Neural network learns from mock-up operation experience: implementing on a solar energy community distribution system with heat storage

Chih-Hsiang Lee

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Department of Engineering

Declaration

This thesis has not been submitted in support of an application for another degree at this or any other university. It is the result of my own work and includes nothing that is the outcome of work done in collaboration except where specifically indicated. Many of the ideas in this thesis were the product of discussion with my supervisor Dr Dénes Csala.

Chih-Hsiang Lee

Lancaster University, UK

Abstract

Inspired by Imitation Learning, this paper trained a LSTM network by a mock-up operation experience of a solar energy community distribution system. Unlike the conventional method that implements LSTM only to predict features for the control programme to calculate an operation action according to a strategy, the LSTM of the proposed model integrates the strategy into its structure and thus can outputs actions directly. To examine whether the proposed model outperforms the conventional model, this paper first describes an operation strategy, adopted by both models, that aims to decrease total operation cost. Since the strategy needs accurate predictions to work effectively, an expert who can perfectly predict the future is created by historical data. The behaviours of the expert that follows the strategy are used as the training data of the LSTM in the proposed model. During simulation, the proposed model has better performance and computation efficiency than the conventional LSTM model by 25% higher and 75 times faster. Many researches have proposed control models for different systems and implemented LSTM only to predict key uncertainty in those models. To these researches, this paper demonstrates a promising result that the performance of a control model can be improved by integrating the strategy of that model into a neural network with mock-up operation experience.

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1 Introduction

This paper presents a practical application of Long Short-Term Memory neural network (LSTM) [1] on a solar energy community distribution system. Unlike other models that predict features individually for supporting operators or control programmes to decide on operation actions, the proposed model in this paper was trained for directly determining the next operation action based on input features.

LSTM is capable of predicting time sequence by learning long-term dependencies in a dataset. It has the power of extracting non-linear relationship between input and output, and the capability of identifying patterns in time sequence. Thus, it has been widely used in electricity systems because key uncertainties, such PV generation, wind speed, demands and electricity price, have a temporal dependency between each time step. Many researches [2, 3, 4, 5, 6, 7] applied LSTM purely to predict key features related to electricity industry, such as weather condition, electricity prices, and energy demands. These predictions can be used to support operator's decision making, but not directly provide operation actions on the electricity equipment or systems.

In the field of sewer system operation, Zhang (2017, 2018) [8, 9] proposed operation strategies for water managements, and then pointed out key uncertainty in these strategies.

LSTM was implemented only to predict the uncertainty, such as future inflow of each wastewater treatment plant or sewer. Similarly, LSTM predictions made in [8, 9] have no connection to their proposed strategies, but only provide better information to operators who use those strategies.

In this paper, we built three models to compare the performance of conventional and our proposed method. Standard Model adopted the idea discussed above that forecast only serves as a reference in operating the system. Operators or control programmes accept the forecast and run the operation strategy to determine the current action. On the contrary, our Proposed Model integrates the operation strategy into its training set, enabling the model to directly control the system. Simulative results show that the Proposed Model outperforms the Standard Model. Moreover, even though the Proposed Model takes more resources to prepare the training set, no calculation need to be done when processing online. In the long run, the Proposed Model consumes less processing time than the Standard Model. Last, for comparison, the Vanilla Model follows a common strategy that the storage always starts at fixed times to be charged or to be discharged.

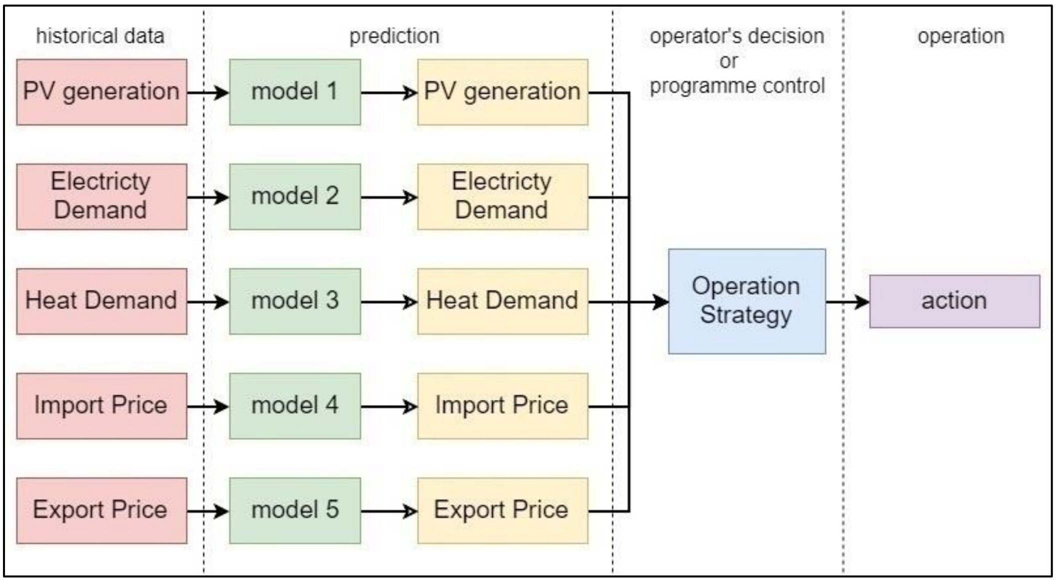
Note that when we use the word, ‘operator,’ in this paper, it usually means the same as ‘control programme’ since the three Models are controlled by computer programmes.

1.1 Standard Model

Applying the concept mentioned above, we build a Standard Model to provide a basis for comparison to the Proposed Model. This concept is a straightforward implementation of LSTM networks on operation of systems with uncertainty and has been adopted by many researches.

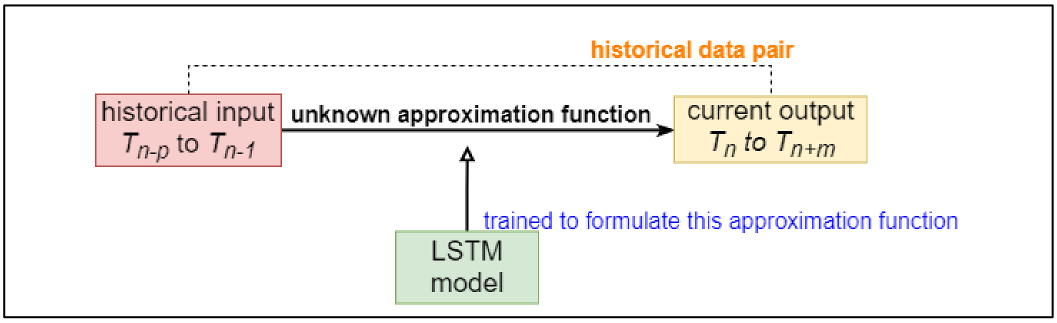
Figure 1.1 depicts the Standard Model of using LSTM predictions to aid operators in operation of a solar energy distribution system. The energy distribution system is showed in Figure 2.1 and detailed in Chapter 2. Each sub-model (green square) in Figure 1.1 has one LSTM network. In the beginning of every half hour, each sub-model accepts input from historical data to make prediction of five key features relevant to operation decision: PV generation, electricity demand, heat demand, importing price of the grid and exporting price of the grid. A computer programme that follows operating strategy (blue square) then accepts those predictions as input for calculating the operation action in current half hour.

Figure 1.1 Concept of Standard Model



Note that sub-models of the Standard Model can be more complicated, taking more features as input to increase its accuracy. However, since the Proposed Model in this paper only use the five input features, we set sub-model of the Standard Model only take its own feature as input for a fair comparison of the two models. Figure 1.2 shows the training method of sub-models. The LSTM sub-models approximate the relationship between two sets of time sequence. Operators or control programmes accept the output sequence as a guideline to decide their operation action.

Figure 1.2 Training of Standard Model



1.2 Proposed Model

To design our Proposed Model, we first formulated an operating strategy that determines the target level of heat storage every half hour, based on the five input features. Following our proposed strategy, the heat storage will be charged if its current energy level is less than the target level. Charging can be done not only by PV generation but also electricity imported from the grid if future importing price is expected to become higher. If the current energy level is more than the target level, the heat storage discharges. This proposed strategy is designed to decrease total operation cost, detailed in Section 2.2. To make the comparison meaningful, 'Operation Strategy (blue square)' in Figure 1.1 is the same as our proposed operating strategy of heat storage in Figure 1.3.

To utilise the proposed strategy, uncertainties of the five input features must be eliminated. Instead of training five LSTM sub-models that predict these features, we trained only one LSTM model that takes these five features as inputs to directly output a target level for every half hour.

We applied the principle behind Imitation Learning, of which a model learns from expert's behaviours. For example, when learning self-driving cars, a model is showed with pairs of state and action for it to interpret the policy behind the decision of actions.

Those demonstrated actions are recorded from an expert, such as a human driver. Imitation Learning is usually implemented when calculation of an action is impossible or too expensive, but the task is easy for a human to perform. In our case, although no person can perfectly predict future when operating heat storage, we can create a mock-up expert from historical data. This expert follows the proposed strategy in simulations of operating a system. The expert's behaviours are then used as the training set for the Proposed Model.

The training method of the Proposed Model is showed in Figure 1.4. In contrast to the training pairs for the Standard Model in Figure 1.2, the Proposed Model learns to interpret the relationship between a time sequence and one output value. The training pairs in Figure 1.4 are 'handcrafted' by following the proposed strategy. Consequently, the Proposed Model is connected to the proposed strategy itself, and its output is directly determining the next operation action.

The working process of the Proposed Model is depicted in Figure 1.3. Compared with the Standard Model, the Proposed Model runs the strategy only once during preparation of training pairs, while the computer programme in the Standard Model must repeat calculation of the strategy each half hour every time when it receives new forecasts of its five predictive features.

