Optimal Energy Management Among Multiple Households with Integrated Shared Energy Storage System (ESS)

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***Abstract*—The integration of artificial intelligence with home energy management systems (HEMS) due to the development of advanced metering infrastructure is a promising scheme to improve the usage of renewable energy in a residential application. In the paper, energy management among multiple co-operative households with PV-Storage integrated generation system in a home micro-grid in the presence of short-term prediction of power generation and consumption is studied. In such a home microgrid system, the central energy storage system (C.ESS) is considered that is connected with multiple household and PV panels. The key parameters that are responsible for optimum scheduling of C.ESS are forecasted PV power generation, forecasted household energy consumption, dynamic state of charge (SOC), and base level of energy consumption. In this paper, firstly, the prediction of short-term generation and consumption based on the long short-term memory (LSTM) algorithm is done. Then, this forecasted data is used as the constraint to the control algorithm for optimum scheduling. Therefore, the amount of power that will be supplied from C.ESS is also determined for properly utilizing the stored energy. The simulation results of the proposed scheme show the robustness and effectiveness in the home microgrid environment.**

***Index Terms*—Central energy storage system (CESS), LSTM, energy management, control system.**

I. Introduction

Because of the large expansion of industries, factories, and higher growth population, the demand for electrical energy in many sectors has increased substantially. Because of this, the integration of electrical devices in various applications grows, resulting in increased power demand. According to the International Energy Agency (IEA), global demand for electrical energy will grow at a rate of 2.1 percent per year until 2040. Furthermore, overall energy consumption will rise from 19 percent in 2018 to 24 percent in 2040 [1]. Consumers' modernistic lifestyles are also to blame for rising energy demand over the previous several decades.

However, the usage of PV systems integrating ESS in the home is rising on a daily basis. However, the ESS is utilized in the network for a variety of services such as peak shaving, islanding, load shaving, capacity firming, power quality enhancements, and intermittency handling [2]-[3]. As a result, ESS may store energy during off-peak hours while still supplying electricity to the grid during peak load hours.

The fundamental feature of the demand response is that it is dynamic, meaning that it is determined by the user's behavior and seasonal conditions. Similarly, the characteristic of PV generation is dynamic and depends on a variety of parameters. When many household appliances are used at the same time, the system experiences peak power consumption. Because of these dynamic characteristics, there is an imbalance between energy consumption and PV generation in a certain home. Furthermore, the problem is exacerbated by the amount of ESS charging and discharging. The combination of traditional ESS with PV seeks to alleviate this difficulty by delivering and storing electricity as needed. However, owing to the lack of a dynamic optimization and management system, it was unable to resolve successfully. To address these dynamic DR and PV production issues, an energy management system [4] in ESS must be built to mitigate their demands. Because of this, an energy management system with multiple households using a shared energy storage system (C.ESS) system may play an essential role in the smart grid environment by keeping up with massive demand.

One of the most difficult challenges for ESS is to manage the scheduling of charging and discharging periods in order to provide optimal power distribution among the households [5]–[7]. In [8], the period of connecting loads is changing according to their preferences and requirements in order to decrease energy costs. An effective scheduling approach is created and implemented in a residential dwelling for reducing energy costs by scheduling energy usage where PV and ESS are coupled in the micro-grid system [9]—[12]. The authors of those articles concentrate on charging and discharging times without taking into account predicted PV power generation and the energy demand of the households. Consequently, the ESS discharges its stored energy even at the time of PV generation instead of charging. In addition, the appliances grain power from the grid at the time of peak demand because of not having

