A Price-elastic Approach for Optimal Scheduling of Small-scale Storage Devices in Smart Houses with Short-term and Long-term Constraints

Kürşat Tanriöven, Ferhat Daldaban, Mahmut Erkut Cebeci, Osman Bülent Tör, and Saeed Teimourzadeh

***Abstract*—Consecutive charging and discharging of storage devices (SDs) might deem beneficial from the perspective of short-term operation. However, it highly impacts the life span of the embedded battery and render restrictions on energy storage capacity. We investigate short-term and long-term constraints of SDs through a three-stage price-elastic approach to the optimal operation of small-scale SDs in smart houses. The first stage deals with data and scenario characterization where the data for determining short-term and long-term operation constraints of SD are acquired. Proper number of scenarios are generated to represent uncertain parameters such as long-term demand forecasting, daily load profile, electricity price, and photovoltaic (PV) generation. The second stage optimizes the long-term operation of SD using the envisioned scenarios subject to the long-term operation constraints and the installment costs of SDs. The outputs of this stage are two indicators referred to as price elasticity and price offset coefficients, which are used as the inputs for the third stage. The third stage is responsible for decision-making on short-term operation of SDs. The outputs of the second stage along with short-term forecasting for daily electricity price, daily load and daily PV generation are acquired. Based on the acquired data, proper price elasticity and price offset are determined for optimal operation. Comprehensive simulations are performed for different demand forecasting and electricity prices. Simulation results confirm the effectiveness of the proposed approach.**

***Index Terms*—Storage device, depth-of-discharge, life span, smart house.**

I. Introduction

THE outstanding merits of distributed energy resources (DERs) integrated into power systems have given rise to their proliferation at regional levels [1], [2]. With DERs in place, considerable enhancements from power system reliability, resilience, economics, security, and sustainability can be achieved [3], [4]. From the customers' point of view, economic factor is more interesting as they can cover considerable portion of their electricity consumption through local DERs [5], [6]. Such customers are called as prosumers, who possess their own electricity sources such as photovoltaic (PV), diesel generators, small-scale wind turbines, and storage devices (SDs). SDs are important as they add to the flexibility of consumers and offer considerable reductions in electricity bills.

To attain the maximum amount of cost reduction, the charging and discharging pattern of SDs should be scheduled with respect to the energy consumption profile and power grid tariff [7]. In addition, the suite of constraints pertaining to the short-term operation of SD should be deliberated. However, the consecutive charging and discharging cycles of SD can negatively affect the embedded battery. The concept of life span is introduced in the literature which defines the relation between the depth-of-discharge (DoD) of SDs and life span of associated batteries [8]. The chemical material within the battery, including lead-acid and lithium-ion (LI), is degraded as SDs and is charged and discharged over the time, which gradually imperils energy storage capability. Consecutive charging and discharging of SDs shortens the life span of the embedded battery and reduces energy storage capacity. The most critical factors in battery degradation are the number of charging and discharging cycles and the maximum DoD. For instance, a battery bank may have 10000 cycles with 20% DoD. However, it enables only 1000 cycles with 80% DoD [9]. Hence, consecutive charging and discharging of SDs might deem beneficial, which is the minimum cost that might be attained by fully charging SD in the low-price time slots and discharging it in high-price time slots. However, consecutive charging and discharging of SDs would shorten the life span of SD in the long-term horizon.

In several existing studies, DoD of the battery is usually set to be a predefined value of 80%, and the associated life

