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Battery capacity determination with respect to optimized energy dispatch schedule in grid-connected photovoltaic (PV) systems

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ABSTRACT

This paper describes an approach to optimize the capacity of battery used in a grid-connected photovoltaic system (PV/storage system). Scheduling of the battery after installation has to be considered for the optimal design; because battery degradation cost is mainly a function of system operation. In this paper, peak shaving and load shifting which are important applications of PV/storage systems are studied. Load shifting is mostly implemented when time-of-use pricing is in effect and peak shaving is beneficial when utility customers are charged for peak of demand. In order to account for seasonality in system net load, data clustering techniques are implemented to produce scenarios for net load of the customer. Then, the proposed Mixed Integer Programming (MIP) model of the optimization problem is solved. To illustrate the important cost of battery degradations, a model of non-ideal battery is also studied and the results are compared with the case which ideal model of battery is used. Results show that sizing determination of the battery highly depends on the exact pricing structure. In addition, it is illustrated that, considering real assumptions for battery ageing is necessary to reliably estimate financial benefits of storages in PV/storage systems.

1. Introduction

With the global economic development and population growth, large amount of energy is required to meet the present electricity demands. Global warming, environment pollution and the rapid depletion of fossil fuel resources, culminated in an increase in the use of renewable energy sources as a viable alternative to fossil fuels. Among renewable energy technologies, grid-connected photovoltaic application has gained a great attention in research because it appears to be one of the most efficient solutions to these environmental problems [1].

In most of countries, the maximum output power of photovoltaic (PV) systems may not be consistent with the period of system peak load. Energy storage systems combined with grid-connected PV systems (PV/storage system), store electricity generated from PV systems during off-peak hours for discharging during peak load hours [2]. Battery energy storage systems are used most commonly as storage devices in grid-connected PV systems [3–5]. The above mentioned potential of storage systems provides benefits for the customers with grid-connected PV system through various applications [6]. Customers with PV/storage system can reap benefits by charging the storage with excess generation of the PV early in the day to support a load later (i.e. load shifting). If a customer is charged for peak of the requested power (i.e. demand charge), the PV/storage system preserves required power above a specified threshold and provides benefits for the system owner (i.e. peak shaving). PV/storage system also allows the customers to contribute to energy load reduction in response to market prices, with little or no effect on local operations; and utilize financial incentives offered by the utilities (i.e. demand response strategies). The financial benefits of PV/storage systems are mostly achieved through the above mentioned applications. However, these benefits highly depend on the exact tariff structure and policies where the consumer lives. Recently with increased implementation of smart meters, net metering policies and electric vehicles, some utility companies introduced time-of-use rates and peak demand charges for their customers. Customers who purchase electricity under these tariffs are more interested to install PV/storage system and achieve financial benefits through load shifting (especially under time-of-use rates) and peak shaving (especially under a demand charge based tariffs) [6].

In addition to the price structure, the sizes of system components and system operation affect the performance of the PV/storage system. This article deals with optimization of battery capacity in a grid-connected PV system for the customers who

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Nomenclature

A. Abbreviations

BESS battery energy storage system
FCM Fuzzy Clustering Method
TOU time-of-use
TOUD time-of-use with specifying demand charge
MIP Mixed Integer Programming

B. Indices

k data point
j cluster
i day
t time-step

C. Parameters

N number of data point
c number of clusters
m degree of fuzziness
η_{Bi} battery inverter efficiency [%]
η_{pi} photovoltaic (PV) inverter efficiency [%]
I global horizontal irradiation [W/m^2]
A total area of PV modules [m^2]
η_{pv} solar conversion efficiency of PV modules [%]
Δt sampling interval [h]
t_0 initial time of the optimization process [h]
Z ageing coefficient
C_{ref} the nominal capacity of battery [Wh]
η_B conversion efficiency of battery [%]
η_{BR} round-trip efficiency of battery [%]
E_P electricity price [$/kWh]
nu number of days of month
D_C demand charge [$/kW]
B_{FC} battery investment cost [$]
SOH_{min} minimum state of health of the battery [%]
P_L the electricity load of the customer [W]
$E_{B\ min}$ minimum stored energy in the battery [Wh]
$P_{Bdc\ min}$ minimum charge/discharge rate of the battery [W]
$P_{Bdc\ max}$ maximum charge/discharge rate of the battery [W]
t_H minimum charge/discharge time of the battery [h]
b indicator variable
n number of studied days
N_{year} number of years in studied dataset
N_{data} number of days in studied dataset
P probability of each cluster
PDT peak demand target [W]

D. Variables

P_{Bdc} charge/discharge rate of the battery [W]
P_{Bac} charging/discharging rate of the battery on AC bus [W]
E_B stored energy in the battery [Wh]
ΔC cumulative battery capacity loss [Wh]
C the usable battery capacity [Wh]
BCL battery capacity loss [Wh]
ECB energy cost and benefit [$]
PDC peak demand cost [$]
C_{BCL} cost of battery capacity loss [Wh]
P_{Net} net power of the grid [W]
P_{demand} peak of the electricity demand [W]
ANP annual net profit [$]
ΔC_{year} battery capacity loss during one year [Wh]
ΔC_{day} battery capacity loss in ith studied day [Wh]
A_C annual cost of the system operation [$]

purchase electricity on a time-of-use basis or a demand charge based tariff. Optimization of battery capacity with respect to operation of the battery after installation in the system is necessary to fully achieve financial benefits of battery storage in a grid-connected PV/storage system. An effective scheduling strategy should be capable of responding to frequent and dynamic load changes [2]. Also, cost of battery ageing should be taken into account in the optimization of energy dispatch schedule of the battery.

To determine optimal battery capacity for a typical customer equipped with PV system, the customers load and PV output through several years should be taken into account. Because, several years of data existing, using data clustering method is the most reasonable approach to determine battery capacity with respect to optimal scheduling of battery [7,8]. In this paper, Fuzzy Clustering Method (FCM) is utilized to produce scenarios for the battery sizing problem. To illustrate the effectiveness of this method under time-varying pricing structures, time-of-use (TOU) and time-of-use with specifying demand charge (TOUD) tariffs proposed by Duke Energy Progress North Carolina [9] are evaluated. A typical customer is considered and optimal battery capacity under each of pricing structures is obtained and important effects of electricity tariff on optimal battery capacity are evaluated. Also, an ideal and a non-ideal model of battery ageing are studied and the importance of battery ageing cost is investigated.

