Virtual storage capacity using demand response management to overcome intermittency of solar PV generation

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Abstract: The integration of solar photovoltaic (PV) systems into the distribution network creates various stability and reliability issues associated with the intermittency of solar PV power generation. Energy storage is a vital component required for overcoming the intermittency of solar PV. This study presents a priority-based demand response management (DRM) for loads with large time constants to create virtual energy storage. The virtual energy storage thus created can be used for partial levelling of intermittent output from solar PVs. The proposed DRM algorithm involves controlling loads with large time constants such as air conditioning systems and refrigerators based on the forecasted solar PV generation. The proposed method is evaluated using data-driven simulations, weather data and mathematical models. The proposed algorithm is highly suitable for megacities that have high number of multi-storey residential buildings. Utilising the virtual storage capacity available from the appliances will reduce the investment as well as the operation cost of renewable energy such as solar PV. Analyses on impact on temperature, percentage of interruptions, cost savings and impact on energy storage sizing are also presented for evaluating the performance of the proposed algorithm.

Nomenclature

$T_n^{\text{ac, on(max)}}$	usual turn ON time of the n th air conditioner
$T_n^{\text{ac, off(max)}}$	usual turn OFF time of the n th air conditioner
$T_n^{\text{ref, on(max)}}$	usual turn ON time of the n th refrigerator
$T_n^{\text{ref, off(max)}}$	usual turn OFF time of the n th refrigerator
$x_{\text{ac, on}}, x_{\text{ac, off}}$	proportion of turn ON and turn OFF time for air conditioners
$x_{\text{ref, on}}, x_{\text{ref, off}}$	proportion of turn ON and turn OFF time for refrigerators
$T_n^{\text{ac, on}}$	current turn ON time of the n th air conditioner
$T_n^{\text{ac, off}}$	current turn OFF time of the n th air conditioner
$T_n^{\text{ref, on}}$	current turn ON time of the n th refrigerator
$T_n^{\text{ref, off}}$	current turn OFF time of the n th refrigerator
$p_j^{\text{vsc, c}}$	estimated virtual storage capacity (charging) during j th interval
$p_j^{\text{vsc, d}}$	estimated virtual storage capacity (discharging) during the j th interval
p_j^{bpd}	power required from the battery during the j th interval
$p_{\text{ave_pv_op}}$	average solar PV output on a given day
$N_{\text{off}}^{\text{ref}}$	number of refrigerators that can be turned off
$N_{\text{off}}^{\text{ac}}$	number of air conditioners that can be turned off
$N_{\text{on}}^{\text{ref}}$	number of refrigerators that can be turned on
$N_{\text{on}}^{\text{ac}}$	number of air conditioners that can be turned on

1 Introduction

There has been a prolific growth in the integration of solar photovoltaics (PVs) into the distribution network of cities such as Singapore in the recent years [1, 2]. The Singapore government has released tenders for installing more solar PV systems in the future and it is estimated that solar PVs will be installed in many Housing Development Board (HDB) blocks and public sector buildings by 2017 [3]. Furthermore, the government is targeting to reach a solar

PV capacity of 350 MW_{peak} by 2020 [3]. As of April 2017 the total installed capacity of solar PV is 129.8 MW_{peak} [4], a 76% increase from April 2016, which indicates that the Singapore government is on track for achieving the target. It is expected that the penetration of solar PV power generation in cities such as Singapore will increase drastically in next few years.

However, large-scale integration of solar PVs will put at risk the reliability and stability of Singapore's power system due to its intermittent nature [5]. Although there are potential issues such as voltage and frequency fluctuations associated with the integration of solar PVs into the distribution network [6, 7], the inherent advantages of distributed generation is a crucial factor to be considered [8, 9].

To overcome the intermittency of solar PV generation, additional spinning reserves are required. The addition of spinning reserves will lead to an increase in fossil fuel consumption and hence the operating cost. Furthermore, spinning reserves usually have a slow response time and might be unable to swiftly compensate for the variations in solar PV generation. Energy storage devices (ESDs) such as storage batteries have a faster response time and can be deployed to overcome the variability in solar PV generation [10]. However, if solely ESDs handle the intermittency of solar PV generation, the energy storage capacities required will be very large and the investment cost will increase significantly. Furthermore, the operation cost will also be higher due to the losses in the process of charging and discharging the ESD.

To reduce the dependency on large-scale ESD at the supply side, demand response management (DRM) can be incorporated to manage and control the energy consumption of different loads. In many of the proposed DRM algorithms such as those presented in [11–13], the main objective of the algorithms is to modify the instantaneous power demand during periods of peak demand. This can be achieved by shedding consumers' interruptible loads based on market conditions, demand limits and priority-based load shedding requirements. However, all of the above algorithms only take into account the variations in the load demand. The inherent intermittent generation characteristics of solar PVs have not been considered in these research works. Although the uncertainties in

Fig. 1 Architecture of sensors for determining distinct turn ON period and a turn OFF period for different equipments

Fig. 2 Block diagram of data-driven model

solar PV generation have been considered in the development of various DRM algorithms in [14, 15], the power consumed by the loads is assumed to be maintained constant at their rated power during their operation without any cycling or variations.

