Day-ahead Energy Sharing Schedule for the P2P Prosumer Community Using LSTM and Swarm Intelligence

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***Abstract*—Prosumer community forms by prosumer who is not only consuming energy but also generating renewable energy (e.g., solar) and capable of selling surplus energy to other consumers. Peer-to-peer (P2P) energy sharing behavior of the smart grid is evolving to reducing the usage of non-renewable energy. However, non-renewable energy is still used in some time intervals due to the unbalance between energy load and generation. Therefore, in this paper, we study an energy scheduling problem that includes the energy amount for battery charge/discharge along with energy sharing scheduling among the prosumer community. First, we formulate an optimization problem and the objective is to minimize the non-renewable energy usage of the entire community. This problem includes the day-ahead energy demand prediction stage and battery charge/discharge, and energy sharing scheduling stage. Second, to solve the formulated problem, a long-short-term memory (LSTM) and particle swarm optimization (PSO) joint approach is proposed, in which the LSTM based model is used to forecast day-ahead energy demand, while PSO is utilized in the second scheduling stage by considering P2P behavior. Finally, the evaluation result shows our proposed LSTM prediction model outperforms the autoregressive integrated moving average (ARIMA) model by comparing the mean squared error, root-mean-square error and total training time. PSO improves the overall usage of non-renewable energy.**

***Index Terms*—Peer-to-Peer, Prosumer Community, Energy Scheduling, LSTM, Particle Swarm Optimization**

I. INTRODUCTION

As the development of smart grid, solar energy generated prosumer community, in which prosumer can not only play the role of purchasing energy from the power provider but also proactive selling excess energy to neighbors in need by installing rooftop solar panels, known as peer-to-peer (P2P) energy sharing which is useful for improving energy efficiency and energy shortage problem. However, solar generation is uneven due to being affected by the solar intensity which causes the energy generation can not fulfill the requirement of each prosumer, namely, mismatch problem between demand and generation. To handle such a problem, the battery is introduced for each prosumer. Obviously, it is necessary and makes sense to schedule the amount of energy not only by P2P energy sharing or receiving behavior but also the amount for battery charge or from discharge.

In recent years, the research in P2P energy sharing area has attracted increasing attention among various researches and a number of studies have proposed various methods. For example, in the study of [1], a non-cooperative game theory based selfish energy sharing mechanism was presented for battery and amount of energy sharing scheduling in prosumer community. The research [2] proposed a game-theoretic based distributed control schemes which aim to reduce energy cost for P2P energy sharing. In [3], a model based on game-theoretic was presented for P2P energy trading in prosumer community which gained significant financial benefit. Another example is [4], in which a P2P energy sharing model incorporates the energy storage optimization was proposed to make the lowest coalitional energy cost for all prosumers using cooperative game theory. However, few researches used deep learning approaches (e.g. recurrent neural network) in the P2P energy sharing area. Deep learning approaches nowadays have gained remarkable success in various areas for the purposes of prediction [5]. For instance, in the energy consumption area, convolutional neural network (CNN) was used to forecast at the level of individual building in the study [6]. GRU based recursive deep learning method was utilized to predict data from smart meter in [7]. However, these researches only considered load forecasting aspects but ignored the impact of storage (e.g., battery) and energy sharing among the community.

In this paper, unlike previous studies, to achieve the minimum day-ahead usage of non-renewable energy, we comprehensively consider energy consumption forecast, scheduling charge/ discharge of battery and energy sharing with neighbors for the upcoming day. However, the unpredictable nature and strong relationship over the history of the energy consumption [8] causes a big challenge for accurate prediction of energy demand. As for the energy sharing and battery scheduling for each household, knowing the optimal value of battery charge/discharge and energy sharing is another big difficulty.