2. Related work

There is a wide literature on battery scheduling and sizing for PV systems, but mostly focused on stand-alone applications. Simulation and optimization of stand-alone systems with PV and battery energy storage have been the subject of several publications [10–14]. Recently, optimization of storages in grid-connected PV systems attracted increasing interest. However, there is little in the way of guidance on battery sizing with respect to optimal scheduling of the battery. Ref. [15] presents a predictive control system based on a dynamic programming approach, which optimizes the power flow management into a grid-connected PV system with energy storage system. In Ref. [2] a short-term optimized dispatch schedule of energy stored in the battery is presented and the effect of grid-connected PV/battery system on locational pricing, peak load shaving, and transmission congestion management is analyzed. Ref. [16] presents the construction and the performance of a distributed power generating system of PV/storage. Accordingly, financial benefit and load-levelling capacity of the system have been studied. The sizing problem is not studied in the mentioned papers. Ref. [17] presents the modelling, simulation, and sizing results of battery energy storage systems for residential electricity peak shaving, with the objective of reducing the peak electricity demand seen by the electricity grid. The model simulates and provides performance results of a range of battery and inverter sizes specific to a variety of residential houses. However, battery life is not considered in daily operation and the economics effects of peak shaving on residential customer bills are not investigated. Paper [18] studies the problem of the battery size determination used in grid-connected PV systems for the purpose of load shifting and peak shaving under time-of-use rates. The optimization problem is modelled to obtain the optimal energy dispatch schedule which minimizes the cost associated with net power purchase from the electric grid and the battery capacity loss.

However, optimal battery capacity has been proposed based on results obtained from solving the optimization problem in a typical day. Therefore, variation in the load during the year is not considered. In Ref. [19] a linear programming optimization was implemented to model optimal energy storage dispatch schedules for demand charge minimization in a grid-connected PV system. For different dispatch strategies, the net present value of the battery storage system is obtained and financial benefits of the dispatch strategy are compared with predefined dispatch strategies. The implemented linear programming model does not optimize on price arbitrage between the on-peak and off-peak energy markets. Ref. [20] assesses the profits of a PV-battery combination considering different assumptions for the remuneration of the PV generated electricity. As mentioned by the author, time aspect is out of the summation, thus the electricity tariff should be flat. This is a disadvantage of this method in comparison with, e.g. linear programming optimization. Ref. [21] assesses the economic and environmental impact of the use of lead-acid batteries in grid-connected PV systems under the flat electricity feed-in tariffs in the UK and the other countries. A model of battery is developed and the model used to calculate the simulated power flows, cost benefits, and environmental impacts associated with the lead-acid batteries.

In this study, a method is proposed which can determine optimal capacity of the battery with respect to optimized energy dispatch schedule of the energy stored in the battery energy storage system (BESS). In this method, the important cost of battery ageing is considered in optimization of battery scheduling. Although this method is based on optimization of daily operation of the system, long-term assessment of the customers load and PV output is conducted to achieve more reliable results. This method can be used to determine optimal capacity of the battery systems for two important applications of grid-connected PV/battery systems: price arbitrage in time-of-use tariffs and peak shaving in demand charge based tariffs. In addition, the importance of battery ageing on changing limits to feasibility is investigated, and the effects of two important electricity tariffs on optimal sizing of the battery energy storage system are evaluated.

3. Methodology

In our proposed method, the problem of battery sizing with respect to dispatch schedule of stored energy in BESS is investigated. It is important to highlight that the aim of this paper is to provide an optimization method that helps electricity consumers equipped with PV system making decision to install economically sized battery storage system. Fig. 1 shows the structure of the optimization algorithm. First, data of electricity load of the customer and solar irradiance in the studied location are collected. Then, FCM is implemented to produce scenarios in order to account for variations in the load and PV output during the studied years (see Section 3.1). For each produced scenarios energy dispatch

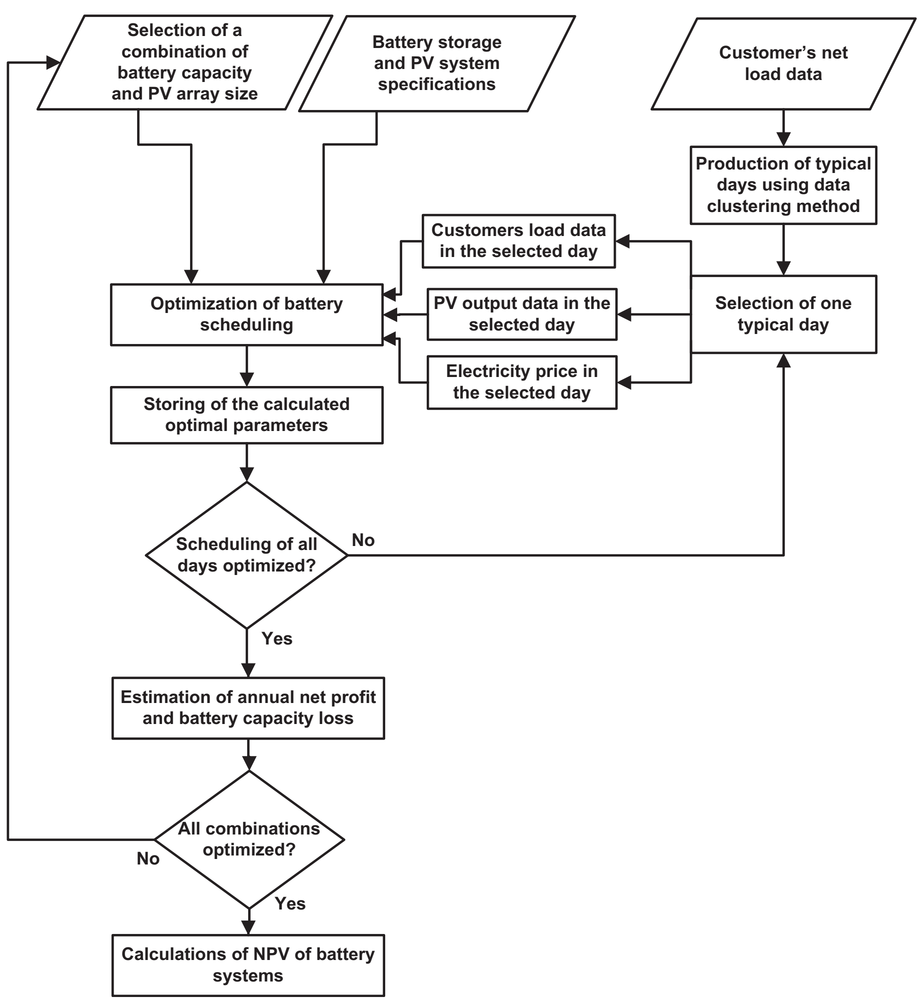

Fig. 1. Flowchart of the proposed optimization methodology.

schedule is optimized to reduce operation costs of the system by managing the power flow in the system (see Section 3.2). In this section, model of the systems components, the objective function and constraints of the optimization process are described. The optimization process is repeated for all the combinations of battery capacity and peak demand targets (when demand charge is considered), and the best combination which minimizes costs of systems operation in all the produced scenarios is selected (see Section 3.3).