Figure 1.3 Concept of Proposed Model

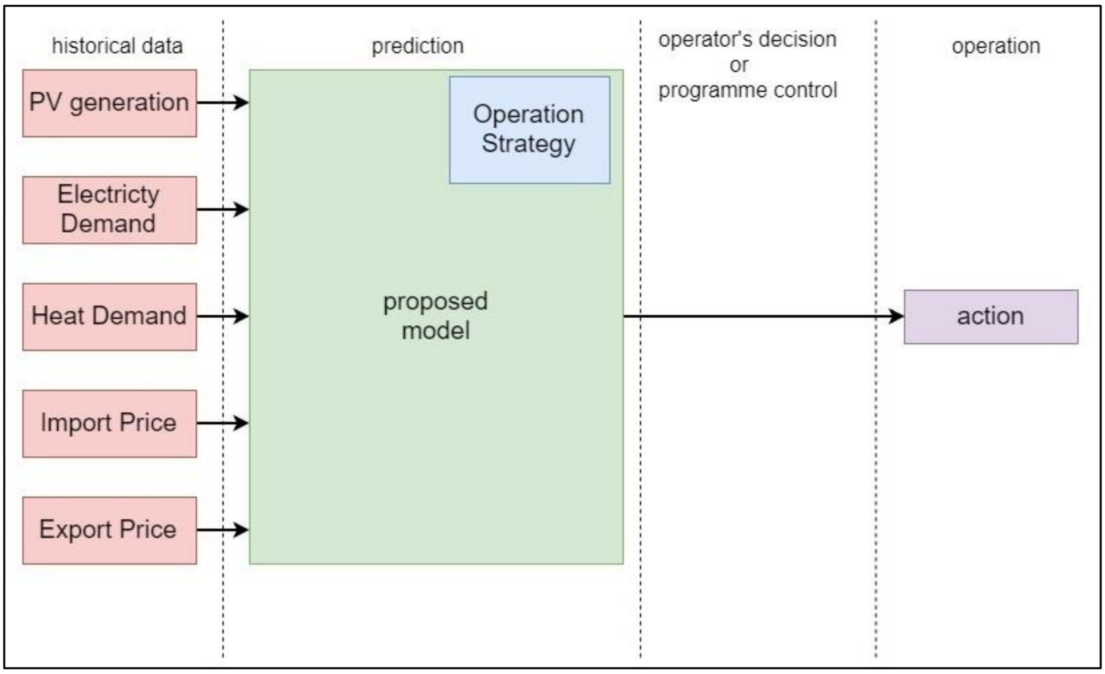
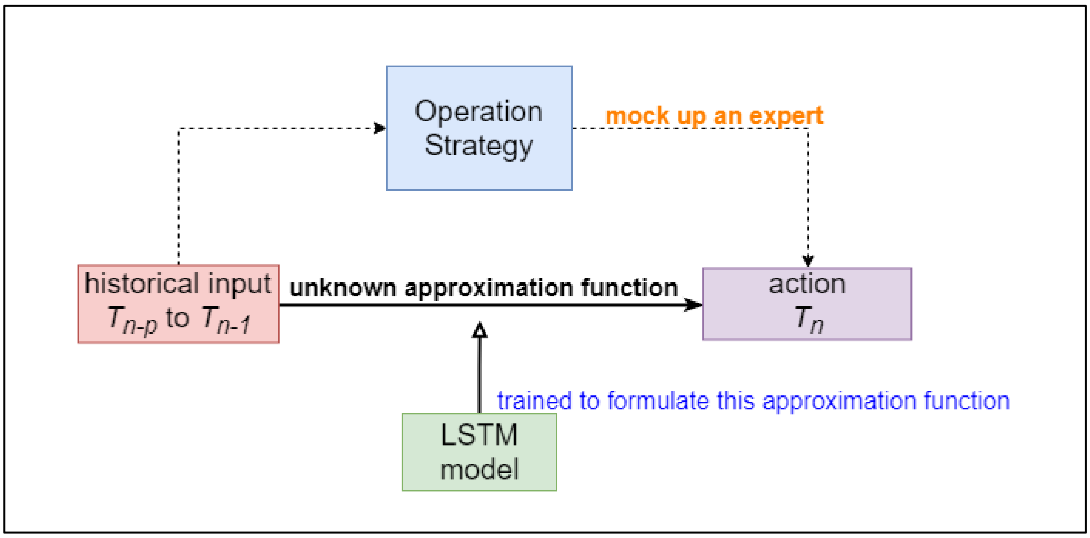


Figure 1.4 Training of Proposed Model



1.3 Vanilla Model

A common strategy is to charge and discharge heat storage at fixed times. Examining the actions performed by the expert discussed in the Proposed Model, we found that most of the time the expert charges the storage at 13:30 and discharges the storage at 17:00.

Therefore, we set the Vanilla Model always charge and discharge at these two times every day. The storage is charged and discharged with a fix rate.

Another key difference between the Vanilla Model and other two models is that during charging the Vanilla Model never imports electricity from the grid if PV-generation is not enough because the Vanilla Model have no ability to forecast electricity price. It would end up in excessive expenditure if allowing the Vanilla Model to import electricity. When there’s no PV-generation during charging, the Vanilla Model would stop charging the storage until PV-generation resumes.

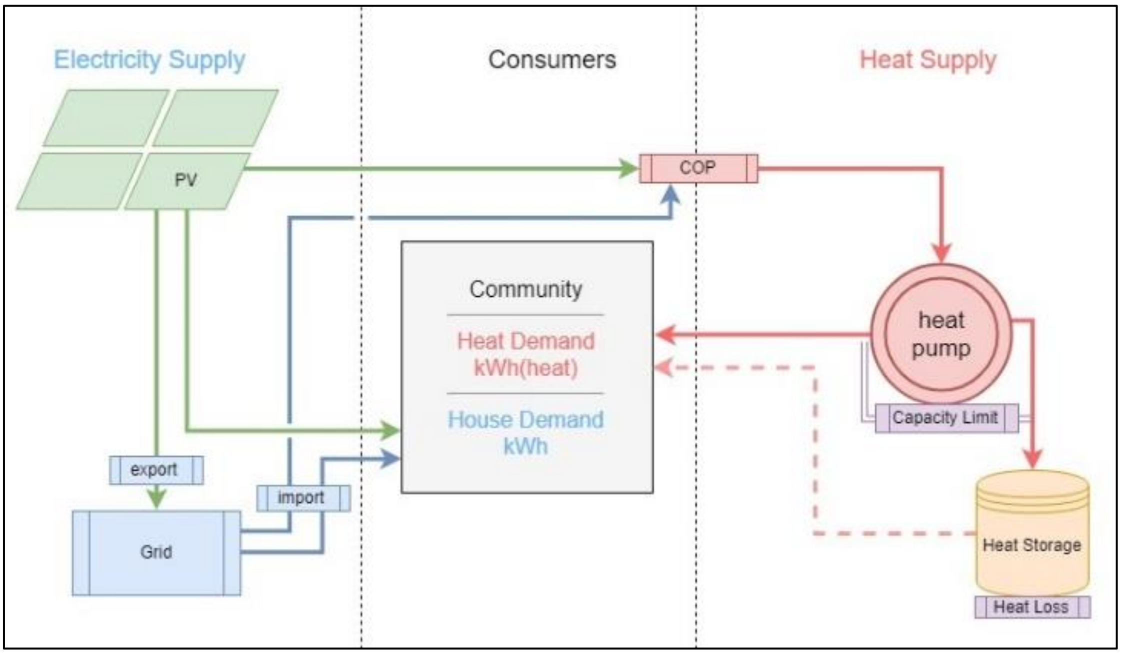
The remainder of this paper is organized in the following way: Chapter 2 details the components of the solar energy community distribution system and the objective of its operation. Chapter 3 introduces the proposed strategy for operation of the community system and describes how an expert is created and the operation behaviour of this expert. Chapter 4 explains the implementation of the three Models and the simulation process in python environment. Chapter 5 discusses and analyses the outcome of simulation. Chapter 6 summarises the results and provides a suggestion of future researches.

2 Solar Energy Community Distribution System

2.1 Details of the System

Showed in Figure 2.1, the design of this system is based on a real proposed project for a community located in North West of England. PV generation is the only domestic supply in the system. During each time interval, such as a half hour, PV generation is used to meets electricity demand first, and any insufficiency is addressed by importing electricity from the grid. After that, surplus of PV generation, if any, is used to run heat pumps for meeting heat demand. Electricity demand takes priority over heat demand because PV generation would suffer loss due to energy conversion in heat pumps. In Figure 2.1, COP stands for Coefficient of Performance, which defines the conversion factor between electricity energy and heat energy.

Figure 2.1 Solar Energy Community Distribution System



If PV generation is insufficient to cover heat demand, the short of heat supply is compensated by importing electricity from the grid to run heat pumps or by discharging heat from the storage. When heat pumps run out of capacity, the only way to provide heat is discharging the storage. In this paper, we assume that heat pump capacity is always sufficient to cover demand peak. The heat pump capacity is set to be a little high than the maximum heat demand in our simulative environment, but not infinite.

Finally, excess PV generation can be sold to the grid, or be used to charge heat storage if heat pumps still has capacity. In this study, we assume that domestic use of PV generation is always more economical than selling to the grid.

Heat storage can be charged by heat pumps that consume PV generation, imported electricity or both. Due to the capacity of heat pumps, charging storage may be limited sometimes.

In each half hour there are two prices: System Sell Price (SSP) and System Buy Price (SBP). When the operator imports electricity from the grid, the operator needs to pay the SBP. Likewise, the grid pays the SSP to the operators who export electricity to the grid. These two prices are called 'imbalance prices' and originally designed to tackle the deficit of imbalance energy. In our study, we use a historical data of SSP and SBP around Lancaster area to simulate the price change faced by operators.

2.2 Objective of Operation

In our system, PV generation is always used to meets electricity demand first and then heat demand. After that if any PV generation remains, it can be used to charge the storage or be sold to the grid. Thus, we defined 'PV Surplus' as the amount of remaining PV generation we can manipulate:

$$\boldsymbol{PV\ Surplus = PV\ generation - electricity\ demand - (heat\ demand \div COP)} \qquad (1)$$

$$\boldsymbol{if\ PV\ Surplus < 0,\ PV\ Surplus = 0}$$

When PV generation is unable to cover all heat demand, we defined a term 'Shortage' as the amount of remaining heat demand that we need to cope with by heat storage:

$$\boldsymbol{Shortage = heat\ demand - [(PV\ generation - electricity\ demand) \times COP]} \qquad (2)$$

$$\boldsymbol{if\ (PV\ generation - electricity\ demand) < 0,\ Shortage = heat\ demand}$$

$$\boldsymbol{if\ Shortage < 0,\ Shortage = 0}$$

Every half hour the operator determines a target level for the heat storage. If current level is high than the target level, the heat storage is discharged until current level drops to the target level. If current level is lower than the target level, the heat storage is charged by PV surplus first. It can also be charged by imported electricity only if importing electricity with current SBP is beneficial, compared to importing electricity with future SBP when the demand actually occurs in the future. In other words, the operator must have the capability to forecast future electricity prices to know when the best time to buy electricity is. Furthermore, the operator must be able to forecast future PV generation and demands to determine what is the actual amount of heat needed to be prepared in advanced. For example, if a sunny day is expected, the operator has no need to import electricity to charge the storage even though current SBP is low

The goal of the operator is to reduce operation cost of the system. Operation cost is equal to the expenditure of importing electricity from the grid subtracted by the income of selling PV generation to the grid. In terms of cost, income is negative:

$$\boldsymbol{Operatoin\ cost} = \boldsymbol{expenditure\ of\ importing} + (-\boldsymbol{income\ of\ exporting}) \qquad (3)$$

With heat storage and a good predictor of future PV generation, demands and system prices, the operator can accomplish several tasks to decrease operation cost:

A. If the operator has PV surplus in the current moment and expects a Shortage in a future moment and importing electricity with future SBP is expensive than not selling PV surplus with current SSP, the operator should charge the storage with current PV surplus:

$(\boldsymbol{i})$ $\boldsymbol{Selling\ PV\ surplus\ right\ now, and\ importing\ electricity\ in\ the\ future}$:

$$\boldsymbol{income} = -\boldsymbol{PV\ surplus} \times \boldsymbol{current\ SSP}$$

$$\boldsymbol{expenditure} = [\boldsymbol{Shortage} \div \boldsymbol{COP}] \times \boldsymbol{future\ SBP}$$

$(\boldsymbol{ii})$ $\boldsymbol{Saving\ PV\ surplus\ right\ now\ for\ the\ future}$:

$$\boldsymbol{income} = \boldsymbol{0}$$

$$\boldsymbol{expenditure} = \boldsymbol{0}$$

$$(\boldsymbol{Assuming}: \boldsymbol{PV\ surplus} \times \boldsymbol{COP} \times \boldsymbol{loss}^{(\boldsymbol{t}_{\boldsymbol{future}} - \boldsymbol{t}_{\boldsymbol{current}})} = \boldsymbol{Shortage})$$

$$\boldsymbol{if\ Operation\ cost(ii) - Operation\ cost(i) < 0}:$$

$$\rightarrow \boldsymbol{0 - (-PV\ surplus \times current\ SSP + [Shortage \div COP] \times future\ SBP) < 0}$$

$$\rightarrow \boldsymbol{PV\ surplus \times current\ SSP < [Shortage \div COP] \times future\ SBP}$$

$$\rightarrow \boldsymbol{PV\ surplus \times current\ SSP < PV\ surplus \times loss^{(t_{future} - t_{current})} \times future\ SBP}$$

$$\rightarrow \boldsymbol{current\ SSP \div loss^{(t_{future} - t_{current})} < future\ SBP} \qquad (4)$$

, where $t_{future} - t_{current}$ is the difference between current and future time. And $loss$ is the heat loss in storage per unit time. In our study, the unit time is equal to a half hour, and transition loss is ignored for simplification.