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To address these challenges, we focus on the approach that not only forecasts energy demand for the next day but also optimizes both the amount of battery charge or discharge and the energy sharing per household within one prosumer community. The main contributions of this paper are summarized as follows:

- We formulate a day-ahead energy scheduling problem and the objective is to minimize the usage of non-renewable energy of a P2P prosumer community. Where we schedule the amount of energy charge to or discharge from battery, and the amount of energy sharing to other households such that the unbalance between total solar generation and energy demand can be reduced. However, due to the formulated problem includes day-ahead prediction and the amount of battery charge/discharge and sharing scheduling stage, it is hard to solve such a problem directly.
- To address the formulated problem, we decompose it into two-stage: Day-ahead prediction stage and optimization stage. For the first stage, an intelligent energy prediction model based on long short-term memory (LSTM) is proposed. In the second stage, particle swarm optimization based method is proposed to get the best amount of battery charge or discharge and best quantity of energy sharing such that to solve the minimization problem of non-renewable energy.
- Finally, the proposed LSTM model is better than the ARIMA model with 0.1599 of mean squared error (MSE), 0.40 of root-mean-square error (RMSE) and only several minutes of total training time. Scheduling of battery charge/discharge and energy sharing of each household shows a significant performance gain, in which the total energy generation can fulfill all the energy demands of one prosumer community.

The rest of the paper is organized as follows. Section II presents the system model and its problem formulation. A detail discussion of the proposed solution approaches are given in Section III. The performance analysis is provided in Section IV, and lastly, Section V concludes this paper.

II. System Model and Problem Formulation

This section describes the proposed system model for the prosumer community and the related formulation. The detailed behaviors such as energy sharing, battery charge or discharge, etc., are also depicted in this section.

A. System Model

The community model is showed as seen in Fig. 1. This includes power supplier and operator of the power grid, multiple households, and their connections. Besides, one household has a solar panel with a battery as the energy storage system, a smart meter (e.g., Linky [9]) and various energy consumption appliances such as refrigerator, lighting, washing machine and the forth.

In this model, on the one hand, the role of smart meter is to record the energy consumption and provide information to the power supplier and grid operator. On the other hand, it can communicate with the home energy management system (HMS). We assume all of the appliances are connected to the HMS through wired or wireless connections (e.g, Power Line Communication, Zigbee) [10].

When the generation exceeds the demand, the battery in this model will be used to save surplus energy. Notably, we assume that DC/AC inverter is already deployed in HMS. When the energy is used for load consumption, the inverter is needed by each household to convert energy type from DC to AC with an efficiency. However, the energy can be directly used when it is used for charging battery [1].

In this model, we consider a prosumer community that consists of a set of households $H = \{1, 2, ..., H\}$ and each household has a set of the load that is defined as $L = \{1, 2, ..., L\}$. We also consider a discrete time intervals $T = \{1, 2, ..., T\}$ and each time slot $t \in T$ is considered as one hour duration [8]. The details of other symbols in this

TABLE I
List of Notation

Symbol	Meaning
$P_h^d(t)$	Energy demand of each household at time slot t
$P_h^g(t)$	Energy generation of each household at time slot t
$P_h^s(t)$	Amount of each household energy sharing at time slot t
$P_h^r(t)$	Amount of each household energy receiving at time slot t
$P_h^{b,c}(t)$	Charge into battery of each household at time slot t
$P_h^{b,d}(t)$	Discharge from battery of each household at time slot t
$P_h^{b,s}(t)$	Battery state of each household at time slot t
$P_h^n(t)$	Non-renewable energy using by each household at time slot t
$P_h^l(t)$	Load in per unit time for each household
$P_h^u(t)$	Energy can be used in per unit time for each household
λ_{inv}	Efficiency of inverter
λ_c	Efficiency of charge
λ_d	Efficiency of discharge
b_{min}	Minimum amount of energy saved in battery
b_{max}	Maximum battery capacity

