested stochastic programming model aims to minimize the cost of operating the islanded MG in the face of uncertainties due to electric cars and power demand, regardless of wind power output uncertainties. The suggested model's goal function is represented as a stochastic planning problem in 1, which is divided into five sections. The first section details the costs of starting up and shutting down DGUs. The operating costs of DGUs are shown in the second portion of the objective function. The third component of the goal function depicts the cost of operating the EVPL. The fourth and fifth parts of the objective function also indicate the cost of operating the EES and carrying out the DRP, respectively.

$$\min \sum_{t=1}^{NT}\sum_{g=1}^{NG}\left(su_{g,t}+sd_{g,t}\right) + \sum_{s=1}^{NS} p_s \left[\begin{array}{l} \sum_{t=1}^{NT}\sum_{g=1}^{NG}\left(\beta_g P_{g,t,s}+c_g I_{g,t}\right)+\sum_{t=1}^{NT}\sum_{pl=1}^{NPL} C_{pl}^{evpl} P_{pl,t,s}^{dis\_evpl} \\ +\sum_{t=1}^{NT}\sum_{es=1}^{NES} C_{es}^{bes} P_{es,t,s}^{dis\_es}+\sum_{t=1}^{NT}\sum_{el=1}^{NEL} C_{el}^{edr} DR_{el,t,s}^{dn} \end{array}\right] \tag{1}$$

B. Constraints

In recent years, DGUs have received much attention due to their unique characteristics, such as rapid response, extremely low pollution, low operating costs, and greater environmental friendliness. A set of limitations related to the operation of DGUs is presented in relationships 2 to 12. Eqs. 2 and 3 show the active and reactive power limits of DGUs. Eqs. 4 and 5 show the power ramp rate limit of DGUs. The minimum up and down time of DGUs is given in 6 to 9. The on and off states cost of the DGUs are also expressed by 10 to 12 [21].

$$P_g^{\min} I_{g,t} \leq P_{g,t,s} \leq P_g^{\max} I_{g,t} \tag{2}$$

$$Q_g^{\min} I_{g,t} \leq Q_{g,t,s} \leq Q_g^{\max} I_{g,t} \tag{3}$$

$$P_{g,t,s} - P_{g,t-1,s} \leq R_g^{up} \tag{4}$$

$$P_{g,t-1,s} - P_{g,t,s} \leq R_g^{dn} \tag{5}$$

$$I_{g,t} - I_{g,t-1} \leq I_{g,t+UT_{g,u}} \tag{6}$$

$$UT_{g,u} = \begin{cases} u & u \leq MUT_g \\ 0 & u > MUT_g \end{cases} \tag{7}$$

$$I_{g,t-1} - I_{g,t} \leq 1 - I_{g,t+DT_{g,u}} \tag{8}$$

$$DT_{g,u} = \begin{cases} u & u \leq MDT_g \\ 0 & u > MDT_g \end{cases} \tag{9}$$

$$0 \leq su_{g,t} \leq SUC_g\left(I_{g,t} - I_{g,t-1}\right) \tag{10}$$

$$0 \leq sd_{g,t} \leq SDC_g\left(I_{g,t-1} - I_{g,t}\right) \tag{11}$$

The set of limitations related to battery performance is given in 12 to17. Battery charge and discharge limits are given in 12 and 13. The logical relationship between charge and discharge, which indicates that the battery can only be in a charge or discharge operation at any one time, is given in Equation 14. The SoC of the battery is given in 15. The equality of the initial and final conditions of battery SoC is given in 16. Finally, the battery SoC should be limited by the minimum and maximum values given in 17 [22].