B. If the operator has no PV surplus in the current moment and expects a Shortage in a future moment and importing electricity with future SBP is expensive than importing electricity with current SBP, the operator should import electricity with current SBP to charge the storage.

$$\boldsymbol{(i)\ Do\ nothing\ right\ now, and\ importing\ electricity\ in\ the\ future}:$$

$$\boldsymbol{expenditure_{current} = 0}$$

$$\boldsymbol{expenditure_{future} = [Shortage \div COP] \times future\ SBP}$$

$$\boldsymbol{(ii)\ Importing\ electricity\ right\ now\ for\ the\ future}:$$

$$\boldsymbol{expenditure_{current} = Importing\ electricity \times current\ SBP}$$

$$\boldsymbol{expenditure_{future} = 0}$$

$$\boldsymbol{(Assuming: Importing\ electricity \times COP \times loss^{(t_{future} - t_{current})} = Shortage)}$$

$$\boldsymbol{if\ Operation\ cost(ii) - Operation\ cost(i) < 0}:$$

$$\rightarrow \boldsymbol{Importing\ electricity \times current\ SBP - [Shortage \div COP] \times future\ SBP < 0}$$

$$\rightarrow \boldsymbol{Importing\ electricity \times current\ SBP < [Shortage \div COP] \times future\ SBP}$$

$$\rightarrow \boldsymbol{Importing\ electricity \times current\ SBP < Importing\ electricity \times loss^{(t_{future} - t_{current})} \times future\ SBP}$$

$$\rightarrow \boldsymbol{current\ SBP \div loss^{(t_{future} - t_{current})} < future\ SBP} \qquad (5)$$

C. If the operator expects several available electricity sources at t_1, t_2, t_3, t_4, and a Shortage at t_5, the operator must compare the prices, which are modified by loss and different time spans. The modified prices could be:

$$\begin{cases} \boldsymbol{current\ SSP \div loss^{(t_{future} - t_{current})},\ if\ the\ source\ is\ PV\ surplus} \\ \boldsymbol{current\ SBP \div loss^{(t_{future} - t_{current})},\ if\ the\ source\ is\ importing\ electricity} \end{cases}$$

After comparison, the operator exploits the sources in order of profitability. Consequently, depending on the amount of heat required by Shortage at t_5, some of the sources may be exhausted, some never used, and some used only part of their available supply. It is important for the operator not to consume an electricity source more than the requirement; otherwise operation cost would increase. For example, if the operator takes the exact amount of electricity, remaining PV generation can be sold to the grid instead of suffering unnecessary loss in the heat storage and being used in somewhere not actually profitable. Similarly, if the operator imports the exact amount of electricity from the grid, no extra expenditure would be incurred.

3 Operation Strategy for the Community System

With historical data, we can assume that there is a perfect predictor, "an expert," who can forecast all we need in next 24 hours, which is divided equally into t_0 to t_{47}. Our operation strategy is to analyse the relationship of PV surplus, Shortage, SSP and SBP at t_0 to t_{47}, to determine the profitability of each available electricity source and to distribute all available electricity sources to all Shortage at t_0 to t_{47} accordingly. Available electricity sources include PV Surplus and importing electricity from the grid.

At the start of t_0, the expert holds the values of PV surplus, Shortage, SSP and SBP at t_0 to t_{47}. First, it creates a profit table, in which each entry is called a 'profit number':

$$\boldsymbol{profit\,number} = \begin{cases} \left(\boldsymbol{SSP_p \div loss^{(t_n - t_p)}}\right) \div \boldsymbol{SBP_n}, & \boldsymbol{if\ using\ PV\ Surplus\ at\ t_p\ to\ charge\ heat\ storage} \\ \left(\boldsymbol{SBP_p \div loss^{(t_n - t_p)}}\right) \div \boldsymbol{SBP_n}, & \boldsymbol{if\ importing\ electricity\ at\ t_p\ to\ charge\ heat\ storage} \end{cases} \quad (6)$$

, where $t_n > t_p$ and $t_n, t_p \in t_0$ to t_{47}. SSP_p is the SSP at t_p, SBP_p is the SBP at t_p and SBP_n is the SBP at t_n. We only consider t_n when there is a Shortage at t_n.

We set $pf_{p,n}^{PV}$ be the profit number when using PV Surplus at t_p to charge heat storage for future Shortage at t_n. Similarly, $pf_{p,n}^{Gd}$ is the profit number when importing electricity from the grid at t_p to charge heat storage for future Shortage at t_n. Refer to Equation (4) and (5), it is obvious that if $pf_{p,n} < 1$, it's profitable to use electricity source at t_p. On the other hand, if $pf_{p,n} \geq 1$, it has no need to use electricity source at t_p and this $pf_{p,n}$ would be excluded from the profit table.

Next, the expert distributes all available electricity source to all Shortage, starting from the smallest $pf_{p,n}$. The expert calculates the exact amount of electricity needed at t_p for the Shortage at t_n :

$$\boldsymbol{electricity\ requirment\ at\ t_p} = (\boldsymbol{Shortage\ at\ t_n} \div \boldsymbol{loss}^{(t_n - t_p)}) \times \boldsymbol{COP} \qquad (7)$$

The expert then adjusts the electricity requirement at t_p according to heat pump capacity at t_p and heat storage capacity at t_p, t_{p+1}, t_{p+2},……, and t_n because heat pump capacity limits the amount of heat that can be charged, and heat storage capacity limits the amount of heat that can be stored in the heat storage.

Finally, the expert decreases the electricity source at t_p as much as possible according to the modified electricity requirement at t_p. If the electricity source is PV Surplus, the expert records how much amount of PV Surplus remains. If the electricity source is from the grid, the expert can import as much as it need, because we assume that the connection to the grid is always available. The amount of electricity consumed at t_p turns into heat, which reduces heat pump capacity at t_p. The expert also records the decrease of Shortage at t_n and the decreases of heat storage capacity at t_p, t_{p+1}, t_{p+2},……, and t_n.

To increase the efficiency of the algorithm, when a heat pump capacity at t_p is exhausted, all $pf_{p,n}$ with t_p will be deleted from the profit table. Similarly, when a heat storage capacity at t_x is used up, all $pf_{p,n}$ with $t_p \leq t_x \leq t_n$ will be deleted. In addition, after a Shortage at t_n is fully fulfilled, all $pf_{p,n}$ with t_n will be deleted.

After the expert goes through all entries of the profit table, all Shortages that are not fully fulfilled will be coped with importing electricity at their current time. We obtain an optimal operation curve, such as showed in Figure 3.1 and Figure 3.2. A pseudo code is showed in Table 3.1.

In Figure 3.1 and Figure 3.2, the heat level of heat storage (purple dot) of t_n is the heat level at the start of t_n, and the bars (orange and indigo) show how much amount of heat is charged into the storage at the end of t_n. For example, at the start of t_0 and t_1 in Figure 3.1 there is no heat in the storage, and the operator charges the storage by 243.18 kWh during t_1. Thus, at the start of t_2 the heat level is equal to 243.18 kWh as showed in the figure.

Note that PV generation in Figure 3.1 and Figure 3.2 has been subtracted by electricity demand first and then converted to heat energy for clearly demonstrating how PV generation is used to charge the storage.

The operation curves in Figure 3.1 and Figure 3.2 demonstrate several behaviours that our Proposed Model must learn:

A. Avoid storing excessive heat:

Comparing the sum of heat demand from t_{12} and t_{17}(approx. 771.36 kWh) and the total heat released from the heat storage from t_{12} and t_{17} (approx. 762.98 kWh) in Figure 3.1, it can be seen that heat prepared in the storage is slightly less than the heat demand because it can be covered by the PV generation at t_{17} (approx. 8.38 kWh). After that, heat demand from t_{18} and t_{29} is fully covered by PV generation. This behaviour demonstrates that our expert knows the optimal amount of heat that needs to be prepared before a certain time, depending on when PV generation begins and what amount of PV generation occurs in the future.

Likewise, expecting a low demand during the evening in Figure 3.2, the expert fills the storage to a sufficient amount of heat (approx. 794.52 kWh), but not to its full capacity (1500 kWh). This shows the expert's capability of operating the storage optimally by knowing PV generation and heat demand in advanced.

B. Charge the storage economically:

Knowing how much amount of heat needs to be prepared is not enough. The expert must figure out how to charge the storage in a cost-effective way. In Figure 3.1, the expert imports electricity at t_1, t_2, t_5 and t_{11} to meet the target level at t_{12} because SBPs at t_1, t_2, t_5 and t_{11} are lower than other SBPs between t_1 to t_{11}. Note that even though SBP at t_1 (0.03232 £/kWh) is lower than SBP at t_{11}(0.03472 £/kWh), the expert still chooses to import electricity at t_{11} due to the modification of SBP made by heat loss, as discussed in Equation (5). Similarly, in Figure 3.2, the expert consumes PV generation at t_{23}, t_{24}, t_{25}, t_{28} and t_{32} because of low modified prices. From t_{18} to t_{32} in Figure 3.1, the expert has several different electricity sources from PV generation or from the grid for meeting the target level at t_{33}. The expert exploits PV generation as much as possible from t_{29} to t_{24} and stop using PV generation at t_{23} because the modified SSP starts to be higher than modified SBP at t_{29} to t_{32}. Note that PV generation between t_{27} and t_{29} is not fully used by the heat pump because PV generation need to meet heat demand first. On the other hand, PV generation between t_{24} and t_{26} is not fully used due to the maximum capacity of heat pump.

