

# Article Handling Load Uncertainty during On-Peak Time via Dual ESS and LSTM with Load Data Augmentation

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Abstract: This paper proposes a scheduling method of dual ESSs (Energy Storage Systems) for the purpose of reducing the peak load when there are sudden loads or generation changes during the onpeak time. The first ESS is scheduled once a day based on a day-ahead load prediction, and the second ESS is scheduled every 15 min during on-peak time based on a short-term load prediction by LSTM (Long Short-Term Memory). Special attention is paid to training the LSTM for the short-term load prediction by using the augmented past load data which is generated by adding possible uncertainties to the past load and temperature data. Based on the load forecast, optimization problems for the scheduling are formulated. The proposed scheduling method is validated using load and temperature data from a real building. In other words, when the proposed method is applied to the real building energy data in the case study, it not only shaves the peak load during on-peak time interval effectively but also results in lower electricity price although there are sudden load or temperature changes during the time interval.

Keywords: building energy management; deep learning; energy storage system; load forecast; real-time control

# 1. Introduction

As the number of big buildings has increased, there has been an increase not only in their energy consumption and  $CO_2$  emission but also in their proportion of global total energy consumption and  $CO_2$  emissions. For instance, electricity consumption in buildings was about 55% of global total electricity consumption in the year 2019 [1]. Hence, it is of the utmost importance to devise building energy management systems (BEMS) in order to manage the total energy consumption efficiently.

In recent BEMS's research, a large amount of effort is directed to integrating renewable energy sources (RES) systematically [2]. Since RES is intermittent by nature and the load is unknown, inevitably BEMS has to be devised in such a way that it can deal with uncertainties in both the load and RES. ESS (Energy Storage Systems) are known to be the most efficient method to handle this problem. Consequently, one of the most important BEMS's tasks is to have an algorithm to charge and discharge ESS in such a way that the management of the building's energy is carried out successfully in terms of supply-demand balance, low electricity prices, and lower peak loads, etc. BEMS charges ESS when the demand is low and discharges it when the demand is high for the purpose of reducing electricity prices or the peak load during on-peak times [3,4].

The optimal ESS charging and discharging during a day has to be performed while taking the load into account. However, the load is unknown in advance, which means that BEMS has to be able to predict the load [5]. Various artificial intelligence-based methods for load prediction have been developed using ANN (Artificial Neural Network) [6,7] and RNN (Recurrent Neural Network) for sequential data prediction [8]. To overcome the weak long-term dependency of RNN, the LSTM (Long Short-Term Memory) network has



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been made and popularly applied to forecast loads [9–11]. Recently, GRU (Gated Recurrent Units) have been developed in order to reduce the number of parameters in LSTM and improve the convergence speed of training, and they are also employed to predict the load [12,13].

Usually, there are two approaches for ESS operation in BEMS. In the first approach, a day-ahead load prediction is made at the beginning of a day, and the schedule of charging and discharging is determined for the day considering the prediction. When a day starts, BEMS charges or discharges ESS following the determined schedule. In the offline scheduling approach, ESS works such that supply–demand balance is maintained and the electricity price according to ToU (Time-of-Use) is minimized [14,15]. This approach cannot deal with any uncertainties in the load or the temperature during the on-peak time since charging and discharging are scheduled at the beginning of a day. The other possible approach is to use another ESS, which is used online using real-time information on load and temperature to achieve the objectives of the BEMS, such as peak reduction. This second ESS is used under the assumption that the first ESS operates in accordance with the schedule made at the beginning of the day. As a compromise of these two approaches, in [16,17], only one ESS is employed, but it is re-scheduled at a certain time during a day based on real-time information.

Recently, renewable generation and EV (Electrical Vehicles) charging stations have been installed in buildings. Although they provide more electrical power and convenience, it is difficult to predict how much power must be generated by renewable generation sources and how much will be consumed by EVs during a day. If during on-peak times renewable generation produces less electricity than forecast or many EVs try to charge simultaneously, then the peak load can be very large. Hence, online real-time monitoring and ESS scheduling are important in order to deal with such situations. For instance, a real-time ESS operation method is developed to handle uncertainties [18–20]. A multi-time scale coordination is devised to reduce the effect of uncertainties [21,22] in BEMS operation. An optimal online ESS operation method to take uncertainties in solar generation and load variation into account using stochastic programming is designed in [23]. Furthermore, real-time energy management for apartment buildings using MPC (Model Predictive Control) [24], and energy management considering random events such as EV charging have been an emerging research area [25,26].

Along this line of research, this paper focuses on real-time ESS scheduling for peak load reduction when there is a large discrepancy in supply and demand during on-peak times. To this end, it is assumed in this paper that there are two ESSs: one (called ESS<sub>off</sub> hereafter) is scheduled offline using a day-ahead load prediction and the other (called ESS<sub>on</sub> hereafter) is scheduled online and is charged or discharged during on-peak time based on real-time short-term load predictions. ESS<sub>on</sub> is necessary because the scheduled plan for ESS<sub>off</sub> might not be effective to reduce the peak load due to the uncertainties during on-peak time period. Hence, the performance of ESS<sub>on</sub> is heavily dependent on real-time short-term load prediction. Roughly speaking, ESS<sub>off</sub> deals with a slowly varying deficient load and ESS<sub>on</sub> works for a rapidly varying deficient load.

