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# Optimal Expansion Planning of Active Distribution System Considering Coordinated Bidding of Downward Active Microgrids and Demand Response Providers

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**Abstract:** This paper addresses an integrated framework for expansion planning of an Active Distribution Network (ADS) that supplies its downward Active MicroGrids (AMGs) and it participates in the upward wholesale market to sell its surplus electricity. The proposed novel model considers the impact of coordinated and uncoordinated bidding of AMGs and Demand Response Providers (DRPs) on the optimal expansion planning. The problem has six sources of uncertainty: upward electricity market prices, AMGs location and time of installation, AMGs power generation/consumption, ADS intermittent power generations, DRP biddings, and the ADS system contingencies. The model uses the Conditional Value at Risk (CVaR) criterion in order to handle the trading risks of ADS with the wholesale market. The proposed formulation integrates the most important deterministic and stochastic parameters of the risk-based expansion planning of ADS that is rare in the literature on this field.

The introduced method uses a four-stage optimization algorithm that uses genetic algorithm, CPLEX and DICOPT solvers. The proposed method is applied to the 18-bus and 33-bus test systems to assess the proposed algorithm. The proposed method reduces the aggregated expansion planning costs for the 18-bus and 33-bus system about 44.04%, and 11.82% with respect to the uncoordinated bidding of AMGs/DRPs costs, respectively.

**Keywords:** Expansion planning; active distribution system; stochastic programming; microgrids; optimization.

## 1. Nomenclature

### Abbreviations

ADS	Active electric Distribution System
AMG	Active Micro Grid
CHP	Combined Heat and Power
CB	Coordinated Bidding
CG	Coordination Gain
CVaR	Conditional Value at Risk
DA	Day-Ahead
DER	Distributed Energy Resource
DRP	Demand Response Provider
ESS	Electrical Storage System
MILP	Mix Integer Linear Programming
MINLP	Mix Integer Nonlinear Linear Programming
MU	Monetary Unit
MMUs	Million MUs
OEPADS	Optimal Expansion Planning of ADS
PV	Photovoltaic Array
RL	Responsive Load
TES	Thermal Storage System
UB	Uncoordinated Bidding

WT Wind Turbine

### Sets and Indices

$n, m$	Index for buses
$t$	Index for hours
$FDR$	Set of feeders
$X_{SITE}$	Set of facilities allocation sites
$g$	Set of loads
$s$	Scenario

### Parameters

$Cap$	Allocated capacity of AMG or DRP
$Capa^{Feeder}$	Capacity of feeder
$CC^{Feeder}$	Capacity cost of feeder
$C_{LENGHT}^{Feeder}$	Length dependent cost of electric feeder (MUs/m).
$C_{O\&M}$	Operation and maintenance cost
$\vartheta$	Present worth factor
$\omega$	Capacity fee
$\varkappa$	Energy fee
$Nyear$	Number of planning years
$Nzone$	Number of electric system zones
$NOS$	Number of operating scenario
$NCS$	Number of contingency scenario
$a, b$	Variable and fixed cost
$\mu$	Probability of contingency
$L$	Length of feeder
$k$	The penalty rate

$\epsilon$	Wholesale market active or reactive power price
$p^{ILmax}, p^{ILmin}$	Upper and lower limits on Involuntary load curtailment active power
$S^{ADSmax}$	ADS maximum apparent power
$V_n^{max}, V_n^{min}$	Maximum/minimum voltage magnitude
<i>Variables</i>	
$\tau$	Time duration of AMG/DRP contribution
$C_{op}$	Operational cost
$B$	Benefit
$P, Q$	Active and reactive power
$P_{DA\_upward}^{active}$	Submitted active power to wholesale market by the ADS
$Q_{DA\_upward}^{active}$	Submitted reactive power to wholesale market by the ADS
$\zeta$	Auxiliary variable used to compute the CVaR
$\alpha$	confidence level
$\beta$	weighting parameter for risk-aversion attitude
$CVaR_\alpha$	Conditional value at risk at the $\alpha$ confidence interval
$p^{IL}, Q^{IL}$	Involuntary load curtailment for active and reactive power, respectively
$V$	Voltage amplitude
$\theta$	Voltage angle
$Y$	Admittance of line
$S, H$	Equality and inequality constraints
$REV$	Revenue of AMGs or DRPs
<i>Binary variables</i>	
$I$	Installation decision variable

## 2. Introduction

Recently, Distributed Energy Resources (DERs) have been widely integrated into power systems planning and operations paradigms based on the fact that the DER-based systems are mainly MicroGrids (MGs) [1].

A microgrid can be introduced as a system, which includes DERs such as Combined Heat and Power (CHP), solar Photovoltaic Array (PV), small Wind Turbine (WT), Electrical Storage System (ESS), and Responsive Load (RL); in a way that it has at least one controllable energy source [2]. From the point of view of the electric distribution system, the downward Active MG (AMG) can be considered as a controllable element that is connected to its main grid and it can transact energy with the distribution system [2]. Further, an Active electric Distribution System (ADS) can transact electrical energy with the downward AMGs and upward electricity market.

The Optimal Expansion Planning of ADS (OEPADS) consists of determining the optimal parameters of the energy resource and network capacity, location, and the time of installation. The OEPADS must consider the stochastic behaviour of the wholesale market prices and intermittent electricity generation facilities, downward AMGs power generation/consumption scenarios, reliability criteria, dynamic interdependency of electric and heat systems and cost-benefit analysis [3].

Over recent years, different aspects of OEPADS have been studied and the literature can be categorized into the following categories. The first category proposes models for device capacity selection, allocation and performance evaluation. The second category introduces different solution techniques and the third category considers new models and heuristic solution methods for the OEPADS.

An integrated model that considers the impact of coordinated and uncoordinated bidding of AMGs and Demand Response Providers (DRPs) on the optimal expansion planning is less frequent in the literature.

Wua et al. [3] proposed a bi-level robust planning model for active management elements including on-load tap changers, electrical storage system, capacitor bank, and static reactive power compensation. The uncertainty of WTs and PVs was modelled and the problem was solved by column and constraint generation algorithm.

Bahrami et al. [4] proposed a decentralized algorithm for energy trading considering uncertainties of the generation and load parameters. The problem was formulated as a bi-level optimization problem and the case study showed that the algorithm helped the load aggregators and generators by increasing their profit by 23.34% and 15.2% on average, respectively.

Moradijooz et al. [5] proposed a probabilistic bi-level optimization problem that the master level optimized the planning phase; meanwhile, the slave level optimized the operation problem. The slave level was modelled as a two-stage model and at the first stage of the slave level, an optimal power flow was performed and at the second level of slave problem, the network reliability was optimized.

Samper et al. [6] presented a risk-based optimization approach that used evolutionary particle swarm optimization. A return-per-risk index was proposed to assess expansion investments an efficient synergy between the expected return and the risk of investments by performing Monte Carlo simulations was achieved.

Zare et al. [7] proposed a chance-constrained programming approach to deal with the uncertain renewables and loads. A robust formulation was proposed for the chance constraints that guaranteed the robustness of the expansion plans against all uncertainty distributions. Linearization techniques were also devised to eliminate the nonlinearities of the proposed formulation.

Bahrami et al. [8] introduced a decentralized algorithm to solve a DRP-based optimal power flow problem. A minimization formulation of aggregated generation cost of the suppliers and the discomfort cost of the consumers was proposed. The results confirmed the effect of the proposed method on reducing the loading of the transmission lines.

Amjady et al. [9] presented an adaptive robust planning model that considered the uncertain nature of loads and power productions of DERs. The AC power flow equations were considered and a tri-level decomposition algorithm was used to solve the problem.

Wang et al. [10] introduced a Mix Integer Linear Programming (MILP) optimization algorithm for energy hubs that considers the coupling of electricity and gas loads. The components of the energy hub include WTs, PVs, heat pump, ESSs, Thermal Storage Systems (TESs). The proposed algorithm uses a process to minimize the energy costs and carbon emissions in the 20 years planning horizon.

Moradi et al. [11] introduced an optimization method for the planning problem of large-scale CHP units that utilized the piecewise linearization technique to linearize the formulated nonlinear problem in the electric system contingencies. The formulated problem utilizes the MILP algorithm and the results reveal a 33% reduction in total costs.

Rastgou et al. [12] proposed an expansion-planning algorithm for the electric distribution system considering uncertainties of load and wholesale market price. The introduced method used harmony search method to optimize the formulated problem and the outputs of the proposed method were compared with the genetic algorithm and particle swarm optimization method.

Weber et al. [13] proposed a mixed-integer optimization algorithm to find the optimal combinations of energy resource and network systems for an eco-town in the United Kingdom. The model minimized costs and the CO<sub>2</sub> environmental emissions.

Soderman et al. [14] determined the optimal configuration and device capacity of energy resource system. The algorithm minimized the investment and operational costs. The MILP optimization algorithm explored the optimality of the system topology and facilities.

Bahrani et al. [15] presented the data centres' problem of choosing utility companies and scheduling workload for the DRPs. The interaction among data centres as a many-to-one matching game with externalities was modelled. Simulation results showed that the data centres costs were reduced by 18.7% with the proposed algorithm.

Bracco et al. [16], presents a MILP solution algorithm of CHP-based systems for Arenzani in Italy that optimizes investment and operating costs. The proposed model used a multi-objective function that minimized capital, operating costs, and CO<sub>2</sub> emissions.