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span cost is assumed to be constant [10]. The dependency of wear cost on DoD of the battery is considered in other studies. In [11], a simple model is assumed which considers life span decrement for discharging time slots and assumes constant life span under other conditions. However, it is important to consider detailed battery degradation models for determining optimal operation strategy [12]. The concepts of aging and wear costs are devised to describe battery degradation phenomena [13]. Electrochemical models capturing physical processes are accurate for computing wear cost. It is difficult to embed electrochemical models in the optimization process due to high-level of nonlinearity and dependency to several parameters [14]. Reference [15] proposes an explicit cost function to incorporate the degradation into a model predictive control based approach to energy storage operation. The cost function contains quadratic terms which describe the degradation in terms of DoD, charge rate, and state of charge (SOC). Peukert's Law is utilized in [16] to model the degradation due to cycle life and DoD. In [17], a new framework is proposed to incorporate several numerical models into a prediction tool for single multi-factor battery degradation. This model captures extreme temperatures, high charging and discharging rates, and the cycle of high and low SOCs to accelerate the degradation in LI batteries. Despite the accuracy of such models, it is challenging to embed them into an optimization process due to the complexity and nonlinearities of the associated cost function.

To evaluate long-term operation of SD, scenario-based approaches should be utilized due to the uncertainties pertaining to future operation conditions of SD. In this regard, several studies are conducted in literature which address operation strategies to maximize the returned value of SD. Strategies are often dependent on future demand and utility price forecasting [18], [19]. Stochastic dynamic programming (SDP) based approach is proposed to optimize the operation of SDs [20]. In [21], a heuristic approach is proposed for optimal generation and storage scheduling problem subject to renewable uncertainties. Although it provides an indication for the optimal scheduling of SD with uncertainties, simple but practical scheduling approach for SDs is still under discussion. In addition, the long-term and short-term operation constraints of SD should be coordinated well to attain optimal operation pattern from the perspective of both short-term and long-term operations.

The performed literature review in this paper might be categorized in three categories.

1) Category 1 contains the studies which consider a predefined value for DoD associated with chemical type batteries. Despite simplifying the calculation, considerable amount of battery capacity remains unused.

2) Category 2 contains the studies which consider the dependency of wear cost on DoD of the battery. Despite the accuracy of such models, embedding the model into an optimization process is a challenge due to the complexity and nonlinearity associated cost function.

3) Category 3 contains the studies which considers uncertainties pertaining to future operation conditions of SD. The indication is provided for optimal scheduling of SDs with uncertainties.

Due to the proliferation of storage systems, especially at household level, simple but practical scheduling approach for SDs is important. In addition, the long-term and short-term operation constraints of SD should be coordinated well to attain short-term and long-term optimal operation patterns. Short-term and long-term restrictions of SDs are investigated through a three-stage price-elastic approach to optimal operation of small-scale SDs in smart houses. The conducted study considers the chemical types of battery storage systems, where the first stage deals with data and scenario characterization, and the required data for determining short-term and long-term operation constraints of SD are acquired. Proper number of scenarios are generated to represent uncertain parameters such as long-term demand forecasting, daily load profile, electricity price, and PV generation. The second stage optimizes long-term operation of SD by using the envisioned scenarios subject to long-term operation constraints and the installment cost of SD. The outputs of the stage are two indicators referred to as price elasticity and price offset coefficients, which are used as the input for the third stage. The third stage is responsible for decision-making on short-term operation of SD. The outputs of the second stage along with short-term forecasting for daily electricity price, daily load and daily PV generation are acquired. Based on the acquired data, the proper price elasticity and price offset coefficients are determined for optimal operation. Comprehensive simulations are performed for different demand forecasting and electricity prices. The results of simulation studies confirm the effectiveness of the proposed approach. The salient features of this paper are as follows.

1) A three-stage price-elastic approach is proposed for optimal operation of small-scale SDs in smart houses.

2) An efficient optimization model is proposed to incorporate short-term operation constraints of SD into long-term scheduling of SDs.

3) Price elasticity and price offset coefficients are proposed to convert the solution of the proposed optimization model into simple indices for decision-making on SD operation.

4) Plausible uncertainties through an efficient scenario-based scheduling model are characterized.

The rest of this paper is organized as follows. Section II presents the problem formulation and the proposed methodology. Section III presents the simulation. Finally, the conclusions are summarized in Section IV.

