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Measuring the value of energy storage systems in a power network

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ABSTRACT

The increased use of renewable generators and their intermittent behavior motivates network operators to deploy energy storage systems. In this study, energy storage types, locations, and capacities are optimized for a capacitated electric power network with renewable generation. Short term operational decisions that include charging/discharging schedules and capacity management of the storage systems are included in this optimization framework to capture hourly, daily, and seasonal fluctuations of the demand, renewable generation, and energy prices. A Mixed Integer Linear Programming (MILP) formulation is developed but because of the computational complexity, a mathematical programming based metaheuristic algorithm is proposed. With a numerical study, the proposed heuristic method is proved to be highly effective compared to the MILP formulation and an existing state of the art algorithm. The effects of storage installation costs, line capacities, demand and generation variance on the values of storage systems and on the installation decisions are analyzed through numerical studies.

1. Introduction

In this study, we consider the energy storage systems (ESS) siting and sizing problem with multiple ESS types on a capacitated electric power network (CEPN) to investigate the benefits of storage systems. Such a problem is especially important for a power network utility company, with an already existing portfolio of renewable generation resources and customers dispersed over a certain geographical region. Such operators use their renewable resources to generate electricity and the spot electricity markets to meet the demand of their customers at each time interval. These operators invest in ESS to compensate; (i) the intermittent behavior of renewable generation, (ii) variance of customer demand at different time periods, (iii) variance of energy prices in the spot market, and (iv) the transmission line capacities. As a result, such companies face a multi-period capacity management problem. In this problem, the operating periods are not independent since the possibility of storing energy links the periods to each other. In particular, the power produced by the renewable generators can be stored in storage units when the prices and the demand are low or the production and network congestion are high. This stored energy can then be released to the system when either the prices and the demand are high or the production is low. In this setup, we investigate the optimal investment plan, i.e., the location, the type, and the capacity of the storage facilities. We also investigate the optimal operation of the whole system. This includes the buy or sell decisions at each period in the spot electricity markets, store or release energy from the storage facilities, and the distribution of electricity among the nodes in the network.

The increase in the share of renewable resources on the energy market necessitates to manage these resources efficiently. Unlike traditional resources, generation schedule of renewable resources depends on the random acts of nature that creates unique challenges. One important tool to deal with these challenges is the ESS [1]. In accordance with the increased usage of renewable resources, ESS have received significant attention in recent years. They are evolving rapidly in terms of technology, capacity, and efficiency and becoming an economically justifiable investment. There are different types of ESS such as high speed flywheels, two-pool dam systems, flow cells, and chemical batteries. Each of these has specific investment and operating costs, efficiency, and construction needs. The introduction of ESS into the energy market has the potential to restructure electricity market models resulting in the emergence of a new market and increase the appeal of renewable resources [2]. The cost of Lithium-Ion batteries, one of the most popular ESS, has been decreasing exponentially for the last 20 years [2]. The total energy that can be stored with $100 had been increased exponentially by 11 folds during the period of 1991–2005 [3].

Since we consider the distributed generation and storage in a capacitated network, the literature on optimal power flow (OPF) is also

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relevant to this study. There are a large number of studies that develop exact or heuristic algorithms for the OPF problem which can be reviewed from [4]. The OPF problem is generally formulated as a large scale mixed integer nonlinear program [5]. Branch and bound [6], Benders decomposition [5], second order cone programming [7] are among the exact solution techniques. Simulated Annealing (SA) [8], Particle Swarm Optimization [9], and Genetic Algorithm [10] are some of the heuristics adapted for the OPF problems. Ref. [11] studied short-term ESS unit commitment problem under stochasticity. However, unlike this study, renewable generators and storage units are not considered in classical OPF.

Storage related decisions can be investigated under four main categories: Locating, sizing, operating (charging/discharging) the storages, and selecting the type. Studies associated with ESS sizing can be reviewed from Ref. [12], which considers ESS sizing criteria, sizing techniques, and applications with renewable resources. The authors reviewed the solution techniques under four categories: probabilistic, analytical, directed search-base and hybrid methods. Sheibani et al. [13] reviewed the studies on power systems regarding ESS planning from both the perspectives of the system operator and the investors. Das et al. [14] reviewed more than 250 articles and sorted them with regards to their problem definitions: optimal ESS locations, ESS sizing, ESS placement & operation and power quality problems. Another recent study by Wong et al. [15] reviewed more than 100 papers on ESS types and solution methodologies for optimal ESS siting and sizing problems. The solution techniques are categorized as analytical approaches, mathematical optimization, and artificial intelligence methods.

Ref. [16] considered the problem of optimizing energy storage, renewable generator, and diesel generator capacities. Ref. [17] presented a method for determining the optimal number of renewable energy generators and storage components in a microgrid for given typical demand profiles, local pricing regime, and capital costs. Based on the renewable energy generations in Hong Kong, Ref. [18] studied the joint optimization of capacity investment and operation decisions for solar and wind energy generation taking the impact of energy storage and demand response into account. Ref. [19] studied the problem of optimally placing large-scale ESS in power grids with both conventional and wind generators. These studies did not consider the fixed cost of establishing ESS.

In addition to storage operation decisions, some articles also consider the storage sizing problem without considering the location decisions. These studies assume predetermined storage locations. Ref. [20] developed a two-stage method to search optimal power and capacity of battery system with thermal plants and wind farms. Ref. [21] proposed a methodology for allocating an ESS in a distribution system with a high penetration of wind energy. Ref. [22] introduced an optimal energy storage control algorithm to develop a greedy heuristic procedure for energy storage placement and sizing. Ref. [23] developed a Simulated Annealing algorithm for optimizing the size of a battery storage in a photovoltaic/wind integrated hybrid energy system. Ref. [24] determined the optimal operating strategies for smart microgrid systems using a mathematical model. They concluded that the optimal battery size should be determined based on demand and supply of the microgrid system. More recently, Cao et al. [25] considered energy storage sizing problem based on a model predictive control strategy model to smooth the fluctuations on wind power.