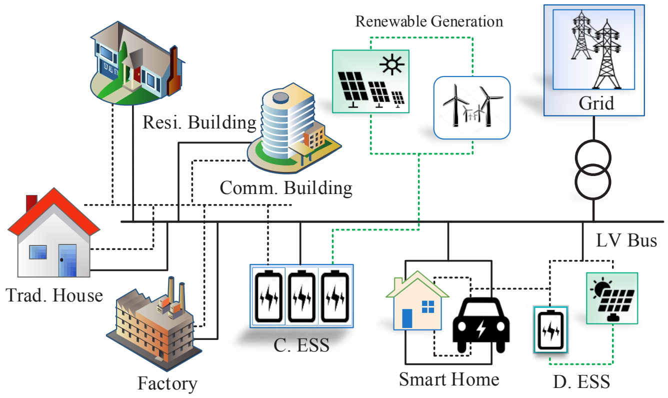

Fig. 1. Overall architecture of the system.

sufficient charge in the ESS.

In this paper, we design a C.ESS by integrating novel optimization and management algorithm for scheduling, supplying, and storing power in the ESS based on State of Charge (SOC) and predicted power generation and consumption. The Long short-term memory (LSTM) algorithm is applied to predict power generation and consumption [13]. Employing the prediction result, we design a heuristic algorithm for scheduling and determining the volume of supplying and storing energy in ESS. In addition, the amount of grid power is also measured in the proposed system.

The main contribution of this article is to design a mathematical model for integrated PV-ESS for multiple households. Therefore, we implement this scheme for scheduling central ESS among multiple households by including a unique optimization and management method which is based on State of Charge (SOC) and forecasted power generation and consumption of each household. To predicted electricity generation and consumption, the long short-term memory (LSTM) algorithm is used [13]. Using the prediction result, we create a heuristic method for scheduling the charging and discharging period of the energy storage.

This paper organizes as follows: Section II describes the mathematical model for the proposed system. Simulation results and the corresponding discussion are illustrated in section III. Finally, the conclusion of this work is presented in section IV.

II. Methodology

The demand of electrical energy is a continuous process. The energy demand of households varies with time governed by many factors such as the consumer's lifestyles, seasonal conditions, and the surrounding conditions of the consumer. Though the energy consumption pattern of the residential customer may follow similar trends, the consumption volume always varies from customer to customer. In the proposed system, we are considering multiple households consisting of a small microgrid integrating with the PV and C.ESS system. The integration of C.ESS in a low voltage (LV) grid is shown in Fig.1. In [14], we have already developed a scheduling approach of D.ESS for single households. In this paper, the proposed algorithm focuses on the scheduling for C.ESS in the case of multiple households with associated residential appliances.

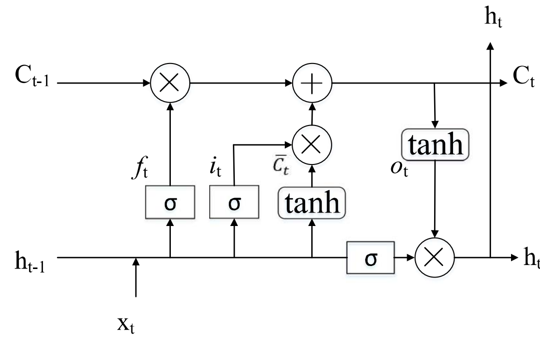

Fig. 2. LSTM model architecture.

In this section, we present the brief working principle of the forecasting algorithm and the scheduling scheme for C.ESS.

A. Long Short Term Memory

In this paper, we have used a time series forecasting model known as Long short-term memory (LSTM) network for forecasting power generation and consumption. The significant reasons for choosing the LSTM model [15] are having short-term memory and the ability to remove the vanishing gradient problem of recurrent neural network (RNN). For the long sequence forecasting problems, the internal gates of LSTM can regulate the flow of information. The data which has a strong correlation with time series is used in the LSTM model for better performance. For this reason, we will train the model by using the six-month energy generation and consumption data of a domestic house. The sampling between each data point was 15 minutes. A typical LSTM unit consists of an entrance gate, a gate, an output gate, and a cell unit [16]. Without making any changes in the LSTM architecture, the cell state (C_t) executes the proper flow of information. Three gates regulate the execution of the cell state. The first gate namely forgets gate controls the forgetting mechanism of the cell vector C_{t-1}. f_t is an output vector of the sigmoid layer with values ranging from 0 to 1.