Ideal model of the battery is considered, sizing issue for both of the studied tariffs is studied, and optimal capacity of the battery for each one is obtained. In addition, non-ideal model of the battery is considered and the sizing optimization problem is studied. Then, the effects of electricity tariffs on optimal sizing of the battery and importance of battery ageing model are evaluated.

3.1. Data clustering

Load data of a typical residential customer collected from January 2007 to December 2010 is used in this paper [22]. The load profile data include electricity demand of the dwelling at 15 min intervals. Solar irradiance data in the studied location is downloaded from Ref. [23]. FCM is chosen to group net load profile of a typical customer into relatively homogeneous clusters. Net load of the system is the load less the possible production from the PV system [8].

FCM is calculated on the base of the degree of memberships assigned to cluster centre of each group. In this method, each point is specified by a membership grade between 0 and 1. The FCM seeks to minimize the distance (dissimilarity) from any given data point to a cluster centre multiplied by membership grade of that data point. An iterative algorithm is used to update the centres of the clusters and the membership grades for each data point to find appropriate location of cluster centres within the data sets [7]. The objective function of the FCM is as follows [8]:

$$F(X;U;V) = \sum_{j=1}^{c}\sum_{k=1}^{N}\left(u_{jk}\right)^{m}\|x_k - v_j\|_{\mathrm{NI}}^{2} \tag{1}$$

where $X=[x_k]$ is a vector of data points, $U=[u_{jk}]$ and $V=[v_j]$ are, respectively, vectors of the resulting degrees of membership and prototypes for clusters, and NI is the norm-inducing matrix used in the distance calculation [8].

Procedure of choosing the “typical days” for both of the pricing structures is not the same. Effective scenario production for each of pricing structures is described in the next two sections.

3.1.1. Time-of-use

When a customer purchases electricity under TOU pricing, economic benefits of load shifting is the most beneficial application of storage systems. In this case, shape of the electricity demand corresponding to dwelling and its overall level is important to produce scenarios. Net load data of the customer during the studied years is divided into some clusters considering shape and level of the systems net load. Each cluster is represented by a prototype, which is reduced representation of the entire set. The probability of each scenario is calculated by first hardening the fuzzy sets to crisp sets and then counting the data points assigned to each cluster [8].

3.1.2. Time-of-use with peak demand charge

Some utility companies charge their customers for maximum requested power ($ per kW) in addition to the amount of energy used ($ per kWh). In this context, the per-unit cost for peak charges may be about 100 times the per-unit cost for total usage [24]. Demand charges are assessed on the utility customers for their maximum load during each month (the load is metered on discrete timeslots for example a 15-min averages). Thus, days with the highest peak demand of each month determines the demand cost. Net load data of each month in our dataset is separated and FCM is used to cluster net load data in each month. Then, representative of cluster with highest demand in each month is considered in our studies.

3.2. Optimized dispatch schedule

Dispatch strategy used in this research minimizes the energy bill of the system owner during a day. The method requires information on electricity prices, daily load and PV output data of the customer. Cost of battery capacity loss is considered into battery dispatch schedule as recently introduced methods [15,16,18]. Presenting a new dispatch strategy is not the main purpose of this work. Therefore, the method used in this study is derived from dispatch schedule optimization described in Ref. [18].

A schematic of the grid-connected PV/storage system is shown in Fig. 2. The PV array, the batteries, the utility grid, and the load are connected to an AC bus. A DC–AC converter is used to connect DC output of the PV array to the AC bus. Conversion efficiency of the PV inverter η_{pi}, assumed to be constant. The battery also operates on DC, thus a bi-directional converter is necessary when the battery is charging or discharging. Conversion efficiency of the bi-directional converter η_{Bi} is assumed to be constant for both charging and discharging. Consequently, we have:

$$P_{\mathrm{Bac}}(i,t) = \begin{cases} \eta_{\mathrm{Bi}} P_{\mathrm{Bdc}}(i,t), & \text{if} \quad P_{\mathrm{Bdc}}(i,t) < 0 \\ \frac{P_{\mathrm{Bdc}}(i,t)}{\eta_{\mathrm{Bi}}}, & \text{otherwise} \end{cases}. \tag{2}$$

The PV modules are assumed to be installed in the studied building. Output of the PV generator has been modelled as a linear power source according to the irradiance level [25].

$$P_{\mathrm{pv}}(i,t) = I(i,t) \times A \times \eta_{\mathrm{pv}}. \tag{3}$$

In this work, parameters of PV modules and their effects on overall system performance are not discussed. Although more complicated modelling of PV system could be used, this modelling of PV system is appropriate for these applications. Because, this study mainly focuses on battery side.

For the electricity price, TOU and TOUD tariffs proposed by Duke Energy Progress North Carolina [9] for residential customers are considered in this research. For each of tariffs, electricity prices are divided into summer season and winter season (Tables 1 and 2). Note that, on-peak hours for summer season are defined as hours between 10 a.m. and 9 p.m., weekdays. For winter season, hours

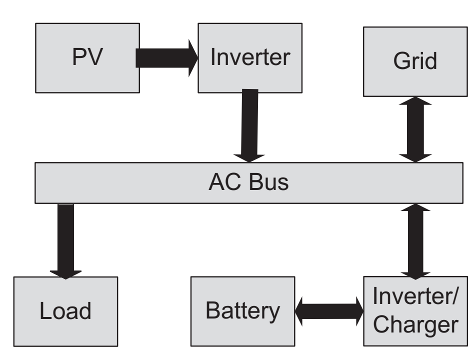

Fig. 2. Schematic of the grid-connected PV/storage system.

between 6 a.m. and 1 p.m. plus 4 p.m. through 9 p.m., weekdays, are defined as on-peak hours. The other hours of week considered as off-peak.

