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Introducing storage operators for coordinating residential batteries in distribution networks under time-of-use tariffs and adaptive power limits

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HIGHLIGHTS

- Uncoordinated charging of batteries under ToU tariff violates network constraints.
- Introducing storage operator for coordinating batteries in distribution networks.
- Storage Operator is modelled by Mixed-Integer Linear Programming (MILP).
- Managing batteries is based on predefined time-varying and adaptive power limits.
- Storage operator optimizes network capacity to maximize customers' satisfactions.

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ABSTRACT

The transition towards Time of Use (ToU) tariffs has become a promising solution for addressing power system challenges resulting from increased installations of renewable energy systems. ToU tariffs encourage residential Battery Energy Storage System (BESS) adoption to reduce customers' bills through maximizing energy storage during low-price intervals (e.g., middle of the day). However, simultaneous BESS charging affects diversity of load, which may lead to the violation of distribution networks constraints. Traditional network management with conservative fixed and static power limits leads to inefficient network capacity use since they do not consider changes in network operating conditions and status of BESS facilities. Specially, these approaches do not allow higher import limits when proportion of BESS facilities are in idling state. To better allocate the capacity of distribution networks to active BESS facilities (charging/discharging), this work introduces an independent storage operator to coordinate BESS control actions by employing time-varying and adaptive power limits. For this purpose, a Mixed Integer Linear Programming (MILP) algorithm is proposed for storage operator to manage BESS facilities while respecting network constraints and customers' desired bills. At each time step, the algorithm decides power limits for active BESS facilities based on predefined linear functions. These functions are generated offline by using Optimal Power Flow (OPF) to establish relationships between power limits and number of active BESS. The application of the algorithm using a real Jordanian distribution network demonstrates its effectiveness to allow a larger number of customers achieving their desired bills compared to using fixed power limits.

1. Introduction

Worldwide low-carbon energy policies have facilitated grid integration of large volumes of renewable generation particularly solar photovoltaic (PV) [1]. The increasing volume of PV systems have placed operational challenges on the power system operators to maintain balancing between demand and generation particularly during the system's minimum net-demand time intervals (i.e., middle of the day) [2]. In particular, negative energy prices have been increasingly occurring in different electricity markets in the last few years to encourage reducing the output power of PV power plants [3]. Also, the volume of PV curtailment particularly from PV connected to distribution networks has been increased significantly [4]. However, the reliance on PV curtailment to cater for system challenges will place barriers in the

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transformation towards a low-carbon energy system. Therefore, it is important to explore alternative solutions to PV curtailment to maintain the security of supply [5–7]. One of the potential solutions is to encourage energy consumption during time intervals with over generation. This requires departing from the existing standard flat volumetric tariff towards Time of Use (ToU) tariff schemes that reflect the operating conditions of the power system [8–10]. By designing ToU tariff, the volume of the transferred energy towards the system's minimum net-demand at the low-price intervals will be increased, thus supporting grid balancing.

The employment of ToU tariff may encourage the uptake of Battery Energy Storage System (BESS) facilities. Currently, BESS is typically owned and controlled by customers to reduce their electricity bills harnessing the differential prices in the ToU tariff [11–13]. The customers' energy consumption at high-price intervals could be locally supplied from the stored energy in BESS during the low-price intervals. However, the simultaneous charging of BESS facilities during the low-price time intervals affects the diversity of load which may result in a new peak demand on distribution networks and the violations of network constraints, specially voltage drop issues and overloading network assets [14–16].

In the literature, constraints of distribution networks are managed using decentralized approaches that are typically led by Distribution Network Operators (DNOs). These approaches are formulated by defining conservative fixed or time-varying power limits to be applied at the customers' energy meters [17,18]. The charging and discharging actions of each BESS are employed to maintain the power exchanges from each meter within the predefined limits. Although the above decentralized approaches allow managing network constraints in a simple and implementable manner, the defined limits are expected to become smaller at the high coverage rate of BESS. This means that the benefits of ToU tariff could be only restricted to customers with low to medium energy charging needs. These approaches also do not allow the adoption of higher import limits when proportion of BESS facilities remains in idling state after achieving their energy charging requirements. Furthermore, the studies in [19–25] provided decentralized-based methods to coordinate the control actions of distributed controllable elements without a central controller. The methods aim to achieve local objectives of individual customers (e.g., reducing bills) as well as improving global objectives across group of customers such as delivering ancillary grid services. This is done by sharing local information and measurements (e.g., excess local energy, available headroom in BESS) among customers to support their decision-making algorithms. The decentralized coordination methods are developed based on advanced concepts of transactive energy, peer-peer energy trading, smart contracts, blockchain and data-driven methods to support cooperation among customers. Few of the previous studies have considered the constraints of distribution networks. The studies in [23–25] provided an iterative-based methods in which each control action to be implemented requires approval from DNOs. However, this creates complexity in coordination and scalability issues as it requires direct interactions from DNOs compared to using predefined rules to model the network constraints.

Centralized management approaches allow establishing communication links to BESS facilities to dynamically update import and export limits based on network operating conditions and BESS operation states. Developing centralized approaches to maximize benefits from BESS facilities requires amending existing regulations and modifying electricity metering systems. Considering that energy suppliers are not allowed to directly manage customers' BESS due to unbundling regulatory rules, it is essential to introduce an independent storage operator that serves as an independent party from energy suppliers and DNOs to coordinate control actions of distributed BESS facilities across distribution networks [26]. The storage operator establishes contracts with individual customers to partially pay the cost of batteries in return of controlling them to maximize potential revenues from the ToU tariff [27]. The recent transition in metering systems in different countries (e.g., Jordan [28] and California [29]) towards reserving a dedicated and separate ToU electricity meter for new controllable facilities particularly BESS and electrical vehicles could support the future role of storage operator [30]. With a dual-meter setup, the storage operator will be able to directly interact with the new electricity meter to coordinate the control operations of distributed BESS facilities without the need for complex computational tasks and billing mechanisms to deal with uncertainties in uncontrollable loads and cater for limited visibility to BESS when they are located behind the customers' meters. In the future, the role of storage operator could be further developed to act as virtual power plants and aggregators to deliver ancillary grid services to the power system operator (e.g., frequency regulation services) and participate in the electricity markets.

Implementing the storage operator in practice requires developing a realistic decision-making algorithm that considers implementation challenges related to the management of distribution networks. In particular, the storage operator will not have access to the full data of distribution networks and real-time measurements. In this respect, it is important for the DNOs to provide the storage operator of network constraints by utilizing predefined import and export limits to manage the charging and discharging of individual BESS [31]. However, the decision-making algorithms for centralized approaches found in the literature [32–37] are based on utilizing advanced and complex full real-time Optimal Power Flow (OPF) [35,36]. The adoption of the OPF is not implementable in practice since it requires the storage operator have full observability of distribution networks and real-time network measurements. Although the studies in [38] assign import and export limits to the aggregate power of controllable elements, the defined limits are fixed, and they are not time-varying according to network conditions. Furthermore, the defined limits are not updated based on the operation states of BESS facilities. The adoption of adaptive power limits allows better allocating the available capacity of distribution networks to active BESS (charging/discharging) rather than reserving capacity for BESS under idling state.

To enable the wide-scale employment of ToU tariff with BESS at residential customers, this work provides a Mixed Integer Linear Programming (MILP) decision-making algorithm to be applied in future storage operator to coordinate the control actions of distributed residential BESS facilities whilst respecting the constraints of distribution networks. Considering that the storage operator does not have access to the details of distribution networks' topology and real-time measurements, the coordination of BESS facilities is carried out in response to time-varying and adaptive import and export power limits. At each time step, the storage operator selects BESS facilities who should be active to be charged/discharged. The storage operator also decides the most adequate power exchange limit for active BESS facilities based on a set of predefined linear functions to be provided in practice by distribution network operators. The functions provide the mathematical relationships between maximum power exchange from individual batteries and number of active BESS facilities. The functions are generated offline by using three-phase stochastic AC Optimal Power Flow (OPF) model that caters for uncertainties in BESS locations and network demand. The performance of the adaptive power limits approach is compared against the adoption of conservative power limits as mostly adopted in the literature. Also, the ability to create additional revenue stream from increasing energy export to the grid during the high-price intervals are quantified (i.e., price arbitrage). The performance of the algorithm is demonstrated using a real integrated Medium Voltage (MV) and Low Voltage (LV) network from the southern region of Jordan, serving 2440 residential customers.