$$P_{es}^{dis,\min} x_{es,t,s}^{dis} \leq P_{es,t,s}^{dis} \leq P_{es}^{dis,\max} x_{es,t,s}^{dis} \tag{12}$$

$$P_{es}^{ch,\min} x_{es,t,s}^{ch} \leq P_{es,t,s}^{ch} \leq P_{es}^{ch,\max} x_{es,t,s}^{ch} \tag{13}$$

$$x_{es,t,s}^{ch} + x_{es,t,s}^{dis} \leq 1 \tag{14}$$

$$SOC_{es,t+1,s} = SOC_{es,t,s} + \eta_{es}^{ch} P_{es,t,s}^{ch} - \frac{P_{es,t,s}^{dis}}{\eta_{es}^{dis}} \quad (15)$$

$$SOC_{es,t=24,s} = SOC_{es,\text{int}} \quad (16)$$

$$SOC_{es}^{\min} \leq SOC_{es,t,s} \leq SOC_{es}^{\max} \quad (17)$$

According to the DR scheme, consumers can shift their load from high-priced hours to lower-priced hours, thereby reducing their electricity bills and receiving a reward for reducing their load. The network load after running the DR program is defined by 18. Eq. 19 states that the total amount of shifted load over the entire time period is zero. In addition, the amount of shiftable load per hour has a limit expressed by 20 and 21 [17].

$$d_{el,t,s}^{DR} = d_{el,t,s} - DR_{el,t,s}^{dn} + DR_{el,t,s}^{up} \quad (18)$$

$$\sum_{t=1}^{NT} (DR_{el,t,s}^{up} - DR_{el,t,s}^{dn}) = 0 \quad (19)$$

$$0 \leq DR_{el,t,s}^{up} \leq DR_{el,t}^{up\_\max} \quad (20)$$

$$0 \leq DR_{el,t,s}^{dn} \leq DR_{el,t}^{dn\_\max} \quad (21)$$

The equations for EVPL are given in 22 to 34. In the proposed model, the EVPL, in addition to the responsibility of charging electric vehicles, taking into account the preferences of vehicle owners, can also work in the V2G mode. In relations 22 to 26, the time of entry and exit of vehicles to/from the parking lot and their SoC at the time of entry and exit to/from the parking lot are expressed by the Gaussian probability distribution function. In these relationships,μ andσ^2 are mean and variance of uncertain parameters, respectively.

$$t_{ev}^{arv} = f_{TG}(\chi; \mu_{arv}, \sigma_{arv}^2, (t_{ev}^{arv,\min}, t_{ev}^{arv,\max})) \quad (22)$$

$$t_{ev}^{arv} \leq t_{ev}^{dep} \quad (23)$$

$$t_{ev}^{dep} = f_{TG}(\chi; \mu_{dep}, \sigma_{dep}^2, (t_{ev}^{dep,\min}, t_{ev}^{dep,\max})) \quad (24)$$

$$SOC_{ev}^{arv} = f_{TG}(\chi; \mu_{SOC_{arv}}, \sigma_{SOC_{arv}}^2, (SOC_{ev}^{arv,\min}, SOC_{ev}^{arv,\max})) \quad (25)$$

$$SOC_{ev}^{dep} = f_{TG}(\chi; \mu_{SOC_{dep}}, \sigma_{SOC_{dep}}^2, (SOC_{ev}^{dep,\min}, SOC_{ev}^{dep,\max})) \quad (26)$$

The number of vehicles in the parking lot at time t is determined by 27 and the parking capacity at time t is obtained from Equation 28 according to the capacity of the vehicles that are in the parking lot at this time.

$$N_{pl,t,s} = N_{pl,t-1,s} + N_{pl,t,s}^{arv} - N_{pl,t,s}^{dep} \quad (27)$$

$$Cap_{pl,t,s} = Cap_{pl,t-1,s} + Cap_{pl,t,s}^{arv} - Cap_{pl,t,s}^{dep} \quad (28)$$

The maximum allowable power between the parking lot and the MG at time t is provided by 29 and **??**. As can be seen, this amount depends on the number of vehicles in the parking lot and the charge and discharge rate. In order to prevent simultaneous discharging and charging in the parking lot, 31 is considered. The SoC of the parking lot is obtained at any given moment from 32. The maximum and minimum parking energy levels are presented as a function of parking capacity in relation 33 [3].