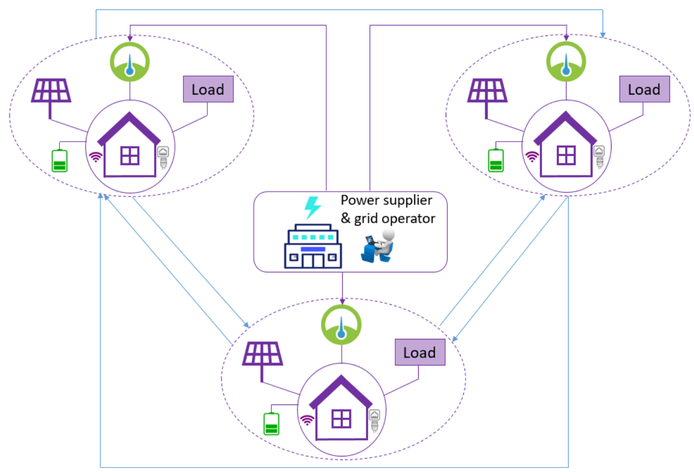

Fig. 1. System Model

paper are depicted in Table I.

In the case of the frequently used battery, the self-discharge rate can be ignored every month without any significant errors [11]. Therefore, this work only considers the charge and discharge process. Based on these two processes, a binary decision variable B is needed and its definition is shown as follows:

$$B = \begin{cases} 1, & \text{if charge into battery} \\ 0, & \text{if discharge from battery,} \end{cases} \tag{1}$$

where $B = 1$ if the battery charge process occurs, and 0, otherwise.

The amount of energy that saved in the battery $P_h^{b,s}$ at next time slot can be defined as follows [1],

$$P_h^{b,s}(t+1) = \begin{cases} B(P_h^{b,s}(t) + \lambda_{inv}\lambda_c P_h^{b,c}(t)), & \text{if } B = 1, \\ (1-B)(P_h^{b,s}(t) - \frac{P_h^{b,d}(t)}{\lambda_{inv}\lambda_d}), & \text{otherwise.} \end{cases} \tag{2}$$

where λ_{inv}, λ_c and λ_d is energy efficiency of inverter, battery charge, and discharge, respectively. $P_h^{b,s}$ indicates the amount of energy that saved in the battery, $P_h^{b,c}$ is the energy used for charge and $P_h^{b,d}$ is the energy from discharge process at time slot t.

The total battery energy E_b at time slot t within the community is represented by,

$$E_b(t) = \Sigma_{\forall h \in H} P_h^{b,s}(t). \tag{3}$$

We define P_h^g is the amount of energy generation of household h at time slot t. Thus, the total amount of energy generation for all the prosumers in the community is determined as follows:

$$E_g(t) = \Sigma_{\forall h \in H} P_h^g(t). \tag{4}$$

Energy is preferentially considered for use by individuals. Therefore, energy sharing occurs only when individuals have excess energy. Conversely, it is necessary to receive energy from other households and/or from traditional energy provided by the power supplier for this household. Additionally, we consider each household in one community is very near each other. Hence, the line loss is ignored in this paper like [12].

For household h, P_h^l is defined as total load at time slot t, P_h^d represents energy demand, P_h^s is the shared energy and $P_h^{b,c}$ is the amount of energy used for charge into battery at time slot t. Therefore, the load at time slot t for household h is represented as follows:

$$P_h^l(t) = P_h^d(t) + P_h^s(t) + P_h^{b,c}(t). \tag{5}$$

Besides, for household h, we define P_h^g is the amount of energy generation, P_h^r is the received energy and $P_h^{b,c}$ is the amount of energy discharged from the battery at time slot t. Hence, the energy can be used at time slot t for household h is represented as below:

$$P_h^u(t) = \lambda_{inv} * P_h^g(t) + P_h^r(t) + P_h^{b,d}(t). \tag{6}$$

Therefore, the non-renewable energy usage of household h at time slot t can be given as follows:

$$P_h^n(t) = \begin{cases} P_h^l(t) - P_h^u(t), & \text{if } P_h^l(t) \geq P_h^u(t) \\ 0, & \text{otherwise.} \end{cases} \tag{7}$$