In this paper, the proposed algorithm involves adjusting the operation of electrical equipment that has large time constants such as air conditioning systems/air conditioners and refrigerators according to variations in the solar PV generation. Time constant in this context refers the time taken for control parameter, i.e. temperature to change from initial value to final value under normal circumstances. Time constant of the system can be segregated as large or small based on heuristic approaches. In this paper, only air conditioners and refrigerators, whose time constant is well over 30 min is considered. The research work conducted in [16] has demonstrated that loads such as air conditioning systems and refrigerators have a cyclic as well as distinct turn ON period and turn OFF period. Lu [17] has made an evaluation on using heating, ventilation and air conditioning (HVAC) load for hourly load balancing services, the authors proposed a direct load control strategy to aggregate small residential and commercial HVAC systems, which can be further used for ancillary services in future. The demand response capability of commercial HVAC systems was explored for renewable energy sources in [18]; the authors utilise the fact that commercial HVAC systems deploy variable frequency drives (VFDs) that facilitate a continuous variable load. However, such VFDs are seldom available in residential air conditioners and refrigerators.

The authors in [19–22] proposed various algorithms and control methods for utilising thermostatically controlled loads (TCLs) to compensate the variations in renewable power generation. In [19], Hao *et al.* focus on providing regulation services for grid using aggregated flexibility of TCLs, in [20, 22] the controller is designed for a similar application and it is assumed that variable power consumption is feasible with individual devices, such a condition may not be applicable for most of the residential applications. In [21], the application is developed for commercial HVAC systems and regulation services also rather than residential applications. In [23], Mathieu *et al.* the authors listed various feasible DRM designs for residential applications of USA and

European power system that could be useful in many cases. However, with Singapore's aggressive policies to increase solar PV installation in high-rise residential buildings a unique opportunity for DRM would be available for locally aggregated residential appliances. In [24], Mathieu and Callaway have designed controllers for aggregating residential TCLs which could be further used for ancillary services and energy arbitrage, different types of real-time data such temperature and reported on-off status were used for the modelling and control. It can be observed that in all the methods proposed for residential TCLs, the appliances are available for control when they are inside the dead band. Hence, the number of switching operations would change based on the control strategy used.

In this paper, a new application of priority-based strategic operation for household air conditioners and refrigerators to create a virtual storage and handle the forecasted changes in PV generation is studied. The novel feature of the proposed algorithm is that the number of switching operations is not modified; only the time for which the appliance is in the 'ON' mode is modified based on forecasted solar PV output. An inherent advantage of the proposed algorithm is that the amount of interruption/modification is uniformly distributed among all the appliances. Furthermore, the proposed method focuses on aggregating the TCLs within the local micro/nano-grid [Each group of multi-storey residential buildings with solar PV can be considered as a micro/nano-grid.] network is controlled and hence results in increased utilisation of renewable energy at the generation site unlike other methods in the literature. Although aggregation of TCLs is a well explored area, the objective of the aggregation in this paper is to increase utilisation of renewable energy on the generation site (group of multi-storey residential buildings) and reduction of power flow in and out of ESD, hence improve overall energy efficiency of the micro/nano-grid network. The proposed algorithm is highly suitable for megacities such as Singapore that have high number of multi-storey residential buildings. The proposed algorithm is evaluated using data-driven simulations and physical models described in Section 3. Weather data of the period January 2011 to December 2011 is also used in the simulations for solar irradiance and ambient temperature.

2 Models derived based on smart meter/sensor data

Vast amount of information is needed to develop a robust and efficient DRM for smart grids. The information includes real-time electrical power consumption and demand profiles, PV output power, electricity pricing information, weather data that typically includes solar irradiance and temperature, and relay/breaker status [25]. In addition, the DRM also requires remote load control capability to seamlessly turn ON–OFF electrical appliances participating in the DRM. Onset of smart grid will offer the opportunity for having such huge data from the smart sensors and meters employed with different equipment that was earlier unavailable. The distinct turn ON period and a turn OFF period for different equipment and other parameters can be collected using various sensors as shown in Fig. 1.

Fig. 1 shows a typical system which can collect data from various appliances using current/voltage and temperature sensors that has the capability to communicate using zig-bee network (could be replaced with other available communication network as well). The appliances can be controlled using the load control relays with communication capability through zig-bee network. Using the collected data, cooling constant required for different household air conditioners and refrigerators can be determined. Such models can be used for equipment with cyclic turn ON period and a turn OFF period. The block diagram for the proposed data-driven model is given in Fig. 2.

