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A two-stage joint operation and planning model for sizing and siting of electrical energy storage devices considering demand response programs

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ABSTRACT

This study describes a computationally efficient model for the optimal sizing and siting of Electrical Energy Storage Devices (EESDs) in Smart Grids (SG), accounting for the presence of time-varying electricity tariffs due to Demand Response Program (DRP) participation. The joint planning and operation problem for optimal siting and sizing of the EESD is proposed in a two-stage optimization problem. In this regard, the long-term decision variables deal were the size and location of the EESDs and have been considered at the master level while the operating point of the generation units and EESDs is determined by the slave stage of the model utilizing a standard mixed-integer linear programming model. To examine the effectiveness of the model in the slave sub-problem, the operation model is solved for different working days of different seasons. Binary Particle Swarm Optimization (BPSO) and Binary Genetic Algorithm (BGA) have been used at the master level to propose different scenarios for investment in the planning stage. The slave problem optimizes the model in terms of the short-term horizon (day-ahead). Additionally, the slave problem determines the optimal schedule for an SG considering the presence of EESD (with sizes and locations provided by the upper level). The electricity price fluctuates throughout the day, according to a Time-of-Use (ToU) DRP pricing scheme. Moreover, the impacts of DRPs have been addressed in the slave stage. The proposed model is examined on a modified IEEE 24-Bus test system.

1. Introduction

1.1. Background

Power systems around the world need to reduce their reliance on fossil-fuel-based generation and instead rely more on renewable energy sources (such as wind or photovoltaic (PV) panels) to generate electricity to meet various environmental targets, such as those detailed in the Paris Climate Agreement [1]. As power systems rely more on these volatile sources of energy, the flexibility of power systems will become ever important [2]. Flexibility, the ability to optimally modulate both supply and demand of electricity depending on certain circumstances, will be especially needed in distribution systems as the use of Distributed Energy Resources (DERs). These devices will allow previously passive consumers to become active prosumers within the system. This will mean a shift away from distribution systems having a one-way flow of electricity (from the centralized power plants) towards a system where bidirectional flows of power are more common as prosumers both produce and consume electricity according to the time of day or other factors. A Smart Grid (SG) will rely on this potential of prosumers to support the energy transition. The DERs owned by the prosumers are often intermittent and thus Electrical Energy Storage Devices (EESDs) will be key if the prosumers are to have a much more active role within the energy system through increased prosumer flexibility.

Increasing flexibility through the incorporation of EESD has been widely researched in the existing literature [3]. Despite this obvious potential, there are several drawbacks to EESD deployment, chief among

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Nomenclature

Sets

d	Index for season
i	Index of bus number
l	Index of line
s	Index of Electrical Energy Storage Device
t, t'	Index for time

Parameter

a_i, b_i, c_i	Cost function coefficient of thermal units
$Budget^{Max}$	Available budget for EESD installation ($)
$Cost_{i,s}$	Investment cost of EESD ($/MWh)
$EESD_{i,s}$	Capacity of EESD (MWh)
$EESD^{Max}$	Maximum capacity of EESD can be installed (MWh)
$Eng^{Max}_{s,i}$	Maximum energy level of EESD (MWh)
$Eng^{Min}_{s,i}$	Minimum energy level of EESD (MWh)
LT	Lifetime
N_B	Number of buses
N_S	Number of EESDs
N_D	Number of seasons
N_T	Number of time slots
NL_i	Number of lines connected to bus i
$PD_{i,t,d}$	Load demand (MW)
$PD^{Old}_{i,t,d}$	Demand before applying DR (MW)
$P^{Dis,Max}_{s,t,d}$	Maximum discharging power of EESD (MW)
$P^{Ch,Max}_{s,t,d}$	Maximum charging power of EESD (MW)
PG^{Min}	Min generation of thermal units (MW)
PG^{Max}_i	Max generation of thermal units (MW)
PL^{Max}_l	Rated capacity of transmission line (MW)
r	Interest rate
RU_i, RD_i	Ramp up/down limit of thermal units (MW)
STU_i	Start-up cost of thermal units ($)
SDU_i	Shut-down cost of thermal units ($)
T^{on}_i, T^{off}_i	Minimum up/down time limit
X_l	Reactance of transmission line
α, β	Load variation percentage for DR
$\lambda_{i,t,d}$	Hourly locational marginal price ($/MWh)
$\eta^{Ch}_{s,i}$	Efficiency of EESD in charging mode
$\eta^{Dis}_{s,i}$	Efficiency of EESD in discharging mode
$+\rho, -\rho$	Binary status of transmission line
$\delta^{ref}_{l,t,d}$	Voltage angle of reference bus
γ	Allowable power change with DR
Δt	Time interval
$\lambda^{Dis}_{i,t,d}$	Hourly price of discharging energy ($/MWh)
$\lambda^{Ch}_{i,t,d}$	Hourly price of charging energy ($/MWh)

Variables

$Eng_{s,t,d}$	Energy level of EESD (MWh)
F_{ci}	Cost function of thermal units ($)
$I_{i,t,d}$	Status of thermal unit
$I^{Ch}_{s,i,t,d}$	Charging status of EESD
$I^{Dis}_{s,i,t,d}$	Discharging status of EESD
$I^{Ch}_{s,i,t,d}$	Charging status of EESD
$INVC$	Investment cost ($)
$K_{i,s}$	Installation decision variable of EESD
$PD^{New}_{i,t,d}$	Demand after applying DR (MW)
$PG_{i,t,d}$	Power generation of thermal units (MW)
$P^{Dis}_{s,t,d}$	Discharge power of EESD (MW)
$P^{Ch}_{s,t,d}$	Charge power of EESD (MW)
$PL_{l,t,d}$	Power flow of transmission lines (MW)
$SUC_{i,t,d}$	Start-up cost of thermal units ($)
$SDC_{i,t,d}$	Shut-down cost of thermal units ($)
$SU_{i,t,d}$	Start-up status of thermal unit
$SD_{i,t,d}$	Shut-down status of thermal unit
TC	Total cost ($)
$TOPC$	Total operation cost ($)
$\delta^S_{l,t,d}, \delta^R_{l,t,d}$	Voltage angle for sending/ receiving buses of transmission lines

Symbols

BGA	Binary Genetic Algorithm
BPSO	Binary Particle Swarm Optimization
CAES	Compressed Air Energy Storage
DERs	Distributed Energy Resources
DR	Demand Response
DRP	Demand Response Program
EESD	Electrical Energy Storage Device
EVs	Electric Vehicles
GAMS	Generalized Algebraic Modeling System
LMP	Locational Marginal Price
LP	Linear Programming
LV	Low Voltage
MICP	Mixed-Integer Convex Programming
MINLP	Mixed-Integer Non-Linear Programming
MILP	Mixed-Integer Linear Programming
OPF	Optimal Power Flow
PV	Photovoltaic
RE	Renewable Energy
RES	Renewable Energy Source
SG	Smart Grid
SoC	State of Charge
ToU	Time-of-Use
UC	Unit Commitment
WECC	Western Electricity Coordinating Council

them is their investment cost. Also, accurately modelling EESDs in both operation and planning environments is challenging. This is due to the high non-linearity of the problem. Thus, a computationally efficient optimization method will be very useful.

1.2. Motivation

These challenges of EESD deployment motivate this study as there is a need to address the problem of determining the optimal size and location of EESDs in SG accurately and efficiently. This is important as EESDs have high upfront capital costs and thus to maximize their benefit, the capacity and siting of these devices need to be planned optimally. Failure to do this reduces their benefits and in some cases can cause negative impacts to the SG, both economically and technically [4].

Increasing levels of intermittent renewable energy generation lead to increasingly complex scheduling decisions for grid assets, including EESDs [5]. This increasingly complex scheduling may increase the value that EESDs can add to the SG as they can both absorb excess generation or inject electricity back into the grid at times of high demand. Thus, investing in EESDs may become more attractive to mitigate uncertainty from renewable energy generators. EESDs may also provide important ancillary services to the grid [6].

In addition to this, increasing participation in Demand Response (DR) programs, using time-dependent electricity tariffs (for example

Time-of-Use (ToU), is becoming more popular. These schemes and other examples of DR programs inform the end-users by price signals. These signals can incentivize the increased use of electricity during periods of low tariffs or reduce the use of electricity during periods of high tariffs. These actions can help to shape the load profile, mostly by moving consumption away from periods of peak-load (high tariff) to off-peak periods (low tariffs).

Using EESDs in SG can increase the effectiveness of DR programs by allowing energy to be stored across time and so, the inclusion of EESDs in SG is an important area of research. Investigating the effects of having EESDs in grids with price-based DR programs (in this case ToU tariffs) is the main objective of this study. These price-based DR programs affect the load profile in an operational (or short term) time frame while the long-term time frame is concerned with identifying both the capacity and siting of the EESDs so that the system can operate optimally. By optimizing the system for both the long and short term, as is done in this paper, the load factor of the EESDs will be increased in the short term which in turn leads to cost-optimal operation of the system in the long term.

1.3. Literature review

Several existing papers have considered the utilization of EESDs within active distribution networks. For example, the authors in [3] determined the optimal size of the EESD to reduce the frequency of both under and overvoltage issues in the network. The research accounted for uncertainties related to demand as well as renewable energy source (RES) based generation. In the study, a novel stochastic two-stage model using new scenario reduction techniques was used to improve both the accuracy and computational burden of the model. The authors considered the optimal sizing of the EESDs in the first stage. In the second stage the control policy of the EESD was devised. The two-stage model was tested on the 37-bus test system while considering load and generation uncertainty.