$$f_t = \sigma\left(W_f\left[h_{t-1}, x_t\right] + b_f\right) \tag{1}$$

Afterwards, the value is updated by input gate i_t within 0 to 1 range.

$$i_t = \sigma\left(W_i\left[h_{t-1}, x_t\right] + b_i\right) \tag{2}$$

The old cell states C_{t-1} gets updated into C_t by the following equation:

$$C_t = f_t * C_{t-1} + (1 - f_t) * \bar{C}_t \tag{3}$$

where, $\bar{C}_t$ is called potential vector ranging from 0 to 1 and can be represented as :

$$\bar{C}_t = tanh\left(W_c\left[h_{t-1}, x_t\right] + b_C\right) \tag{4}$$

where, $tanh$ is defined as hyperbolic tangent function. Finally, the output o_t of the output gate which is governed by the following equation:

$$o_t = \sigma\left(W_o\left[C_t, h_{t-1}, x_t\right] + b_o\right) \tag{5}$$

The hidden state h_t is calculated by:

$$h_t = o_t.tanh(C_t) \tag{6}$$

Fig. 2 shows the general architecture of the LSTM model. We apply this model in the solar power generation and household energy consumption data in this paper.

B. Scenario of Household Demand

In this section, the constraints and dependencies for the proposed algorithm based on the demand of the multiple households are described. Now consider the energy consumption of the household is $P^{H}_{D,t}(t)$. Since we have considered the prediction model, the forecasted energy consumption can be defined as $P^{H}_{FD,t}(t)$. If, the house contains $N \in Z$ number of appliances, total power consumption at time t can be expressed as follows:

$$P^{H}_{D,t}(t) = \sum_{i=1}^{N} P^{H,A_i}_{D,t}(t) \tag{7}$$

Similarly, we can determine $P^{H2}_{D,t}(t)$, $P^{H2}_{D,t}(t)$, and $P^{H3}_{D,t}(t)$ for household no. 1 (H_1), household no. 2(H_2), and household no. 3 (H_3). The total power consumption from t end of the present day (t_{ed}) is defined as follows as:

$$P^{H}_{D,t-t_{end}}(t) = \sum_{j=1}^{e}\sum_{i=1}^{N} P^{H,A_i}_{FD,\tau}(j\tau) - \sum_{j=1}^{k}\sum_{i=1}^{N} P^{H,A_i}_{D,t}(t - j\tau)) \tag{8}$$

$t \in [0, 24],\ e = \dfrac{24}{\tau}$, and $k = (\dfrac{t}{\tau} - 1)$ where, t = hour

$t \in [0, 1440]$, $e = \dfrac{1440}{\tau}$, and, $k = (\dfrac{t}{\tau} - 1)$ where t = minute

The average forecasted power consumption in a household for 24 hours can be defined as follows:

$$P^{H,Avg}_{FD,t_{st}-t_{ed}} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{e} P^{H,A_i}_{\tau,d}(j\tau)}{e} \tag{9}$$

For dynamic average power from t to t_{ed} can be expressed as:

$$P^{H,Avg}_{FD,t-t_{ed}}(t) = \frac{P^{H}_{FD,t-t_{ed}}(t)}{e-k} \tag{10}$$

Similarly, the average power of single day for three household can be defined as $P^{H_1,Avg}_{FD,t_{st}-t_{ed}}$, $P^{H_2,Avg}_{FD,t_{st}-t_{ed}}$, and $P^{H_3,Avg}_{FD,t_{st}-t_{ed}}$. Therefore, the dynamic average power for three household can be express as $P^{H_1,Avg}_{FD,t-t_{ed}}(t)$, $P^{H_2,Avg}_{FD,t-t_{ed}}(t)$, and $P^{H_3,Avg}_{FD,t-t_{ed}}(t)$. The constraints for the power consumption can be expressed as follows:

$$P^{H_1,Base}_{D,t} \leqslant P^{H_1}_{D,t}(t) \leqslant P^{H_1,Peak}_{D,t} \tag{11}$$

$$P^{H_2,Base}_{D,t} \leqslant P^{H_2}_{D,t}(t) \leqslant P^{H_2,Peak}_{D,t} \tag{12}$$

$$P^{H_3,Base}_{D,t} \leqslant P^{H_3}_{D,t}(t) \leqslant P^{H_3,Peak}_{D,t} \tag{13}$$