Figure 3.1 Expert's Operation Curve on a cold day

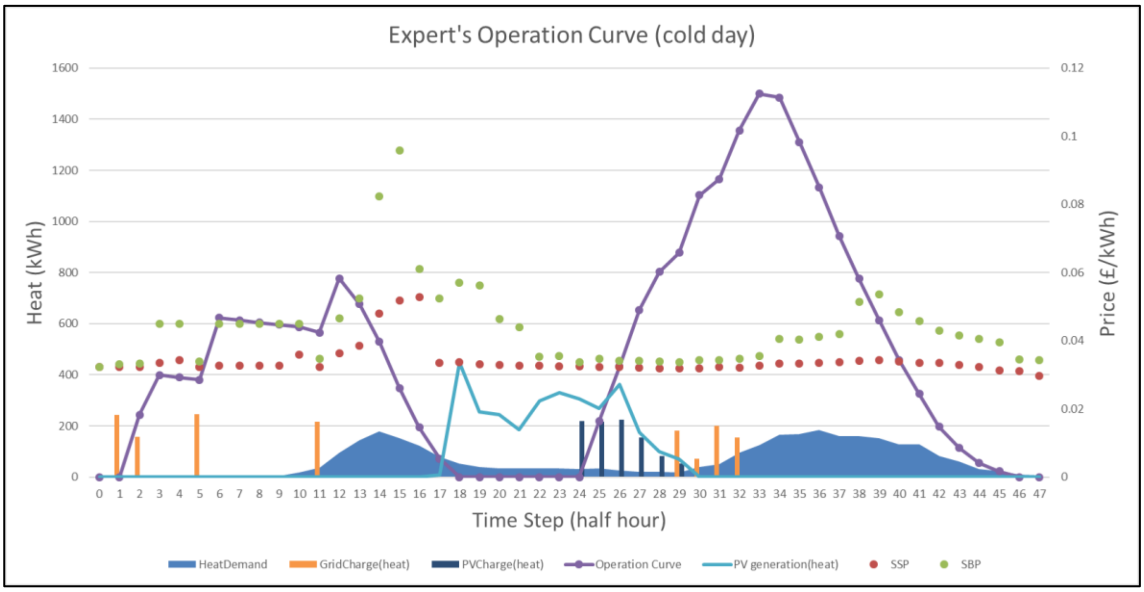


Figure 3.2 Expert's Operation Curve on a warm day

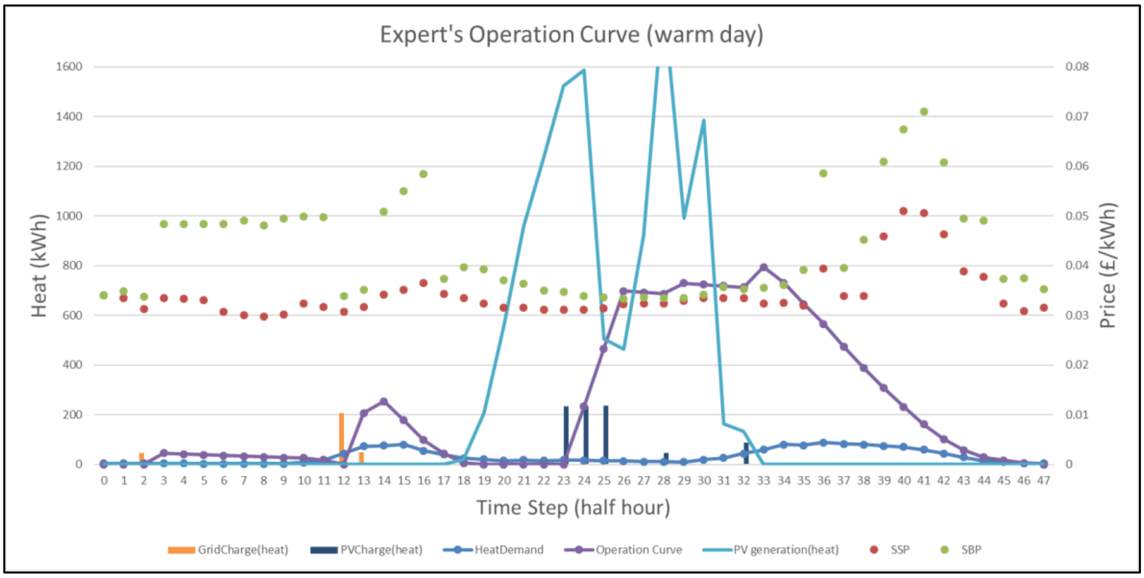


Table 3.1 Pseudo Code: Operation strategy for optimal operation curve

Algorithm 1 operation strategy for optimal operation curve
(Note that COP must be considered in actual codes)

1. **Input** PV generation, Electricity Demand, Heat Demand, SSP and SBP of t_0 to t_{47}
2. $PV\ Surplus = max(0, PV\ generation - Electricity\ Demand)$
3. **Create Cost Table:**

    Table = []

    for $n \in t_n$ when there is a Shortage **do**

     for $p = n-1, n-2, n-3, \ldots$ **do**

      calculating $pf_{p,n}$

      if $pf_{p,n} < 1$**:** Table.append($pf_{p,n}$)

      else: break

    Table.sort(ascending)
4. **Distribute energy:**

    for $pf_{p,n}$ in Table **do**

     supply = Shortage at t_n

     A. **check** remaining heat pump capacity at t_p,

      reduce supply if need

     B. **check** remaining heat storage capacity at t_p, t_{p+1}, t_{p+2},……, and t_n (heat loss considered)

      reduce supply if need

     C. According to supply:

      update PV Surplus **or** Importing electricity at t_p

       if remaining PV Surplus at t_p = 0:

        delete all $pf_{p,n}^{PV}$ at t_p in Table

      update remaining heat pump capacity at t_p

       if remaining heat pump capacity at t_p = 0:

        delete all $pf_{p,n}$ at t_p in Table

      update remaining heat storage capacity at t_p, t_{p+1}, t_{p+2},……, and t_n (heat loss considered)

       if any remaining heat storage capacity at t_p, t_{p+1}, t_{p+2},……, or t_n = 0:

        delete all $pf_{p,n}$ that use heat storage at t_p, t_{p+1}, t_{p+2},……, or t_n in Table

      update Shortage at t_n

       if Shortage at t_n = 0:

        delete all $pf_{p,n}$ at t_n in Table

4 Python Implementation

We use Python and Jupyter Notebook to create the Models and to conduct simulations. The implement of LSTM networks is constructed by Keras, a neural networks API of Python [10].

4.1 Simulation Environment

The pseudo code of simulation environment is showed in Table 4.1.

We first set up a four-year database of the five features (PV generation, electricity and heat demand, SSP and SBP):

A. PV generation is based on a four-year real data.
B. We assumed that electricity demand per dwelling per year is set to be 3000 kWh and there are 180 houses in the community. Electricity demand curve is based on a one-year real data.
C. Heat demand per dwelling is set to be 4500 kWh. Heat demand curve is based on a one-year estimated data.
D. SBP and SSP are based on a one-year real data. The average of SBP is 0.04756 £/kW, and of SSP is 0.0366 £/kWh. SBP is always greater than or equal to SSP.

After picking a day, the simulation environment loads the five features at t_{-48}, t_{-47}, …, t_0, t_1, …, and t_{47}, of which t_0 is 12:00 AM of that day. The output of simulation is an operation curve of each Model between t_0 and t_{47}, and the total operation cost of each Model during t_0 to t_{47}.

4.2 Standard Model

In Standard Model, we trained five networks to predict each feature (PV generation, heat demand, electricity demand, SSP and SBP). Each network receives a value sequence of t_{n-48} to t_{n-1} to forecast the sequence of t_n to t_{n+47}, as showed in Figure 1.2, in which $p = 48$ and $m = 47$. The operator then put these predicted sequences of t_n to t_{n+47} into Algorithm 1 (Table 3.1) to determine the target level of heat storage at t_n. The pseudo code of Standard Model is showed in Table 4.2.

The training sets of Standard Model are prepared by pairing the sequences of t_{n-48} to t_{n-1} with the sequences of t_n to t_{n+47} for each feature in the four-year database.

These five networks have the same figuration that the first layer is a LSTM layer with a hard-sigmoid function as its activation function. The second layer is a dropout layer with a dropout rate equal to 0.5, connected to the last layer which is a simple Dense layer with hard-sigmoid function. The cost function is MSE. Input of the first layer is scaled to a range of 0 to 1, and the output of the Dense layer is also between 0 to 1, which will be transformed back to the original range based on the training set. This is because normalization can make learning process faster.

4.3 Proposed Model

In Proposed Model, we trained only one network. The network receives five sequences of t_{n-48} to t_{n-1} to forecast one value: the target level for t_n, as showed in Figure 1.4, in which $p = 48$. The operator has no need to run Algorithm 1 (Table 3.1) repeatedly. The pseudo code of Proposed Model is showed in Table 4.3.

The training set of Proposed Model is prepared by putting five sequences of t_{n-48} to t_{n-1} of the four-year database into Algorithm 1 (Table 3.1) to obtain the target level for t_n.

The figuration of the network in Proposed Model has similar structure of which the first layer is a LSTM layer with a hard-sigmoid function as its activation function. The second layer is a dropout layer with a dropout rate equal to 0.3, connected to the last layer which is a simple Dense layer with hard-sigmoid function. Similarly, the cost function is MSE, input of the first layer is scaled to a range of 0 to 1, and the output of the Dense layer is also between 0 to 1, which will be transformed back to the original range based on the training set. This is because normalization can make learning process faster.

Table 4.1 Pseudo Code: Simulation Environment

Algorithm 2 Simulation Environment
(Note that COP must be considered in actual codes)

1. **Load** Features (PV generation, Electricity Demand, Heat Demand, SSP and SBP) of t_{-48} to t_{47}
2. **Set** $Cost_S = 0,\ Cost_P = 0,\ Cost_V = 0$ ## $Cost_x$ is the operation cost, x = S, P or V
   ## S = Standard Model, P = Proposed Model, V = Vanilla Model
3. $heat\ level_S = [\,], heat\ level_P = [\,], heat\ level_V = [\,]$
4. **For** n = 0, 1, 2, …,46, 47 **do**

(A). Input Features of t_{n-48} to t_{n-1} **into** Standard Model (Algorithm 3)

  Return $Target_S$ *## target level predicted by Standard Model*

Do step (B)., **with** $Target = Target_S,\ Cost = Cost_S, heat\ level = heat\ level_S$

(B). Load $HP\ capacity_n, Storage\ capacity_n, Shortage_n, PV\ Surplus_n$

  $HP\_capacity \leftarrow HP\ capacity_n$

  $Storage\_capacity \leftarrow Storage\ capacity_n$

  $Shortage \leftarrow Shortage_n$

  $PV\_Surplus \leftarrow PV\ Surplus_n$

Let $HP\_capacity, Storage\_capacity, Shortage, PV\_Surplus$ **always ≥ 0**

whenever it's a negative number, set it to be 0

if $Target > heat\ level_{n-1}$:

  $charge_n \leftarrow min(Target - heat\ level_{n-1}, HP\_capacity, Storage\_capacity)$

  $export_n \leftarrow 0$

  Let $charge_n, export_n$ **always ≥ 0**

  $heat\ level_n \leftarrow heat\ level_{n-1} + charge_n$

  if $PV\_Surplus > 0$:

    while $charge_n > 0$:

      $export_n \leftarrow PV\ Surplus - charge_n$

      $charge_n \leftarrow charge_n - PV\_Surplus$

      $import_n \leftarrow charge_n$

      $charge_n \leftarrow 0$

    $Cost \leftarrow Cost + import_n \times SBP_n$

    $Cost \leftarrow Cost - export_n \times SSP_n$

  else if $Shortage > 0$:

    $Cost \leftarrow Cost + Shortage \times SBP_n$

    while $charge_n > 0$:

      $import_n \leftarrow charge_n$

      $charge_n \leftarrow 0$

    $Cost \leftarrow Cost + import_n \times SBP_n$

else if $Target \leq heat\ level_{n-1}$:

$discharge_n \leftarrow\ min(heat\ level_{n-1} - Target, Discharge\_Rate)$

Let $discharge_n$ **always ≥ 0**

$heat\ level_n \leftarrow heat\ level_{n-1} - discharge_n$

if $PV\_Surplus > 0$:

$Cost \leftarrow Cost - PV\_Surplus \times SSP_n$

else if $Shortage > 0$:

$Shortage \leftarrow Shortage - discharge_n$

$Cost\ \leftarrow\ Cost + Shortage \times SBP_n$

(C). Input Features of t_{n-48} to t_{n-1} **into** Proposed Model (Algorithm 4)

Return $Target_P$ ***##** target level predicted by Proposed Model*

Repeat step (B).,

but with $Target = Target_P,\ Cost = Cost_P, heat\ level = heat\ level_P$

(D). Repeat step (B).,

but with $Target_V,\ Cost_V, heat\ level = heat\ level_P, and\ this\ condition$:

if n<27:

$Target_V = heat\ level_{n-1}$

else if n<34:

$Target_V = Full\ Storage\ Capacity$

Set $import_n$ **always = 0**

else:

$Target_V = 0$

5. **Print** $Cost_S,\ Cost_P,\ Cost_V$

Plot $heat\ level_S, heat\ level_P, heat\ level_V, and\ features\ of\ t_0\ to\ t_{47}$

Table 4.2 Pseudo Code: Standard Model

Algorithm 3 Standard Model

1. **Receive** $Features$ of t_{x-48} to t_{x-1} **from Algorithm 2**
2. **Load** $Predictor_{PV}, Predictor_{ED}, Predictor_{HD}, Predictor_{SSP}, Predictor_{SBP}$
   ## five trained LSTM network
3. **For** (item, label) **in** [(PV generation, PV), (Electricity Demand, ED), (Heat Demand, HD), (SSP, SSP), (SBP, SBP)] **do**
   input $Feature(item)$ of t_{x-48} to t_{x-1} **into** $Predictor_{label}$
   return $Feature(item)$ of t_x to t_{x+47}
4. **input** $Features$ of t_x to t_{x+47} **into Algorithm 1**
   return $operation\ curve$ of t_x to t_{x+47}
5. $Target_S \leftarrow$ *the value of* $operation\ curve$ *at* t_x
6. **return** $Target_S$ **to Algorithm 2**

Table 4.3 Pseudo Code: Proposed Model

Algorithm 4 Proposed Model

1. **Receive** $Features$ of t_{x-48} to t_{x-1} **from Algorithm 2**
2. **Load** $Predictor_P$ **## trained LSTM network of Proposed Model**
3. **input** $Features$ of t_{x-48} to t_{x-1} **into** $Predictor_P$
   return $Target_P$ of t_x
4. **return** $Target_P$ **to Algorithm 2**

5 Results and Discussion

5.1 Training result of the networks in Standard Model

Figure 5.1 demonstrates six comparisons of predictive values and true values. More examples can be found in Appendix A. Blue lines in the figures are the true values of one day and red lines are the values predicted by the five networks in Standard Model. Networks that predict PV generation, electricity and heat demands show the ability to match a rough pattern to the curve of true values. However, the networks are unable to fit those small and rapid changes on the curve delicately.

Predictions made for SBP and SSP are unsatisfying. Predictive values always fluctuate around the average number. This means that the networks are not trained enough, resulting in a bad approximation that sticks around average number to bring a smaller MSE.

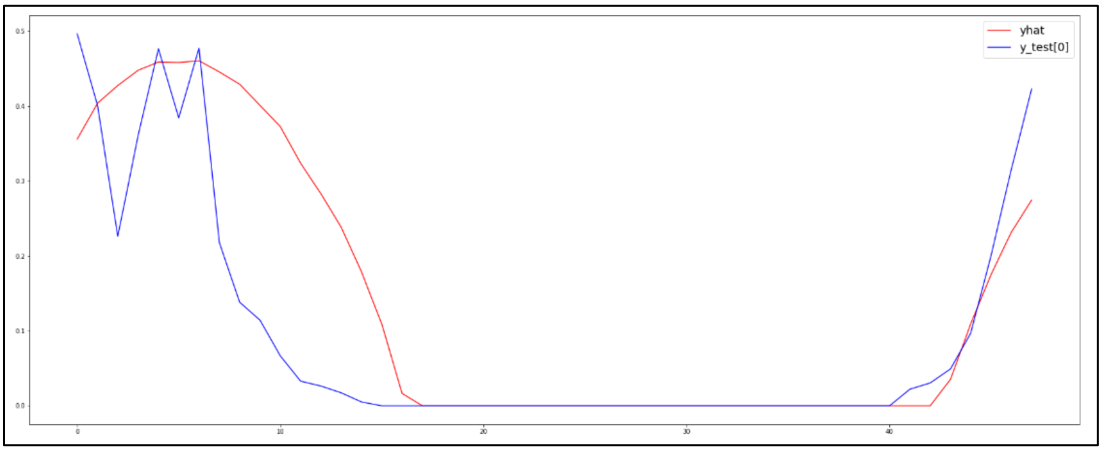
One reason could be that the networks need more features to better define an approximation between input and output of the prices. Many factors influence the variations of SBP and SSP, such as real-time changes of generation and consumption, unexpected shutdowns of some units and grid imbalance caused by other occurrence.

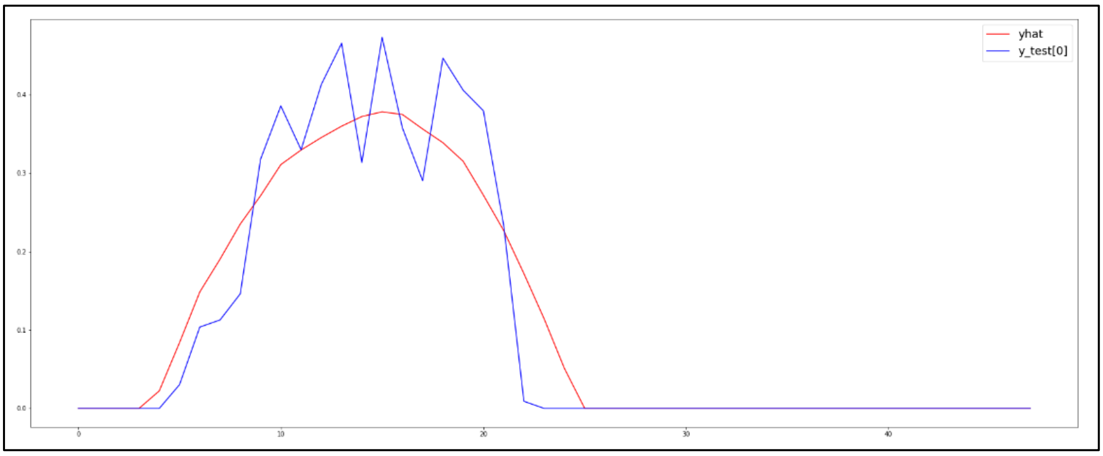
In our study, we did not improve the SBP and SSP predictors of the Standard Model because we aim to demonstrate the difference of performance between the Standard Model and the Proposed Model. Therefore, the Standard Model can only receive the same five features as used in the Proposed Model.

Figure 5.1 Comparisons of predictive and true values in the Standard Model

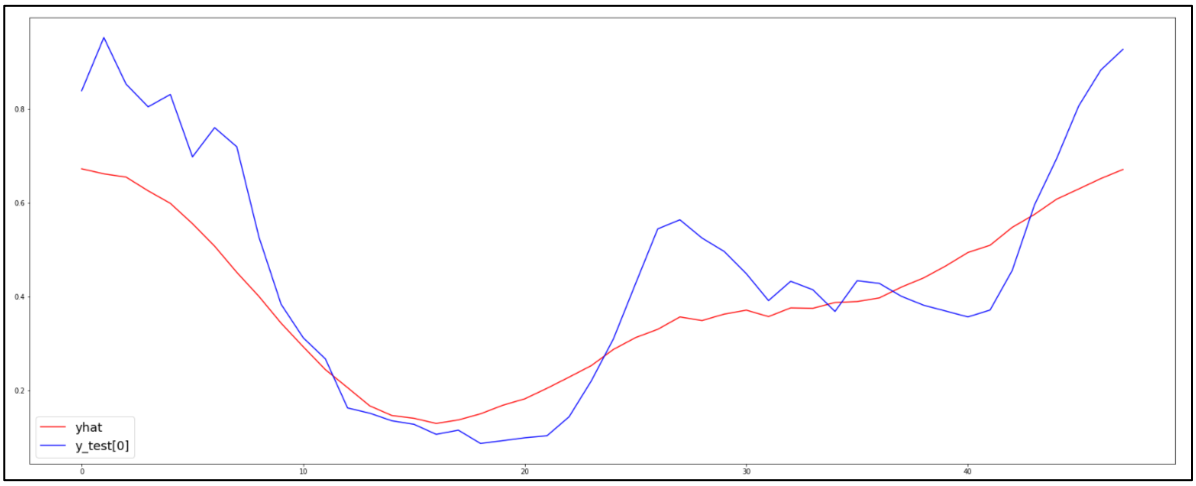
(1) PV Generation

The x-axis shows feature values (PV generation in this case), which is varied in the range of 0 and 1 since we've normalized the data. The y-axis is between 0 and 48, which denotes t_0 and t_{48} respectively. However, t_0 is not always match 12:00 AM because all input sequences have been randomized.