These existing models use a wide range of techniques from simple economic dispatch to multi-period optimal power flow models, considering different types of uncertainty as was shown in the paper above. Also, the modelling horizon varies significantly ranging from short term market models to long term planning models. Distribution systems may also have several different topologies which will influence the performance of EESDs. This was investigated by [4], where a review considering various network topologies which have been studied to investigate the optimal size, location, type and operational regime for EESDs. The authors of the paper recommended that future research should focus on incorporating the various costs elements into EESD modelling and using hybrid models consisting of metaheuristics and traditional optimization methods.

As with the network topology, the market structure may also impact the technical and financial performance of EESDs. For example, a market structure for EESDs operating in energy arbitrage activities was presented by [5]. The model derived the locational marginal prices for the system to help analyze the impacts of various characteristics of EESD on arbitrage opportunities. The paper focused on long-term storage systems to exploit energy arbitrage opportunities. The mixed-integer linear programming (MILP) model was composed of two layers: the first maximized the EESD arbitrage revenue while the lower level focused on the market-clearing procedure. The authors tested the system on both the PJM 5-bus system as well as the IEEE 118 bus test system.

Also considering the economic impacts of EESDs in active distribution networks, an economic dispatch model was presented by [7], where an analysis of the economic impacts of EESD integration in a microgrid with time-varying tariffs is conducted. The authors used an improved hybrid particle swarm algorithm and a cost-benefit approach to study the effects of EESD integration using both investment and operational costs. The sizing of the EESD compared to the system size had a significant impact with both over and undersized EESDs resulting in a negative return on investment. The model considered a TOU tariff. No technical constraints of the distribution were considered or the optimal siting of the EESD which may impact the actual economic performance of the EESD.

Considering some basic technical constraints as opposed to a purely economic study, a techno-economic analysis for the optimal sizing of EESDs in SG using residential load profiles was conducted by [8]. In the paper, the effects of having a single centralized EESD were compared to having numerous smaller EESD distributed throughout the grid. The study found that while smaller EESD had smaller capital costs, they also provided smaller cost savings and benefits to the grid. In contrast, the centralized EESD required higher upfront capital costs but delivered higher cost savings to the grid. A clear trade-off was discovered between the location and size of the EESD, and the cost savings and operational convenience provided by the EESD.

Energy prices in both the day ahead and real-time markets may also introduce uncertainty. The authors of [9] present a model that considered the variance in price uncertainties to reduce revenue volatility to maximize expected revenue from both day-ahead and real-time markets. The authors considered only a basic formulation of the EESDs in the model. The problem was solved using the mixed-integer convex programming (MICP) solver in the Generalized Algebraic Modeling System (GAMS) with MOSEK solver.

Further research on energy arbitrage opportunities for EESDs in both day-ahead and real-time markets was presented by [10] to maximize the expected profit for the owner of the EESD. The paper considered a stochastic formulation reformulating the problem into a MILP problem. The model only considered the economic assessment of the EESD and no considerations for power flows through the lines were included. In addition, the bidding strategy is focused on the short term so no long-term investment decisions are taken.

A planning model for the effects of EESDs in energy as well as reserve markets was studied in [11], where the authors utilized a bi-level optimization problem to determine the size and location of EESD while respecting profit constraints using an economic dispatch model. To analyze the accuracy and scalability of the algorithm, the authors provide a comparison between a primal decomposition method making use of sub-gradient cutting planes and an exact linear programming approach. The study made use of two types of EESD, which were Compressed Air Energy Storage (CAES) as well as Lithium-ion batteries to compare the behavior of each of these technologies under different market and regulatory regimes. The authors considered the 240-bus system of the Western Electricity Coordinating Council (WECC). The upper level considered the total system cost for all days considered in the optimization horizon while the lower level minimized the operating costs for each smaller system. The model was solved through CPLEX.

Looking past the market structure at a long-term planning model is also important as was shown by the model developed in [12] which investigated the planning and operational strategies of EESDs in distribution networks. The paper made use of a model for long-term planning which was decomposed into a two-stage model to determine the optimal location and size of the EESDs. The model used mixed integer programming to ease the computation burden with the objective function of minimizing the total investment and operating costs.

Using mixed-integer programming but this time non-linear programming, [13] presented a model to determine the optimal spinning reserve of a system with significant penetrations of RES and EESDs. The size of the EESDs was chosen to minimize the uncertainty surrounding RES generation. The model used a Security Constrained Unit Commitment model for a general 6 bus test system. The authors incorporated uncertainties around demand and RES output using a scenario-based process.

The impacts of uncertain RES generation, specifically wind power, on the optimal operation of EESD were investigated in [14]. The authors used three, competing, objective functions, namely operating costs, voltage deviations in the network and associated emissions from

Table 1
Summary of relevant literature.

Paper	Problem formulation	Uncertainty	Sizing	Siting	Test system	Horizon considered	Demand response
[3]	Semidefinite programming	Load, RE generation	Yes	No	37 bus test system	Operational	No
[11]	MILP	No	Yes	Yes	Western Electricity Coordinating Council 240-bus model	Operational and investment	No
[12]	MINLP combined with heuristic methods	Load, RE generation	Yes	Yes	30 bus test system	Operational and investment	No
[15]	Stochastic Model predictive control	RE generation, SOC of EESD	Yes	No	IEEE-57 bus test system	Operational	No
[20]	MILP	No	No	No	None	Operational	No
[21]	MILP	Load, RE generation	No	No	None	Operational	Yes
This paper	**MILP combined with heuristic methods**	**Seasonal Load**	**Yes**	**Yes**	**IEEE 24 bus test system**	**Both operational and investment**	**Yes**

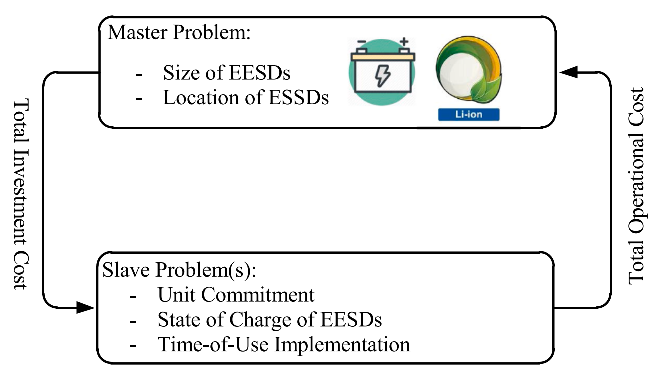


Fig. 1. The conceptual model for the two-stage framework for optimal EESD sizing and siting.

generators. This was done by using a framework comprised of a gravity search and a hybrid algorithm using Particle Swarm Optimization and a Genetic Algorithm. This was combined with multi-criteria decision making to determine the optimal solution considering the output uncertainty of wind power plants. The authors used the IEEE 30 bust test system. Constraints relating to the EESD were not described and did not consider the effects of DR programs.

In [15], a two-stage stochastic model using predictive control was developed to optimize the operation and size of the EESD, as well as levels of output from the generators. Interestingly, the authors considered five different types of EESD, each with its technical characteristics. The model accounted for the uncertainty surrounding wind generation and sought to optimize the storage for a wide number of potential scenarios. The model minimized total cost and was solved in MATLAB using the CPLEXQP solver. The authors recommended that future research

Table 2
Case studies and their assumptions.

Cases	Algorithm		EESD Allocation	DR Programs	Load Uncertainty
	BPSO	BGA			
1	×	×	×	×	×
2	×	×	×	✓	×
3	✓	×	✓	×	×
4	×	✓	✓	×	×
5	✓	×	✓	✓	×
6	×	✓	✓	✓	×
7	×	✓	✓	✓	✓

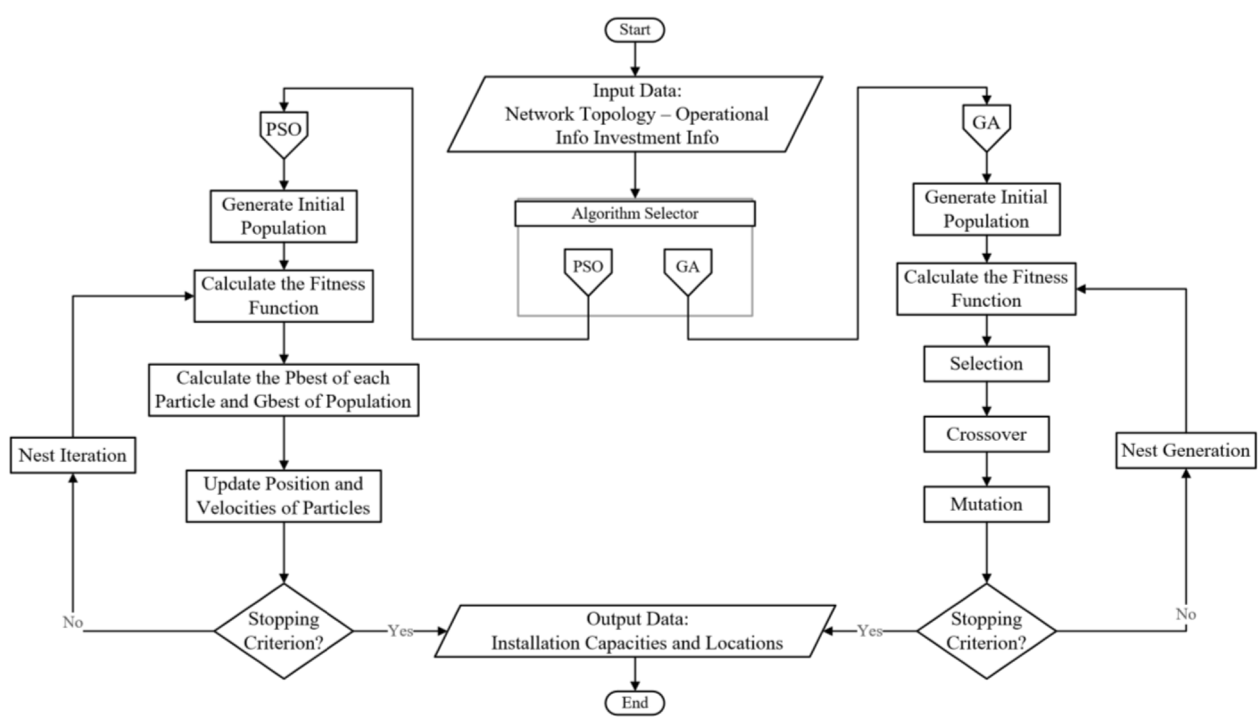


Fig. 2. The flowchart of the proposed model.