Ref. [3-16] did not consider AMGs and DRPs coordinated bidding impact on the OEPADS problem. The ADS can pay capacity and energy fees to the AMGs and DRPs to encourage them to coordinate their biddings with the ADS. The ADS can sell the surplus electricity of its system and AMGs/DRPs to the upward wholesale market and maximizes its benefits. Thus, the DERs and electrical network expansion-planning algorithm that considers WTs, PVs, ESSs, and AMGs/DRPs coordinated bidding is less frequent in the previous researches. The present research introduces an OEPADS algorithm that uses the MINLP model. The main contributions of this paper can be summarized as:

- The proposed fourth-level algorithm considers the impacts of coordinated bidding of downward AMGs and DRPs on OEPADS,
- The integrated model of expansion planning considers the CHPs, electrical network, renewable energy resources, electrical storage systems, reactive power compensation devices, and DRPs,
- The proposed stochastic algorithm models the six sources of uncertainty: upward electricity market price, AMGs location and time of installation, AMGs power generation/consumption, ADS intermittent power generation, DRP biddings, and contingencies,

- The model encounters the Conditional Value at Risk (CVaR) criterion to explore the trading risks of ADS with the wholesale market,
- The problem explores the coordination of system resources in the normal and contingent conditions.

The following sections of this paper are organized as follows: The modelling and formulation of the OEPADS problem is introduced in Section 3. In Section 4, the solution algorithm is presented. In section 5, the simulation results for different scenarios are presented. Finally, the conclusions are included in Section 6.

### 3. Problem Modelling and Formulation

The ADS is equipped with different energy resources consists of CHPs, gas –fired boilers, PVs, WTs, and ESSs as well as Reactive Power Compensation Facilities (RPCF) such as fixed capacitor banks. There is not any heat transmission system and all of the heating loads must be supplied by CHPs and boilers. The ADS operator commits its CHP systems and boilers to supply the downward heat and electricity loads and it can purchase electricity from the upward wholesale market. The electricity surplus of each AMG can be sold to the ADS main grid. Further, the ADS can pay capacity and energy fees to its downward AMGs and DRPs to encourage them to coordinate their biddings with the ADS; in a way that the ADS can maximize his/her profit. Thus, the ADS may have an extra active/reactive power generation capacity that can sell its surplus active/reactive power to the upward electricity market. Hence, the OEPADS problem must consider the coordinated bidding of AMGs/DRPs procedure in investment practices. The OEPADS must minimize the investment and operation cost; meanwhile, it must maximize the reliability of provided services for the downward loads [3].

#### 3.1. Uncertainty Characterization

The OEPADS problem has six sources of uncertainty: upward electricity market price, AMGs location and time of installation, AMGs power generation/consumption, ADS intermittent power generation, DRP biddings, and contingencies.

Considering the inherent uncertainties associated with the above parameters, stochastic programming is utilized in this paper and each uncertain parameter is modelled as a stochastic process. As a result, the objective function is transformed into a random variable, and for its evaluation, the expected value is utilized. The stochastic process is presented by different scenarios. The scenario generation is done by sampling of white noises in the fitted models. Auto Regressive Integrated Moving Average (ARIMA) models for the purpose of generating scenarios for stochastic processes [17]. However, from a computational viewpoint, solving such problems are time-consuming to be solved or irresolvable. Hence, the scenario reduction method must be applied. The forward selection algorithm proposed in [18] is used to reduce the scenarios.

$$\text{Min } Z_1 = \sum_{\text{Nyear}} \sum_{\text{Nzone}} \sum_{\text{NOS}} \text{prob} \times \left( \begin{array}{c} (C_{CHP} \times I^{CHP} + C_{Feeder} \times I^{Feeder} + C_{PV} \times I^{PV} + \\ C_{SW} \times I^{SW} + C_{WT} \times I^{WT} + C_{ESS} \times I^{ESS} + C_{Boiler} \times I^{Boiler}) \\ C_{RPCF} \times I^{RPCF} + C_{IC} + C_{Purchase} + C_{DRP} - B_{Active\_Sold}^{WASM} - B_{Reactive\_Sold}^{WASM} \end{array} \right) \quad (3)$$

S. t:  $S_1(x, y, z) = 0$ ,  $H_1(x, y, z) \leq 0$

### 3.2. Assumptions

The ADS forecasts day-ahead wholesale pool market prices. The ADS will only submit its bids if its estimation shows that the entire volume of the submitted bid will be purchased by the Independent System Operator (ISO). Any deviation from the submitted values of active and reactive power markets will be penalised by the ISO. The operational cost of ESS is modelled as Eq. (1):

$$C_{op}^{ESS}(P_t^{ESS}) = a_t^{ESS} |P_t^{ESS}| + b_t^{ESS} \quad (1)$$

The cost of RPCF is modelled as Eq. (2):

$$C_t^{RPCF}(\bar{Q}_t^{RPCF}) = a_t^{RPCF} \cdot \bar{Q}_t^{RPCF} \quad (2)$$

where,  $\bar{Q}_t^{RPCF}$  is the discrete value of each RPCF step, and  $a^{RPCF}$  is the fixed cost of RPCF.

The OEPADS problem is formulated as a four-stage stochastic program. At the first stage, the ADS forecast wholesale electricity market prices; meanwhile, it estimates the location, capacity and time of installation of the downward AMGs facilities and the volume of electricity exchanges with the AMGs and DRPs. Then it optimizes the location, capacity and time of installation of its facilities for different wholesale market, AMGs location and capacity scenarios. At the second stage, the bidding scenarios of AMGs and DRPs is generated and the scenario reduction procedure is performed. Then the feasibility of estimated AMGs and DRPs biddings are evaluated and the coordinated bidding of AMGs/DRPs are recognized. At the third stage, the optimal scheduling of ADS energy resources is determined. At this stage, the ADS uses the estimated hourly electric and heat loads, coordinated bidding of AMGs' and DRP, and intermittent power generation to determine the optimal generation schedules of its resources, electricity transactions with wholesale market and AMGs/DRPs. At the fourth stage, the involuntary load shedding, corrective DRPs and AMGs electricity interruptions are determined for each contingency scenario.

### 3.3. First Stage Problem Formulation

An optimal OEPADS must minimize total investment costs and the aggregated operation costs; meanwhile, it must maximize the system reliability. The objective function of OEPADS problem can be proposed as (3).

The uncertainties of the AMGs' location and capacity scenarios and wholesale electricity market scenarios are described as the probability of the NOS parameter.

The objective function is decomposed into five groups:

1) the investment plus aggregated operation costs of CHP, electric feeder, PV, switching device (SW), WT, ESS, boiler, and RPCF, 2) the involuntary load shedding interruption cost, 3) the electricity purchased costs, 4) the costs of DRPs, 5) the benefit of active power sold to the upward electricity market,

and 6) the benefit of reactive power transactions with upward electricity market.

The CHP, ESS, PV, WT and boiler costs can be written as:

$$C_X = \vartheta * \sum_{X_{SITE}} (C_{INVEST}^X + \sum_{NOS} \text{prob} \times \tau^X \times C_{O\&M}^X) \quad (4)$$

$\forall X \in \{CHP \cup Boiler \cup ESS \cup PV \cup WT \cup RPCF\}$

The feeder costs can be presented as a function of its capacity and length:

$$C_{Feeder} = L \times \sum_{FDR} (C_{CAP}^{Feeder} \times \text{Capa}^{Feeder} + C_{LENGHT}^{Feeder}) \quad (5)$$

The interruption cost is a function of power that is involuntary interrupted and Customer Damage Function (CDF):

$$C_{IC} = \sum_{NCONTS} (\mu \times P_{SHED} \times CDF) \quad (6)$$

Active power balance constraint of ADS can be written as:

$$P^{ADS} = - \sum_g P^{Load} + \sum_{X_{SITE}} P^X - P^{Loss} \quad (7)$$

$\forall X \in \{DERs \cup DRPs \cup ILs\}$

Reactive power balance constraint is written as:

$$Q^{ADS} = - \sum_g Q^{Load} + \sum_{X_{SITE}} Q^X - Q^{Loss} \quad (8)$$

$\forall X \in \{DERs \cup RPCFs \cup DRPs\}$

The energy purchased costs can be presented as:

$$C_{Purchase} = P^{ADS} \times \epsilon_{Purchased}^{Active} + Q^{ADS} \times \epsilon_{Purchased}^{Reactive} \quad (9)$$

The electric network constraints consist of electric device loading constraints and the load flow constraints.

### 3.4. Second Stage Problem Formulation

At the second stage, the bidding scenarios of AMGs and DRPs is generated and the scenario reduction procedure is performed.

Then the feasibility of estimated AMGs and DRPs biddings are evaluated. The AMGs/DRPs might be dispatchable by paying an appropriate capacity and energy fee. The ADS maximizes the expected profit of AMGs and DRPs. The objective function of the second stage problem can be written as Eq. (10).

$$\text{Max } Z_2 = \sum_{NOS} \text{prob}_s \times [B_{AMG} + B_{DRP}] \quad (10)$$

$$\text{S. t: } S_2(x, y, z) = 0, \quad H_2(x, y, z) \leq 0$$

$$B_{AMG} = \sum_{N_T} \sum_{N_G} \text{REV}_{AMG} - C(P^{AMG}) \quad (11)$$

$$\text{REV}_{AMG} = \omega_t^{AMG} \times \text{Cap}_t^{AMG} + \sum \kappa_t^{AMG} \times P_t^{AMG} \times \tau_t^{AMG} + \sum \kappa_t^{AMG} \times Q_t^{AMG} \times \tau_t^{AMG} + \quad (12)$$

$$B_{DRPs} = \sum_{N_T} \sum_{N_G} \text{REV}_{DRPs} - C(P^{DRP}) \quad (13)$$

$$\text{REV}_{DRP} = \omega_t^{DRP} \times \text{Cap}_t^{DRP} + \sum \kappa_t^{DRP} \times P_t^{DRP} \times \tau_t^{DRP} + \sum \kappa_t^{DRP} \times Q_t^{DRP} \times \tau_t^{DRP} \quad (14)$$

Eq. (11) denotes that the AMG benefit can be formulated as its revenue of electricity sold to ADS minus its electricity generation costs. Further, the DRP benefit consists of the revenue of electricity sold to ADS minus its costs.

