



Stochastic Optimal Scheduling of Microgrids Considering Demand Response and Commercial Parking Lot by AUGMECON Method

M. Sedighzadeh^{*(C.A.)}, S. M. M. Alavi*, and A. Mohammadpour*

Abstract: Regarding the advances in technology and anxieties around high and growing prices of fossil fuels, government incentives increase to produce cleaner and sustainable energy through distributed generations. This makes trends in the using microgrids which consist of electric demands and different distributed generations and energy storage systems. The optimum operation of microgrids with considering demand-side management increases efficiency and reliability and maximize the advantages of using distributed generations. In this paper, the optimal operation scheduling and unit commitment of generation units installed in a microgrid are investigated. The microgrid consists of technologies based on natural gas that are microturbine and phosphoric acid fuel cell and technologies based on renewable energy, including wind turbine and photovoltaic unit along with battery energy storage system and plug-in electric vehicle commercial parking lot. The goal of the paper is to solve a multi-objective problem of maximizing revenues of microgrid operator and minimizing emissions. This paper uses an augmented epsilon constraint method for solving the multi-objective problem in a stochastic framework and also implements a fuzzy-based decision-maker for choosing the suitable optimal solution amid Pareto front solutions. This new model implements the three type of the price-based and incentive-based demand response program. It also considers the generation reserve in order to enhance the flexibility of operations. The presented model is tested on a microgrid and the results demonstrate the efficacy of the proposed model economically and environmentally compared to other methods.

Keywords: Augmented Epsilon Constraint Method (AUGMECON), Battery Electrical Storage System (BESS), Distributed Generation (DG), Energy Management System (EMS), Microgrid (MG), Plug-in Electric Vehicle (PEV).

Nomenclature

Sets

T	Set of times.
S	Set of scenarios.
N	Set of DGs.
I	Set of industrial consumers.

R	Set of residential consumers.
C	Set of commercial consumers.
N_r	Set of DGs admitted for participating in GR scheduling.
K	Set of optimization variables.
M	Set of objective functions.
L	Set of Pareto solutions.
$S_{trip}(t)$	Signal of trip: 1 if PEV is connected to grid in period t ; 0 otherwise.
$W_{G2V}(t)$	1 if PEV is charged by MG in period t ; 0 otherwise.
$W_{V2G}(t)$	1 if PEV is discharged into MG in period t ; 0 otherwise.

Binary Variables

$u(i.t.s)$	On/off state of i th DG in time period t
------------	--

Iranian Journal of Electrical and Electronic Engineering, 2020.

Paper first received 01 September 2019, revised 08 November 2019, and accepted 09 November 2019.

* The authors are with the Faculty of Electrical Engineering, Shahid Beheshti University (SBU), Evin, Tehran, Iran.

E-mails: m_sedighi@sbu.ac.ir, salandpub@gmail.com, and corna2010@yahoo.com.

Corresponding Author: M. Sedighzadeh.

and scenario s : 1 if DG is in on state; 0 otherwise.

Continuous Variables

T_{cost}	Total cost of operation of MG [\$].
$cost^{DG}(s)$	Total cost of operation of DGs for scenario s [\$].
$cost^{grid}(s)$	Total cost of power imported/exported between the MG and the upstream main grid for scenario s [\$].
$cost^{(DB/BP)}(s)$	Total cost of participating in DB/BP for scenario s [\$].
$cost^{ASMP}(s)$	Total cost of participating in ASMP for scenario s [\$].
$cost^{CL}(s)$	Total cost of mandatory curtailed loading for scenario s [\$].
$cost^{BESS}(s)$	Total cost of power charged/discharged between the MG and the BESS in scenario s [\$].
$cost^{PEV}(s)$	Total cost of power charged/discharged between the MG and the PEV in scenario s [\$].
$cost^{SU}(i,t,s)$	Cost of startup and shut-down of i -th DG in time period t for scenario s [\$].
$cost^{Gen}(i,t,s)$	Cost of active power generated by i -th DG in time period t for scenario s [\$].
$P^{Gen}(i,t,s)$	Active power generated by i -th DG in time period t for scenario s [kW].
$P^{grid}(t,s)$	Active power exported/imported by upstream grid in time period t for scenario s [kW].
$L_{In}^{redu}(d,t,s)$	Amount of load reduction offered by d -th industrial consumer in time period t for scenario s [kW].
$L_{Com}^{redu}(c,t,s)$	Amount of load reduction offered by h -th residential consumer in time period t for scenario s [kW].
$L_{Com}^{redu}(c,t,s)$	Amount of load reduction offered by c -th commercial consumer in time period t for scenario s [kW].
$L_{In}^{res}(d,t,s)$	Amount of load reduced by d -th industrial consumer in ASMP in time period t for scenario s [kW].
$L_{Res}^{res}(h,t,s)$	Amount of load reduced by h -th residential consumer in ASMP in time period t for scenario s [kW].
$L_{Com}^{res}(c,t,s)$	Amount of load reduced by c -th commercial consumer in ASMP in time period t for scenario s [kW].
$P_{DG}^{res}(j,t,s)$	Amount of generation reduced by j -th DG in GR in time period t for scenario s [kW].
$ENS(t,s)$	Amount of demand unsupplied by MG in time period t for scenario s [kW].
$P_{ch}^{BESS}(t,s)$	Charging active power of BESS in time period t for scenario s [kW].
$P_{disch}^{BESS}(t,s)$	Discharging active power of BESS in time period t for scenario s [kW].
$T_{pollutant}$	Total contaminant emissions of MG

	[kg].
$pollutant^{DG}(s)$	Total contaminant emissions of DGs for scenario s [kg].
$pollutant^{grid}(s)$	Total contaminant emissions of upstream grid for scenario s [kg].
$SOC(t,s)$	SOC of BESS in time period t for scenario s [kW].
$g_i(x)$	i -th objective function.
$P^{Gen}(PV,t,s)$	Active power generated by PV in time period t for scenario s [kW].
$P^{Gen}(WT,t,s)$	Active power generated by WT in time period t for scenario s [kW].
$P_{PEV.G2V}(t,s)$	Charging power of PEV battery in time period t for scenario s [kW].
$P_{PEV.V2G}(t,s)$	Discharging power of PEV battery in time period t for scenario s [kW].
$q_{PEV}(t,s)$	PEV battery energy in time period t for scenario s [kWh].

Parameters

$\rho(s)$	The probability of occurrence of scenario s .
$B^{BESS}(t)$	Price of charging/discharging power of BESS in time period t [\$/kW].
$B^{PEV}(t)$	Price of charging/discharging power of PEV in time period t [\$/kW].
η^{disch}	BESS efficiency in discharging mode.
$voll(t)$	Cost of unsupplied demand in time period t [\$/kW].
$Price_{DG}^{res}(t)$	Price proposed by DGs to contribute in GR in time period t [\$/kW].
$B^{Gen}(i,t)$	Price of active power generated by i -th DG in time period t [\$/kW].
$cost^{Start}(i,t)$	Price of startup and shut-down of i -th DG in time period t [\$/action].
η_{ch}	BESS efficiency in charging mode.
$E^{Gen}(i,t)$	Contaminant emissions generated by i -th DG in time period t [kg/kW].
$E^{grid}(t)$	Contaminant emissions generated by upstream grid in time period t [kg/kW].
$E_{CO2}^{DG}(i,t)$	CO ₂ scattered by i -th DG in time period t [kg/kW].
$E_{SO2}^{DG}(i,t)$	SO ₂ scattered by i -th DG in time period t [kg/kW].
$E_{NOx}^{DG}(i,t)$	NO _x scattered by i -th DG in time period t [kg/kW].
$E_{CO2}^{grid}(i,t)$	CO ₂ scattered by main grid in time period t [kg/kW].
$E_{SO2}^{grid}(i,t)$	SO ₂ scattered by main grid in time period t [kg/kW].
$E_{NOx}^{grid}(i,t)$	NO _x scattered by main grid in time period t [kg/kW].
$B^{grid}(t)$	Electricity price of upstream main grid in time period t [\$/kW].
$Price_{In}^{redu}(t)$	Price proposed by industrial consumers for DB/BP in time period t [\$/kW].

$Price_{Res}^{redu}(t)$	Price proposed by residential consumers for DB/BP in time period t [\$/kW].
$Price_{Com}^{redu}(t)$	Price proposed by commercial consumers for DB/BP in time period t [\$/kW].
$Price_{In}^{res}(t)$	Price proposed by industrial consumers to contribute in ASMP in time period t [\$/kW].
$Price_{Res}^{res}(t)$	Price proposed by residential consumers to contribute in ASMP in time period t [\$/kW].
$Price_{Com}^{res}(t)$	Offered price by commercial consumers to contribute in ASMP in time period t [\$/kW].
$D(t)$	Total electric demand of MG in period t [kW].
$P_{min}^{Gen}(i)$	Minimum limit of active power for i -th DG [kW].
$P_{max}^{Gen}(i)$	Maximum limit active power for i -th DG [kW].
$UR(i)$	Limit of ramp up rate for i -th DG [kW/h].
$DR(i)$	Limit of ramp down rate for i -th DG [kW/h].
Δt	Time interval [h].
SOC_{max}	Maximum SOC for BESS [kW].
SOC_{min}	Minimum SOC for BESS [kW].
$P_{dch}^{max}(t)$	Maximum limit to discharge BESS in time period t [kW].
$P_{ch}^{max}(t)$	Maximum limit to charge BESS in time period t [kW].
$P_{forecast}^{PV}(t)$	Forecasted output of PV in time period t [kW].
$P_{forecast}^{WT}(t)$	Forecasted output of WT in time period t [kW].
ϵ	Positive constant of AUGMECON $\in [10^{-6} 10^{-3}]$.
e_j	Equality constraint parameter.
s_j	Surplus variables of the j -th constraint.
$grid_j$	Number of grid points of objective.
$Iter_j$	Parameter of iteration.
$Range_j$	Range of objective function.
UB_j	Upper bound of objective.
$P_{PEV,G2V}^{max}$	Maximum charge rate of PEV battery [kW].
$P_{PEV,V2G}^{max}$	Maximum discharge rate of PEV battery [kW].
$P_{PEV,G2V}^{min}$	Minimum charge rate of PEV battery [kW].
$P_{PEV,V2G}^{min}$	Minimum discharge rate of PEV battery [kW].
q_{PEV}^{min}	Minimum limit of energy stored by PHEV battery [kWh].
q_{PEV}^{max}	Maximum limit of energy stored by PHEV battery [kWh].
t_a	PEV arrival time.
t_d	PEV departure time.

η_{G2V}	Charging efficiency of PEV.
η_{V2G}	Discharging efficiency of PEV.
Abbreviations	
ASMP	Ancillary Services Market Program.
AUGMECON	Augmented Epsilon Constraint Method.
AMFA	Adaptive Modified Firefly Algorithm.
AMPSO	Adaptive Modified Particle Swarm Optimization.
BESS	Battery Energy Storage System.
CQGA	Chaotic Quantum Genetic Algorithm.
DB/BP	Demand bidding/buyback program.
DER	Distributed Energy Resource.
DiG	Diesel Generator.
DG	Distributed Generation.
DSM	Demand Side Management.
DR	Demand Response.
ESS	Energy Storage System.
BESS	Battery Energy Storage System.
EMS	Energy Management System.
EED	Environmental/Economic Dispatch.
GR	Generation Reserve.
GSA	Gravitational Search Algorithm.
IB-DR	Incentive-Based DR.
MG	Microgrid.
MACO	Multi-layer Ant Colony Optimization.
GA	Genetic Algorithm.
MILP	Mixed-Integer Linear Programming.
MOCPSO	Multi-Objective Chaotic Particle Swarm Optimization.
MOPSO	Multi-Objective Particle Swarm Optimization.
MOO	Multi Objective Optimization.
MT	Micro Turbine.
MOP	Multi Objective Problem.
MGO	Microgrid Operator.
NBI	Normal Boundary Intersection.
PB	Price-based DR.
PEV	Plug in Electric Vehicle.
PSO	Particle Swarm Optimization.
PAFC	Phosphoric Acid Fuel Cell.
PV	Photovoltaic.
PEV	Plug in Electric Vehicle.
QP	Quadratic Programming.
RES	Renewable Energy Sources.
SOC	State of Charge.
SOP	Single Objective Problem.
ToU	Time of Use.
UC	Unit Commitment.
WT	Wind Turbine.