C. Scenario of PV Power

The proposed model emphasis on the single PV generation system integrated with C.ESS. For modeling the PV power constraints and dependencies, we can consider PV power generation and forecasted PV power generation which is defined as $E^{PV}_{t,d}(t)$ and $E^{PV}_{t,dh}(t)$, respectively. The total power generation at time t can be expressed as follows:

$$E^{PV}_{G,t}(t) = \sum_{i=1}^{N} E^{PV,M_i}_{G,t}(t) * \xi^{M_i}_{PV}(t) \tag{14}$$

where $\xi^{M_i}_{PV}(t)$ is describes On/Off status of the PV module at time t. Depending on the activity of the PV power generation, the $\xi^{M_i}_{PV}(t) \in [1, 0]$ continuously varies with time t. Since the PV power generation significantly depends on the solar irradiance, the generation of PV will be start from the time when the PV panel will touch in sun light. The generation starting time is $t \in [t_{st}, t_{ed}]$, where $j = 0$ at starting time and $p = t_{ed}/\tau$ and $q = \frac{(t-t_{st})}{\tau}$. The total power generation from t is defined as follows as:

$$E^{PV}_{G,t}(t) = \sum_{j=0}^{p}\sum_{i=1}^{N} E^{PV,M_i}_{G,t+\tau}(t_{st} + j\tau) * \xi^{M_i}_{PV}(t) \tag{15}$$

The average generation of a single day can be defined as:

$$E^{PV}_{Avg,d} = \frac{E^{PV}_{G,t}(t)}{p} \tag{16}$$

The total power generation from t to t_{ed} can be defined as follows:

$$\begin{aligned} E^{PV}_{G,t-t_{ed}}(t) = &\sum_{j=0}^{p}\sum_{i=1}^{N} E^{PV,M_i}_{G,\tau}(t_{st} + j\tau) * \xi^{PV}_{M_i}(t) \\ &- \sum_{j=0}^{q}\sum_{i=1}^{N} E^{PV,M_i}_{G,t+\tau}(t - j\tau) * \xi^{PV}_{M_i}(t) \end{aligned} \tag{17}$$

For dynamic average power from t to t_{ed} can be expressed as:

$$E^{PV}_{Avg,dr}(t) = \frac{E^{PV}_{G,t-t_{ed}}(t)}{p-q} \tag{18}$$

D. Scenario of ESS Power

In this paper, we consider a shared energy storage system that is connected to the local PV site. We call this ESS a central energy storage system (C.ESS). The constraint for charging and discharging of the ESS must be governed by the parameters of the PV generation system. Now, we consider the state of charge of the C.ESS is $SOC^{C.ESS}_{t}$. The constraints for delivering power to C.ESS can be expressed as follows: a) the PV power generation should be greater than a certain threshold level, and b) the $SOC^{C.ESS}_{t}$ of the C.ESS must be less than the maximum charging capacity of the ESS.

$$SOC^{C.ESS}_{t}(t) \leqslant SOC^{C.ESS}_{t,min},\ S^{C.ESS}_{t,c} \tag{19}$$

$$SOC^{C.ESS}_{t}(t) \geqslant SOC^{C.ESS}_{t,max},\ (1 - S^{C.ESS}_{t,c}) \tag{20}$$

where $S^{C.ESS}_{t,c}$ are binary variables expressing the charging/discharging status of the ESS. $SOC^{C.ESS}_{t,min}(t)$ and