There are also some recent studies that consider the ESS location and sizing problems simultaneously. Celli et al. [26] studied siting, sizing and scheduling problem as a whole and created an algorithm named as Non-dominated Sorted Genetic Algorithm-II. Ref. [27] presented a three-stage planning procedure to determine the capacities and locations of distributed ESS. Ref. [28,29] studied the placement, sizing, and control of ESS by assuming that the Smart Grid Operator controls and operates the ESS. Ref. [30] developed a model including the same decisions in a power network to minimize generation costs by load shifting. Ref. [31] developed a model and a SA algorithm to determine the ESS locations and the optimal storage control strategy. However, their model does not include renewable resources and storage capacities. Unlike these studies, we consider the ESS sizing and location problems simultaneously with a longer planning horizon and allow the possibility of different ESS types and sizes at the same location.

Ref. [32] showed that ESS can help system to delay constructing new lines by using a mathematical model. Ref. [33] developed an MIP model for optimal ESS siting and sizing problem considering renewable, conventional, and hydropower generators. They used stochastic programming to solve the problem. They did not consider the fixed cost of ESS investment and energy trading. Ref. [34] used Benders decomposition to solve ESS siting problem on a power system. They considered a single ESS type and did not consider energy trading. Ref. [35] solved dynamic renewable generations and ESS deployment problem with stochastic programming. The fixed cost of ESS is not considered. Ref. [36] studied long term ESS siting and sizing problem with considering reliability. They did not consider energy trading and fixed cost of ESS. They developed an MILP model which could be solved for smaller networks. Ref. [37] studied ESS siting and sizing problem and developed a hybrid-metaheuristic. Energy trading and fixed cost of ESS are not considered and numerical tests are done only for 24 h planning horizon. Ref. [38] introduced Whale Optimization Algorithm for optimal ESS siting and sizing problem with the objective of minimizing the power loss. They used a single ESS type, did not consider energy trading and the fixed cost of ESS.

In most of the existing studies, the type, location, and the capacity of the ESS are assumed to be given. Unlike them, we consider the problem as a design problem and include all these decisions in our model. On the other hand, there are some recent studies that consider the siting and sizing problems jointly. However, these studies either consider a single ESS type, do not consider energy trading, consider a larger time granularity, or very short planning horizon. Furthermore, most of these studies do not consider the ESS installation cost in their model. Establishing an ESS requires a fixed cost of investment. That is why storage location problems should include binary decision variables. Neglecting this fixed cost is an oversimplification of the real practice. Including binary decision variables changes the problem structure and increases the problem complexity. Therefore, most of the earlier solution procedures are not directly applicable when the fixed costs are considered.

In this study, we consider the ESS design and planning problem on a CEPN. This problem includes both long term strategic ESS location, type, and capacity decisions as well as short term ESS hourly operation decisions to capture the hourly, daily, and seasonal fluctuations in energy demand, renewable generation, and energy prices. For the same purpose, the planning horizon must span at least one year. The time is discretized into one-hour time intervals. As a consequence of the model size and complexity, a SA algorithm is developed as an alternative solution procedure. In summary the main contributions of this study can be listed as follows:

- We consider the siting and sizing decisions for multiple type ESS simultaneously in a more realistic problem setting. This includes indicator decision variables for fixed costs, longer time horizon to capture the hourly, daily, and seasonal fluctuations in demand, energy prices, and generation, and a capacitated electric power network.
- We develop an efficient metaheuristic algorithm. It is shown by a numerical study that it outperforms an earlier state of the art solution method and generates near optimal solutions in reasonable computational times.
- We measure the value of ESS and demonstrate the effects of several parameters (ESS prices, distribution line capacities, the variance of demand, and variance of renewable generation) on ESS location & capacity decisions.

The remainder of the study is organized as follows: In Section 2, we describe the ESS design problem in detail and introduce the corresponding MILP formulation. In Section 3, we propose a heuristic solution procedure for the problem. Numerical studies are conducted in Section 4 to compare the performance of the proposed algorithm with existing methods and to obtain insights on ESS allocation decisions under various model parameters. Concluding remarks are provided in Section 5.

2. Problem statement

We consider a network consisting of n demand points and m generators located on demand points, $m \leqslant n$. This network can be defined as a graph $G = (N, A)$ with n nodes. The central grid is denoted as node 0 and is assumed to have infinite power supply. We also assume that selling the excess energy to the central grid is possible. However, its amount is limited by the maximum generation in that time interval. The reason for this limit is to prevent buying when the prices are low and selling when they are high, in which case the benefit of the ESS mainly comes from trading but not from smoothing the intermittency of the renewable generation or the variance of the demand. Additionally, as a result of the distribution line and ESS capacities, grounding of the surplus energy is allowed. Renewable generators (wind turbines) are located on predetermined nodes.

We assume that generation amounts, demands, and electricity prices are known at each node for each period. Generation and demand data points are obtained from [39]. It is possible to install different storage types (such as pumped hydro, compressed air energy, and lithium-ion battery etc.) at the same node. Each storage type has an associated construction cost that also changes from one node to another. This is because the special installation requirements of the storage systems and the suitability of the nodes for these requirements. Due to these requirements, we also assume that it may not be possible to built certain storage types at a given node. The construction cost of the storage device also depends on its capacity, which has a limit. This limit may arise from the capacity of the dam system or the maximum capacity of the produced battery units. Hence, there is a different capacity for each ESS type. This capacity can also differ from one node to another for the same ESS type since the physical limitations for each node can be different. Furthermore, the storage devices cannot be charged or discharged with 100% efficiency. Therefore, our model includes charge/discharge efficiencies.

Storage locations and capacities are considered as long-term strategic decisions. However, flow between nodes, which is the result of voltage angle differences and storage management are hourly operational decisions. Periods are chosen as one-hour-long time intervals to capture the fluctuations in demand, generation, and spot market prices. Transmission lines are assumed to allow two way flow. The generators' locations are given and considered as model input parameters. The spot electricity market prices are handled under purely deterministic conditions. The resulting MILP formulation is given below:

Sets and Parameters

$\mathcal{N}$	Set of nodes, $\mathcal{N} = \{1,\ldots,N\}$.
$\bar{\mathcal{N}}$	Set of nodes including the central grid, $\bar{\mathcal{N}} = \{0,\ldots,N\}$.
$\mathcal{T}$	Set of time periods, $\mathcal{T} = \{0,\ldots,T\}$.
$\mathcal{B}$	Set of ESS types, $\mathcal{B} = \{0,\ldots,B\}$.
g_{it}	Energy generated by wind generator at node $i \in \mathcal{N}$ in period $t \in \mathcal{T}$.
d_{it}	Demand of node $i \in \mathcal{N}$ in period $t \in \mathcal{T}$.
f_{ib}	Fixed cost of opening ESS type $b \in \mathcal{B}$ at node $i \in \mathcal{N}$.
u_{ij}	Capacity of transmission line between nodes $i, j \in \mathcal{N}$.
e_b	Construction cost of one unit capacity of ESS type $b \in \mathcal{B}$.
P_t	Cost of buying one unit of energy from the central grid in period $t \in \mathcal{T}$.
V_t	Price of selling one unit of energy to the central grid in period $t \in \mathcal{T}$.
M_{ib}	Maximum capacity of ESS type $b \in \mathcal{B}$ that can be established at node $i \in \mathcal{N}$.
ρ_b^c	Charge efficiency of ESS type $b \in \mathcal{B}$.
ρ_b^d	Discharge efficiency of ESS type $b \in \mathcal{B}$.
a_{ib}	Binary parameter indicating whether ESS type $b \in \mathcal{B}$ can be established at node $i \in \mathcal{N}$ ($a_{ib} = 1$) or not ($a_{ib} = 0$) due to special requirements of the ESS.
B_{ij}	Admittance of the line between node $i, j \in \bar{\mathcal{N}}$.

Decision Variables

z_{ib}	$= \begin{cases} 1, & \text{if storage type } b \in \mathcal{B} \text{ is established at } i \in \mathcal{N}, \\ 0, & \text{otherwise.} \end{cases}$
θ_{it}	Voltage angle value at node $i \in \bar{\mathcal{N}}$ in period $t \in \mathcal{T}$.
s_{ibt}	Amount of energy available at node $i \in \mathcal{N}$ in storage type $b \in \mathcal{B}$ in the beginning of period $t \in \mathcal{T}$.
r_{ibt}	Discharge power from storage type $b \in \mathcal{B}$ at node $i \in \mathcal{N}$ during period $t \in \mathcal{T}$.
y_{ibt}	Charge power to storage type $b \in \mathcal{B}$ at node $i \in \mathcal{N}$ during period $t \in \mathcal{T}$.
o_{ib}	Capacity of storage type $b \in \mathcal{B}$ established at node $i \in \mathcal{N}$.
Φ_b^c	Upper limit on charging rate of ESS type $b \in \mathcal{B}$.
Φ_b^d	Upper limit on discharging rate of ESS type $b \in \mathcal{B}$.
η_{it}	Amount of energy grounded at node $i \in \mathcal{N}$ in period $t \in \mathcal{T}$.

MILP Formulation

$$\text{Min} \sum_{i \in \mathcal{N}} \sum_{b \in \mathcal{B}} (e_b o_{ib} + f_{ib} z_{ib}) + \sum_{i \in \mathcal{N}} \sum_{t \in \mathcal{T}} (P_t B_{0i} + V_t B_{i0})(-\theta_{it} + \theta_{0t}) \tag{1}$$

$$-u_{ij} \leqslant B_{ij}(\theta_{it} - \theta_{jt}) \leqslant u_{ij} \qquad i, j \in \mathcal{N}: i \neq j, t \in \mathcal{T} \tag{2}$$

$$(y_{ibt} + r_{ibt})\Delta t \leqslant o_{ib} \qquad i \in N, b \in B, t \in \mathcal{T} \tag{3}$$

$$o_{ib} \leqslant M_{ib} z_{ib} \qquad i \in \mathcal{N}, b \in \mathcal{B} \tag{4}$$

$$s_{ibt} \leqslant o_{ib} \qquad i \in \mathcal{N}, b \in \mathcal{B}, t \in \mathcal{T} \tag{5}$$

$$g_{it} + \sum_{j \in \mathcal{N}} B_{ji}(\theta_{jt} - \theta_{it}) + \sum_{b \in \mathcal{B}} \rho_b^d r_{ibt} \Delta t = \sum_{j \in \mathcal{N}} B_{ij}(\theta_{it} - \theta_{jt}) + d_{it} + \sum_{b \in \mathcal{B}} y_{ibt} \Delta t + \eta_{it} \qquad i \in \mathcal{N}, t \in \mathcal{T} \tag{6}$$

$$s_{ib0} = \frac{o_{ib}}{2} \qquad i \in \mathcal{N}, b \in \mathcal{B} \tag{7}$$

$$s_{ibT} = \frac{o_{ib}}{2} \qquad i \in \mathcal{N}, b \in \mathcal{B} \tag{8}$$

$$s_{ibt} = s_{ib(t-1)} + \rho_b^c y_{ibt} \Delta t - r_{ibt} \Delta t \qquad i \in \mathcal{N}, b \in \mathcal{B}, t \in \mathcal{T} \tag{9}$$

$$z_{ib} \leqslant a_{ib} \qquad i \in \mathcal{N}, b \in \mathcal{B} \tag{10}$$

$$-\pi \leqslant \theta_{it} \leqslant \pi \qquad i \in \mathcal{N}, t \in \mathcal{T} \tag{11}$$

$$y_{ibt} \leqslant \Phi_b^c \qquad i \in \mathcal{N}, b \in \mathcal{B}, t \in \mathcal{T} \tag{12}$$

$$r_{ibt} \leqslant \Phi_b^d \qquad i \in \mathcal{N}, b \in \mathcal{B}, t \in \mathcal{T} \tag{13}$$

$$z_{ib} \in \{0, 1\} \qquad i \in \mathcal{N}, b \in \mathcal{B} \tag{14}$$

$$\theta_{it} = \text{urs};\ y_{ibt}, r_{ibt}, o_{ib}, \eta_{it}, \Phi_b^c, \Phi_b^d \geqslant 0 \qquad i \in \bar{\mathcal{N}}, b \in \mathcal{B}, t \in \mathcal{T} \tag{15}$$