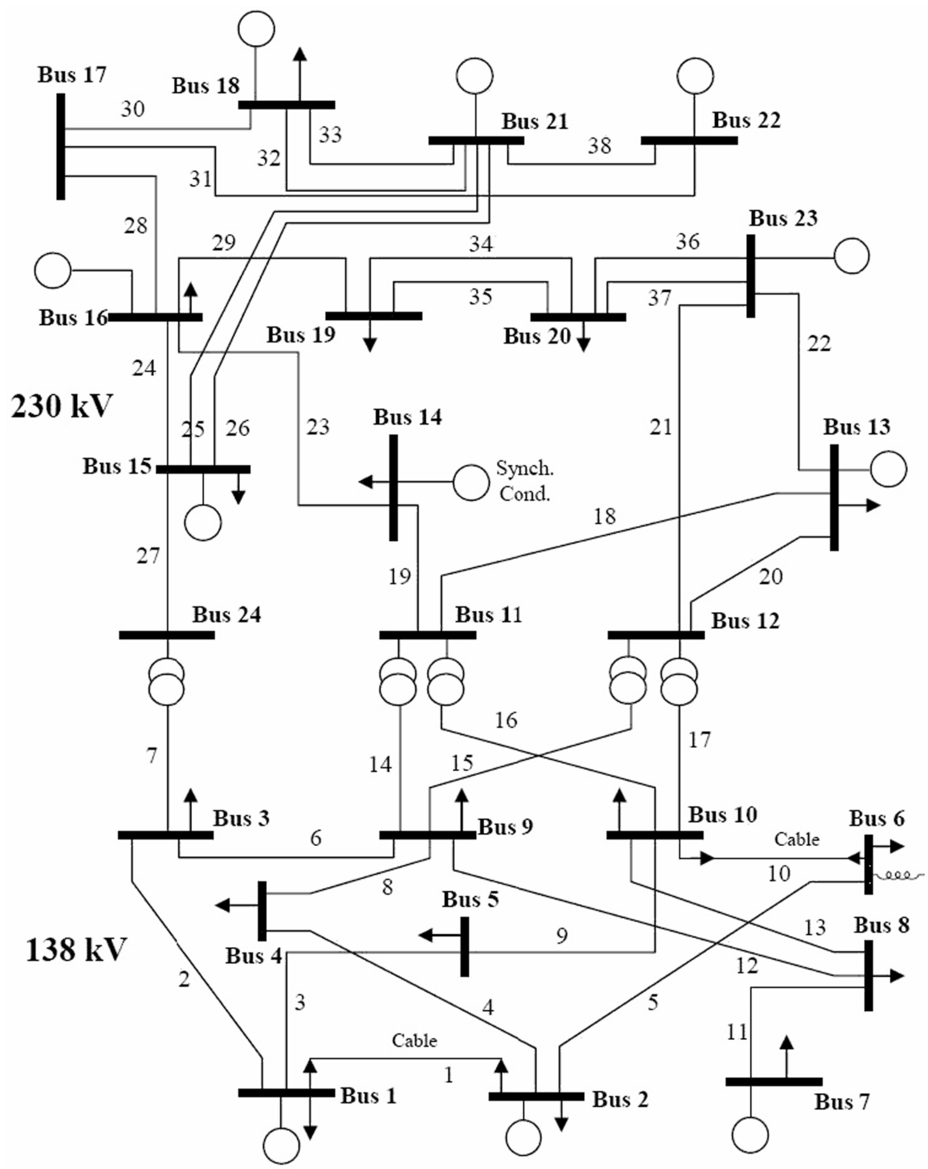


Fig. 3. The single line diagram of the IEEE 24-Bus test system.

Table 3
The list of candidates.

Capacity of EESDs (MW)				
75	100 125	150	175 200	250 300
$Eng^{EESD,Min}$	$Eng^{EESD,Max}$	$P^{EESD,Ch.,Max}$	$P^{EESD,Dis.,Max}$	$Eng^{EESD,\ Initial}$
0.20	1.00	0.2	0.2	0.50

should investigate the optimal placement of the EESD as well as the optimal number of EESD to deploy, additionally the authors recommended that future work should include line constraints. These recommendations have been incorporated into the currently proposed model.

Researchers in [16] proposed a multi-period non-linear Optimal Power Flow (OPF) to model high penetrations of Electric Vehicles (EVs) and RES in addition to the inclusion of EESDs for voltage support for active distribution grids. The paper presented the effects of a wide range in the penetration of EV and RES and the corresponding utilization of the EESD. This analysis showed that EESDs provided significant benefits to the system and proper sizing of the EESD is crucial to maximize these benefits. The model had the objective to minimize the operational costs of a diverse set of DERs and help to mitigate issues related to nodal voltage fluctuations and reducing curtailed generation from RES. The authors deployed the model on the IEEE benchmarked low-voltage (LV) European network with a fixed location and size for the single EESD considered.

A bi-level robust programming model was developed in [17] to determine the optimum operation schedule of a multi-microgrid system using a ToU tariff structure and robust programming. The types of uncertainty included in the model were renewable energy (RE) generation, day-ahead market prices and EV use and these were modelled in a stochastic manner. The lower level minimized the expected cost of the microgrids while the upper level optimized the operational costs of the entire system. The model was formulated as a mixed-integer non-linear programming (MINLP) problem.

Some of the preceding papers have considered various types of uncertainty and a paper that focused specifically on the uncertainty from solar PV generation was investigated in [18] and showed the benefits of using a time-flexible operational regime to account for the variation in power output from the PV system.

The combination of PV systems, this time combined with EESD

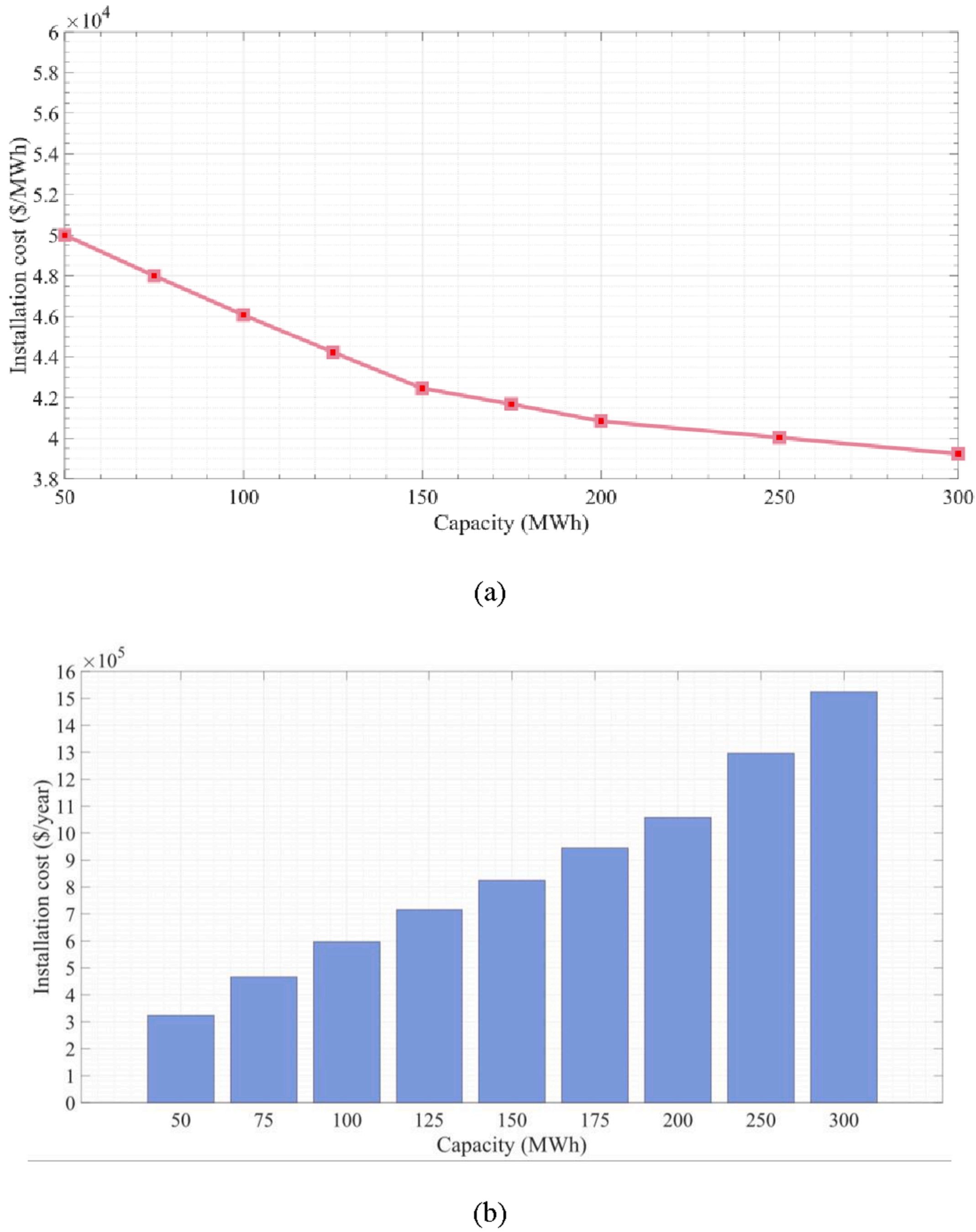


Fig. 4. Installation cost of the EESDs, (a) real investment cost per MWh, (b) annualized investment cost per year.