The rest of this paper is structured as follows: Section 2 provides an overview of storage operators in distribution networks. Section 3 presents the formulations of the AC OPF based approach to define time-varying functions of power limits. The modelling of the decision-making algorithm for storage operators using the adaptive time-varying power limit is provided in Section 4. The role of storage operator is demonstrated in Section 5 using a real MV/LV network from Jordan. Section 6 discusses implementation aspects and potential metering arrangements to be applied in countries with different regulatory rules. Finally, the conclusions are drawn in Section 7.

2. Role of storage operator: an overview

The structure of the proposed storage operator is shown in Fig. 1. The storage operator aims to coordinate the control actions from residential BESS to maximize the potential revenues/benefits from the ToU tariff whilst respecting the constraints of distribution networks (i.e., voltages and thermal constraints). In the proposed structure, the storage operator establishes contracts with individual customers to install batteries at residential premises for the mutual benefits of both the storage operator and customers while sharing the cost of batteries. In exchange for customers' participation in the cost of batteries, the storage operator provides customers with guaranteed monthly revenues to be earned from the charging and discharging actions under the ToU tariff. Under the ToU tariff, it is assumed that the buying and selling prices are the same. Therefore, the storage operator is incentivized to sell energy from the BESS ToU meter particularly during the highest-price interval. The storage operator also aims to maximize the potential revenues from the differential prices in the ToU tariff (i.e., price arbitrage) by increasing the volume of charge energy in the low-price intervals to be exported later at the high-price intervals. From the regulation perspective, the metering system in the proposed BESS coordinated management system considers two electricity meters at each residential customer. The first meter is the conventional meter with either flat-rate or ToU electricity tariff that deals with the electrical energy of the property. The second meter is a newly installed ToU meter that is dedicated to BESS. Dedicating a separate meter for residential BESS provides an implementable solution for the storage operator to directly manage the charging and discharging actions of BESS. The presence of a dual-meter setup also facilitates the billing mechanism and the reconciliation between the storage operator and the residential customers compared to dealing only with the net-demand of a single meter.

To achieve customers' contractual bill reduction, the storage operator is required to ensure that the volume of stored energy in each individual battery during the low-price intervals is adequate to support customers' energy consumption in high-price intervals (i.e., achieving desired bills). It is also worth to note that due to the adoption of two sperate meters, it could not be distinguished that the power flows to the customer's meter is supplied from the battery discharged power. However, the customer will be still financially benefitted from the battery since the storage operator will pay to the customer a percentage of revenues earned from selling energy to the grid particularly at the high price interval.

The decision-making algorithm for storage operator embeds the constraints of distribution networks in the forms of mathematical linear functions that define the maximum power exchanges from individual batteries in terms of the proportion levels of active BESS facilities (charging/discharging). At each time step, the defined power limits are dynamically varying according to the proportion of active batteries under charging/discharging state. This allows the adoption of higher import limits in the low-price period when proportion of BESS facilities remain in idling states after fulling their desired volume of charging needs.

To demonstrate the importance of utilizing adaptive time-varying operating power limits to manage BESS during low-price intervals, Fig. 2 shows the stored energy in batteries owned by customers with different energy consumption needs (i.e., low, medium, and high). Also, the stored energy is compared against the levels that could be achieved with the utilization of fixed power charging limit (as commonly adopted in most studies in the literature). In this example, the storage.

operator aims to charge the batteries of three residential customers during the low-price interval (i.e., three-time steps). Each of the customers has different energy consumption needs in the high-price interval. The size of the box in the figure corresponds to the desired energy needs. Customer 1 has the lowest energy consumption needs while customer 3 has the maximum needs. The charging process in Fig. 2 (a) is carried out to maintain the charged power throughout the time steps below a relatively low value of P_1 to comply with the constraints of distribution networks. As can be seen, customer 1 is able to meet the desired needs quickly (at time step T_1) even though with the adoption of a small limit. In particular, the battery of customer 1 goes into idling state at time step T_2 and T_3. In contrast, the adoption of a small charging limit significantly affects customer 3. For this customer, the level of charged energy at the end of the low-price interval only reaches a small portion of the customer' desired needs. Thus, a larger volume of imported energy will be drawn from the grid during the high-price periods. Although the fixed charging limit is a simple and implementable approach to model the constraints of distribution networks, it negatively affects customers with large energy consumption needs and prevents

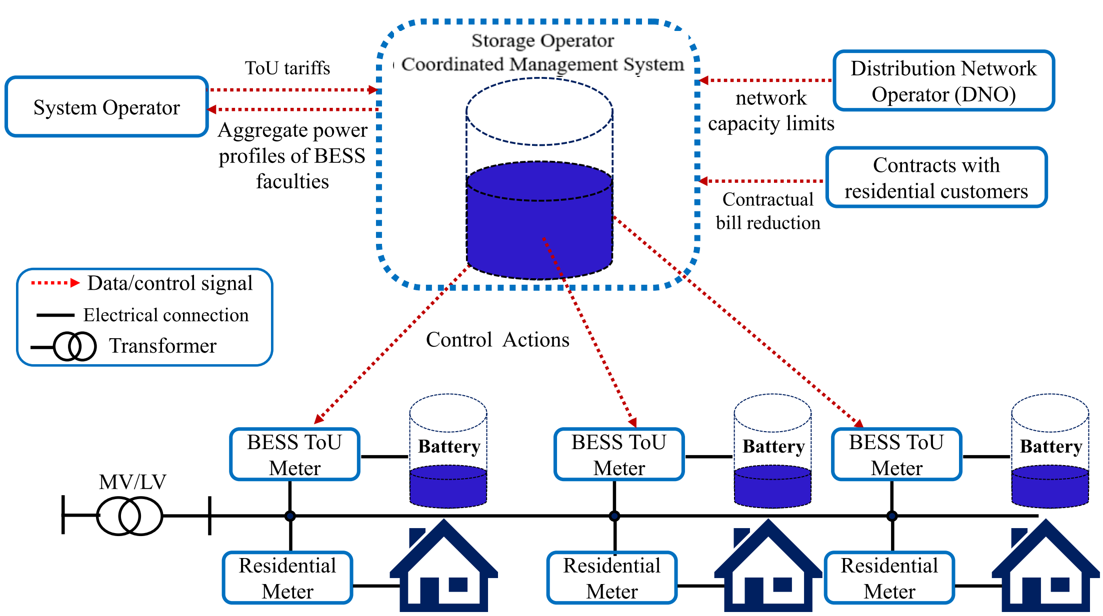


Fig. 1. Storage operator structure.

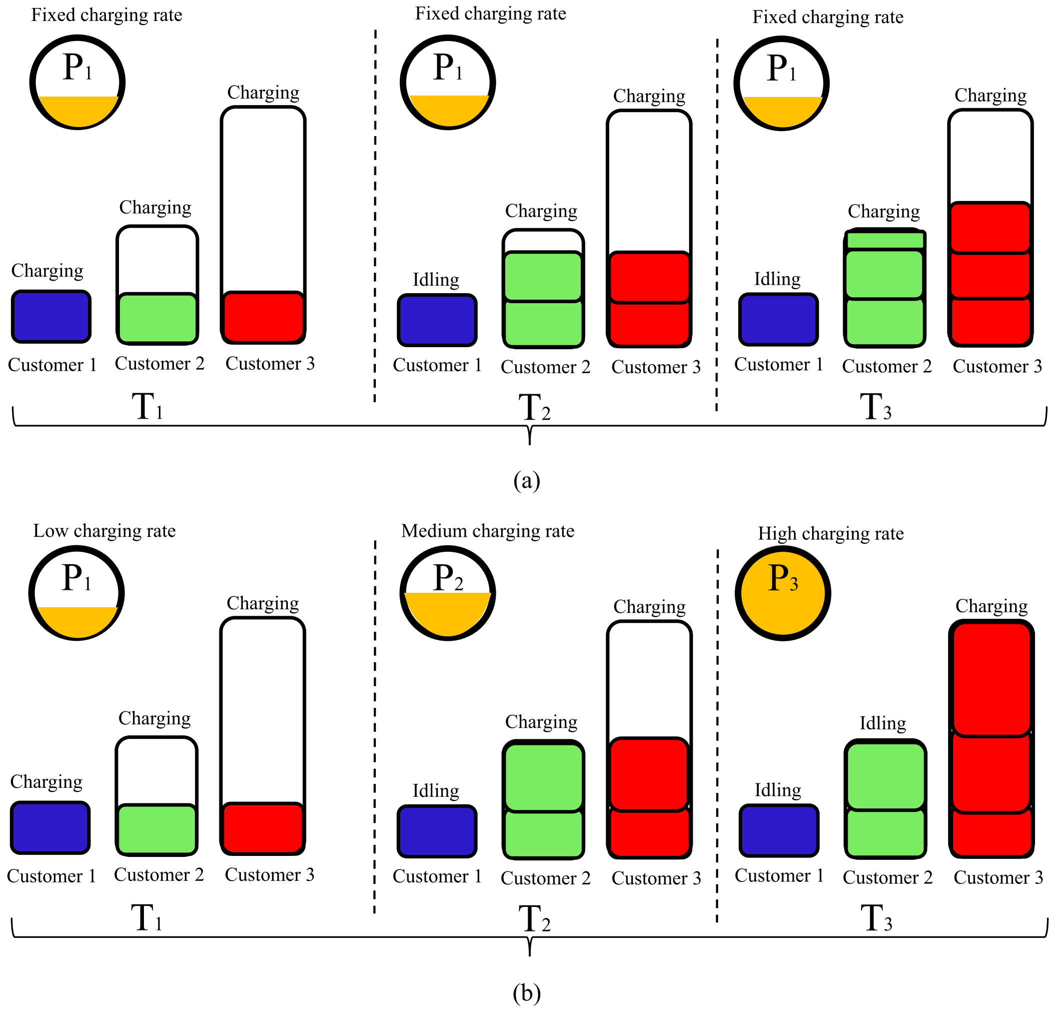


Fig. 2. Illustrative example during low-price intervals with (a) fixed power limits and (b) adaptive time-varying power limits.