The objective function (1) minimizes the sum of storage installation cost, size-dependent variable cost, and the cost of buying energy from the central grid minus the revenue obtained by selling energy to the central grid. Constraint (2) states that amount of power transmission between two nodes cannot exceed line capacity limits. Constraint (3) ensures that if there is no storage, there will be neither charging nor discharging. The same constraint also restricts the amount of energy that can be stored in the ESS. If a node does not have a storage, it cannot have a positive storage capacity as satisfied by Constraint (4). The amount left in the ESS at the end of each period cannot be greater than its capacity as stated by Constraint (5). Constraint (6) is the flow balance constraint. For each node, the incoming flow from other nodes and/or the ESS plus the renewable generation at that node must be equal to the sum of the demand at that node, flow sent to the other nodes, energy stored in ESS, and the grounded energy. In order to make the generated ESS operating plan feasible for the upcoming planning horizons, we enforce that the initial and the final energy amounts in the ESS to be equal. This value is set to the half of the total storage capacity as modeled in Constraints (7) and (8). Constraint (9) models the amount of energy left in the storage devices at the end of each period. In this constraint Δt represents the length of each period. In this study, $\Delta t = 1$ h is used. A storage type can only be established at a node if it is possible to construct that storage type at that node as indicated by Constraint (10). Constraint (11) states that voltage angle value at each node and each period must be between $-\pi$ and π. Constraints (12) and (13) impose an upper limit on the charge and discharge rates for the ESS at each time period, respectively. Constraints (14) and (15) are the sign restrictions and the integrality constraints on the decision variables. Note that, charging and discharging of the ESS cannot occur at the same time. However, there is no need to impose this as an additional constraint. Because of the losses during charging and discharging, those solutions become inferior and the above formulation already satisfies this restriction.

Note that, this MILP model uses linear approximation for power flow which is appropriate for transmission networks. However, although it can yield erroneous solutions for distribution networks, it is still preferred to obtain quick solutions and insights about the problem. Therefore, we believe the obtained insights are not only limited to the transmission networks but can also be used for the distribution networks.

In order to capture the fluctuations in demand, generation, and spot energy prices, this formulation needs to be solved with a planning horizon of at least one-year with a one-hour time granularity. However, due to its complexity, it is not possible to solve this model optimally within a reasonable running time. Therefore, a heuristic algorithm is developed in the next section.

3. Heuristic algorithm

We developed a SA heuristic for this complex problem. Initial solutions are determined by relaxing the binary ESS type and location decisions in the MILP formulation which converts it into a linear program (LP). If the optimal solution of this LP is not feasible for the MILP, it is converted to an integer feasible solution by rounding the fractional values. To improve this initial solution, alternative location and size combinations are evaluated by solving the OPF problem for the given planning horizon. However, this LP still requires a very large computational time for longer planning horizons. To estimate the resulting objective function values in an efficient way without losing the daily, weekly, and seasonal variations in the electricity prices, demand, and renewable generation, we selected four representative weeks from each season and solved the problem with a planning horizon of these four weeks. We explain the steps of the algorithm in the following sections.

3.1. Initial solution

An initial solution must be constructed to start the SA algorithm. The steps of this algorithm can be seen in Algorithm 1. The initial solution is determined using the LP relaxation of the MILP model. After the optimal solution of this LP relaxation is found, the fractional values for the z_{ib} variables having a greater value than a predetermined threshold are set to 1. All other z_{ib} variables are set to 0. We performed preliminary tests to determine the best threshold value. For this purpose we used the RTS-96-1 and RTS-96-3 test sets with 24 and 73 nodes, respectively, for which the details are explained in Section 4. 0.2, 0.4 and 0.6 are used as the alternative values. 0.2 provided 2.83% (2.20%) better than both of the others for RTS-96-1 (RTS-96-3) test set. Therefore, the threshold value is fixed to 0.2. When z_{ib} values are fixed with this procedure, the remaining formulation is an LP, which will be referred to as *RelModel* in the paper.

To improve the initial solution, a local search procedure is used. z_{ib} values of the LP relaxation solution are sequenced in a non-increasing order. Starting from the first one the corresponding ESS is closed. If the *RelModel* is still feasible, algorithm moves to the next z_{ib}. Otherwise, the closed ESS is re-opened and algorithm moves to the next z_{ib}. This procedure can be seen in Lines 10–24 of Algorithm 1.

In this algorithm, obj^* and obj represent the incumbent objective value and the objective value of the current iteration, respectively. κ_1 denotes stopping criteria which is defined as the maximum non-improving iteration number.

Algorithm 1. Construction heuristic

1: Solve the LP relaxation of the MILP model
2: Sort the z_{ib} variables according to relaxation values in non-increasing order
3: **if** $z_{ib} >$ threshold **then**
4:     Set $z_{ib} = 1$
5: **else**
6:     Set $z_{ib} = 0$
7: **end if**
8: Solve the *RelModel* and $obj^* \leftarrow obj$
9: counter= 0
10: **while** counter $\leqslant \kappa_1$ **do**
11:     Close the storage with the smallest relaxation value
12:     Solve the *RelModel*
13:     **if** the *RelModel* is infeasible **then**
14:         Revert the change made at this iteration
15:         counter$++$
16:     **else**
17:         **if** $obj < obj^*$ **then**
18:             $obj^* \leftarrow obj$
19:             counter $= 0$
20:         **else**
21:             counter$++$
22:         **end if**
23:     **end if**
24: **end while**

3.2. Simulated annealing algorithm

The SA algorithm makes a search on z_{ib} values using three different operations: (i) – open a new storage (set $z_{ib} = 1$), (ii) – close an existing storage (set $z_{ib} = 0$), and (iii) – simultaneously close an existing storage and open a closed one. Each of these operations are equally likely to be selected. Probabilities for opening a new ESS at node i are calculated based on the index values γ_i, given in Eq. (16). In this equation, μ_d^i and μ_g^i are the mean demand and the mean generation; and σ_d^i and σ_g^i are the variances of the demand and generation at node i, respectively. cor_{dg}^i is the correlation between the demand and the generation at node i, and $\sum_{j \in N} u_{ij}$ is the total in-line and outline capacity of node i.

$$\gamma_i = \frac{(|\mu_d^i - \mu_g^i| + (\sigma_d^i + \sigma_g^i))(1 + |min\{0, cor_{dg}^i\}|)}{\sum_{j \in N} u_{ij}}, \forall\, i \in N. \tag{16}$$

According to this equation, a node with (i) – a large difference between demand and generation, (ii) – a low total line capacity, and (iii) – a negative correlation between demand and generation has a larger γ_i

value. This leads to a larger node selection probability given by $(\gamma_i / \sum_{i \in \mathcal{N}} \gamma_i)$. ESS closing probabilities are calculated using the reciprocals of the index values γ_i as $(\gamma_i^{-1} / \sum_{i \in \mathcal{N}} \gamma_i^{-1})$. After a node is selected as a candidate for opening or closing an ESS, the next step is to determine the storage type. For this purpose, again a probability is assigned to each type of ESS using their associated fixed and variable installation costs. The probability of selecting an ESS of type b to establish at node i is given by $(\alpha_{ib}^{-1} / \sum_{b \in \mathcal{B}} \alpha_{ib}^{-1})$, where $\alpha_{ib} = f_{ib} + e_b M_{ib}$.