The data required for the proposed method is obtained based on Newton's law of cooling and is given by

$$\frac{dT}{dt} = k(T_{\text{out}} - T) \quad (1)$$

Fig. 3 Temperature profile of a typical room with air conditioner model LG LW1212 ER

where k is a positive constant called as cooling coefficient, T_{out} and T are the outside temperature and inside temperature, respectively. Using (1), the temperature change due to outside temperature and air conditioner coil can be derived as

$$\frac{dT_{room}}{dt} = k(T_{out} - T_{room}) + k_{ac}(T_{coil} - T_{room}) \quad (2)$$

where k_{ac} is the cooling coefficient of air conditioner coil. T_{out} , T_{room} and T_{coil} are the outside temperature, room temperature and temperature of the air conditioner coil, respectively.

It can be observed from Fig. 3 that the temperature of the room can be obtained using Newton's law of cooling. The data required for the turn ON and turn OFF period of air conditioners are obtained from the experimental results presented in [16]. A typical temperature profile of a room simulated using $k = 0.006$ and $k_{ac} = 0.023$ is given in Fig. 3. The ON-OFF data of air conditioner model LG LW1212 ER given in [16] is used to determine the temperature profile. The values of k and k_{ac} can also be determined using the data that is used for forecasting the temperature. The value of k_{ac} is zero when the air conditioner is turned off. The values of k and k_{ac} are determined by curve fitting (MATLAB curve fitting toolbox was used for simulations in this paper).

Using (1) the temperature change due to outside temperature and refrigerator coil can be derived as

$$\frac{dT_{ref}}{dt} = k(T_{out} - T_{ref}) + k_{ref}(T_{coil} - T_{ref}) \quad (3)$$

where k_{ref} is the cooling coefficient of refrigerator coil. T_{out} , T_{ref} and T_{coil} are the outside temperature, refrigerator indoor temperature and temperature of the refrigerator coil, respectively.

The proposed data-driven model can capture any change in power consumption pattern and other parameters that may occur due to ageing of the equipment and other miscellaneous conditions. The same procedure can be applied for refrigerator as well. However, the refrigerators provide higher time constants and higher flexibility. Using the real-time data-driven models, a priority-based scheduling and control of the turn ON period can be executed. The occupants' comfort would not be affected if the temperature is maintained within the allowed hysteresis loop. A virtual storage can be created to handle the changes in PV generation partially and it is described in Section 4.

3 Priority-based strategic control of appliances for achieving virtual storage capacity

A residential smart grid is considered for the proposed DRM; hence, the loads which can be used to achieve VSC are household air conditioners and refrigerators. Let $T_{n,j}^{ac, on(max)}$ and $T_{n,j}^{ac, off(max)}$ be the usual turn ON and turn OFF time of the n th air conditioner,

respectively. $T_{n,j}^{ac, on}$ and $T_{n,j}^{ac, off}$ correspond to turn ON time and a turn OFF time of the n th air conditioner at the j th interval, respectively. Priority values are used as measure for determining the importance of operating the appliances at the current interval. The priority values for turning off the air conditioners are given by

$$\sigma_{n,j}^{ac, off} = 1 - \frac{T_{n,j}^{ac, on(max)} - T_{n,j}^{ac, on}}{T_{n,j}^{ac, on(max)}} \quad (4)$$

$$\forall T_{n,j}^{ac, on} \geq x_{ac, on} \cdot T_{n,j}^{ac, on(max)}$$

Moreover, the priority values for turning on the air conditioner is given by

$$\sigma_{n,j}^{ac, on} = 1 - \frac{T_{n,j}^{ac, off(max)} - T_{n,j}^{ac, off}}{T_{n,j}^{ac, off(max)}} \quad (5)$$

$$\forall T_{n,j}^{ac, off} \geq x_{ac, off} \cdot T_{n,j}^{ac, off(max)}$$

Let $T_n^{ref, on(max)}$ and $T_n^{ref, off(max)}$ be the usual turn ON and turn off time of the n th refrigerator, respectively. $T_{n,j}^{ref, on}$ and $T_{n,j}^{ref, off}$ correspond to turn ON time and a turn OFF time of the n th refrigerator at the j th interval, respectively. The priority value for turning off the refrigerator is given by

$$\sigma_{n,j}^{ref, off} = 1 - \frac{T_n^{ref, on(max)} - T_{n,j}^{ref, on}}{T_n^{ref, on(max)}} \quad (6)$$

$$\forall T_{n,j}^{ref, on} \geq x_{ref, on} \cdot T_n^{ref, on(max)}$$

Moreover, the priority value for turning on the refrigerator is given by

$$\sigma_{n,j}^{ref, on} = 1 - \frac{T_{n,j}^{ref, off(max)} - T_{n,j}^{ref, off}}{T_{n,j}^{ref, off(max)}} \quad (7)$$