II. Proposed Methodology

Figure 1 shows the schematic of a smart house which encompasses an SD, PV generation, and the connection to the upstream network. A controller is envisioned for SD, which acquires the data for the price through web-services and controls SD operation. From the perspective of short-term operation, load characteristics, electricity price, and PV generation are changing continuously so that SD controller is required to consecutively change charging and discharging patterns of SD to attain the minimum cost operation. On the contrary, from the perspective of long-term operation, such a charging and discharging pattern might shorten the life span of SD. The proposed approach provides optimal scheduling of SD operation in short term, offering reasonable life span for SD deployment in long term. The three stages of the proposed approach are presented as follows.

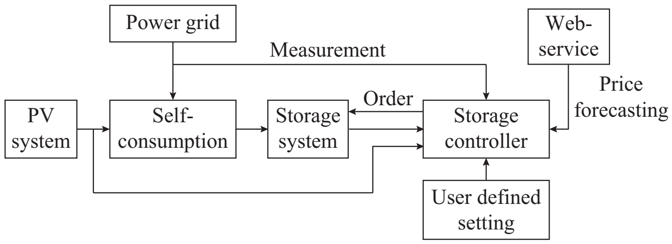

Fig. 1. Schematic of a smart house.

A. Stage 1: Data and Scenario Characterization

In this stage, the required data for driving the proposed approach are acquired, which are categorized into two groups: SD-related data and operation data of smart house. SD-related data include permissible operation range of SD, energy capacity of SD, permissible SOC of SD, conversion efficiency of SD, and life span cost function of SD. The required operation data of smart house include long-term demand forecasting, seasonal load profile (spring, summer, fall, winter), daily load profile (weekday, weekend), electricity price, and PV generation. Once the operation data of smart house are acquired, a set of scenarios representing plausible realization of uncertainties are generated. Proper probability distribution function (PDF) is dedicated to uncertain parameters, i.e., demand forecasting, seasonal load profile, daily load profile, electricity price, and PV generation. For demand forecasting, electricity price, PV generation, and normal distribution function are used. However, for seasonal and daily load profiles, uniform distribution function is envisioned. PDFs are shown in Fig. 2.

The envisioned PDFs in Fig. 2 are used for scenario generation. Note that the Beta, Weibull, and Log-normal distributions are common distribution functions used in the literature to model solar irradiance from historical data [22]. The main index to select the proper distribution function out of aforementioned distributions is the fitting error [23]. We use solar irradiance and PV generation data for Turkey [24] and fitted Beta, Weibull, and Log-normal distributions for the historical data. The best fit is for the normal distribution. The generation and reduction processes of the scenario are depicted in Fig. 3. To cover all possible realizations, a great number of scenarios should be generated which negatively affects the tractability of the problem.

About 1000000 scenarios are generated by using Monte-Carlo process. Afterwards, the number of scenarios are trimmed down to a reasonable number of 20 representative scenarios by using probability distance algorithm [25].

B. Stage 2: Assessment for Long-term Operation

In this stage, the long-term operation of SD is assessed, and for each scenario, the optimal operation strategy of SD during its life span is calculated. The objective is the minimum cost OF_ω, which satisfies technical constraints pertaining to nodal power balance and permissible operation range of elements. The problem can be formulated as:

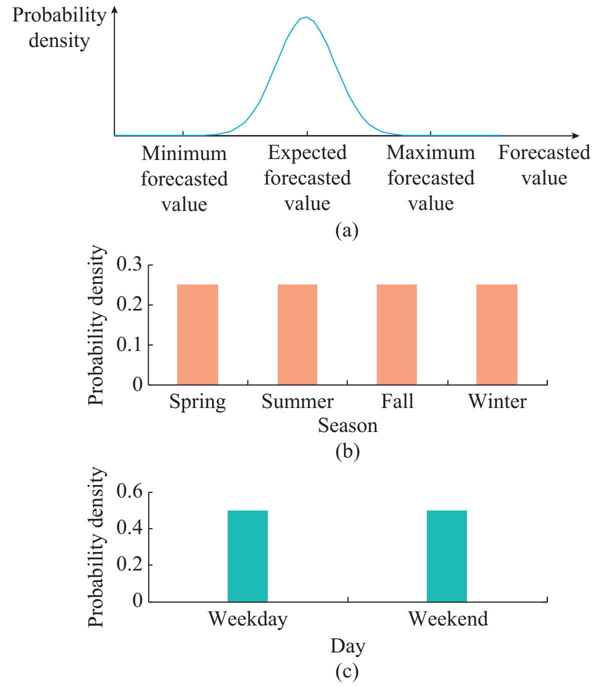

Fig. 2. PDFs. (a) Continuous normal distribution function for demand forecast, electricity price, PV generation. (b) Discrete uniform distribution function for seasonal profile. (c) Discrete uniform distribution function for daily load profile.

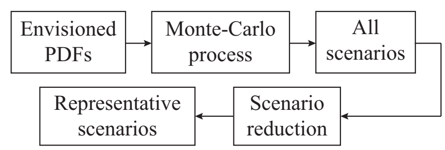

Fig. 3. Generation and reduction processes of scenario.

$$\min OF_\omega = \sum_{t\in I_T} \lambda_{t,\omega}^{buy} P_{t,\omega}^{buy} + \sum_{t\in I_T} DCSD(P_{t,\omega}^{SD-}) \quad \forall \omega \in I_\Omega \tag{1}$$

s.t.

$$P_{t,\omega}^{gen} - P_{t,\omega}^{load} = 0 \quad \forall t \in I_T, \forall \omega \in I_\Omega \tag{2}$$

$$P_{t,\omega}^{gen} = P_{t,\omega}^{buy} + P_{t,\omega}^{PV} + P_{t,\omega}^{SD-} \quad \forall t \in I_T, \forall \omega \in I_\Omega \tag{3}$$

$$P_{t,\omega}^{load} = P_{t,\omega}^{L} + P_{t,\omega}^{SD+} \quad \forall t \in I_T, \forall \omega \in I_\Omega \tag{4}$$

$$P_{t,\omega}^{L} + P_{t,\omega}^{SD+} - P_{t,\omega}^{PV} - P_{t,\omega}^{SD-} \geq 0 \quad \forall t \in I_T, \forall \omega \in I_\Omega \tag{5}$$

$$P_{t,\omega}^{PV,\min} \leq P_{t,\omega}^{PV} \leq P_{t,\omega}^{PV,\max} \tag{6}$$

$$DCSD\left(P_{t,\omega}^{SD-}\right) = a\left(P_{t,\omega}^{SD-} + P_{t,\omega}^{SD+}\right)^2 + b\left(P_{t,\omega}^{SD-} + P_{t,\omega}^{SD+}\right) + c \quad \forall t \in I_T, \forall \omega \in I_\Omega \tag{7}$$

$$\sum_{t\in I_T} \alpha_{t,\omega}^{SD} \leq MOT^{SD} \tag{8}$$

$$0 \leq P_{t,\omega}^{SD+} \leq \alpha_{t,\omega}^{SD} P^{SD+,\max} \tag{9}$$

$$0 \leq P_t^{SD-} \leq \eta^{SD}\left(1 - \alpha_t^{SD}\right) P^{SD-,\max} \tag{10}$$

$$SOC_{t,\omega}^{SD} = SOC_{t-1,\omega}^{SD} + \frac{\eta^{SD}\Delta t}{E^{SD,\max}}\left(P_{t-1,\omega}^{SD+} - \left(\eta^{SD}\right)^{-2} P_{t-1,\omega}^{SD-}\right) \tag{11}$$

$$SOC^{SD,\min} \leq SOC_{t,\omega}^{SD} \leq SOC^{SD,\max} \tag{12}$$

where t and I_T are the index and set of time, respectively; I_Ω

is the set of scenario; ω is the scenario; a, b, c are the quadratic deteriorations of SD; $DCSD(\cdot)$ is the deterioration cost function of SD; λ is the hourly electricity price known for each scenario; E is the energy capacity; MOT is the maximum operation time of SD in its life span; P is the active power; SOC is the SOC for storage unit; T is the time required for complete operation of the equipment; η is the conversion efficiency coefficient for storage unit; $\alpha_{t,\omega}^{SD}$ is the binary variable; the superscript *buy* represents purchasing from electricity market; the superscripts min and max represent the lower and upper limits, respectively; the superscripts L, PV and SD represent the chemical material within the battery, the solar generation, and SD, respectively; and the superscripts + and – represent the charging and discharging stages, respectively.