B. Problem Formulation of Prosumer Community Energy Scheduling

The objective of this work is to minimize the usage of non-renewable energy of the entire community through scheduling the energy sharing and battery charge/discharge. The problem formulation is as follows:

$$\min_{P_h^s(t), P_h^{b,d}(t), P_h^{b,c}(t)} \quad \Sigma_{\forall h \in H} \Sigma_{\forall t \in T} P_h^n(t), \tag{8}$$

$$\text{s.t.} \quad 0 < \lambda_{inv}, \lambda_d, \lambda_c < 1, \tag{8a}$$

$$\Sigma_{\forall h \in H}(1-B)(P_h^{b,s}(t) - \frac{P_h^{b,d}(t)}{\lambda_{inv} * \lambda_d}) \geq \Sigma_{\forall h \in H} b_{min}, \tag{8b}$$

$$\Sigma_{\forall h \in H} B(P_h^{b,s}(t) + \lambda_{inv}\lambda_c P_h^{b,c}(t)) \leqslant \Sigma_{\forall h \in H} b_{max}, \tag{8c}$$

$$\Sigma_{\forall h \in H} P_h^s(t) \leq \lambda_{inv} * (E_g(t) + \lambda_d * E_b(t)), \tag{8d}$$

$$B \in \{0, 1\}, t \in T. \tag{8e}$$

In problem (8), (8a) is the constraint that illustrates the efficiency of inverter, battery charge and discharge are in the range of [0,1]. Constraint (8b) enables the total remaining energy not less than the total minimum battery state of the entire community when battery discharge occurs. Constraint (8c) ensures that after charging, the energy saved in the battery of the entire community is not greater than the maximum battery capacity. The variable B in constraint (8b) and (8c) takes decision regarding whether it is charge or discharge process. Notably, constraints (8d) determines that the amount of energy that can be shared no greater than the aggregate of energy from solar generation and battery with the efficiency of the inverter. Finally, constraint (8e) defines the binary decision variable.

III. Solution with LSTM and Swarm Intelligence

The system model and problem formulation for minimizing non-renewable energy usage through energy sharing scheduling in the P2P prosumer community are proposed in Section II. To devise the solution of the formulated problem, we decompose it into the day-ahead prediction and optimization stage. Accordingly, we introduce long short term memory for energy demand prediction and swarm intelligence for energy sharing scheduling with considering battery storage of the next day in this section, as shown in Fig. 2.

A. Energy Demand Forecasting via Long Short Term Memory

Long short term memory network (LSTM) is a kind of optimized version of RNN which is able to handle time series problem by sequence-based model [13] [14]. Through LSTM, the difficulty of learning long-range dependencies with RNN due to gradient vanishing or exploding problems are solved. Therefore, we use LSTM to forecast the day-ahead energy demand. The related process is showed in Fig. 2 prediction stage.

