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A systemic model predictive control based on adaptive power pinch analysis for load shifting and shedding in an isolated hybrid energy storage system

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Abstract: This paper presents a novel systemic algorithm based on conservative power pinch analysis principles using a computationally efficient insight-based binary linear programming optimization technique in a model predictive framework for integrated load shifting and shedding in an isolated hybrid energy storage system. In a receding 24-hour predictive horizon, the energy demand and supply are integrated via an adaptive power grand composite curve tool to form a diagonal matrix of predicted hourly minimum and maximum energy constraints. The intgrated energy constraints must be satisfied recursively by the binary optimisation to ensure the energy storage's state of charge only operates within 30% and 90%. Hence, the control command to shift or shed load is contingent on the energy storage state of the charge violating the operating constraints. The controllable load demand is shifted and/or shed to prevent any violations while ensuring energy supply to the most critical load without sacrificing the consumers' comfort. The proposed approach enhances efficient energy use from renewable energy supply as well as limits the use of the Hydrogen resources by a fuel cell to satisfy controllable load demands which can be shifted to periods in the day with excess renewable energy supply.

Keywords: *Binary-linear programming optimization, Demand side management, Model predictive control, Power pinch analysis*

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Nomenclature	
BAT	Battery
C_l	The capacity of accumulator l
DSL	Diesel generator
EL	Electrolyzer
FC	Fuel cell
HT	Hydrogen Tank
$SOAcc$	Accumulator or energy storage
LD_C, LD_{NC}	Controllable load and uncontrollable load respectively
$SOAcc_l^n$	State of accumulator l
S_{Lo}	Lower pinch limit or utility
S_{Up}	Upper pinch limit or utility
$PGCC$	Power grand composite curve
$W1, W2$	Penalty weights for wattage running cost and preference index respectively
WT	Water tank
Δk	Time interval
$x_i(k)$	Binary variable for the state of the i^{th} dispatchable unit
k	Time interval in the predictive horizon
l	Accumulator
i,j	Matrix row and column
h	hour

1. INTRODUCTION

Demand-side management (DSM) could be described as the adjustment of consumer demand for energy, applying various techniques to encourage less energy usage during peak electricity demand hours. Load shifting as a concept can be described as one of the main aspects of demand-side management. Load shifting is the movement of electrical energy consumption from one time period to another to reduce energy consumption. Since there is a growing increase in electrical power usage especially in residential buildings during peak demand periods, the need to reduce energy consumption during these periods cannot be overemphasized as not only the utility companies but also consumers will benefit [1,2].

Generally, load shifting is achieved by controlling the operational status of energy-consuming devices and time. To identify opportunities for consumer-driven load shifting in commercial and industrial buildings, several metrics showed how site peak can be easily reduced considering some factors like typical building operations [3,4]. Besides, an analysis of load reduction and load shifting in industrial and commercial buildings under flexible electricity pricing plans was presented in Ref. [5]. The authors suggested several methods for load shifting and reduction of peak electricity demands. A robust optimization method to manage uncertainties associated with the use of air conditioners and water heaters was proposed in [6], using cost and trade-off schemes, without renewable energy systems integration. Spatial load migration is also seen as an alternative form of demand-side management compared to load shifting and load shedding as presented in [7].

Several optimal control techniques have been performed by researchers to achieve energy efficiency and load shifting through the coordination of the operational status of pumps and time-period in pumping stations [8]. In Ref. [9], a dynamic programming optimization was successfully used to study the control of heating systems in buildings and optimize energy cost during winter, by shifting a load of heating to off-peak hours. A model for global solar radiation was presented in [10], used as a part of a mobile load demand management application that helped in maximizing utilized energy for heating systems, thereby reducing cost and emissions. The combination of Electric System Cascade Analysis with load shifting was used to reduce energy consumption in a renewable distributed energy generation system as presented in [11], the application of the model in the case study showed a 3.1% reduction for the solar installation area and 3.9% reduction for the biomass power generation.

Furthermore, since smart grids are considered an important feature in future energy scenarios, several measures have been proposed to promote the demand side response in smart grids [12]. The authors in Ref. [13] proposed that smart grid designs must recognize smart users, who are actively engaged in energy consumption as critical as what is proposed by demand-side management. A smart grid optimization model based on demand-side management was also proposed in [14], by defining agents responsible for load, generation and storage management. The authors showed that the model when applied to the grid loads and Electric vehicle charging, helped in allocating demand more efficiently.

A proposed combined multi-objective dynamic economic and emission dispatch model with demand-side management (DSM) was presented in [15], to take advantage of the benefits of DSM for utility and generation. The DSM used a day ahead-based load shifting technique used for handling domestic loads. Also, a day-ahead self-healing scheduling approach in isolated networked microgrid systems presented in [16] was based on a two-level energy management system (EMS). Results showed the efficiency of the EMS model in enhancing the network and reducing the operational cost of the microgrid system. The authors in [17] proposed a demand-side response method for smart microgrids mainly for controllable domestic loads in the case of renewable energy penetration. The method showed improved flexibility of the controlled loads. A set of DSM approaches used to enhance flexibility in the energy management system of an off-grid system with renewable energy sources was presented in Ref. [18].