The second stage objective function is subjected to AMGs facilities loading constraints and DRPs estimated constraints.

### 3.5. Third Stage Problem Formulation

At the third stage problem, the optimal operational coordination of the ADS resources is explored. The third stage objective function minimizes the expected value of cost and penalties; meanwhile, it maximizes the benefit of active and reactive power that is sold to the wholesale market.

Further, the objective function minimizes the CVaR that is defined at the  $\alpha$  confidence level ( $CVaR_\alpha$ ) to control the risk that is defined as the expected value of the profit smaller than the  $(1 - \alpha)$ -quantile of the profit distribution

$$\begin{aligned} \text{Min } Z_3 = & \sum_{NOS} \text{prob} \times (C_{OP}^{CHP} + C_{OP}^{Boiler} + C_{OP}^{ESS} + C_{OP}^{Boiler} + C_{Purchase} + C_{DRP} + C_{OP}^{RPCF} - B_{ActiveSold}^{WSM} - B_{ReactiveSold}^{WSM} \\ & - B_{AMGs} - B_{DRPs} + (\sum_{NOS} \text{prob} \times \text{Penalty}^{Active} + \text{prob} \times \text{Penalty}^{Reactive}) \\ & + \beta \left( \zeta - \frac{1}{1 - \alpha} \sum_{s=1}^{NOS} \text{prob}_s \times \eta_s \right) \\ \text{S. t: } & S_3(x, y, z) = 0, \quad H_3(x, y, z) \leq 0 \\ \text{Penalty}^{reactive} = & \begin{cases} k \times Q^{Reactive} & \text{if } |\text{Cos } \varphi^{ADS}| \leq \text{Cos } \varphi^{\min ADS} \\ 0 & \text{if } |\text{Cos } \varphi^{ADS}| \geq \text{Cos } \varphi^{\min ADS} \end{cases} \quad \text{Cos } \varphi^{ADS} = \frac{P_{DA\_upward}^{active}}{\sqrt{(P_{DA\_upward}^{active})^2 + Q_{DA\_upward}^{reactive}^2}} \end{aligned} \quad (15)$$

[19]. Eq. (15) comprises three terms: the first term corresponds to the sum of the expected costs minus profits of ADS, the second term is the penalties of the active and reactive power mismatches, and the third term is the CVaR multiplied by the factor  $\beta$  that is a weighting parameter determines the risk-aversion attitude. A risk-neutral attitude corresponds to  $\beta = 0$ , while a risk-averse attitude would correspond to  $\beta > 0$ . The constraints of this stage can be categorized as follows.

#### 1) Supply-demand balancing constraints:

The supply-demand constraints must be considered for each interval of simulation.

$$\begin{cases} \sum (P_t^{CHP} + P_t^{AMG} + P_t^{DRP} + P_t^{WT} + P_t^{PV}) - \\ \sum \eta^{ESS} \cdot P^{ESS} + \sum (P_t^{DRP} + P_t^{IL}) \\ - \sum |V_{nt}| \cdot |V_{mt}| \cdot |Y_{nm}| \cdot \text{cos}(\theta_n^{ADS} - \theta_n^{ADS}) = 0, \end{cases} \quad (16)$$

$$\begin{cases} \sum (Q_t^{DERs}) + \sum (Q_{zt}^{IL}) \\ + \sum |V_{nt}| \cdot |V_{mt}| \cdot |Y_{nm}| \cdot \text{sin}(\theta_n^{ADS} - \theta_n^{ADS}) = 0, \end{cases} \quad (17)$$

#### 2) Steady-state security constraints:

The apparent power flow limit of the lines and voltage limit of the buses can be written as:

$$\begin{aligned} & \sqrt{P_{nmt}^{ADS^2}(V, \delta) + Q_{nmt}^{ADS^2}(V, \delta)} \\ & \leq S_{nmt}^{ADSmax}, \quad \forall n, \forall m, \forall t \end{aligned} \quad (18)$$

$$V_{nt}^{min} \leq |V_{nt}| \leq V_{nt}^{max}, \quad \forall n, \forall t \quad (19)$$

The third problem objective function is constrained by device loading and AC load flow constraints.

### 3.6. Fourth Stage Problem Formulation

At the fourth stage problem, the involuntary load shedding, corrective DRPs and AMGs interruptions are determined for each contingency scenario.

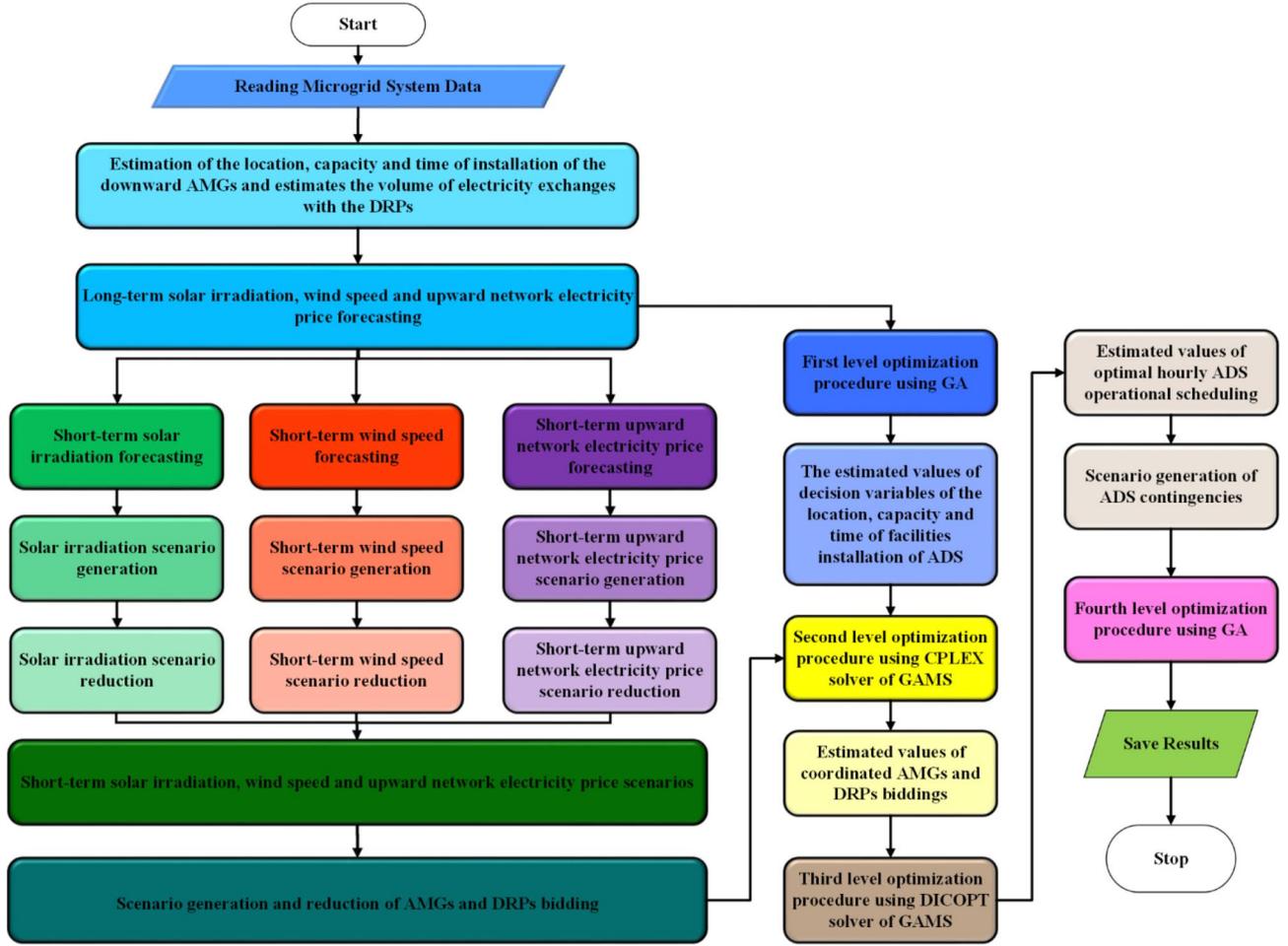


Fig. 1. The proposed OEPADS algorithm

The objective function of the fourth stage problem can be written as:

At the fourth stage problem, the optimization problem minimizes the total interruption costs of systems in contingent conditions by switching of tie switches. If the electrical system resources are not adequate to supply the electrical load, then the load shedding procedure is performed. The constraints of the fourth stage problem consist of AC load flow, device-loading constraints. The involuntary load shedding constraints are presented as Eq. (21) and Eq. (22).

$$P^{ILmin} \times I^{IL} \leq P^{IL} \leq P^{ILmax} \times I^{IL} \quad (21)$$

$$Q^{IL} = (P^{IL}) \times \sqrt{\frac{1}{\cos\varphi^{IL}} - 1} \quad (22)$$

#### 4. Solution Algorithm

The proposed MINLP model of OEPADS has a large state space that involves thousands of non-convex, non-linear discrete and continuous variables in the expansion-planning horizon. A four-stage optimization algorithm is proposed and Fig. 1 shows the flowchart of the proposed OEPADS algorithm. For the first stage optimization problem, a Genetic Algorithm (GA) with variable fitness functions is used. A list of suitable candidates is selected for the first generation of the chromosomes and for the implementation of operational

constraints; a penalty factor representation is used. The behaviour of each GA operator is modified by changing its parameter values. The details GA algorithm and its mutation and crossover operators are presented in [20]. At this stage, it is assumed that the installed facilities are working at their maximum capacity and the capacity installation variables are presented as the continuous variables. Further, the first stage problem uses the monthly load curves.