This study has been performed with flat plate lead-acid batteries. The presented model corresponds to this technology and has already been used and described in Refs. [18,15]. Discrete dynamic equation of battery is expressed by Eq. (4):

$$\frac{E_B(i,t)-E_B(i,t-\Delta t)}{\Delta t} = P_{Bdc}(i,t). \tag{4}$$

The battery is charging if P_{Bdc} $(i,t)>0$ (stored energy in the battery increases) and discharging if P_{Bdc} $(i,t)<0$ (stored energy in the battery decreases). Model of battery ageing has been formulated by Eqs. (5)–(8) as:

$$\frac{d\Delta C(i,t)}{dt} = \begin{cases} -Z\times P_{Bdc}(i,t), & \text{if} \quad P_{Bdc}(i,t)<0 \\ 0, & \text{otherwise} \end{cases}, \tag{5}$$

$$\Delta C(i,t) = C_{ref}-C(i,t), \quad \Delta C(i,t_0) = 0, \tag{6}$$

$$\mathrm{BCL}\ (i,t) = \Delta C(i,t)-\Delta C(i,t-\Delta t), \tag{7}$$

$$\Delta C(i,t) = \begin{cases} \Delta C(i,t-\Delta t)-Z\times\frac{P_{Bac}(i,t)}{\eta_B}\times\Delta t, & \text{if} \quad P_{Bac}(i,t)<0 \\ \Delta C(i,t-\Delta t), & \text{if} \quad P_{Bac}(i,t)>0 \end{cases}. \tag{8}$$

Using conversion efficiency of the battery and sampling interval, Eq. (5) is rewritten as Eq. (8). Conversion efficiency of battery is equal with conversion efficiency of battery inverter multiplied by round-trip efficiency of battery. Eq. (8) demonstrates that, in this modelling of battery ageing, battery degradation is modelled only in discharge process [15]. However, it does not mean that, in real operation of batteries degradation occurs only in discharge process. Indeed, the same value of battery capacity loss due to a certain discharge/charge cycle is considered for discharge process. Parameter Z is the linear ageing coefficient, which has been obtained for different battery technologies from experimental results [15]. The value of Z for lead-acid batteries is considered in this work.

Operation of system contains benefits and costs for the system owner. The system operation costs include the amount of electricity purchased from grid (i.e. energy costs), cost of peak of the requested power (i.e. peak demand cost) and cost of battery capacity loss. Using the stored energy in the batteries for self-consumption or selling to the grid, constitute benefits of system operation (i.e. energy benefits). The objective function J expressed by Eq. (9) amounts to minimize the expected daily operation costs and benefits of the system over a selected day

$$\min J = \min[\mathrm{ECB}+\mathrm{PDC}+C_{BCL}]. \tag{9}$$

It should be noted that, peak demand cost (PDC) is calculated when demand charge is specified in pricing structure. C_{BCL}, energy cost and benefit (ECB) and PDC are as follows:

Table 1
Electricity price for time-of-use tariff.

	Summer season	Winter season
On-peak	0.17037 $/kWh	0.16154 $/kWh
Off-peak	0.05386 $/kWh	0.05386 $/kWh

Table 2
Electricity price for time-of-use with demand charge tariff.

		Summer season	Winter season
Energy price	On-peak	0.0670 $/kWh	0.0670 $/kWh
	Off-peak	0.05386 $/kWh	0.05386 $/kWh
Demand price	On-peak	5.02 $/kW	3.73 $/kW
	Off-peak	–	–

$$\mathrm{ECB}\ (i,t) = \left[E_p(i,t)\times P_{Net}(i,t)\right]_{P_{Net}(i,t)>0} + \left[E_p(i,t)\times P_{Net}(i,t)\right]_{P_{Net}(i,t)<0}, \tag{10}$$

$$\mathrm{PDC}\ (i) = (D_C(i)/\mathrm{nu}(i))\times(P_{demand}(i)), \tag{11}$$

$$C_{BCL}(t) = \frac{B_{FC}\times \mathrm{BCL}\ (t)}{1-\mathrm{SOH}_{min}}. \tag{12}$$

The first term of ECB is cost of purchasing electricity from grid; and the second term is the expected benefits of selling excess generation of electricity to the grid. The electricity is importing from the grid if $P_{Net}>0$; and the electricity is exporting to the grid if $P_{Net}<0$. As mentioned before, the demand charge is calculated for peak of demand in each month. Thus, day with the highest demand of each month determines peak demand cost of the month. Therefore, to consider peak demand cost into the daily operation costs, peak demand costs of each month is divided by number of days of month, as expressed by Eq. (11). It should be mentioned that, P_{demand} is a function of system operation, which can be controlled by charging/discharging rates of the battery. In our formulation, P_{demand} is defined and the optimization problem determines charging/discharging rates of the battery to keep the peak demand target under the defined threshold (P_{demand}) while minimizing other operation costs of the system.

According to Eq. (8), cumulative capacity loss of the battery "ΔC" at the moment i,t is equal with the previous moment, if the battery is charging at i,t. In other words, battery capacity loss (BCL) at moment i,t is equal to zero when the battery is charging. Therefore, calculation of C_{BCL}, depends on the state of battery which is charging or discharging.

Optimization problem should satisfy operation constraints expressed by Eqs. (13)–(16). Generated and consumed power at each time should satisfy Eq. (13), which guarantees supplying the load at each time. Eq. (14) expresses that, the stored energy in the battery E_B should be less than available battery capacity at each time.

$$P_{Net}(i,t) = P_{Bac}(i,t)+P_L(i,t)-\eta_{pv}P_{pv}(i,t), \tag{13}$$

$$E_{B\ min}\le E_B(i,t)\le C_{ref}-\Delta C(i,t). \tag{14}$$

Charging/discharging rate of the battery depends on available battery capacity and minimum charging/discharging time of the battery. For simplicity t_H assumed to be equal for both charging and discharging.

$$P_{Bdc\ min}(i,t)\le P_{Bdc}(i,t)\le P_{Bdc\ max}(i,t), \tag{15}$$

$$P_{Bdc\ max}(i,t) = -P_{Bdc\ min}(i,t) = \frac{C(i,t)}{t_H} = \frac{C_{ref}-\Delta C(i,t)}{t_H}. \tag{16}$$

As mentioned before, the studied system is assumed to be net metered. In other words, electricity price for purchasing electricity from the grid and selling back to the grid is assumed to be identical. Using Eqs. (8) and (13), and considering the fact that electricity price is net metered, energy costs and benefits and C_{BCL} is combined as:

$$f_1(i,t)=\left[\left(E_p(i,t)\times\left(P_L(i,t)-\eta_{pv}P_{pv}(i,t)\right)\right)+\left(E_p(i,t)\times P_{Bac}(i,t)\right)_{P_{Bac}(i,t)>0}+\left(E_p(i,t)-Z\times\frac{\Delta t}{\eta_B}\times B_{FC}\times P_{Bac}(i,t)\right)_{P_{Bac}(i,t)<0}\right]. \tag{17}$$

Now, for the objective function J, we have:

$$\min J(i) = \min\sum_{t=t_0}^{t_0+24}[f_1(i,t)]+\text{PDC}(i). \tag{18}$$

It is clear that, the only independent variable in our mathematical model is P_{Bac}. The objective function J minimizes all of the operation costs of the system including cost of purchasing electricity from the grid and cost of battery capacity loss in a selected day. In addition, when demand charge is assessed, the objective function keeps peak demand cost of the customer at determined value.

