Optimal Sizing and Siting of Electrical Energy Storage Devices for Smart Grids Considering Time-of-Use Programs

Mohammad Sadegh Javadi
Center for Power and Energy Systems, INESC TEC, Porto, Portugal

Kimia Firuzi, Maedeh Rezanejad
Department of Electrical Engineering, Islamic Azad University, Shiraz, Iran

Mohamed Lotfi, Matthew Gough, and João P. S. Catalão
FEUP and INESC TEC, Porto, Portugal

***Abstract*—This paper focuses on the long-term planning of power systems considering the impacts of Electrical Energy Storage Devices (ESSD) as well as Demand Response Programs (DRPs). The proposed model incorporates a two-stage optimization strategy in order to reduce the computational burden of the nonlinear problem. The upper-level of optimization model includes investment decision variables (long-term planning) while in the lower-level, the optimal operation of the model for short-term horizon has been addressed. In the operational stage, the optimal scheduling of power system in the presence of suggested ESSD size and location from the upper level is evaluated. Moreover, the Time-of-Use (ToU) Demand Response (DR) pricing scheme has been applied in the operational stage to evaluate its capability to reduce the total operating costs. The simulation results on the standard 6-bus test system validates the applicability of the proposed two-stage optimization model and illustrates that the optimal sizing and location of ESSDs along with DRP implementation could effectively reduce the total systems costs and improve the power system load factor.**

Keywords—Demand Response Programs, Electrical Energy Storage Devices, Smart Grids, Time of Use Strategy, Two-Stage Optimization.

NOMENCLATURE

Indices

i	Index for bus
d	Index for day
s	Index for EES
l	Index for line
t,t'	Index for time

Variables

$PG_{i,t,d}$	Power generation of unit i at time t
$PD_{i,t,d}$	Demand at bus i at time t
$SU_{i,t,d}$	Binary decision variable of start-up
$SUC_{i,t,d}$	Start-up cost of unit i at time t
$SD_{i,t,d}$	Binary decision variable of shut-down
$SDC_{i,t,d}$	Shut-down cost of unit i at time t
$I_{i,t,d}$	Binary decision variable of unit commitment
$K_{i,s}$	Binary decision variable of EES s at bus i
$P_{s,t,d}^{EES,\sim}$	Charge/discharge power of EES s
$Eng_{s,t,d}^{EES}$	Stored energy at EES s
$\delta_{i,t,d}$	Voltage bus angle
$\lambda_{i,t,d}$	Locational marginal price at bus i at time t

Parameters

N_B	Number of thermal units
N_T	Number of hours under study
N_L	Number of transmission lines
N_{EES}	Number of EES devices
$Cost_{i,s}$	Capital cost of EES s per kWh
$Budget^{max}$	Maximum budget for EES installation investment
EES^{max}	Maximum capacity addition of EES devices
RU_i	Ramp-up for unit i
RD_i	Ramp-down for unit i
X_l	Reactance of transmission line l
α, β	Acceptable range for DR implementation
ω	Maximum acceptable change for hourly demand
T_i^{on}, T_i^{off}	Minimum up/down time of unit i
STU_i, SDU_i	Start-up/shut-down cost of unit i

Symbols

max, min	Maximum and Minimum
New, Old	After and before DR implementation
S, R	Sending, Receiving end bus

I. INTRODUCTION

The need for flexibility in distribution grids will increase as they evolve from ones characterized by the unidirectional flow of electricity (from large centralized generators) to a system characterized by bi-directional power flow between traditional generators and increasingly small-scale prosumers. Prosumers utilize Distributed Energy Resources (DER), which are often intermittent, allowing them to take on a more proactive and dynamic role in electricity consumption and production. Key to this increased flexibility will be the use of Electrical Energy Storage Devices (EESD). The role of EESD in increasing the flexibility of distribution grids has been widely discussed [1], [2]. However, EESDs are still relatively expensive to procure and install and therefore, it is essential to determine the optimal size and location of these devices.

A. Motivation

This need to determine the optimal size and location of EESD within a distribution network motivates the study presented in this paper. Investments in EESDs typically carry a high upfront capital cost and thus it is essential that their size and location are optimized for the given system.