For the second stage problem and for risk control, the confidence level used to calculate  $CVaR_\alpha$  is  $\alpha = 0.95$ . The model is linearized and implemented using CPLEX 10.2 under GAMS. All of the second stage decision variables are assumed as a linear parameter and a linearization algorithm is adopted.

At the third stage, the facilities capacity installation alternatives are changed to their corresponding available capacity. Then for the fixed set of installation alternatives, the second stage problem optimizes the coordination of system resources based on the detailed AC load flow model. The third stage optimization problem is a MINLP. The MINLP model is solved by the GAMS software, using the DICOPT solver. It iteratively invokes the CONOPT3 and CPLEX solvers for non-linear and mixed-integer programming solutions, respectively [21].

At the fourth stage problem, the optimization problem explores the optimal operation of systems in contingent conditions. A GA is considered for the fourth stage optimization problem [20].

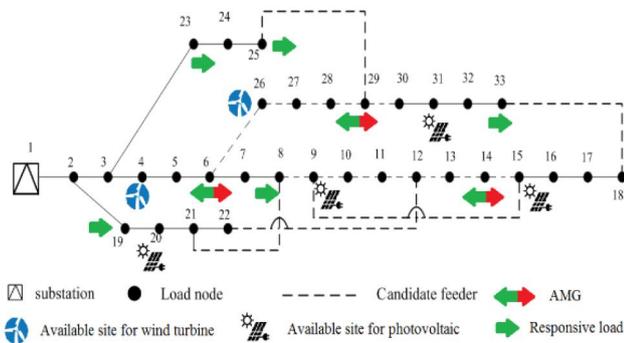
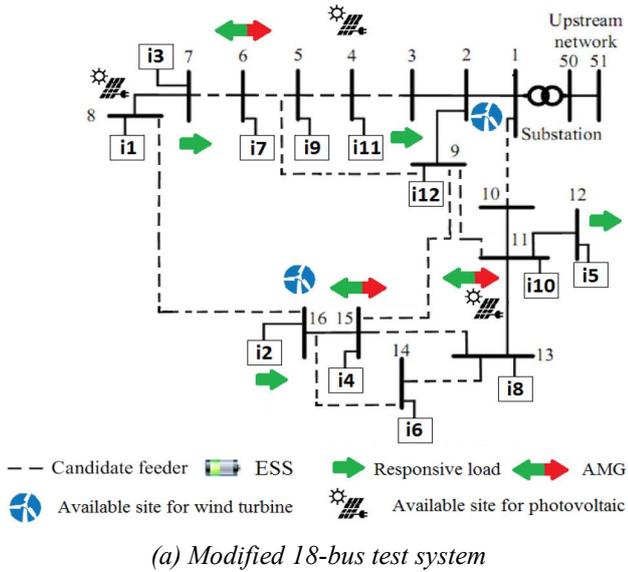
## 5. Simulation Results

Two systems were used to assess the proposed OEPADS algorithm. The 18-bus and 33-bus test systems were considered.

Table 1 presents the optimization input data for the 18-bus test system. Fig. 2 (a) and (b) depict the 18-bus and 33-bus test systems, respectively. For the first case study, the capacity of CHPs of 18-bus test system was assumed constant for the planning horizon and the impacts of coordinated bidding of AMGs/DRPs on OEGADS procedure was assessed.

**Table 1** The optimization input data for the 18-bus test system

Parameter	Value
Planning horizon year	5
Discount rate (%)	12.5
Load power factor	0.9
Load growth rate of (%)	3
Number of solar irradiation scenarios	4500
Number of wind turbine power generation scenarios	5000
Number of upward market price scenarios	500
Number of solar irradiation reduced scenarios	40
Number of wind turbine power generation reduced scenarios	45
Number of upward market price reduced scenarios	5



**Fig. 2.** Case study test systems

However, for the second case study, the capacity of CHPs of 33-bus system was considered as a decision variable. The algorithm codes were developed in MATLAB and GAMS and the simulation was carried out on a PC (Intel Core 2, 2.93 GHz, 4 GB RAM).

### 5.1. The 18-bus test system

The 18-bus test system, data wind turbine and solar panel data are presented at [22-23]. Three sets of scenarios were generated for the wholesale market prices, solar irradiation, and wind speed of each year of planning. Then the scenario reduction procedure was performed. The ADS must simulate the feasibility and optimality of the probable AMGs' power transactions.

Two cases are considered to classify the results:

Case 1- The AMGs and DRPs did not coordinate their bidding (Uncoordinated Bidding (UB)),

Case 2- The AMGs and DRPs coordinated their bidding (Coordinated Bidding (CB)).

The Coordination Gain (CG) criteria in order to compare case 1 and case 2, which is calculated based on Eq. (23).

$$CG = \frac{Profit_{CB} - Profit_{UB}}{Profit_{UB}} \quad (23)$$

Fig. 3 shows the expected generation of AMGs and the expected energy traded with ADS by the AMGs and DRPs in UB and CB strategies. According to Fig. 3, AMGs and DRPs tend to be more committed in CB in order to maximize their aggregated profit. Total expected power generation of AMGs/DRPs in uncoordinated and coordinated cases are 1203.03 kWh and 1431.05 kWh, respectively that shows 18.95% increase in the coordinated case.

Fig. 4 (a) and (b) show the effect of risk-aversion on the coordinated bidding of AMGs/DRPs and the sum of the uncoordinated bidding for hours 8 and 18. The coordinated bidding strategy considerably changes the bid volume of AMGs and DRPs. The effect of risk-aversion on coordinated bidding and the sum of the uncoordinated bidding, implying that risk-averse bids are always less than or equal to risk-neutral bids.

Fig. 4 (c) and (d) depict the optimal topology of the 18-bus system for the 5<sup>th</sup> year of the expansion planning horizon and for  $\beta=0$  and  $\beta=1$ , respectively.

The expected profit of AMGs and DRPs for the uncoordinated and coordinated bidding strategies were 4.1826 MMUs and 6.2415 MMUs, respectively. The CG is 49.22% that indicates the impact of coordinated bidding of AMGs/DRPs on their profit.

Fig. 5 (a) and (b) shows the sum of bidding power of ADS for uncoordinated and coordinated bidding of AMGs/DRPs for the worst-case scenario of electricity generation of DERs, respectively. For the uncoordinated bidding of AMGs/DRPs, the ADS has very limited surplus electricity that it can transact with wholesale market. However, for the coordinated bidding of AMGs/DRPs, the ADS can sell its surplus electricity to the wholesale market.