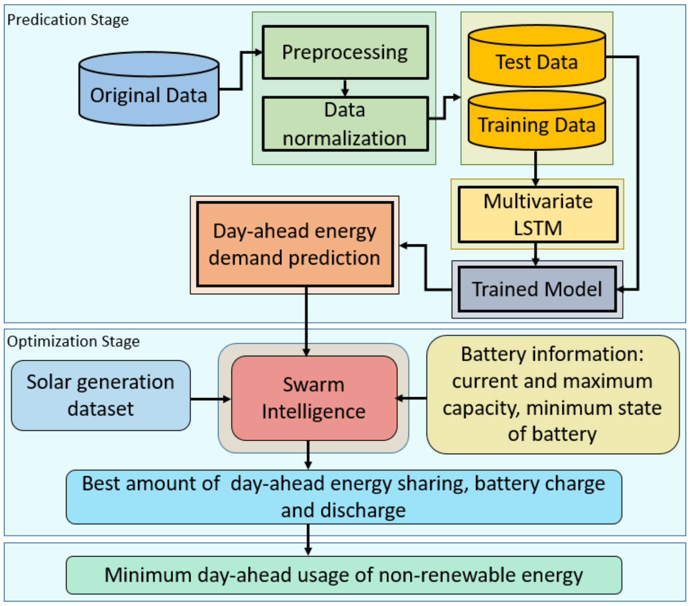

Fig. 2. Solution with LSTM and Swarm Intelligence

In this stage, we firstly preprocess the original data into the matrix format. Secondly, we use min-max normalization to scale the range of the preprocessed data into [0,1] by the following formula.

$$X_h^t = \frac{x_h^t - x_{min}}{x_{max} - x_{min}}. \tag{9}$$

where x_h^t is the original energy consumption data of household h at time slot t, X_h^t is the normalized value, x_{min} is the minimum and x_{max} is the maximum amount of energy demand in all time intervals.

Then we divide the data into a training dataset and test dataset. Based on these datasets, we adopt the LSTM as the solution for the day-ahead energy demand forecast. Lastly, we rescale the predict data by using the formula as below,

$$Y_h^t = x_{min} + \frac{(X_h^t - X_{min})(x_{max} - x_{min})}{X_{max} - X_{min}}. \tag{10}$$

Where X_{min} is the minimum and X_{max} is the maximum value of the predicted data before rescaling. Y_h^t is the real forecast of day-ahead energy demand of household h at time slot t.

B. Optimization with Swarm Intelligence

In Fig. 2 optimization stage, particle swarm optimization (PSO) is used. It is a population-based technique introduced by Kennedy and Eberhart in 1995, which gets the best performing particles (global best) and location (personal best) by allowing particles to fly around the solution space [15].

Initially, particles are placed randomly in the solution space and then get the optima by flying around. The movements are affected by the histories and other particles [16]. In each iteration, each particle will be updated by following the personal best (pb) and the global best (gb). All particles will eventually settle at and around the optima.

Algorithm 1 Swarm Intelligence (Global best)

Input : $w, c_1, c_2, \lambda_{inv}, \lambda_d, \lambda_c, b_{min}, b_{max}, particalNum, MAX\_ITERATIONS, Demand, Generation$

Output: X^*

Step 1: Initialization
Randomly assign initial state of battery
for each time slot t **do**
  for each particle i **do**
    generate random value P_t^s that satisfies (8d)
    generate random value P_t^c that satisfies (8c)
    generate random value P_t^d that satisfies (8b)
    initialize personal best: pb_i
  end for
  get global best: gbest
end for
Step 2: Iteration
repeat
  for each time slot t **do**
    for each particle i **do**
      using eq. (8): $F(x_i)$
      if $F(x_i) < F(pb_i)$ **then**
        $pb_i = x_i$
      end if
      if $F(pb_i) < F(gbest)$ **then**
        $gbest = pb_i$
      end if
    end for
    for each particle i **do**
      update its velocity (11) and its position (12)
    end for
  end for
  $it = it + 1$
until $it > MAX\_ITERATIONS$

The movement of particle is illustrated by its position $P = \{1, 2, ..., P\}$ and its speed $V = \{1, 2, ..., V\}$. And it can be represented as following equations.

$$V_i^{t+1} = wV_i^t + c_1 r()(pb_i^t - p_i^t) + c_2 r()(gb_i^t - p_i^t). \tag{11}$$
$$P_i^{t+1} = p_i^t + V_i^{t+1}. \tag{12}$$

Where w is the inertia factor, c_1, c_2 are weighting factors that determine the best position of both personal and global, and $r()$ is a uniform random value within [0,1].

As for the performance of PSO, it is determined by evaluating the fitness function $F()$. In this research, we define the objective (8) as the fitness function. The observation for each time slot t is denoted by $X_t = \{P_t^s, P_t^c, P_t^d\}$, which means the total amount of energy sharing, battery charge, and discharge of the entire community. The detail process is showed in Algorithm 1.