The main contribution of the paper is twofold. First, for the purpose of scheduling ESS<sub>on</sub>, a short-term prediction based on LSTM and past temperature and load is developed. Especially, the training data for the LSTM is augmented such that the possible uncertainties during on-peak time are added to the past load and temperature data. The trained LSTM is used to predict the load during the on-peak time period. Second, using the short-term prediction by the LSTM, an optimization is formulated to make a plan for charging and discharging of ESS<sub>on</sub>. In the optimization, various requirements on, for example, SoC (State of Charge) limit of the amount of charging and discharging at a time are modeled as constraints in the optimization. A case study using real temperature and load data of a building shows that the proposed scheduling method for ESS<sub>on</sub> successfully reducing the peak load and thereby reducing the on-peak time efficiently.

In this paper, the variables with subscript 'off' mean that they are determined offline while the variables with subscript 'on' are determined online.

The paper is organized as follows. In Section 2, the configuration and objective of the paper are introduced. In Section 3, the proposed online ESS scheduling method is presented, which is followed by a case study based on real building data in Section 4. Section 5 concludes the paper.

#### 2. Objective and Description of the Proposed Method

In this section, the problem under consideration and the structure of the proposed BEMS are described. The proposed BEMS schedules a dual ESS (ESS<sub>off</sub> and ESS<sub>on</sub>) by solving optimization problems. The optimization problems rely on load predictions made by LSTM (Long Short-Term Memory). Figures 1 and 2 describes the proposed BEMS. The mathematical symbols in Figure 2 are explained in the next section.



Figure 1. Structure of the proposed BEMS.





To be specific, in offline mode, the two-deep learning networks LSTM<sub>off</sub> and LSTM<sub>on</sub> are trained using the past temperature and load data set. Then, at the beginning of a day, the trained LSTM<sub>off</sub> computes a day-ahead load prediction and the prediction is used to define an optimization problem with decision variables  $P_{off,0}^{ESS}$  ...,  $P_{off,23}^{ESS}$  for scheduling ESS<sub>off</sub> where  $P_{off,t}^{ESS}$  denotes the amount of charging or discharging for ESS<sub>off</sub> every hour (i.e., 24 times of charging or discharging a day). In addition, during an on-peak time period, LSTM<sub>on</sub> generates the load prediction every 15 min for the next 1 h to consider uncertain situations which are not taken into account in LSTM<sub>off</sub> (or scheduling ESS<sub>off</sub>). Based on short-term predictions by LSTM<sub>on</sub> including current load (i.e.,  $P_0$ ,  $\hat{P}_{on,1}$ , ...,  $\hat{P}_{on,4}$ ), an optimization problem with decision variables  $P_{on,0}^{ESS}$ , ...,  $P_{on,4}^{ESS}$  (i.e.,  $5 \times 15$  min) is defined for charging and discharging plan for ESS<sub>on</sub>. Then, only the first element  $P_{on,0}^{ESS}$  of the optimal

solution is applied to ESS<sub>on</sub>, and this procedure is repeated every 15 min similar to the receding horizon implementation in MPC (Model Predictive Control) [27].

The main objective of the BEMS design in this paper is to reduce the peak load during on-peak times by scheduling  $ESS_{on}$  based on short-term load prediction by  $LSTM_{on}$ , which is trained using the augmented load data to deal with abrupt large load changes. In achieving the objective, physical constraints such as SoC bounds or the limit of ESS output are taken into account.

## 3. Proposed Method

In this section, details of the proposed method are described. The results consist of offline ESS scheduling and online scheduling. The offline ESS scheduling is a modified result of that in [17] and the focus of this paper is mainly placed on the online ESS scheduling. Hence, offline ESS scheduling is briefly reviewed for the self-sufficient presentation of the main result and then the proposed online ESS scheduling is presented.

#### 3.1. ESS<sub>off</sub> Scheduling

3.1.1. Training  $\mathrm{LSTM}_{\mathrm{off}}$  for a Day-Ahead Load Forecast Using Past Load and Temperature Data

In building energy management, a day-ahead load prediction is indispensable for optimization-based ESS scheduling. Since LSTM is efficient at predicting time series data [28], it is employed to forecast the load demand of the building. Since LSTM is already a well-known deep learning technique, it is not explained here. For details, see [17,28].

For a day-ahead prediction, LSTM<sub>off</sub> is trained using past building loads. In this work, the load data are assumed to be measured and saved every hour. Moreover, to enhance the prediction accuracy, hourly measured outdoor temperature data are also used. Hence, the input data to LSTM<sub>off</sub> for training is of the form  $\{P_{t-j}, T_{t-j}\}$  ( $j = 1, \dots, 24$ ) and  $\{P_t, P_{t+1}, \dots, P_{t+23}\}$  is used as the output of the network. When LSTM<sub>off</sub> is trained, if  $\{P_{t'-j}, T_{t'-j}\}$  ( $j = 1, \dots, 24$ ) is injected into the trained LSTM<sub>off</sub>, LSTM<sub>off</sub> generates  $\{\hat{P}_{off,t'}, \hat{P}_{off,t'+1}, \dots, \hat{P}_{off,t'+23}\}$  as the load prediction for the next 24 h.