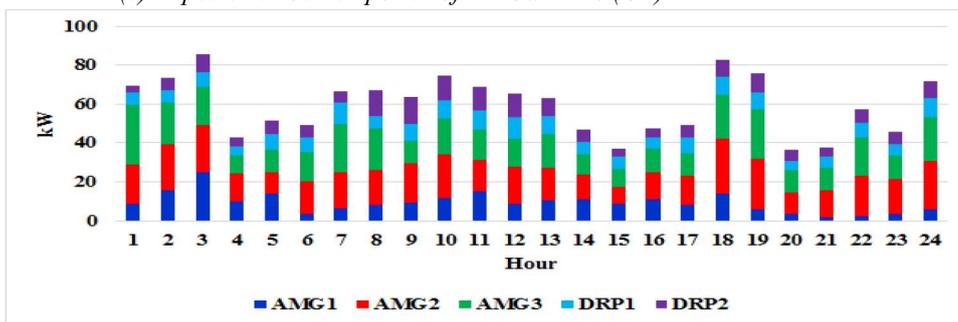
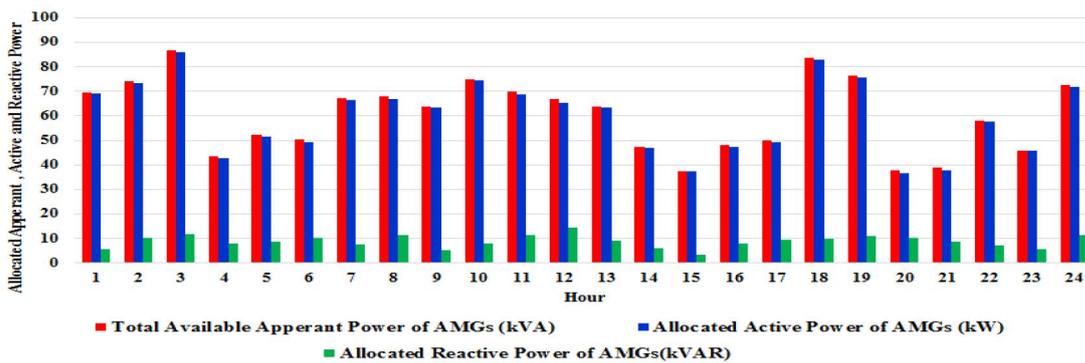
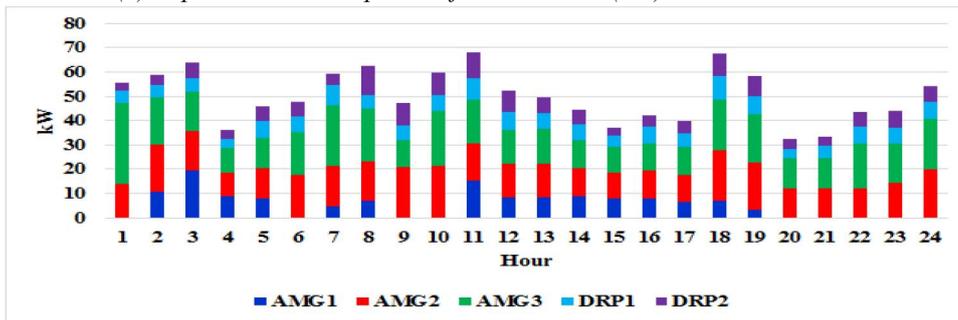
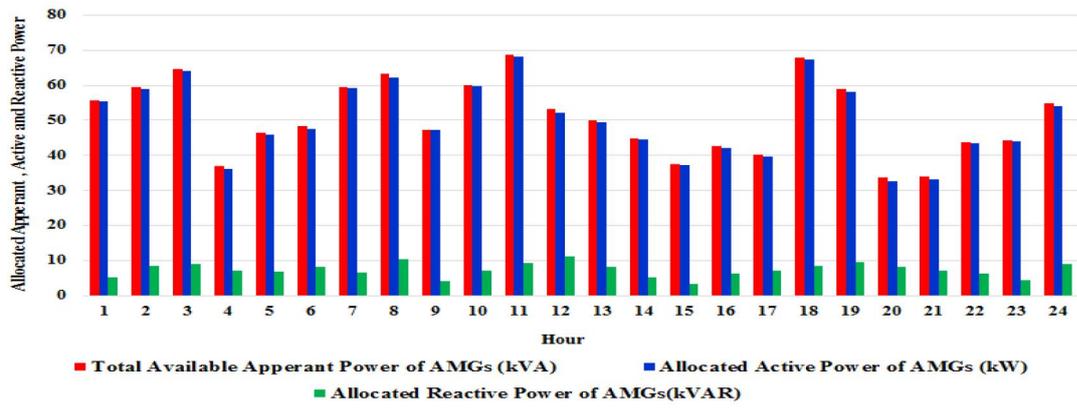
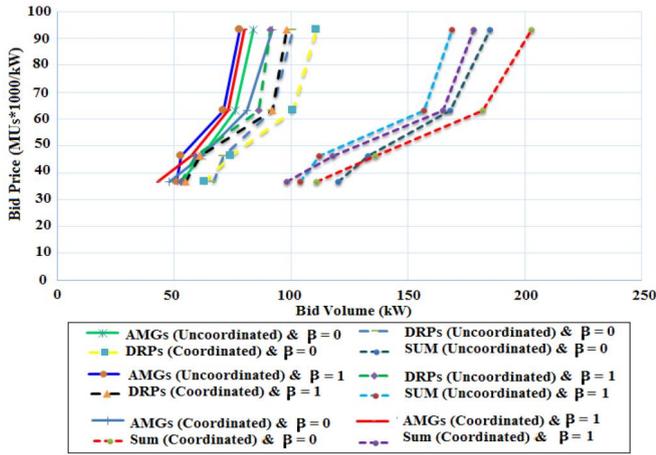
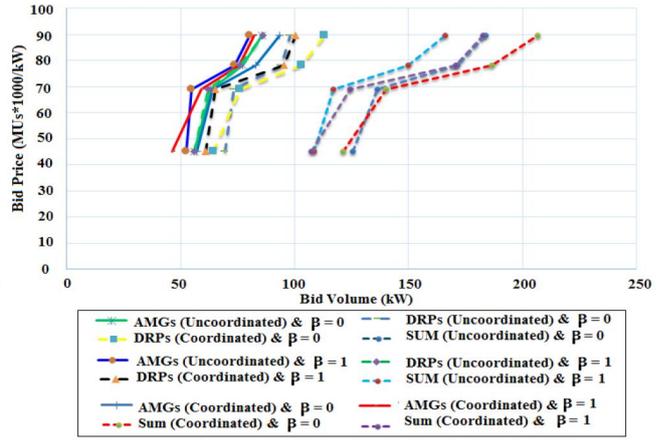


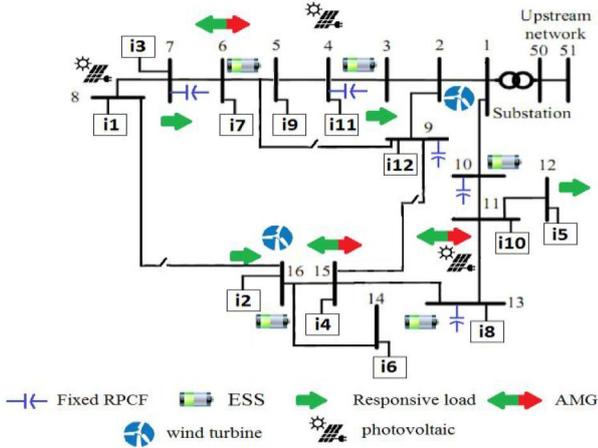
Fig. 3. Expected allocated power of 18-bus system AMG/DRPs and expected active power generation of AMG/DRPs in the two cases



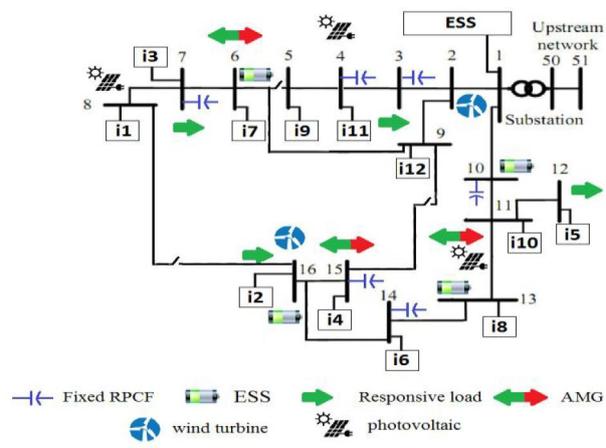
(a) Sum of bidding curves of AMGs/DRPs in hour 8



(b) Sum of bidding curves of AMGs/DRPs in hour 18

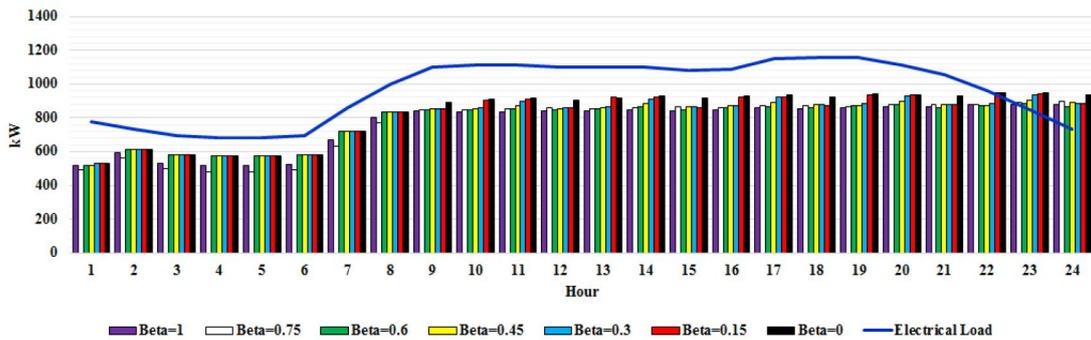


(c) The optimal topology of 18-bus system for  $\beta=0$ , coordinated bidding of AMGs/ DRPs and for the 5<sup>th</sup> year of the expansion planning horizon

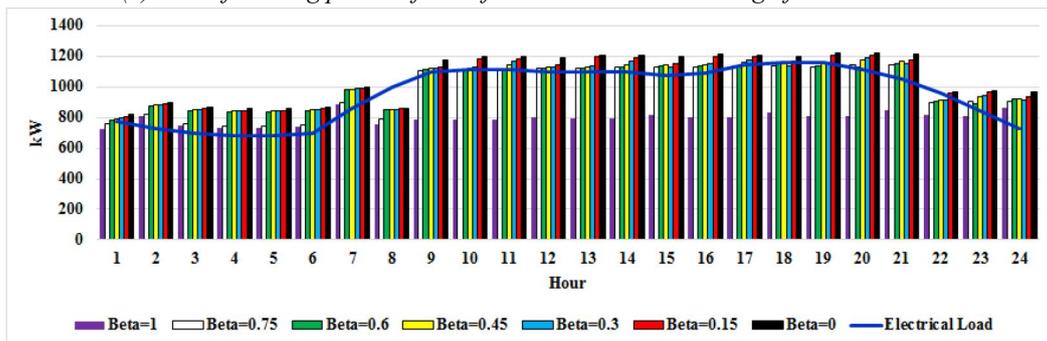


(d) The optimal topology of 18-bus system for  $\beta=1$ , coordinated bidding of AMGs/ DRPs and for the 5<sup>th</sup> year of the expansion planning horizon

**Fig. 4.** Sum of bidding curves of AMGs/DRPs in different hours and topology of 18-bus system for different values of  $\beta$



(a) Sum of bidding power of ADS for uncoordinated bidding of AMGs/DRPs



(b) Sum of bidding power of ADS for coordinated bidding of AMGs/DRPs

**Fig. 5.** Sum of bidding curves of 18-bus ADS for different values of  $\beta$  without and with AMGs/DRPs coordinated bidding for the scenario of electricity generation of DERs

Table 2 depicts the optimal outputs of OEPADS for the 18-bus test system for  $\beta=1$ . The expected benefits of electricity sold to the wholesale market were 8.2145 MMUs and 0.02154 MMUs for  $\beta=1$  and  $\beta=0$ , respectively. The total investment and operational costs of the 18-bus system for the coordinated and uncoordinated bidding of AMGs/DRPs and for  $\beta=1$  take on a value 138.3132 MMUs and 247.1854 MMUs that means the coordinated bidding of AMGs/DRPs reduces the OEPADS costs about 44.04%.