them from meeting their desired electricity bills. This means that the benefits of ToU tariff could be only restricted to customers with low to medium energy consumption needs (i.e., non-fair access). Also, the fixed power limit does not harness the existing communication links between the storage operator and BESS to update the power limits. Alternatively, the usage of adaptive time-based power limits allows better utilization of the available capacity in distribution networks. The available network capacity is fully assigned to only those batteries at the charging state. As can be seen in Fig. 2 (b), a higher power charging limit is defined for customer 3 at T_3. Thus, a larger percentage of the customer's energy needs at high-price intervals could be supplied from the stored energy that is charged within the low-price interval. This means that a higher proportion of customers could benefit from the ToU tariff.

3. Defining time-varying functions of power limits: planning approach

This section provides the formulations to define time-varying functions of import and export limits. At each time step, a series of linear functions are defined to provide relationships between power limits and proportion levels of active BESS (e.g., starting from 0% to 100% in steps of 10%). The functions are determined by DNOs to be provided to the storage operator to coordinate the control actions of residential batteries whilst respecting network constraints. To define the functions of import limits, a two-stage approach is adopted.

The first stage illustrated in Fig. 3 is an iterative approach that aims to define power limits for multiple OPF simulations, per each time step (set T indexed by t), proportion level of active batteries (set R indexed by r) and scenario of BESS locations (set SC indexed by sc). For this purpose, the three-phase AC OPF model is formulated to decide the maximum charging power (i.e., import limit) of active BESS facilities.

At each time step, the OPF is run for different proportion levels of active BESS (i.e., 10%, 20%… 100% of the total number of batteries). To cater for uncertainties in BESS locations, multiple OPF simulations are carried out per each specific proportion level by considering unique scenarios of BESS locations. To define a single import limit at each proportion level, the minimum value across all the OPF simulations is selected. This means that the first stage produces multiple discrete import limits at each time step. Each of them corresponds to a specific proportion level of active BESS. To enhance flexibility for storage operator in selecting a proportion level within the analyzed range, the second stage is employed. The defined import limits at each time step are then processed using curve fitting technique to generate a series of linear functions of import limits. Each function corresponds to a specific range of active BESS proportion levels. The two-stage approach is also adopted to define the time-varying functions of export limits. For this purpose, the OPF objective is adjusted to define maximum discharging power (i.e., export limit) of active BESS in discharging state.

3.1. First stage: AC OPF

For each time step, the AC OPF is run for different proportion levels of active batteries and scenarios of BESS locations. The time-series data of active and reactive power of loads and generators are obtained from historical data. The objective function of the AC OPF is formulated to maximize charging power (import power) from active BESS (p^{import}).

$$Max\ p^{import} \tag{1}$$

The model employs a Quadratic Constrained Programing (QCP) formulations for the AC OPF [39,40] to calculate the three-phase power flows throughout lines and transformers (set L indexed by l) and network voltages at each bus (set B indexed by b). The voltage drop is modelled in the QCP by eliminating angles of voltages and by using the active and reactive power at the start bus of each line and transformer and for each phase (set PH indexed by ph), $p_{l,ph}$ and $q_{l,ph}$; respectively. For each phase, lines and transformers, the QCP formulations calculate the voltage drop in terms of the square of voltage magnitude, $V^{sqr}_{b,ph}$ at the start and end bus of line l and the square of current magnitude, $I^{sqr}_{l,ph}$ throughout line l, as given in (2).

$$\sum_{d\in D\left|\rho_{d=b},\ \gamma_d=ph\right.} q_{d,ph} = \sum_{x\in X\left|\rho_{x=b},\ \gamma_x=ph\right.} q^{BSP}_{x,ph} + \sum_{g\in G\left|\rho_{g=b},\gamma_g=ph\right.} q_{g,ph} + \sum_{l\in L\left|\rho^{start}_{l=b},\ \gamma_l=ph\right.} \left(q_{l,ph} - X_l I^{sqr}_{l,ph}\right) \tag{4}$$

$$\sum_{B\in b\left|\rho^{start}_{l=b}\right.} V^{sqr}_{b,ph} - \sum_{B\in b\left|\rho^{end}_{l=b}\right.} V^{sqr}_{b,ph} = 2\left(\sum_{l\in L\left|\rho^{start}_{l=b}\right.} R_l\, p_{l,ph} + X_l\, q_{l,ph}\right) - \sum_{l\in L\left|\rho^{start}_{l=b}\right.} I^{sqr}_{l,ph}\left(R_l^2 + X_l^2\right) \tag{2}$$

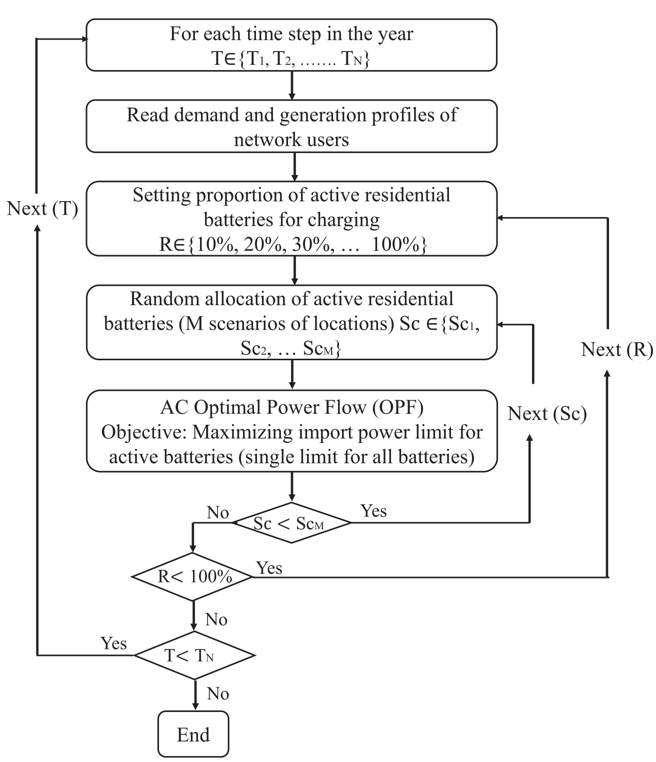


Fig. 3. First Stage: Iterative approach to define import limits.

where R_l and X_l are the resistance and reactance of line l respectively, ρ_l^{start} and ρ_l^{end} maps the start bus and the end bus of line l. The active and reactive power balance equations at each bus and for each phase are modelled in (3) and (4), respectively. In this model, the locations of active BESS (set BT indexed by bt) are modelled by using a binary parameter $A^{BESS}_{bt,ph}$. This parameter is predefined as inputs to the OPF, and it is set to one with the existence of an active BESS at bus b and phase ph.

$$\sum_{d\in D\left|\rho_{d=b},\ \gamma_d=ph\right.} p_{d,ph} + \sum_{bt\in BT\left|\rho_{bt=b},\ \gamma_{bt}=ph\right.} p^{import} A^{BESS}_{bt,ph} = \sum_{x\in X\left|\rho_{x=b},\ \gamma_x=ph\right.} p^{BSP}_{x,ph} + \sum_{g\in G\left|\rho_{g=b},\gamma_g=ph\right.} p_{g,ph} + \sum_{l\in L\left|\rho^{start}_{l=b},\ \gamma_l=ph\right.} \left(p_{l,ph} - R_l I^{sqr}_{l,ph}\right) \tag{3}$$

where $p_{d,ph}$ and $q_{d,ph}$are the active and reactive power of demand (set D indexed by d); $p_{g,ph}$ and $q_{g,ph}$ are the active and reactive power of generators (set G indexed by g); $p^{BSP}_{x,ph}$ and $q^{BSP}_{x,ph}$ are the active and reactive power imported/exported from the grid (Set X indexed by x); γ_u maps the bus b and the phase ph to which each network element is connected ($u\subset\{d, g, bt, x, l\}$).