The authors in [19] discussed recent progress in energy efficiency policy frameworks from the demand-side management on the part of the utility towards the reduction of carbon emission footprints. In Ref. [20], DSM ensured the reduction of peak load demand in smart grids and a perspective on the interaction between non-ideal grids and LED lamps in residential buildings was presented in [21], which by extensive analysis of voltage harmonics, sustained abnormal voltage, supply frequency variations on LED lamps and showed its effect on the LED lighting program adopted worldwide. A model of hybrid Particle Swarm optimization algorithm with Sinusoidal and Cosine acceleration coefficient in [22] showed a reduction in peak load, reduction in consumer's energy bill and production cost savings in a microgrid.

Similarly, in [23] the energy management of microgrids was achieved using a demand-response program that incorporated artificial intelligence (AI) based particle swarm optimization technique, to minimize the fuel cost of a distributed generation (DG) while concurrently accounting for uncertainties. In [24], the grey wolf accretive satisfaction algorithm based on a binary grey wolf optimization was successfully used to obtain an optimal switching pattern of domestic appliances thereby enabling maximum customer satisfaction under a limited budget. The authors in [25] proposed a resilient home energy management system, which coordinates domestic energy resources during planned outages using scenario analysis techniques to tackle the stochastic behavior of renewable energy sources.

An algorithm for instantaneous load shifting was proposed in Ref. [26]. The algorithm was a practical linearized demand control algorithm to run regularly and promptly as new hourly price signals become obtainable using a realistic price simulation model. The work showed that reinforcement learning was a good alternative to other well-known methods. The use of reinforcement learning algorithms for load shifting in a cooling system was presented in [27], where, two algorithms were used to control the operation of the central cooling system for price changes. The results showed 14% weekly cost savings.

In Ref. [28], reinforcement learning was used for energy management in a stand-alone hybrid energy storage system (HESS) considering uncertainty. The authors used reinforcement learning based on adaptive power pinch analysis (PoPA) for energy management. Power pinch analysis, which is a conservative approach for targeting energy deficit as well as waste recovery of surplus or excess energy was used in [29] as a day ahead predictive energy management strategy for the control of HESS. Furthermore, PoPA was used in Refs. [30,31] for off-peak load shifting with optimal storage sizing in a standalone hybrid energy storage system. The proposed load shifting approach in the case study in [30] showed that a reduction of about 30% in storage size was achieved.

1.1. Problem Statement and Motivation

In Ref. [32] an elegant mathematical formulation for load shifting in a home energy management system was achieved using linear optimization in which a running stage cost and constant constraints were used to optimize the system. However, since the approach in Ref. [32] was based on one-time step optimization with no predictive horizon, hence the algorithm was disposed to sub-optimality. Furthermore, to ensure the Bellman's optimality [28] to obtain the least global stage cost, the entire control horizon must be analyzed within a predictive horizon along with any interdependences of the dynamic constraints on the entire energy system.

1.2. Proposed Algorithm

This paper proposes at a systems-level a systemic load shifting model predictive control (MPC) algorithm formulated as a binary (mixed) linear optimization (written in MatLab 2021 script) which incorporates the concept of the conservative adaptive power pinch analysis approach [28] in a predictive horizon with solutions inferred hourly in the control horizon. The systemic formulation is not only computationally efficient but also offers the advantage of versatility as it can be extended to optimize varied problems involving optimal load (electricity, water irrigation etc.) scheduling. However, as a case study, the proposed load shifting DSM MPC-adaptive PoPA algorithm is deployed in an isolated hybrid energy system [28,33,34] as shown in Fig. 1, which consists of photovoltaic panels (PV), a backup diesel generator (DSL), consumer load demands (LDs), fuel cell (FC), electrolyzer (EL), battery storage (BAT), water (WT) and hydrogen storage tanks (HT). The DC/DC and AC/DC converters have been omitted in Fig. 1 for conciseness. The violation of the lower and upper operating constraints of the battery and the number of unserved controllable loads are used as evaluation indices to ascertain the performance of the proposed algorithm and in contrast to the consumers' default operating condition of the controllable load demand.

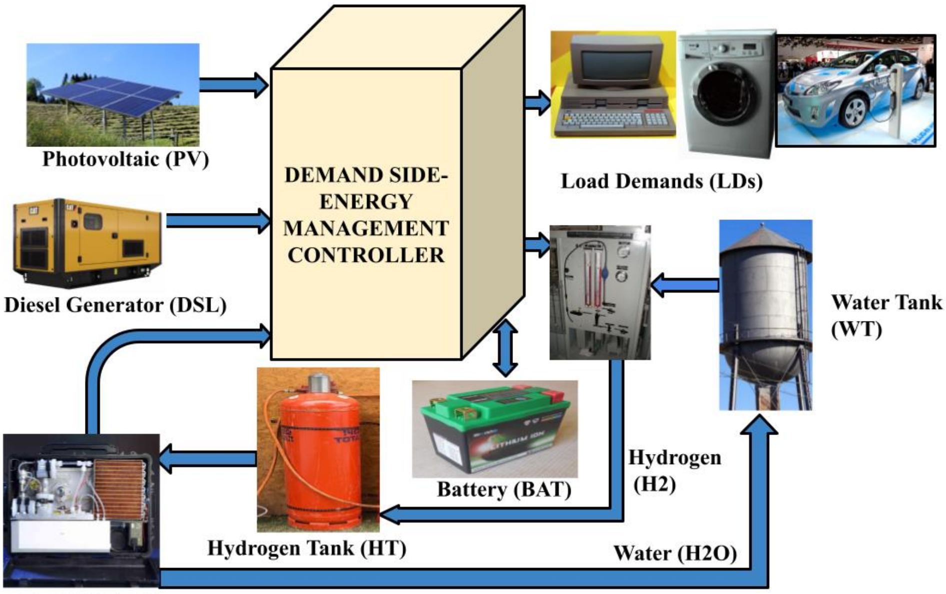


Figure 1. Isolated hybrid energy storage system used as experimental case study [28, 33, 34].