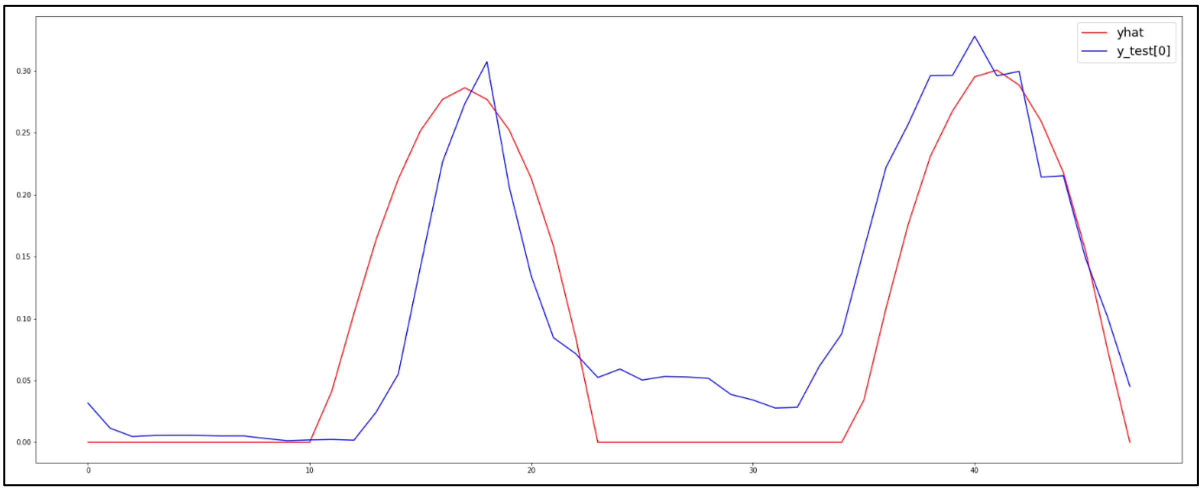




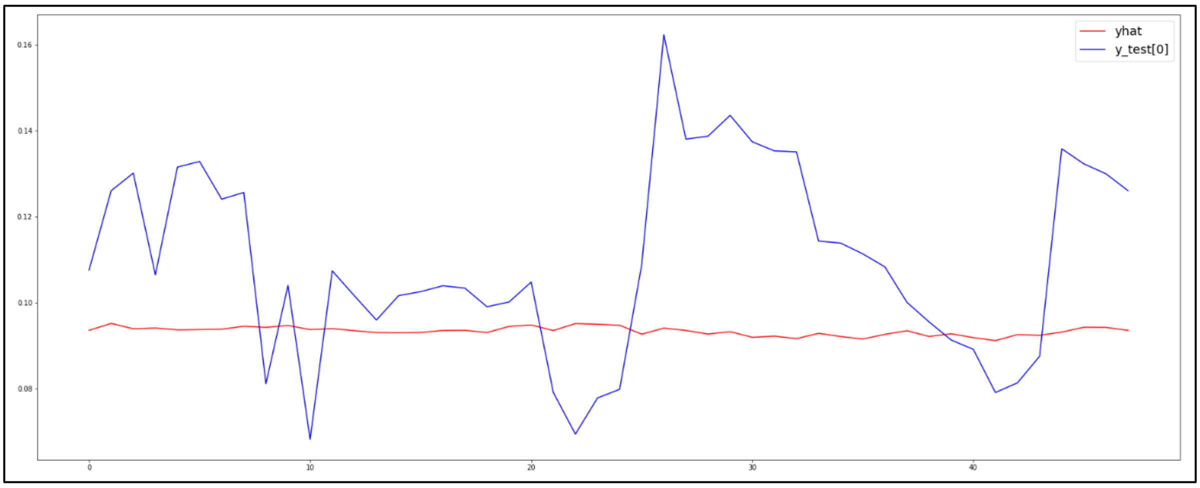
(2) Electricity Demand Prediction



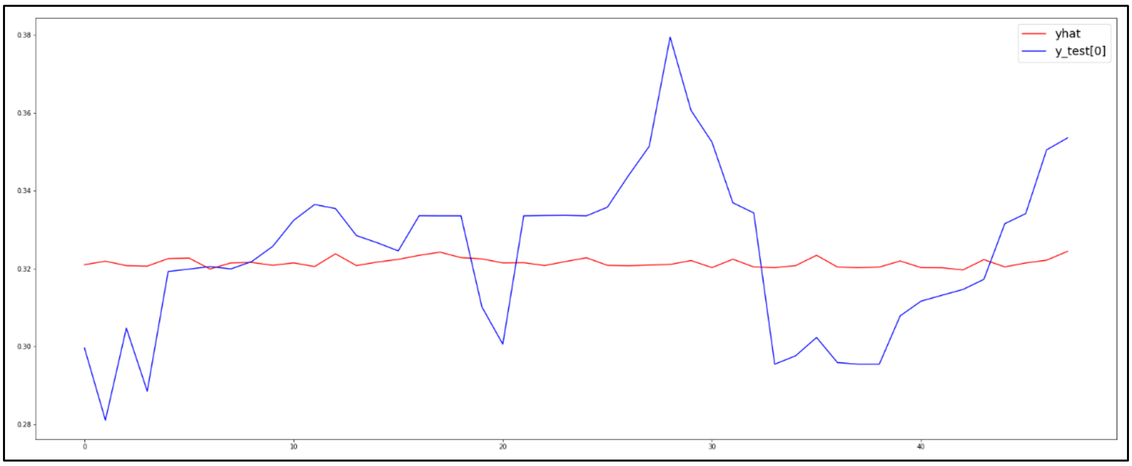
(3) Heat Demand Prediction



(4) SBP Prediction



(5) SSP Prediction



5.2 Operation Performance

Showed in Figure 5.2, the Standard Model and the Proposed Model exhibit a similar behaviour of the expert. Both Models identified the two demand peaks in the morning and the evening. It is obvious that the Vanilla Model has no ability to predict future heat demand. Therefore, the Vanilla Model saved more PV generation than the evening demand and lost the income of exporting PV generation to the grid. The Vanilla Model can be improved by setting two sets of on-and-off time, one for summer and another for winter, since the averages of heat demand in summer and winter are different.

We can conclude that accurate predictions of heat demand are crucial to the operation of heat storage. Figure 5.3 shows one example that the Standard Model incorrectly predicts two demand peaks. Consequently, it prepared more heat than the actual need. The excess use of heat storage in the morning leads to extra import of electricity. Another excess use in the evening consumes PV generation unnecessarily.

Correct prediction of SBP and SSP is another key factor of a good performance. Even though a Model accurately identifies the heat demand, its performance still can be compromised by inaccurate prediction of price. In Figure 5.4, the Standard Model predicts heat demand in the morning with accuracy to a certain extent. However, it expects a low SBP at t_3; accordingly, the Standard Model starts to charge the heat storage too early, hence unnecessary heat loss in the heat storage occurred and, more importantly, the Standard Model imports electricity with a relative high SBP at t_3, as showed in Figure 5.4 in which the SBP (red dot) at t_3 (approx. 0.048 £/kWh) is much higher than t_{10} (approx. 0.036 £/kWh), of which time the expert starts to charge the storage in the morning.

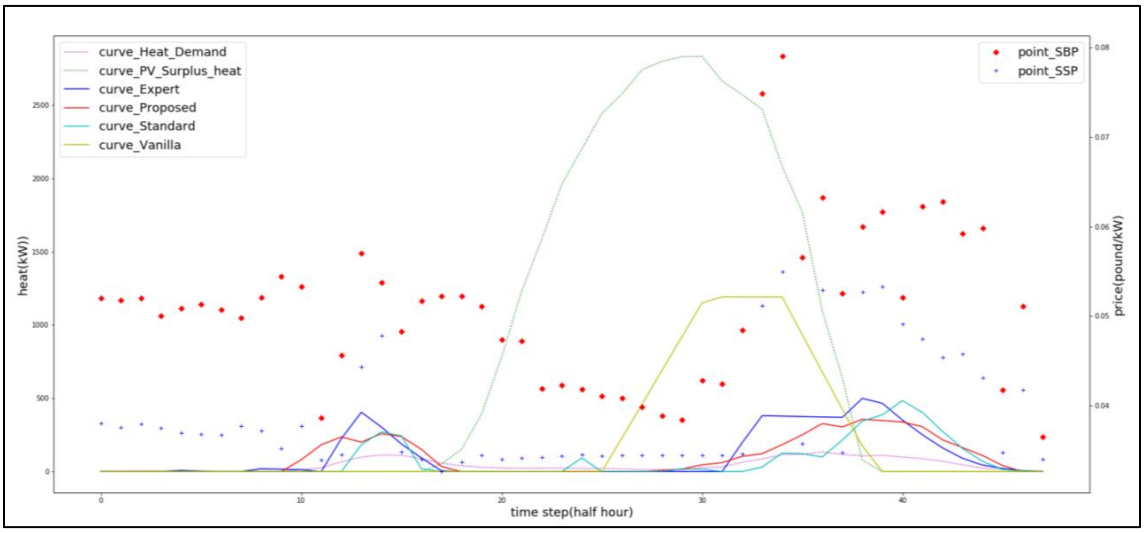
The same behaviour of the Standard Model can be seen in Figure 5.5 during the morning. Since outputs of the unreliable SBP predictor in the Standard Model are stuck around the average of SBPs, it's hard for the Standard Model to detect the sudden drop of SBP at t_{10} in Figure 5.5.

In addition, incorrect prediction of PV generation can also weaken the performance of the Standard Model. In Figure 5.4, there are two PV generation peaks at t_{23}, and t_{29}. Unlike the Proposed Model and the expert, the Standard Model charges no heat into the storage during the peak at t_{29} because it does not expect this PV generation peak. It uses PV generation peak at t_{23} to charge the storage, and hence suffers from unnecessary heat loss in the heat storage.

Note that in Figure 5.4 the true values of SSP during the midday are nearly the same. Thus, the reason for the expert to choose to consume PV generation at t_{29}, instead of t_{23}, is not because of a notable difference of SSP but considering on heat loss over the course of time. The predictive SSPs provided by SSP predictor in the Standard Model are almost the same as the average number and therefore we can conclude that in Figure 5.4 the Standard Model uses PV generation peak at t_{23} because it didn't expect another peak at t_{29}, but not because it expects a higher SSP around t_{29}.

The operation curve of the Proposed Model demonstrates roughly the same pattern as of the expert. Unlike the Standard Model, the network in the Proposed Model is trained to directly predict a target level. We cannot discuss the behaviour of the Proposed Model like we do with the Standard Model in above paragraphs because the network in the Proposed Model does not predict each feature separately.

Figure 5.2 One-day simulation (Result 1)



The blue, red, indigo and yellow lines are the operation curves of the expert, the Proposed Model, the Standard Model and the Vanilla Model, respectively. Green dash line is the PV generation that has been subtracted by electricity demand and converted into heat by COP. Pink dash line is the heat demand. Red and Blue dots are SBP and SSP.

Figure 5.3 One-day simulation (Result 2)

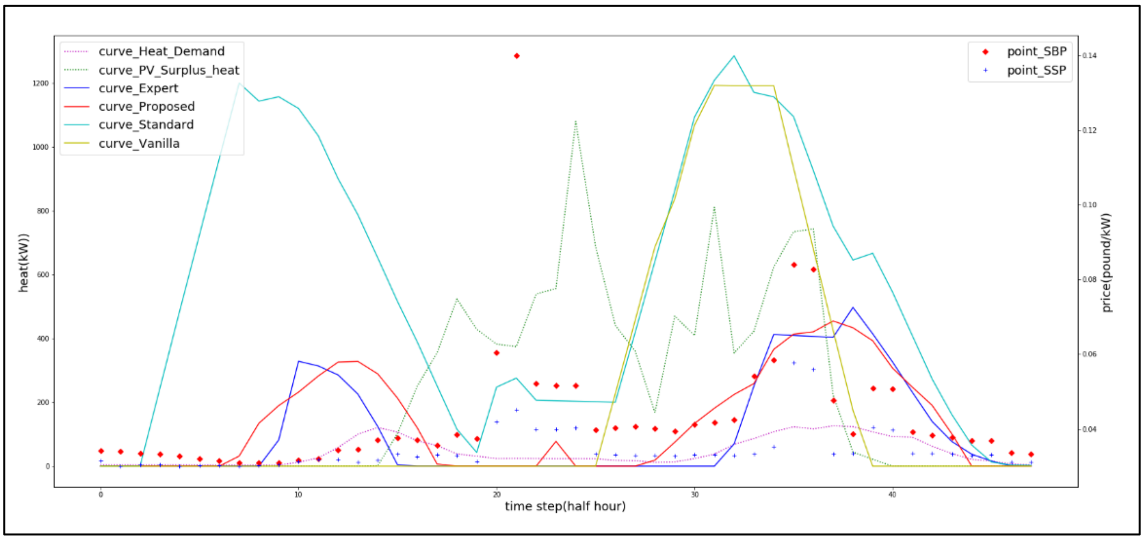


Figure 5.4 One-day simulation (Result 3)