978-1-7281-4878-6/19/$31.00 ©2019 IEEE

If the EESDs are sized incorrectly or placed in the wrong location, it could negate their positive benefits and even results in economic and technical repercussions for the grid [3].

As opposed to the traditional flat-rate electricity tariffs, increased participated in price-based Demand Response (DR) programs is making time-varying Time-of-Use (ToU) electricity rates more popular. The main premise of price-based DR programs is to provide price signals to end users, incentivizing them to use electricity during periods of low prices and reduce consumption during periods of high prices, which results from shifting consumption from peak-load periods to off-peak load periods. The incorporation of EESD into grids with ToU program participation is an important area for research as EESD can assist with the temporal shift of energy and could have a major impact on the success of ToU programs. This scenario of having EESDs in grids with ToU program implementation motivates this study.

While ToU DR programs are applied on the short-term operational time frame, the determination of the optimal size and location of EESDs is a long-term planning decision. Thus, by investigating the optimization of both long-term and short-term time frames, it is thought that the load factor of the EESD will be increased which will result in a cost-optimal operation of a distribution grid.

B. Literature Review

The use of EESD in active distribution networks was considered by [1] who investigated the optimal sizing of a EESD in order to minimize occurrences of over- and under-voltage issues within the distribution network. Uncertainties associated with demand and generation from RES were considered. A two-stage stochastic model was formulated using novel techniques of scenario reduction so to improve the accuracy and computational time needed to determine an optimal solution. The need to install EESDs in distribution networks is becoming more important with the increased penetration of variable renewable energy sources (RES). This has been recognized by a large and growing body of research into the optimal sizing, placement, type, and operation of EESD in various electrical grid typologies [2], [3].

The optimal planning and operation of energy storage devices was investigated in [4]. This paper decomposed the long term-planning model into a two-stage one in order to determine the co-optimal siting and sizing of RES and EESD in low-voltage distribution networks. The computational burden of this problem was also reduced by using mixed-integer programming techniques.

A mixed-integer non-linear programming model was developed in [5] and determines the optimal spinning reserve for power system taking into account the presence of RES and EESD and the sizing of the EESD was done so as to minimize the uncertainties normally associated with RES. A two-stage stochastic predictive control model was developed by [6] in order to determine the optimal operation of the EESD as well as generation outputs and the size of the EESD. The main source of uncertainty in this paper was the fluctuations in the wind energy resource.

The optimal operation of a multi-microgrid system using a bi-level problem was developed by [7]. This paper used a ToU tariff regime and roust programming which took into account the uncertainty surrounding RES, day-ahead market prices, the use of Electric Vehicles in a stochastic manner. The planning of EESD in energy and reserve markets was undertaken by [2] where the authors again used a bi-level problem to determine the optimal sizing and placement of EESD devices subject to profit constraints. The authors compare a primal decomposition method with sub-gradient cutting planes against an exact linear programming approach in order to investigate the accuracy and scalability of the proposed algorithm. The authors also chose two EES technologies, namely Compressed Air Energy Storage (CAES) and lithium-ion batteries in order to investigate the performance of the two technologies under different regulatory and market constructs.

The effects of uncertainties associated with RES, specifically wind power, on the ESSD optimal configuration were investigated by [8]. The authors sought to minimize three different and unharmonious objective functions which were operating costs, deviation of the voltage in the network and the emission associated with the operation of the energy system. A framework using two metaheuristic algorithms, the gravity search algorithm and a hybrid Particle Swarm Optimization/Genetic algorithm was used to find the solution and multi-criteria decision-making techniques were applied to help to determine an optimal solution considering the three separate optimization functions. While the uncertainties associated with wind energy were studied by [8], the uncertainties associated with Solar photovoltaic (PV) generation were studied by [9]. The study showed that using time-flexible operational regimes can help account for the natural variation normally associated with PV generation. Another study which investigated the sizing and location of EESDs in conjunction with PV was carried out by [10], which sought to use EESDs to minimize the voltage fluctuations associated with the use of PV through real-power injections and absorptions by EESDs. A bi-level optimization model based on a genetic algorithm was used.