# 3.1.2. Scheduling ESS<sub>off</sub> via Optimization

For the purpose of scheduling  $\text{ESS}_{off}$ , the trained  $\text{LSTM}_{off}$  generates the load prediction  $\hat{P}_{off,t}$  at midnight for the next 24 h using the load and temperature data from the previous day. Then, to decide the amount of charging and discharging  $P_{off,t}^{\text{ESS}}$  for the next 24 h, an optimization problem is formulated on the basis of the prediction as follows:

$$\min_{\substack{P_{\text{off},t} \\ \text{e0}, \dots, 23}} \sum_{t=0}^{23} \left\{ C_{g,t} \hat{P}_{g1,t} + w_1 P_{gL1,t} + w_2 \left( P_{\text{off},t}^{\text{ESS}} - P_{\text{off},t-1}^{\text{ESS}} \right)^2 + w_3 P_{\text{off},t}^{\text{ESS}^2} \right\}$$
(1a)

subject to  $\forall t \in \{0, 1, \cdots, 23\}$ 

t =

$$\hat{P}_{g1,t} = \hat{P}_{\text{off},t} + P_{\text{off},t}^{\text{ESS}} \tag{1b}$$

$$P_{gL1,t} = \begin{cases} P_{g,min} - \hat{P}_{g1,t}, & \hat{P}_{g1,t} < P_{g,min} \text{ and } t \in \{\text{on-peak time}\}\\ 0, & \text{otherwise} \end{cases}$$
(1c)

$$SoC_{\text{off},t} = SoC_{\text{off},t-1} + \frac{\eta}{E_{c1}} P_{\text{off},t}^{\text{ESS}}$$
(1d)

$$SoC_{min} \le SoC_{off,t} \le SoC_{max}$$
 (1e)

$$|P_{\text{off},t}^{\text{ESS}}| \le P_{\text{off},max}^{\text{ESS}} \tag{1f}$$

$$|\sum_{t=0}^{23} P_{\text{off},t}^{\text{ESS}}| \le \alpha \tag{1g}$$

where  $C_{g,t}$  is the constant denoting the electricity price at time *t* and  $\hat{P}_{g1,t}$  is the estimated amount of electricity to be used. Hence, the first term  $C_{g,t}\hat{P}_{g1,t}$  in the objective function

denotes the estimated electricity cost that will be paid.  $w_i$  (i = 1, 2, 3) are weights that make each term contribute similarly to the entire objective function.  $P_{g,min}$  in (1c) represents the contracted minimum amount of electricity from the main grid during on-peak time. It is assumed that the operator of the building's energy provides the main grid operator with this information. It is useful to define  $P_{g,min}$  for not only the energy manager of the building's energy but also the main grid operator since the existence of such a value can help make a long-term energy plan for both the building and the main grid.  $P_{gL1,t}$  is the difference between  $P_{g,min}$  and  $\hat{P}_{g1,t}$  at time t during the on-peak time. Since the contract is made between the building energy operator and the grid operator such that the building spends at least  $P_{g,min}$  electricity during the on-peak time, a penalty has to be imposed on  $P_{gL1,t}$ , which is expressed using the second term  $w_1 P_{gL1,t}$ .  $P_{\text{off},t}^{\text{ESS}}$  is the amount of charging or discharging from ESS<sub>off</sub> at time t. Hence, the third and fourth terms in the objective function imply that the variation and amount of charging or discharging have to be small. Such consideration is helpful for both health and lifetime of the ESS. Note that  $P_{\text{off},t}^{\text{ESS}} \ge 0$  implies charging and  $P_{\text{off},t}^{\text{ESS}} < 0$  means discharging. (1d) denotes how  $SoC_{\text{off},t}$  changes according to  $P_{\text{off},t}^{\text{ESS}}$  where  $\eta$  and  $E_{c1}$  denote the efficiency of  $P_{\text{off},t}^{\text{ESS}}$  and the capacity of  $\text{ESS}_{\text{off}}$ . (1e,f) are the constraints on  $SoC_{off,t}$  and  $P_{off,t}^{ESS}$ , respectively. The last constraint (1g) is used to maintain the initial radius of  $C_{off,t}$ the initial value of  $SoC_{off,t}$  to a constant value at the beginning of a day by setting the  $\alpha$ small enough. Note that  $\alpha \equiv 0$  leads to an equality constraint that can restrict the feasibility of the problem. The optimization problem is a modified version of that in [17].

After computing the prediction  $\hat{P}_{off,t}$  by LSTM<sub>off</sub>, if the operator solves the optimization problem (1), the result can be depicted by Figure 3. In Figure 3, *k* is the start point of the on-peak time period and *p* is the length of the on-peak time period, and  $\hat{P}_{off,t}$  and  $\hat{P}_{g1,t}$ denote the load power prediction before and after ESS<sub>off</sub> is applied, respectively. Note that the peak of  $\hat{P}_{off,t}$  is reduced thanks to ESS<sub>off</sub>. Mostly, ESS<sub>off</sub> discharges during on-peak time  $\in [k, k + p]$  to reduce the electricity cost with  $P_{g,min}$  being the minimum, and charges during off-peak time to satisfy (1g). Therefore, comparing  $\hat{P}_{off,t}$  with  $\hat{P}_{g1,t}$  employing ESS<sub>off</sub>, peak reduction is achieved, thereby resulting in lower cost. Note that reducing the peak of  $\hat{P}_{g1,t}$ can bring about a reduction of the real consumed power.



Figure 3. Offline ESS optimization.

On the other hand, if the load uncertainty in real-time is denoted by  $\varphi_t$ , then the real load can be expressed by  $P_{g1,t} = \hat{P}_{off,t} + P_{off,t}^{ESS} + \varphi_t$ . This means that the cost for buying electricity from the main grid can vary significantly depending on the load uncertainty from the offline forecast. If the uncertainty is small, the cost variation becomes acceptable, but the cost will not be trivial if the uncertainty is significant due to, for example, abrupt large load changes such as charging electric vehicles. To deal with these situations, we present strategies on how to reduce the effect of the uncertain load during the on-peak times by improving the performance of the short-term load prediction, and how to operate ESS<sub>on</sub> based on the enhanced short-term load prediction.