1 Introduction

1.1 Motivation and Incitement

MICROGRIDS with small-scale renewable energy based DGs has been a capable solution to face with environmental and economic issues of conventional electrical power generation [1]. The

advantages of MGs in terms of efficiency, reliability, power quality, losses, and environmental factors have been investigated in literature [2]. Yet, assimilation of MGs into traditional power system grid results in several challenging issues that have been the topic of many researches [3]. There is an EMS at the core of MGs, with the responsibility to control and manage the overall operations. EMS aims to improve grid security and reliability, especially during contingencies and peak hours of electrical demands, while saving the energy and reducing the generation and operational costs by controlling the electrical power transfer between MG and upstream main grid with respect to market policies. EMS determines optimal generation scheduling and UC of DGs, while manages the uncertainties that exist in renewable sources, generation and demand by using ESSs [4-11].

1.2 Literature Review

Various methods have been proposed for energy scheduling of MG, which are formulated as the optimization of single or multi-objective functions. In single objective optimal scheduling of MG, the operational cost is reduced, whereas the multi-objective optimal MG scheduling aims the minimization of both the operational cost and emissions. In [12], the minimization of operational cost and optimal scheduling of BEES are carried out by a model predictive controller. It doesn't consider the stochastic pattern of renewable generations and it doesn't give a role to DR programs in EMS. In [13], a single-objective AMFA is developed for optimal management of MGs to minimize operational cost, with and without uncertainties. In [14] an alternative algorithm is proposed based on MACO for energy scheduling in MGs that minimizes the cost of electrical power generation by day-ahead energy scheduling. In [15], the day-ahead energy scheduling of MG is presented that is based on reconfiguration of MG and UC. In [16], a GA-based method was proposed to minimize the generation cost with respect to the energy and power capacities of the storage system.

In order to enhance the efficacy of MGs, consideration of the environmental pollutions is also essential. In [17], an NBI technique is suggested to optimal schedule DGs in an MG for minimization of the total generation cost and greenhouse gasses, simultaneously. In [18], an alternative approach is proposed based on CQGA for optimal energy management of MGs considering several operational factors including operational and maintenance costs and emissions. In [19], a new algorithm based on a combined PSO and QP is presented to determine the optimal sizing of DGs as well as optimal energy management of MG. In [20], the GSA method is proposed to decrease the greenhouse gasses and fuel cost of the MG which consists of conventional generation units and WTs. In [21], a MOCPSO algorithm is extended for solving the EED

problem taking into consideration the technical, economic, and environmental concerns. In [22], the energy management of the MG equipped by RESs is performed by a multi-objective AMPSO algorithm. In [23] DSM is addressed by using a multi-objective optimal energy management strategy developed by a MOPSO algorithm. By using a MILP model, in [24] a generic optimization framework is presented to elucidate a single or multi objective optimal scheduling problem in MGs. In [25], optimal energy management of the MG is carried out using a MILP model by taking into consideration stochastic pattern of generation, electrical demand, and thermal demand. It combines the rolling horizon and stochastic programming to formulate the proposed problem. Reference [26] presents a stochastic MOP which is solved by a mathematical optimizer to minimize operation cost and emissions in MGs considering the DR program. The uncertainty of electrical demand and WS is considered in the modelling. In [27], the minimization operation cost of the MG is formulated as a stochastic SOP which is solved by an analytical solver. Moreover, the stochastic behavior of wind speed and solar radiation is included in the formulation. Authors in [28] proposes a deterministic MOP which is solved by a heuristic optimizer. The aim of optimization is to simultaneously minimize operation cost and emissions in MGs. The references [29-32] present the stochastic SOP which involves minimizing the operation cost of the MG. Table 1 shows the details of formulation and optimizer for these references. The authors of [22] solve their proposed model by means of a hybrid algorithm named FSAPSO [33] and simulation results demonstrates the efficiency of the proposed algorithm. Reference [34] proposes a stochastic model for optimal energy management with the goal of minimization of cost and emission. In this model, the uncertainties related to electrical demand, WS, and SR are modeled by a scenario-based stochastic programming.

Regarding DR programs, there are different approaches available in the literature [23]. For example, IB-DR can be classified as Direct Control, Demand bidding/buyback programs, Ancillary Service Market, Emergency DR, and Capacity Market. On the other hand, PB-DR programs can be classified as TOU, Critical Peak Pricing, and Real Time Pricing. Among available DR programs, we have chosen two types of IB-DR and one type of PB-DR programs to be included in our method because of their popularity in literature works. They are as follows:

- **DB/BP (IB-DR):** this type of program encourages the consumers to bid load reductions at a price at which they are ready to be curtailed.
- **ASMP (IB-DR):** In this type of program, customers can offer load reduction as reserve capacity of the system. If their bids are accepted, they are paid at the reserve price for their participation in the reserve. If their load reductions

are needed, they are called by the MGO and are also paid at their accepted offer price for load reduction.

- **TOU (PB-DR):** In this type of program, there is a multi-tariff system with peak period pricing. Customers have a tendency to use electrical power at lower tariff hours in order to reduce their electricity bill.

The studies that are performed for simultaneous energy management of MG can be classified from different perspectives, including the type of formulation, the selected objective functions, considering the uncertainty in the formulation, solving method, type of DR program and etc. Table 1 lists the recent references regarding the above-mentioned perspectives.

1.3 Contributions and Organization

In the present work, the MG energy management is applied while taking into account several types of DERs in order to supply electrical loads at minimum operating cost and emissions. As demonstrated in Table 1, the present study compared to other studies has used various technologies of DERs in the MG energy management. The aforementioned resources are composed of WT, PV, MT, PAFC, BESS, and PEVs. With respect to Table 1, the majority of studies have not addressed joint generation reserve (GR) scheduling and DR; Nonetheless, in this study, these features are

simultaneously considered to efficiently manage the MG. Also, three types of DR program are considered in the proposed model. Besides, a stochastic MOP is formulated to simultaneously minimize the operational cost and emissions of MG. The proposed MOP is solved by AUGMECON method.

The main contribution of the proposed energy management framework is as follows:

- Proposing a scenario-based stochastic integrated model considering the wide range of DERs that are dispatchable/non- dispatchable DGs and ESSs.
- Considering the IB-DR and PB-DR programs and GR scheduling simultaneous in EMS.
- Considering the BESS and PEVs simultaneous as two ESSs to enhance flexibility of proposed EMS.
- Comparing the AUGMECON and weighted sum as two methods for solving proposed model.
- Evaluating role of the initial SOC in operating cost and emissions of the proposed EMS.

The organization of presented paper is expressed as follows. Section 2, defines and formulates the multi-objective EMS problem that is addressed in this paper. In Section 3, a method is developed based on AUGMECON that solves the problem. The efficacy of the presented AUGMECON EMS method is evaluated by Section 4, and Section 5 states the conclusions.

Table 1 Literature works related to MG energy management.

Reference No.	Formulation Type		Objective function		Uncertainty			Solution method		Type of DR			DER						
	Stochastic	Deterministic	Operation Cost	Emissions	Demand	WS	SR	Mathematical	Heuristic	PB	IB	GR	WT	PV	PAFC	MT	DiG	BESS	PEV
[35]	✓	-	✓	✓	-	-	-	✓	-	-	-	✓	-	✓	✓	-	-	✓	-
[12]	-	-	✓	-	-	✓	-	✓	-	-	-	✓	-	-	-	-	-	-	-
[13]	✓	-	✓	-	-	✓	✓	-	✓	-	-	✓	✓	✓	-	-	-	✓	-
[14]	-	✓	✓	-	-	-	-	-	✓	-	✓	-	✓	-	-	✓	-	-	-
[15]	✓	-	✓	-	-	✓	-	-	✓	-	-	✓	-	-	-	-	-	-	-
[16]	-	✓	✓	-	-	-	-	✓	-	-	-	✓	-	-	-	-	-	-	-
[17]	-	✓	✓	✓	-	-	-	✓	-	-	-	✓	-	-	-	-	-	-	-
[18]	-	✓	✓	✓	-	-	-	-	✓	-	-	✓	-	-	-	-	-	-	-
[19]	✓	-	✓	-	-	✓	-	-	✓	-	-	✓	-	-	-	-	-	-	-
[20]	-	✓	✓	✓	-	-	-	-	✓	-	-	✓	-	-	-	-	-	-	-
[21]	-	✓	✓	✓	-	-	-	-	✓	-	-	-	-	-	-	-	-	-	-
[22]	-	✓	✓	✓	-	-	-	-	✓	-	-	✓	-	-	-	-	-	-	-
[23]	-	✓	✓	✓	-	-	-	-	✓	-	-	-	✓	-	-	-	-	-	-
[26]	✓	-	✓	✓	✓	✓	-	✓	-	-	-	✓	✓	✓	-	-	✓	-	-
[27]	✓	-	✓	-	-	✓	✓	✓	-	-	✓	✓	✓	-	-	-	✓	✓	-
[28]	-	✓	✓	✓	-	-	-	-	✓	-	-	✓	✓	✓	-	-	-	✓	-
[29]	✓	-	✓	-	-	✓	✓	✓	✓	-	✓	-	✓	✓	✓	-	-	✓	-
[30]	✓	-	✓	-	-	-	✓	✓	✓	-	-	✓	✓	✓	-	-	-	✓	-
[31]	✓	-	✓	-	-	-	✓	✓	✓	-	-	-	✓	✓	-	-	✓	✓	-
[32]	✓	-	✓	-	-	✓	✓	✓	✓	-	-	-	✓	✓	-	-	-	✓	-
[33]	-	✓	✓	✓	-	-	-	-	✓	-	-	-	✓	✓	✓	-	-	✓	-
[34]	✓	-	✓	✓	✓	✓	✓	✓	-	✓	-	-	✓	✓	✓	-	-	✓	-
Current paper	✓	-	✓	✓	✓	✓	✓	✓	-	✓	✓	✓	✓	✓	✓	-	-	✓	✓

2 Problem Formulation

The EMS in a MG aims to optimally control UC of generation units, dispatch of generated energy, scheduling charging/discharging of BESS and EVs, and importing/exporting active power between MG and the upstream main grid, with respect to the given single or multi-objective cost function and constraints, during a given time duration. In this paper, the following standard assumptions are made:

- The MGO is allowed to access 24 hours a day-ahead price of the electrical energy market as well as the average greenhouse gasses produced by the generation units in the period of the next 24 hours.
- The scheduling of electrical energy is carried out by MGO which procurements its energy necessities from the upstream grid.

2.1 Objective Functions

Both the operational cost and environmental pollutions are minimized in the proposed EMS.