Moreover, C_{BCL} (which is now merged with ECB and it is shown by f_1) depends on the state of battery which is charging or discharging. Therefore, the value of f_1 for $P_{Bac} > 0$ and $P_{Bac} < 0$ is not the same. By introducing an indicator variable "$b(i,t)$", in which $b(i,t) = 0$ if $P_{Bac}(i,t) > 0$ and $b(i,t) = 1$ if $P_{Bac}(i,t) < 0$, the optimization problem can be modelled as a Mixed Integer Programming (MIP) problem with indicator constraint [18].

3.3. Determination of battery capacity

Our objective function is a function of battery charging/discharging rate which itself is a function of battery capacity. The proposed MIP model of battery sizing problem is solved using the CPLEX solver in GAMS [26]. For all combinations of battery capacities (range of 3–30 kWh) and maximum allowed peak demand (range of 800–1800 W), optimization problem for each of the typical days is solved to find the best combination which minimizes the operation cost of the system during all the studied days. Considering the probability of each cluster, operation cost of the system during one year can be estimated. In order to find annual net profit (ANP) of the system during the life of the project, estimation of battery lifetime is necessary. However, battery life highly depends on various operation conditions and it is difficult to be predictable [27]. Calculations of ANP and battery life are described in the next two sections.

3.3.1. Time-of-use

In order to estimate battery life, battery capacity loss for the representative of each cluster is calculated. The calculated value is assumed to be the same for all memberships of that cluster. Considering battery degradation of all clusters with their probabilities, battery capacity loss during one year of operation is estimated as:

$$\Delta C_{\text{year}} = \frac{\sum_{i=1}^{n}P(i)\times\Delta C_{\text{day}}(i)}{N_{\text{year}}}\times N_{\text{Data}}. \tag{19}$$

In order to estimate ANP of the system operation, annual cost of the system operation should be estimated using Eq. (20):

$$A_C = \frac{\sum_{i=1}^{n}P(i)\times J(i)}{N_{\text{year}}}\times N_{\text{Data}}. \tag{20}$$

Cost of system operation with and without battery system is calculated and ANP of the battery scheduling is obtained. Cost of system operation with battery system includes cost of purchasing electricity and investment cost of the battery and the inverter. Note that, investment cost of the system components have been converted to a stream of daily cost.

3.3.2. Time-of-use with peak demand charge

In this case, battery capacity loss in the selected day of each month is considered to be equal for all days of the month. Therefore, battery capacity loss during one year of operation is estimated as:

$$\Delta C_{\text{year}} = \frac{\sum_{i=1}^{12}\Delta C_{\text{day}}(i)}{12\times N_{\text{year}}}\times N_{\text{Data}}. \tag{21}$$

It should be noted that, this is a conservative estimation. Because, battery degradations in day with the highest demand in month is usually more than the other days of the month. However, this method is appropriated for this application, because losing the battery capacity is important when demand charge is assessed.

In order to estimate ANP, cost of the system operation in the selected day of each month is considered to be the same for all days of month. Annual net profit of the system operation is estimated using the calculation of annual cost of the system as Eq. (22):

$$A_C = \frac{\sum_{i=1}^{12}J(i)}{12\times N_{\text{year}}}\times N_{\text{Data}}. \tag{22}$$

4. Results and discussion

The primary results obtained from the solution of the optimization problem are the values for the capacity of battery storages and the amount of charging/discharging rates (energy dispatch schedule) of the battery in selected days. The formulation of the optimization problem includes several parameters which must be defined. Installation cost of the storage system assumed to be 150 $/kWh based on [18]. For the battery inverter, 606 $/kW is assumed for the cost of the inverter and 10 years for its lifetime based on [21]. To takes into account discount rate and converting the fixed cost of system installation to a stream of daily cost, annualization factor is used [8,28]. Considering 4% for annual discount rate and 10 years for its lifetime, value of annualization factor for the inverter was found to be 0.000337.

It should be noted that, cost of the battery cannot be converted to a stream of daily cost in the same way; because lifetime of the battery highly depends on operation of the system and could not be roughly estimated. Thus, the battery investment cost is taken into account in daily operation of the system as a function of discharge rate of the battery. The remaining parameter values are given in Table 3.

4.1. Case A: ideal model of the battery

In this case, results of the sizing optimization process for both the studied tariffs are shown when the ideal model of the battery ageing is used. In the ideal model of battery ageing, it is assumed that all the capacity of battery is useful. In the other words, it is assumed that 100% decreasing in battery reference capacity means end of battery life ($SOH_{min} = 0\%$). Another assumption is maximum allowed depth of discharge of the battery, which in the ideal model

Table 3
Optimization parameter values.

A	24 m^2
η_{pv}	15%
η_{Bi}	90%
η_{pi}	90%
Z	3×10^{-4}
Δt	0.25 h
B_{FC}	150 $/kWh
t_H	10 h
N_{year}	4
N_{data}	1461

of battery ageing, is assumed to be 100%. In other words, minimum energy stored in the battery should be more than zero ($E_{B\ min} = 0$). In addition, round-trip efficiency of the battery is assumed to be 100%. The model of battery ageing uses these assumptions, is exactly as the model of battery ageing implemented in Ref. [18].

4.1.1. Time-of-use (TOU)

First, net load data are divided into two groups according to the electricity price. A cluster validity index called "Compose Within and Between Scattering" is used to determine number of clusters [29]. The number of scenarios for winter season and summer season are obtained twelve and fourteen respectively. Results of FCM analysis for each of groups are shown in Fig. 3 and probabilities of the clusters are shown in Table. 4.