The optimization is also subject to the voltage and thermal constraints, as given in (5) and (6); respectively.

$$V_b^{sqr\ (-)} \le V^{sqr}_{b,ph} \le V_b^{sqr(+)} \tag{5}$$

$$I^{sqr}_{l,ph} \le I_l^{sqr\ (+)} \tag{6}$$

where $V_b^{sqr\ (-,+)}$ are the limits of the square voltage magnitude at each bus and $I_l^{sqr\ (+)}$ is the square of the line current limit.

To guarantee convexity in the QCP problem, it is important to ensure that the apparent power throughout line l equals the product of voltage and current, as expressed in (7).

$$\sum_{l\in L\left|\rho^{start}_{l=b},\gamma_l=ph\right.} \left(p_{l,ph}\right)^2 + \left(q_{l,ph}\right)^2 = \sum_{l\in L\left|\rho^{start}_{l=b},\gamma_l=ph\right.} V^{sqr}_{b,ph} I^{sqr}_{l,ph} \tag{7}$$

For a time step, a single import limit is defined per each proportion level of active BESS $\left(p^{import}_{t,r}\right)$ whose value is decided as the minimum among the import limits identified in the corresponding scenarios ($p^{import}_{t,r,sc}$).

$$p^{import}_{t,r} = min_{sc}\left\{p^{import}_{t,r,sc}\right\}, \forall t \in T, \forall r \in R \tag{8}$$

Similarly, the export limit per each proportion level of batteries under discharging state at a time step t ($p^{export}_{t,r}$)is formulated in (9).

$$p^{export}_{t,r} = min_{sc}\left\{p^{export}_{t,r,sc}\right\}, \forall t \in T, \forall r \in R \tag{9}$$

3.2. Second stage "defining linear functions of power limits

By the application of curve fitting technique, a series of linear functions (I indexed by i) of power limits is defined at each time step.

The mathematical expressions of the functions of import limits are modelled in (10) and (11). Each function corresponds to a specific range of active BESS. For example, the function $f_{t_1,1}$ is applied at time step t_1 when the proportion level of active BESS falls within the range of 0% and 10%. Similarly, functions of export limits are generated per each time ($p_{t,i}^{export}$).

$$p_{t,i}^{import} = \left\{ f_{t,i}(r_{t,i}), c_{t,i-1} \le r_{t,i} < c_{t,i} \right\} \tag{10}$$

$$f_{t,i}(r_{t,i}) = a_{t,i} r_{t,i} + b_{t,i} \tag{11}$$

where $a_{t,i}$, $b_{t,i}$ are the slope and the intersection of each function; respectively. Each function is assigned to a particular percentage range whose start and end values are given by $c_{t,i-1}$ and $c_{t,i}$; respectively.

4. Storage operator decision-making algorithm

This section provides the modelling of the Mixed Integer Linear Programming (MILP) decision-making algorithm for storage operators. The algorithm aims to control charging and discharging powers of BESS facilities $p_{bt,t}^{ch}$, $p_{bt,t}^{dis}$ (both have non-negative values) in response to the ToU price signal π_t. Further to catering for the constraints of distribution networks, the storge operator also aims to improve the satisfaction level for each individual customer (i.e., achieving the customer' contractual bill reduction). This is done by making sufficient revenue from each BESS to offset the corresponding customer's energy consumption cost. To do so, a customer satisfaction index (CSI_{bt}) is defined, and it is expressed as the ratio of the revenue from the BESS to the customer's contractual bill reduction ($C_{bt}^{contract}$). Having a CSI_{bt} of 100% for a specific customer, for instance, means that the storage operator has fully achieved the contractual bill reduction. Mathematically, the CSI for a customer is formulated in Eq. (12) whose numerator represents the revenue obtained from the BESS with purchasing and selling energy.

$$CSI_{bt} = \frac{\sum_{t \in T} \left(p_{bt,t}^{dis} \pi_t - p_{bt,t}^{ch} \pi_t \right)}{C_{bt}^{contract}} \tag{12}$$

The objective of the algorithm is formulated in (13) as a multi-objective function. The first term of the objective aims to minimize the overall energy costs for the storage operator associated with the purchase and sale of energy from BESS facilities (i.e., maximizing revenues from BESS facilities). The objective also aims to minimize the deviation of each customer's satisfaction index from unity. Considering customers' satisfactions in the objective function prevents leaving proportion of batteries without charging. This allows a larger number of customers to achieve the contractual bill reduction (i.e., a unity CSI metric).

$$Min \sum_{bt \in BT} \sum_{t \in T} \left(p_{bt,t}^{ch} \pi_t - p_{bt,t}^{dis} \pi_t \right) + \omega \sum_{bt \in BT} (1 - CSI_{bt}) \tag{13}$$

where ω is a weighting coefficient, whose value is smaller than one to provide higher priority to the first term of the objective function. The CSI metric for each individual customer is maintained within CSI^{min} and CSI^{max}. The upper limit of CSI is selected as one when the focus of storage operator is to only achieve customers' contractual bill reduction. A higher value than unity is adopted to allow the creation of additional revenues from BESS facilities than the defined values in the customers' contracts. By relaxing the upper limit of CSI (e.g., CSI^{max}=2), the storage operator will aim to maximize the volume of charged energy in each BESS during the low-price intervals to be exported back to the grid at the high-price intervals (i.e., price arbitrage).

$$CSI^{min} \le CSI_{bt} \le CSI^{max} \tag{14}$$

The storage operator decides the best states of each BESS (i.e., charging and discharging). For this purpose, the binary variable $u_{bt,t}^{ch}$ is defined to denote the charging and discharging states of BESS (i.e., a binary variable $u_{bt,t}^{ch} = 1$ means that the battery is at charging state and $p_{bt,t}^{dis}$ is set zero). The charging and discharging power of BESS are controlled within its power rating P_{bt}^{rated}. The constraints in (15) and (16) are formulated to prevent the simultaneous charging and discharging of BESS.

$$p_{bt,t}^{ch} \le u_{bt,t}^{ch} \times P_{bt}^{rated} \tag{15}$$

$$p_{bt,t}^{dis} \le \left(1 - u_{bt,t}^{ch}\right) \times P_{bt}^{rated} \tag{16}$$

Moreover, the energy stored in the battery $E_{bt,t}^{store}$ is calculated as in (17), and it is constrained to remain below its energy rating, E_{bt}^{rated}. To preserve the storage life, one cycle of charging and discharging is allowed by enforcing the initial stored energy $E_{bt,t=t1}^{store}$ equal to the final stored energy $E_{bt,T}^{store}$. Also, the stored energy is allowed to decrease to a minimum limit, E_{bt}^{min}.

$$E_{bt,t}^{store} = E_{bt,t-1}^{store} + \left(p_{bt,t}^{ch} \eta^{ch} - \frac{p_{bt,t}^{dis}}{\eta^{dis}} \right) \times \Delta t \tag{17}$$

where Δt is the time step, $\eta^{ch}$and η^{dis} are the charging and discharging efficiencies; respectively.

The storage operator manages the operation of batteries according to the functions of import and export limits established in Section III. At each time step, the storage operator prevents different batteries from being in both charging and discharging modes simultaneously. During the time intervals of charging, the storage operator establishes a uniform power limit for charging that is applied for all batteries, p_t^{import}. During periods of discharging, the storage operator also maintains the discharge power of each active BESS below a specified export limit (p_t^{export}).

$$p_{bt,t}^{ch} \le p_t^{import} \tag{18}$$

$$p_{bt,t}^{dis} \le p_t^{export} \tag{19}$$

During periods of charging, the optimization engine is required to select the highest percentage of active charging batteries r_t and the corresponding charging limit p_t^{import}. This means that only a single function from the DNO's functions will be adopted per each time step. However, the direct formulation of the DNO's functions (in Eq. (11)) will not maintain the linear formulation of the optimization problem. For this purpose, the linearization approach in [41] is adopted. As proven in [41], the function $f_{t,i}(r_{t,i})$ can be reformulated as provided in (20)–(23).

$$f_{t,i}(r_{t,i}) \le a_{t,i} r_{t,i} + b_{t,i} + M(1 - z_{t,i}) \tag{20}$$

$$f_{t,i}(r_{t,i}) \ge a_{t,i} r_{t,i} + b_{t,i} - M(1 - z_{t,i}) \tag{21}$$

$$f_{t,i}(r_{t,i}) \le M z_{t,i} \tag{22}$$

$$f_{t,i}(r_{t,i}) \ge -M z_{t,i} \tag{23}$$

where M represents a sufficiently large constant and the binary variables, $z_{t,i}$, are introduced to ensure that the optimization selects only a single percentage range of active charging batteries, as given in (24).

$$\sum_{i \in I} z_{t,i} = 1 \tag{24}$$

At the time step t, the constraints in (25)–(26) are also formulated to specify the minimum and the maximum values of the percentage of active charging batteries; respectively.

$$r_{t,i} \geq \sum_{i \in I} c_{t,i-1} z_{t,i} \tag{25}$$

$$r_{t,i} \leq \sum_{i \in I} c_{t,i} z_{t,i} \tag{26}$$

Deciding the active charging battery percentage r_t and the corresponding charging limit p_t^{import} that are defined using (27) and (28); respectively.

$$r_t = \sum_{i \in I} r_{t,i} \tag{27}$$

$$p_t^{import} = \sum_{i \in I} a_{t,i} r_{t,i} + b_{t,i} z_{t,i} \tag{28}$$

The functions related to export limit are also linearized following the same procedure as provided above in (20)–(28).