systems was studied in [19] where the aim was to reduce the voltage fluctuations associated caused by the PV systems by utilizing EESDs through injecting and absorbing real power. The paper made use of a bi-level optimization approach based on a Genetic Algorithm (GA) for the upper level for the sizing and siting of the EESDs. The lower level makes use of a linear programming (LP) model to determine the operating schedule of each EESD. An economic assessment but with some technical constraints relating to the battery. The paper did not consider line losses during operation. The authors tested the system on the IEEE 8500-bus test system.

Using EESDs to provide flexibility in community energy initiatives were researched in [20] and [21]. A multi-objective framework was used in [20] to analyze optimal energy arbitrage scenarios for the community. A total of six types of EESD technologies were analyzed to determine those solutions which were technically and economically feasible. The authors considered a multi-objective, MILP model to minimize the operational and emissions costs. The model considered a fixed size of the EESD and did not include the power flows into the formulation.

Also considering flexibility offered by EESDs but this time focusing on the resiliency of the distribution network, work in [21] leveraged EESDs in both normal and contingent events resulting in islanding operation. The authors coordinated the operation of DR programs and EESD under various forms of uncertainty. The model was formulated as a MILP model.

A system for the monitoring of grid-scale EESDs was introduced by [22]. The authors considered a single EESD at the substation level and this may lead to sub-optimal performances as there may be system-level

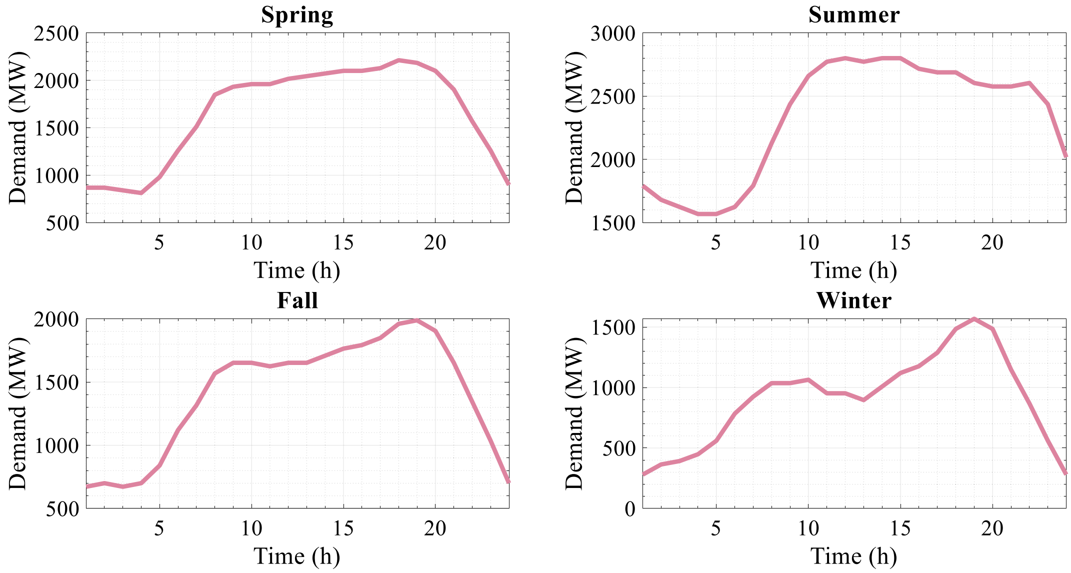


Fig. 5. The hourly Load demand at each season.

Table 4
Optimal site and size of EESDs in different cases.

Cases	EESD Bus Number				Capacity (MW)				Investment ($)
3	8	14		23	300	300		300	4573098.25
4	8	11		20	300	250		300	4344961.83
5	14	15		23	250	300		250	4116825.41
6	10	14	15	20	200	250	250	250	4946835.66

Table 5
The hourly operating cost in each case.

Cases	**Case 1**	**Case 2**	**Case 3**
Spring ($/day)	387244.95	391088.64	364914.82
Summer ($/day)	802338.49	778768.14	766040.07
Fall ($/day)	292414.56	286203.27	269736.9
Winter ($/day)	154367.03	143850.36	138486.53
Operation Cost ($/year)	149,318,309	145991824.9	140450021.7

Cases	**Case 4**	**Case 5**	**Case 6**
Spring ($/day)	368535.81	369446.79	365946.02
Summer ($/day)	770008.75	728665.55	722958.47
Fall ($/day)	271459.5	266678.16	263239.74
Winter ($/day)	140341.71	132831.28	130546.44
Operation Cost ($/year)	141469051.5	136657987.4	135295523.6

improvements if the EESDs are optimally dispersed throughout the network as is done in the currently proposed model. The authors of [22] ensure that the EESD may operate in the flexibility markets which may provide important sources of additional revenue for the EESD owner however, the authors only considered a short-term operating horizon.

The effects of EESDs on the power quality within power grids were investigated by [23]. The authors showed how an EESD can improve the power quality within a system containing a single wind power plant along with several other advantages. The authors consider different discreet EESD capacities but do not optimally determine the size which may improve the results even further. The test system used was a 12-bus system focused on the United Kingdom. The effects of uncertainty on the results were not investigated and there was no discussion of the effects of the EESD on the power flows within the system, in contrast with our currently proposed model. The authors of the paper recommend that the effects of demand-side management should be incorporated in future models as they may provide important sources of flexibility to avoid relying on expensive peak generation plants.

A further paper that considered the effects of EESDs on power quality within a system with intermittent generation was done by [24]. However, this investigation was purely conducted from an economic aspect. The EESD considered was a flywheel energy storage system. Economically, the installation of the EESD was not feasible unless there were strong government subsidies offered. Results showed that the EESD can improve the load factor of the wind power plant.

Table 1 presents a summary of relevant literature in this field. These six papers were chosen as they were the most similar to the proposed model, especially as they use two-stage optimization to solve problems related to EESDs in active distribution networks. In addition, the table shows how the current proposed model provides novel contributions in various aspects. Notably, these are in the optimization of both sizing and siting of EESDs, considering both operational and investment horizons and the investigation into the effect of demand response programs.

1.4. Contribution

The previous section has shown that while the topic of EESDs in active distribution networks has received some research interest, there are clear research gaps that still need to be addressed. This paper addresses these research gaps through the development of a two-stage optimization model to determine the optimal sizing and location of EESD within a given system. This is done through the following main contributions:

- A two-stage model concerning both planning and operational horizons of EESDs
- Two different heuristic algorithms are applied to the master problem to improve the results of the problem
- An improved linearized slave problem formulation to reduce the computational burden.

This two-stage model relies on a linear unit commitment model that was used to solve the slave problem whose objective was to optimize the status of the network operation, including generators. The ToU tariff was included in the slave problem and used with the EESD to reduce the gap between peak demand and off-peak demand. This is done by using techniques such as peak shaving and valley filling which also improves

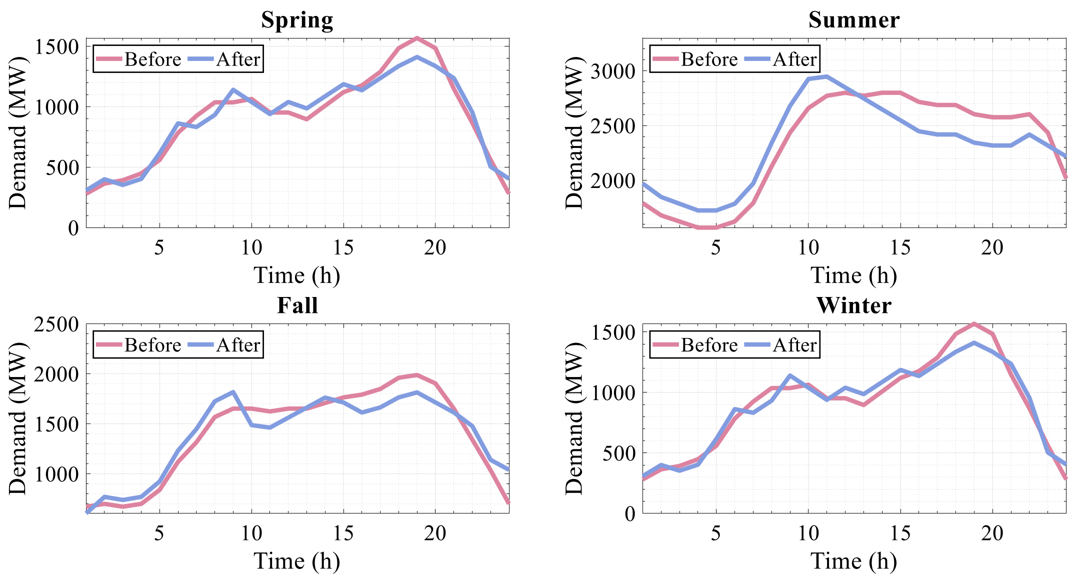


Fig. 6. Load demand curves in each season (before and after implementation of DR program).