$SOC^{C.ESS}_{t,max}$ presented the minimum and maximum state of charge of the ESS. Therefore, the discharging range of the ESS can be represented as:

$$SOC^{C.ESS}_{t,min} \leqslant SOC^{C.ESS}_{t}(t) \leqslant SOC^{C.ESS}_{t,max} \tag{21}$$

E. Scheduling Approach for C.ESS

In the proposed scheduling scheme, we have considered multiple households that are connected with C.ESS which share its energy among households. From the C.ESS, each household will take energy based on some conditions and dependencies. Since the charging and discharging process in energy storage is not possible at the same time, we consider the charging time at the time of generation, and the rest of the time will be considered as discharging time based on the level of SOC. The constraints of scheduling for the charging ESS is described as follows:

$$E^{PV}_{G,th} \leqslant E^{PV}_{G,t}(t),\ S^{C.ESS}_{t,c} \tag{22}$$

$$SOC^{C.ESS}_{t+1}(t+1) = E^{PV}_{G,t}(t) + SOC^{C.ESS}_{t}(t) \tag{23}$$

$$E^{PV}_{G,th} > E^{PV}_{G,t}(t),\ (1 - S^{C.ESS}_{t,c}) \tag{24}$$

The proposed scheme is scheduled in a such way that the C.ESS will supply energy to two different households simultaneously. The constraints of scheduling for discharging ESS can be expressed as:

$$P^{H_1,Avg}_{FD,t_{st}-t_{ed}}(t) \geqslant P^{H_2,Avg}_{FD,t_{st}-t_{ed}}(t) \tag{25}$$

$$P^{H_1,Avg}_{FD,t_{st}-t_{ed}}(t) < P^{H_2,Avg}_{FD,t_{st}-t_{ed}}(t) \tag{26}$$

$$P^{H_1,Avg}_{FD,t_{st}-t_{ed}}(t) \geqslant P^{H_3,Avg}_{FD,t_{st}-t_{ed}}(t) \tag{27}$$

$$P^{H_1,Avg}_{FD,t_{st}-t_{ed}}(t) < P^{H_3,Avg}_{FD,t_{st}-t_{ed}}(t) \tag{28}$$

$$P^{H_2,Avg}_{FD,t_{st}-t_{ed}}(t) \geqslant P^{H_1,Avg}_{FD,t_{st}-t_{ed}}(t) \tag{29}$$

$$P^{H_2,Avg}_{FD,t_{st}-t_{ed}}(t) < P^{H_1,Avg}_{FD,t_{st}-t_{ed}}(t) \tag{30}$$

$$P^{H_2,Avg}_{FD,t_{st}-t_{ed}}(t) \geqslant P^{H_3,Avg}_{FD,t_{st}-t_{ed}}(t) \tag{31}$$

$$P^{H_2,Avg}_{FD,t_{st}-t_{ed}}(t) < P^{H_3,Avg}_{FD,t_{st}-t_{ed}}(t) \tag{32}$$

$$P^{H_3,Avg}_{FD,t_{st}-t_{ed}}(t) \geqslant P^{H_1,Avg}_{FD,t_{st}-t_{ed}}(t) \tag{33}$$

$$P^{H_3,Avg}_{FD,t_{st}-t_{ed}}(t) < P^{H_1,Avg}_{FD,t_{st}-t_{ed}}(t) \tag{34}$$

$$P^{H_3,Avg}_{FD,t_{st}-t_{ed}}(t) \geqslant P^{H_2,Avg}_{FD,t_{st}-t_{ed}}(t) \tag{35}$$

$$P^{H_3,Avg}_{FD,t_{st}-t_{ed}}(t) < P^{H_2,Avg}_{FD,t_{st}-t_{ed}}(t) \tag{36}$$