2.1.1 Operational Cost

The total operational cost of the MG for the time horizon of scheduling is formulated as follows:

$$\begin{aligned} \text{Min } g_1 &= T_{\text{cost}} \\ &= \sum_{s \in S} \rho(s) \times \left[\text{cost}^{DG}(s) + \text{cost}^{grid}(s) \right. \\ &\quad + \text{cost}^{DB/BP}(s) + \text{cost}^{ASMP}(s) \\ &\quad + \text{cost}^{CL}(s) + \text{cost}^{BESS}(s) \\ &\quad \left. + \text{cost}^{PEV}(s) \right] \quad \forall s \in S \end{aligned} \quad (1)$$

where,

$$\text{cost}^{DG}(s) = \sum_{t \in T} \sum_{i \in N} \left[\text{cost}^{SU}(i,t,s) + \text{cost}^{Gen}(i,t,s) \right] \quad \forall s \in S \quad (2)$$

$$\text{cost}^{Gen}(i,t,s) = u(i,t,s) \times P^{Gen}(i,t,s) \times B^{Gen}(i,t) \quad \forall i \in N, \forall t \in T, \forall s \in S \quad (3)$$

$$\text{cost}^{SU}(i,t,s) = \text{cost}^{Start}(i,t) \times (u(i,t,s) - u(i-1,t,s)) \quad \forall i \in N, \forall t \in T, \forall s \in S \quad (4)$$

Regarding the electricity price in the market, the cost of transferring the electrical power between the MG and the upstream main grid is expressed as follows:

$$\text{cost}^{grid}(s) = \sum_{t \in T} P^{grid}(t,s) \times B^{grid}(t) \quad \forall s \in S \quad (5)$$

The cost of implementation of DP/BP in EMS is formulated as follows:

$$\text{cost}^{DB/BP}(s) = \sum_{t \in T} \left[\sum_{d \in I} L_{In}^{redu}(d,t,s) \times Price_{In}^{redu}(t) \right. \\ \left. + \sum_{h \in R} L_{Res}^{redu}(h,t,s) \times Price_{Res}^{redu}(t) \right. \\ \left. + \sum_{c \in C} L_{Com}^{redu}(c,t,s) \times Price_{Com}^{redu}(t) \right] \quad \forall s \in S \quad (6)$$

The total expected ASMP cost is given by:

$$\begin{aligned} \text{cost}^{ASMP}(s) &= \sum_{t \in T} \left[\sum_{d \in I} L_{In}^{res}(d,t,s) \times Price_{In}^{res}(t) \right. \\ &\quad + \sum_{h \in R} L_{Res}^{res}(h,t) \times Price_{Res}^{res}(t) \\ &\quad + \sum_{c \in C} L_{Com}^{res}(c,t) \times Price_{Com}^{res}(t) \\ &\quad \left. + \sum_{j \in N_r} P_{DG}^{res}(j,t) \times Price_{DG}^{res}(t) \right] \quad \forall s \in S \end{aligned} \quad (7)$$

The penalty that MGO would confront in the event that it cannot supply all customers is the cost of required truncated load, which is given by

$$\text{cost}^{CL}(s) = \sum_{t \in T} ENS(t,s) \times voll(t) \quad \forall s \in S \quad (8)$$

The cost of transferring the electrical power between MG and BESS is formulated as follows:

$$\text{cost}^{BESS}(s) = \sum_{t \in T} \left[P_{ch}^{BESS}(t,s) - P_{disch}^{BESS}(t,s) \right] \times B^{BESS}(t) \quad \forall s \in S \quad (9)$$

2.1.2 Pollutant Emissions

One of the goals of the proposed EMS also is minimization of emissions, including NO_x, SO₂, and CO₂. The objective function corresponding to the pollutant emission is formulated as as:

$$\begin{aligned} \text{Min } g_2 &= T_{\text{pollutant}} \\ &= \sum_{s \in S} \rho(s) \times \left[\text{pollutant}^{DG}(s) + \text{pollutant}^{grid}(s) \right] \end{aligned} \quad (10)$$

where,

$$\text{pollutant}^{DG}(s) = \sum_{t \in T} \sum_{i \in N} \left[u(i,t,s) \times P^{Gen}(i,t,s) \times E^{Gen}(i,t) \right] \quad \forall s \in S \quad (11)$$

$$\text{pollutant}^{grid}(s) = \sum_{t \in T} \left[P^{grid}(t,s) \times E^{grid}(t) \right] \quad \forall s \in S \quad (12)$$

$$E^{Gen}(i,t) = E_{CO_2}^{DG}(i,t) + E_{SO_2}^{DG}(i,t) + E_{NO_x}^{DG}(i,t) \quad \forall i \in N, \forall t \in T \quad (13)$$

$$E^{grid}(i,t) = E_{CO_2}^{grid}(i,t) + E_{SO_2}^{grid}(i,t) + E_{NO_x}^{grid}(i,t) \quad \forall i \in N, \forall t \in T \quad (14)$$

2.2 Constraints

The several constraints are considered to the given multi-objective EMS problem.

2.2.1 Constraint of Power Balance

The constraint of the power balance in the MG assures the hourly power balance between loads, the sum of the output powers of all renewables, storage units, and the main grid, and is given by:

$$\sum_{i \in N} P^{Gen}(i.t.s) + P^{grid}(t.s) + \frac{1}{\eta_{disch}} \times P_{disch}^{BESS}(t.s) - \eta_{ch} \times P_{ch}^{BESS}(t.s) = D(t) - \sum_{d \in I} L_{In}^{redu}(d.t.s) + \sum_{h \in R} L_{Res}^{redu}(h.t.s) + \sum_{c \in C} L_{Com}^{redu}(c.t.s) \quad \forall t \in T, \forall s \in S \quad (15)$$

2.2.2 Constraint of Capacity of DGs

The output energy and GR of DGs have to be less than the limit of their maximum electrical power, as follows:

$$P_{min}^{Gen}(i) \times u(i.t.s) \leq P^{Gen}(i.t.s) \leq P_{max}^{Gen}(i) \times u(i.t.s) + P_{DG}^{res}(i.t.s) \quad \forall i \in N, \forall t \in T, \forall s \in S \quad (16)$$

2.2.3 Ramp Rate Limits of DGs

The limitation of the ramp up and ramp down rate of DGs are taken into account as follows:

$$\frac{P^{Gen}(i.t.s) - P^{Gen}(i.t-1.s)}{\Delta t} \leq UR(i) \quad \forall i \in N, \forall t \in T, \forall s \in S \quad (17)$$

$$\frac{P^{Gen}(i.t-1.s) - P^{Gen}(i.t.s)}{\Delta t} \leq DR(i) \quad \forall i \in N, \forall t \in T, \forall s \in S \quad (18)$$

2.2.4 Constraints of BESS

A constraint is applied to SOC of BESS. The battery SOC at time t is computed based on its SOC at t-1 and the amount of charge/discharge electrical power, as follows:

$$OC(t.s) = SOC(t-1.s) + \frac{1}{\eta_{disch}} \times P_{disch}^{BESS}(t.s) - \eta_{ch} \times P_{ch}^{BESS}(t.s) \quad \forall t \in T, \forall s \in S \quad (19)$$

The battery SOC must be within an acceptable interval.

$$SOC_{min} \leq SOC(t.s) \leq SOC_{max} \quad \forall t \in T, \forall s \in S \quad (20)$$

A maximum limit is also considered for battery charge

and discharge powers as follows:

$$0 \leq P_{disch}^{BESS}(t.s) \leq P_{dch}^{max}(t) \quad \forall t \in T, \forall s \in S \quad (21)$$

$$0 \leq P_{ch}^{BESS}(t.s) \leq P_{ch}^{max}(t) \quad \forall t \in T, \forall s \in S \quad (22)$$

2.2.5 Constraints of PEVs

As regards the electricity price in the wholesale market, the PEVs can contribute in electrical power generated/consumed in the MG in an economical way, so that the charging/discharging of them is performed at off-peak and on-peak hours, respectively. The following constraints manage the PEVs charging or grid to vehicle (G2V) and discharging or vehicle-to-grid (V2G) mechanisms. The $cost^{PEV}(s)$ in (1) is defined as follows:

$$cost^{PEV}(s) = \sum_{t \in T} [P_{PEV.G2V}(t.s) - P_{PEV.V2G}(t.s)] \times B^{PEV}(t) \quad \forall s \in S \quad (23)$$

The charging and discharging limits of PEV during each interval t are defined as follows:

$$\frac{P_{PEV.G2V}^{min}}{\eta_{G2V}} \cdot W_{G2V}(t.s) \cdot S_{trip}(t) \leq P_{PEV.G2V}(t.s) \leq \frac{P_{PEV.G2V}^{max}}{\eta_{G2V}} \cdot W_{G2V}(t.s) \cdot S_{trip}(t) \quad \forall t \in T, \forall s \in S \quad (24)$$

$$P_{PEV.V2G}^{min} \cdot \eta_{V2G} \cdot W_{V2G}(t.s) \cdot S_{trip}(t) \leq P_{PEV.V2G}(t.s) \leq P_{PEV.V2G}^{max} \cdot \eta_{V2G} \cdot W_{V2G}(t.s) \cdot S_{trip}(t) \quad \forall t \in T, \forall s \in S \quad (25)$$

The battery of PEV during each time interval t is charged or discharged. Therefore, the following constraint applies to optimization:

$$W_{G2V}(t.s) + W_{V2G}(t.s) \leq 1 \quad \forall t \in T, \forall s \in S \quad (26)$$

The owner of the vehicle has previously sent trip signal of $S_{trip}(t)$ to MGO. The status of the trip signal is one when the vehicle is parked and zero when it is driven.

The stored energy of PEV is bounded by the following the upper and lower limits:

$$q_{PEV}^{min} \leq q_{PEV}(t.s) \leq q_{PEV}^{max} \quad \forall t \in T, \forall s \in S \quad (27)$$

The stored energy of PEVs during time frame $t \geq 1$ is formulated as:

$$q_{PEV}(t.s) = q_{PEV}(t-1.s) + P_{PEV.G2V}(t.s) \Delta \eta_{G2V} \Delta t - \frac{P_{PEV.V2G}(t.s) \Delta t}{\eta_{V2G}} \geq 1 \quad \forall t \in T, \forall s \in S \quad (28)$$

For a cycle of scheduling, the stored energy of PEVs have to touch its initial value, the following limits can guarantee this assumption.

$$\eta_{G2V} \sum_{t=1}^{24} P_{PEV.G2V}(t.s) \Delta t = \frac{\sum_{t=1}^{24} P_{PEV.V2G}(t.s) \Delta t + q_{arrival}}{\eta_{V2G}} \quad \forall t \in T, \forall s \in S \quad (29)$$

To guarantees that stored energy of PEV is maximum at the departure time, the following constraint can be used.

$$q_{PEV}(t_d.s) = q_{PEV}^{max} \quad \forall t \in T, \forall s \in S \quad (30)$$

The stored electrical energy of PEV after a daily trip in time t_a is as follows:

$$q_{PEV}(t_a.s) = q_{arrival} \quad \forall t \in T, \forall s \in S \quad (31)$$

2.2.6 ASMP Constraint

ASMP constraint assures that the sum of industrial reserve, residential reserve, and commercial reserve is equal to or greater than a certain fraction of the total electrical demand per hour. Consequently, 10% of the total electrical load is considered for the ASMP, hence,

$$\sum_{d \in I} L_{In}^{res}(d.t.s) + \sum_{h \in R} L_{Res}^{res}(h.t.s) + \sum_{c \in C} L_{Com}^{res}(c.t.s) \geq 0.1 \times D(t) \quad \forall t \in T, \forall s \in S \quad (32)$$

2.2.7 GR Constraint

The GR constraint is modeled as the sum of the deviation active power of non-dispatchable DGs (PV and WT) from the forecasted values that it has to satisfy the following constraint.

$$\sum_{j \in N_r} P_{DG}^{res}(j.t.s) \geq (P^{Gen}(PV.t.s) - P_{forecast}^{PV}(t)) + (P^{Gen}(WT.t.s) - P_{forecast}^{WT}(t)) \quad \forall t \in T, \forall s \in S \quad (33)$$

3 Multi-Objective Optimization by Using AUGMECON Method

Notwithstanding the SOP can be optimized by optimizers, however, the objective functions in the MOP may not be simultaneously optimized by MOO. Therefore, the concept of a single optimal solution can be replaced by the most preferred solution in a Pareto optimality space. A Pareto optimal solution should its enhancement leads to worsen the performance of at least of the other objectives. A capable MOO technique can find these trade-off solutions due to prefer users and higher-level information [36].