Equation (1) shows the objective function to be minimized during each optimization stage. Equation (2) deals with nodal power balance by neutralizing the load with the generation. The load and generation elements are represented by (3) and (4). In (5), it is guaranteed that the smart house is regarded as a net load from the perspective of upstream network. The permissible operation range associated with the solar system is modeled by (6). The deterioration cost function used in the objective function is calculated by (7). In (8), the life span constraint of SD is modeled which impels that the total charging and discharging of SD should be limited to a predefined value. $\alpha_{t,\omega}^{SD}$ used in (8) is calculated by (9) and (10). In (9) and (10), $\alpha_{t,\omega}^{SD}$ controls the charging and discharging and avoids enabling both charging and discharging at the same time. The SOC of storage at each time period is calculated by (11) and (12) to model the limitations on SOC.

The main parameters of the devised optimization model are electricity price and rated parameters of SD. For the electricity price, the suite of plausible scenarios is generated using the probability density function as shown in Fig. 2. For the rated parameters of SD, common practical values are used as described in Section III.

Once the optimization model is devised, (1) is solved subject to (2)-(12). In the proposed approach, we convert the outcome of the proposed optimization model into simple indices for decision-making on SD operation, which is performed by introducing price offset and price elasticity coefficients. In this regard, the solution of long-term operation optimization of SD is used to stablish a linear relationship between daily price and SD commitment status. In the defined linear model, the x-intercept and slop of the attained line are entitled as price offset and price elasticity coefficients, respectively.

$$\boldsymbol{\lambda} = \boldsymbol{P}\boldsymbol{C} \tag{13}$$

$$\boldsymbol{\lambda} = \left[\lambda_{1,\omega}^{buy} \quad \lambda_{2,\omega}^{buy} \quad \dots \quad \lambda_{24,\omega}^{buy}\right]^{\mathrm{T}} \quad \forall \omega \in I_{\Omega} \tag{14}$$

$$\boldsymbol{P} = \begin{bmatrix} P_{1,\omega}^{SD} & P_{2,\omega}^{SD} & \dots & P_{24,\omega}^{SD} \\ 1 & 1 & \dots & 1 \end{bmatrix}^{\mathrm{T}} \quad \forall \omega \in I_{\Omega} \tag{15}$$

$$P_{t,\omega}^{SD} = P_{t,\omega}^{SD+} + P_{t,\omega}^{SD-} \quad \forall t \in I_T, \forall \omega \in I_{\Omega} \tag{16}$$

$$\boldsymbol{C} = \begin{bmatrix} \beta_{\omega} \\ \psi_{\omega} \end{bmatrix} \tag{17}$$

where $\boldsymbol{\lambda}$ is the vector of hourly electricity price known for each scenario; $\boldsymbol{P}$ is the matrix of charging and discharging of SD which is attained by solving (1) subject to (2)-(12); $\boldsymbol{C}$ is the vector of coefficients that links the charging and discharging status and amounts to the electricity price; and β_{ω} and ψ_{ω} are the price elasticity and price offset coefficients, respectively. Equations (13)-(17) represent the proposed linear model to calculate price elasticity and price offset coefficients. For scenario ω, the vector of hourly electricity price is known from the input data. The elements of charging and discharging of SD are known from (1) subject to (2)-(12). The unknown parameters are the vectors of coefficients for which the least squares error approach is deployed to specify the maximum likelihood approximation:

$$\begin{bmatrix} \beta_{\omega} \\ \psi_{\omega} \end{bmatrix} = (\boldsymbol{P}^{\mathrm{T}}\boldsymbol{P})^{-1}\boldsymbol{P}^{\mathrm{T}}\boldsymbol{\lambda} \tag{18}$$

β_{ω} and ψ_{ω} establish a linear link between the charging and discharging status and the amount of the electricity price. Practically, ψ_{ω} discriminates the charging and discharging regions. For the prices which are lower than the determined price offset, SD starts charging, and for the prices which are higher than the price offset, SD acts as a generator and discharges. The amount of charging and discharging is determined by β_{ω}.