From LSTM, the predicted consumption and generation data have driven algorithm 1 by considering several conditions for scheduling. For ensuring the good health of the battery the SOC^{ESS}_{min} and SOC^{ESS}_{max} are defined by the consumer.

$$SOC^{C.ESS}_{t+1}(t+1) = SOC^{C.ESS}_{t}(t) - P^{H}_{Dis,t}(t) \tag{37}$$

$$\left\{P^{H_1}_{Dis,t}(t), P^{H_2}_{Dis,t}(t), P^{H_3}_{Dis,t}(t)\right\} \in P^{H}_{Dis,t}(t)$$

Algorithm 1 ESS power management algorithm

Input:

- Predicted power consumption and PV power generation data
- Threshold SOC of C.ESS and threshold value of PV generation

Output:

- Charging and discharging schedule of C.ESS

begin
ask $E^{PV}_{G,th}$, $SOC^{C.ESS}_{t,min}$ and $SOC^{C.ESS}_{t,max}$ of ESS
Determine $SOC^{C.ESS}_{t}(t)$ at the beginning
for every household and PV system **do**
  for every certain interval **do**
    Total actual and forecasted energy demand
    Average actual and forecasted energy demand
    Total actual and forecasted power generation
    Average actual and forecasted power generation
  end for
end for
for every certain interval **do**
  if $E^{PV}_{G,th} > E^{PV}_{G,t}(t)$, and $SOC^{C.ESS}_{t,min} \leqslant SOC^{C.ESS}_{t}(t) \leqslant SOC^{C.ESS}_{t,max}$ **then**
    if Compare $P^{H,Avg}_{FD,t_{st}-t_{ed}}(t)$ with each other household **then**
      Discharge period for two highest demanded households
      No discharge period for rest of the household
      Compute $SOC^{C.ESS}_{t+1}(t+1)$ by eqn. (37)
    else
      Discharge period for households
      Compute $SOC^{C.ESS}_{t+1}(t+1)$ by eqn. (37)
    end if
  else if $E^{PV}_{G,th} > E^{PV}_{G,t}(t)$ **then**
    Only charging period is available
    Compute $SOC^{C.ESS}_{t+1}(t+1)$ by eqn. (23)
  end if
end for
end

III. Result and Discussion

In this paper, we take into account multiple households connected with a central energy storage system integrated with the PV site. The historic data of energy consumption the households and PV generation are taken from the smart meter and PV site, respectively. we have used a six-month data-set of PV power generation and energy consumption of three households. The simulation result of the proposed scheduling algorithm is presented in Fig. 3 and Fig. 4. The simulation results cover from 10/08/2020 to 10/09/2020 days power generation and consumption data which is shown in both figures. Fig. 3 presents the scheduling time of charging C.ESS, actual PV power generation, and forecasted PV power generation. From this figure, it can be found that the maximum power generation is approximate 0.7 (kW). When the volume

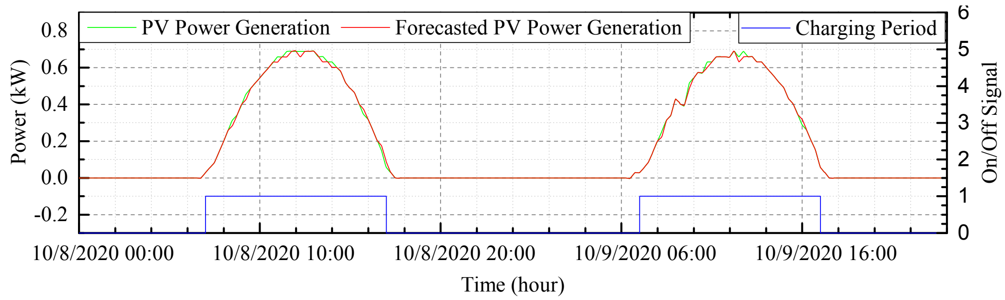

Fig. 3. PV power generation and schedule for charging C.ESS.