**Table 2** The optimal outputs of OEPADS for the 18-bus test system for  $\beta=1$ .

Costs (MMUs)	
Feeders installation costs	9.2651
Transformer and ESS installation costs	19.6514
ENSCs	0.4921
CHP operation costs	18.2174
PVA installation and maintenance costs	3.9215
Feeder and EES operation costs	9.8417
Expected benefit of electricity sold to the wholesale market	8.2145
CHP installation costs	19.5641
Energy loss costs	0.9814
Wind turbine installation costs	3.7145
Electricity purchased from upward network costs	32.1784
Expected AMGs/DRP coordinated bidding costs for ADS	6.2415
Expected AMGs benefits	4.8711
Expected DRPs benefits	1.3704

## 5.2 The 33-bus test system

The 33-bus test system data is presented at [24]. For this case study, the capacity of CHPs of 33-bus system was considered as a decision variable. Table 3 shows the CHP technical characteristics, installation and operation costs.

**Table 3** The CHP technical characteristics, installation and operation costs

DG type	Maximum output power $P_{max}$ (kW)	Installation Fixed cost (MUs)	Installation variable cost (MUs/kVA)	Operation Fixed cost (MUs/kW)	Operation variable cost (MUs/kWh)
1	330	63283.5	350	0.2588	1.0853
2	844	166584.5	550	0.2373	1.0569

Fig. 6 shows the expected generation of AMGs and the expected energy traded with ADS by the AMGs and DRPs in UB and CB strategies. According to Fig. 3, AMGs and DRPs tend to be more committed in CB in order to maximize their aggregated profit. Total expected power generation of AMGs/DRPs in uncoordinated and coordinated cases are 1910.03 kWh and 2264.71 kWh respectively that shows 18.56% increase in the coordinated case.

Fig. 7 (a) and (b) show the effect of risk-aversion on the coordinated bidding of AMGs/DRPs and the sum of the uncoordinated bidding for hours 6 and 19. The coordinated bidding strategy considerably changes the bid volume of AMGs and DRPs. The Fig. 7 (c) and (d) depict the optimal topology of the 33-bus system for the 5<sup>th</sup> year of the expansion planning horizon and for  $\beta=0$  and  $\beta=1$ , respectively.

The expected profit of AMGs and DRPs for the uncoordinated and coordinated bidding strategies were 4.1826 MMUs and 6.2415 MMUs, respectively. The CG is

49.22% that indicates the impact of coordinated bidding of AMGs/DRPs on their profit.

Fig. 8 (a) and (b) show the sum of bidding power of ADS for uncoordinated and coordinated bidding of AMGs/DRPs for the worst-case scenario of electricity generation of DERs, respectively. For the uncoordinated bidding of AMGs/DRPs, the ADS has very limited surplus electricity that it can transact with wholesale market. However, for the coordinated bidding of AMGs/DRPs, the ADS can sell its surplus electricity to the wholesale market.

Table 4 depicts the optimal outputs of OEPADS for the 33-bus test system for  $\beta=1$ . The expected benefits of electricity sold to the wholesale market were 17.2416 MMUs and 2.1936 MMUs for  $\beta=1$  and  $\beta=0$ , respectively. The total investment and operational costs of the 33-bus system for the coordinated and uncoordinated bidding of AMGs/DRPs and for  $\beta=1$  take on a value 314.717 MMUs and 356.914 MMUs that means the coordinated bidding of AMGs/DRPs reduces the OEPADS costs about 11.82%.

**Table 4** The optimal outputs of OEPADS for the 33-bus test system for  $\beta=1$ .

Costs (MMUs)	
Feeders installation costs	17.5698
Transformer and ESS installation costs	39.5412
ENSCs	0.9815
CHP operation costs	57.1235
PVA installation and maintenance costs	5.62314
Feeder and EES operation costs	12.5417
Expected benefit of electricity sold to the wholesale market	17.2416
CHP installation costs	76.2351
Energy loss costs	0.9814
Wind turbine installation costs	3.7891
Electricity purchased from upward network costs	59.1264
Expected AMGs/DRP coordinated bidding costs for ADS	11.9817
Expected AMGs benefits	7.9563
Expected DRPs benefits	4.0254

According to Table 2 and Table 4, the OEPADS reduces the aggregated total costs for the 18-bus and 33-bus systems about 44.04%, and 11.82% with respect to the uncoordinated bidding of AMGs/DRPs scenario costs, respectively. Further, the ADS expected benefits of electricity sold to the wholesale market are about 8.2145 (MMUs), and 17.2416 (MMUs) for the 18-bus and 33-bus test systems, respectively. It means that the ADS can gain benefit from the coordinated biddings of AMGs/DRPs.

Table 5 shows the number of continuous and discrete variables and the number of equations for different case studies. The number of equations for the 33-bus test system is 2015914 that indicate the curse of dimensionality and the maximum CPU time required to solve the scenarios was about 5325 seconds for the 33-bus test system.

**Table 5** Number of variables for different case studies

Case	continuous variables	discrete variables
18-bus	762144	36942
33-bus	1249448	26987
Case	total equations	CPU time (sec)
18-bus	1326412	3892
33-bus	2015914	5325