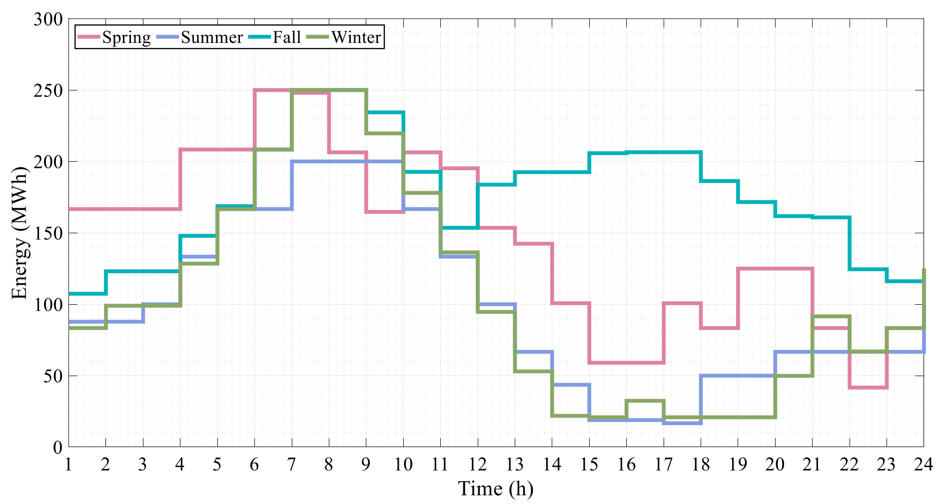


Fig. 7. The state of charge of the EESDs in case 6.

Table 6
Worst and best solutions obtained in each case.

Case	Cost (M$/year)	Worst	Best	Computational Time (s)
3	Operation	143.737	140.450	7456
	Investment	2.820	4.573	
	Total	146.557	145.023	
4	Operation	143.798	141.469	6552
	Investment	4.116	4.344	
	Total	147.914	145.813	
5	Operation	139.186	136.658	7654
	Investment	3.851	4.116	
	Total	143.037	140.774	
6	Operation	137.967	135.296	7152
	Investment	5.181	4.946	
	Total	143.148	140.242	

the load factor of the EESD. The State of Charge (SoC) of the EESD was considered for the optimization of the operational regime. In the master problem, the long-term planning problem is solved to determine the optimal size and location of the EESD using two different metaheuristic optimization algorithms, i.e. Binary Particle Swarm Optimization (BPSO) and binary Genetic Algorithm (BGA). The proposed hybrid optimization model is investigated to deal with the complexity and scalability of the joint operation and planning problem. The short-term problem is dependent on the results of the long-term problem [25]. This two-stage approach reduces the computational effort required to solve the problem and the model is validated on the modified IEEE 24-bus test system.

1.5. Organization

The paper has the following structure, the proposed optimization model, including the improvements relating to the model's computational burden is described in Section 2. Section 3 details the mathematical formulation of the model, including how the EESD were included in the optimization model. The hybrid optimization model utilizing metaheuristic optimization algorithms is provided in Section 4. The results of the model for the modified IEEE 24-bus test system are presented in Section 5. Finally, Section 6 contains the relevant conclusions and suggestions for further work.

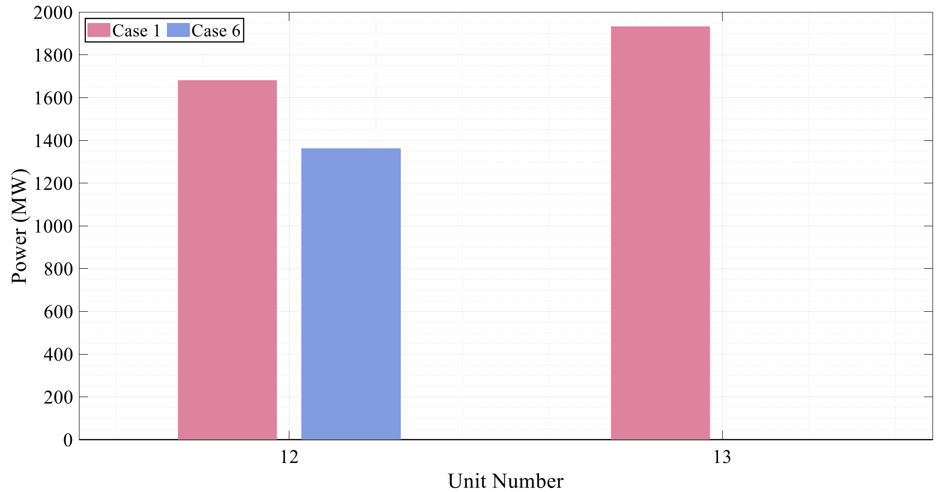
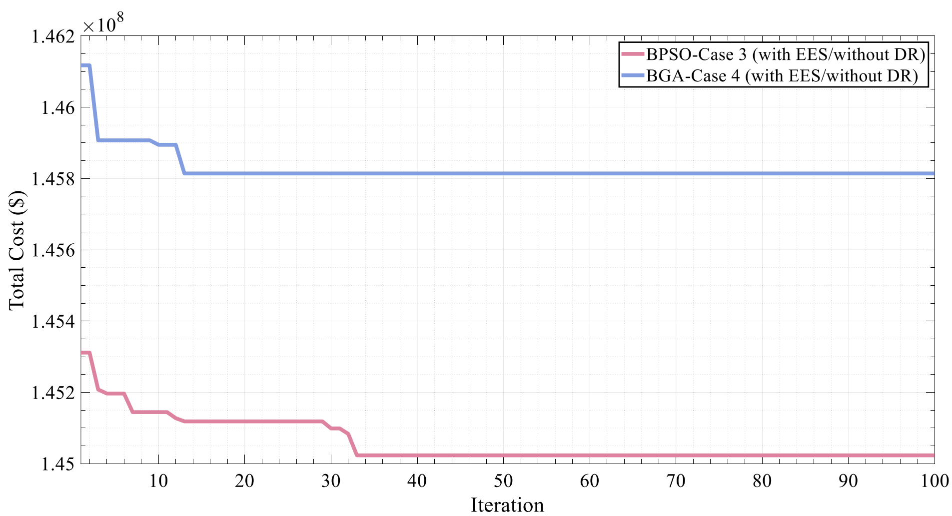


Fig. 8. The amount of power generated by expensive units in summer.



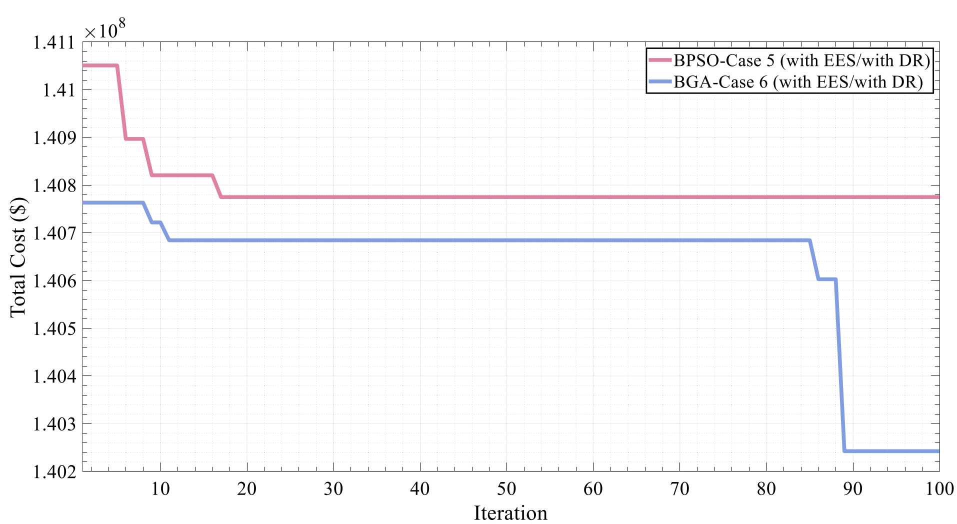


Fig. 9. The convergence curves of BPSO and BGA algorithms (a): Case 3&4, (b): Case 5&6.

Table 7
The specific settings of BPSO and BGA.

BPSO					
Numberof Runs	Iter.	Pop.	Personal Learning Coefficient	Global Learning Coefficient	Inertia Weight
10	100	10	1.5	2	1
BGA					
Numberof Runs	Iter.	Pop.	Crossover Percentage	Mutation Percentage	Mutation Rate
10	100	10	0.8	0.3	0.02

*Iter.: Iterations, Pop.: Populations.