The SA algorithm is stopped after a fixed number of iterations without an improvement in the incumbent solution. This algorithm is run for the selected four weeks and the locations, types, and sizes of the ESS are determined separately for these weeks. Then, the following merging algorithm is used to combine the solutions of all weeks into a single solution.

3.3. Merging heuristic

At the end of the SA algorithm, there is a solution for each of the representative weeks. In each of these solutions, the locations, the types, and the sizes of the ESS can be different. The merging algorithm combines these into a single, unified solution that minimizes the total cost. The steps of the merging algorithm is provided in Algorithm 2, where *obj* denotes the total objective value of all weeks and *obj** denotes its current best value. $\varkappa_2$ denotes the maximum iteration number, *rand* denotes a uniform random number between zero and one, and *Temp* denotes the temperature parameter that is used in a similar way as in the SA algorithm to calculate the probability of accepting a non-improving solution.

Algorithm 2. Merging heuristics

```
1: obj* ← obj
2: Let S_h be the set of z_ib values in the solution for week h
3: Let A = {(i, b): z_i,b = 1 in S_h, ∀ h = 1, ...,4}
4: for All (i, b) ∈ A do
5:    if z_ib = 1 for all four weeks then
6:       Set z_ib = 1
7:    else
8:       Set z_ib = 0
9:    end if
10: end for
11: Set counter= 0
12: while counter ⩽ ϰ_2 do
13:    Calculate the opening probabilities for each (i, b) ∈ A using Eq. (17)
14:    Select the (i, b) pair using roulette wheel method and set z_ib = 1
15:    Resolve the RelModel for all weeks
16:    if The model is infeasible for any one of the weeks then
17:       Go to Step 14
18:    else
19:       if obj < obj* then
20:          Update the solution
21:          obj* ← obj
22:       else if rand ⩽ e^((obj* − obj)/Temp) then
23:          Update the solution
24:       end if
25:    end if
26:    counter+ +
27: end while
```

According to this algorithm, if $z_{ib} = 1$ in all four weeks, then the corresponding z_{ib} is set to 1 in the combined solution. All others are initially set to 0. The algorithm opens a new ESS at each iteration to reach a feasible and a better solution. An ESS of type b is opened at node i with a probability, ϕ_{ib}, where:

$$\phi_{ib} = \lambda \frac{\xi_{ib}}{\Gamma} + (1 - \lambda) \frac{\omega_{ib}}{\Omega_{ib}} \tag{17}$$

In this equation, ξ_{ib} denotes the number of weeks that $z_{ib} = 1$ in the considered weeks, Γ denotes the total number of weeks, which we selected as 4. ω_{ib} denotes the total storage capacity of ESS type b opened at node i and Ω_{ib} denotes the maximum capacity of ESS type b that could be established at node i. In this study, $\Omega_{ib} = 4 \times M_{ib}$ is used. As a consequence, Eq. (17) is a weighted normalized sum of the number of times an ESS type is opened and its capacity. $\lambda \in [0, 1]$ is the weighting parameter, where $\lambda = 0.6$ provided the best results in our tests.

Merging heuristic opens new ESS by selecting their types and locations according to the probabilities calculated in Eq. (17). A new ESS is opened if the current solution is infeasible or if opening that ESS reduces the cost. Additionally, an ESS has still a probability of being opened even it increases the cost, which is calculated as in the SA algorithm in Line 22 of Algorithm 2.

4. Case study

In this section, we first provide the system settings, the scenarios, and the data used in the case study. Then, we test the performance of the heuristic algorithm, discuss the results for the base scenario and provide insights about the effects of different parameters on the benefits of ESS.

4.1. System settings and data

In this case study, we use the modified IEEE-RTS 96 test set firstly suggested by Wong et al. [40]. We use both the IEEE one-area RTS-96 that has 24 nodes and three-area RTS-96 that has 73 nodes. We denote these as RTS-96-1 and RTS-96-3, respectively. Ref. [41] modified the benchmark and included 19 renewable resources. Wind generation output can be maximized by optimizing several operation parameters of the wind turbines [42] and/or by designing the layout of the wind farms [43]. Here, we assume this output is already maximized and we focus on siting and sizing the storage systems in such a network. Considering the efficiency, cycle, and capital costs provided by Beaudin et al. [44], Pumped Hydro Storage (PHS), Compressed Air Energy Storage (CAES), and Lithium-Ion Battery (LB) are selected as storage types in this case study. Ref. [44] does not give capital costs directly for CAES and LB. So, we assume LB has a relatively lower fixed cost and CAES's fixed cost to be less than PHS. However, CAES's variable cost is assumed to be greater than PHS. We use a one year planning horizon for which the annual equivalent of the capital costs are determined by an engineering economic analysis considering their life cycles. One hour time granularity is used which results in a planning horizon of 365 days × 24 h making a total of 8760 one-hour-long stages. Fixed and unit storing costs, and charge/discharge efficiencies are obtained from the same reference. Charge/discharge efficiencies are calculated as square root of round trip efficiency [27]. Renewable generation values and yearly demands for all one-hour time intervals are obtained from [39]. Transmission line capacities and admittances are given in IEEE-RTS 96. Spot market prices are obtained from EPEX [45]. 2014 hourly spot market prices for France are used for the model. Buying and selling from/to the grid costs are calculated as + 20%, −20% of the EPEX prices, respectively. To estimate the solution for one year, four weeks are chosen from each season, which are the weeks including the dates December 21, March 21, June 21, and September 23.

The developed algorithms are coded in Java and run in a computer with Intel(R) Xeon(R) E5645 2.4 GHz CPU with 12 cores and 18 GB RAM. The mathematical models are solved with CPLEX 12.6.2 solver.

The following scenarios are used for these tests, where $S0$ denotes the base scenario, $S1$ is used to compare the systems with and without ESS. $S2$, $S3$, $S4$, and $S5$ are used to test the effects of the variable costs, line capacities, demand variances, and generation capacities, respectively. μ_i denotes the mean demand at node i.