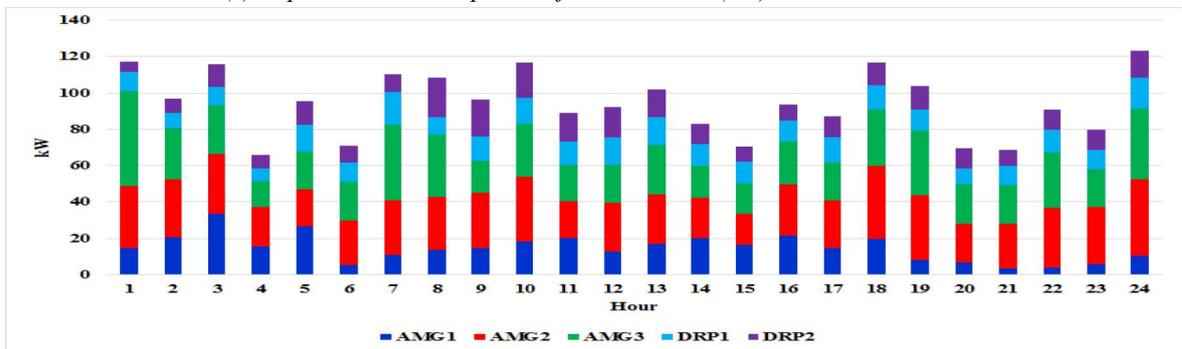
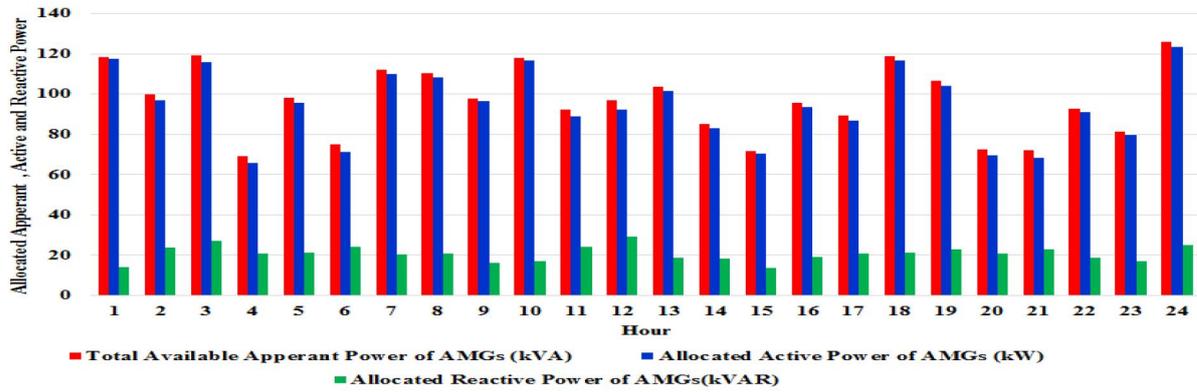
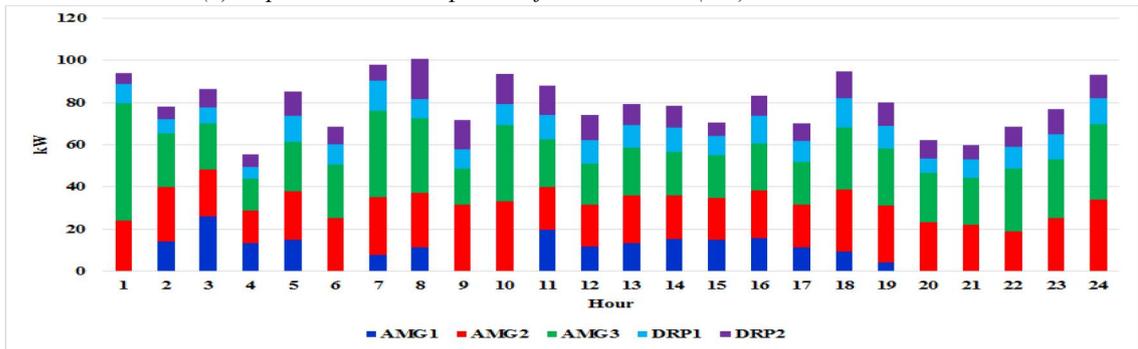
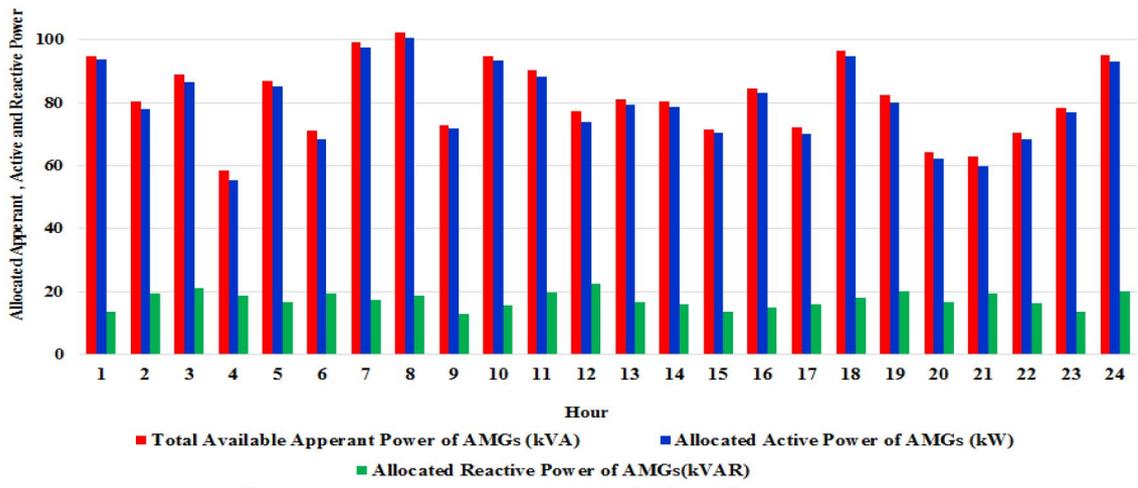
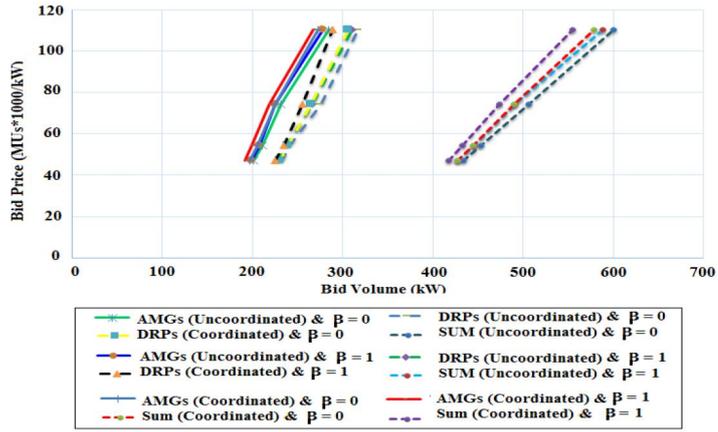
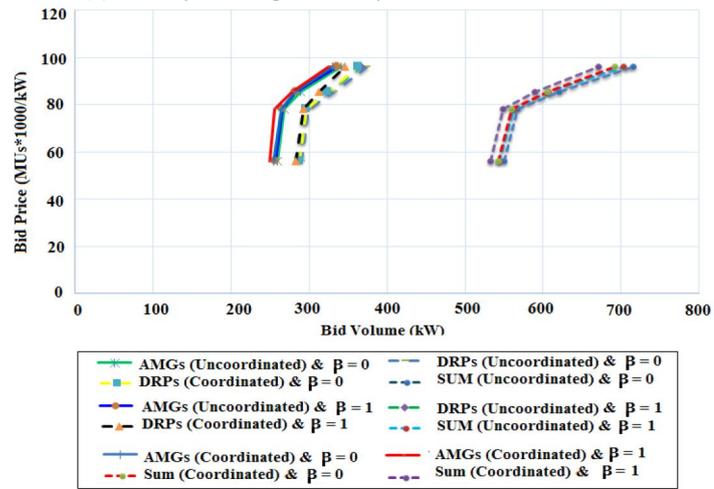


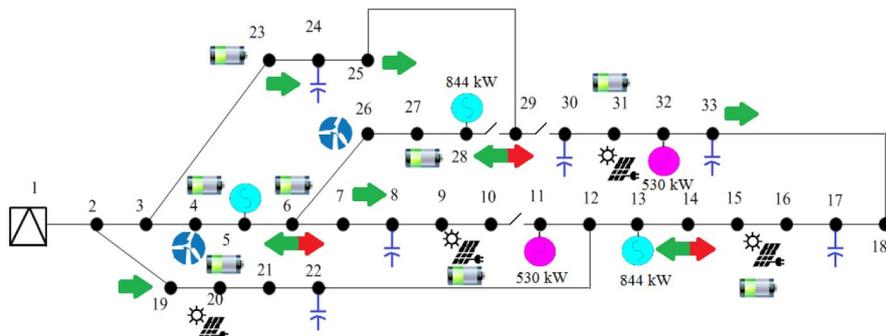
Fig. 6. Expected allocated power of 33-bus system AMG/DRPs and expected active power generation of AMG/DRPs in two cases



(a) Sum of bidding curves of AMGs/DRPs in hour 6

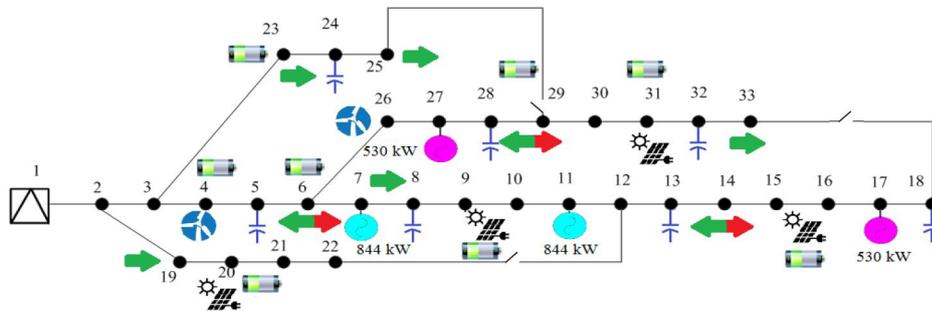


(b) Sum of bidding curves of AMGs/DRPs in hour 19



(c) The topology of 33-bus system for  $\beta=0$ ,

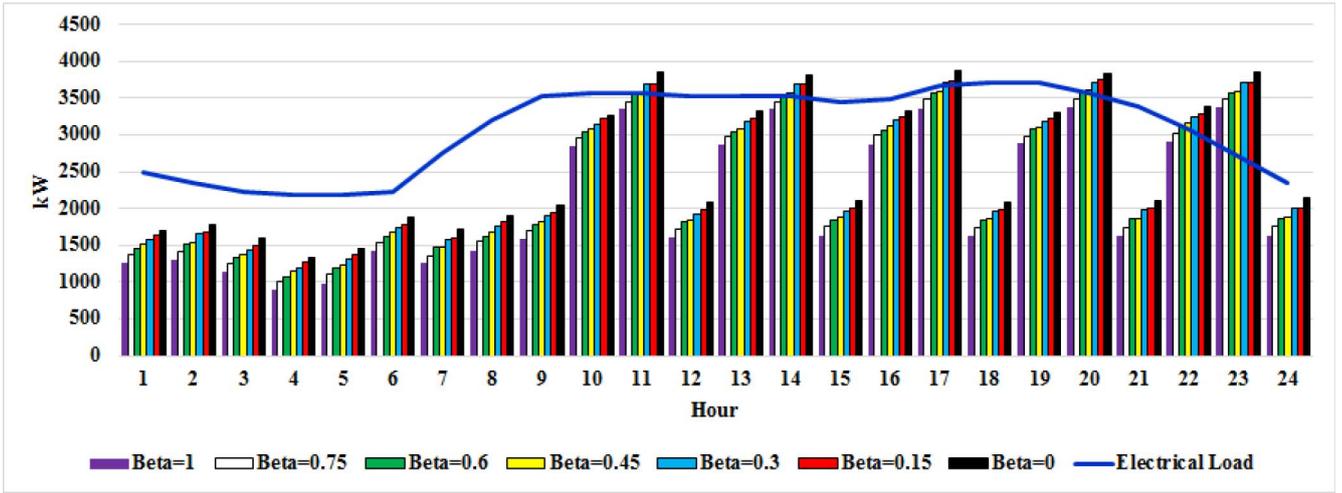
coordinated bidding of AMGs/ DRPs and for the 5<sup>th</sup> year of the expansion planning horizon