2. METHODOLOGY

The net energy in the system is modelled in consistency with recent works [28,33,34] but with the DSL, EL and FC deactivated since they conservatively operate to serve the uncontrollable load LD_{Nc} only, while the controllable load LD_{Nc} is served by the PV. Hence, during the operation of the LD_c shifting/scheduling algorithm, the mathematical expression for the net energy in the BAT with the DSL, EL and FC deactivated is reduced or simplified to the following:

$$SOC(k) = SOC(k-1) + \sum_{k=1}^{N} [PV(k) - (LD_c(k) + LD_{Nc}(k))\,] * \Delta k / C_l \qquad l \in [BAT] \qquad (1)$$

Here, hourly time interval is the storage capacity C_l and subscript $l \in [BAT,\ WT, HT]$ in general but for load shifting l refers to the BAT, $SOC(k-1)$ are the initial percentage state of charge in the battery and $SOC(k)$ is the percentage state of charge of the BAT at time step k (such that the net power from the PV and the loads LDs $\in [LD_c, LD_{Nc}]$ that is both the controllable $LD_c(k)$ and uncontrollable load $LD_{Nc}(k)$is expressed as follows:

$$P(k:N) = \sum_{k=1}^{N} PV(k) - (LD_c(k) + LD_{Nc}(k)) \qquad (2)$$

and in an elegant systemic representation as follows:

$$P(k{:}N) = \sum_{k=1}^{N}\sum_{i=1}^{n}(PV(k) - (LD_c(k) + LD_{Nc}(k))\,_i \quad (3)$$

where, subscript i denotes the i^{th} number of array of devices, $i \in [1{:}n]$, $P(k{:}N)$ represents the accumulated energy from time k to the end of the horizon N, $PV(k)$ denotes the energy supplied by the PV at time interval k, $LD_c(k)$ represents the energy demand ensured from the controllable load device which can be shifted and/or de/activated by the proposed load shifting DSM algorithm. $LD_{Nc}(k)$ denotes the energy demanded by the non-controllable load which must remain ON or energized. By extension in matrix form, let P_{ij} defined in Eq. (3) be a left diagonal matrix of the predicted power flow in the HESS from time instance k to N as follows:

$$\sum_{i=1}^{N}\sum_{j=1}^{k} P_{ij} = \begin{bmatrix} P_{1,1}(k) & 0 & 0 & 0 & 0 \\ P_{2,1}(k) & P_{2,2}(k+1) & 0 & 0 & 0 \\ P_{3,1}(k) & P_{3,2}(k+1) & P_{3,3}(k+1) & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & 0 \\ P_{i,1}(k) & P_{i,2}(k+1) & \cdots & P_{i,j-1}(N-1) & P_{i,j}(N) \end{bmatrix} [X_i] \quad (4)$$

In Eq. **(**4), X_i is a nx1 vector of ones of i elements in the P_{ij} matrix only for regularization. Thus, the diagonal P_{ij} aggregated over $i{:}j$ similarly, infers the cumulative energy in the system which must be within the operating limits.

The decision taken which might de/activate the controllable load is based on a cost function, which is the weighted priority scale of preference for load usage and the necessary constraints needed to prevent violation of the constraints of the system**.** The cost function is such that the energy (or cumulative net power per time) to be consumed by the controllable load is minimized. Therefore, contingent on the prediction of the SOC of BAT, a decision to either activate or de-activate the controllable load, such that the predicted energy level when excess or insufficient and would not lead to a violation of the SOC of BAT upper or lower limits respectively is imperative. Furthermore, the energy requirement of controllable loads which have strict operational time dependences is treated as a single energy utility or entity.

Furthermore, the objective of the optimization is to minimize the global cost of electricity usage between different appliances (such as washing machines, heaters, air conditioners etc.) while satisfying the consumers' load demand. Thus, satisfying the consumers' load demand is achieved by shifting and scheduling load appliances based on a weighted priority index on a scale of 0 - 1 and the availability of energy supply is represented mathematically as follows:

$$min \sum_{k=1}^{N}\sum_{i=1}^{n} c_i^T\, x_i\,.\,t_i(k)\ , \qquad x \in \{0,1\} \quad (5)$$

Where, c_i^T, x_i and t_i is the cost, the binary decision variables and time of use of the $i^{th} \in [1{:}n]$ appliances n respectively at each time step k.

Subject to upper S_{UP} and lower S_{LO} pinch constraints:

$$\frac{1}{C_l}\sum_{i=1}^{n}\sum_{j=k}^{m} a_{ij}\,.\,x_j\,.\,t_i(k) \le \left[SoAcc(k-1)_i + \frac{1}{C_l}\sum_{i=1}^{N}\sum_{j=k}^{i} diag([P_{i\,j}\,(k)]) \right] - S_{UP} \quad (6)$$

$$-\frac{1}{C_l}\sum_{i=1}^{n}\sum_{j=k}^{m} a_{ij}\,.\,x_j\,.\,t_i(k) \le -\left| SoAcc(k-1)_i + \frac{1}{C_l}\sum_{i=1}^{N}\sum_{j=k}^{i} diag([P_{i\,j}(k)]) \right| + S_{LO}\,, j \in \{k{:}N\} \quad (7)$$

Where, $j \in \{k: N\}$ is the current time step of the horizon which terminates at N.