$$\forall T_{n,j}^{ref, off} \geq x_{ref, off} \cdot T_{n,j}^{ref, off(max)}$$

where ' $x_{ref, on}$ ', ' $x_{ref, off}$ ', ' $x_{ac, on}$ ' and ' $x_{ac, off}$ ' can be determined using experiments for different models. In this paper, the values of ' $x_{ref, on}$ ', ' $x_{ref, off}$ ', ' $x_{ac, on}$ ' and ' $x_{ac, off}$ ' are taken as 0.8, 0.96, 0.75 and 0.94 respectively. The impact of changes in the values of ' $x_{ref, on}$ ' and ' $x_{ac, on}$ ' is also studied in the following section. It is to be noted that the above values should be selected in a manner such that the reduction in turn ON time is equal to reduction in turn OFF time.

With these conditions, the VSC (power) at any instant or interval can be calculated as below:

$$p_j^{vsc, d} = p_n^{ref} + p_n^{ac} \quad (8)$$

$$\forall T_{n,j}^{ref, on} \geq x_{ref, on} \cdot T_n^{ref, on(max)} \text{ and } \forall T_{n,j}^{ac, on} \geq x_{ac, on} \cdot T_n^{ac, on(max)}$$

$$p_j^{vsc, c} = 0 - (p_n^{ac} + p_n^{ref}) \quad (9)$$

$$\forall T_{n,j}^{ac, off} \geq x_{ac, off} \cdot T_n^{ac, off(max)} \text{ and } \forall T_{n,j}^{ref, off} \geq x_{ref, off} \cdot T_n^{ref, off(max)}$$

where $p_j^{vsc, d}$ and $p_j^{vsc, c}$ are the estimated VSC (discharging and charging powers, respectively) available from refrigerators and air conditioners during the interval ' j '. p_n^{ref} is the power consumption of the n th refrigerator during turn ON period and p_n^{ac} is the power consumption of the n th air conditioner during turn ON period. $j = 1, 2, 3, \dots, k$ are the intervals during which the solar PV output is available. Equation (8) represents the virtual power that can be generated by switching off the appliances and (9) represents the power that can be consumed by switching on the appliances.

The process of achieving and utilising the VSC (discharging and charging powers) is governed by the following equations:

$$p_j^{\text{bpd}} = p^{\text{ave_pv_op}} - p_j^{\text{pv_op}} \quad (10)$$

$$p^{\text{ave_pv_op}} = \frac{\sum_{j=1}^k p_j^{\text{pv_forecasted_op}}}{k} \quad (11)$$

where p_j^{bpd} is the power required from the battery/energy storage system (ESS) during interval j to supply $p^{\text{ave_pv_op}}$ during all the intervals $j = 1, 2, 3, \dots, k$. $p_j^{\text{pv_forecasted_op}}$ is the forecasted solar PV output. $p_j^{\text{pv_op}}$ is the actual solar PV output during interval j . One of the preferred ways to handle the fluctuations in solar PV generation is to supply the difference in power required by the load using a battery/ESS. In this paper, the evaluation is carried out for the case where the power required by load/grid from the solar PV is fixed to the forecasted average power generated by the solar PV ($p^{\text{ave_pv_op}}$) on the given day. The average solar PV output $p^{\text{ave_pv_op}}$ for the period of operation can be determined using the methods explained in [26] or [27]. It is to be mentioned that the effectiveness of the algorithm depends on the accuracy of $p_j^{\text{pv_forecasted_op}}$. However, the mismatch in predicted and actual output could easily tackle the ESS. In this paper, both $p_j^{\text{pv_forecasted_op}}$ and $p_j^{\text{pv_op}}$ are same and calculated using irradiance data.

The pseudo-code of the algorithm used for achieving and utilising the VSC (discharging and charging power) given below.

Pseudo-code:

1. **Calculate** $p^{\text{ave_pv_op}}$ and p_j^{bpd} .
2. **If** $p_j^{\text{bpd}} > 0$, **count** the number of refrigerators ($N_{\text{off}}^{\text{ref}}$) that can be turned off to obtain virtual storage capacity (VSC).
3. **Else go to** step 8.
4. **For** 1 to $N_{\text{off}}^{\text{ref}}$, **if** $p_j^{\text{bpd}} > 0$, **then** $n = n$ with $\max(\sigma_{n,j}^{\text{ref, off}})$, $p_j^{\text{bpd}} = p_j^{\text{bpd}} - p_n^{\text{ref}}$, **Else go to** step 8.
5. **If** $p_j^{\text{bpd}} > 0$, **count** the number of air conditioners ($N_{\text{off}}^{\text{ac}}$) that can be turned off to obtain VSC.
6. **Else go to** step 8.
7. **For** 1 to $N_{\text{off}}^{\text{ac}}$, **if** $p_j^{\text{bpd}} > 0$, **then** $n = n$ with $\max(\sigma_{n,j}^{\text{ac, off}})$, $p_j^{\text{bpd}} = p_j^{\text{bpd}} - p_n^{\text{ac}}$, **Else go to** step 8.
8. **If** $p_j^{\text{bpd}} < 0$, **count** the number of air conditioners ($N_{\text{on}}^{\text{ac}}$) that can be turned on to obtain VSC.
9. **Else go to** step 14.
10. **For** 1 to $N_{\text{on}}^{\text{ac}}$, **if** $p_j^{\text{bpd}} > 0$, **then** $n = n$ with $\max(\sigma_{n,j}^{\text{ac, on}})$, $p_j^{\text{bpd}} = p_j^{\text{bpd}} + p_n^{\text{ac}}$, **else go to** step 14.
11. **If** $p_j^{\text{bpd}} < 0$, **count** the number of refrigerators ($N_{\text{on}}^{\text{ref}}$) that can be turned on to obtain VSC.
12. **Else go to** step 14.
13. **For** 1 to $N_{\text{on}}^{\text{ref}}$, **if** $p_j^{\text{bpd}} > 0$, **then** $n = n$ with $\max(\sigma_{n,j}^{\text{ref, on}})$, $p_j^{\text{bpd}} = p_j^{\text{bpd}} + p_n^{\text{ref}}$, **else go to** step 14.
14. **End.**

With the proposed algorithm p_j^{bpd} is reduced by $p_j^{\text{vsc, d}}$ or $p_j^{\text{vsc, c}}$. The algorithm determines $N_{\text{off}}^{\text{ref}}$ and $N_{\text{off}}^{\text{ac}}$ when p_j^{bpd} has negative value, i.e. there is power deficit in solar PV generation. $N_{\text{off}}^{\text{ref}}$ and $N_{\text{off}}^{\text{ac}}$ are the number of refrigerators and air conditioners which satisfy the conditions $T_{n,j}^{\text{ref, on}} \geq x_{\text{ref}} \cdot T_n^{\text{ref, on(max)}}$ and $T_{n,j}^{\text{ac, on}} \geq x_{\text{ac}} \cdot T_n^{\text{ac, on(max)}}$, respectively. As first resort, the refrigerators with minimum priority, i.e. maximum value for $\sigma_{n,j}^{\text{ref, off}}$ is turned OFF. The procedure is repeated either until the value of p_j^{bpd} is zero or $N_{\text{off}}^{\text{ref}}$ refrigerators are turned OFF.

Once all the refrigerators are turned OFF, air conditioners with minimum priority, i.e. maximum value for $\sigma_{n,j}^{\text{ac, off}}$ is turned OFF. The procedure is repeated either until the value of p_j^{bpd} is zero or $N_{\text{off}}^{\text{ac}}$ air conditioners are turned OFF. If p_j^{bpd} is < 0 after the shutting down all possible appliances, command is given to energy storage management system to dispatch the remaining power. When p_j^{bpd} is > 0 , command is given and the reverse process is carried out. In this case, air conditioners are turned on first followed by the refrigerators as indicated in the pseudo-code. This is due to the fact that the refrigerators have higher time constant compared with air conditioners. The turn ON and turn OFF operation is controlled by controlling the switching signals of relays powering the appliances and is given below:

$$x_{n,j}^{\text{ref}} = \begin{bmatrix} x_{1,j}^{\text{ref}} \\ x_{2,j}^{\text{ref}} \\ \vdots \\ x_{n,j}^{\text{ref}} \end{bmatrix} \quad (12)$$

$$x_{n,j}^{\text{ac}} = \begin{bmatrix} x_{1,j}^{\text{ac}} \\ x_{2,j}^{\text{ac}} \\ \vdots \\ x_{n,j}^{\text{ac}} \end{bmatrix} \quad (13)$$

where $x_{n,j}^{\text{ref}}$ and $x_{n,j}^{\text{ac}}$ is 1 for the n th refrigerator and n th air conditioner, respectively, during turn ON period, $x_{n,j}^{\text{ref}}$ and $x_{n,j}^{\text{ac}}$ is 0 for the n th refrigerator and n th air conditioner, respectively, during turn OFF period. Important aspect of the algorithm is that only the ON time or OFF time is modified and the number of turn ON and turn OFF operations is not changed. Hence, the algorithm has zero impact on life of the appliances.