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## 3.2. ESS<sub>on</sub> Scheduling

Under the assumption that ESS<sub>off</sub> is scheduled, this section presents a scheduling method for ESS<sub>on</sub> which works mainly during the on-peak time period. LSTM<sub>on</sub> is trained using augmented past load and temperature data for online short-term load forecasting first, and then a charging and discharging strategy is proposed using the online load forecast by using LSTM<sub>on</sub> and convex optimization.

## 3.2.1. Online Short-Term Load Forecast via LSTM with Data Augmentation

ESS<sub>on</sub> is employed in this work for the purpose of handling sudden large variations in load or temperature during the on-peak time period and is scheduled based on short-term load forecasts by LSTM<sub>on</sub>. Hence, LSTM<sub>on</sub> has to be trained such that it can generate short-term load forecasts even when there are unexpected load or temperature variations that do not exist in the past data. To this end, the past load and temperature data can be augmented [29]. The augmented data can be generated by adding possible values of sudden uncertainties (synthetic uncertainties) considering the possible situations in the building to past load and temperature data. To generate the synthetic uncertainties systematically, a probability density function (PDF) such as a Gaussian distribution can be used [30].

In other words, the synthetic uncertainties are generated by sampling data using a PDF, and it is added to the past data. For details, see the next section.

With this augmented data, LSTM<sub>on</sub> is trained such that its input  $\{P_{t-i\Delta t_m}, T_{t-i\Delta t_m}\}$  ( $i = 0, \dots, 7$ ) and its output  $\{P_{t+\Delta t_m}, \dots, P_{t+4\Delta t_m}\}$ , where  $\Delta t_m$  is 15 min. When the training is complete, the trained LSTM<sub>on</sub> generates  $\{\hat{P}_{on,t'+\Delta t_m}, \dots, \hat{P}_{on,t'+4\Delta t_m}\}$  when  $\{P_{t'-i\Delta t_m}, T_{t'-i\Delta t_m}\}$  is given as the input to LSTM<sub>on</sub>. Hence, the trained LSTM<sub>on</sub> forecasts the next one-hour load and its resolution is 15 min. Such LSTM<sub>on</sub> is expected to generate more accurate short-term load forecasts compared with the day-ahead load forecast when there are nontrivial variations in load or temperature.

## 3.2.2. Online ESS Operation

This subsection presents a scheduling  $\text{ESS}_{on}$  via convex optimization based on the short-term load forecast  $\hat{P}_{on,t}$  by  $\text{LSTM}_{on}$ .

During on-peak times, a short-term load prediction is made every 15 min for the next hour. In other words, at time *k* during the on-peak time period, the short-term load fore-cast  $\{\hat{P}_{\text{on},k+\Delta t_m}, \cdots, \hat{P}_{\text{on},k+4\Delta t_m}\}$  is generated every  $\Delta t_m$ . Then, the following optimization problem is solved with the forecast.

$$\min_{\substack{P_{\text{on,t}}^{\text{ESS}}\\t=k,\cdots,k+4\Delta t_{m}}} \sum_{t=k}^{k+4\Delta t_{m}} \left\{ w_{4}P_{gU2,t} + w_{5}P_{gL2,t} + w_{6}P_{\text{on,t}}^{\text{ESS}^{2}} \right\}$$
(2a)

subject to  $\forall t \in \{k, k + \Delta t_m, \cdots, k + 4\Delta t_m\}$ 

$$\hat{P}_{g2,t} = \hat{P}_{\text{on},t} + P_{\text{off},t}^{\text{ESS}} + P_{\text{on},t}^{\text{ESS}}$$
 (2b)

$$P_{gU2,t} = \begin{cases} \hat{P}_{g2,t} - (\hat{P}_{g1,t} + \delta), & \hat{P}_{g2,t} > \hat{P}_{g1,t} + \delta \\ 0, & else \end{cases}$$
(2c)

$$P_{gL2,t} = \begin{cases} P_{g,min} - \hat{P}_{g2,t}, & \hat{P}_{g2,t} < P_{g,min} \\ 0, & else \end{cases}$$
(2d)

$$SoC_{\text{on},t} = SoC_{\text{on},t-\Delta t_m} + \frac{\eta}{E_{c2}} P_{\text{on},t}^{\text{ESS}} \Delta t_m$$
 (2e)

$$SoC_{min} \le SoC_{on,t} \le SoC_{max}$$
 (2f)

$$|P_{\text{on},t}^{\text{ESS}}| \le P_{\text{on},max} \tag{2g}$$

where  $P_{\text{on},t}^{\text{ESS}}$  denotes the amount of charging or discharging from ESS<sub>on</sub> at time *t*. In the cost function (2a),  $w_4 P_{gU2,t}$  penalizes the power when it is higher than  $\hat{P}_{g1,t} + \delta$ . The first term

makes  $\text{ESS}_{on}$  work only when the difference between the required load  $\hat{P}_{g2,t}$  computed online and  $\hat{P}_{g1,t}$  computed offline is higher than  $\delta$ . Since  $\text{ESS}_{on}$  is usually expensive equipment, it is used only when there are large uncertainties. As depicted in Figure 4,  $\text{ESS}_{on}$  makes  $\hat{P}_{g2,t}$  be between the two red dashed lines,  $\hat{P}_{g1,t} + \delta$  and  $P_{g,min}$ , during on-peak time. In other words, if the uncertainties predicted by the online load forecast are small,  $\text{ESS}_{on}$  does not do anything, which is helpful for the lifetime of  $\text{ESS}_{on}$ . On the contrary, if the estimated uncertainty is nontrivial,  $\text{ESS}_{on}$  tries to reduce the effect of the uncertainty.



Figure 4. Online ESS optimization.