$S0$	Base scenario
$S1$	No storage
$S2(h)$	Modify storage variable cost by $(1-\frac{h}{15})\times e_b$, $\forall\ h\in\{0, 1, ..., 10\}$.
$S3(h)$	Modify line capacities by $(1+\frac{h}{15})\times u_{ij}$, $\forall\ i, j\ ; \forall\ h\in\{0, 1, ..., 10\}$.
$S4(h)$	Modify demand variance by $\max\{0, (\frac{h+2}{4})\times(d_{it}-\mu_i)+\mu_i\}$, $\forall\ i, t\ ; \forall\ h\in\{-4, -3, ..., 3, 4\}$.
$S5(h)$	Modify generation by $(1+\frac{h}{4})\times g_{it}$, $\forall\ i, t\ ; \forall\ h\in\{0, 1, ..., 8\}$.

4.2. Performance of the proposed heuristic

To test proposed algorithm's performance, we compare the solutions of the proposed heuristic with the 3-stage planning procedure proposed by Pandzic et al. [27]. Note that, although that study does not consider multiple ESS types, fixed costs, and energy trading, it is still the most relevant state of the art solution method in the literature. Therefore, we adapted their solution method for the current study.

In this method's first stage, the algorithm is run separately for each of the 365 days to determine the locations of the ESS. If the number of days in which a storage is established at a specific location is greater than a threshold value then, the model fixes that locations. In the second stage, considering the fixed locations, the remaining model is run for each day again, this time to determine the storage capacities. The average of the capacity values resulting from each of these days and locations is assigned to the corresponding storage. In the last stage, the problem is again solved by fixing the storage locations and their capacities to determine the actual flows and storage charging/discharging schedules. The total cost is calculated as the sum of the daily costs.

We used the same 3-stage solution idea by using our MILP formulation. We made the tests over the same time span of four weeks. We used two values (5 and 8) as the threshold values for the number of days to fix the ESS locations in the first stage of the procedure.

RTS-96-1 and RTS-96-3 test sets are used for the tests. The results are summarized in Table 1. In this table, the percent gap value between solution method A and B (A vs B) is calculated as follows:

$$100\times\frac{f(A)-f(B)}{f(B)}$$

where $f(\cdot)$ denotes the objective function value of the corresponding solution procedure. The MILP formulation is run with a 2-h time limit. In both cases, it could not find the optimal solution within the time limit. The MILP Gap column in Table 1 is the gap value reported by CPLEX solver which represent the percent deviation of the best solution found after 2 h from its lower bound. As it can be seen, for RTS-96–1, the MILP Gap value is very small. The deviation of the proposed heuristic from the best MILP solution is also very small as shown in the "PH vs MILP" column. On the other hand, for the larger test set, the performance of the MILP reduced drastically providing a 33.6% gap. For this test set, the proposed heuristic was able to find a 17.44% better solution (negative gap) than the best MILP solution. In addition to these, the proposed heuristic provides approximately 10% better results than the 3-stage solution procedure in both test problems with both threshold values (P5 and P8).

Table 1
Performance comparison of the proposed heuristic (PH), Pandzic et al. [27] with threshold values of 5 (P5) and 8 (P8) and with MILP.

		P5 vs PH		P8 vs PH			
	PH Time (s)	Gap (%)	Time (s)	Gap (%)	Time (s)	MILP Gap (%)	PH vs MILP (%)
RTS-96-1	227.4	10.13	71.9	9.44	67	0.34	0.34
RTS-96-3	1933.4	9.07	5428.6	8.66	5403.3	33.60	−17.44

When the solution times are investigated, for smaller test set, the 3-stage solution procedure is faster than the proposed heuristic. However, for the larger instance, the proposed heuristic outperforms the other methods with a reasonable solution time. These results prove that the proposed heuristic is an effective solution method with respect to both solution quality and computation time.

4.3. Base scenario results

In the base scenario, a total of 22 ESS are established in RTS-96-1. Among these, 11 of them are LB, 1 is CAES, and 10 are PHS type. In RTS-96-3, a total of 68 ESS are established which includes 34 LB; 3 CAES; and 31 PHS type storages. When we consider all the scenarios, approximately 52% of the established ESS are LB, 4% are CAES, and 43% are PHS. These results reveal that all types of ESS can be established at several nodes in the optimal solution. However, in our tests, CAES is used only when both LB and PHS storages reached their maximum allowable capacities. This is due to the disadvantage of CAES with respect to fixed and variable costs when compared with LB and PHS.

When the locations of established ESS are investigated, 11 of the 22 ESS are on different nodes in RTS-96-1. There are a total of 9 nodes that includes a generation in this network. ESS are established on 6 of these. In other words, 67% of the nodes with generation contains ESS. This percentage drops to 33% for the nodes without generation. In RTS-96–3, ESS are established on 34 separate nodes. In this network, there are a total of 16 nodes that includes a generation. ESS are established on 9 of these nodes. That is, 56% of the nodes with generation and 44% of the nodes without generation contains ESS. On the other hand, the mean demand and the variance of the demand on the nodes that include ESS are approximately 10% less than that of the nodes without an ESS in RTS-96-1. This pecentage drops to 5% in RTS-96-3.

There are studies [46] that show that ESS should be established near generation sites to reduce transmission losses. However, when the power network transmission constraints are taken into account, an ESS established near high demand nodes helps during peak times when the transmission line capacities are insufficient. Our results show that, although there is a tendency to establish ESS closer to the generation facilities, this tendency is not too strong. The rule of thumb to establish an ESS near a generation facility, or on a node with large mean demand or with large demand variance will not provide the optimal solution in a general CEPN.

4.4. Cost benefits of establishing ESS

One of the contributions of this study is the quantification of the benefits of establishing ESS. Scenarios $S0$ and $S1$ are used for this purpose. Under the $S1$ scenario, we assumed that there are no storages on the network. Therefore, only the OPF problem is solved. The objective function values of these two scenarios are compared with each other. The total cost in $S0$ is reduced by 33.3% in RTS-96-1 and 26% in RTS-96-3 with respect to $S1$. These values prove that establishing storages has significant cost benefits. In the following, we will analyze the effects of several parameters on these benefits.