4 Simulation studies

4.1 Typical residential smart grid system

The residential smart grid in Singapore would typically have five HDB buildings [28], which are built close to each other and form an HDB block. Each building typically will have 90 units. Hence, a total of 450 units are considered for simulation studies. It is assumed that 30% of the households will operate the air conditioners during daytime (as many will be at working place during this period) and all the refrigerators are available for control. The VSC (discharging and charging power) increases with the number of air conditioners and refrigerators available for control. 70 kW_{peak} solar PV is considered to be installed on the rooftop of all the HDB buildings. The intermittent solar PV output can be observed from the typical output of a PV system as shown in Fig. 4. The typical output shown in Fig. 4 is for all PVs installed in all the five HDB buildings considered (350 kW_{peak}), any change in the number of HDBs considered for analysis will have a proportional impact on the analysis.

The power required during the low-irradiance period is also shown. Whenever the output power is greater than $p^{\text{ave_pv_op}}$ the excess power is stored in the ESS. The time interval ' j ' is considered as 1 min each for the simulation studies. In this paper, it is considered that ESS is a stationary battery system with high-energy density and power density. Lithium iron phosphate (LFP) batteries are considered for the application, characteristics of Model-SP-LFP60AHA (A) LFP cells from the supplier 'SinoPoly' is considered for the simulations. Associated power electronic converters are also considered in the simulations. Function of the ESS is to handle (charge/discharge) the difference in power between $p^{\text{ave_pv_op}}$ and $p_j^{\text{pv_op}}$.

Fig. 5 illustrates the simulated load demand of air conditioners and refrigerators for the considered system of five HDB buildings. It can also be observed that with the proposed method, the load demands of air conditioners and refrigerators are either reduced or

Fig. 4 Typical output of solar PV system

Fig. 5 Simulated load demand of air conditioners and refrigerators for the considered system of five HDB buildings

Fig. 6 VSC

Fig. 7 CDF plot for percentage of VSC available with respect to the power required

increased to obtain a virtual storage. The VSC (power) obtained can be used as a first resort for overcoming the intermittency and remaining power can be obtained from the ESS. For example, the average power required during the period 09:00–11:30 h for a typical day as shown in Fig. 5 is calculated to be 68.28 kW. The average VSC (power) achieved during the same interval is 15.53 kW. The VSC (power) obtained is 22.74% of the required power and contributes to significant reduction in the amount of energy drawn from the ESS.

The mean percentage of VSC (power) that was achieved for the typical day considered (from 09:00 to 17:00 h) is 26.02%. The VSC (power) achieved with the proposed method is shown in Fig. 6. Negative power indicates the charging mode of the ESS.

Although the obtained VSC (power) is variable and depends on the status of the air conditioners and refrigerators, it can reduce the energy required from the ESS by a significant amount. Furthermore, the VSC (power) varies with the number of air conditioners and refrigerators available for control as well as their status at different times during the day. It is to be noted that the ESS is inevitable for buffering the variations and proposed method only reduces the energy drawn from the ESS or supplied to the ESS.

4.2 Performance analysis

The effectiveness of the proposed method can be determined by repeating the experiment for a period of 1 year. The output power of the solar PV system considered for the simulation is determined for period between January 2011 and December 2011 using the real irradiance data. The temperature data of the same period is used as the ambient/outside temperature. The power required from ESS is calculated using (10). The load demands of air conditioners and refrigerators are extracted from the experimental results presented in [18] and randomisation of ON and OFF periods of both the appliances. In case of actual application, the data for ON and OFF periods are to be collected directly from the sensors. Using the strategy proposed in Section 3, the operation of air conditioners and refrigerators are modified and the VSC (power) obtained is calculated and is compared with the power required during the low-irradiance period.

Fig. 7 shows the cumulative distribution function (CDF) plot for the percentage of VSC (power) available with respect to the power required for a period of 1 year. It can be observed from Fig. 7 that the probability of the VSC (power) being >10% is very high and is 0.9. This shows that for 90% of the time, minimum 10% savings in the required storage capacity can be achieved using the proposed strategy. Hence, the proposed strategy can be effectively employed for residential high-rise buildings.

The percentage of interruptions/appliance/day is an important criterion for determining the effectiveness of the proposed strategy. It is given by