In the first term of the cost function,  $\hat{P}_{g2,t}$  means estimates of the required load power since it is the sum of the estimated power  $\hat{P}_{on,t}$  and the outputs of the two ESSs. The other terms in the cost are similar to the cost function (1).

Figure 5 summarizes how the online load forecast and ESS<sub>on</sub> work during on-peak time. At time t = k, LSTM<sub>on</sub> generates short-term load forecast { $\hat{P}_{on,k+\Delta t_m}, \cdots, \hat{P}_{on,k+4\Delta t_m}$ }. Based on this short-term forecast, the optimization problem (2) is solved to determine  $P_{on,k'}^{\text{ESS}}, P_{on,k+\Delta t_m}^{\text{ESS}}, \cdots, P_{on,k+4\Delta t_m}^{\text{ESS}}$ . Pess is applied for 15 min, and this procedure is repeated during on-peak time.



Figure 5. Online ESS operation process.

After the on-peak time, to maintain the initial value of  $SoC_{on,t}$ , the following optimization problem is solved. This procedure can be seen as (1g) in ESS<sub>off</sub> scheduling. The cost function is similar to the third and fourth terms in the objective function (1), considering the health and lifetime of the ESS<sub>on</sub>. At time t = k + p + 1, right after the on-peak time, ESS<sub>on</sub> charges or discharges for two hours considering  $P_{on,t}^{ESS}$  during the on-peak time. Note that  $\gamma$  is a small constant.

$$\min_{\substack{P_{\text{ess}}^{\text{ESS}}\\ p_{\text{on},t}^{\text{ESS}}}} \sum_{t=k+p+1}^{k+p+1} \left\{ w_6 P_{\text{on},t}^{\text{ESS}^2} + w_7 \left( P_{\text{on},t}^{\text{ESS}} - P_{\text{on},t-\Delta t_m}^{\text{ESS}} \right)^2 \right\}$$
(3a)

subject to  $\forall t \in \{k + p + 1, k + p + 1 + \Delta t_m, \cdots, k + p + 2 + 3\Delta t_m\}$ 

$$|\sum_{t=p}^{k+p+2+3\Delta t_m} P_{\text{on},t}^{\text{ESS}}| \le \gamma$$
(3b)

Algorithm 1 summarizes the proposed energy management method using LSTM with the augmented dataset, dual ESSs, and convex optimization. Moreover, Figure 2 illustrates Algorithm 1.

Algorithm 1: Proposed energy management method.
Offline
Train LSTM <sub>off</sub> using past load and temperature data set
Train LSTM <sub>on</sub> using augmented past load and temperature data set
Online
<b>Repeat</b> at <i>t</i> = 00:00
A day-ahead load forecast using LSTM <sub>off</sub>
Make charging and discharging scheduling of ESS <sub>off</sub> by solving the optimization (1)
/st Repeat the following every 15 min during on-peak time $st$ /
for $t \in \text{on-peak}$ time do Short-term load forecast using LSTM <sub>on</sub>
Make charging and discharging scheduling of $ESS_{on}$ by solving the optimization (2)
end for
Initialize $SoC_{\text{on},t}$ by solving the optimization (3)

# 4. Case Study

This section shows the application of the proposed energy management scheme using data from a real building. It is shown that the online short-term forecast-based ESS scheduling can reduce the peak load effectively even when there are nontrivial load uncertainties during the on-peak time. This is because the trained LSTM<sub>on</sub> using augmented datasets generate better load forecasts, which is not easy to accomplish for a day-ahead load forecast.

#### 4.1. Training Data and Data Augmentation

For training LSTM<sub>off</sub>, load and outdoor temperature datasets are taken from [31] and they are measured for a commercial building located in Richland, WA, during the summer season (June–September) from 2009 to 2011.

For training the LSTM<sub>on</sub>, the dataset is augmented for the purpose of obtaining a better load prediction when there are severe load uncertainties during on-peak time. To be specific, the dataset is augmented by adding the synthetic uncertainties to the original dataset. To augment the dataset systematically, the value of the synthetic uncertainty is generated using the normal distribution in (4) with a mean  $\mu$  and a standard deviation  $\sigma$  as follows:

$$f_{aug}(t) = \frac{\beta}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(t-\mu)^2}{2\sigma^2}\right)$$
(4)

where  $\beta \in [-40, 40]$  is a scaling factor.  $\mu \in [10, 18]$  and  $\sigma \in [1, 3]$  are chosen to create a variety of uncertainties. Several examples of synthetic uncertainties generated by  $f_{aug}(t)$  are shown in Figure 6.



Figure 6. Load uncertainty data.

Figure 7 shows the original load and temperature dataset and the augmented dataset using the synthetic uncertainties calculated by (4).



**Figure 7.** Original data and data with synthetic uncertainties. (a) Original load data, (b) Load with uncertainty data, (c) Original temperature data, (d) Temperature data with uncertainty.

4.2. Offline and Online Load Forecast by the Trained LSTMs

This section shows how accurately the trained LSTM<sub>off</sub> using the past dataset and LSTM<sub>on</sub> using the augmented past dataset generate load forecasts when there are uncertainties. Table 1 summarizes the structures and hyperparameters of LSTM<sub>off</sub> and LSTM<sub>on</sub>. For training the LSTMs, Tensorflow 2.0 in Intel(R) Core(TM) i7-4790 with 8GB memory was used [32].

Parameter	LSTM <sub>off</sub>	LSTMon
Number of layers	3	3
Number of neurons	$128\times128\times24$	128  imes 128  imes 4
Batch size	128	64
Number of epochs	100	100
Learning rate	0.001	0.001
Loss function	MAE	MAE
Optimizer	ADAM	ADAM

Table 1. LSTM Network parameters for training.