$$P_{pl,t,s}^{PL2G} \leq \gamma^{dis} N_{pl,t,s} U_{pl,t,s}^{PL2G} \quad (29)$$

$$P_{pl,t,s}^{G2PL} \leq \gamma^{ch} N_{pl,t,s} U_{pl,t,s}^{G2PL} \quad (30)$$

$$U_{pl,t,s}^{PL2G} + U_{pl,t,s}^{PL2G} \leq 1 \quad (31)$$

$$\begin{aligned} SOE_{pl,t,s} &= SOE_{pl,t-1,s} + SOE_{pl,t,s}^{arv} - SOE_{pl,t,s}^{dep} \\ &+ \eta_{ch} P_{pl,t,s}^{G2PL} - \frac{P_{pl,t,s}^{PL2G}}{\eta_{dis}} \end{aligned} \quad (32)$$

$$SOC_{PL}^{\min} Cap_{PL,t,s} \leq SOE_{PL,t,s} \leq SOC_{PL}^{\max} Cap_{PL,t,s} \quad (33)$$

The set of limitations related to the power grid, including the balance constraints and the power flow relationships, is stated in the set of relations 34 to 38. The limits of active and reactive power balance and power flow of different sources are expressed in **??** and **??**. The AC power flow relationships for active and reactive power are shown in 36 and 37, respectively. The heat limit of the transmission line is given in 38 and 39. Finally, the voltage limit for each network bus is given in 40.

$$\begin{aligned} &\sum_{g}^{G_b} P_{g,t,s} + \sum_{wp}^{WP_b} P_{wp,t,s} + \sum_{es}^{ES_b} \left(P_{es,t,s}^{es\_dis} - P_{es,t,s}^{es\_ch} \right) \\ &+ \sum_{pl}^{PL_b} \left(P_{pl,t,s}^{PL2G} - P_{pl,t,s}^{G2PL} \right) - \sum_{el}^{EL_b} d_{el,t,s}^{dr} = \sum_{b'} PF_{b,b',t,s} \end{aligned} \quad (34)$$

$$\sum_{g}^{G_b} Q_{g,t,s} + \sum_{wp}^{WP_b} Q_{wp,t,s} - \sum_{el}^{EL_b} Q_{el,t,s}^{dr} = \sum_{b'} QF_{b,b',t,s} \quad (35)$$

$$0 \leq PF_{b,b',t,s} \leq PF_{b,b'}^{\max} \quad (36)$$

$$0 \leq QF_{b,b',t,s} \leq QF_{b,b'}^{\max} \quad (37)$$

$$0 \leq PF_{b,b',t,s} \leq PF_{b,b'}^{\max} \quad (38)$$

$$0 \leq QF_{b,b',t,s} \leq QF_{b,b'}^{\max} \quad (39)$$

$$V_b^{\min} \leq V_{b,t,s} \leq V_b^{\max} \quad (40)$$

3. 3. PROBLEM FORMULATION UNDER HYBRID STOCHASTIC-IGDT

As previously stated, the IGDT technique was employed in this research to simulate the uncertainty of wind power output. In general, the following is the mathematical explanation of the problem uncertainty:

$$U = U(\overline{\Psi}, \varepsilon) = \left\{ \Psi : \left| \frac{\Psi - \overline{\Psi}}{\overline{\Psi}} \right| \leq \varepsilon \right\} \quad (41)$$

Where and are the forecasted and actual values of the uncertain parameter. is the difference between the forecasted and the actual value of the uncertain parameter [19].

This approach, which is frequently employed by conservative decision-makers, improves the objective function's performance against the potential of mistakes in estimating the unknown input parameter. The collection of decision variables must be established in such a manner that the real objective function is computed against the uncertainty parameter's deviation from the anticipated value. When the goal function is secured against the maximum uncertainty radius, a risk-averse decision is taken. In other words, the decision-maker will be confident that the value of the objective function does not exceed the allowed limit for an undefined parameter within the range of the obtained uncertainty radius. These are the mathematical connections that describe this strategy:

$$\alpha(X, \Delta_C) = Max\left\{\varepsilon : \left(\underset{\Psi \in U(\bar{\Psi},\varepsilon)}{Max} \quad OF \leq \Delta_C = (1+\beta)OF_b\right)\right\} \tag{42}$$

In the above relation, and are the critical value and the base value of the objective function and X are the problem decision variables, respectively. The unknown parameter has a negative impact on the objective function in the risk aversion strategy. As a result, the system operator considers a higher cost in proportion to the undesired wind energy deviation in this plan, which is expressed as a two-level problem in the following equations.