$$\text{percentage of time interrupted} = 1 - \frac{A}{B} \quad (14)$$

where

$$A = \sum \text{turn - on period of the appliance with the proposed method}$$

$$B = \sum \text{turn - on period of the appliance under normal operation}$$

This is attributed to the fact that the occupant comfort should not be compromised in any case for the strategy to be successful. Even with the values for ' $x_{\text{ref,on}}$ ', ' $x_{\text{ref,off}}$ ', ' $x_{\text{ac,on}}$ ' and ' $x_{\text{ac,off}}$ ' considered in Section 3; not all the appliances encounter interruptions at all instants. It can be observed from Fig. 8 that the interruption time is ~ 8.5 and 2.5% for air conditioners and refrigerators, respectively. The above two factors indicate that with a minor reduction in the operation time of air conditioners and refrigerators (ON time), the proposed strategy can achieve a significant VSC. As well as it can be observed from Fig. 8 that the reduction in operation time is executed in a fair manner as percentage reduction in ON time is approximately same for all the devices. It can be observed that the percentage of interruption time for air conditioners is higher than the percentage of interruption time for refrigerators. This is due to the fact that the number of refrigerators available for control is higher than the number of air conditioners available for control. Any change in the number of appliances available for control will affect the percentage of interruption time. However, the impact on the operation (temperature) of the devices is to be examined. Cumulative probability (from CDF) of the temperature inside the room (for air conditioners) without and with the proposed method for a period of 1 year is shown in Fig. 9. It can be observed from Fig. 9 that a cumulative probability (from CDF) is higher in the

Fig. 8 Percentage of interruptions for air conditioners and refrigerators

Fig. 9 CDF plot for temperature inside the room with and without the proposed algorithm

Fig. 10 Turn ON and turn OFF periods with and without proposed method

Table 1 Impact of values of $x_{ac,on}$ on the performance of the proposed algorithm

Values $x_{ac,on}$	Cumulative probability of percentage of VSC (power) >10%	Percentage of interruptions
0.80	0.9	8.5
0.85	0.85	7.9
0.90	0.82	7.2

lower temperature range with the proposed method. However, with reduction in operation time (by 8.5%) according to Fig. 8, a reverse phenomenon is expected. The rationale behind the behaviour can be explained using Fig. 10.

From Fig. 10, it can be observed that there is a reduction in total number of minutes for which the air conditioners are turned ON during the ON period; however, there is an increase in total number of minutes for which the air conditioners are turned ON during the OFF period. The above fact can also be correlated to the equivalent positive and negative VSCs in Fig. 6. Furthermore, the reduction in total number of minutes for which the air conditioners are turned ON during the ON period occurs during low-irradiation period, when the ambient temperature is expected to be lower. Also, increase in total number of minutes for which the air conditioners are turned ON during the OFF period occurs during high-irradiation period, when the ambient temperature is expected to be higher. The

combinational impact of above two factors results in increase ON period during high-irradiation period and vice versa; consequently an increased cumulative probability (from CDF) in the lower temperature range is observed.

In the proposed algorithm, the deadbands are controlled by the appliances themselves, hence there is feasibility for maintaining the temperature profile within the deadbands. In this paper, the loads are operated in such a manner that the upper deadband is not violated. However, the limit on the lower deadband is removed so as to utilise the thermal storage of the appliances. This can be visualised from Fig. 9; the cumulative probability (from CDF) is non-zero for 18.5–19°C which ideally should have been zero. It is due to the fact that when the ON time is controlled (i.e. when the operation time is decreased during low irradiance) the temperature is within the deadband but greater than the lower cut-off, whereas when the OFF time is controlled (i.e. when the operation time is increased during high irradiance) the temperature is supposed to go below the lower cut-off to facilitate the extended operation. Since the proposed algorithm lets the appliances to work slightly below the lower cut-off temperature, reducing the probability of the appliances working below the lower cut-off is crucial for the successful adoption of the proposed method. The priority values are such that the appliances are turned OFF for longer duration will be turned ON first and vice versa, which reduces the probability of number of instances the appliances are working outside the deadband. This can be observed from Fig. 9, which gives cumulative probability (from CDF) based on simulations for 1 year.

The values of cumulative probability (from CDF) of percentage of VSC (power) available and percentage of interruptions depend on the value of $x_{ac,on}$ ($x_{ref,on}$ for refrigerator). An analysis for impact of values of $x_{ac,on}$ on the performance of the proposed algorithm is presented in Table 1. It can be observed that the cumulative probability (from CDF) of percentage of VSC (power) available and percentage of interruptions decrease with increase in value of $x_{ac,on}$. A similar analysis is applicable for refrigerator as well. The VSC energy ($E_{vsc,j}$) available in any particular interval 'j' can be obtained using the below equation:

$$E_{vsc,j} = \frac{\left\{ \left(\sum T_{n,j}^{ref, on(max)} - T_{n,j}^{ref, on} \right) \cdot p_n^{ref} + \left(\sum T_{n,j}^{ac, on(max)} - T_{n,j}^{ac, on} \right) \cdot p_n^{ac} \right\}}{60} \quad (15)$$

$$\forall T_{n,j}^{ref, on} \geq x_{ref, on} \cdot T_{n,j}^{ref, on(max)} \text{ and}$$

$$\forall T_{n,j}^{ac, on} \geq x_{ac, on} \cdot T_{n,j}^{ac, on(max)}$$

However, as only energy required for the power mismatch is to be derived from the VSC, all the available energy need not be supplied. Hence, the value cannot be used for calculating the cost savings.