5. Results

The storage operator framework is demonstrated using a real integrated MV/LV network from the southern region of Jordan, serving 2440 residential customers [31]. The details of the network are available in [31]. The daily load profiles of residential customers were derived from a dataset obtained from smart meters data along the studied feeder. Further, the load profiles of non-residential customers are defined based on the real power measurements. The modelling language AIMMS [42] is utilized for both defining the power limits (as per the OPF formulations in Section III) and modelling the decision-making algorithm (Section IV). The optimization problems are solved using the CPLEX solver [43]. The distribution network analysis software package OpenDSS [44] is used to assess the technical impacts of the adaptive time-varying power limits framework on the real MV/LV network.

In the analyzed network, each residential customer has two distinct meters; one for house consumption and another dedicated to a 14-kWh battery with a power rating of 3.6 kW [27]. The Jordanian ToU tariff is adopted as shown in Fig. 4. The low-price period (i.e., 10:00–15:00) aligns with high PV production, while the high-price period corresponds to the peak demand of the Jordanian power system (i.e., 19:00–23:00). The remaining hours in the day represent the intermediate-price periods.

In this section, the impacts of residential ToU tariff on the analyzed network before the application of the proposed BESS management system are presented in Section V.A. The impacts are found for different ToU penetration levels starting from 0% and up to 100% in steps of 10%. The impacts are assessed in terms of voltage violations and thermal overloads. To capture the effects of BESS locations, stochastic power flows simulations are employed. The BESS coordinated management system is then utilized to mitigate the impacts and allow higher ToU penetration. In Section V·B, the time-varying functions of import and export power limits are defined at each time step in the day and for 10 proportion levels of active BESS (i.e., from 10% to 100%). In Section V·C, the defined function are then utilized in the decision-making algorithm to coordinate the operations of residential BESS in response to the ToU tariff whilst achieving the customers' contractual bill reduction ($C_{bt}^{contract}$). To assess the performance of storage operator under a challenging scenario, it is assumed that each customer aims to pay the cost of energy used during high-price intervals with the lowest price in the ToU tariff. Mathematically, the contractual bill reduction per customer is calculated by multiplying the customer' amount of energy used during high-price intervals by the price difference between high and low-price intervals.

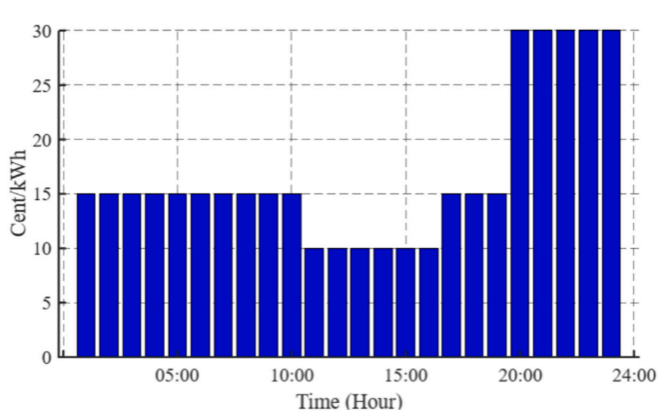


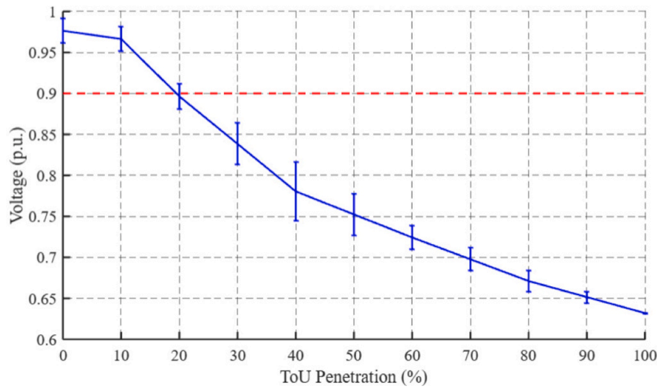
Fig. 4. ToU tariff.

5.1. *Impact assessment of ToU Tariff on distribution networks: No BESS coordination*

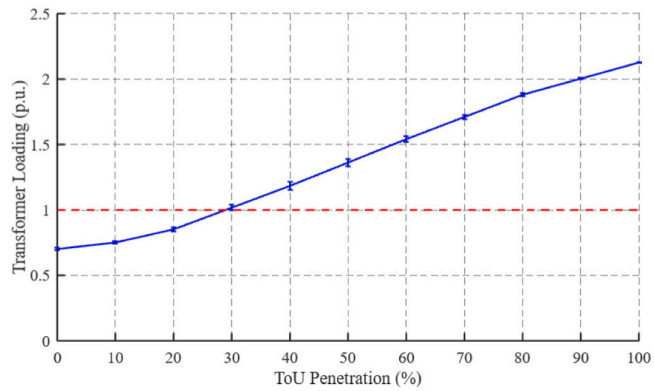
This section presents the technical impacts on the MV/LV distribution network resulting from deploying ToU tariff and BESS for residential customers, without the application of power limits (i.e., no BESS coordination). To do so, a range of ToU penetration levels is adopted starting from 0% and increasing up to 100% in steps of 10%. A ToU penetration level corresponds to the number of customers who have adopted ToU tariff. For instance, a 50% penetration level among 2440 customers means that 1220 customers adopt the ToU tariff. Each customer with ToU tariff is equipped with a 14 kWh BESS. To cater for the uncertainties in the BESS locations, the impact assessment is performed at each penetration level across different scenarios of BESS locations. The methodology to generate the scenarios is adapted from [4]. Specifically, 100 scenarios of BESS locations at each ToU penetration level are considered. As the penetration level increases, more BESS installations are added to the existing ones from the previous penetration level and for the same scenario. This process continues until each customer's location is assigned a single BESS, along with ToU tariff, reaching 100% penetration.

Each battery management system controls the charging and discharging actions locally to minimize the customer's electricity bill. Specifically, each BESS goes into charging state during the low-price intervals between 10:00 and 15:00. The objective of each battery management system is to store energy up to customer's energy needs during the high-price periods. The stored energy is then utilized during the high-price intervals to support the customer's energy needs so that the import energy from the grid can be reduced. Based on both the demand of each residential customer and BESS power output, three-phase time-series unbalanced power flows are conducted by using the distribution network analysis software package OpenDSS. For each time step, customers' voltages are evaluated against the statutory voltage limits (i.e., based on the distribution performance standard in Jordan [45], the voltage limits for LV customers are ± 10% of nominal voltage 230 V line-to-neutral [45]). Then, the minimum voltage for each scenario and ToU penetration is recorded. Similarly, the maximum loading level of MV and LV lines and for each distribution transformer are also assessed (i.e., expressed in per unit relative to their ratings).

Fig. 5 (a) presents the median value (the solid line) of the minimum voltage across residential customers for all the scenarios and per each penetration level. The bottom and the top bars represent the 25th and the 75th percentile of all scenarios. It can be noticed that the provision of ToU tariff along with BESS start creating voltage drop issues at 20% penetration. This is due to the loss of diversity as most BESS will be charged during low-price intervals. The voltage issues increase significantly at higher ToU and BESS penetrations. For example, the median of the minimum voltage at 100% penetration is 0.64 p.u. Fig. 5 (b) shows the maximum loading of the distribution transformers at various ToU and BESS penetration levels. The results show that transformer overloading issues appear at 30% penetration. The MV feeders, however, remain within capacity limits. Furthermore, Fig. 6 shows the power



(a)



(b)

Fig. 5. Impact assessment of different ToU penetration levels without BESS coordination on (a) network's minimum voltage and (b) maximum loading of transformers. The solid line is the median of the scenarios. The bottom, and top bars are the 25th and 75th percentile, respectively.