In Algorithm 1, we input the predicted energy demand data from the previous stage, solar generation data, maximum number of iterations, number of particles, minimum and maximum capacity of battery, efficiency of inverter/battery

TABLE II
PARAMETERS OF LSTM

Parameter	Value
Hidden layer	2
Neurons	32
Learning rate	0.001
Batch size	32
Look back	24

charge/discharge and coefficients of PSO, aims to get optimal X_t at each time slot. Lines 1 to 11 show the initialization step, in which we generate random value of X_t that satisfies (8b), (8c), (8d) for each particle per time slot. Then we get the initial personal best of each particle and global best of all particles. Lines 12 to 29 show the iteration step. In this step, the velocity and position will be updated in each iteration by (11) and (12), respectively. Based on the new position, if better fitness value appears, the personal best or global best will be updated. Finally, the global best will be the solution after all iterations.

IV. PERFORMANCE EVALUATION

The proposed LSTM and PSO joint approach is implemented on the python platform. To achieve the objective of this paper, two well-known datasets [17] [18] are used, where [17] is the solar panel dataset used as renewable energy generation and demand of 17 households that selected from [18] will be used in hourly day-ahead demand prediction via LSTM. Based on the generation data and predicted demand, we use PSO to do optimization.

A. Evaluation of LSTM

For the energy demand forecast, we use LSTM and the detailed parameters are shown in Table II. Here, two layers LSTM with 32 neurons for each hidden layer, and the look back state set to 24 hours is adopted. And also, the learning rate is 0.001 and batch size is set to 32. Furthermore, one-year data from [18] is divided into two parts, data from January to August as the training dataset and September to December as test dataset, in the preprocessing stage. First, we use eight months training dataset to train the model. Second, based on that model, we use test data to get the day-ahead demand prediction. In the case of comparison, ARIMA is selected because it is widely and also powerful in time series prediction. From Table III, it can be seen that the mean square error (MSE) of the LSTM model is 0.1599 and the root mean square error (RMSE) is 0.40, while the related values of ARIMA model are 0.652 and 0.81, respectively. Therefore, the LSTM model gains higher accuracy than the ARIMA model since it has lower MSE and RMSE.

Fig. 3 shows one week's forecast data based on LSTM and ARIMA, respectively. These data are selected from the prediction results of the test dataset. In this figure, it can be seen that LSTM based test dataset forecast gains higher accuracy than ARIMA. Besides, it costs more than 20 hours for predicting four months of data with the ARIMA model, while the LSTM model only takes several minutes in the same environment. Accordingly, LSTM has better superiority compared with the ARIMA model.