2. Conceptualization of the two-stage optimization model

A highly non-linear formulation results from optimizing the size and location of EESDs within an SG and this carries a computational burden that varies exponentially with the size of the problem [26]. Thus, in this study, we present a two-stage formulation (slave and master problem) which helps diminish the problem's computational burden.

The slave problem, which is a unit commitment problem presented based on the work in [27], is modeled as an MILP model. This model uses ToU DR programs to schedule the day-ahead operation of generators. In our model, the EESD with hourly SoC is introduced into the day-ahead optimization.Fig. 1

This operational problem requires that the locations and sizes of the EESD are known [41]. This information is passed to the slave problem from the solution to the master problem. Thus, the short-term problem is reliant on the long-term planning problem. The solution to the master problem (the size and location of EESDs) is found by using a time horizon of one year with a day-to-day granularity, i.e., 365 days are considered. For each day, the optimal size and location for the EESDs are obtained with the corresponding investment costs. These solutions are used to run the slave problem. While it is technically possible to solve the slave problem daily, computationally is not feasible to do so. Therefore, in this paper a representative day is used to find the operational costs for that day and these operational costs are then fed back into the master problem to determine the new optimal locations and sizes of the EESDs. This process continues until the solutions converge to the final capacity and placement of EESD in the network.

The long-term problem is still non-linear but the short-term problem has linearized. The objective of this paper is to present this novel formulation and provide validated results. Thus, an enumeration-based exhaustive search algorithm is used to determine the master problem's optimal solution. This approach will not affect the computational burden significantly in small grids and possibly be faster than other approaches. However, in bigger grids, using more computationally efficient algorithms would be advantageous. Examples of these are meta-heuristic approaches to determine the master problem's optimal solution.

3. Mathematical formulation

In this section, the formulation of the two-stage optimization problem that was used to solve the problem is presented. The formulation aimed to determine the optimal capacity and placement of EESDs in SGs utilizing ToU tariffs.

3.1. Objective function

The model's main objective function is to minimize both the investment costs (INVC) and the total operating costs (TOPC) of EESDs for the duration of the planning horizon. This is given by:

$$Min(TC) = Min(INVC + TOPC) \tag{1}$$

$$INVC = \sum_{s=1}^{N_S} \sum_{i=1}^{N_B} \frac{r(1+r)^{LT}}{(1+r)^{LT}-1} \left[EESD_{i,s} K_{i,s} Cost_{i,s} \right] \tag{2}$$

$$\begin{aligned} TOPC = & \sum_{d=1}^{N_D} \sum_{t=1}^{N_T} \sum_{i=1}^{N_B} \left[F_{ci}\left(PG_{i,t,d}\right) + SUC_{i,t,d} + SDC_{i,t,d} \right] \\ & + \sum_{d=1}^{N_D} \sum_{t=1}^{N_T} \sum_{i=1}^{N_B} \sum_{s=1}^{N_S} \left[P^{Dis}_{s,i,t,d} \lambda^{Dis}_{i,t,d} \Delta t - P^{Ch}_{s,i,t,d} \lambda^{Ch}_{i,t,d} \Delta t \right] \end{aligned} \tag{3}$$

The master problem's objective function is shown as the INVC part of (1) while the TOPC part has to do with the solution to the slave problem. Note that interest rate (r) and a lifetime of ESSDs (LT) are considered in the investment cost calculation The operating costs are determined for

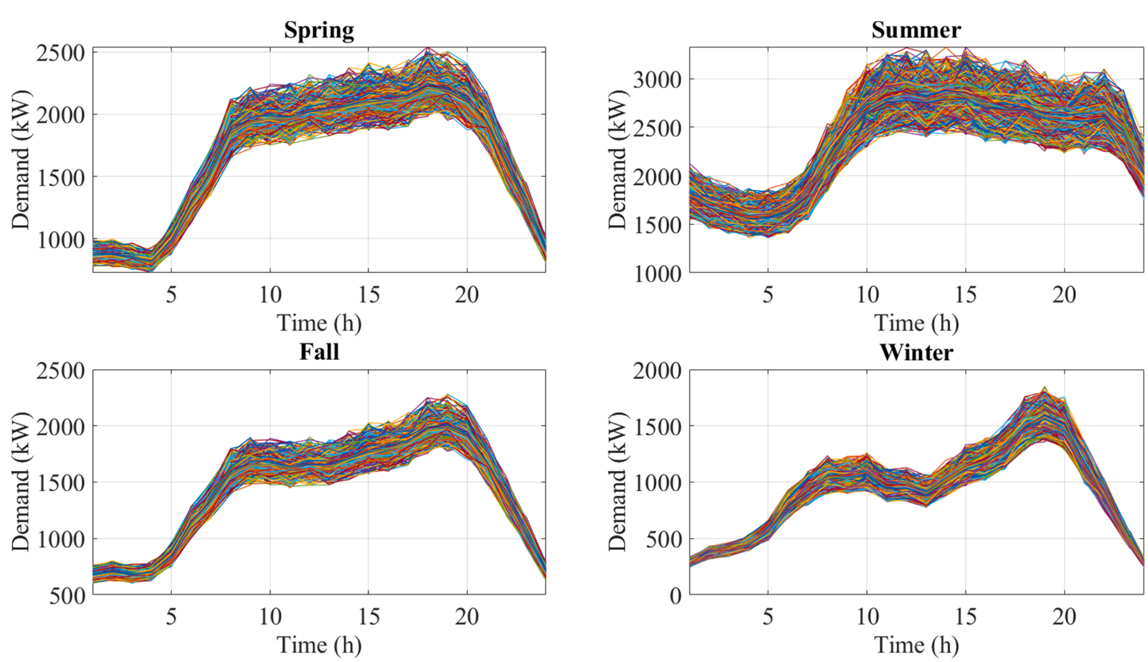


Fig. 10. Load scenarios generated by a normal distribution function.

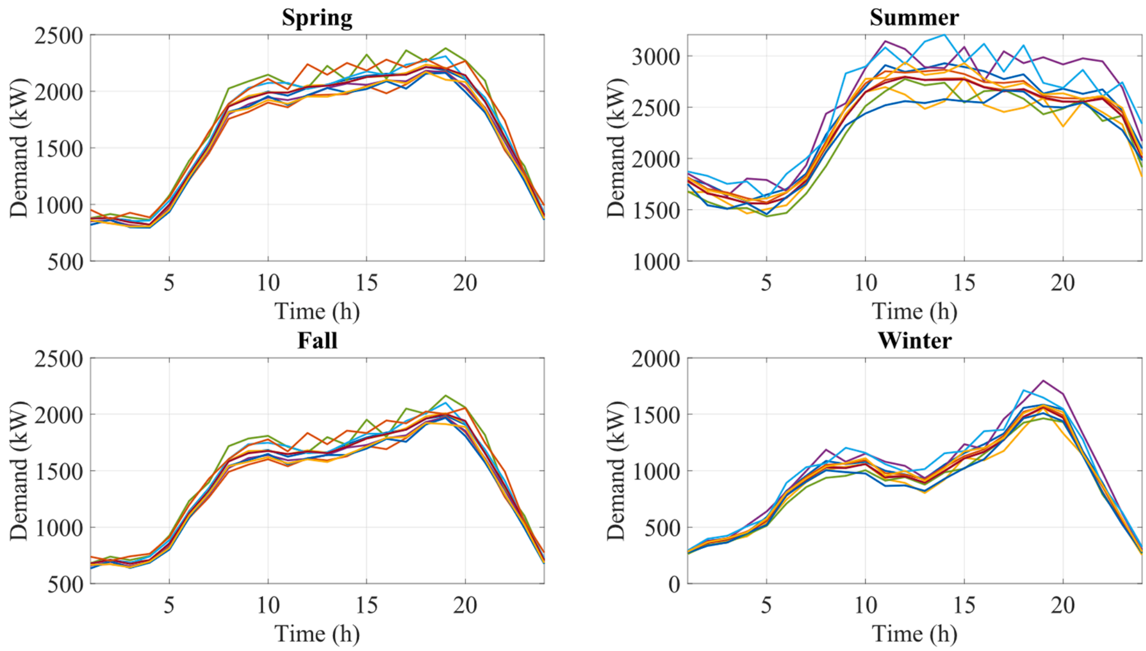


Fig. 11. Load scenarios reduced by ScenRed tool.

Table 8
Results obtained from case 7.

ESSD								**Investment ($)**
Bus Number				**Capacity (MW)**				
10	14	15	23	300	250	300	300	5869327.92
Seasonal Operation Costs ($/day)						**Operation Cost ($/year)**		
Spring	**Summer**	**Fall**		**Winter**				
375810.15	757820.2	272785.57		132843.24		140457398.4		

Table 9
Sensitivity analysis on investment costs of the EESDs.

Investment Cost Change (%)	Investment Cost (M$)	Operation Cost (M$/Day)				Total Operation Cost (M$)	Total Cost (M$)	Change
		Spring	Summer	Fall	Winter			
+10%	5.403	0.403	0.799	0.288	0.14	148.709	154.112	+5.32%
−5%	5.641	0.387	0.774	0.28	0.135	143.92	149.561	−2.21%
0%	5.869	0.376	0.758	0.273	0.133	140.457	146.327	0%
−5%	6.097	0.368	0.74	0.266	0.13	137.259	143.357	−2.03%
−10%	6.839	0.354	0.713	0.255	0.126	132.093	138.933	−5.05%

each day and the unit commitment problem is carried out by the system operator to determine the ideal status and output of the generation units and the SoC of the EESDs. The corresponding charging and discharging costs of the EESDs have been considered in the second part of the operational cost. The costs associated with both the master and slave problem are then summed to produce the Total Cost (TC).