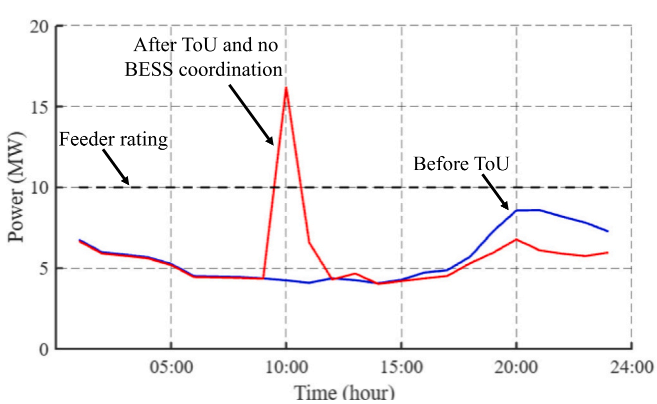


Fig. 6. Head of MV feeder loading before ToU tariff (Blue line) and after employing 100% ToU penetration (red line). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

flows at the feeder's head along with the thermal limit at 100% ToU and BESS penetration. BESS responses to price signals create new peak demand during the low-price periods (i.e., between 10:00–15:00), reaching 16.2 MW, which exceeds the feeder's thermal limit by 62% overloading. Since batteries discharge stored energy during high-price hours (19:00–23:00), the original peak demand during night periods reduces from 8.6 MW to 6.8 MW with the implementation of ToU tariff.

Based on the above, the widespread adoption of batteries and controlling them for the benefits of customers under the ToU tariff affects demand diversity, creating a new peak during the low-price intervals. The resulting new peak demand exceeds the original peak demand observed before implementing ToU tariff. This operating condition violates distribution network constraints, requiring network reinforcement to enable the ToU tariff. Alternatively, the charging of batteries must be coordinated to maintain network constraints within their limits.

5.2. *Defining time-varying functions of power limits*

This section aims to define time-varying functions of import and export limits based on the process described in Section III. The AC OPF is run multiple times to decide the optimal import/export limits considering 10 proportion levels of active BESS ranging from 10% to 100%. For each proportion level of active BESS, 100 scenarios were generated to address uncertainties related to battery locations. Multiple AC OPF simulations were conducted each hour throughout the day (24 h) considering the defined scenarios and proportion levels of active BESS. This in turn results in performing 24,000 OPF simulations (i.e., 10 $\times$ 100 $\times$ 24). During each simulation run, the maximum limits for battery charging and discharging were calculated. Fig. 7 shows the import limits for battery charging across all the 24,000 simulations. It can be noticed that the charging limits vary based on the proportion level of active BESS in the charging state. As the proportion levels rise from 10% to 100%, the corresponding import limits are in the range from 4.5 kW to 0.6 kW. For a particular proportion level of active BESS, the defined charging limits also vary according to the spatial distribution of BESS. For example, the charging limit varies from 1.2 kW to 4.5 kW at 10% proportion level of active batteries in the charging state. However, these variations become smaller at proportion level close to 100%. For each proportion level of active BESS, a set of 24 import limits is defined (i.e., one for each hour of the day). The selected limits are determined by taking the minimum value across all scenarios for each hour. This results in defining 10 profiles of import limits across the day. For demonstration purposes, Fig. 8 provides the profiles of import limits for five proportion levels of active BESS (i.e., 20%, 40%, 60%, 80% and 100%). It can be noticed that the charging limit has higher values during the middle of the day (10:00–15:00) while it is restricted during peak-demand periods (19:00–23:00). Once the profiles of import limits are defined, it is important to generate linear functions at each time step to preserve linear formulations required by the storage operator decision-making algorithm (Section III-B). Fig. 9 shows examples of the resulting linear functions at 10:00 a.m. The power limit may increase by 370% compared to the adoption of a conservative small value of import limit of 1.2 kW. The functions clearly show the importance of dynamically adjust the import limit based on the number of active BESS. This in turn provides further flexibility for the storage operator to manage BESS and enhances the percentage of customers achieving their desired energy needs.

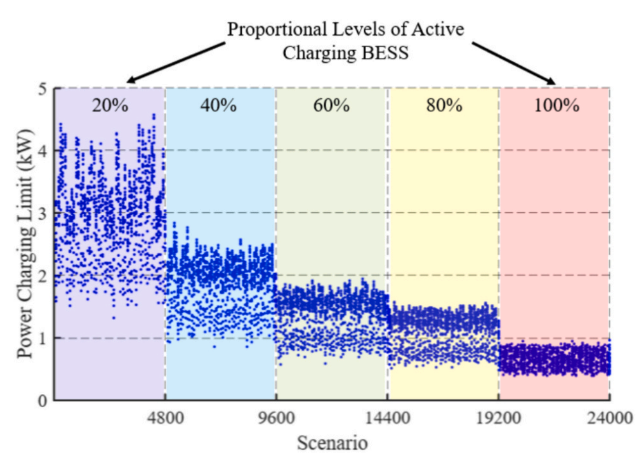


Fig. 7. Power charging limits for all the simulations.

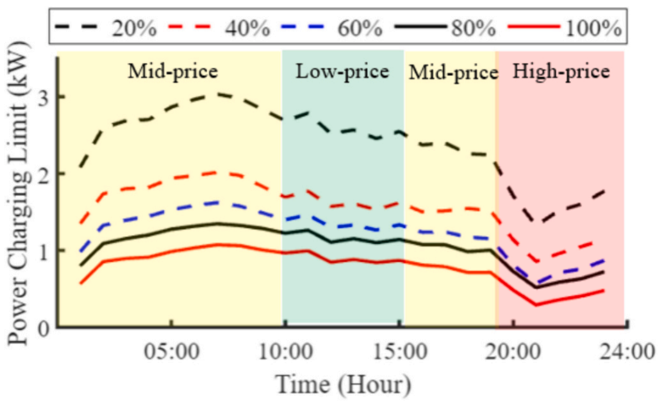


Fig. 8. Time-varying power charging limits.

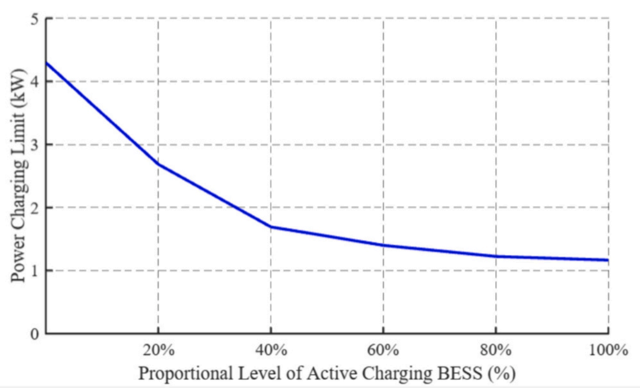


Fig. 9. Set of linear functions for power charging limit at 10:00 a.m.

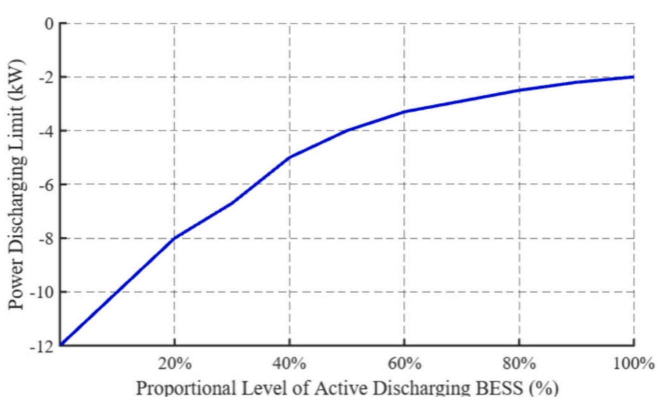


Fig. 10. Set of linear functions for power discharging limit at 19:00.

For each time step during the high-price intervals (19:00–23:00), linear functions of export limits are also generated. For illustration, Fig. 10 shows the set of linear functions of export limits at 19:00. The functions determine the maximum discharge power of BESS facilities. It is worth noting almost identical functions of export limits are obtained for the other hours within the high-price intervals.