TABLE III
COMPARISON BETWEEN LSTM AND ARIMA

Demand Forecast Model	MSE	RMSE
ARIMA	0.652	0.81
LSTM	0.1599	0.40

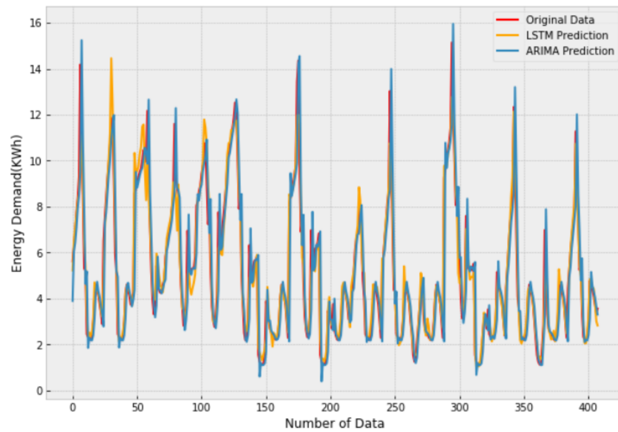

Fig. 3. Test Dataset Energy Demand Prediction by LSTM and ARIMA

B. Optimization based on PSO

TABLE IV
PARAMETERS FOR OPTIMIZATION

Parameter	Value
λ_{inv}	0.96
λ_c	0.958
λ_d	0.958
b_{min}	0 KWh
b_{max}	13.5 KWh

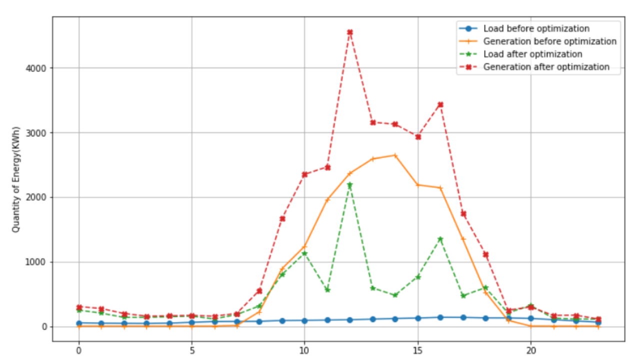

Fig. 4. PSO Optimization

The related parameters of the energy scheduling used in this paper are shown in Table IV, the same as [19]. In the previous

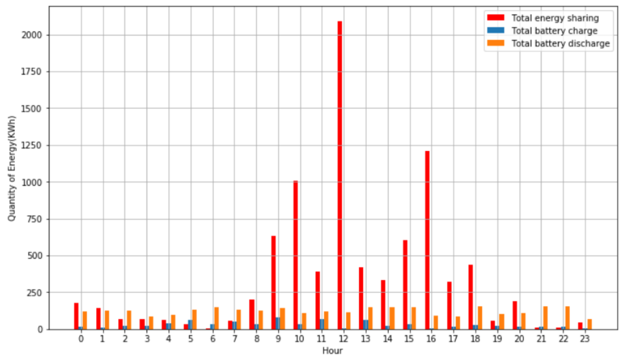

Fig. 5. Related Parameters scheduled by PSO

stage, we have used LSTM to predict hourly based demand and the output will be used as the input of PSO optimization in this stage. The proposed approach can be adapted to every future day, but we only randomly select a day for a case study.

Fig. 4 describes total energy load and solar generation of a specified community before scheduling without considering battery storage and energy sharing. And also, it shows load and generation after scheduling the battery and sharing. In this figure, it illustrates that from 0:00 to around 7:00 and after 20:00, solar generation tends to be zero before scheduling. However, during this period, the energy is still being consumed. Besides, solar generation is much greater than energy consumption at other times. Namely, energy usage and generation are in an uneven state. As a consequence, it is important and necessary to do energy scheduling to achieve the goal of using the least amount of non-renewable energy. Therefore, PSO optimization is used and after optimization, it becomes able to reach the energy balance of the community by scheduling the battery charge/discharge and sharing process of each household. That is, the solar generation can fulfill the usage of energy in every hour with optimization of the proposed method. Specifically, through the PSO optimization, the total usage of non-renewable energy of the community has been reduced by approximately 814.375 KWh.

Fig. 5 shows the total amount of energy that can be used for energy sharing, battery charge, and discharge at each time slot of the entire community. It can be seen that energy can be used for sharing at around 9:00 to 18:00 is larger than other times. This is because solar energy is mainly generated during this time.

V. Conclusion and Future work

In this research, we formulated the minimization problem of non-renewable energy usage. To handle this problem, we proposed a joint approach based on LSTM and swarm intelligence with the consideration of battery and P2P sharing process within a community such that to improve the unbalance between load and solar generation. In the performance evaluation section, the prediction method based on the LSTM outperform ARIMA model by reaching the higher accuracy and better performance in time-consuming problem of model training. In the optimization stage, the total generation can satisfy the total requirements of the specified community with PSO. In the future, we will consider the energy scheduling of multiple communities and the benefit of each household.

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