4.3 Cost savings

VSC will also help in reducing the operation cost as less amount of power is discharged from the ESS during low irradiance and charging of ESS is reduced during high irradiance. The cost savings has two parts and is given by

$$C_s = ((1 - \eta_{conv}) \cdot E_{vsc}) \cdot \text{Cost}_E + \left(\frac{E_{vsc}}{C_{ES} \cdot N} \right) \cdot \text{Cost}_{ES} \quad (16)$$

where C_s is the savings in cost as a result of the proposed method, η_{conv} is the charging/discharging efficiency of the converters used, E_{vsc} is energy obtained from the VSC (power), C_E is the cost of the energy/kWh, C_{ES} is the capacity of the ESS used, N is the total number charge/discharge cycles of the ESS and Cost_{ES} is the cost of the ESS. The first part is to represent the cost savings in the energy losses during charging and discharging processes of the ESS. The second part is to represent the cost savings that results from reduction in the loss of life of ESS. The cost savings obtained for 1 year is S\$ 20,946. The values of parameters in (15) are

Table 2 Impact of values of $x_{ac,on}$ and $x_{ref,on}$ on the cost savings

Values $x_{ac,on}$	Cost savings in S\$	Values $x_{ref,on}$	Cost savings in S\$
0.80	20,946	0.75	20,946
0.85	19,826	0.80	20,006
0.90	18,026	0.85	19,226

Fig. 11 Histogram with normal fit for VSC energy over a period of 1 year

$\eta_{conv} = 0.85$, E_{vsc} (obtained simulations), $C_E = 0.2$ (mean price of electricity obtained from SP services), $C_{ES} = 70$ kWh, $N = 2500$ and $Cost_{ES} = S\$ 100,000$ (obtained based on quotations from battery suppliers for LFP batteries). The cost saving for individual parts are S\$ 1044 (losses) and S\$ 19,902 (energy storage life). It can be observed that the significant savings are due to the savings in cost of energy storage. It can be observed that the cost savings due to savings in energy losses contributes only around 5% and the remaining is due to the cost savings in the life of ESS. Any significant reduction in the pricing of the ESS would result in corresponding reduction in savings that could be achieved by the proposed algorithm. A reverse effect, i.e. any increase in the price of electricity would result in corresponding increased savings from the proposed algorithm; however, the impact of ESS pricing is the crucial factor.

However, the cost savings shown is for test case, where the values of ' $x_{ref,on}$ ', ' $x_{ref,off}$ ', ' $x_{ac,on}$ ' and ' $x_{ac,off}$ ' are taken as 0.8, 0.96, 0.75 and 0.94, respectively. Table 2 shows the variations in cost savings with changes in values of ' $x_{ac,on}$ ' and ' $x_{ref,on}$ '. It is to be noted that while changing ' $x_{ac,on}$ ' the values of ' $x_{ref,on}$ ' and ' $x_{ref,off}$ ' are not changed but corresponding changes in ' $x_{ac,off}$ ' is implemented such that the reductions in ON time and OFF are proportional. It can be observed that increase in ON time results in reduction of cost savings in both the cases. However, the scale of reduction is different in both the cases due to the difference in power rating of the appliances. Apart from the cost savings due to usage of battery, there would be cost savings as a result of reduced replacement of ESS and prolonged life. However, such savings are subjective to many economic factors and hence are not included in the calculations.

Besides, with DRM participation, the ESS could be resized to reduce the initial investment cost. However, the cost savings described above will reduce proportionally in case of ESS with reduced capacity. Using the same simulations in Section 5.2 (Fig. 7), the mean VSC (energy) available is calculated for a period of 1 year and the results are shown in Fig. 11. From Fig. 11, it can be inferred that the capacity of ESS can be reduced by 10% with participation from DRM and corresponding cost reduction in initial investment.

5 Conclusion

In this paper, an algorithm for DRM of loads with large time constant was proposed. The algorithm is priority-based algorithm and is capable of generating a VSC. The VSC generated has various applications; one such is for levelling of intermittent output of renewable energy. In this paper, simulation studies for utilising the VSC generated to partially level the intermittent output from solar PVs were carried out. A typical case of residential multi-

storey buildings with solar PV was considered. Various performance analyses were carried out and the results were presented. It was observed that the proposed algorithm was capable of reducing the energy required from ESS by a significant amount. The above advantage was achieved without compromising on the performance. Furthermore, the amount of interruption was fairly distributed among all the appliances available for control. A cost-benefit analysis for considered system revealed that even with little reduction in operation time of the appliances, a significant cost saving could be achieved. Moreover, the majority of the savings is due to the reduction of energy usage from the ESS rather than the energy savings. Furthermore, as the simulation studies were based on data-driven simulations, the proposed method can be easily implemented with minimal modification and it is also feasible to implement the proposed method with the existing technology.

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