$$\alpha = \max \quad \varepsilon \tag{43}$$

$$\max \sum_{t=1}^{NT}\sum_{g=1}^{NG}(su_{g,t}+sd_{g,t}) + \sum_{s=1}^{NS} p_s \left[\begin{array}{l} \sum_{t=1}^{NT}\sum_{g=1}^{NG}(\beta_g P_{g,t,s}+c_g I_{g,t}) \\ +\sum_{t=1}^{NT}\sum_{pl=1}^{NPL} C_{pl}^{evpl} P_{pl,t,s}^{dis\_evpl} \\ +\sum_{t=1}^{NT}\sum_{es=1}^{NES} C_{es}^{bes} P_{es,t,s}^{dis\_es} \\ +\sum_{t=1}^{NT}\sum_{el=1}^{NEL} C_{el}^{edr} DR_{el,t,s}^{dn} \end{array}\right] \leq \Delta_C \tag{44}$$

$$(1-\varepsilon)\,\bar{P}_{wp,t} \leq P_{wp,t} \leq (1+\varepsilon)\,\bar{P}_{wp,t} \tag{45}$$

$$(2)-(41) \tag{46}$$

In this section, the suggested two-level optimization problem has been reduced to a single-level problem in order to be solved by standard solvers. As previously stated, forecast error in wind power output is modelled using a risk aversion methodology, which raises operational costs. As a result, only the decrease in wind power output has a negative impact on the MG operating cost in this methodology. As a consequence, the two-level problem denoted by 43 to 46 may be reduced to a single-level problem, as shown below. The flowchart of how to solve the introduced model is presented in Figure1.

$$\alpha = \max \quad \varepsilon \tag{47}$$

$$\sum_{t=1}^{NT}\sum_{g=1}^{NG}(su_{g,t}+sd_{g,t}) + \sum_{s=1}^{NS} p_s \left[\begin{array}{l} \sum_{t=1}^{NT}\sum_{g=1}^{NG}(\beta_g P_{g,t,s}+c_g I_{g,t}) \\ +\sum_{t=1}^{NT}\sum_{pl=1}^{NPL} C_{pl}^{evpl} P_{pl,t,s}^{dis\_evpl} \\ +\sum_{t=1}^{NT}\sum_{es=1}^{NES} C_{es}^{bes} P_{es,t,s}^{dis\_es} \\ +\sum_{t=1}^{NT}\sum_{el=1}^{NEL} C_{el}^{edr} DR_{el,t,s}^{dn} \end{array}\right] \leq \Delta_C \tag{48}$$

$$P_{wp,t} = (1-\varepsilon)\,\bar{P}_{wp,t} \tag{49}$$

$$(2)-(41) \tag{50}$$

4. RESULTS

An islanded MG with the existence of developing energy sources under uncertainties is investigated in order to assess the suggested model. The studied MG with respect to developing sources is shown in Figure2. Information about the MG is given in the reference [22]. Information on DGUs can be found in[23]. In addition, the entry time of vehicles into the parking lot, their exit time and their SoC when entering and leaving the parking lot are determined based on the Monte Carlo simulation, with an average entry time of 8, an exit time of 16, and an initial and final energy level of 0.4 and 0.8. The maximum charge and discharge rate of the EES is 20 kW. The EES capacity is also considered to be 100 kWh. The efficiency of charging and discharging EES and EVPL are also assumed to be 0.9. The consumer participation factor in DRP is assumed to be 10% and the cost of implementing the DRP is estimated at 5 cents per kilowatt-hour. The electrical demand and predicted power of the wind unit is shown in Figure3. To simulate the uncertainty of power load and the behaviour of electric cars, 1000 scenarios are created using Monte Carlo simulations, which are then reduced to ten scenarios with the probability given in TAble2. To simplify the scenario, the SCENRED tool in GAMS software was utilised [25]. The suggested model is represented as a mixed-integer linear programming (MILP) problem that is handled using GAMS' CPLEX solver. The proposed method is a convex optimization model and can be solved by commercial solvents such as CPLEX. The solution time of the proposed model is less than 5 seconds, which can be easily used for MGs with more DGUs, loads, and lines. To assess the suggested model, the following two cases are studied:

Case 1: Optimal operation of islanded MG under two-stage stochastic programming

Case 2: Optimal operation of islanded MG under hybrid IGDT-stochastic model

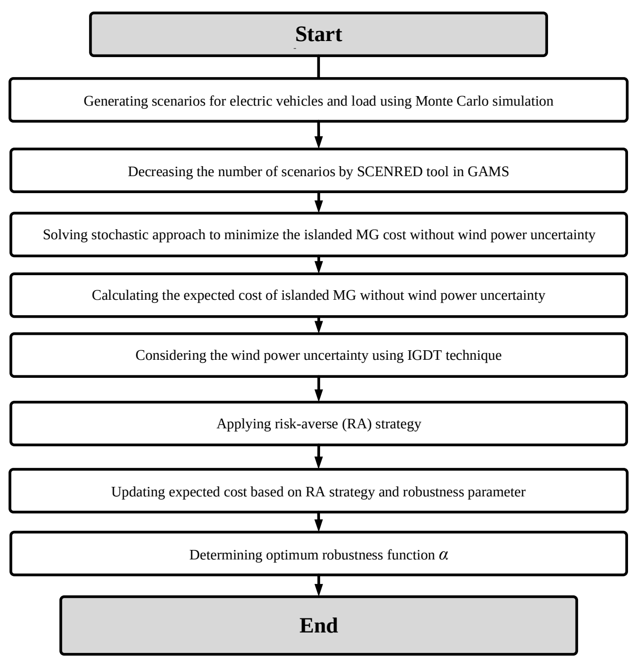

Fig. 1. Flowchart related to how to solve the proposed problem

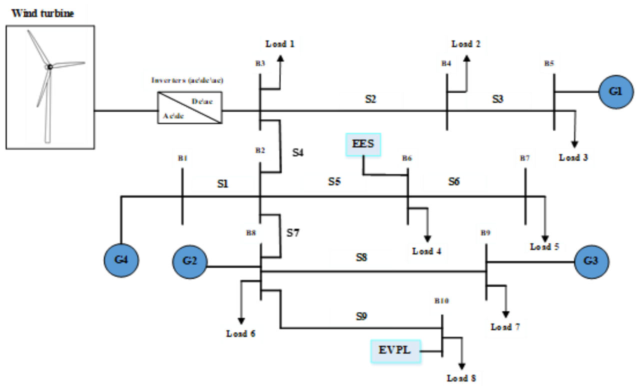

Fig. 2. The studied MG with emerging resources

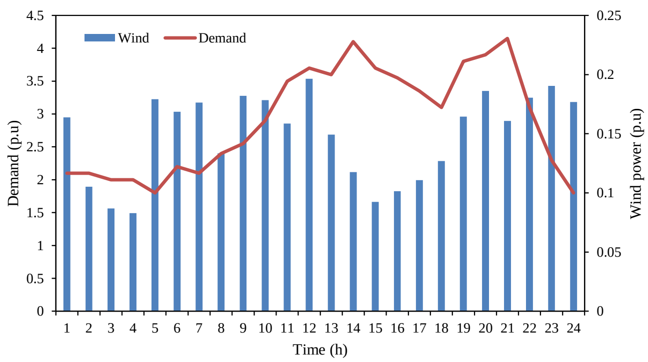

Fig. 3. Forecasted electrical demand and wind power

Table 2. The probability of scenarios

Scenarios	1	2	3	4	5
Probability	0.11	0.04	0.07	0.13	0.15
Scenarios	6	7	8	9	10
Probability	0.07	0.18	0.1	0.07	0.08

Case 1: In this case, uncertainties related to electric demand and electric vehicles are considered and uncertainties related to wind units are ignored. Figure 4 shows the hourly scheduling of DGUs. It can be seen that units G1 and G2 are committed at all hours in order to meet the maximum demand for electricity since these units are the cheapest power plants. Unit G3 also participates in all hours, but the amount of participation depends to some extent on the amount of demand. Unit G4, as the most costly unit, also participates between hours 10 and 22, when the demand is high and the production capacity of the wind unit is low, and provides part of the electricity demand required by the system. In this case, the operating cost is $1217.62. Figure5 depicts the EES charging and discharging schedule during a 24-hour cycle. It can be observed that the EES system is in charging mode in the early hours when the network's electrical demand is minimal. It is subsequently worked in discharging process during the hours when the network demand is mostly increased, resulting in a reduction in operating costs. Furthermore, while the EES system is in the charging mode, the energy level in the EES is boosted, and when the EES system is in the discharged mode, the energy level in the EES is decreased. The EES's goal is to decrease the power output of costly power plants during peak hours of energy pricing. Without taking into account the EES, the operating cost is $1235.9.