The cost function c_i^T is defined as a weighted running sum $w1$, and a descending scale of preference index [1 - 5], $w2$ at a k^{th} interval. This is such that for instance at an interval k+5 the cost is the cumulative sum of the energy consumed by an i^{th} appliance from k to $k+4$ in addition with an equivalent scale of preference arbitrarily defined by the consumer such that an index of '5' denotes the least preferred and '1' is the most preferred.

The constraint in Eq. (6) ensures the total energy in the BAT is less than or equal to S_{UP} hence, the upper pinch is not violated, by activating and/ shifting suitable controllable load LD_c accordingly to absorb any excess energy in advance. Similarly, the constraint in Eq. (7) takes cognizance of the lower pinch violation by deactivating and/shifting load the controllable load LD_c to a later but suitable hour of the day.

Thus, Eq. (8) is the expansion of Eq. (6,7) which results in twenty-three in-equality constraints corresponding to the time interval horizon $(k-N)$ as follows which must satisfy the upper S_{UP} and lower S_{LO} operating pinch constraints:

$$S_{LO} \leq \begin{bmatrix} SoAcc(k-1)_i \\ SoAcc(k)_i \\ SoAcc(k+1)_i \\ \vdots \\ SoAcc(N-1)_{i=1:n} \end{bmatrix} - \frac{1}{C_l}\left[\begin{bmatrix} a_{i=1,j=1:n} \cdot x_{j=1:n} \cdot t_{i=1:24} \\ a_{i=2,j=1:n} \cdot x_{j=1:n} \cdot t_{i=2:24} \\ a_{i=3,j=1:n} \cdot x_{j=1:n} \cdot t_{i=3:24} \\ \vdots \\ a_{i=N,j=1:n} \cdot x_{j=1:n} \cdot t_{i=1} \end{bmatrix} + \begin{bmatrix} P_{1,1} \\ P_{2,2} \\ P_{3,3} \\ \vdots \\ P_{i=N,j=N} \end{bmatrix}\right] \leq S_{UP} \tag{8}$$

The load-shifting decision-making variable $x_{j=1:n}$ is contingent on the multiple n^{th} electrical appliances which have a corresponding power rating $a_{i=k:N,j=1:n}$ at time interval $i = k$, for a maximum duration in a N hours receding horizon $t_{i=1:N}$.

$$\sum_{i=1}^{n} x_i \cdot t_i(k) \leq Z_i \tag{9}$$

where the piecewise binary equivalent function of the constraint in Eq. (9) is achieved as follows:

$$Z_i = \left\{ \begin{matrix} 1 & \sum_{k=1}^{N-1} \sum_{i=1}^{n} x_i \cdot t_i(k) \leq W_i \\ 0 & otherwise \end{matrix} \right\} \quad , \quad \forall\, k = 1,2,3, \dots N \tag{10}$$

Such that,

W_i denotes the total number of intervals an i^{th} appliance can be activated and $Z_i$is a binary variable that enables or disables constraint in Eq. (10).

The binary constraint in Eq. (10), enforces a maximum duration for which the i^{th} appliances can be activated contingent on the function in Eq. (11) which attains a 1 (ON) or 0 (OFF) logic state only if the number of activations was less than or greater than the desired number of activations for any i^{th}controllable appliances respectively.

$$x_i = 0 - 1 \tag{11}$$

The equality constraint binary variable expressed in Eq. (12) ensures that the decision variable or logic state is binary 0 or 1 only. Thus, the controllable load as defined by the consumer is de/activated by x_i as follows:

$$LD_c(k)_i \triangleq [LD_c(k)_{i=1} + LD_c(k)_{i=2}, \dots + LD_c(k)_{i=n}] * \begin{bmatrix} x_{i=1} \\ x_{i=2} \\ \vdots \\ x_{i=n} \end{bmatrix}, \forall_{k=1,2,3,..N-1} \text{ and } i \in [1-n] \quad (12)$$

The flow chart for the load shifting and shedding based on the MPC-based adaptive PoPA is shown in Fig. 2.