One of clusters in winter season with the centre of the cluster is shown in Fig. 4. It illustrates that, the centre of a cluster significantly represents the shape and level of the all memberships of that cluster.

Results from optimal scheduling of the battery for a typical value of battery capacity ($C_{ref} = 18$ kWh) in one of the typical days, are shown in Figs. 5 and 6. Net load of the system with and without using battery system in the studied day are shown in Fig. 5. The battery is charged at maximum allowed rate during off-peak hours from midnight (initial time of the optimization process) until 6 a.m., as Figs. 5 and 6a show it. With the beginning of on-peak hours, the stored energy in the battery discharges to meet the house demand

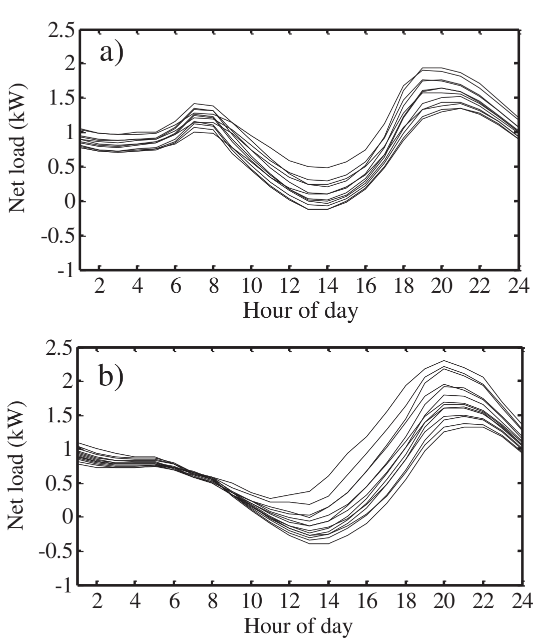

Fig. 3. Clustering results: winter season (a), summer season (b).

Table 4
Probabilities of clusters.

	Winter season	Summer season
1	0.0349	0.0390
2	0.0527	0.0294
3	0.0643	0.0144
4	0.0684	0.0246
5	0.0540	0.0274
6	0.0705	0.0280
7	0.0479	0.0280
8	0.0746	0.0267
9	0.0609	0.0109
10	0.0534	0.0376
11	0.0568	0.0219
12	0.0280	0.0315
13	–	0.0109
14	–	0.0034

and selling back the excess energy to the grid until about 12 a.m., as Fig. 5 illustrates. Degradations of the battery occur during these hours because the battery is discharging (Fig. 6b). During off-peak hours from 1 p.m. to 4 p.m. battery is re-energized. The remaining stored energy in the battery discharges during on-peak hours from 4 p.m. until about 10 p.m. when the battery is fully discharged (Figs. 5 and 6a). Note that, from 2 p.m. to 3 p.m., net load of the house without using battery is negative which means that there is surplus PV generation in addition to supplying the houses demand. However, the surplus generation is stored in the battery and is not sold back to the grid because currently the electricity price is not high. It should be noted that, when net load of the system with battery is under the net load without battery system, battery is discharging. Fig. 6b shows that, battery capacity loss during daily operation was about 4.26 Wh. Maximum demand of the customer during off-peak hours was 1442 W, which has been increased to 2988 W after using the storage system.

Annual net profit of the system for different battery capacities are calculated using Eq. (20). The capacity of battery which maximizes net profit of the battery system was found to be $C_{ref} = 30$ kWh. With this value of battery capacity, annual cost of the system operation was found to be 632.7 $ which has been 884.7 $ before installing the battery system. From this value, 231.2 $ corresponds to battery inverter cost and 401.5 $ corresponds to battery degradation cost and cost purchasing electricity from the grid. As mentioned before, in the resultant value of battery degradation cost, discount rate is not taken into account. In order to find the real battery degradation cost (considering discount rate); the lifetime of the battery should be estimated. Using Eq. (19) battery lifetime for this value of battery capacity was found to be almost 13 years. Now the cost of purchasing electricity from the grid and cost of battery degradations can be disaggregated. Because a linear relation between battery capacity loss and battery investment cost has been assumed, it can be said that all the investment

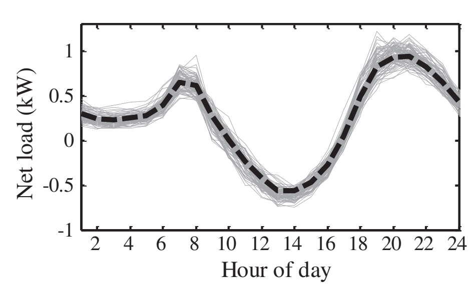

Fig. 4. One of clusters with the cluster centre and all memberships of the cluster.

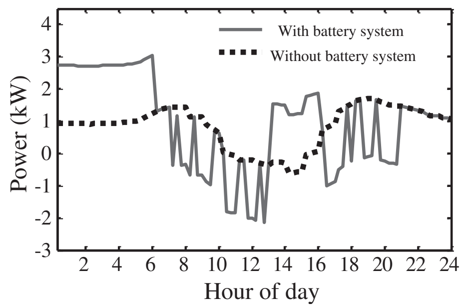

Fig. 5. Net load of the system with and without using battery system in the studied day under TOU.

cost of the battery (4500 $) last 13 years; it means 364.15 $ per year. Therefore, the cost of purchasing electricity from the grid had been 37.35 $. After estimating the lifetime of the battery, the real cost of the battery degradation can be estimated using the annualization factor. The real cost of the battery degradation with the obtained battery lifetime has been found about 450.5 $ per year. Thus, annul net profit of the system for this value of battery capacity was found to be about 164.15 $. It means that under the mentioned assumptions for battery ageing model, installing battery with 30 kWh capacity provides net profit for the system owner about 164.15 $ per year thorough 13 years. However, it does not give any information about the payback period of the investment costs. ANP of the system for different battery capacities are shown in Fig. 7.

Due to unlimited peak demand of the customer and high enough margin between on-peak and off-peak prices, it is profitable to purchase electricity from the grid and charge the battery in low-price hours and discharge the battery in high-price hours. Thus, increasing battery capacity results in an increase in the benefits of the customer in an almost linear relation, as the best illustrated by Fig. 7.

4.1.2. Time-of-use with peak demand charge (TOUD)

In this case, net load data of each month is separated and FCM is used to cluster the net load data of each month according to the method, which is described in the previous section. Note that, we study the net load on 15-min intervals because the demand charge is calculated on 15-min intervals. However, load and PV output data are collected hourly; so, values of data in timeslots between the hours are estimated in our studies.