The provision of flexibility using EESD in community energy programs was investigated by [11]. In the paper, a multi-objective optimization framework was developed to investigate energy arbitrage situations for the community energy project. Six different EESD technologies, namely chemical batteries, were studied and used in feasibility and a techno-economic model of a community energy system.

The effects of integrating DR programs taking into account wind energy sources were studied by [12]. Prospect theory was used to characterize customer attitudes towards risk and Variant Roth-Erev (VRE) was used to determine the uncertainty surrounding participation in the DR program. A DR scheduling tool was developed and used to assess the expected impact of demand response on the generation adequacy of the system.

C. Contribution

The main contribution of this paper is the development of a two-stage optimization framework from which the optimal size and location of EESDs can be determined (Fig. 1).

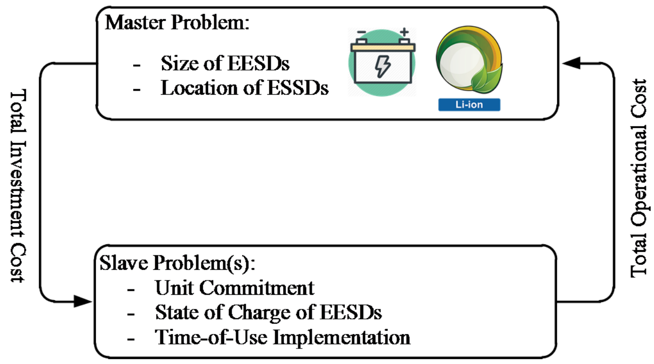

Fig. 1. Conceptual model for two-stage planning framework.

This is done by decomposing the problem into:

- A slave problem for the short-term operational timeframe.
- A master problem for the long-term planning timeframe.

The slave problem was solved as a linear unit commitment problem with the objective of finding the optimal operational status of the network (including generation units). In the slave problem, the impacts of ToU rates are considered. The ToU pricing regime was combined with EESDs to attempt to level out differences between the peak-demand and off-peak times. This will improve the ESSDs load factor through the use of peak shaving and valley filling. In addition, EESD states-of-charge (SoC) are considered for the short-term operational timeframe optimization. The slave problem is dependent on the master problem, in which the long-term problem is solved, determining the optimal siting and sizing of the EESDs. This approach, which is formulated and tested in this paper helps reduce the computational burden associated with the optimization of EESD employment in smart grids.

D. Paper Organization

This manuscript is organized as follows: Section II introduces the conceptualization of the proposed optimization model and explains how this formulation can help reduce the computational burden. The mathematical formulation is presented in Section III which also includes details of how the EESDs were incorporated into the optimization problem. The results testing the proposed model are shown in Section IV. Corresponding conclusions and discussion are in Section V.

II. Conceptualization of Two-Stage Model

Attempting to model the optimal sizing and siting problem in of ESSDs in SG will result in a highly non-linear formulation, with the computational burden varying exponentially with the problem size [13]. In this study we propose a two-stage formulation in order to reduce the computational complexity of the problem. The optimization problem is decomposed into a slave problem (short-term) and a master problem (long-term).

The slave problem is formulated as a mixed-integer linear programming problem (MILP), based on the unit commitment problem presented in [14], which takes into consideration ToU DR program implementation for day-ahead operation.

In the current formulation, the hourly EESD SoC is also considered for the day-ahead operation optimization. However, in order to compute the optimal solution for this problem, the siting and sizing of the EESDs in the network need to be predetermined. This is the output of the master problem, and hence the slave problem is dependent on it.

In the master problem, the optimal sizing and siting of EESDs is determined by considering the year-ahead time horizon with a daily resolution (365 days considered). The optimal solution for the EESD size and location is obtained for each day along with the corresponding total investment cost, which can then be used as inputs for the slave problem. Although possible, it is not feasible to solve the slave problem for every single day considered. Instead, a representative day(s) can be used to obtain the total operational cost, which can then be used as an input to re-compute new EESDs sizing and siting from the master problem. This iterative procedure is undergone until there is a convergent solution for the size and location of the EESDs in the network. Note that although the slave problem is formulated as a linear one, the master problem is non-linear. In this paper, since the main objective is to propose this formulation and validate its applicability, we use an exhaustive search algorithm (enumeration-based) to compute the optimal solution of the master problem. In small grids this will not affect the computational effort and may fact be faster than other alternatives. However, for application on larger networks, it may be better to employ more computationally-efficient algorithms such as meta-heuristic optimization techniques to solve the master problem.