Based on the above statements, the EMS MOO problem is given by:

$$\begin{aligned} \min_s & \quad (g_1(s) \cdot g_2(s)) \\ \text{subject to} & \quad (15)-(33) \end{aligned} \quad (34)$$

In this paper, the AUGMECON method is employed for solving (25). AUGMECON is a Pareto solution generation method introduced by Mavrotas in [37]. It is an improvement of the original ϵ -constraint method which is along with the weighting method one of the two most popular methods for generating representations of the Pareto front. As it is described in [37], the ϵ -constraint method has certain advantages in relation to the weighting method, especially in the presence of discrete variables (Mixed Integer or Pure Integer problems). It avoids the production of weakly Pareto optimal solutions and accelerates the whole process by avoiding redundant iterations. It solves the MOO problems by optimizing one of the objective functions while varying the others within a priori determined range. AUGMECON is a modified version of the epsilon constraint method [38] that is used in MOO. The efficiency of AUGMECON for applications has been demonstrated and compared with weighted summation in [38]. In this work, a fuzzy-based decision maker is applied to pick up the best solution.

3.1 AUGMECON Method

The AUGMECON method takes one of the objective function as the main, and considers the others as constraints. Subsequently, the MOO problem (34) is transferred into:

$$\arg_{x,s_2} \min \left(g_i(x) - \epsilon \sum_{\substack{j \in M \\ i \neq j}} s_j \right) \quad (35)$$

$$\text{subject to: } g_j(x) + s_j = e_j \quad \forall j \in M, j \neq i \quad (36)$$

where,

$$e_j = UB_j - \frac{(Iter_j \times Range_j)}{grid_j} \quad (37)$$

To define the range of the 2nd objective function, a $p \times p$ payoff table is provided by the lexicographic method [37]. Details of implementation of AUGMECON method are discussed in [36], and omitted due to the space limitation. In this study, the total operational cost is taken into consideration as the main objective function, and pollutant emission is addressed as a constraint.

3.2 Fuzzy-Based Method to Select the Best Compromised Solution

One of the set of Pareto solutions provided by the multi-objective algorithm can be a candidate for the final optimal solution of proposed MOP (25). However,

this paper selects the best compromised solution by a fuzzy-based method as follows [39]:

$$\mu_j^l = \frac{g_j^{max} - g_j^l}{g_j^{max} - g_j^{min}} \quad \forall l \in L, \forall j \in M \quad (38)$$

$$\mu^l = \frac{\sum_{j=1}^n \mu_j^l}{\sum_{l \in L} \sum_{j \in M} \mu_j^l} \quad \forall l \in L \quad (39)$$

$$opt = \{o | \mu^0 = \max(\mu^l)\} \quad (40)$$

Fig. 1 shows the flowchart of the proposed method.

4 Simulation Results

The proposed EMS is tested on the low voltage MG shown by Fig. 2. The PV, WT, PAFC, MT as DGs, and BESS and PEVs as ESSs are considered in the under study MG. Regarding Fig. 2, the MG supplies feeders that have two commercial and three residential consumers. It is assumed that all the DGs only generates active power. In addition, the under study MG is a grid-connected MG which exchanges the electrical power with the upstream main grid.

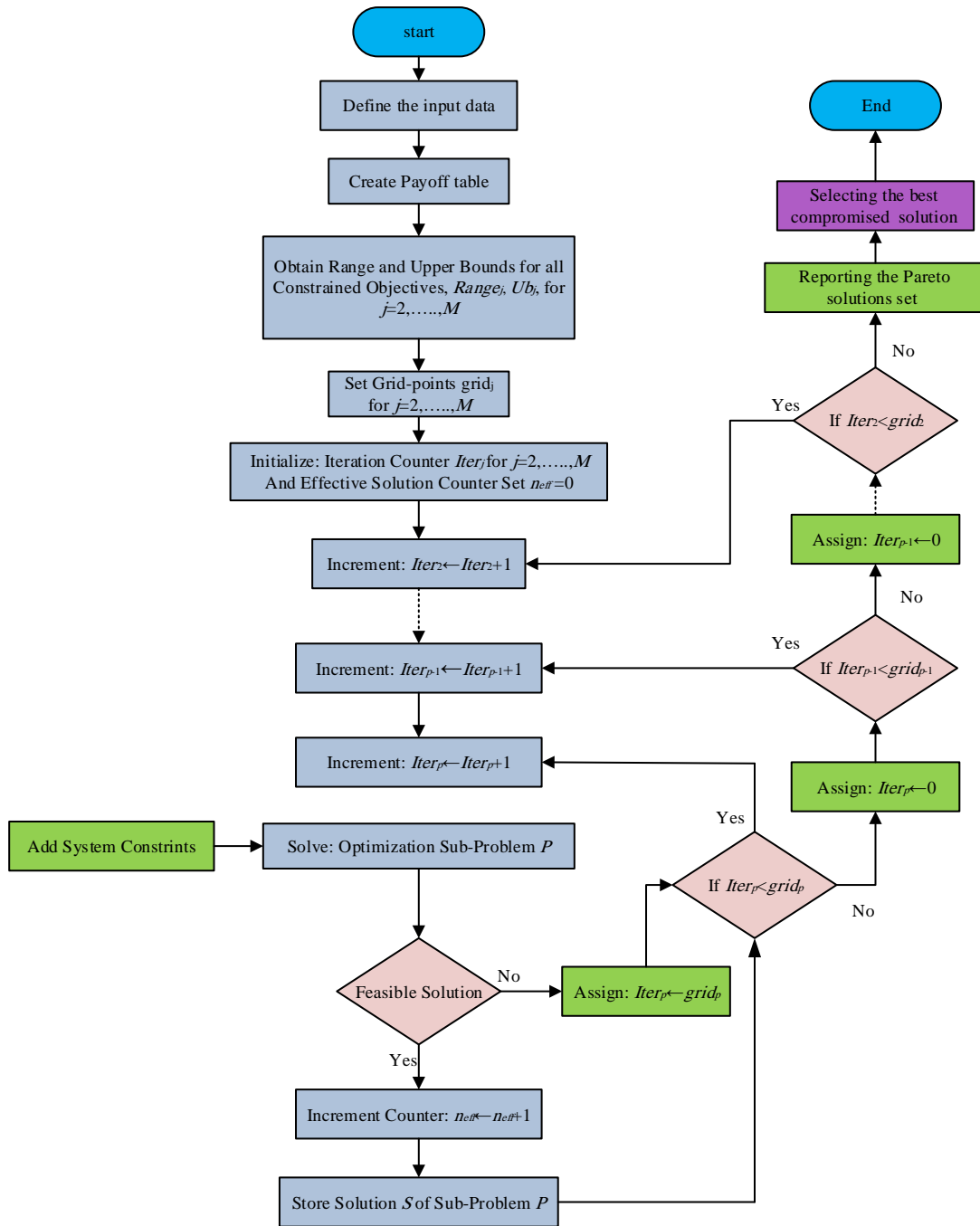


Fig. 1 Flowchart of the proposed method.

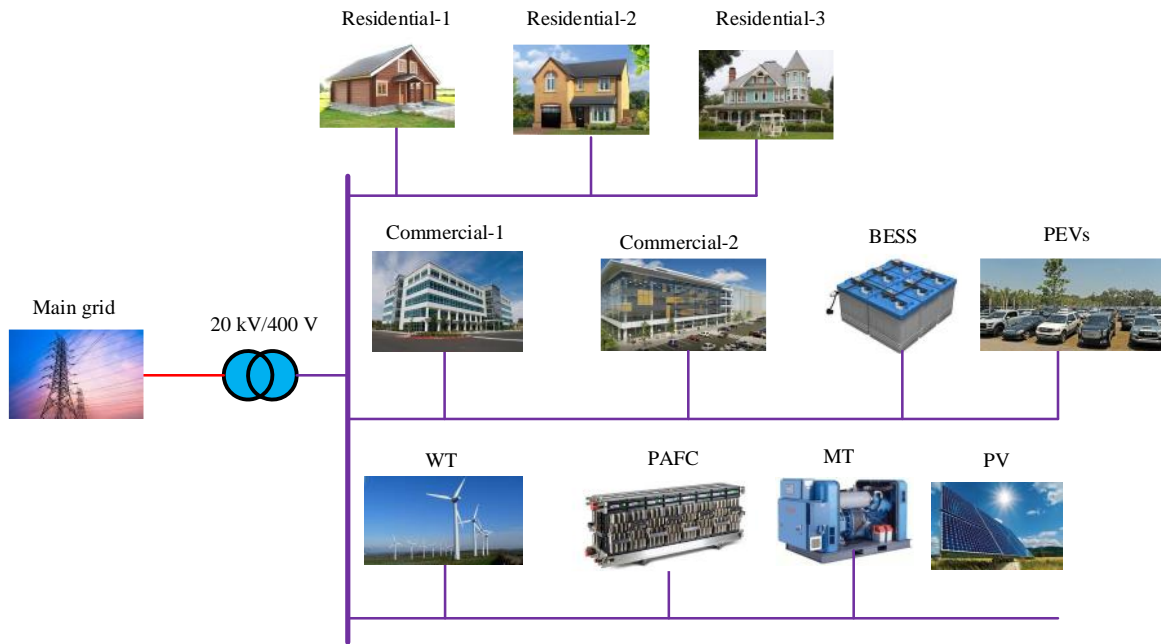


Fig. 2 The understudy microgrid.

Table 2 The specifications of DGs and BESS [19, 33].

Generation Unit	P_{min} [kW]	P_{max} [kW]	Startup/Shutdown cost [€ct]	CO ₂ [kg/MWh]	SO _x [kg/MWh]	NO _x [kg/MWh]	Bids [€ct/kWh]
MT	6	30	0.96	720	0.0036	0.1	0.457
PAFC	3	30	1.65	460	0.003	0.0075	0.294
PV	0	25	0	0	0	0	2.584
WT	0	15	0	0	0	0	1.073
BESS	-40	40	0	10	0.0002	0.001	0.38
Main grid	-30	30	0	49.037	0.4641	0.752	N/A

Table 3 Technical specifications of each PEV [38].

Parameter	Value	Unit
$q_{PEV}^{min}, q_{PEV}^{max}$	6, 20	[kWh]
η_{G2V}, η_{V2G}	94, 94	%
$P_{PEV,G2V}^{max}, P_{PEV,G2V}^{min}$	6, 0	[kW]
$P_{PEV,V2G}^{max}, P_{PEV,V2G}^{min}$	6, 0	[kW]
$q_{PEV}(0)$	8	[kWh]
$q_{arrival}$	10	[kWh]

The details of the features of the MG are found in [33].

The maximum and minimum capacity of BESS are 150kWh and 5kWh respectively. The charging and discharging processes are carried out at a rate of 30kW per hour and the efficiency of charging and discharging is 0.9. The commercial parking lot has space for 20

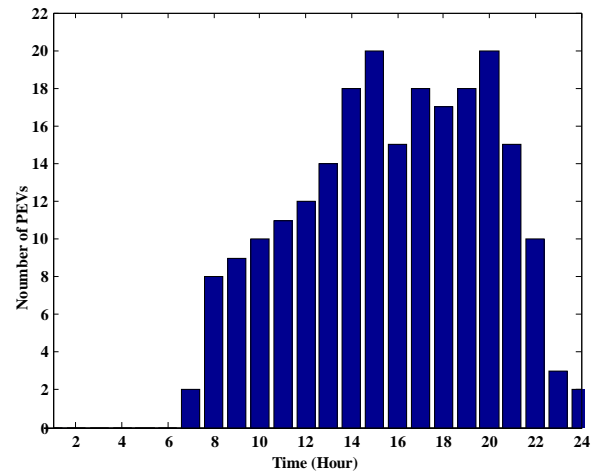


Fig. 3 Predicted number of PEVs in the commercial parking lot during the day ahead [38].