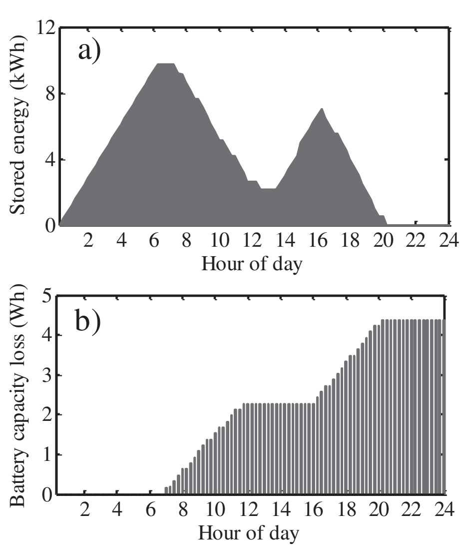

Fig. 6. Energy stored in the battery (a); and battery capacity loss (b); during system operation in the studied day under TOU.

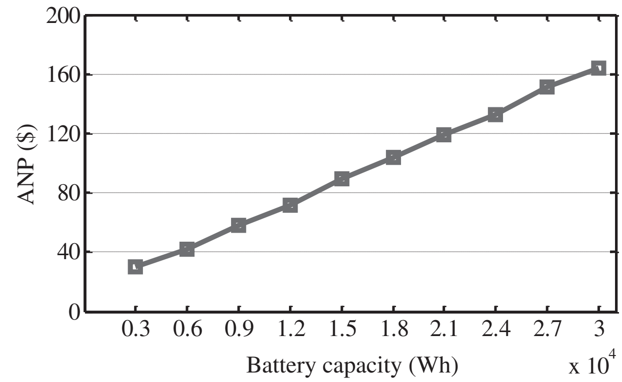

Fig. 7. ANP of the system for different battery capacities under TOU rates.

Results of battery scheduling for typical battery capacity ($C_{\mathrm{ref}} = 18$ kWh) for the same studied day in the last section are shown in Figs. 8 and 9.

Fig. 8 illustrates that, battery is charged from 2 a.m. to 3 a.m. This stored energy is used to curtail net load of the house to the targeted peak demand (1300 W in this case) during on-peak hours from 7 a.m. to almost 9 a.m. and 17 p.m. to 21 p.m. as Fig. 9a indicates. Unlike the previous case, the electricity is not purchased from the grid to meet the houses demand and selling back to the grid. It illustrates that, cost of the battery capacity loss during operation of the system is more than the potential gain expressed as the margin between on-peak and off-peak prices. Consequently, battery is not used to sell back electricity to the grid and the stored energy in the battery is restricted to hold peak demand under the targeted threshold, as illustrated in Fig. 8. Battery capacity loss during operation was found to be 0.45 Wh as shown in Fig. 8b. In this case, loss of battery capacity is less than the previous case; because the use of battery has been much decreased.

Now, the ANP of the system for different combination of battery capacity and peak demand target (PDT) is calculated. ANP of the system without considering the inverter cost for three battery capacities and all considered PDTs are shown in Fig. 10. As it can be seen, even without associating the inverter cost in the system costs, there is no considerable benefit with this price rates.

According to Eq. (16), batteries with lower capacities have lower discharging rate. So, they may fail to hold the peak demand under the targeted threshold. For example, a 9 kWh battery is not able to hold the peak demand for all the days less than 1600 W (maximum peak demand of the customer load among all the selected days has been 2448 W). Fig. 10 indicates that decreasing the PDT less than the optimum value of 1600 W decreases the profits of the system. Decreasing PDT lead to an increase in the use of battery that culminates in more battery capacity loss. Negative profit for PDT less than 1500 W means, benefits from decreasing peak of the demand is not high enough to compensate cost of battery degradation. Under this pricing structure, the maximum value of ANP was found to be 1.85 $ which is not an inciting result for a customer to install battery storage system (even without considering inverter cost). It should be noted that, the data for 3 kWh and 6 kWh batteries are not shown in Fig. 10. Because they were not able to hold peak demand of the customer under any value of studied PDTs.

4.2. Case B: non-ideal model of the battery

In this case, optimal battery capacity determination is studied when non-ideal model of battery ageing is used. In the previous

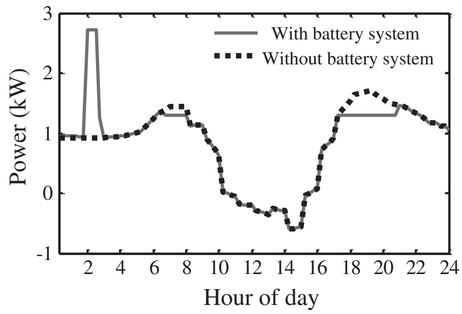

Fig. 8. Net load of the system with and without using battery system in the studied day under TOUD.

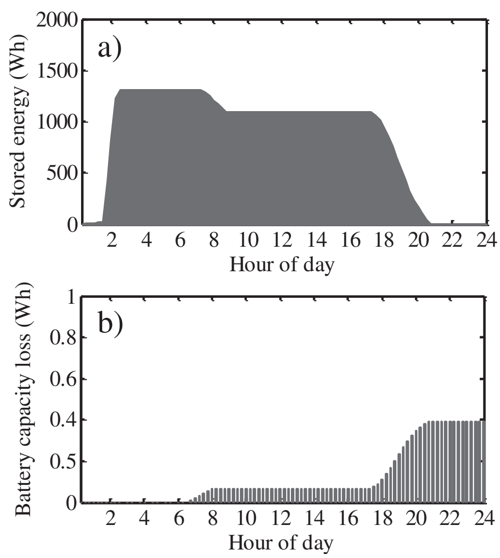

Fig. 9. Energy stored in the battery (a); and battery capacity loss (b); during system operation in the studied day under TOUD.

case, it was assumed that all of the battery capacity is useful. However, in real operation of the batteries decreasing about 20–50 percent of battery reference capacity means end of battery life [27,30]. In this non-ideal modelling of battery ageing, it is assumed that 40% decreasing in battery reference capacity means end of battery life ($SOH_{min} = 60\%$). In addition, maximum allowed depth of discharge is assumed to be 50% ($E_{B\ min} = 0.5 \times C_{ref}$); and round-trip efficiency of the battery is assumed to be 85%.

The financial benefit of battery storage systems is studied considering these assumptions, which have to be taken into account in the real operation of the batteries. First, optimal scheduling of the battery for the same studied day with the same battery capacity ($C_{ref} = 18$ kWh), is studied. The results of optimal scheduling for both the tariff are shown in Fig. 11a and b.