4.5. Sensitivity to ESS requirements

Some ESS types have special requirements. For example, CAES requires suitable space such as underground caverns or PHS requires water reservoirs at different levels. The a_{ib} parameter in the problem definition is used for this purpose. The number and locations of the ESS types also depends on this parameter. To analyze its effect on the results we repeated our runs considering three different cases. Since LB does not have special requirements, in all these cases we assumed that LB can be established at each node. In the first case, we assumed that CAES and PHS can also be established at all nodes, meaning that $a_{ib}=1$ for all

Table 2
Effect of a_{ib} parameter on the number of ESS.

	RTS-96-1			RTS-96-3		
Scenario	LB	PHS	CAES	LB	PHS	CAES
1	11	10	1	34	31	3
2	12	5	1	36	12	1
3	14	4	0	42	7	0

i and b. In the second and third cases, randomly selected 50% and 20% of a_{ib} values are set to 1, respectively for these ESS types.

The numbers of established LB, CAES, and PHS are shown in Table 2. As it can be seen in this table, when PHS and CAES locations are restricted, this affects the total number of established storages as well as the number of specific ESS types. As a consequence of the change, the numbers of PHS and CAES reduce, as expected, whereas the number of LB increases. However, at the end, the total number of established ESS also reduces. At some nodes PHS and CAES are replaced with another type, mostly LB. However, at some nodes this was not possible since the total established capacity of the other ESS can already be in its highest value. Also, establishing a different ESS type at that node may not be profitable due to its fixed and variable costs and this can be another reason of the reduction in the total number of ESS.

4.6. Sensitivity to ESS variable costs

With the technological advancements, the variable cost of Lithium-Ion batteries decreases day after day. Here, we investigate the effect of this reduction on the ESS location and sizing decisions. For this purpose, we reduced the cost of establishing one unit of LB (e_{ib};$b = 3$ for LB) storage capacity gradually by a factor of $1 - \frac{h}{15}$ for $h = 0, \ ..., 10$ creating a total of 11 scenarios including the base scenario ($h = 0$). Fig. 1 depicts the effect of reducing the variable costs on the total costs and the total capacity of established ESS in RTS-96-1 and RTS-96-3. The results prove that the total cost is highly dependent on the variable cost as expected. When variable costs are reduced by two thirds ($h = 10$), the total cost reduces be 100% and 70% for RTS-96-1 and RTS-96-3, respectively. This change increases the total capacity of established ESS by approximately 50%. This proves that, the number of established ESS will increase day by day with the reduction in the storage costs in the near future. Reduction of the variable costs of LB storage also effects the share of them among all ESS. In the base scenario 50% of the ESS appears to be LB, whereas this share increases to 70% when the variable costs are reduced by two thirds.

4.7. Sensitivity to line capacities

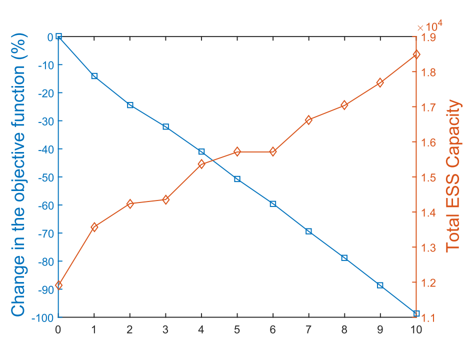
One of the reasons to establish ESS may be the congestion in the network. Large amounts of power flow may be required to satisfy varying demand on different nodes using the generated power by the renewable generators. If the line capacities are not satisfactory, it may not be possible to transmit the generated power from the renewables to the demand points. In such a case, the required energy is bought from the central grid and the generated excess power could not be used to satisfy the demand, but grounded. This leads to large total cost values. To see the effects of line capacities on the total cost and the number of established ESS scenario $S3(h)$ is used where the line capacities (u_{ij}) are modified. The results are depicted in Fig. 2. According to this, the total cost reduces with the increase in the line capacities as expected. However, it may be thought as counter-intuitive to see that the total capacity of established ESS also increases with the line capacities. This behavior occurs because with larger line capacities it becomes possible to transmit the generated energy to different nodes and store at those locations. By this way, the generated energy is used more efficiently and the amount of grounded energy is reduced.

4.8. Sensitivity to demand variance

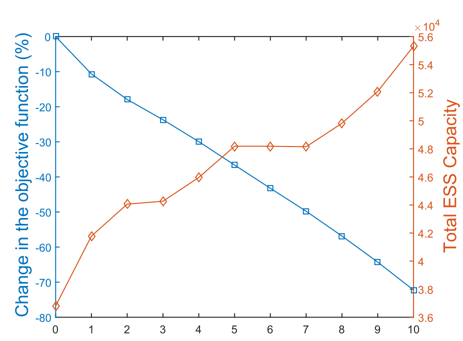
If the demand variance from one period to another is large, this may motivate to establish more ESS to store the generated excess amount when the demands are low and use it when the demands are high. Also, more energy can be bought and stored when the energy prices in the central grid are lower, which can be used later when the energy prices are higher. Scenario $S4(h)$ is used to test this, where the demand at each node is modified with a factor. According to this procedure, if the demand is above average, it is shifted upwards and if it is below average, it is shifted downwards. As it can be seen in Fig. 3, the increase in the demand variance increases the total cost as expected. However, the change in the total capacity of ESS is not significant.

4.9. Sensitivity to renewable generation amount

When the output of the renewable generators increases, more demand can be satisfied from these and less energy is bought from the central grid. This may reduce the total cost. However, due to line capacities and less demand at some periods, all the generated power may not be used. Hence, ESS can be utilized to store this excess energy and use at later periods. To test this, the generation amount (g_{it}) is increased gradually up to three times in scenario $S5(h)$ as depicted in Fig. 4. This change leads to a significant reduction in the total cost. On the other hand, the change in the total capacity of established ESS is not monotonic. This is because, when generation is lower it may be preferable to



(a)



(b)

Fig. 1. Effect of Variable Cost (a) RTS-96-1, (b) RTS-96-3.