Figures 8–10 show load forecast results by LSTM<sub>off</sub> and LSTM<sub>on</sub> for positive, negative, and sign indefinite synthetic uncertainties, respectively. In the figures, the red dotted lines denote the original load data and the black solid lines show the augmented load data. On the left of Figures 8–10, the blue solid lines are the load forecast  $\hat{P}_{off,t}$  by LSTM<sub>off</sub>. As seen in the figures, the load forecast by LSTM<sub>off</sub> is not accurate. This is natural since LSTM<sub>off</sub> is trained using the red lines but actually used the black lines (i.e., input to the trained LSTM<sub>off</sub>) for the forecast. On the other hand, on the right of Figures 8–10, the short lines with various colors denote the one-hour load forecast by LSTM<sub>on</sub>. Note that the online load forecast by LSTM<sub>on</sub> for the next one hour period is carried out every 15 min repeatedly during the on-peak time.



**Figure 8.** Offline and online load forecasts with positive synthetic uncertainties. (**a**) Offline load forecast, (**b**) Online load forecast.



**Figure 9.** Offline and online load forecasts with negative synthetic uncertainties. (**a**) Offline load forecast, (**b**) Online load forecast.



**Figure 10.** Offline and online load forecasts with sign indefinite synthetic uncertainties.(**a**) Offline load forecast, (**b**) Online load forecast.

In view of the forecast results in Figures 8–10, LSTM<sub>on</sub> generates better load forecasts for a load with uncertainties than LSTM<sub>off</sub>. For quantitative comparison, the forecast errors are computed using Root Mean Square Error (RMSE) for the test data. Each RMSE for offline and online is given in (5a,b) considering the different resolutions. *N* is the number of test data and only the forecast during the on-peak time is calculated. Note that the online load forecast is repeated every 15 min. LSTM<sub>off</sub> results in 5.611 kW and LSTM<sub>on</sub> does 2.022 kW. Hence, the load forecast by LSTM<sub>on</sub> can be used for ESS scheduling in scenarios where there are sudden load changes during on-peak times.

$$\text{RMSE}_{\text{off}} = \sqrt{\frac{1}{N} \cdot \frac{1}{p+1} \sum_{i=1}^{N} \sum_{t=k}^{k+p} (P_{\text{aug},t}^{i} - \hat{P}_{\text{off},t}^{i})^{2}}$$
(5a)

$$\text{RMSE}_{\text{on}} = \sqrt{\frac{1}{N} \cdot \frac{1}{4p+1} \cdot \frac{1}{4} \sum_{i=1}^{N} \sum_{t=k}^{k+p} \sum_{j=0}^{3} (P_{\text{aug},t+j\Delta t_m}^i - \hat{P}_{\text{on},t+j\Delta t_m}^i)^2}$$
(5b)

# 4.3. ESS Scheduling Based on Online Load Forecast

Using the offline load estimate  $\hat{P}_{off,t}$  and online estimate  $\hat{P}_{on,t}$ ,  $P_{off,t}^{ESS}$  and  $P_{on,t}^{ESS}$  are determined by solving the convex optimization (1) and (2), respectively. For optimization, the CVX MATLAB toolbox is employed [33] and the tuning parameters for the optimization problems are given in Table 2. Each weight  $w_i$  is chosen such that each term in the objective function has a similar influence on the entire cost function.

Offline $P_{\text{off},t}^{\text{ESS}}$		Online $P_{\text{on},t}^{\text{ESS}}$		Common	
Parameter	Value	Parameter	Value	Parameter	Value
$w_1, w_2, w_3$	5, 0.05, 0.1	$w_4, w_5, w_6, w_7$	3, 50, 50, 0.1	η	0.95
E <sub>c1</sub>	120 kWh	$E_{c2}$	40 kWh	$SoC_{min}$	0.1
α	3 kW	δ, γ	1 kW, 5 kW	SoC <sub>max</sub>	0.9
P <sub>off,max</sub>	30 kW	Pon,max	20 kW	$P_{g,min}$	54 kW

Table 2. Parameters for ESS optimization.

For both ESS<sub>off</sub> and ESS<sub>on</sub>, the initial SoC are set to 0.5, and  $P_{g,min}$  is 0.8 times the peak of the average real load data. During the on-peak time, when the real power  $P_{g1,t}$  and  $P_{g2,t}$  bought from the main grid are smaller than  $P_{g,min}$ , then the penalty is calculated as

$$C_{\text{off}}^{pen} = \sum_{t \in j} C_{p,t} (P_{g,min} - P_{g1,t}); \{j | P_{g1,j} < P_{g,min}\},$$
(6a)

$$C_{\text{on}}^{pen} = \sum_{t \in i} C_{p,t} (P_{g,min} - P_{g2,t}); \{i | P_{g2,i} < P_{g,min}\}$$
(6b)

where the penalty price  $C_{p,t}$  is adjusted as double the value of  $C_{g,t}$ . Hence, the resulting costs for offline ESS scheduling and online ESS operations are given by

$$C_{\rm off} = \sum_{t=0}^{23} C_{g,t} P_{g1,t} + C_{\rm off}^{pen},$$
(7a)

$$C_{\rm on} = \sum_{t=0}^{k-1} C_{g,t} P_{g1,t} + \sum_{t=k}^{k+p+2+3\Delta t_m} C_{g,t} P_{g2,t} + \sum_{t=k+p+3}^{23} C_{g,t} P_{g1,t} + C_{\rm on}^{pen}$$
(7b)

where period  $t \in [k, k + p + 2 + 3\Delta t_m]$  is the time when ESS<sub>on</sub> is operated.