3.2. Master problem formulation

As was discussed previously, the outcome of the master problem is the optimal location and size of the EESDs with the given system. Therefore, the sizes of the EESDs and the budget for investment in EESDs are the main constraints to this problem. The total acceptable size or capacity of the EESDs in the grid is given in Eq. (4). Eq. (5) details the total available budget for the investment in EESDs from the system planner's point of view.

$$\sum_{s=1}^{N_S}\sum_{i=1}^{N_B} EESD_{i,s}K_{i,s} \leq EESD^{Max} \tag{4}$$

$$\sum_{s=1}^{N_S}\sum_{i=1}^{N_B} EESD_{i,s}K_{i,s}Cost_{i,s} \leq Budget^{Max} \tag{5}$$

Worth noting is the fact that commercial EESDs have standard sizes and thus investment costs per kWh of capacity. This also changes between the different types of EESDs for several reasons. Crucially, a binary variable is needed at each bus to determine if EESDs should be installed at that specific bus. This binary variable is given by $K_{i,s}$. The variable $EESD^{Max}$ places an upper limit on the allowable capacity for EESDs while $Budget^{Max}$ provides the upper limit to the available budget.

3.3. Slave problem constraints

The Unit Commitment (UC) problem is at the heart of the slave problem. In this study, the UC problem is framed as an adapted MILP model. The main features of such a model have been shown in [27]. The polynomial cost functions for the thermal generation units are shown in Eq. (6). Piece-wise linearization was used in this research with 200 segments being chosen to represent the quadratic function.

There are some inherent constraints of the UC problem when including EESDs and these are shown in (7)–(24). The thermal generating units have minimum and maximum allowable output levels and these are shown in Eq. (7). The units also have decision variables relating to their start-up and shut down and these are shown in Eq. (8) and the costs associated with these decision variables are shown in Eqs. (9) and (10) [28]. Hourly ramping rates for the generators are shown in Eqs. (11) and (12) [29]. There are also minimum generation outputs, as discussed previously and these affect the output of the first hour after start-up and the hour before shut down. The minimum uptime and minimum downtime constraints are shown in Eqs. (13) and (14).

The constraint representing the hourly load balance is shown in Eq. (15) and it includes any effects of charging or discharging from the EESDs if they are specified by the long-term problem. The Locational Marginal Price (LMP) represents the marginal value of this constraint for each hour relating to the day-ahead market [30,31]. Thus, this is taken as the representative real-time price for the ToU tariff regime. The ToU regime adopted in this study allows the consumers to have the choice to alter their demand depending on both consumer's preferences as well as the market price. This approach has been discussed further in [32,33].

The constraints relating to the EESDs are shown in Eqs. (16)–(21) and are taken into account if the master problem determines that EESDs should be installed. Eq. (16) describes the dynamic energy level for the EESD while the minimum and maximum allowable energy levels are shown in Eq. (17). Eq. (18) models the initial and final energy levels of the EESD [34,35]. The initial and final levels of energy stored are considered to remain the same for all days considered. The acceptable hourly charging and discharging power for the EESDs are governed by Eqs. (19) and (20) respectively [36,37]. As the model considers an hourly time resolution, the EESD can only operate in one mode (charging or discharging) for each hour. This condition is enforced through the binary decision variable in Eq. (21).

Equations for the DC OPF model are given in Eqs. (22)–(24). The power transmitted through a given line is given by Eq. (22) while the line capacities are shown in Eq. (23). The parameter, ρ, restricts the maximum transmission capacity of the network if this is needed. For the reference bus, the bus voltage angle is considered to be zero and is shown in Eq. (24) [38].

$$F_{ci}\left(PG_{i,t,d}\right) = a_i + b_i PG_{i,t,d} + c_i PG_{i,t,d}^2 \tag{6}$$

$$PG_i^{Min} I_{i,t,d} \le PG_{i,t,d} \le PG_i^{Max} I_{i,t,d} \tag{7}$$

$$SU_{i,t,d} - SD_{i,t,d} = I_{i,t,d} - I_{i,t-1,d} \tag{8}$$

$$SUC_{i,t,d} = SU_{i,t,d} STU_i \tag{9}$$

$$SDC_{i,t,d} = SD_{i,t,d} SDU_i \tag{10}$$

$$PG_{i,t,d} - PG_{i,t-1,d} \le RU_i I_{i,t-1,d} + PG^{Min}\left(I_{i,t,d} - I_{i,t-1,d}\right) \tag{11}$$

$$PG_{i,t-1,d} - PG_{i,t,d} \le RD_i I_{i,t,d} + PG^{Min}\left(I_{i,t-1,d} - I_{i,t,d}\right) \tag{12}$$

$$\sum\nolimits_{t'=t}^{t+T_i^{on}-1} I_{i,t',d} \ge T_i^{on}\left(I_{i,t,d} - I_{i,t-1,d}\right) \quad \forall t = 1 \cdots N_T - T_i^{on} + 1 \tag{13}$$

$$\sum\nolimits_{t'=t}^{t+T_i^{off}-1} \left(1 - I_{i,t',d}\right) \ge T_i^{off}\left(I_{i,t-1,d} - I_{i,t,d}\right) \quad \forall t = 1 \cdots N_T - T_i^{on} + 1 \tag{14}$$

$$PG_{i,t,d} + \sum_{s=1}^{N_S} P_{s,i,t,d}^{Dis} - PD_{i,t,d} - \sum_{s=1}^{N_S} P_{s,i,t,d}^{Ch} = \sum_{l \in NL_i} PL_{l,t,d} \perp \lambda_{i,t,d} \tag{15}$$

$$Eng_{s,i,t,d} = Eng_{s,i,t-1,d} + P_{s,i,t,d}^{Ch} \eta_{s,i}^{Ch} \Delta t - P_{s,i,t,d}^{Dis} \Delta t / \eta_{s,i}^{Dis} \tag{16}$$

$$Eng_{s,i}^{Min} \le Eng_{s,i,t,d} \le Eng_{s,i}^{Max} \tag{17}$$

$$Eng_{s,i,t=1,d} = Eng_{s,i,t=24,d} \tag{18}$$

$$0 \le P_{s,i,t,d}^{Ch} \le P_{s,i,}^{Ch,Max} I_{s,i,t,d}^{Ch} \tag{19}$$

$$0 \le P_{s,i,t,d}^{Dis} \le P_{s,i,}^{Dis,Max} I_{s,i,t,d}^{Dis} \tag{20}$$

$$0 \le I_{s,i,t,d}^{Ch} + I_{s,i,t,d}^{Dis} \le 1 \tag{21}$$

$$PL_{l,t,d} = \frac{1}{X_l}\left(\delta_{l,t,d}^S - \delta_{l,t,d}^R\right) \tag{22}$$

$$-\rho PL_l^{Max} \le PL_{l,t,d} \le +\rho PL_l^{Max} \tag{23}$$

$$\delta_{l,t,d}^{ref} = 0 \tag{24}$$

A simulated ToU framework is used in this model to better assess the ToU program as is also done in [27]. This model has the main advantage of considering the LMPs as proxies for real-time price signals. Thus, consumers can modify their consumption, or alter the schedule of the EESD in the case that EESDs are utilized, according to the ToU regime.

Within the slave problem, the ToU regime is implemented as a Linear Programming (LP) model and is given by the following:

$$Min \sum_{i=1}^{N_B} \sum_{t=1}^{N_T} PD_{i,t,d}^{New} \lambda_{i,t,d} \tag{25}$$

$$\sum_{t=1}^{N_T} PD_{i,t,d}^{New} = \sum_{t=1}^{N_T} PD_{i,t,d}^{Old} \tag{26}$$

$$(1-\beta) PD_{i,t,d}^{Old} \le PD_{i,t,d}^{New} \le (1+\alpha) PD_{i,t,d}^{Old} \quad 0 \le \alpha, \beta \le 1 \tag{27}$$

$$PD_{i,t,d}^{New} - PD_{i,t-1,d}^{New} \le \gamma \tag{28}$$

$$PD_{i,t-1,d}^{New} - PD_{i,t,d}^{New} \le \gamma \tag{29}$$

Simulating the ToU regime using this LP model allows for daily load change strategies. The LMP is given by $\lambda_{i,t,d}$ and it is obtained from simulating the clearing of the day-ahead market. The decision variable for this stage, represented by the superscript "*New*" is the simulated demand. Eq. (26) accounts for the total energy demanded during the planning horizon and should be equal to the sum of the energy requests carried out by the aggregators before the implementation of the DR program. The aggregators' participation in the DR program is bounded by Eq. (27). The ability of the aggregators to actively engage in the DR program leads to the hourly load demand also being constrained and these constraints are shown in Eqs. (28) and (29). A parameter, γ, is included to represent the inclination of aggregators to alter their demand from one hour to another.

4. Methodology

In this paper, two different meta-heuristic optimization algorithms have been utilized. BGA and BPSO are selected in this study to show the effectiveness and possibility of solving the problem for a complex power system. Fig. 2 depicts the flowchart for solving the proposed model. According to the figure, BGA [39] and BPSO [40] algorithms have been utilized to optimize the location and size of EESDs.

As can be seen, in the first step, the input data of the problem, including network topology, investment costs of EESDs and operating parameters of conventional generating units, are fed to the mentioned algorithms. In the second step, the optimization algorithm is selected. It should be mentioned that if the PSO algorithm is selected, the problem will be solved in 5 steps.