PEVs and due to the limitations, only 5 PEVs can be simultaneously charged/discharged. The details of features of DGs, and the BESS are shown in Table 2. Table 3 shows the specification of each PEV. Fig. 3 displays the predicted number of PEVs in the commercial parking lot during the day ahead.

The hourly prices of the electricity market during the

day ahead are illustrated in Fig. 4. Fig. 5 exemplifies the total electrical demand in day-ahead. It is worthwhile to note that the peck electricity price and electrical peak demand usually coincide each other, but the Fig. 4 and Fig. 5 do not show this fact. However, it can be noted that electricity price in the Fig. 4 is pertaining to the electricity market in the upstream grid and Fig. 5 shows the electrical demand of the local MG. Moreover, the electricity price in the upstream market depends on numerous factors such as type of generations participated in the energy market, climate condition in the wide geographical area, and etc. However, the electrical demanded by MG is only related to climate and patterns of consumer in the limited and local district. Therefore, these two curves should not necessarily have similar trends. Besides, the residential and commercial consumers offer the reduction rate of their demand for executing DB/BP as Figs. 6 and 7, respectively.

Four scenarios are considered to model the uncertainty of non-dispatchable units of WT and PV, as depicted in Figs. 6 and 7, respectively [40]. Consequently, the 16 scenarios for each hour and $16 \times 24 = 384$ scenarios in total are considered. This number of scenarios is usually

enough for operational problems such as our problem [2, 40]. It is worthwhile to note that it is possible to use a higher number of stochastic scenarios at the cost of higher computational burden. However, since the problem is operational, the problem should be solved in a reasonable time. To use a higher number of scenarios, it is enough to increase the number of elements in set S in (1) without any change in the formulation. Regarding [40], it is assumed that the probability of occurrence of scenarios is same equal to $(1/384)$ in this paper. The proposed model is implemented using the SCIP solver of GAMS 24.1 software on a computer that has a 2.4GHz processor and a 4GB memory.

In order to evaluate the proposed EMS, the several case studies are considered as follows:

4.1 Stochastic Energy Management of MG to Minimize Operational Cost and emissions (Worst Case Scenario)

The proposed EMS considers a BESS with the infinite capacity that has been studied in many of the references [13, 33, 34]. The infinite capacity of the

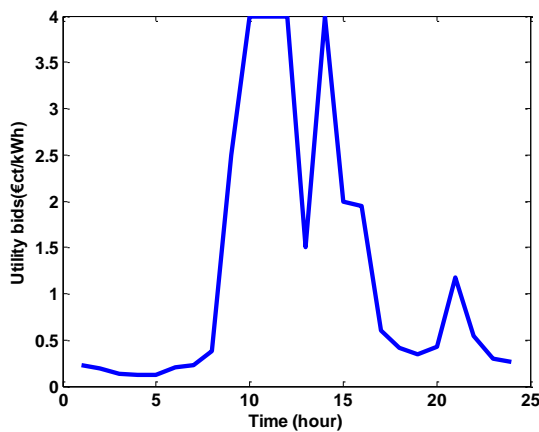


Fig. 4 The electricity price in the upstream grid [22, 33].

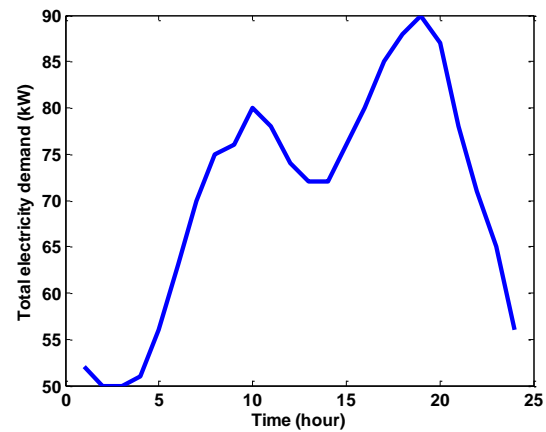


Fig. 5 The electrical demand of MG [22, 33].

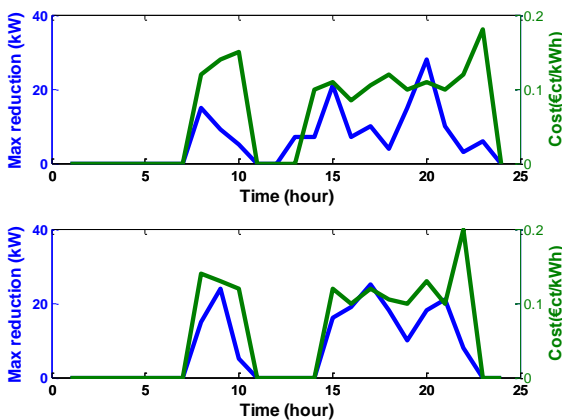


Fig. 6 The reduction rate of the electrical demand. Up: commercial 1, down: commercial 2.

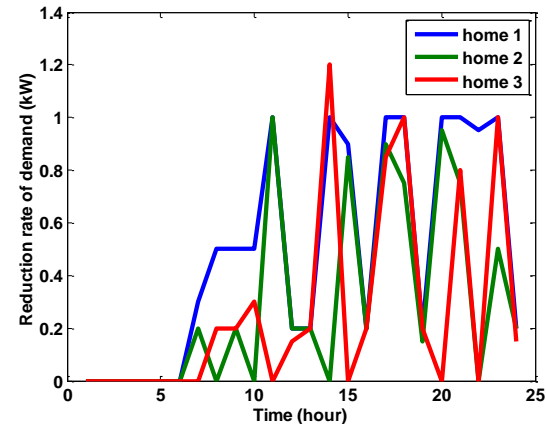


Fig. 7 The reduction rate of the electrical demand for residential consumers.

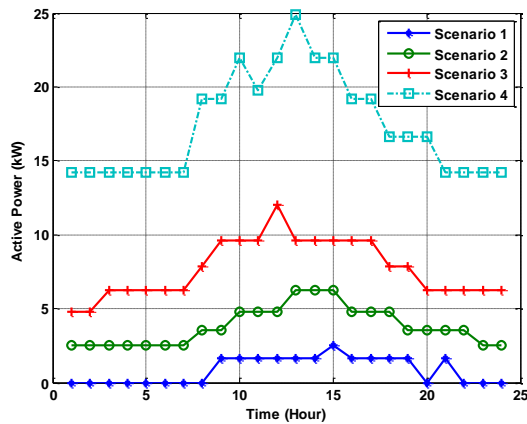


Fig. 8 The power generation of WT in different scenarios [2].

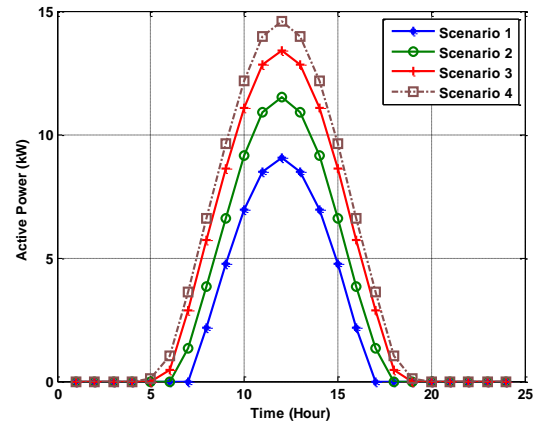


Fig. 9 The power generation of PV in different scenarios [2].

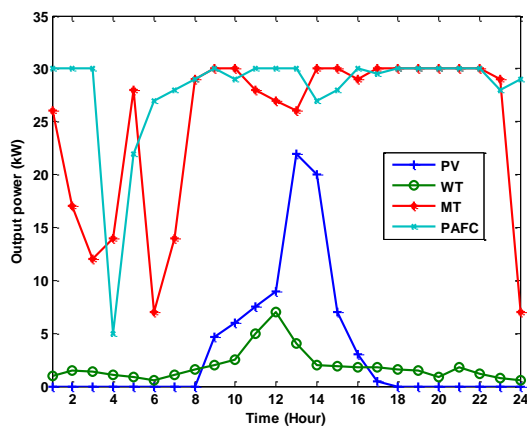


Fig. 10 The output power of DGs without DR (DB/BP).

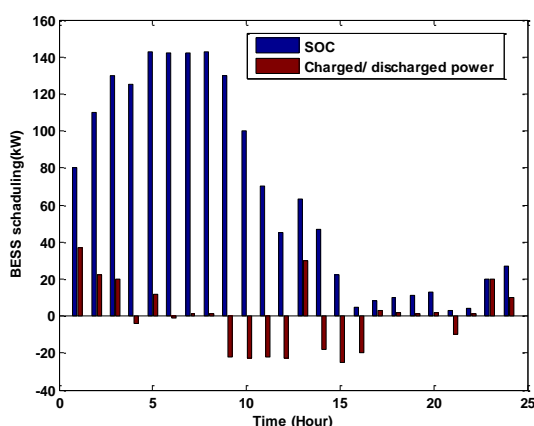


Fig. 11 The output power of BESS without DR (DB/BP).

BESS leads to simplifying the problem and decreasing the operational cost compared to a limited capacity BESS. The stochastic optimization has advantages over deterministic ones, because whenever the MGO is faced with one of the stochastic scenarios, he/she can optimally assign the requested electrical demand between the DGs and ESSs. Consequently, the stochastic scheduling avoids the burden of additional costs to the MGO when the PV and WT cannot generate the forecasted output power. To carry out simulations with considering uncertainties, the proposed EMS is run for the worst scenario at each hour. The worst scenario is happened when the generation of PV and WT have the highest negative deviation from its forecasted output. To evaluate efficacy of proposed EMS, two case studies are run that are only minimization of operational cost as an SOP and minimization of operational cost and greenhouse gases simultaneously as a MOP, respectively. Two case studies consider the GR, TOU, and ASMP. However, each case study is run for two scenarios that are with and without considering DB/BP.

Case 1: Minimizing Operational Cost

The optimal EMS is executed with and without considering DB/BP. Figs. 10-13 show the simulation results for hourly scheduling DGs, BESS, PEVs and GR

provided by dispatchable DGs, respectively, without taking into consideration DB/BP. It can be observed that all the requested electrical energy for charging BESS and PEVs are supplied by MT and PAFC. Therefore, a part of the output power of MT and PAFC should be used to charge BESS and PEVs and as a result, the MT and PAFC for all hours should be on.

The Fig. 14 shows the simulation results for hourly scheduling DGs with considering DB/BP. It can be observed that considering DB/BP for scheduling DGs, BESS, and PEVs causes the contribution of FC and MT to provide electrical energy are somewhat decreased compared to the previous simulation. Fig. 15 illustrates the hourly scheduling DB/BP. As this figure implies, the DR program contributes in optimal EMS in the high electrical energy price situation. Moreover, in the condition that the electricity price in the wholesale market is higher than the price offered by DGs, the electrical output power of DGs is managed to provide the electrical demands of MG, whereas the load reduction created by the DB/BP program is used to provide the GR.

Figs. 16 and 17 illustrate the hourly scheduling BESS, and PEVs with considering DR DB/BP. Fig. 16 shows that from 1th to 8th hours that the electricity price has low values, the BESS is charged. However, from 9th to

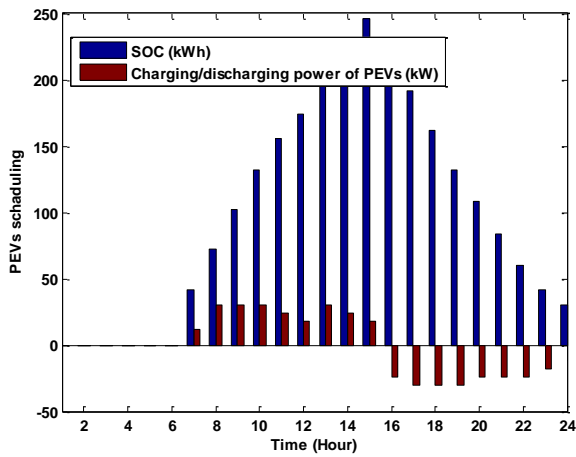


Fig. 12 The output power of PEVs without DR (DB/BP).