III. Mathematical Problem Formulation

In this section, the mathematical formulation of the proposed two-stage optimization model is provided. The aim of the proposed planning problem is to determine the optimal size and location for EES devices in SGs considering the ToU regime.

A. Objective Function

The main objective function of the two-stage optimization model is to minimize the investment costs (*INVC*) of EES devices and the total operating cost (*TOPC*) over the planning horizon:

$$\begin{aligned}
&Min\ TC = INVC + TOPC \\
&INVC = \sum_{s=1}^{N_{ESS}} \sum_{i=1}^{N_B} ESS_{i,s} K_{i,s} Cost_{i,s} \\
&TOPC = \sum_{d=1}^{365} \sum_{i=1}^{N_B} \sum_{t=1}^{N_T} \left[F_{ci}\left(PG_{i,t,d}\right) + SUC_{i,t,d} + SDC_{i,t,d} \right]
\end{aligned} \tag{1}$$

The objective function of the master problem is shown as the first part of the objective function while the second part of the objective function is associated with the annual operational cost addressed by the slave problem. The operational cost is calculated on a daily basis and the system operator performs the unit commitment (UC) problem to determine the optimal status and generation levels of power plants as well as the state of charge (SoC) of EES devices if they are available. The total cost (TC) is the summation of both master and slave sub-problems.

B. Master Problem Constraints

As it is stated before, the master problem aims to find the optimal location and size of the EES devices. In this regard, the maximum capacities of the EES devices and the budget available for investment are the main constraints of the master problem. Eq. (2) expresses the total acceptable capacity for EES installations in the grid while Eq. (3) deals with the total budget that can be considered for the investment in this section from the point of view of the planner.

$$\sum_{s=1}^{N_{EES}} \sum_{i=1}^{N_B} ESS_{i,s} K_{i,s} \le EES^{\max} \tag{2}$$

$$\sum_{s=1}^{N_{EES}} \sum_{i=1}^{N_B} ESS_{i,s} K_{i,s} Cost_{i,s} \le Budget^{\max} \tag{3}$$

It should be noted that the commercial EES devices have discrete standard sizes and the investment cost per kWh of capacity of various batteries is different due to various reasons. Moreover, it is essential to define a binary decision variable for the optimal selection of EES devices at each bus ($K_{i,s}$). The maximum allowable capacity for EES is assumed to be EES^{max} while the annual budget for battery capacity addition is considered to be $Budget^{max}$.

C. Slave Problem Constraint

The main core of the slave problem is the UC problem. In this study, a mixed integer linear programming (MILP) model was adopted in order to solve the UC problem. The main features of the UC based on a MILP framework have been reported in [14]. Eq. (4) deals with the polynomial quadratic cost function assumed in this paper for thermal power generating units. The piecewise linearization approach is adopted in this study and 200 segments are used to approximate the quadratic function. The UC problem considering the presence of EES devices has some inherent constraints as (5)-(22) demonstrate. For thermal power generating units, the minimum and the maximum acceptable generation level are shown in Eq. (5) whenever the unit is committed. The start-up and shut-down decision variables are associated with the status of power generating units and can be seen in (6). The start-up and shut-down costs are addressed by the unit start-up and shut-down costs and their binary decision variables yield, Eq. (7) and (8), respectively. Eq. (9) and (10) deal with the constraint of the hourly ramp rates for thermal power generating units. It is stated in the aforementioned constraints that the minimum generation levels of such units can be met at the first hour of start-up and before shutting-down. The minimum up and down time constraints are addressed in Eq. (11) and (12), respectively. The hourly load balance constraint is addressed in Eq. (13) considering the charging and discharging power of EES devices if they are to be used as determined by the master problem. The marginal value of this constraint is supposed to be the locational marginal price (LMP) for each hour in the day-ahead market equilibrium. Therefore, it can be used as the real-time prices for implementing the ToU programs. In this study, a ToU program was adopted based on this feature of market settlement. Therefore, the decision-making procedure can be performed by the consumers to modify their consumption level based on their preferences and power market signals. Details of this strategy can be found in [14].