Once the price elasticity and price offset coefficients for scenario ω are calculated, a lookup table is developed with the order represented by (19), which is used at Stage 3 for decision-making for short-term operation. The main reason for developing a lookup table is to ease the application of the proposed approach in small-scale SDs at household levels.

$$\boldsymbol{LT}_{\omega} = \left[\sigma_{\omega} \quad \mu_{\omega} \quad \beta_{\omega} \quad \psi_{\omega}\right] \tag{19}$$

where $\boldsymbol{LT}_{\omega}$ is the vector of lookup table corresponding to scenario ω; and σ_{ω} and μ_{ω} are the standard deviation and average of electricity price in the day, respectively.

C. Stage 3: Decision-making for Short-term Operation

In this stage, decision-making for short-term operation is realized. The price forecasting at day-ahead stage is acquired. Then, the standard deviation and average of electricity price are calculated and the associated price elasticity and price offset coefficients are adapted from the lookup table presented by (19).

III. Simulation Studies

This section examines the performance of the proposed approach. The generic daily load profile representing four seasons, days of weekday and weekend, and the generic daily electricity prices in hourly resolution are identified as shown in Figs. 4 and 5, respectively. The typical daily load curves of DisCOs are publicly available in Turkey for weekdays and weekends. The load curve and data are derived from Turkish Electricity Market Regulatory Authorities (EMRA) [26]. Common data are also used in the literature [27], [28]. In addition, the price profiles are assumed to represent in the range of 40-55 \$/MWh for daily average price in four steps and 2.5-12.5 \$/MWh for daily price standard deviation in five steps, which are the ranges for real day-ahead price in 2018 [24].

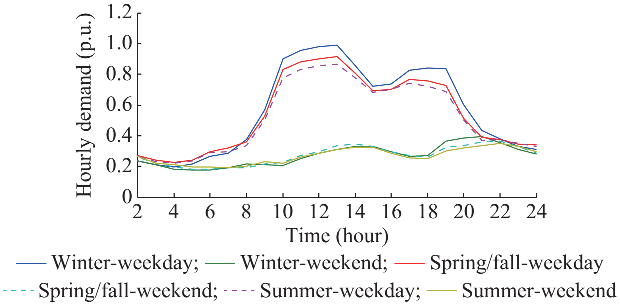

Fig. 4. Generic daily load profiles.

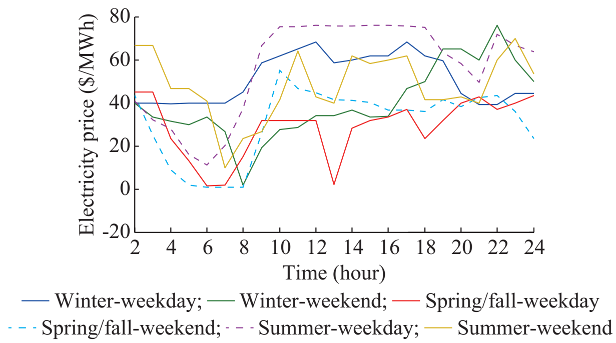

Fig. 5. Generic daily electricity prices.

A household is modelled with an annual peak demand of 20 kW, a PV installment of 8 kW (the generation profile is determined via Renewable Ninja website), and a LI battery-based SD installment of 2.5 kW to 10 kWh is also considered. To represent long-term constraints, the calculation horizon is defined as 10 years. The costs of SD installment are changed as 100/200/400/600/800 \$/kWh, respectively. Simulation results for long-term assessment are shown in Fig. 6 for three days.