The simulation results are given in Figures 11–13 when  $P_{\text{off},t}^{\text{ESS}}$  and  $P_{\text{on},t}^{\text{ESS}}$  are applied to the cases with positive, negative, and sign indefinite synthetic uncertainties. Scheduling results are given on the left column in Figures 11–13 when only  $\text{ESS}_{\text{off}}$  (i.e.,  $P_{\text{off},t}^{\text{ESS}}$ ) is used. On the other hand, scheduling results are given on the right column in Figures 11–13 when both  $\text{ESS}_{\text{off}}$  and  $\text{ESS}_{\text{on}}$  (i.e.,  $P_{\text{off},t}^{\text{ESS}}$ ) are used.



**Figure 11.** Offline ESS scheduling and online ESS operations with positive synthetic uncertainties. (a) Offline load forecast, (b) Online load forecast, (c) The estimated power  $\hat{P}_{g1,t}$  and real power  $P_{g1,t}$  from the main grid by using only ESS<sub>off</sub>, (d) The estimated power  $\hat{P}_{g1,t}$  and real power  $P_{g2,t}$  from the main grid by using both ESS<sub>off</sub> and ESS<sub>on</sub>, (e) The amount of charging or discharging of ESS<sub>off</sub> and  $SoC_{on,t}$ .

Figure 11 is the operation result when the uncertainty is positive. In Figure 11a,b,  $\hat{P}_{off,t}$  and  $\hat{P}_{on,t}$  are given, which are also presented in Figure 8. In Figure 11c,d, the power  $P_{g1,t}$  and  $P_{g2,t}$  bought from the main grid are depicted together with corresponding estimate

 $\hat{P}_{g1,t}$  and  $P_{g,min}$ . The green solid line denotes the electricity price  $C_{g,t}$ ; ToU pricing, where the start point of on-peak time *k* is 11:00; and the peak period *p* is 4 h. The price for off-peak time is 1 USD/kWh and on-peak time is 5 USD/kWh. In Figure 11e,f,  $P_{off,t}^{ESS}$ ,  $P_{on,t}^{ESS}$  (i.e., amount of charging and discharging of ESS<sub>off</sub> and ESS<sub>on</sub>), and corresponding SoC (i.e.,  $SoC_{off,t}$ ,  $SoC_{on,t}$ ) are presented. The grey solid line denotes the constraints of SoC,  $SoC_{min}$  and  $SoC_{max}$ , respectively.

When Figure 11a,c are compared, the estimated power  $\hat{P}_{g1,t}$  denoted by the blue line is reduced during on-peak time based on the optimization (1) but the real power  $P_{g1,t}$  denoted by the brown line becomes higher than  $\hat{P}_{g1,t}$  due to uncertain load that is not predicted by  $\hat{P}_{off,t}$ . In the case of offline scheduling, since using only ESS<sub>off</sub> based on a day-ahead load forecast cannot consider the uncertainties during on-peak times, this results a higher cost.

On the other hand, when the brown lines denoting  $P_{g1,t}$  in Figure 11c and the red lines denoting  $P_{g2,t}$  in Figure 11d are compared, it is verified that the proposed scheduling method for ESS<sub>on</sub> effectively reduces the peak load during the on-peak time. To be more specific, the effect of the uncertain load is eliminated by optimization (2c) based on the online short-term load forecast  $\hat{P}_{on,t}$ , which has better performance than  $\hat{P}_{off,t}$ . By adding ESS<sub>on</sub>, peak load reduction is achieved when considering the uncertain load and reducing the required payment. This can be confirmed by the final cost paid. For Figure 11c, it costs 2072 but only 2042 for Figure 11d.



**Figure 12.** Offline ESS scheduling and online ESS operations with negative synthetic uncertainties. (a) Offline load forecast, (b) Online load forecast, (c) The estimated power  $\hat{P}_{g1,t}$  and real power  $P_{g1,t}$  from the main grid by using only ESS<sub>off</sub>, (d) The estimated power  $\hat{P}_{g1,t}$  and real power  $P_{g2,t}$  from the main grid by using both ESS<sub>off</sub> and ESS<sub>on</sub>, (e) The amount of charging or discharging of ESS<sub>off</sub> and  $SoC_{on,t}$ .

Figure 12 shows the operation results obtained by the proposed scheduling method when the uncertainty is negative. Similar observations to those in Figure 11 are possible. The brown line denoting  $P_{g1,t}$  in Figure 12c becomes lower than  $P_{g,min}$  during the on-peak

time due to the negative uncertain load, resulting in a penalty, but in the case of  $P_{g2,t}$  as denoted by the red line in Figure 12d, it does not deviate from  $P_{g,min}$  constraints through ESS<sub>on</sub>. It is verified that the proposed scheduling for ESS<sub>on</sub> can effectively reduce the effect of the negative variations. Quantitatively, for Figure 12c, it costs 2079 but only 2042 for Figure 12d.



**Figure 13.** Offline ESS scheduling and online ESS operations with indefinite synthetic uncertainties. (a) Offline load forecast, (b) Online load forecast, (c) The estimated power  $\hat{P}_{g1,t}$  and real power  $P_{g1,t}$  from the main grid by using only ESS<sub>off</sub>, (d) The estimated power  $\hat{P}_{g1,t}$  and real power  $P_{g2,t}$  from the main grid by using both ESS<sub>off</sub> and ESS<sub>on</sub>, (e) The amount of charging or discharging of ESS<sub>off</sub> and  $SoC_{on,t}$ .