Eqs. (14)-(19) deal with the EES constraints if the master problem suggests installing the storage devices in the system. The dynamic energy levels for EESs are provided in (14). Minimum and maximum acceptable levels for stored energy in the EESs are modelled by (15), while Eq. (16) deals with the initial and the final stored energy in the EES system. It is considered to be at the same levels for each day of operation. Eqs. (17) and (18) address the acceptable charging and discharging power of EES devices at each hour of operation, respectively. Since the operation strategy is based on an hourly resolution, the operator accepts one mode of operation for EES devices, i.e, charging or discharging mode. Eq. (19) enforces the operation of the EES devices in only one mode by adopting the corresponding binary decision variables for each mode of operation. The DC power flow equations are addressed in Eq. (20)-(22). The transmitted power through the lines is given by Eq. (20) and transmission lines capacities are shown in Eq. (21). The bus voltage angle of reference bus is considered to be zero, Eq. (22).

$$F_{ci}\left(PG_{i,t,d}\right) = a_i + b_i PG_{i,t,d} + c_i PG_{i,t,d}^2 \tag{4}$$

$$PG_i^{\min} I_{i,t,d} \le PG_{i,t,d} \le PG_i^{\max} I_{i,t,d} \tag{5}$$

$$SU_{i,t,d} - SD_{i,t,d} = I_{i,t,d} - I_{i,t-1,d} \tag{6}$$

$$SUC_{i,t,d} = SU_{i,t,d} STU_i \tag{7}$$

$$SDC_{i,t,d} = SD_{i,t,d} SDU_i \tag{8}$$

$$PG_{i,t,d} - PG_{i,t-1,d} \le RU_i I_{i,t-1,d} + PG_i^{\min}\left(I_{i,t,d} - I_{i,t-1,d}\right) \tag{9}$$

$$PG_{i,t-1,d} - PG_{i,t,d} \le RD_i I_{i,t,d} + PG_i^{\min}\left(I_{i,t-1,d} - I_{i,t,d}\right) \tag{10}$$

$$\sum_{t'=t}^{t+T_i^{\text{on}}-1} I_{i,t',d} \ge T_i^{\text{on}}\left(I_{i,t,d} - I_{i,t-1,d}\right) \; \forall t = 1 \ldots N_T - T_i^{\text{on}} + 1 \tag{11}$$

$$\sum_{t'=t}^{t+T_i^{\text{off}}-1} \left(1 - I_{i,t',d}\right) \ge T_i^{\text{off}}\left(I_{i,t-1,d} - I_{i,t,d}\right) \; \forall t = 1 \ldots N_T - T_i^{\text{off}} + 1 \tag{12}$$

$$PG_{i,t,d} + P_{s,t,d}^{EES,Dis.} - PD_{i,t,d} - P_{s,t,d}^{EES,Ch.} = \sum_{l \in NL_i} PL_{l,t,d} \;\perp\; \lambda_{i,t,d} \tag{13}$$

$$Eng_{s,t,d}^{EES} = Eng_{s,t-1,d}^{EES} + P_{s,t,d}^{EES,Ch.}.\eta^{EES,Ch.} - P_{s,t,d}^{EES,Dis.} / \eta^{EES,Dis.} \tag{14}$$

$$Eng^{EES,Min} \le Eng_{s,t,d}^{EES} \le Eng^{EES,Max} \tag{15}$$

$$Eng_{s,t=1,d}^{EES} = Eng_{s,t=24,d}^{EES} \tag{16}$$

$$0 \le P_{s,t,d}^{EES,Ch.} \le P^{EES,Ch.,Max} I_{s,t,d}^{EES,Ch.} \tag{17}$$

$$0 \le P_{s,t,d}^{EES,Dis.} \le P^{EES,Dis.,Max} I_{s,t,d}^{EES,Dis.} \tag{18}$$

$$0 \le I_{s,t,d}^{EES,Ch.} + I_{s,t,d}^{EES,Dis.} \le 1 \tag{19}$$

$$PL_{l,t,d} = \frac{1}{X_l}\left(\delta_{l,t,d}^{S} - \delta_{l,t,d}^{R}\right) \tag{20}$$