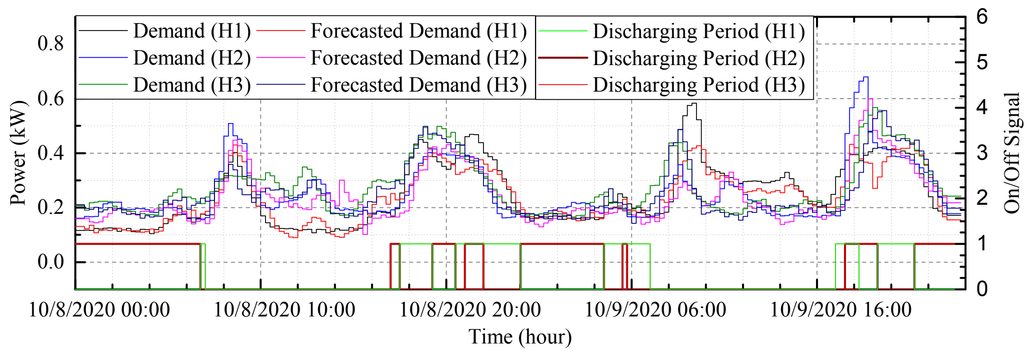

Fig. 4. Actual and forecasted enegy consumption with discharging schedule for C.ESS.

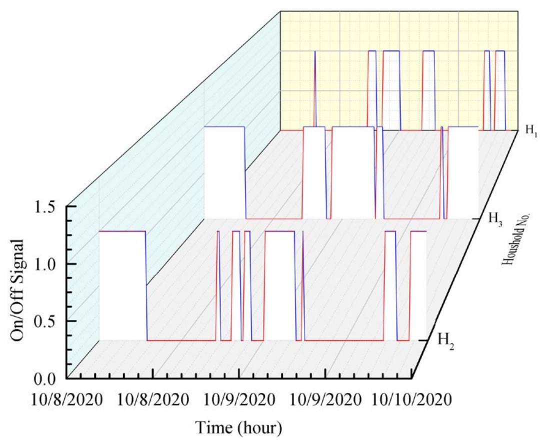

Fig. 5. Periods of discharging of each households.

of PV power generation crosses the minimum threshold value, the C.ESS will start charging. In this case, we have chosen the threshold value which is .05 (kW). At the period of PV power generation, the generated PV power is stored in C.ESS and the appliances have taken power from the grid. In the rest of the period, HESS and grid provide power to the system for removing peak demand that leads the C.ESS for efficient discharging.

Fig. 4 illustrates the actual and forecasted energy demand of H_1, H_2, and H_3 at every 15 minutes interval. Since the system is considered a dynamic process, the average power of any certain time is different from other times. The discharging schedule depends on the forecasted power (i.e., total and average). According to the proposed algorithm, the scheduling period is determined. From the figure, it can be seen that the C.ESS supplies power to multiple households at the same time. Fig. 5 presents discharging period for better observation. from this figure, We can see that the shortest scheduling time for discharging belongs to H_1 due to having the least amount of energy demand. On the other hand, the H_3 provides the longest discharging period among all households. From both graphs, it can be observed that the proposed system managing charging and discharging time C.ESS is the function of the predicted power generation and power consumption.

IV. Conclusion

Effective power management among the loads is considered a significant process of utilizing renewable energy resources. In this study, we have designed and developed an algorithm for the optimal scheduling period of a shared ESS among multiple households. For developing the scheme, we have considered a prediction model for better optimal results. The forecasting task is performed by a deep learning-based LSTM algorithm. The prediction models provide satisfactory results with higher accuracy. Afterward, we have investigated the performance of the scheduling algorithm. The charging-discharging scheduling pattern of C.ESS evaluates the efficacy of our designed scheduling algorithm. We have found the longest discharging time for H_2 and shortest for H_1 due to the volume of demanded energy. In the future, hybridization of optimization algorithm with the proposed scheduling algorithm will provide better and efficient solutions in the sector of home energy management systems.

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