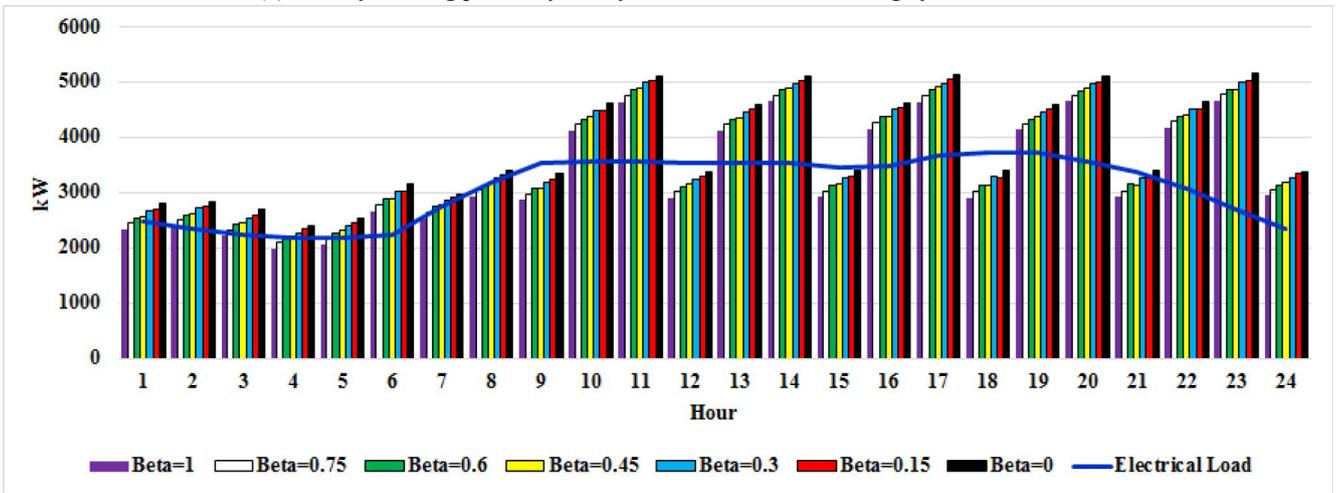
(d) The topology of 33-bus system for  $\beta=1$ ,

coordinated bidding of AMGs/ DRPs and for the 5<sup>th</sup> year of the expansion planning horizon

**Fig. 7.** Sum of bidding curves of AMGs/DRPs in different hours and the topology of 33-bus system for different values of  $\beta$



(a) Sum of bidding power of ADS for uncoordinated bidding of AMGs/DRPs



(b) Sum of bidding power of ADS for coordinated bidding of AMGs/DRPs

**Fig. 8.** Sum of bidding curves of 33-bus ADS for different values of  $\beta$  without and with AMGs/DRPs coordinated bidding

## 6. Conclusion

This paper presented an algorithm for expansion planning of an active distribution system that supplies its downward AMGs and it participates in the upward wholesale market to sell its surplus electricity. The energy resources of ADS were CHPs, small wind turbines, photovoltaic systems, electric storage, and gas-fired boilers. The proposed method considered the impacts of AMGs and DRPs coordinated on the expansion-planning problem and minimized investment, operational and emission cost; meanwhile, maximized the system reliability.

The model used the CVaR criterion in order to handle the trading risks of ADS with the wholesale market. The proposed formulation integrated the most important deterministic and stochastic parameters of the risk-based expansion planning of ADS that is rare in the literature on this field.

The conclusion can be summarized as follows:

- The problem model had six sources of uncertainty: upward electricity market price, AMGs location and time of installation, AMGs power generation/consumption,

ADS intermittent power generation, DRP biddings, and the ADS system contingencies.

- A four-stage optimization algorithm was proposed. At the first stage, the ADS optimized the location, capacity and time of installation of its facilities for different wholesale market scenarios and AMGs location and capacity alternatives. At the second stage, the bidding scenarios of AMGs and DRPs was generated and the scenario reduction procedure is performed. Then the feasibility of estimated AMGs and DRPs biddings were evaluated and the coordinated bidding of AMGs/DRPs was recognized. At the third stage, the optimal scheduling of ADS energy resources was determined. At this stage, the model utilized the CVaR criterion in order to handle the trading risks of ADS with the wholesale market. At the fourth stage, the involuntary load shedding, corrective DRPs and AMGs interruptions were determined for each contingency scenario.
- Two test systems were considered by different configurations, electrical and heating loads, and operational paradigms. The OEPADS reduced the aggregated total costs for the 18-bus and 33-bus system about 44.04%, and 11.82% with respect to the

uncoordinated bidding of AMGs/DRPs scenario costs, respectively. Further, the ADS expected benefits of electricity sold to the wholesale market were about 8.2145 (MMUs), and 17.2416 (MMUs) for the 18-bus and 33-bus test systems, respectively. It means that the ADS can gain benefit from the coordinated biddings of AMGs/DRPs.

In conclusion, the adoption of the proposed OEPADS includes AMGs/DRPs coordinated biddings allows increasing significantly the ADS benefits and the reliability. The authors are investigating the use of other heuristic optimization method to speed up the calculation of the OEPADS procedure.

## 7. References

- 1- Chicco, G., Mancarella, P., 'Distributed multi-generation: a comprehensive view', *Renew. Sustain. Energy Revs.*, 2009, 13, pp. 535–551.
- 2- Chowdhury, S., Chowdhury, S.P., Crossley, P., 'Microgrids and active distribution networks', (The institution of engineering and technology Press), 2009.
- 3- Wu, M., Kou, L., Hou, X., Ji, Y., Xu, B., Gao, H., 'A bi-level robust planning model for active distribution networks considering uncertainties of renewable energies', *Int. J. Electr. Power Energy Syst.*, 2019, 105, pp. 814-822.
- 4- Bahrami, S., Amini, M., Shafie-khah, M., Catalão, J. P.S., 'A decentralized renewable generation management and demand response in power distribution networks', *IEEE Trans. on Power Sys.*, 2018, 33, (4), pp. 4218-4227.
- 5- Moradijoz, M., Parsa Moghaddam, M., Haghifam, M.R., 'A flexible active distribution system expansion planning model: A risk-based approach', *Energy*, 2018, 145, pp. 442-457.
- 6- Samper, M., Vargas, A., 'Investment decisions in distribution networks under uncertainty with distributed generation -part I: Model formulation', *IEEE Trans. on Power Sys.*, 2013, 28, (3), pp. 2341-2351.
- 7- Zare, A., Chung, C. Y., Zhan, J., Faried, S.O., 'A distributionally robust chance-constrained MILP model for multistage distribution system planning with uncertain renewables and loads', *IEEE Trans. on Power Sys.*, 2018, 33, (5), pp. 5248-5262.
- 8- Bahrami, S., Amini, M., Shafie-khah, M., Catalão, J. P.S., 'A decentralized electricity market scheme enabling demand response deployment', *IEEE Trans. On sustainable energy*, 2018, 9, (4), pp. 1783-1797.
- 9- Amjady, N., Attarha, A., Dehghan, S., Conejo, A.J., 'Adaptive robust expansion planning for a distribution network with DERs', *IEEE Trans. on Power Sys.*, 2018, 33, (2), pp. 1698-1715.
- 10- Wang, H., Zhang, H., Gu, C., Lid, C., 'Optimal design and operation of CHPs and energy hub with multi objectives for a local energy system', *Energy Procedia*, 2017, 142, pp. 1615–1621.
- 11- Moradi, S., Ghaffarpour, R., Ranjbar, A.M., Mozaffari, B., 'Optimal integrated sizing and planning of hubs with midsize/large CHP units considering reliability of supply', *Energy Convers. Manage.*, 2017, 148, pp. 974–992.
- 12- Rastgou, A., Moshtagh, J., 'Improved harmony search algorithm for electrical distribution network expansion planning in the presence of distributed generators', *Energy*, 2018, 151, pp. 178-202.
- 13- Weber, C., Shah, N., 'Optimization based design of a district energy system for an eco-town in the united kingdom', *Energy*, 2011, 36, pp.1292–1308
- 14- Soderman, J., Petterson. F., 'Structural and operational optimization of distributed energy systems', *Appl. Thermal Engineering*, 2006, 26, pp. 1400–1408.
- 15- Bahrami, S., Wong, V.W.S., Huang, J., 'Data center demand response in deregulated electricity markets', *IEEE Trans. on smart grid*, Early access, 2018.
- 16- Bracco, S., Gabriele, D., and Silvia, S., 'Economic and environmental optimization model for the design and the operation of a combined heat and power distributed generation system in an urban area', *Energy*, 2013, 55, pp. 1014–1024.
- 17- Box, G. E. P., Jenkins, G. M., Reinsel, G. C., 'Time Series Analysis', John Wiley & Sons, 2013.
- 18- Heitsch, H., Römisch, W., 'Scenario reduction algorithms in stochastic programming', *Comput. Optim. Appl.*, 2003, 24, (2), pp 187-206
- 19- Conejo, A.J., Carrión, M., Morales, J.M., 'Decision making under uncertainty in electricity markets' (Springer, 2010).
- 20- Setayesh Nazar, M., Haghifam, M.R., Nazar, M., 'A scenario driven multiobjective primary–secondary distribution system expansion planning algorithm in the presence of wholesale–retail market', *Int. J. Electr. Power Energy Syst.*, 2012, 40, pp. 29–45.
- 21- 'Generalized Algebraic Modeling Systems (GAMS)'. <http://www.gams.com> accessed 9 October 2018.
- 22- Masoum, M.A., Jafarian, A., Ladjevardi, M., Fuchs, E.F., Grady, W.M., 'Fuzzy approach for optimal placement and sizing of capacitor banks in the presence of harmonics', *IEEE Trans. Power. Del.*, 2004, 19, (2), pp. 822–829.
- 23- Derakhshandeh, S.Y., Masoum, A.S., Deilami, S., Masoum, M., A., S., Golshan, M., E., 'Coordination of generation scheduling with PEVs charging in industrial microgrids', *IEEE Trans. Power. Syst.*, 2013, 28, (3), pp. 3451–3461.
- 24- Baran, M.E., Wu, F.F.: 'Network reconfiguration in distribution systems for loss reduction and load balancing', *IEEE Trans. Power. Del.*, 1989, 4, (2), pp. 1401-1407.