$$PL_l^{\min} \le PL_{l,t,d} \le PL_l^{\max} \tag{21}$$

$$\delta_{l,t,d}^{ref} = 0 \tag{22}$$

In order to assess the ToU program in this study, a stimulated ToU framework was adopted as is suggested in [14]. The main advantage of this model is to consider the LMPs as real-time price signals. Therefore, the prosumers can easily formulate their strategies for optimal scheduling of the EES devices as well as ToU implementations during the operational horizons. Inside the slave model, a ToU implementation as a Linear Programming (LP) optimization problem was adopted and is as follows:

$$Min \sum_{i=1}^{N_B}\sum_{t=1}^{N_T} PD_{i,t,d}^{New} \times \lambda_{i,t,d} \quad (23)$$

$$\sum_{t=1}^{N_T} PD_{i,t,d}^{New} = \sum_{t=1}^{N_T} PD_{i,t,d}^{Old} \quad (24)$$

$$(1-\beta)PD_{i,t,d}^{Old} \le PD_{i,t,d}^{New} \le (1+\alpha)PD_{i,t,d}^{Old} \quad 0 \le \alpha, \beta \le 1 \quad (25)$$

$$PD_{i,t,d}^{New} - PD_{i,t-1,d}^{New} \le \omega \quad (26)$$

$$PD_{i,t-1,d}^{New} - PD_{i,t,d}^{New} \le \omega \quad (27)$$

This LP model for simulating the ToU implementation adopts the daily load change strategies. As it is stated before, $\lambda_{i,t,d}$ is the locational marginal price obtained from the day-ahead market clearing mechanism. The stimulated demand is denoted by the "*New*" superscript and it is the decision variable for this stage. Constraint (24) deals with the total consumed energy over the planning horizon and it should be the same as the energy requested by the aggregators before implementing the DRP. Constraint (25) confirms that the participation of the aggregators in the DRP is bounded. The hourly justification of the load demands is also constrained by the ability of aggregators to participate in the DRP, as shown in (26) and (27). The tendency of aggregators to change the demand from one hour to another is limited to ω.

IV. Simulation Results

In order to evaluate the proposed model, the 6-bus standard test system has been considered in this paper. The single line diagram of the mentioned test system is provided in Fig. 2. The network has three thermal power generating units and three load centres.

The power grid includes seven transmission lines. The hourly load demand before applying the demand response program is detailed in Table I. The load demand is distributed at 20%, 40%, and 40%, among buses 3, 4, and 5, respectively.

Techno-economic data of the generating units and transmission lines are provided in Table II and Table III, respectively. The techno-economics data for EES devices are provide in the Tables IV and V, as well. For linearization of the quadratic generation cost function of the thermal units, the number of segments considered to be 200.

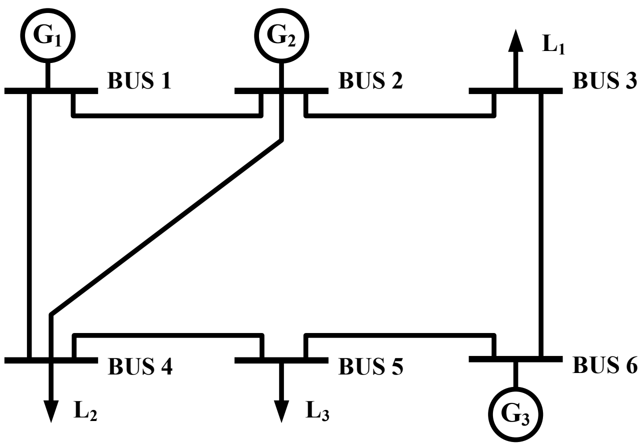

Fig. 2. Single-line diagram of 6-Bus test system [14]

In the DRP implementation, the maximum allowed participation rate of each aggregator per hour is assumed to be 15% of the total load demand. In other words, the α and β are assumed to be 0.15. Moreover, the maximum change in the responsive load demand is considered to be 15 MW, i.e., ω=15 MW.