In the first step, the initial population is generated, which includes the capacity and installation location of the EESDs. In the second step, the fitness function is calculated, which is the minimization of the total investment and operation costs. In the third step, the best values obtained for each particle (*Pbest*$_i$) and the best value obtained by the particles (*Gbest*$_i$) are determined. In the fourth step, the position and velocity of each particle are updated. Finally, in the fifth step, the stop criterion is checked, which, if satisfied, stops the algorithm, and otherwise, steps 1 to 4 are repeated until the algorithm converges. The velocity of each particle is calculated by Eq. (30). Where x_i^t is the position of each particle and V_i^t is the velocity of each particle. r_1 and r_2 are random variables with values between zero and one. c_1 and c_2 are learning coefficients, and w is a weight factor. Finally, the position of each particle in each iteration is updated based on Eq. (31).

$$V_i^{t+1} = \omega V_i^t + c_1 r_1 \left(Pbest_i - x_i^t\right) + c_2 r_2 \left(Gbest_i - x_i^t\right) \tag{30}$$

$$x_i^{t+1} = x_i^t + V_i^{t+1} \tag{31}$$

In the case of selecting the GA algorithm, the optimization problem will be solved in 6 steps. In the first step, the initial population of the genetic algorithm is generated randomly. It should be noted that the selected members are assigned to the installation location and size of the EESDs. Then, according to the location and capacity of the EESDs, the fitness function is calculated. In the third step, the best solutions are selected and used in the fourth and fifth steps to generate new members. This process will continue until the stop criteria are satisfied (Step 6). Finally, the best solution is determined, which includes the lowest total cost.

5. Simulation results

In this section, the problem of optimal operation of the distribution system is solved in the form of seven case studies according to Table 2. As this table shows, the optimal placement of EESDs is performed using BGA and BPSO algorithms and the effect of optimal placement of EESDs and implementation of DR program on the operating results is investigated in detail. The single line diagram of the system under study is provided in Fig. 3. To more accurately simulate operating conditions, the problem is solved by considering seasonal variations in load demand. Information on installation candidates is also provided in Table 3. It should be noted that the EESD investment cost is calculated according to a nonlinear function. Fig. 4(a) illustrates the per unit real investment cost of batteries, while Fig. 4(b) provides the annualized investment cost per battery for the static planning problem developed in this paper. Finally, the load demand curve for each season is presented in Fig. 5.

In the proposed model, locating and operating problems are modeled as a two-stage optimization problem and solved by MATLAB and GAMS software, respectively. In the first stage, the capacity and location of ESSD systems are determined by BPSO/ BGA algorithm in MATLAB and then the final results are delivered to GAMS software. Then in the second stage, the operating problem of the distribution system is formulated as a MILP problem and solved by CPLEX solver in GAMS software. The presented model is simulated by MATLAB 2019b and GAMS 27.2 installed on a computer with a Core i5 CPU 2.6 GHz and 8 GB RAM.

Table 4 indicates the location and capacity obtained for EESDs in cases 3 to 6. The results of this table illustrate that in cases 3, 4 and 5, three EESDs are to be installed, while in case 6, four EESDs are required. The lowest and highest investment costs are obtained in cases 5 and 6, respectively. It should be noted that in these cases the DR program is implemented and only the solving algorithm is different. Table 5 shows the operating costs in cases 1–6. The analysis of this table indicates that despite the high investment cost in case 6, the lowest operation cost has been obtained in this case. Numerical results illustrate that the annual operating cost of case 6 has decreased by about 1,362,463$ compared to case 5. In addition, the analysis of operating costs illustrates that in case 6 the annual operating costs are reduced by about 7.5% compared to case 2. Therefore, the results prove the high impact of the presence of EESDs on reducing operating costs. A closer look at the results indicates that in case 6 the operating cost decreased by 4.36% compared to case 4, while in case 2 the operating cost decreased by 2.18% compared to case 1. It should be mentioned that in cases 1 and 2, the operation problem is solved without considering EESs. Therefore, the results demonstrate that the DR program in the presence of EESDs has a much greater impact on reducing costs. To investigate the effect of DR program implementation on demand curves, in Fig. 6, the load demand curves of different seasons are presented. As can be seen, demand has decreased during peak hours and shifted to valley hours.

This transfer of demand leads to lower power purchases during peak hours and consequently reduces operating costs. Fig. 7 depict the performance of EESDs in case 6. Evaluations of these figures demonstrate that EESDs are charged in the early hours of the day and discharged in the middle hours, thus not only increasing system flexibility but also reducing operating costs.

Table 6 indicates the best and worst solutions obtained from each algorithm in cases 3 to 6. The results of this table illustrate that despite the lower total cost in case 5, the results obtained in case 6 are more affordable. It should be noted that the EESD payback period is about 5 years. Therefore, after this period, due to the lower operating cost of case 6, its higher investment cost will be compensated. The computation time of each case is given in Table 6. Comparison of computation time in different cases proves the higher speed of the BGA algorithm.

Fig. 8 indicates the amount of power generated by the expensive units (thermal units located on bus 13) in summer. Analysis of this figure illustrates that in case 6 due to the presence of EESDs and the DR program, the power generated by expensive units has decreased compared to case 1. It should be noted that EESDs are charged by low-cost units during valley hours and discharged during peak hours, thereby leading to less power generation by expensive units.

Fig. 9a and b depicts the convergence curves of the BPSO and BGA algorithms in cases 5 and 6, respectively. As can be seen, the BGA algorithm converged after 11 iterations, while the BPSO algorithm converged after 17 iterations. The specific features of each algorithm are provided in Table 7.

5.1. Results of stochastic case (case 7)

In this section, the results of case 7 are presented. In this case, the problem of ESSD allocation is solved by considering the load uncertainties. In this regard, 1000 scenarios are generated by the normal distribution function for load demand and then the number of these scenarios is reduced to 10 by the ScenRed tool. It should be mentioned that reducing the number of scenarios leads to increased computational speed. Figs. 10 and 11 depict the generated and reduced scenarios, respectively. Table 8 also presents the results obtained from case 7. As can be seen, the capacities of ESSDs have been increased. Table 8 illustrates that investment and operating costs increased by 15% and 17% compared to case 6, respectively.

5.2. Sensitivity analysis

A sensitivity analysis to examine the functionality of the model according to the change of the investment cost of the EESDs. In this case, 5 scenarios have been considered as shown in Table 9. As it is expected, the increase in the investment cost of the EESDs will result in a lower investment in the installation of the EESDs. However, the operational cost and the total cost of the system will be increased accordingly. On the other hand, lower investment costs will result in more capacity additions for the EESDs, resulting in lower operating costs and total cost, accordingly.

6. Conclusions

This study presented a computationally efficient two-stage optimization framework to determine both the optimal size and placement of EESDs in SG while also considering the participation in a price-based DR program. The model thus decomposes the problem into master (long-term planning) and slave (short-term operational) problems. These two problems are solved iteratively to minimize the total operating costs of the system. The MILP optimization approach is used with the constraints of the security-constrained unit commitment problem applied in the slave problem. The master problem for determining the location and the sizes of the EESDs have been solved using BPSO and BGA. The proposed model was tested on the standard IEEE 24-bus system while also taking a ToU tariff regime, hourly SoC of the EESDs as well as both the operational and investment costs into account. Results show that significant cost savings can be achieved using the proposed approach. It is also shown that the combination of the EESD with the DR program has synergistic benefits by reducing operating costs while improving the load factor. This is shown when by comparing case 3 to case 5 (both use the BPSO algorithm) and case 4 to case 6 (both use the BGA algorithm). Case 3 and 4 do not include DR programs while case 5 and case 6 do include DR. The comparison shows that in both case 5 and case 6 the total costs are reduced when compared to case 3 and case 4 respectively. In the best-case scenario, costs in case 5 are reduced by 3% compared to the total costs from case 3. Additionally, the best-case costs for case 6 are reduced by 3.8% compared to the best-case total costs for case 4. The reduction in costs and improvement in load factor is especially important in larger networks where just installing EESDs may have adverse effects on the load factor. Due to the two-stage nature of this proposed model, there are several avenues for future research. Concerning the first stage, the problem can be extended to a dynamic planning model considering the installation time, annual budget, reliability issues and recycling of the batteries can be considered for each year. Additionally, considering the degradation of the EESDs could provide interesting results. When discussing the future research directions for the second stage, considerations regarding fuel allocation, maintenance scheduling and congestion management issues can be added to the model. Additionally, including revenue streams for the EESDs from other services (for example reserve or flexibility markets) can be investigated. Furthermore, the system can be extended to include multi-objective optimization to include an objective function related to the load factor. Other meta-heuristic techniques could also be applied to the master problem to evaluate the computational burden. The scalability of the model and computational performance has shown to be adequate, especially as this is a long term planning model where the main focus is on providing acceptable results for the next stage of assessment for planning entities.

CRediT authorship contribution statement

Mohammad Sadegh Javadi: Conceptualization, Methodology, Software, Data curation, Validation. **Matthew Gough:** Data curation, Writing – original draft. **Seyed Amir Mansouri:** Methodology, Software, Data curation. **Amir Ahmarinejad:** Data curation, Conceptualization. **Emad Nematbakhsh:** Visualization, Software. **Sergio F. Santos:** Investigation, Data curation. **João P.S. Catalão:** Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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