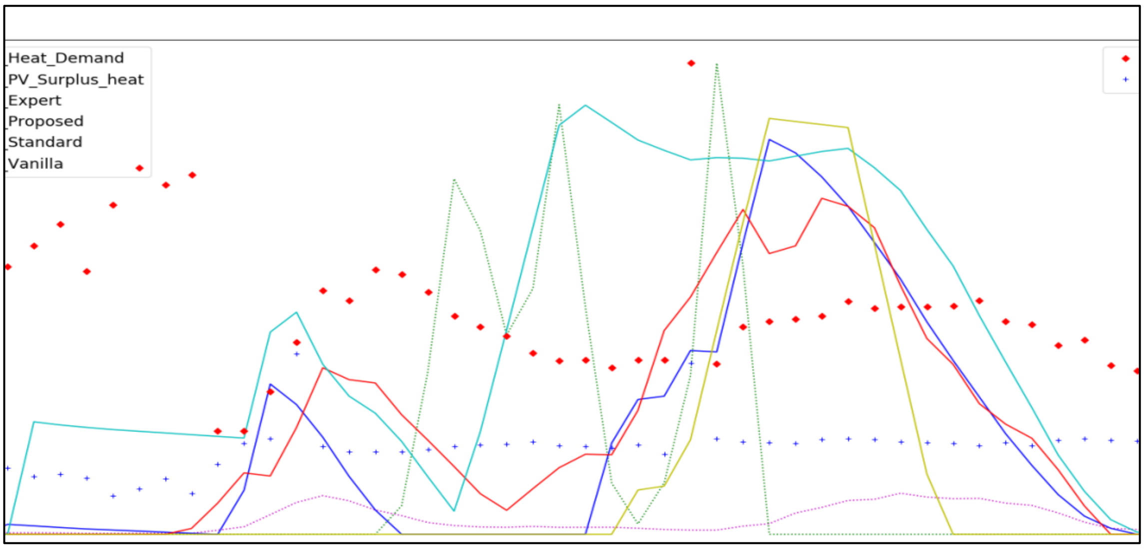
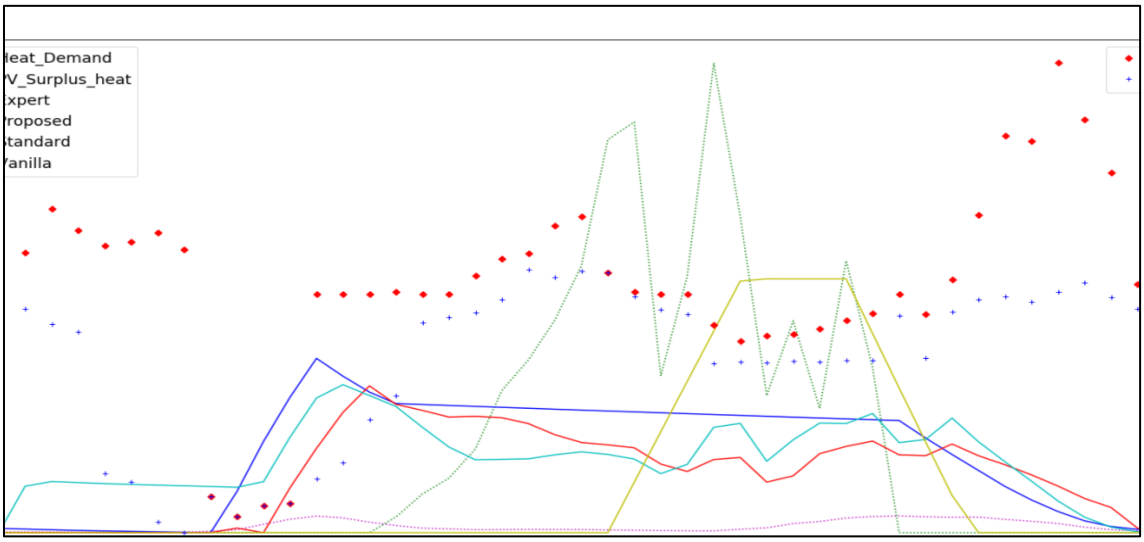


Figure 5.5 One-day simulation (Result 4)



5.3 Annual Cost

One way to examine the performance is to compare the operation costs of each Model in simulation. We run three one-year simulations for the all the Models and summed the daily operation cost according to Equation (3). The results are showed in Table 5.1. Note that the last Model in the table has no heat storage. It sells all PV Surplus to the grid, and whenever there is a Shortage, it imports electricity.

Negative operation cost indicates that the system exported more electricity than imported from the grid in a year. Model without storage has the highest income of importing electricity in all three simulations, as showed in Column (A) in Table 5.1.

Expenditure of importing in Equation (3) can be further separated depending on its purpose, as showed in Column (B) and (C). Since the Vanilla Model and the Model without storage cannot charging the heat storage by importing electricity, both shows zero in Column (C).

Column (D) shows that the expert outperforms other four Models. Our Proposed Model has close performance to the Model without heat storage. The Standard Model and the

Vanilla Model fail to reduce overall operation cost, compared to the Model without heat storage.

To compare the performance of these Models, we defined a number, e_{op}, that describes the effectiveness of operation. Operating the heat storage, a Model decreases the total revenue of exporting electricity and increases the total expenditure of importing electricity from the grid for charging the heat storage, as showed in Equation (8) and (9). Similarly, the operation of heat storage reduces the total expenditure of importing electricity for meeting the heat demand, as Equation (10). The Models aim to decrease $E_{PV} + E_{Grid}$ and increase R as much as possible because a higher e_{op} indicates that a Model profits from its operation more effectively, as Equation (11). It is profitable to implement a Model only if the e_{op} of that Model is larger than 1.

$$\begin{aligned} \boldsymbol{E_{PV}} &= \textbf{\textit{Expenditure of PV Surplus for charging the storage}} \\ &= (\textbf{\textit{Revenue of a Model}}) - (\textbf{\textit{Revenue of the Model without storage}}) \end{aligned} \tag{8}$$

$$\boldsymbol{E_{Grid}} = \textbf{\textit{Expenditure of importing electricity for charging the storage}} \tag{9}$$

$$\begin{aligned} \boldsymbol{R} &= \textbf{\textit{Reduction in Expenditure of importing electricity for heat demand}} \\ &= (\textbf{\textit{Expenditure of the Model without storage}}) - (\textbf{\textit{Expenditure of a Model}}) \end{aligned} \tag{10}$$

$$\boldsymbol{e_{op}} = \frac{\boldsymbol{R}}{\boldsymbol{E_{PV}} + \boldsymbol{E_{Grid}}} \tag{11}$$

Table 5.2 shows each e_{op} of each Model in the three simulations. As the same we observe from the comparison of total operation cost of each Model, the expert has the highest e_{op} around 1.55. Our Propose Model nearly meets the requirement with a e_{op} around 0.98. The Standard Model and the Vanilla Model fails with e_{op} around 0.75 and 0.45 respectively.

We also calculated different e_{op} in each week in the simulation result 1, as showed in

Table 5.3, to examine how PV generation and heat demand affects e_{op} of each Model.

During the cold weeks, such as week 1, 2, 12 and 13, we have smaller amount of PV generation to meet the heat demand directly or to be charged into the heat storage in advanced. Since SBP are always larger or equal to SSP, using PV Surplus is usually more economical than importing electricity. Consequently, with less amount of economical PV generation, the operation costs of these weeks are positive.

It should be note that the term, 'cold' or 'warm,' does not mean that the weather is colder or warmer in those weeks. 'Cold' means the system must import more electricity from the grid because the total PV generation is relative lower, and/or the total heat demand is relative higher.

The e_{op} of the Proposed Model, Standard Model and Vanilla Model is greater than 1 during the cold weeks. In addition, e_{op} of the expert during the cold weeks are greater than during the warm weeks. This is because most of the time during the cold weeks the Models has no need to predict PV generation correctly since PV generation in cold weeks is relative less and has less influence on operation. Consequently, the Models need only reliable predictions on demand and prices, and thus it is easier for the Models to make a better decision. Since the price predictors of the Standard Model are less effective, the e_{op} of the Standard Model is lower than of others in the cold weeks.

The Vanilla Model sometimes has better e_{op} during cold weeks because most of the time in a cold week the remaining PV Surplus is usually small, and the heat demand is usually large. Therefore, with a lower risk of suffering from unnecessary heat loss in the storage, it's tolerable to always store all remaining PV Surplus for the heat demand in the evening.

Note that even though the e_{op} of the Vanilla Model is greater, it does not guarantee that the Vanilla Model can outperform other Models because the Vanilla Model has no concern with price prediction and importing electricity. Table 5.4 shows the e_{op} and the total reduction, R, of operation cost during cold weeks. In week 1, the e_{op} of the Vanilla Model (1.54) is greater than the Proposed Model (1.32). However, R of the Vanilla Model (£65) is less than the Proposed Model (£197). The same occurs in week 13.

Table 5.1 Yearly Operation Cost

Result 1:

Model	(D) Operation Cost (£) (D)=(A)+(B)+(C)	(A) Sell to the Grid	(B) Buy for Heat Demand	(C) Buy for Charging
Expert	-48999	-53150	1494	2657
Proposed Model	-46429	-53377	3889	3059
Standard Model	-44744	-52577	3212	4621
Vanilla Model	-44433	-51245	6812	0
Without Storage	-46459	-54913	8454	0

Result 2:

Model	Operation Cost (£) (A)+(B)+(C)	(A) Sell to the Grid	(B) Buy for Heat Demand	(C) Buy for Charging
Expert	-51713	-55934	1428	2793
Proposed Model	-49154	-56131	3763	3214
Standard Model	-47452	-55345	3144	4749
Vanilla Model	-47151	-54062	6911	0
Without Storage	-49272	-57608	8336	0

Result 3:

Model	Operation Cost (£) (A)+(B)+(C)	(A) Sell to the Grid	(B) Buy for Heat Demand	(C) Buy for Charging
Expert	-42620	-46884	1619	2645
Proposed Model	-40072	-47185	4103	3010
Standard Model	-38491	-46326	3325	4510
Vanilla Model	-38236	-45116	6880	0
Without Storage	-40223	-48689	8466	0

Table 5.2 Operation effectiveness, e_{op}

Model	Result 1		Result 2	Result 3
Expert	1.57		1.55	1.54
Proposed Model	0.99		0.97	0.97
Standard Model	0.75		0.74	0.75
Vanilla Model	0.45		0.40	0.44

Table 5.3 Operation effectiveness, e_{op}, of each week in Result 1

Week	Expert	Proposed Model	Standard Model	Vanilla Model	Operation Cost
1	1.74	1.32	1.16	1.54	positive
2	1.6	1.16	0.99	1.47	positive
3	1.43	0.89	0.75	0.77	negative
4	1.43	0.71	0.58	0.31	negative
5	1.42	0.68	0.47	0.12	negative
6	1.63	0.62	0.41	0.07	negative

Week	Expert	Proposed Model	Standard Model	Vanilla Model	Operation Cost
7	1.46	0.36	0.26	0.05	negative
8	1.56	0.46	0.39	0.06	negative
9	1.43	0.65	0.49	0.13	negative
10	1.46	0.81	0.62	0.29	negative
11	1.45	0.85	0.75	0.49	negative
12	1.59	1.19	1.01	1.01	positive
13	1.72	1.27	1.06	1.50	positive

Table 5.4 e_{op} and R of operation cost during cold weeks in Result 1

	Expert	Proposed Model	Standard Model	Vanilla Model
Week 1				
e_{op}	1.74	1.32	1.16	1.54
R	462	197	106	65

	Expert	Proposed Model	Standard Model	Vanilla Model
Week 2				
e_{op}	1.6	1.16	0.99	1.47
R	379	90	-7	103
Week 12				
e_{op}	1.59	1.19	1.01	1.01
R	363	113	7	2
Week 13				
e_{op}	1.72	1.27	1.06	1.50
R	440	169	46	63

5.4 Training and Computation Efficiency

Since the Standard Model and the Proposed Model follow the different concept as showed in Figure 1.1, Figure 1.2, Figure 1.3 and Figure 1.4, it is interesting to examine the training and computation efficiency of the two Models.

5.4.1 Preparation of Training Dataset

For the five predictors in Standard Model, time spent for preparing the training dataset is neglectable because it is only a rearrangement of values according to each time steps. On the contrary, it took approx. 6 hours to prepare the dataset for the Proposed Model due to the computation caused by running Algorithm 1 for a four-year historical data.

5.4.2 Training of Models

It is meaningless to compare the training time of each LSTM networks because the total number of trainable weights/varaiables is different in different Model. In addition, the training time can also be influenced by the complexity of the dataset, which is different for each predictor.

5.4.3 Computation Efficiency

For a one-day simulation, it took approx. 0.8 second for the Proposed Model to make decision, while for the Standard Model it took approx. 1 minute. The difference between 0.8 second and 1 minute is neglectable compared to one day (24 hours), though it demonstrates to what extend an improvement of computation efficiency can be achieved if we build models and train networks in a different way, as discussed in Figure 1.1, Figure 1.2, Figure 1.3 and Figure 1.4.