We evaluated four case studies in this section (Fig. 3). In the base case scenario, we perform the UC problem without implementation of DRP and there is no ESS device installed in the power system. In the second scenario, we evaluate the optimal placement of ESS devices in order to reduce the total operation and investment cost of batteries in the long-term planning horizon. For the third and fourth scenarios the assessments of DRP and DRP with the ESS installation have been considered, respectively. It is noteworthy that the maximum size of ESS devices have been considered to be 100 MWh with the size of 50 MWh or 100 MWh. In the base case scenario, the daily operational cost is obtained as 91515.189 $/day.

In the second scenario, the optimal solution is obtained as 86669.15 $/day by installation of a 100 MWh ESS at bus B.4. The total cost for one year considering the investment cost of the suggested EES is obtained as M$ 32.63. In the third scenario, the optimum daily cost is obtained as 84186.967 $/day and it means that by considering just the DRPs the daily operational cost will be reduced about 7328.222 $/day.

In other words, with the 7.5% reduction of peak load demand, the amount of cost reduction is about 8.0%. In the last scenario, by considering the DRP and ESS installation simultaneously, the daily operational cost would be 82456.638 $/day which is the least cost operation obtained in this paper. The total cost in this case study considering the annual operating and installation costs of EES devices is M$ 30.696. It is noteworthy that the annual cost without considering the EES installation for this case is M$ 30.728. Finally, the simulation results suggest that there is one ESS with the size of 50 MWh needed to be installed at bus B.4.

TABLE I. Daily Forecasted Load

Time	PD^{Old}	Time	PD^{Old}	Time	PD^{Old}
T1	179.2	T9	243.6	T17	268.8
T2	168.0	T10	266.0	T18	268.8
T3	162.4	T11	277.2	T19	260.4
T4	156.8	T12	280.0	T20	245.4
T5	156.8	T13	277.2	T21	225.6
T6	162.4	T14	280.0	T22	208.2
T7	179.2	T15	280.0	T23	195.6
T8	212.8	T16	271.6	T24	180.4

TABLE II. Generation Unit data

Unit	a	b	c	PG^{max}	PG^{min}
G1	177	13.5	0.00045	220	100
G2	130	40.0	0.00100	100	10
G3	137	17.7	0.00500	70	10
Unit	**MUT**	**MDT**	**RD, RU**	**SU**	**SD**
G1	4	4	110	100	50
G2	3	2	100	200	100
G3	1	1	40	0	0

TABLE III. TRANSMISSION LINE DATA

Line	From	To	X_l	PL^{max}
L1	1	2	0.170	200
L2	1	4	0.258	100
L3	2	4	0.197	100
L4	5	6	0.140	100
L5	3	6	0.018	100
L6	2	3	0.037	100
L7	4	5	0.037	100

TABLE IV. TECHNICAL CHARACTRISTICS OF EESS (P.U)

$Eng^{EES,Min}$	$Eng^{EES,Max}$	$P^{EES,Ch.,Max}$	$P^{EES,Dis.,Max}$	$Initial\ Eng^{EES}$
0.20	1.00	0.2	0.2	0.50

TABLE V. ECONOMIC DATA OF EESS

Size (*MWh*)	*Cost* (*\$/MWh*)	EES^{Max} (*MWh*)	$Budget^{Max}$ (*M\$*)
50	12000	2x50	1.5
100	10000	1x100	

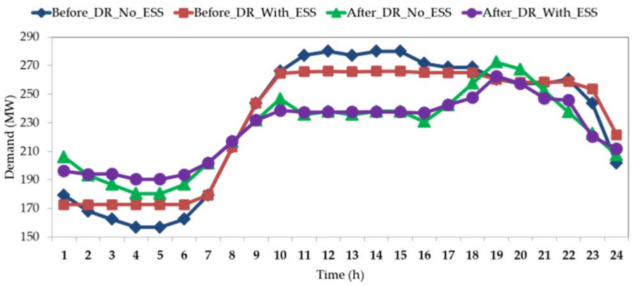

Fig. 3. Resulting hourly demand (MW) for each scenario.