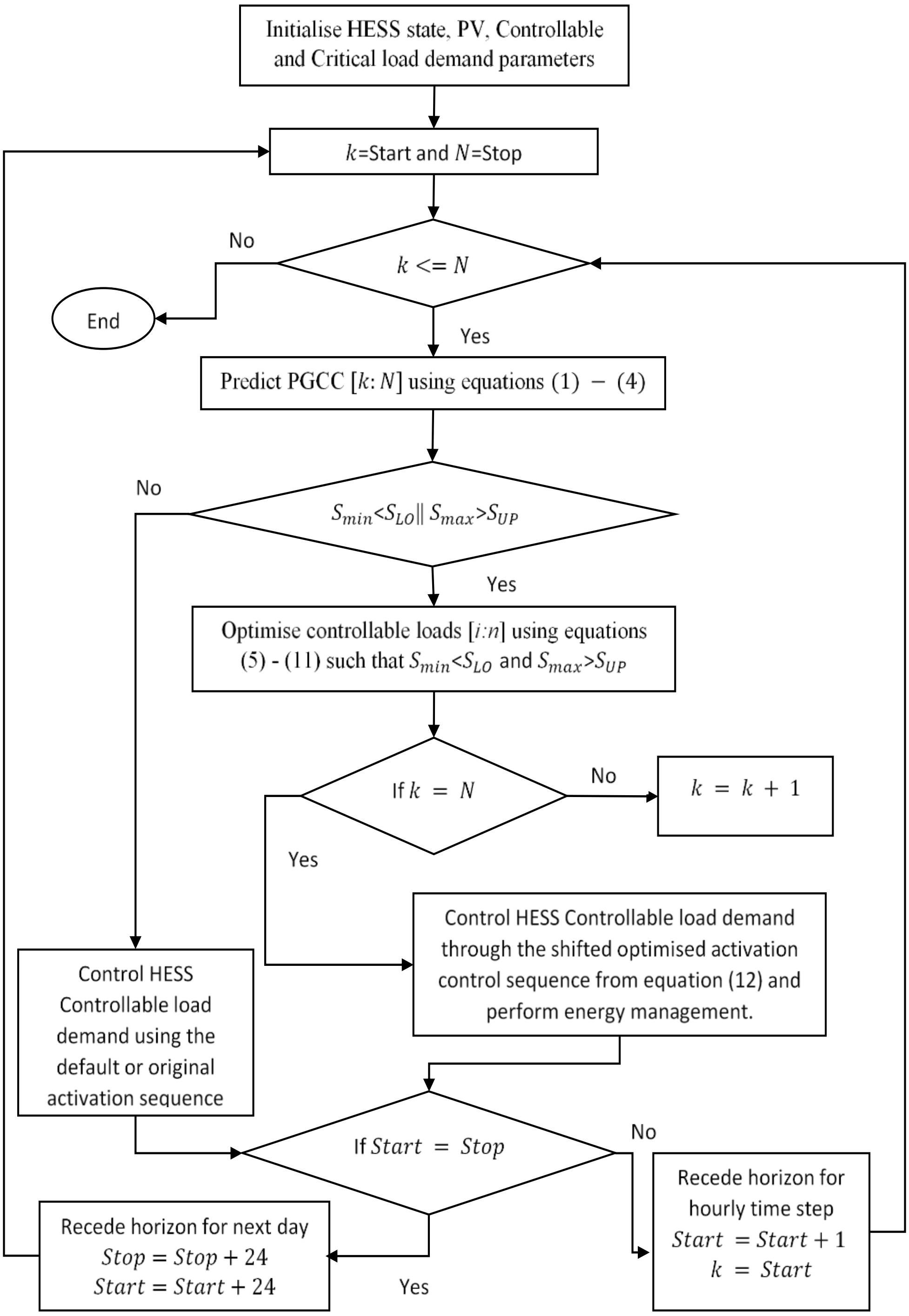


Figure 2. Flow chart for MPC Based on Adaptive PoPA for Load Shifting and Shedding algorithm

3. SIMULATION RESULTS AND DISCUSSION

This section compares the system response with and without load shifting algorithm for energy deficit and excess energy violation of the operating constraints and unserved load demand. The load shifting algorithm operates by shifting or shedding the controllable load such that the minimum or maximum state of charge S_{min} and S_{max} must stay within S_{LO} and S_{UP} (i.e. 30% and 90%), respectively (60% depth of discharge) while successfully supplying the critical load. Hence, S_{min} and S_{max} , indicates the lowest and highest values of the predicted PGCC. Thus, the BAT only serves the critical load demand while the non-critical or controllable load demand is shifted optimally when the available energy in the system is insufficient to cater for the entire load demands without the PGCC violating the S_{LO}.

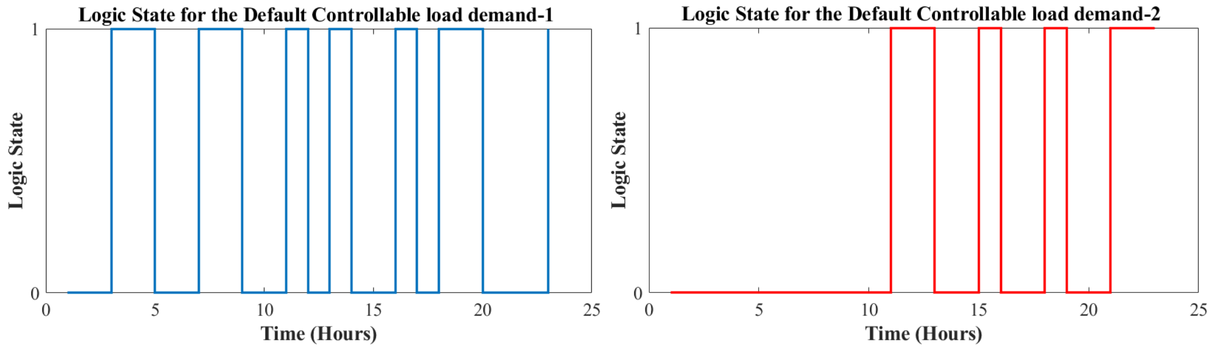
To evaluate the algorithm, the SoC of BAT is set at an initial condition of 50%, while the consumer is assumed to have only two appliances (but can be any realistic amount); termed appliances 1 and 2 are denoted as $LD_c(k)_1$and $LD_c(k)_2$ respectively. The corresponding time of use for $LD_c(k)_1$and $LD_c(k)_2$ which are arbitrary are defined as $t_1(k) = [0\ 0\ \ 0\ 0\ 1\ 1\ 1\ 1\ 1\ 1\ 0\ 1\ 1\ 0\ 0\ 0\ 1\ 1\ 0\ 0\ 0\ 0\ 0]$ and $t_2(k) = [0\ 0\ 1\ 1\ 1\ 1\ 1\ 1\ 0\ 0\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1]$. The wattage for appliance 1 (Freezer) $LD_c(k)_1$ are 500W and appliance 2 (a Desktop PC x 2) $LD_c(k)_2$ is 300W [35] with a priority scale of preference set to 5 and 3 having a total amount of operational time (h) for both appliances are 10h and 7h respectively.