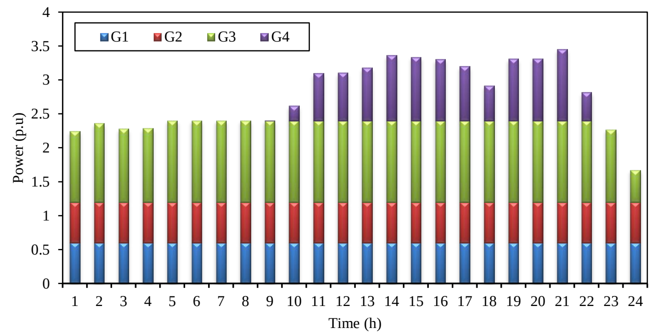

Fig. 4. . Power dispatch of units

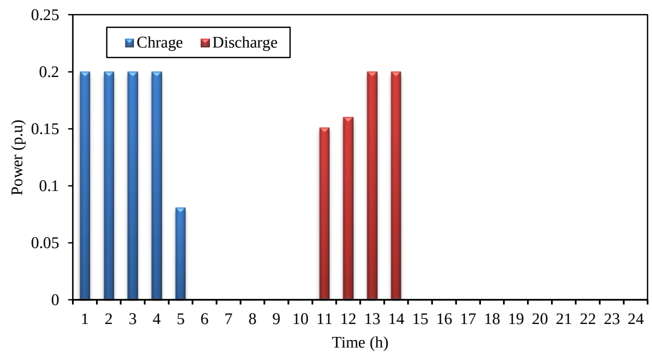

Fig. 5. . Optimal schedule of EES

DR also transfers the load from peak to low demand hours, lowering the cost of daily operation. Figure6 illustrates that a substantial percentage of the load is moved from peak to non-peak hours, resulting in a decrease in the involvement of costly unit G4 to satisfy part of the peak demand. Electric vehicles are also charged based on the time of entry, exit and their initial and final energy level in the MG. It can be seen from Figure7 that in the early hours of entering the parking lot, the operator tends to charge the vehicles because the amount of electricity demand is lower during these hours. In addition, smart parking acts as a producer during peak hours of electricity demand and can inject some power into the grid, reducing the participation of expensive power plants G4 to provide part of the load. The operation cost without the presence of DR and V2G mode of EVPL is equal to $1259.41. It should be noted that without the presence of all emerging energy sources, the cost of operation is equal to $1276.31.

Case 2: In this case, in addition to the uncertainties stated in the previous case, the uncertainties associated with wind energy are taken into account. The value of β is raised from 0 to 0.05 in order to assess the IGDT-based robust strategy. The base operating cost is assumed to be $1217.62, which is equivalent to the expected operating cost in the presence of emerging energy sources. Figure8 shows that as β increases, the value of the optimal function α and the daily operating cost increase. This means that the operator must incur higher operating costs to handle a broader range of the wind energy prediction error. For example, for β equal to 0.01 and 0.04, the optimal value of