As the last case study, Figure 13 presents the operation results of the proposed ESS scheduling when the variation can be indefinite (i.e., either positive or negative). In Figure 13, both positive and negative variations are used. Again, similar observations to Figures 11 and 12 are also possible. Quantitatively, for Figure 13c, it costs 2031 but only 1962 for Figure 13d.

# 5. Discussion

This section analyzes the effect of parameters  $\delta$  and the initial value of  $SoC_{on,t}$  on  $P_{on,t}^{ESS}$  (i.e., amount of charging or discharging of ESS<sub>on</sub>).

## 5.1. Effect of $\delta$

Figures 14 and 15 represent the operation results with both ESS for the same condition as in Figure 11 with different values of  $\delta$ .  $\delta = 1$  is used in Figure 11. Figure 14 corresponds to  $\delta = 0$  and results in a cost value of 2035, and Figure 15 shows  $\delta = 4$  and cost of 2062. As the value of  $\delta$  becomes smaller, ESS<sub>on</sub> has to deal with more uncertainties according to the optimization (2c). This is verified by comparing Figure 11 ( $\delta = 1$ ) with Figure 14 ( $\delta = 0$ ) since  $P_{\text{on},t}^{\text{ESS}}$  discharges more in Figure 14. On the other hand,  $P_{\text{on},t}^{\text{ESS}}$  discharges less in Figure 15 since  $\delta = 4$  makes ESS<sub>on</sub> cover less uncertainties compared with the previous cases. Therefore, the proper choice of  $\delta$  must be used since ESS<sub>on</sub> has to consider the constraints in (2f).



**Figure 14.** Online ESS operation at  $\delta = 0$ . (a) Online load forecast, (b) The estimated power  $\hat{P}_{g1,t}$  and real power  $P_{g2,t}$  from the main grid by using both ESS<sub>off</sub> and ESS<sub>on</sub>, (c) The amount of charging or discharging of ESS<sub>on</sub> and  $SoC_{on,t}$ .



**Figure 15.** Online ESS operation at  $\delta = 4$ . (a) Online load forecast, (b) The estimated power  $\hat{P}_{g1,t}$  and real power  $P_{g2,t}$  from the main grid by using both ESS<sub>off</sub> and ESS<sub>on</sub>, (c) The amount of charging or discharging of ESS<sub>on</sub> and  $SoC_{on,t}$ .

# 5.2. Effect of SoC<sub>on,t</sub> on the Initial Value

Figures 16 and 17 validate why it makes sense to set the initial value of  $SoC_{on,t}$  to 0.5. The configuration of Figure 16 is the same as that of Figure 11 except for the initial value of  $SoC_{on,t} = 0.2$ . As seen in Figure 16, ESS<sub>on</sub> starts to discharge in order to handle the uncertainties but stops discharging after a short time due to the SoC constraints. This makes  $P_{g2,t}$  violate the constraint on  $\hat{P}_{g1,t} + \delta$ , thereby leading to the value of the cost being 2050, which is larger than the case in Figure 11 with the initial value of  $SoC_{on,t}$  0.5.

Conversely, in Figure 17, the initial value of  $SoC_{on,t}$  is set to 0.8 and all the other settings are the same as those in Figure 12. At this time,  $ESS_{on}$  has to charge to deal with the negative uncertainties, but it reaches the upper limit soon. Hence, it can not charge any more. As a result,  $P_{g2,t}$  becomes smaller than  $P_{g,min}$  sometimes. This results in the value of the cost being 2028, which is larger than that in Figure 12 with the initial value of  $SoC_{on,t}$  set to 0.5.

Hence, since it is unknown which uncertainties occur during on-peak times, it is reasonable to set the initial value of  $SoC_{on,t}$  to 0.5.



**Figure 16.** Online ESS operations with initial  $SoC_{on,t}$  value being 0.2. (a) Online load forecast, (b) The estimated power  $\hat{P}_{g1,t}$  and real power  $P_{g2,t}$  from the main grid by using both ESS<sub>off</sub> and ESS<sub>on</sub>, (c) The amount of charging or discharging of ESS<sub>on</sub> and  $SoC_{on,t}$ .



**Figure 17.** Online ESS operations with initial  $SoC_{on,t}$  value being 0.8. (a) Online load forecast, (b) The estimated power  $\hat{P}_{g1,t}$  and real power  $P_{g2,t}$  from the main grid by using both ESS<sub>off</sub> and ESS<sub>on</sub>, (c) The amount of charging or discharging of ESS<sub>on</sub> and  $SoC_{on,t}$ .

## 6. Conclusions

In this paper, a method for building energy management through real-time ESS operations is presented for a case where a sudden load variation occurs. For this, the LSTM network-based load forecast method was used for both the offline and online forecasts. In addition, to increase the prediction accuracy, the load of the building and the outdoor temperature were selected as input variables for the network. For the online load forecast, the LSTM network was trained using augmented past load and temperature data. Based on the day-ahead load forecast, the offline ESS was scheduled. On top of this, the online ESS is scheduled to reduce the effect of load uncertainties during on-peak times by using short-term load forecasts. For the scheduling of the two ESSs, optimization problems were formulated considering various physical constraints. In a case study, it was confirmed that the proposed method can reduce the effect of the uncertainties during on-peak times, which then leads to lower costs.

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## Abbreviations

The following abbreviations are used in this manuscript:

- BEMS Building Energy Management System
- ESS Energy Storage System
- LSTM Long Short-Term Memory
- SoC State of Charge
- ToU Time-of-Use
- MAE Mean Absolute Error
- RMSE Root Mean Square Error

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