Further, the critical or uncontrollable aggregated load demand which is a typical duck-shaped residential load profile, and PV irradiation profile are consistent with the previous research work [28]. To evaluate the load shifting algorithm only, the state of the HESS converters/energy transformation devices; FC, EL and DSL will remain deactivated. The initial condition of the controllable appliances is such that it is activated for all 24 hours of the day, typically as would be depicted in an extreme case of energy mismanagement by perhaps the most naive consumer a worst-case scenario.

3.1. Results for Excess Energy Case Study

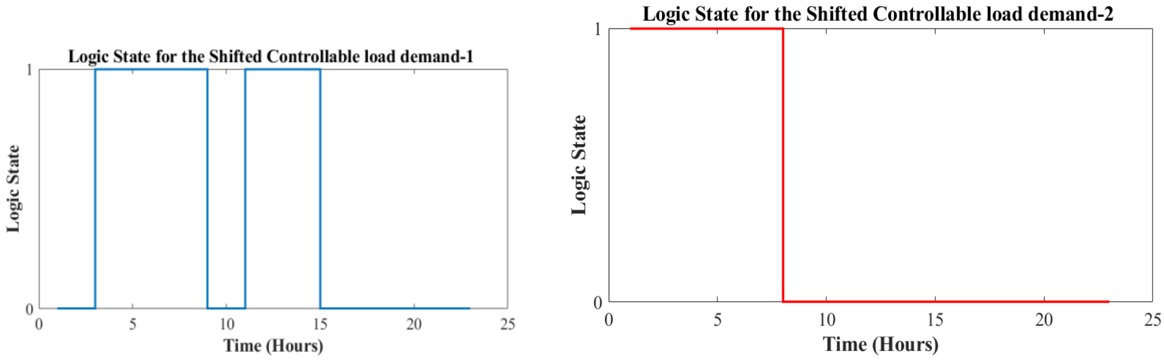
The case study examines the algorithm using a corresponding critical load demand and PV energy generation profile of a bright summer day when enough excess energy sufficient to cause overcharging of the BAT on noonday is generated. The BAT initial SOC is set to 80%, and the controllable loads (1 and 2) which are randomly activated using an approach presented in [35], result in a 10 h and 7 h total ON time for $LD_c(k)_1$ and $LD_c(k)_2$ respectively. The original logic state activation sequence for $LD_c(k)_1$=[0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 0, 1, 0, 0, 1, 0, 1, 1, 0, 0, 0, 1], and $LD_c(k)_2$=[0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 1] are shown in Figs. 3(a,b), respectively while, Fig. 4(a) and 4(b) shows the load shifted activation sequence for $LD_c(k)_1$ and $LD_c(k)_2$.

The original and load shifted response of state of charge of the BAT plotted over 24 h which represents the power grand composite curve (PGCC) is indicated by the brown and blue coloured plot respectively in Fig. 5. The original BAT state of charge shows the occurrence of 5 violations of the S_{UP} (indicated as the dashed green line) which indicates the BAT was overcharged with excess energy from the PV between the 9th and 14th hours. However, with the load shifting algorithm deployed, these 5 violations which had previously occurred between the 9th and 14th hours are avoided by rescheduling the controllable loads as follows: $LD_c(k)_1$ = [0, 0, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0] and $LD_c(k)_2$ = [1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0] as shown in Figs. 4(a,b).



(a) *(b)*

Figure 3. (a) Original logic state of the controllable load demand 1 in summer, (b) original Logic state of the shifted controllable load demand 2 in summer



(a) *(b)*

Figure 4. (a) Logic state of the shifted controllable load demand 1 in summer, (b) logic state of the shifted controllable load demand 2 in summer.

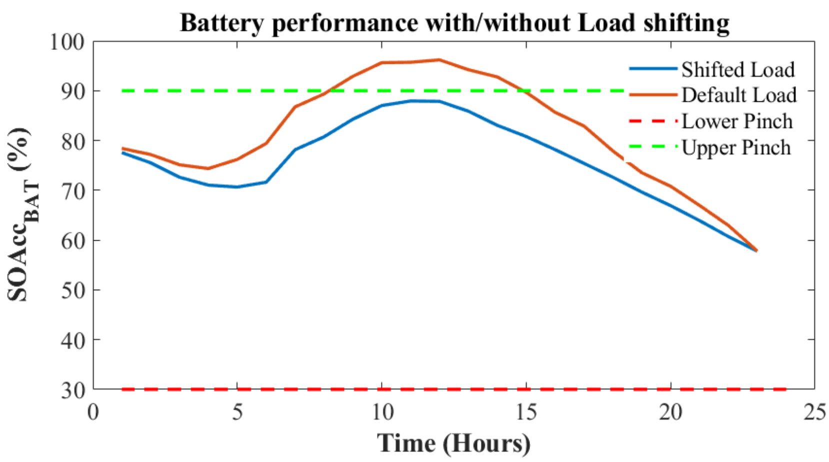
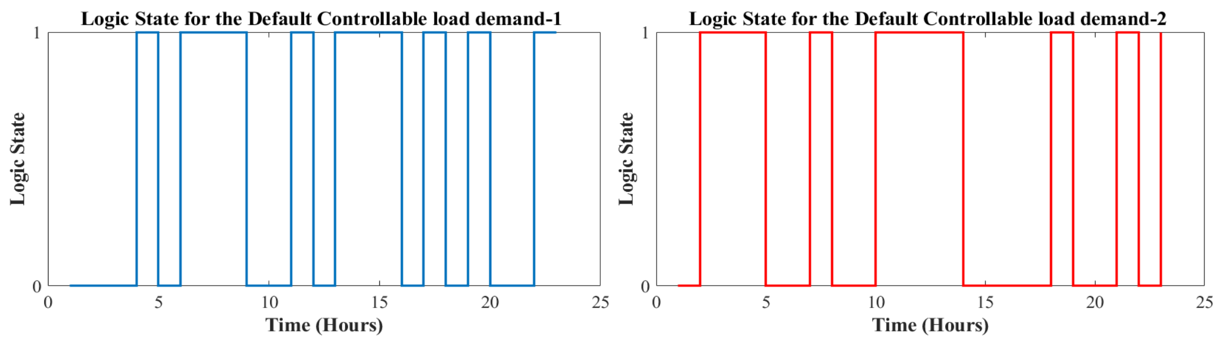