5.3. Storage operator: performance assessment

The resulting set of linear functions for charging and discharging at each hour are utilized in the storage operator decision-making algorithm (Section IV) considering 100% ToU penetration. The performance of the algorithm is assessed from both network and customers perspectives. Here, the focus of storage operator to achieve customers' contractual bill

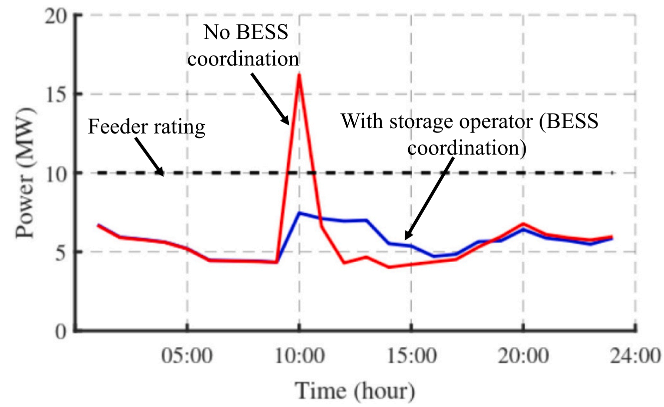


Fig. 11. Head of MV feeder loading after introducing storage operator with time-varying and adaptive power limits.

reduction. For this purpose, the upper limit of CSI is selected as one (CSI^{max}=1).

5.3.1. Network's perspective

Fig. 11 shows the head of the feeder loading after introducing the storage operator. For comparison purposes, the figure also presents the loading of the feeder in Section IV.A (i.e., no power limits are placed on BESS control actions). The figure shows the effectiveness of storage operator in reducing the peak demand of the feeder during the low-price interval. The peak demand is reduced significantly from 15.9 MW to 7.4 MW. Furthermore, the loadings of all the distribution transformers and lines as well as customers' voltages are all maintained within their limits. This shows that it is possible to achieve 100% ToU penetration with introducing storage operator compared to only 20% ToU penetration

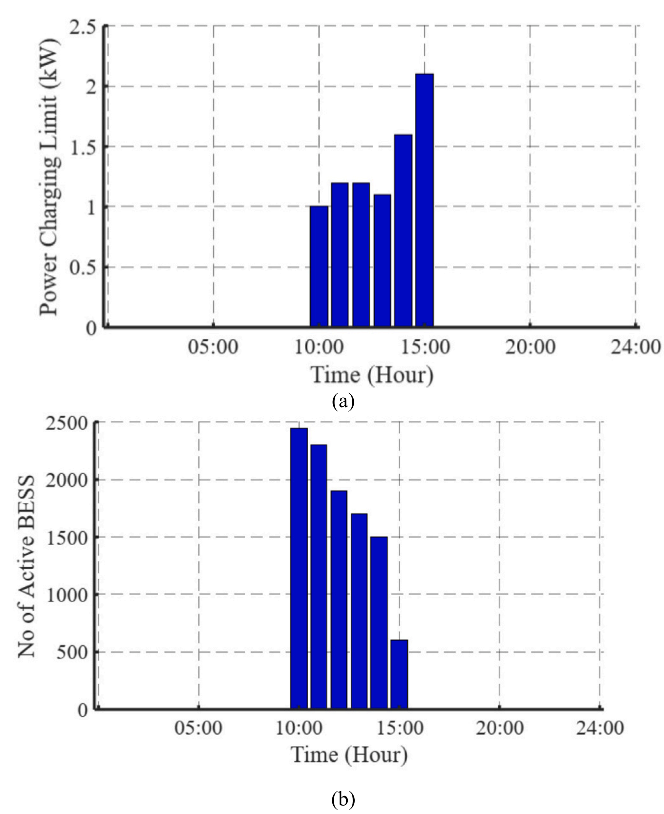


Fig. 12. (a) Power charging limit and (b) Number of active BESS under charging state after introducing storage operator with time-varying and adaptive power limits.

without utilizing power limits. Although the network constraints are effectively managed, the benefits from the ToU almost the same and equals to 12.9 MWh. The decision-making algorithm of the storage operator allows distributing the required volume of charged energy throughout the time steps rather than the simultaneous charging of all the BESS at the same time step. The storage operator supports better utilization of network capacity by adjusting the charging power limit at each hour so that each BESS could achieve its desired volume of charged energy.

Fig. 12 shows the applied charging power limit for each time step in the day and the corresponding number of active BESS in the charging state. It can be noticed that the number of active batteries in the charging state decreases during the interval between 10:00 to 15:00 since 40% of BESS achieve their desired charging needs by 13:00. In response to the reduction of active BESS, the storage operator keeps adjusting the power charging limits according to the import power profiles determined in Section V.B. In particular, the number of active batteries reduces from 2440 at 10:00 to 600 at 15:00 with associated power limit increases from 1.0 to 2.2 kW. It is worth noting that although the number of active BESS reduces between 10:00–12:00, the power charging limit increases slightly. This is since the variations in the slope of predefined import profiles are small for proportion level of active BESS larger than 40%.

5.3.2. Customers' perspective

To assess the performance of storage operator in achieving the customers' contractual bill reduction, the CSI metric for each individual customer is evaluated as per (12). It is found 90% of customers have a 100% CSI while the minimum value of CSI reaches 82% for customers with large energy consumption needs. This shows the effectiveness of storage operator to maintain high levels of customers' satisfactions. For comparison purposes, the performance of storage operator is assessed against a decentralized control approach that adopts fixed import and export power limits to manage power exchanges from individual BESS with the grid. In this approach, the charged and discharge power of BESS are managed below a conservative fixed limits whose values are predefined as per the approach in [31] to maintain voltage and thermal constraints of the grid. Therefore, a conservative power limit of 0.8 kW is adopted. This limit represents the minimum power limit during low-price intervals (10:00–15:00) at 100% proportion level of active batteries in the charging state (see Fig. 8). The histogram in Fig. 13 illustrates the distribution of customers across different levels of CSI for both the fixed power limit and the storage operator with time-varying and adaptive power limits. The figure clearly demonstrates that the storage operator results in a better performance than the fixed power limits. Specifically, only 37% of the customers achieve a 100% |CSI with the fixed power limits. Furthermore, the CSI for 15% of the customers is relatively low (i.e., below 60%).

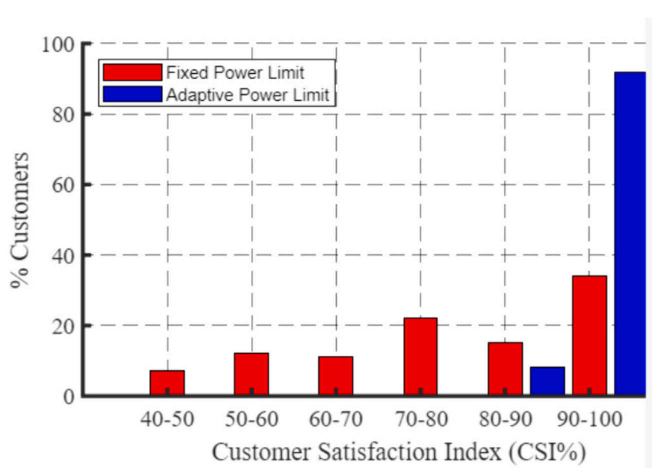


Fig. 13. Customer Satisfaction Index (CSI) with fixed power limit (red) and after introducing storage operator with time-varying and adaptive power limits (blue). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

5.3.3. Maximizing revenues for storage operator (price Arbitrage)

In the previous Sections, the storage operator manages the operations of BESS for the benefit of customers to achieve their contractual bill reductions (i.e., $CSI^{max}=1$). Here, the storage operator aims to maximize the potential revenues by buying and selling energy based on ToU market prices (i.e., price arbitrage). The volume of energy exports during the high-price interval is maximized. For this purpose, the upper limit of CSI metric is relaxed above unity (i.e., $CSI^{max}=2$). It is found that the total energy transferred from the high-price intervals to the low-price intervals for the analyzed day is increased from 12.9 MWh to 15.2 MWh (18% increase). For the adopted ToU price, the additional revenue is about $500 per day. The revenues could be further increased when the role of storage operator is developed to be an aggregator to deliver ancillary grid services to the power system operator (e.g., frequency regulation services).

6. Discussions

This Section discusses the implementation aspects and potential improvements Furthermore, this Section discusses the modifications in the metering arrangements to be applied in countries with different regulatory rules.