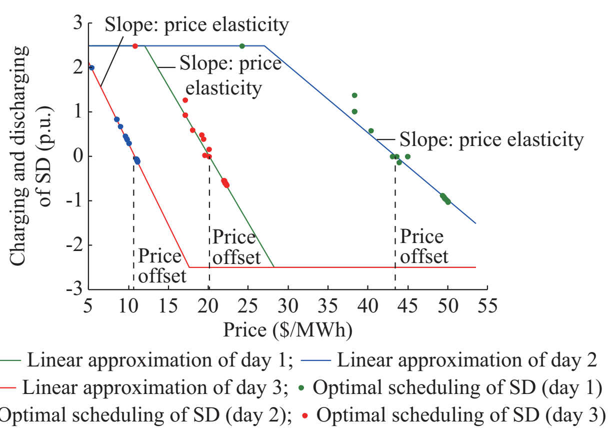

Fig. 6. Simulation results for long-term assessment.

As can be observed from Fig. 6, the optimal scheduling of SD in each day follows a linear pattern versus price alterations, which implies the effectiveness of the proposed linear approximation in (13)-(17). The price offset shows the limit where the SD controller switches from the charging mode to the discharging mode or vice versa. Therefore, the price offset can be considered as the threshold value for SD controller where it decides to charge or discharge SD. Subsequent to mode identification, the amount of charging and discharging is determined through the price elasticity. As can be observed from Fig. 6, price elasticity is the slope of the proposed linear approximation. The sensitivity of charging and discharging of SD for different values of price elasticity is shown in Fig. 7.

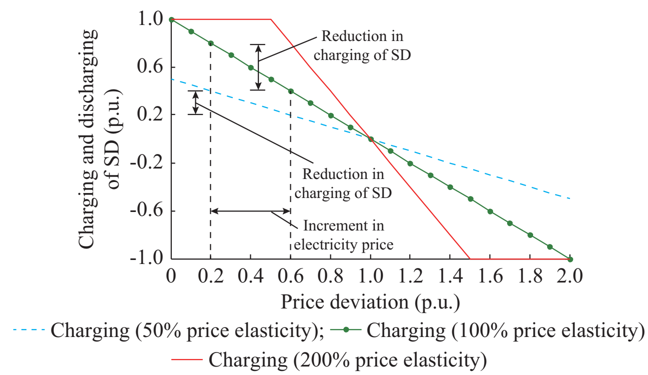

Fig. 7. Sensitivity of charging and discharging of SD for different values of price elasticity.

As shown in Fig. 7, 0.4 p.u. increment in the electricity price results in 0.2 p.u. reduction in the charging of SD if 50% price elasticity is used. However, with 100% price elasticity, 0.2 p.u. increment in the electricity price contributes to 0.4 p.u. reduction in the charging of SD. It can be concluded that the permissible amount of charging and discharging of SD changes as we change the price elasticity. Comprehensive simulations are conducted to find out the relation between daily electricity price, installment cost of SD, and price elasticity.

In Fig. 8, the simulation is presented for different daily electricity price and installment cost of SD with 5% standard deviation for load with respect to annual peak. The figure indicates that if the load is almost constant throughout the day, the price deviations does not affect the selection of price elasticity. However, the installation cost C_{SD} has a strong impact on the selection of price elasticity. As the installment cost increases, the optimal price elasticity reduces, which reduces the responsiveness of SD to price deviations.

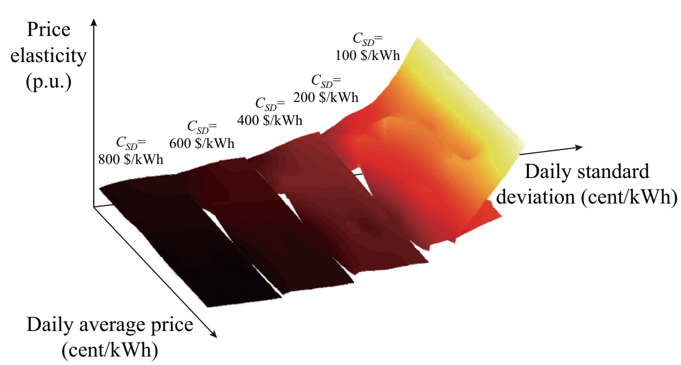

Fig. 8. Simulation results for different daily electricity price and installment cost of SD with 5% standard deviation for load with respect to annual peak.