Figure 5. Original and shifted battery state of charge response in summer.

3.2. Result for Energy Deficit Case Study

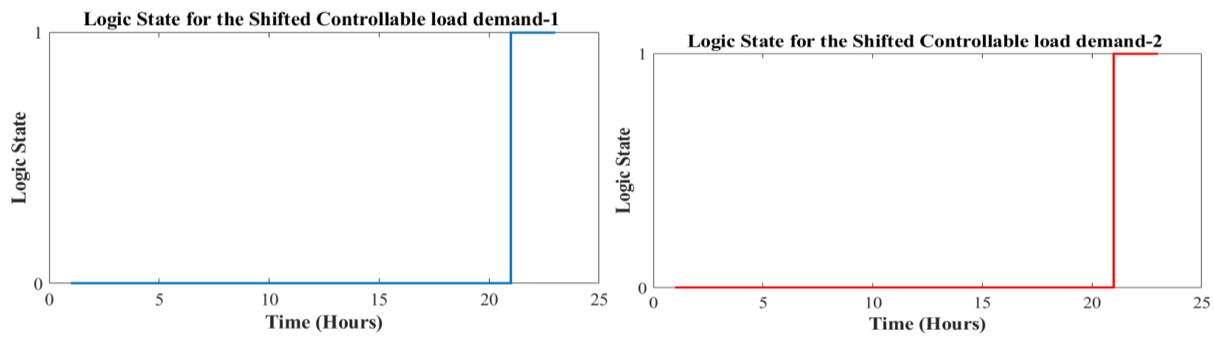
This case study evaluates the algorithm with critical load demand and PV energy generation profile corresponding to a cloudy day in Winter when the energy from the PV is insufficient to adequately charge the BAT. The BAT SOC is initialized to 55%, and the controllable loads (1 and 2) which are randomly activated as in the previous case study, result in a 12 h and 11h total ON time for $LD_c(k)_1$ and $LD_c(k)_2$ respectively. The original logic state activation sequence for $LD_c(k)_1$=[0, 0, 0, 1, 0, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 0, 1, 0, 1, 0, 0, 1, 1] and $LD_c(k)_2$=[0, 1, 1, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1] are shown in Fig. 6(a) and 6(b) respectively. Fig. 7(a) and 7(b) show the load shifted activation sequence for $LD_c(k)_1$ and $LD_c(k)_2$ while Fig. 8 shows the original and load-shifted response of the state of charge of the BAT plotted over 24h.

The original BAT state of charge shows the occurrence of 5 violations of the S_{LO} (indicated as the dashed red line) which denotes the BAT was over-discharged due to insufficient energy in the system between the 19th and 23rd h. Nevertheless, with the load shifting algorithm deployed, these 5 violations which had previously occurred between the 19^{th} and 23^{rd} h are avoided by shedding the controllable loads as follows: $LD_c(k)_1$ = [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1] and $LD_c(k)_2$ = [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1] as shown in Fig. 7(a) and 7(b). Hence, out of a total of 12 and 11 activations for $LD_c(k)_1$ and $LD_c(k)_2$ only a total of 3 activations each are scheduled by the algorithm to avoid the 5 violations of S_{LO}.



(a) *(b)*

Figure 6. (a) Original logic state of the controllable load demand 1 in winter, (b) original logic state of the controllable load demand 2 in winter.



(a) *(b)*

Figure 7. (a) Logic state of the shifted controllable load demand 1 in winter, (b) logic state of the shifted controllable load demand 2 in winter.

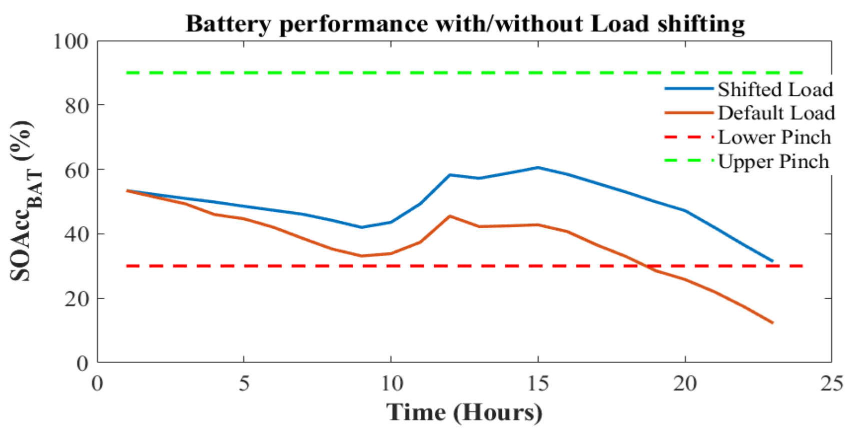


Figure 8. Original and shifted battery state of charge response in winter.