6.1. Step size of proportion levels of active BESS

The time-varying linear functions of power limits are defined in the case study considering a 10% step of proportion levels of active BESS (i.e., 10%, 20%… 100% of the total number of batteries). This assumption allows adequately capturing the relationships between power limits and proportion levels of active BESS, therefore effectively managing network constraints. However, using a small step size of 10% increases the computation burden since the OPF at the first stage (i.e., planning stage) is required to be run at each time step for 10 proportion levels. To cater for the computation burden, it is required to adopt fewer number of proportions levels. However, the adoption of fewer proportion levels may affect the effectiveness of managing network constraints. To decide the best number of proportion levels, the technical impacts on both distribution networks and customers are assessed considering different step sizes of proportion levels (10%, 25%, 50% and 100%). For demonstration purposes, the resulting linear power functions of import limits at 10:00 are shown in Fig. 14. The figure shows that using a single

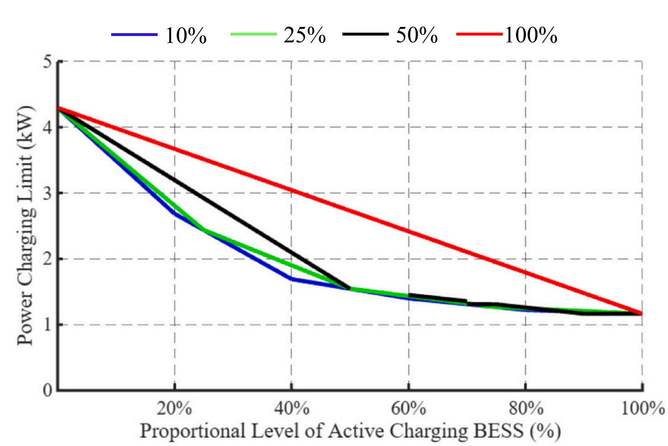


Fig. 14. Linear functions of import limits at 10:00 a.m. considering different step sizes of proportion levels of active BESS (10%, 25%, 50% and 100%).

Table 1
Impact assessment of different step sizes of proportion levels of active BESS (10%, 25%, 50% and 100%).

Linear functions		Technical performance			
		Network's perspective			Customer's perspective
Step size of proportion levels of active BESS	Number of linear functions	Voltage drops (Yes/No)	Transformer overloads (Yes/No)	Line overloads (Yes/No)	CSI (above 90%)
100%	1	Yes	Yes	No	95%
50%	2	Yes	Yes	No	93%
25%	4	No	No	No	91%
10%	10	No	No	No	90%

linear function with a step size of 100% (red line) leads to higher import limits compared to the adoption of 10 linear functions with 10% step size (blue line). Although this allows improves the CSI metrics for customers, the constraints of distribution networks could be violated. The figure also clearly shows that the limits found at step sizes of 10% and 25% are almost the same. This indicates that it is possible to adopt the 25% step size of proportion level to reduce the computation burden while respecting network constraints. For completeness, the impacts of different step sizes of proportion levels on both distribution networks and customers are summarized in Table 1. The results show that the adoption of a single and two linear function to define power limits (i.e., step sizes of 100% and 50%) are not adequate and will lead to voltage drop issues and overloading distribution transformers. In contrast, the adoption of a step size of 25% allows effectively managing network constraints, thus reducing the computation time by 60% compared to using a step size of 10%.

6.2. Behind-the-meter BESS

The existing structure of storage operator is based on creating revenues from the BESS ToU meter assuming that the selling and buying prices are the same. For regulatory schemes with selling price smaller than the buying price, adjustments to the structure of storage operator are required. The BESS could be located behind the original residential meter with ToU tariff rate (i.e., a single meter arrangement). With the BESS behind-the-meter, the proposed storage operator's decision-making algorithm could be utilized with slight modifications to consider daily power consumption profiles of individual customers. In contrast, the planning approach to define the time-varying and adaptive power limits can be directly adopted. It is worth to highlight that the adoption of a single meter may result in increasing implementation complexity due to the need to deal with uncertainties in uncontrollable loads and billing reconciliation particularly when the storage operator is required in the future to respond to system's price signals to provide grid services like aggregators.

6.3. Sub-metering arrangement

This work assumes the presence of two separate meters per each customer. One of them is the BESS ToU meter while the other is the original residential meter. The adoption of two separate meters per each customer may require additional LV installations which may not be technically feasible in some cases. Also, regulatory frameworks may not support the dual-metering setup. The adoption of a sub-meter with ToU tariff could be placed behind the main original meter to be directly controlled by the storage operator. This sub metering arrangement has been trailed in California [29] to support the integration of residential EVs with TOU tariffs. From modelling perspective, the decision-making algorithm proposed in this work could be modified to co-optimize the power flows transactions between the main and the sub meters to maximize the potential revenues for both the customers and storage operators.

6.4. Residential solar rooftop PV

The structure of the storage operator does not consider the role of residential solar PV systems. To increase the revenues for storage operator, solar PV systems could be placed behind the BESS ToU meter which will in turn reduce the cost of BESS charging. This will also enhance the potential to deliver larger volume of additional grid services, therefore increasing the revenues to the storage operator. Based on the applied PV incentive scheme (i.e., net-metering), it might be also feasible from the customers' perspective to install the PV systems behind the original residential meter. Therefore, further investigations and analysis are needed to better define the role of residential solar PV considering the interactions with different regulation and tariff schemes.

7. Conclusions

The employment of Time of Use (ToU) tariffs supports grid balancing with the evolution of solar photovoltaic systems. By assigning the low-price intervals in the ToU tariffs to the middle of the day, residential customers are incentivized to adopt Battery Energy Storage System (BESS) to increase the energy transferred towards the system's minimum demand. To enable the wide-scale adoption of BESS facilities, it is important to ensure that the constraints of distribution networks are effectively managed. Existing network management schemes are typically led by Distribution Network Operators (DNOs) by placing conservative power limits at customers' energy meters. The depart towards centralized management it is important to better utilize the capacity of distributionnetworks through the adaptive adjustments of power limits according to network operating conditions and BESS operation states. Centralized schemes allow utilizing higher import limits when proportion of BESS facilities remains in idling state after achieving their energy charging requirements. Taking into account that energy suppliers are not allowed to directly interact with BESS due to existing unbundling regulatory rules, it is essential to introduce an independent storage operator to coordinate the control actions of BESS facilities.

This work aims to develop a decision-making algorithm that allows storage operator to manage the operations of residential BESS facilities under ToU tariff to maximize the benefits for residential customers while respecting the constraints of distribution networks. Taking into the account that the storage operator does not have in practice full access to the topology and real-time measurements of distribution networks, the algorithm embeds the constraints of distribution networks in the forms of mathematical linear functions that define the maximum power exchanges from individual batteries in terms of the proportion levels of active BESS (charging/discharging). The functions are produced offline by developing a stochastic three-phase AC Optimal Power Flow (OPF) that caters for uncertainties in BESS locations and network demand. The resulting time-varying adaptive limits are then processed to be adequate for delivery to the storage operator in terms of a set of linear functions. The coordinated decision-making algorithm is formulated as a Mixed Integer Linear Programming (MILP) to optimally select the applied power limit at each time step to maximize the percentage of customers who can achieve their desired energy bill reduction. The algorithm is demonstrated using a real integrated Medium Voltage (MV) and Low Voltage (LV) network from the southern region of Jordan, serving 2440 residential customers.

The results show that leaving BESS facilities without any form of coordination affects diversity in load resulting in a new network peak demand at the low-price interval. Particularly, voltage drop issues and transformer overloading have been identified when the coverage of ToU tariff exceeds 20% among residential customers. In contrast, the utilization of time-varying adaptive power limits allows both managing the network constraints effectively and support most of residential customers achieving their desired bill reductions under the ToU tariff. In particular, the storage operator supports distributing the required volume of charged energy throughout the time steps in the low-price interval. The results also demonstrate the ability of storage operator to create additional revenue stream through increasing the volume of charged energy during the low-price interval to be exported back to the grid at the high-price interval (i.e., price arbitrage). For comparison purposes, the performance of the algorithm is also assessed against the adoption of fixed power limits to manage power exchanges from individual BESS. The results show that both approaches manage network constraints effectively. However, the time-varying adaptive power limits effectively utilize the capacity of distribution networks to support larger percentage of residential customers to achieve their desired energy bill reductions compared to the adoption of fixed power limits.

This work could be further extended to consider future role of storage operator to serve as aggregators to deliver ancillary grid services to the power system operator. To do so, the algorithm has to be developed to respond to both grid price signal as well as to the ToU tariff to co-optimize the operation of BESS facilities along with other future residential controllable elements. The time-varying and adaptive power limits proposed in this paper has to be integrated in future algorithms to effectively manage network constraints when the functions of storage operator are extended to provide grid services.

CRediT authorship contribution statement

Sereen Z. Althaher: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Conceptualization. **Sahban W. Alnaser:** Writing – review & editing, Visualization, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Chao Long:** Writing – review & editing, Methodology, Investigation, Conceptualization. **Yue Zhou:** Writing – review & editing, Methodology, Conceptualization.

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.

Data availability

The data that has been used is confidential.

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