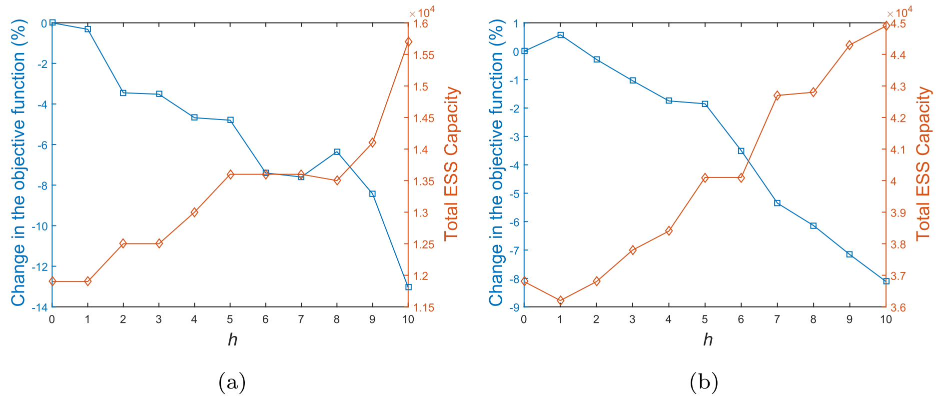


Fig. 2. Effect of Line Capacities (a) RTS-96-1, (b) RTS-96-3.

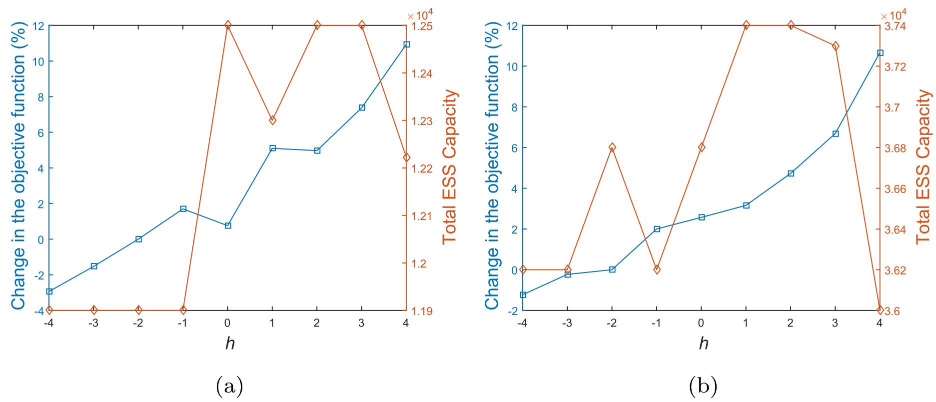


Fig. 3. Effect of Demand Variance (a) RTS-96-1, (b) RTS-96-3.

establish ESS so that the excess energy can be stored to satisfy the demand at another period, when the generation is not satisfactory. However, as the generation increases gradually, after some point, the generation starts to satisfy the demand (or a large proportion of it) at these periods also. In this case, instead of establishing ESS with large fixed costs, the central grid is used to satisfy any necessary energy.

5. Conclusion

In this study, we considered the ESS siting and sizing problem with multiple ESS types. To capture the hourly, weekly, and seasonal fluctuations of the demand, the renewable generation, and the energy prices, we considered a one-year planning horizon with one-hour time granularity. We developed the MILP formulation of this problem which appeared to be a large scale model. To determine solutions in reasonable times, we developed a heuristic algorithm that first develops an initial solution and then improves it in an SA algorithm.

We showed the effectiveness of the proposed heuristic by comparing its solutions with the MILP formulation and the 3-stage solution method of Pandzic et al. [27] through a numerical study. We also performed numerical studies to measure the benefits of establishing ESS in a distribution network. Our results reveal that ESS can reduce the total cost approximately by 30%. This value is highly dependent on the variable cost of ESS and the amount of renewable generation in the network.

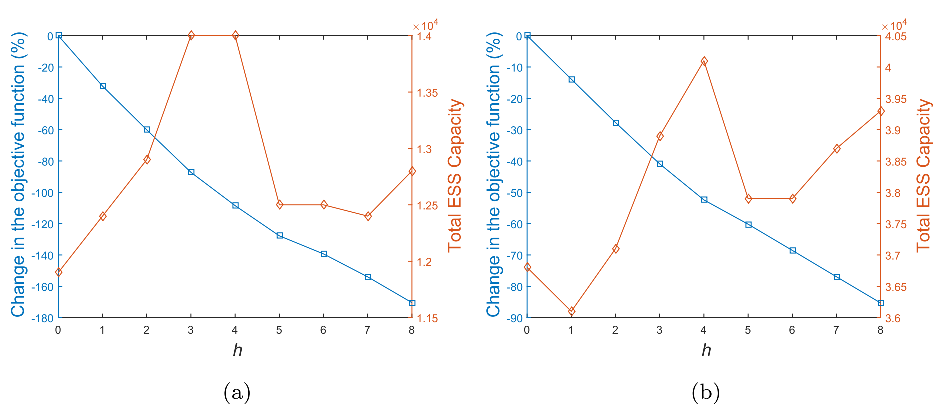


Fig. 4. Effect of Generation Increase (a) RTS-96-1, (b) RTS-96-3.

Therefore, as the cost per unit capacity of ESS reduces and the share of renewable generation capacity increases, the value of establishing ESS throughout the power system will increase in the near future. The cost benefit of ESS is also moderately dependent on the line capacities and the demand variance. As opposed to the common belief, increasing renewable generation capacity does not always imply increased need for energy storage. There are other factors that should be considered like the demand and price variabilities, locations as well as the line capacities. Depending on different requirements, different types of ESS can be established on different nodes. However, consistent with the current world practice, LB systems turns out to be the preferred method of energy storage among the ones considered in the numerical study. In summary, many factors including the cost of ESS, the spot market energy prices, the line capacities, the maximum possible ESS capacity, magnitudes and variances of the demand and generation are affecting the optimum number, type, location, and size of ESS. Some of them are more dominant in certain instances but their joint effect must be considered in making the best decision. This reveals the importance of having an effective solution procedure, which is one of the contributions of the current study.

As a future research, the problem can be modeled as a stochastic programming formulation to handle the inherent uncertainty of generation, demand, and spot market prices. Furthermore, the problem can be considered as a power network design problem where the storage sizing and siting decisions and network expansion decisions are made simultaneously.

CRediT authorship contribution statement

Cansu Agrali: Conceptualization, Methodology, Software, Validation, Writing - original draft, Project administration, Funding acquisition. **Hakan Gultekin:** Conceptualization, Methodology, Validation, Writing - review & editing, Supervision, Project administration. **Salih Tekin:** Conceptualization, Methodology, Writing - review & editing, Supervision, Project administration. **Nihat Oner:** Conceptualization, Methodology, Writing - review & editing, Supervision, Project administration.

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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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.ijepes.2020.106022.

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