As it is illustrated by Fig. 11a, the battery has not been used during all the day. It means that, in daily scheduling of the battery, cost of battery capacity loss is more than cost of purchasing electricity from the grid. It should be noted that, the inverter cost is not considered in daily scheduling of the battery. Results illustrate that, using non-ideal model of battery ageing imposes higher cost of battery capacity loss. In this case, battery capacity loss is not compensated even without considering the inverter cost. The same results for all the studied days are obtained. Thus, using the battery storage system is not reasonable under this TOU pricing rates. In Fig. 11b, daily scheduling of the battery under TOUD rates is shown. In this case, the battery is used to hold peak demand under the targeted threshold. However, the cost of battery capacity loss has been increased in comparison with the case of ideal model of the battery.

The results obtained in this section illustrated that though considering the ideal model of the battery, ageing approves the effectiveness of battery system to reduce cost of the system operation, but in real conditions of battery operation is not reasonable to use battery storage systems. However, with making changes in the price of the electricity or giving incentives for the customers who use battery systems, reasonable conditions for these systems could be found. For example in the studied TOU rates, if price of on-peak hours increases to 0.26 $/kWh and the off-peak prices decreases to 0.033 $/kWh, using a 20 kWh battery annual net profit of about 103$ can be obtained. In this case, battery lifetime was found to be almost 5 years, which is a usual lifetime for the batteries in these applications. Giving incentives to the battery systems owners is another way to increase use of these systems. For example, paying 0.12 $/kWh to the battery system owner for the discharged energy from the battery in on-peak hours, leads to profitable conditions for these systems. In this case, with a 20 kWh battery annual net profit of about 131 $ can be obtained.

5. Conclusion

In this paper, we proposed a method to determine battery capacity in a grid-connected PV/storage system with respect to optimal scheduling of the battery. In the utilized method, operation of the battery after installation in the system was considered in the sizing optimization of the battery storage by the use of FCM. As a result, optimization of energy dispatch schedule and battery sizing were de-coupled, which culminated in more reliable sizing determination. Two time-varying pricing structures, a time-of-use rate without specifying demand charge and a time-of-use rate with demand charge were considered in our study. Optimal sizes of battery storages for a typical residential customer with PV system

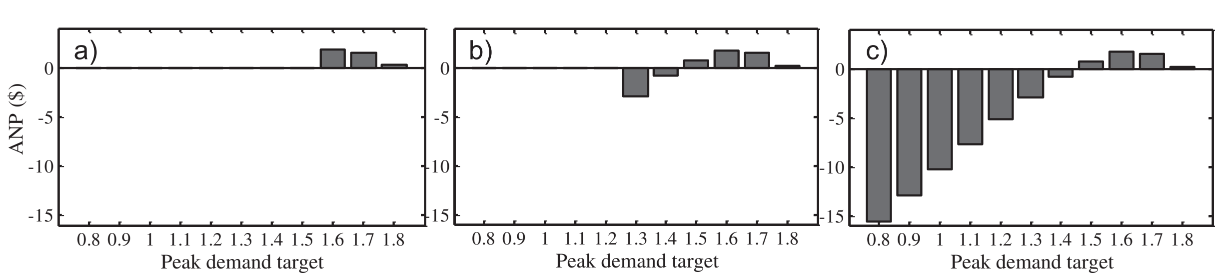

Fig. 10. Annual net profit of battery system: 9 kWh (a), 12 kWh (b), 27 kWh (c) under TOUD.

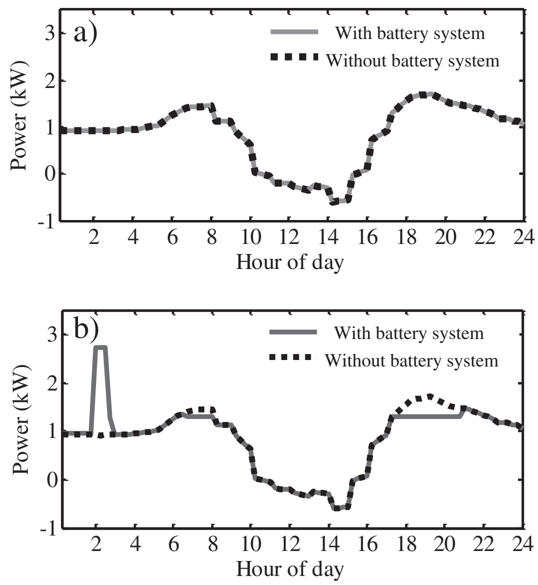

Fig. 11. Net load of the system with and without using battery system in the studied day when non-ideal model of the battery is used; under TOU (a); under TOUD (b).

under both of the tariffs were determined and the results were evaluated. A model ideal and a model of non-ideal battery were also studied and the results were compared.

Our results illustrated that, sizing optimization for battery used in PV/storage system highly depends on electricity rates and battery ageing cost. For the ideal model of battery ageing, PV/storage systems have more financial benefits for the system owner under TOU rates. Due to high enough margin between on-peak and off-peak prices, it was beneficial to purchase electricity from the grid during off-peak hours to charge the battery and sell it back to the grid during on-peak hours. However, under the TOUD rates, the margin between on-peak and off-peak and was not high enough to cover cost of battery degradations, and also demand charge was not high enough to compensate costs of battery degradation. Consequently, it was not beneficial to use storages even with the ideal model of the battery.

The results obtained for non-ideal modelling of battery ageing approves that, considering the real conditions of battery operation is necessary to achieve reliable sizes of battery storage systems. It is illustrated that, although using battery storages to reduce cost purchasing electricity on demand charge or time-of-use based tariffs seems to be beneficial, but economic profitability of these systems are not guaranteed. The exact tariff structure and considering real assumptions for battery ageing determines financial benefits of storages in grid-connected PV systems. However, with making changes in the price of the electricity or giving incentives to the PV/storage system owners, reasonable conditions for these systems could be found. It should be noted that, changing the electricity prices or giving incentives to these systems depend on benefits of PV/storage systems from the aspect of utilities. Though PV/storage system could be potentially beneficial from the aspect of the utilities, but benefits and environmental impacts of using these systems by a variety of customers should be investigated to clarify effects of using these systems from the aspect of utilities. If positive impacts of using the PV/storage systems have been approved, the rate structures could be designed to provide benefits for both system owners and utilities. These investigations could be part of our future studies.

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