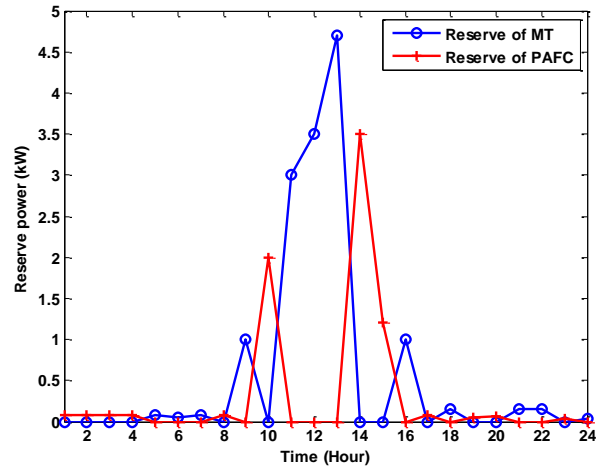


Fig. 13 The hourly GR of the non dispatchable DGs without DR (DB/BP).

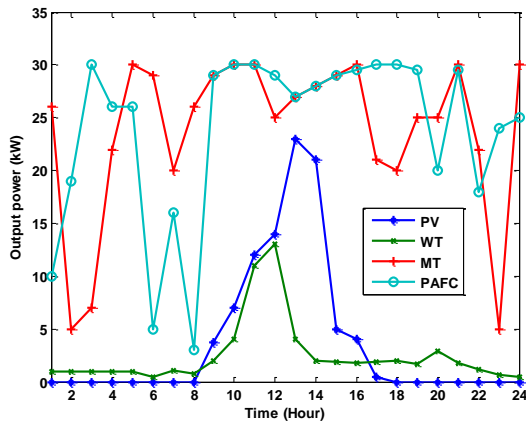


Fig. 14 The output power of PEVs without DR (DB/BP).

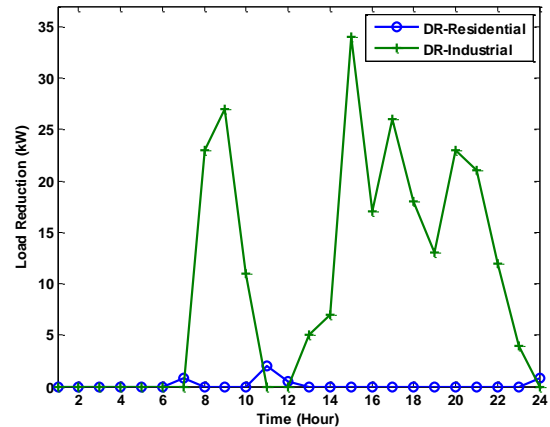


Fig. 15 The scheduled DR (DB/BP).

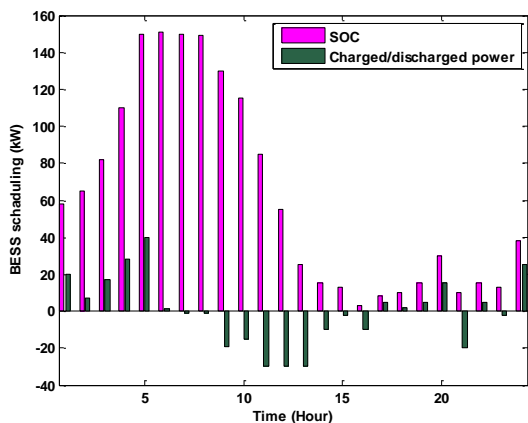


Fig. 16 The optimal BESS output power with DR (DB/BP).

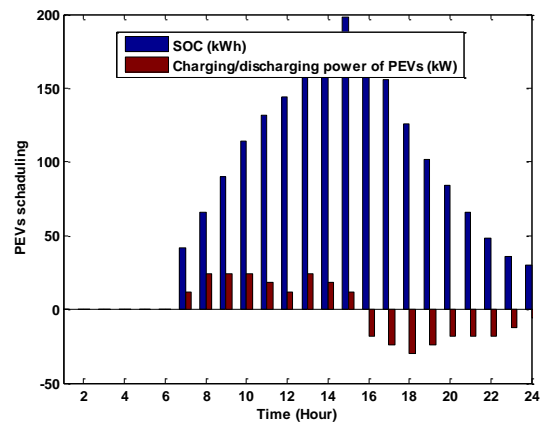


Fig. 17 The optimal PEVs electrical output power with DR (DB/BP).

16th and 21th hours, the BESS is discharged to cover electrical demands of MG due to high electricity price in the main grid. Fig. 17 displays the similar trend during hours that the PEVs are accessible by MGO. Fig. 18 illustrates the scheduling of GR for dispatchable DGs which takes into consideration the DB/BP. It can be observed that the electrical demand is supplied by the

MT while the electricity price is high. The load reduction initiated by DB/BP is used to provide reserve; accordingly, the income of DGs is improved.

Fig. 19 displays the transferred electrical power with upstream grid with/without taking into account DB/BP. As shown in this figure, performing DB/BP program alleviates the exchanged electrical power traded with

the upstream grid during some hours. Decreasing the imported electrical power happens for the hours which the electricity price of upstream grid is high; Accordingly, the electrical demand is reduced by the DB/BP program at those hours. In this figure, the imported electrical power from upstream main grid is considered as a positive value and the exported electrical power is a negative value. Hence, the MG exports more electrical power to upstream main grid from 9th to 16th and at 21th hours due to high electricity price in the upstream main grid. The MG imports less electrical power from the upstream main grid at 1th, 2th, 6th, and 17th, 18th, and 23th because of the low electricity price of upstream main grid. However, Fig. 19 depicts that the electrical power imported/exported to the

upstream main grid is reduced considering DB/BP program compared to without ones. Fig. 20 delineates the electrical demand profile. It can be observed that performing DB/BP program causes reducing the total electrical power demand and the peak of ones and consequently enhancing reliability in MG.

Table 4 depicts the operation costs of microgrid with/without considering DB/BP. It takes into account ASMP and GR. Regarding this table, executing DB/BP program reduces the total the operation costs of MG in comparison to without DB/BP. Fig. 21 displays the scheduled electrical power of MG with considering DB/BP. As regards this figure, the BESS is charged from 1st to 6th hours when the electricity has a lower price in the upstream grid and its discharging time is in

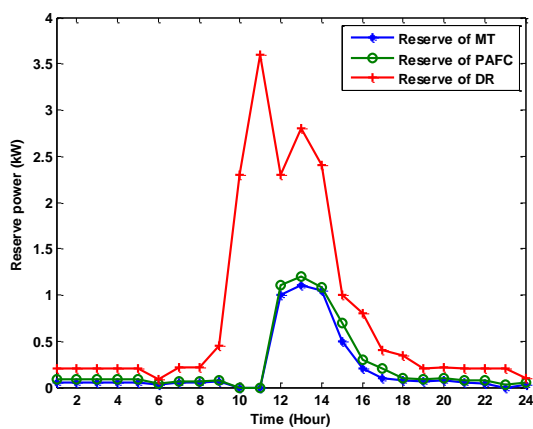


Fig. 18 The GR scheduling of the dispatchable DGs and DR program (ASMP).

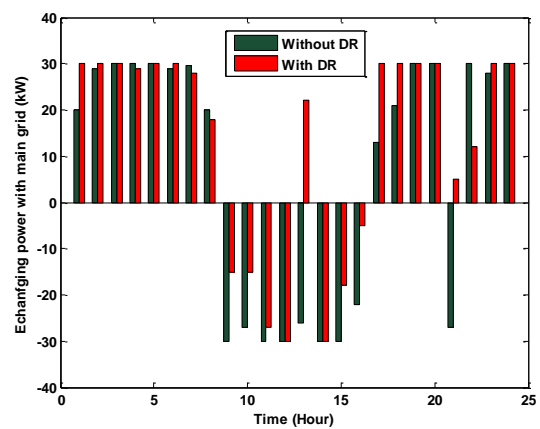


Fig. 19 The traded electrical power with upstream grid with/without DR (DB/BP).

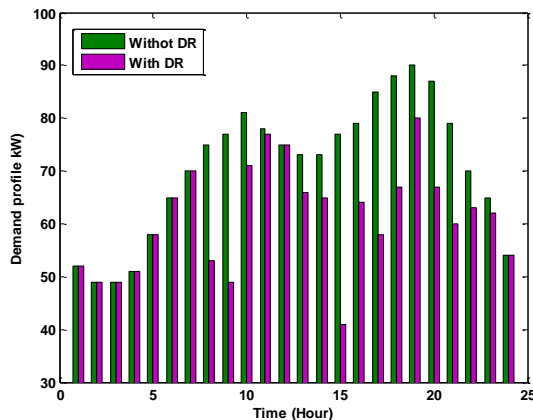


Fig. 20 The electrical demand with/without DR (DB/BP).

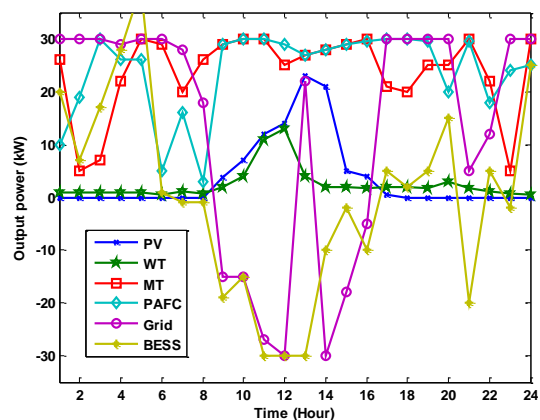


Fig. 21 The electrical output power to minimize the operation cost.

Table 4 The cost of operation of MG for with/without considering DR (DB/BP).

	Operation costs [€/day]	Generation of dispatchable DGs [kWh/day]	Total electrical demand [kWh/day]	Total electrical power imported/exported with upstream grid [kWh/day]
with GR and without DB/BP	437.24	1263.2	1695	302.76
with ASMP and without DB/BP	510.37	1191.3	1695	403.43
with GR and DB/BP	241.25	1188.3	1459.4	138.54
with ASMP and DB/BP	267.33	1281.7	1336.3	44.5

peak hours when the electricity price has higher values in the upstream market. Accordingly, the BESS alleviates the operation cost by generating electrical power at on peak hours. Besides, the WT and PV have the high generation of electrical power at each hour. Moreover, the PAFC generates more the electrical power than MT at all hours, due to having less operational cost.

Case 2: Minimizing Operational Cost and Emission as MOP

Here, the proposed problem is formulated as an MOP which is solved by the AUGMECON method and the simulation results are compared to weighted summation method presented by [38]. Fig. 22 depicts the resulted Pareto fronts acquired by both methods. For the weighted summation, the variation of w is from 0 to 1 with intervals of 0.02 and the resulted SOPs are calculated 77 times. Regarding Fig. 22(a), only 15 unique solutions are gathered as the Pareto front and repetitive solutions are ignored. Notwithstanding, to implement AUGMECON method, $Iter_j$ is equal to 77 and it is observed in Fig. 22(b) that 77 solutions are achieved and generate the Pareto front. Despite of having a convex model, it is seen that Pareto solutions are different. This is due to the fact that the proposed model is a MOP and solving MOP with different method even for convex problem can be lead to different results [38, 41].

Table 5 indicate the payoff table for the AUGMECON method.

Table 6 depicts the best compromised solution resulted through the decision maker.