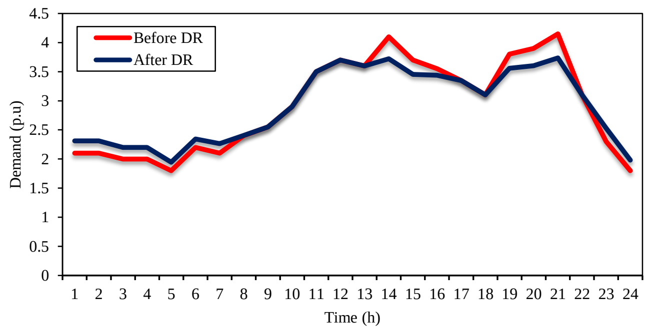

Fig. 6. The effect of DR on the power demand

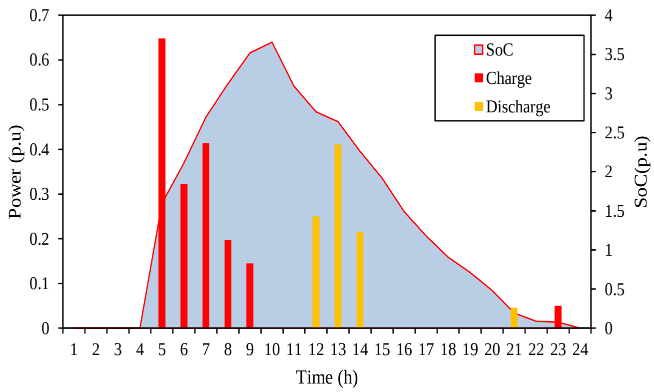

Fig. 7. Optimal schedule of EVPL

α is equal to 0.07 and 0.33, respectively, which means that by increasing β by 0.04, the operator can guarantee a maximum operating cost of $1266 if the error in wind energy prediction does not exceed 33%. Figure9 shows the impact of the parameter β on the power dispatch of unit G4. It is observed that with increasing β, the participation rate of unit G4 has increased significantly in order to supply the network load. This is due to the fact that with enhancing β, the operator takes a more risky approach in order to make the robust strategy to wind power uncertainty. Therefore, under the risk aversion strategy, the operator's dependence on changes in wind production capacity decreases, and instead, the participation rate of expensive power plants and the daily operating cost increase.

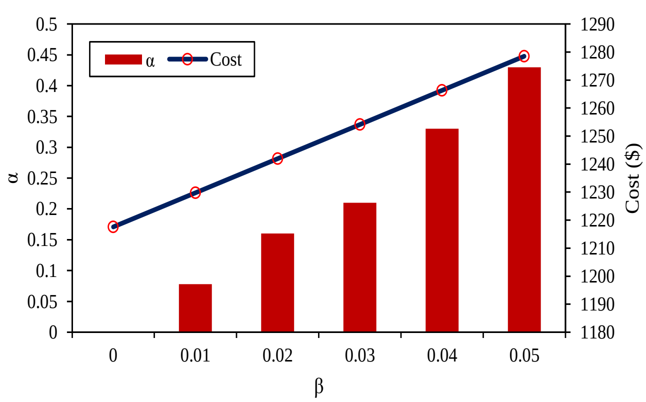

Fig. 8. The effect of robustness parameter β on α and cost

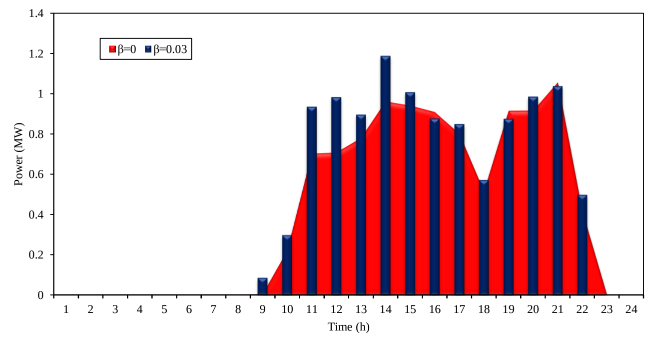

Fig. 9. The effect of robustness parameter β on power dispatch of unit G4

5. CONCLUSION

This paper presented a two-stage hybrid IGDT-stochastic approach to the optimal energy management of an islanded MG under uncertainties. In the proposed model, wind energy uncertainty was modeled based on the IGDT method without the use of scenario generation. Uncertainty related to electric charge and the behavior of electric vehicles were also modeled under a two-stage stochastic approach. The proposed hybrid approach simultaneously benefits from both IGDT approaches and scenario-based stochastic programming. In the investigated approach, the MG operator was able to achieve an acceptable operating cost within a tolerable range of wind power generation errors and plan the resources under its ownership accordingly. In addition, the operator must incur higher operating costs to achieve a robust model to managing fluctuations in wind power. Also, the proposed MG was equipped with emerging energy sources such as EES systems, EVPL and DRP, which the optimal use of these resources under the integrated approach reduced the daily operating costs by 4.8%. In future works, we will mainly focus on the optimal scheduling of energy-water MGs in the presence of multiple conversion resources. In addition, new hybrid models will be adopted to control uncertainties.

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