3.3 Discussion for Excess Energy Case Study

In the deficit energy scenario, the original activation of $LD_c(k)_1$ as shown in Fig. 3(a) is rescheduled by the load shifting algorithm such that the activation of $LD_c(k)_1$ occurs during the early hours of the day (between the 2nd and 8th h, 11th and 14th h) in other to absorb the excess energy in the BAT as shown in Fig. 4(a). Similarly, as shown in Fig. 3(b) the original profile of $LD_c(k)_2$ is shifted to the early hours of the day as the $LD_c(k)_1$ is activated 7 times, between the 1st and 7th h of the day as shown in Fig. 4(b). Hence, $LD_c(k)_1$ and $LD_c(k)_2$ were successfully shifted and activated by the optimisation algorithm based on the user's preference, and allowable time of use. Further, load satisfaction was 100% as the total number of usage hours for the controllable and critical appliance were adequately met while the BAT is operated without violating any operating limits. Moreso, the approach will allow usage of the electrolyser only if there is still excess energy in the system after optimal load shifting hence, improving the overall regenerative system's efficiency. Table 1, presents the summarized result for the analysis performed hourly over a 24 h horizon span during an excess energy scenario in the summer season.

Table 1. 24 h operational parameters with/without load shifting algorithm deployed at 55% and 80% SOC summer seasonal profile (Excess energy case study).

Operational Parameters	No-load shifting and SOC at 80% initial condition	Load shifting and SOC at 80% initial condition
Upper pinch violation	5	0
Lower pinch violation	0	0
Critical Pinch violation	0	0
Controllable load 1 satisfaction (%)	100	100
Controllable load 2 satisfaction (%)	100	100
Critical load Satisfaction (%)	100	100

3.4 Discussion for Deficit Energy Case Study

In the deficit energy case study performed in winter season, the original controllable load demands, $LD_c(k)_1$ and $LD_c(k)_2$ shown in Figs. 6(a,b) were shifted and shed by the optimal load shifting algorithm such that out of a total of 12 and 11 activations for $LD_c(k)_1$ and $LD_c(k)_2$ respectively only a total of 3 activations each were scheduled by the algorithm to avoid the 5 violations of S_{LO} as shown in Figs. 7(a,b), respectively. This indicates that out of the total amount of energy, i.e., 9.3KWh, which is needed to sufficiently supply $LD_c(k)_1$ and $LD_c(k)_2$ only 2.4KWh was available. Hence, an equivalent of 6.9KWh indicates 74.2% of the total amount of energy demand which must be outsourced from the FC or DSL, if $LD_c(k)_1$ and $LD_c(k)_2$ are to be successfully satisfied without over-discharging the BAT. In the research study [36], the effect of increasing the depth of discharge beyond the optimal operating range underscored the detrimental impact on the life cycle of BAT. In contrast to the optimal load shifting, without shitting or shedding load demand as shown in Fig. 8, the supply of energy that would have catered for the critical load would be consumed in the early hours of the day based on the original activation sequence of the controllable load which was not shifted or shed to meet all the load demands. Therefore, the over-discharging action will adversely reduce the life cycle of the BAT and consequent prompt the avoidable use of the hydrogen fuel cell when the SoC of the BAT is below 30%. Table 2, presents the summarized result for the hourly analysis performed over a 24h horizon span in winter to investigate the holistic load shifting/shedding algorithm under a deficit energy scenario in the winter season.

Table 2: 24h Operational Parameters with/without load shifting algorithm deployed at 55% and 80% SOC Winter seasonal profile (Energy deficit case study)

Operational Parameters	No-load shifting and SOC at 80% initial Condition	Load shifting and SOC at 80% initial Condition
Upper pinch violation	0	0
Lower pinch violation	5	0
Critical Pinch violation	2	0
Controllable load 1 satisfaction (%)	100	12.5
Controllable load 2 satisfaction (%)	100	12.5
Critical load satisfaction (%)	79.1	100

4. CONCLUSION

This work presented a novel algorithm for load shifting and shedding in a model predictive framework based on the principles of conservative power pinch analysis using an insight-based binary linear programming optimization technique. The algorithm was evaluated using two case studies: a bright summer day and a cloudy winter day (i.e. on 24 h horizon). The performance of the algorithm evaluated on a typical day in the summer season showed the effectiveness of load shifting. This was such that the excess energy in the system which led to over-charging above the limit of the energy storage was avoided by shifting the loads to periods before such excesses occurred. Similarly, in the winter day scenario, due to the predicted occurrence of deficit energy in the system, the algorithm shed the controllable load such that over-discharging of the energy storage never occurs. Thus, the proposed algorithm did not only ensure 100% satisfaction of the critical load demand it also traded off some of the controllable load demand to prevent the detrimental operation of the energy storage beyond the specified depth of discharge. Finally, the proposed algorithm was shown to improve systems reliability concerning critical load demand satisfaction while enhancing the operation of the energy storage.

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