In regard to Fig. 22(a), the more solutions achieved by the weighted sum method are repeated and therefore, they aren't considered in the final Pareto set; hence, the precise estimation of the shape of Pareto front is difficult as a result of no having sufficient solutions. To conclude, in spite of the computational complication, the MGO prefers using the AUGMECON method in comparison to the weighted sum. Regarding the simulation results of Table 6 and Pareto front in Fig. 22(b), it is seen that the optimal solution based fuzzy method is more suitable due to proximity the knee point for weighted sum and AUGMECON method. Consequently, AUGMECON method based on fuzzy method is used to obtain the best compromised solution in the rest of simulations. Also, Table. 6 shows that [33] has the less emission in comparison to other methods, while the it shows a higher cost. This is due to the fact that [33] uses a decision maker with the priority of emission reduction and the its best compromised solution has a low emission.

The energy management of the worst case scenario is shown in Table 7 as an MOP. The DR program has been considered in this simulation.

As regards the Table. 7, shutting down the some of DGs leads to reducing the operation cost of MG at some

hours. It is observed that the EMS turns off the FC at 6th and 18th hours. Besides, the BESS does not discharge at 3rd, 8th, 18th and 19th hours. Table. 8 shows the brief of results in comparison to the other algorithm.

4.2 Stochastic Energy Management of MG to Minimize Operation Cost and Emissions Considering BESS (Limited Initial SOC)

Two case studies are considered for MG energy

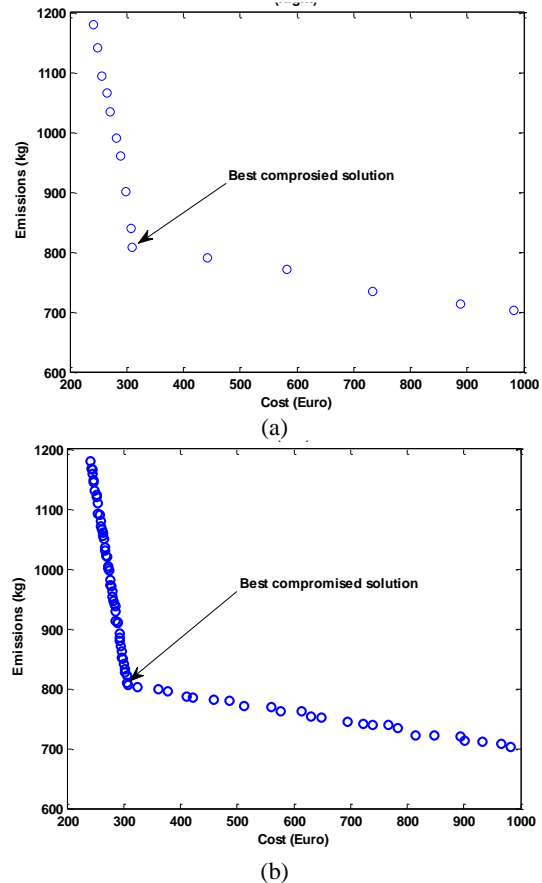


Fig. 22 The resulted Pareto front obtained through a) weighted sum and b) the AUGMECON methods.

Table 5 The boundaries of objective functions for AUGMECON method.

	Minimizing operation cost	Minimizing emissions
Operation cost (€/day)	243.36	988.34
Emissions (kg/day)	1221.12	713.34

Table 6 The best compromised solution for the worst-case scenario.

MOP Method	Best compromised solution
Weighted summation	Cost = 312.34 [€/day] Emission = 818.36 [kg/day]
AUGMECON	Cost = 307.23 [€/day] Emission = 815.56 [kg/day]
[33]	Cost = 735.15 [€/day] Emission = 440.41 [kg/day]

Table 7 MG energy management as MOP for AUGMECON method.

Time	Output Electrical Power							Total Demand [kW]	Status of Units							
	MT	PAFC	BESS	Grid	PV	WT	PEVs		MT	PAFC	BESS	Grid	PV	WT	PEVs	
1	8.5	26.84	-30	-45.32	0	1.34	0	6.68	52	1	1	1	1	0	1	0
2	8.3	27.35	-30	-43.01	0	1.34	0	6.99	50	1	1	1	1	0	1	0
3	30	21.35	0	2.69	0	1.34	0	52.69	50	1	1	0	1	0	1	0
4	30	6.24	-30	-43.42	0	1.34	0	7.58	51	1	1	1	1	0	1	0
5	0	27.28	-30	-57.38	0	1.34	0	-1.38	56	0	1	1	0	0	1	0
6	7.5	0	-30	-84.79	0	0.71	0	-21.79	63	1	0	1	1	0	1	0
7	7.78	13.32	-30	-89.64	0	1.26	-12	-19.64	70	1	1	1	1	0	1	1
8	14.50	30	0	-47.35	0.18	0.97	-18	27.65	75	1	1	0	1	1	1	1
9	12.47	30	-30	-89.71	2.24	1.58	-30	-13.71	76	1	1	1	0	1	1	1
10	22.37	21.08	30	-30.17	5.32	1.06	-30	49.83	80	1	1	1	0	1	1	1
11	30	18.97	30	5.02	8.43	7.62	-12	83.02	78	1	1	1	1	1	1	1
12	27.21	6.28	30	-3.34	10.96	8.21	-12	70.66	74	1	1	1	1	1	1	1
13	12.97	5.17	30	-31.01	20.88	1.97	-30	40.99	72	1	1	1	0	1	1	1
14	23.97	27.13	30	15.52	17.08	1.34	-12	87.52	72	1	1	1	1	1	1	1
15	24.21	15.82	30	-12.33	4.77	0.87	-12	63.67	76	1	1	1	0	1	1	1
16	27.02	11.71	30	9.90	2.76	0.41	18	89.9	80	1	1	1	1	1	1	1
17	11.32	9.21	30	-9.77	0.42	0.28	24	75.23	85	1	1	1	1	1	1	1
18	29.32	0	0	-27.81	0	0.87	30	60.19	88	1	0	1	1	1	1	1
19	30	29.44	0	-6.11	0	0.45	24	83.89	90	1	1	0	1	1	1	1
20	0	26.23	30	-11.98	0	0.785	18	75.015	87	0	1	1	1	1	1	1
21	29.21	18.34	30	18	0	0.45	18	96	78	1	1	1	0	1	1	1
22	0	30	-30	-52.67	0	0.33	18	18.33	71	0	1	1	1	1	1	1
23	5.52	2.54	-30	-74.23	0	0.71	12	-9.23	65	1	1	1	1	1	1	1
24	0	17.16	-30	-62.63	0	0.21	6	-6.63	56	0	1	1	1	1	1	1

* Total is composed of generations from MT, PAFC, PEVs, BESS, PV, and WT.

Table 8 MG energy management in two BESS initial SOC (5 and 150kWh).

Optimizer	Minimizing Operation Cost		Minimizing Emissions	
	5kWh	150kWh	5kWh	150kWh
Proposed Algorithm	Cost = 313.5315 [€] Emission = 792.0855 [kg]	Cost = 367.3735 [€] Emission = 701.0765 [kg]	Emission = 923.4695 [kg] Cost = 931.8077 [€]	Emission = 835.1330 [kg] Cost = 920.4294 [€]

management. In the first case study, Minimizing the operation cost and emissions are considered as separate objective functions and in the second case study, it is taken into consideration the MOP. It is assumed that the initial charging of BESS is limited. Because one of the most significant factor in the operation of BESS is the initial charging of BESS, which can affect the operation cost and emissions.

Case 1: Minimizing Operational Cost and Emission Separately as Single Objective Fitness Functions

At the 1st to 7th hours, while the upstream grid has a lower electricity price, the EMS commands purchasing the electricity from upstream grid and charging the BESS, instead of using the electricity generated by DGs in the MG., it is better to purchase electricity from the upstream grid and charging the BESS in the MG. However, when the main grid has the high price of electricity, the discharging BESS and selling the electrical power to upstream grid is preferable for MGO. The results of EMS for two BESS initial SOC that are 5 and 150kWh are displayed in Table 8. As the sole objective function is to minimize operational cost while the BESS initial SOC is 150kWh, the BESS is not charged in the morning and the operation cost is higher than other ones that is 5kW. However, when the

objective function is only minimization of emissions, these results are quite the opposite, so that the case of 150kW initially charging has the lowest operational cost. It is due to this fact that the emissions generated by main grid are higher than DGs and for supplying the demand of MG in the case of 150kW, the lowest electrical power is provided by upstream grid.

Case 2: Minimization of Operation Cost and Emission Simultaneously as MOP

In this case, the energy management is considered as the MOP. The results obtained in this subsection have trend similar to the previous section. As described in the previous section, so as to operate with lower cost, at the beginning of the day when the electricity price is low in upstream grid, the MGO has to purchase the electrical power from the upstream electricity market instead of DGs, and the initial charging of BESS must be held at the minimum capacity till it is charged by upstream grid. However, at the peak hours that upstream grid has the highest electricity price the BESS is discharged to supply the electrical demand of MG and the excess of ones is sold to the main grid. The simulation results of proposed modelling for a BESS with initial SOC 5 and 150kWh are displayed in Table 9, respectively.

Regarding the Table 9, to the economical operation

Table 9 The results of proposed method for a BESS with initial SOC 5 and 150kW.

Optimizer	Initial SOC = 5kWh	Initial SOC = 150kWh
Proposed Algorithm	Emission = 857.765 [kg] Cost = 622.8077 [€]	Cost = 643.537 [€] Emission = 768.086 [kg]

of MG, the BESS must have the lowest initial charging, i.e. 5kW, however, the maximum initial charging that is 150kW is better for reducing the emissions. By comparing the simulation results of Tables 8 and 9, it is observed that the limiting the initial charging of BESS cause raising the operational cost and emissions.

5 Conclusions

This paper proposes a day ahead EMS model considering stochastic generation patterns of non-dispatchable DGs for MGs. To enhance the flexibility of the EMS, this paper uses the ESSs that are BESS and PEVs. Moreover, the proposed model applies GR and three types of DR programs that are TOU, DB/BP, and ASMP. The proposed model is formulated as a MOP (operation cost and emission) which is solved by AUGMECON method. The simulation results show that considering the TOU, DB/BP, and ASMP alleviates the operational costs and emissions in the MG. Besides, relaxation of constraints of the initial SOC of the BESS can enhance the operation of MG in the viewpoint of cost and emissions aspects. The main achievements of the proposed model are given as follows:

- 1) The operational cost is reduced by 44.85% and 47.67% by considering the DB/BP and ASMP, respectively, compared to without them for SOP simulation.
- 2) The AUGMECON method decreases the operational cost by 1.6% and 58.23% in comparison to weighted sum and [33], respectively. However, this method reduces the emission by 0.3% compared with weighted sum and increase 46.3% in comparison to [33].
- 3) Limiting initial SOC of BESS to 5 kW and 150 kW increase the operational cost by 50.65% and 52.25%, respectively, compared with relaxation of these constraints. Besides, the emission increase by 4.9% for 5kW and reduces 5.7% for 150kW, whenever, these constraints are not considered in the EMS.

Some suggestions for future works can be expressed as 1) adding stochastic patterns of electrical demand and availability of the PEVs, 2) adding reliability indices and their cost to the problem, 3) considering CCHP as a dispatchable DG and thermal and cooling demands.