On the contrary, in Fig. 9, the standard load deviation is in the range of 25%-30%. The optimal scheduling indicates much more responsive characteristics with higher values of price elasticity. Further, price elasticity has the tendency to increase in quadratic manner as the installation cost of SD reduces. It implies that as the installation costs reduce, SDs can be utilized more aggressively to increase the benefit from the device, whereas the costs associated with life span will be relatively reduced.

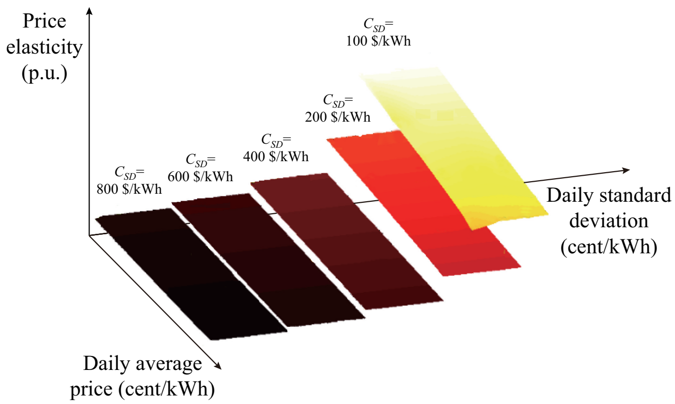

Fig. 9. Simulation results for different daily electricity price and installment cost of SD with 25%-30% standard load deviation with respect to annual peak.

With the proposed approach, and price offset and price elasticity coefficients, the optimal operation of SD in short time can be realized. Figure 10 shows the operation of SD in three consecutive days. The charging and discharging patterns of SD differ in each day.

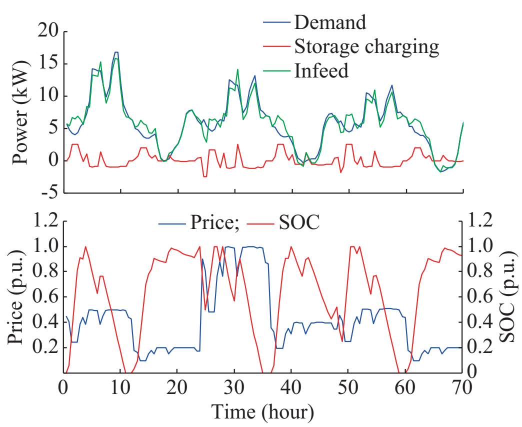

Fig. 10. SD operation in three consecutive days.

IV. Conclusion

Optimal scheduling of SD is proposed, considering short-term and long-term constraints through a three-stage price-elastic approach. We aim to respond the query that how an SD could be scheduled to minimize electricity cost while considering long-term constraints pertaining to the life span and instalment cost of SD. Price offset and price elasticity coefficients are introduced, which are calculated by optimizing long-term operation of SD. A linear approach is proposed which converts the results of long-term optimization into price offset and price elasticity coefficients. Price offset is considered as the threshold value for SD controller where it decides to charge or discharge SD. Based on the simulation, it can be concluded as follows.

1) The optimal scheduling of SD in each day follows a linear pattern versus price alterations, which implies the effectiveness of the proposed linear approximation.

2) The permissible amount of charging and discharging of SD changes as we change the price elasticity.

3) If the load is almost constant throughout the day, the price deviations do not affect the selection of price elasticity.

4) As the installation cost increases, the optimal price elasticity reduces, which in return, reduces the responsiveness of SD to price deviations.

5) Price elasticity has the tendency to increase in quadratic manner as the installation cost of SD reduces, which implies that as the installation costs reduce, SDs can be utilized more aggressively to increase the benefit from the device.

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