V. CONCLUSIONS

In this study we propose a computationally-efficient method to determine optimal sizing and location of EESDs in smart grids. The proposed model decomposes the problem into a master (long-term) and a slave (short-term) problems. By testing the model on a six-bus test system, taking into account ToU pricing, hourly EESD SoC, and investments and operating costs, it was shown that a significant improvement of the load factor is achieved (5.3% without ToU and 3.75% with ToU, relative to the peak hour). For future work, it is suggested to investigate the use of meta-heuristics to solve the master problem in the case of larger networks.

ACKNOWLEDGEMENTS

M.S. Javadi, M. Lotfi, M. Gough, and J.P.S. Catalão acknowledge the support by FEDER funds through COMPETE 2020 and by Portuguese funds through FCT, under 02/SAICT/2017 (POCI-01-0145-FEDER-029803).

REFERENCES

[1] M. Bucciarelli, S. Paoletti, and A. Vicino, “Optimal sizing of energy storage systems under uncertain demand and generation,” Appl. Energy, vol. 225, pp. 611–621, Sep. 2018.

[2] B. Xu et al., “Scalable Planning for Energy Storage in Energy and Reserve Markets,” IEEE Trans. Power Syst., vol. 32, no. 6, pp. 4515–4527, Nov. 2017.

[3] C. K. Das, O. Bass, G. Kothapalli, T. S. Mahmoud, and D. Habibi, “Overview of energy storage systems in distribution networks: Placement, sizing, operation, and power quality,” Renew. Sustain. Energy Rev., vol. 91, pp. 1205–1230, Aug. 2018.

[4] M. S. Javadi and J. M. Guerrero, “Optimal Planning and Operation of Hybrid Energy System Supplemented by Storage Devices,” 7th Int. Sol. Integr. Workshop, Oct. 2017.

[5] M. S. Javadi, M. Lotfi, M. Gough, A. EsmaeelNezhad, and J. P. S. Catalao, “Optimal Spinning Reserve Allocation in Presence of Electrical Energy Storage Devices and Renewable Energy Sources,” Proc. 19th Int. Conf. Environ. Electr. Eng., Jun. 2019.

[6] K. Baker, G. Hug, and X. Li, “Energy Storage Sizing Taking Into Account Forecast Uncertainties and Receding Horizon Operation,” IEEE Trans. Sustain. Energy, vol. 8, no. 1, pp. 331–340, Jan. 2017.

[7] M. S. Misaghian et al., “Hierarchical framework for optimal operation of multiple microgrids considering demand response programs,” Electr. Power Syst. Res., vol. 165, pp. 199–213, Dec. 2018.

[8] V. Jani and H. Abdi, “Optimal allocation of energy storage systems considering wind power uncertainty,” J. Energy Storage, vol. 20, pp. 244–253, Dec. 2018.

[9] S. Watson, D. Bian, N. Sahraei, A. G. Winter, T. Buonassisi, and I. M. Peters, “Advantages of operation flexibility and load sizing for PV-powered system design,” Sol. Energy, vol. 162, pp. 132–139, Mar. 2018.

[10] O. Babacan, W. Torre, and J. Kleissl, “Siting and sizing of distributed energy storage to mitigate voltage impact by solar PV in distribution systems,” Sol. Energy, vol. 146, pp. 199–208, Apr. 2017.

[11] T. Terlouw, T. AlSkaif, C. Bauer, and W. van Sark, “Multi-objective optimization of energy arbitrage in community energy storage systems using different battery technologies,” Appl. Energy, vol. 239, pp. 356–372, Apr. 2019.

[12] J. Gao, Z. Ma, and F. Guo, “The influence of demand response on wind-integrated power system considering participation of the demand side,” Energy, vol. 178, pp. 723–738, Jul. 2019.

[13] M. G. Damavandi, J. R. Martí and V. Krishnamurthy, "A Methodology for Optimal Distributed Storage Planning in Smart Distribution Grids," in IEEE Transactions on Sustainable Energy, vol. 9, no. 2, pp. 729-740, April 2018. doi: 10.1109/TSTE.2017.2759733

[14] M. Lotfi, J.P.S. Catalão, M.S. Javadi, A.E. Nezhad, M. Shafie-khah, “Demand response program implementation for day-ahead power system operation”, in: Proceedings of the IEEE Power Tech 2019 Conference, Milano, Italy, 23-27 June, 2019.