References

- [1] M. Sedighizadeh, M. Esmaili, A. Jamshidi, and M. H. Ghaderi, "Stochastic multi-objective economic-environmental energy and reserve scheduling of microgrids considering battery energy storage system," *International Journal of Electrical Power & Energy Systems*, Vol. 106, pp. 1–16, 2019.
- [2] M. Sedighizadeh, G. Shaghaghi-shahr, M. Esmaili, and M. R. Aghamohammadi, "Optimal distribution feeder reconfiguration and generation scheduling for microgrid day-ahead operation in the presence of electric vehicles considering uncertainties," *Journal of Energy Storage*, Vol. 21, pp. 58–71, 2019.
- [3] M. S. Mahmoud, S. Azher Hussain, and M. A. Abido, "Modeling and control of microgrid: An overview," *Journal of the Franklin Institute*, Vol. 351, No. 5, pp. 2822–2859, 2014.
- [4] P. Basak, S. Chowdhury, S. H. nee Dey, and S. Chowdhury, "A literature review on integration of distributed energy resources in the perspective of control, protection and stability of microgrid," *Renewable and Sustainable Energy Reviews*, Vol. 16, No. 8, pp. 5545–5556, 2012.
- [5] F. Farzan, S. Lahiri, M. Kleinberg, K. Gharieh, and M. Jafari, "Microgrids for fun and profit: The economics of installation investments and operations," *IEEE Power and Energy Magazine*, Vol. 11, No. 4, pp. 52–58, 2013.
- [6] A. H. Fathima and K. Palanisamy, "Optimization in microgrids with hybrid energy systems—A review," *Renewable and Sustainable Energy Reviews*, Vol. 45, pp. 431–446, 2015.
- [7] H. A. Mostafa, R. El Shatshat, and M. Salama, "A review on energy management systems," in *IEEE T&D Conference and Exposition*, pp. 1–5, 2014.
- [8] M. Sadeghi and M. Kalantar, "The analysis of the effects of clean technologies from economic point of view," *Journal of Cleaner Production*, Vol. 102, pp. 394–407, 2015.
- [9] B. Zhao, Y. Shi, X. Dong, W. Luan, and J. Bornemann, "Short-term operation scheduling in renewable-powered microgrids: A duality-based approach," *IEEE Transactions on Sustainable Energy*, Vol. 5, No. 1, pp. 209–217, 2014.
- [10] M. Sedighizadeh, M. Esmaili, and S. M. Mousavi-Taghiabadi, "Optimal energy and reserve scheduling for power systems considering frequency dynamics, energy storage systems and wind turbines," *Journal of Cleaner Production*, Vol. 228, pp. 341–358, 2019.
- [11] M. Sedighizadeh, M. Esmaili, and A. Eisapour-Moarref, "Voltage and frequency regulation in autonomous microgrids using Hybrid Big Bang-Big Crunch algorithm," *Applied Soft Computing*, Vol. 52, pp. 176–189, 2017.

- [12] I. Prodan and E. Zio, "A model predictive control framework for reliable microgrid energy management," *International Journal of Electrical Power & Energy Systems*, Vol. 61, pp. 399–409, 2014.
- [13] S. Mohammadi, S. Soleymani, and B. Mozafari, "Scenario-based stochastic operation management of microgrid including wind, photovoltaic, micro-turbine, fuel cell and energy storage devices," *International Journal of Electrical Power & Energy Systems*, Vol. 54, pp. 525–535, 2014.
- [14] M. Marzband, E. Yousefnejad, A. Sumper, and J. L. Domínguez-García, "Real time experimental implementation of optimum energy management system in standalone microgrid by using multi-layer ant colony optimization," *International Journal of Electrical Power & Energy Systems*, Vol. 75, pp. 265–274, 2016.
- [15] R. Jabbari-Sabet, S. M. Moghaddas-Tafreshi, and S. S. Mirhoseini, "Microgrid operation and management using probabilistic reconfiguration and unit commitment," *International Journal of Electrical Power & Energy Systems*, Vol. 75, pp. 328–336, 2016.
- [16] J. P. Fossati, A. Galarza, A. Martín-Villate, and L. Fontán, "A method for optimal sizing energy storage systems for microgrids," *Renewable Energy*, Vol. 77, pp. 539–549, 2015.
- [17] M. Izadbakhsh, M. Gandomkar, A. Rezvani, and A. Ahmadi, "Short-term resource scheduling of a renewable energy based micro grid," *Renewable Energy*, Vol. 75, pp. 598–606, 2015.
- [18] G. C. Liao, "Solve environmental economic dispatch of Smart MicroGrid containing distributed generation system—Using chaotic quantum genetic algorithm," *International Journal of Electrical Power & Energy Systems*, Vol. 43, No. 1, pp. 779–787, 2012.
- [19] M. H. Moradi and M. Eskandari, "A hybrid method for simultaneous optimization of DG capacity and operational strategy in microgrids considering uncertainty in electricity price forecasting," *Renewable Energy*, Vol. 68, pp. 697–714, 2014.
- [20] S. Mondal, A. Bhattacharya, and S. H. Nee Dey, "Multi-objective economic emission load dispatch solution using gravitational search algorithm and considering wind power penetration," *International Journal of Electrical Power & Energy Systems*, Vol. 44, No. 1, pp. 282–292, 2013.
- [21] J. Cai, X. Ma, Q. Li, L. Li, and H. Peng, "A multi-objective chaotic particle swarm optimization for environmental/economic dispatch," *Energy Conversion and Management*, Vol. 50, No. 5, pp. 1318–1325, 2009.
- [22] A. A. Moghaddam, A. Seifi, T. Niknam, and M. R. A. Pahlavani, "Multi-objective operation management of a renewable MG (micro-grid) with back-up micro-turbine/fuel cell/battery hybrid power source," *Energy*, Vol. 36, No. 11, pp. 6490–6507, 2011.
- [23] G. Aghajani, H. Shayanfar, and H. Shayeghi, "Presenting a multi-objective generation scheduling model for pricing demand response rate in micro-grid energy management," *Energy Conversion and Management*, Vol. 106, pp. 308–321, 2015.
- [24] N. E. Koltsaklis, M. Giannakakis, and M. C. Georgiadis, "Optimal energy planning and scheduling of microgrids," *Chemical Engineering Research and Design*, Vol. 131, pp. 318–332, 2018.
- [25] J. Silvente, G. M. Kopanos, V. Dua, and L. G. Papageorgiou, "A rolling horizon approach for optimal management of microgrids under stochastic uncertainty," *Chemical Engineering Research and Design*, Vol. 131, pp. 293–317, 2018.
- [26] A. Zakariazadeh, S. Jadid, and P. Siano, "Smart microgrid energy and reserve scheduling with demand response using stochastic optimization," *International Journal of Electrical Power & Energy Systems*, Vol. 63, pp. 523–533, 2014.
- [27] A. Zakariazadeh, S. Jadid, and P. Siano, "Economic-environmental energy and reserve scheduling of smart distribution systems: A multiobjective mathematical programming approach," *Energy Conversion and Management*, Vol. 78, pp. 151–164, 2014.
- [28] M. Motevasel and A. R. Seifi, "Expert energy management of a micro-grid considering wind energy uncertainty," *Energy Conversion and Management*, Vol. 83, pp. 58–72, 2014.
- [29] S. Talari, M. Yazdaniejad, and M. R. Haghifam, "Stochastic-based scheduling of the microgrid operation including wind turbines, photovoltaic cells, energy storages and responsive loads," *IET Generation, Transmission & Distribution*, Vol. 9, No. 12, pp. 1498–1509, 2015.
- [30] M. Petrollese, L. Valverde, D. Cocco, G. Cau, and J. Guerra, "Real-time integration of optimal generation scheduling with MPC for the energy management of a renewable hydrogen-based microgrid," *Applied Energy*, Vol. 166, pp. 96–106, 2016.

- [31] W. Su, J. Wang, and J. Roh, "Stochastic energy scheduling in microgrids with intermittent renewable energy resources," *IEEE Transactions on Smart Grid*, Vol. 5, No. 4, pp. 1876–1883, 2014.
- [32] D. Wang, J. Qiu, L. Reedman, K. Meng, and L. L. Lai, "Two-stage energy management for networked microgrids with high renewable penetration," *Applied Energy*, Vol. 226, pp. 39–48, 2018.
- [33] A. A. Moghaddam, A. Seifi, and T. Niknam, "Multi-operation management of a typical microgrids using Particle Swarm Optimization: A comparative study," *Renewable and Sustainable Energy Reviews*, Vol. 16, No. 2, pp. 1268–1281, 2012.
- [34] T. Niknam, R. Azizipanah-Abarghooee, and M. R. Narimani, "An efficient scenario-based stochastic programming framework for multi-objective optimal micro-grid operation," *Applied Energy*, Vol. 99, pp. 455–470, 2012.
- [35] B. Zhao, Y. Shi, X. Dong, W. Luan, and J. Bornemann, "Short-term operation scheduling in renewable-powered microgrids: A duality-based approach," *IEEE Transactions on Sustainable Energy*, Vol. 5, No. 1, pp. 209–217, 2014.
- [36] M. L. Crow, "Electric Vehicle Scheduling Considering Co-optimized Customer and System Objectives," *IEEE Transactions on Sustainable Energy*, Vol. 9, No. 1, pp. 410–419, 2018.
- [37] G. Mavrotas, "Effective implementation of the ϵ -constraint method in multi-objective mathematical programming problems," *Applied mathematics and computation*, Vol. 213, No. 2, pp. 455–465, 2009.
- [38] M. Sedighizadeh, M. Esmaili, and N. Mohammadkhani, "Stochastic multi-objective energy management in residential microgrids with combined cooling, heating, and power units considering battery energy storage systems and plug-in hybrid electric vehicles," *Journal of Cleaner Production*, 2018.
- [39] G. D. Yalcin and N. Erginel, "Determining weights in multi-objective linear programming under fuzziness," in *Proceedings of the World Congress on Engineering*, Vol. 2, pp. 6–8, 2011.
- [40] M. López, S. De La Torre, S. Martín, and J. Aguado, "Demand-side management in smart grid operation considering electric vehicles load shifting and vehicle-to-grid support," *International Journal of Electrical Power & Energy Systems*, Vol. 64, pp. 689–698, 2015.
- [41] R. Qiu, H. Zhang, X. Gao, X. Zhou, Z. Guo, Q. Liao, and Y. Liang, "A multi-scenario and multi-objective scheduling optimization model for liquefied light hydrocarbon pipeline system," *Chemical Engineering Research and Design*, Vol. 141, pp. 566–579, 2019.



M. Sedighizadeh received the B.Sc. degree in Electrical Engineering from the Shahid Chamran University of Ahvaz, Iran and M.Sc. and Ph.D. degrees in Electrical Engineering from the Iran University of Science and Technology (IUST), Tehran, Iran, in 1996, 1998, and 2004, respectively. From 2000 to 2007 he was with power system studies group of Moshanir Company, Tehran, Iran. Currently, he is as an Associate Professor with the Faculty of Electrical Engineering, Shahid Beheshti University, Tehran, Iran. His research interests are Power system control and modeling, FACTS devices, Microgrids, and Distributed Generation.



S. M. M. Alavi is currently an Assistant Professor at the Faculty of Electrical Engineering, Shahid Beheshti University, Tehran, Iran. He received the B.Sc. and M.Sc. degrees from the K. N. Toosi University of Technology, Tehran, Iran, in 2001 and 2003, respectively, and the Ph.D. degree from the University of Limerick, Limerick, Ireland, in 2009. He held post-doctoral positions at Simon Fraser University (2009–2011), University of Windsor (2011–2014), University of Oxford (2014–2015), Duke University (2015–2016), and University of Calgary (2016–2017). His research is in the design of control and (power) electronic systems for battery energy storage systems and brain stimulation engineering.



A. Mohammadpour received the B.Sc. and M.Sc. degrees in Electrical Engineering from Islamic Azad University, Tehran, Iran in 2012 and 2014, respectively, and the Ph.D. degree from the Shahid Beheshti University, Tehran, Iran, in 2019. He is currently a postdoctoral fellow at Faculty of Electrical Engineering, Shahid Beheshti University. His research interests are distribution systems, smart grid, electric vehicles and renewable energies.



© 2020 by the authors. Licensee IUST, Tehran, Iran. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution-NonCommercial 4.0 International (CC BY-NC 4.0) license (<https://creativecommons.org/licenses/by-nc/4.0/>).