6 Conclusion

In this paper we proposed a LSTM model for the operation of heat storage in a solar energy community distribution system with PV generation as the only domestic generation and a connection to the main grid. Unlike conventional LSTM model that the networks are only used to predict features for supporting an operator or a control programme to make a decision, our proposed model integrates the operation strategy into the network, and thus provide an operation action directly.

With historical data, we created an expert who can perfectly predict future. This expert follows the operation strategy we proposed in this paper, and then the operation behaviours of this expert are used to train a LSTM network in our proposed model.

We set up three different Models:

A. The Standard Model has five LSTM networks that receive past values of PV generation, electricity demand, heat demand, SSP and SBP to predict future values. These predictive values are then passed to a control programme that follows the operation strategy proposed in this paper to calculate the current target level of the heat storage.

B. The Proposed Model has only one LSTM network that is trained by the operation behaviour of the mock-up expert. This network receives past values of PV generation, electricity demand, heat demand, SSP and SBP to provide the current target level of the heat storage.

C. The Vanilla Model always starts to charge and to discharge the heat storage at fixed times every day. This model has no LSTM network.

We conducted one-year simulations for the expert, the three Models and a system without heat storage. To decrease the total cost of importing electricity to meet the heat demand, each model consumes PV generation that could have been sold to the grid or imports electricity to charge the heat storage when SBP is relative low. We defined a number, e_{op}, to describe the operation effectiveness of a Model:

$$\boldsymbol{e_{op}} = \frac{\boldsymbol{R}}{\boldsymbol{E_{PV}+E_{Grid}}}$$

$$\boldsymbol{R = Reduction\ in\ Expenditure\ of\ importing\ electricity\ for\ heat\ demand}$$

$$\boldsymbol{E = \ Expenditure\ of\ PV\ Surplus\ or\ importing\ electricity\ for\ charging\ heat\ storage}$$

The results of one-year simulations show that the expert has the highest e_{op} around 1.55, and the Propose Model has e_{op} around 0.98. The Standard Model and the Vanilla Model fails with e_{op} around 0.75 and 0.45 respectively. The performance of our Proposed Model is nearly to be profitable if its e_{op} can be further improved to be greater than 1.

We found that during the weeks when the PV generation is low, and the heat demand is high, the e_{op} of the Proposed Model, Standard Model and Vanilla Model is greater than 1. This is because the accuracy of prediction on PV generation has less influence on the performance of a Model. Thus, it is easier for a Model to operate the heat storage during a ‘colder’ week.

Since the Standard Model and the Proposed Model introduces different concepts of implementing LSTM networks, computation efficiency of each Model during the simulation is different. The Standard Model first runs its five LSTM networks to predict features related to operation, and then run the operation strategy to decide an operation action. On the other hand, the Proposed Model directly predicts an operation action. The computation time spent by the Standard Model is 75 times larger than the Proposed Model.

With the same input (five features at t_{n-48} to t_{n-1}), our Proposed Model has a better operation efficiency and less computation time in simulation than the Standard Model that follows the conventional way of implement LSTM networks in decision making of system operation.

In further studies, we intend to create other experts by new operation strategies or by real experience of human operator. By introducing new operation strategy, the number of input features may increase or decrease and further affect e_{op} of the model. On the other hand, if we introduce human operation experience, the selection of input features would be the key decision for constructing the model. Alternatively, the model can learn directly from extracting a policy from the human operation experience [11] without conducting a supervised learning.

We also aim to examine different scenario for this solar energy community distribution system, such as an increase or decrease in the number of houses or solar panels. This would affect e_{op} of the models because it changes the amount of PV generation and heat demand in certain weeks, and thus makes a week ‘warmer’ or ‘colder,’ as we discussed in Chapter 5.3. Another scenario is that we can put the solar energy community distribution system into another electricity market which is different from the imbalance prices we used in this paper. We can also consider how carbon tax or subsidy for solar energy influences the operation strategy and the performance of our Proposed Model.

7 References

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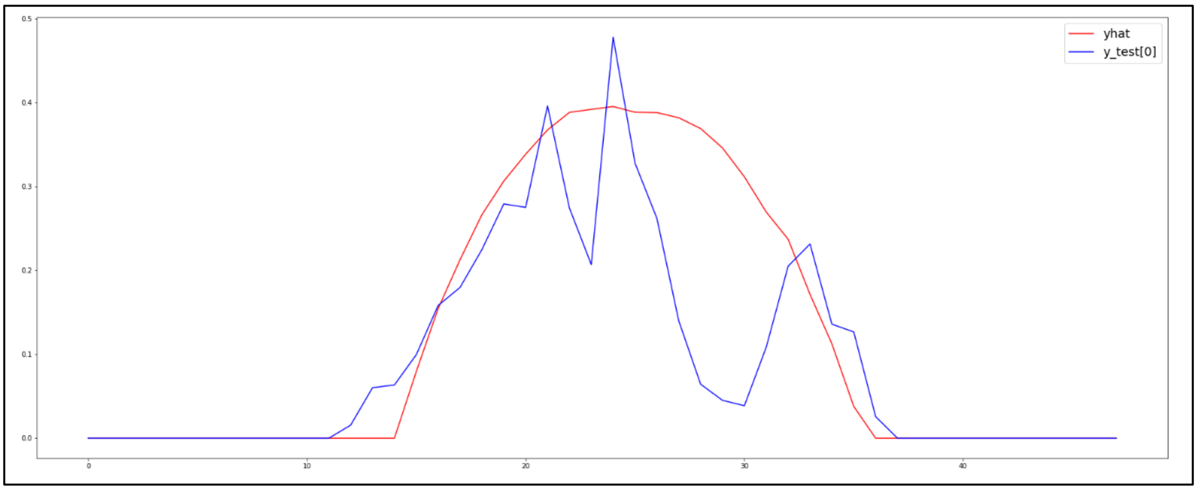
8 Appendices

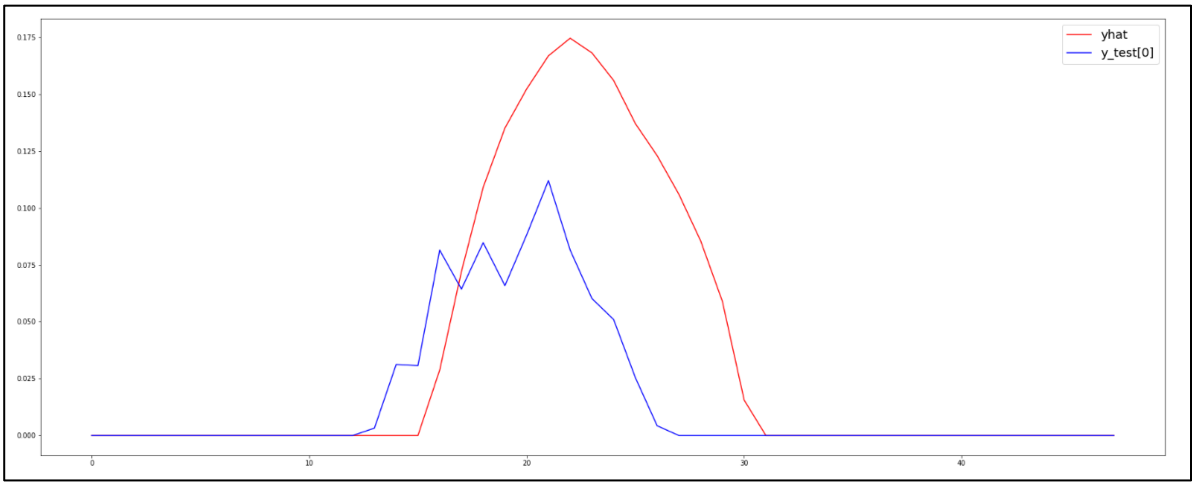
Appendix 1 Comparisons of predictive and true values in the Standard Model 48

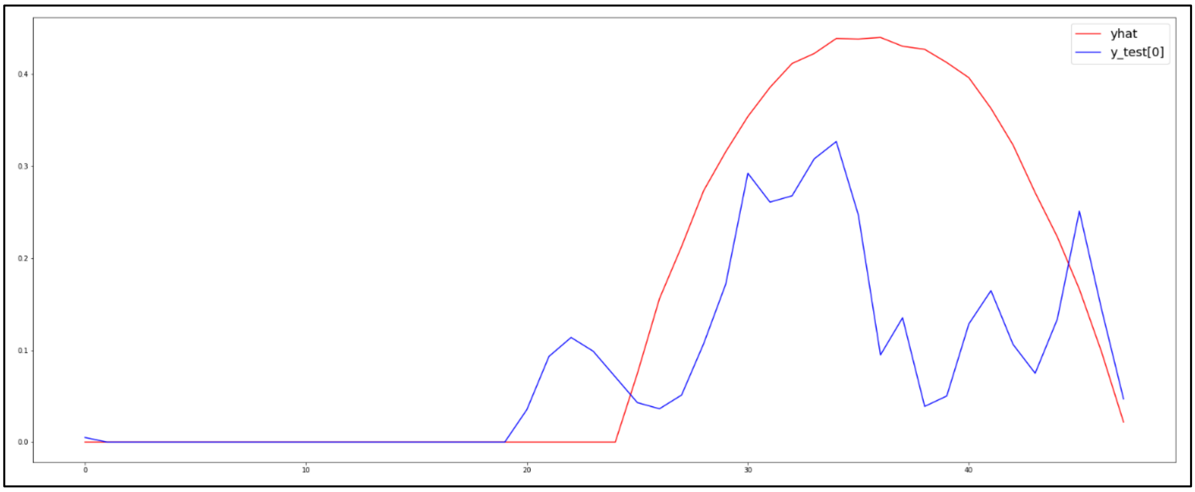
Appendix 2 Python Code 58

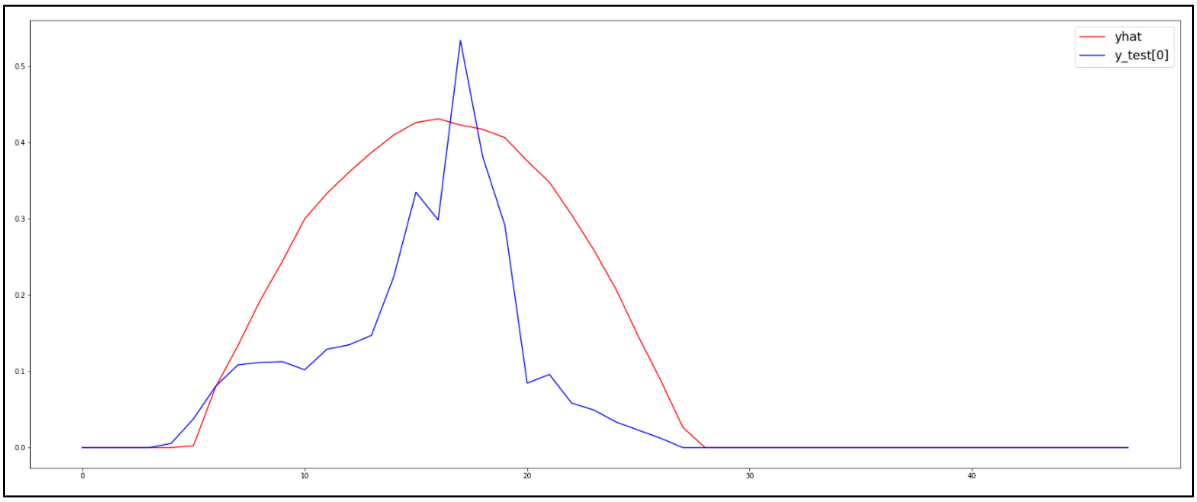
Appendix 1 Comparisons of predictive and true values in the Standard Model

(1) PV generation Prediction





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0.3
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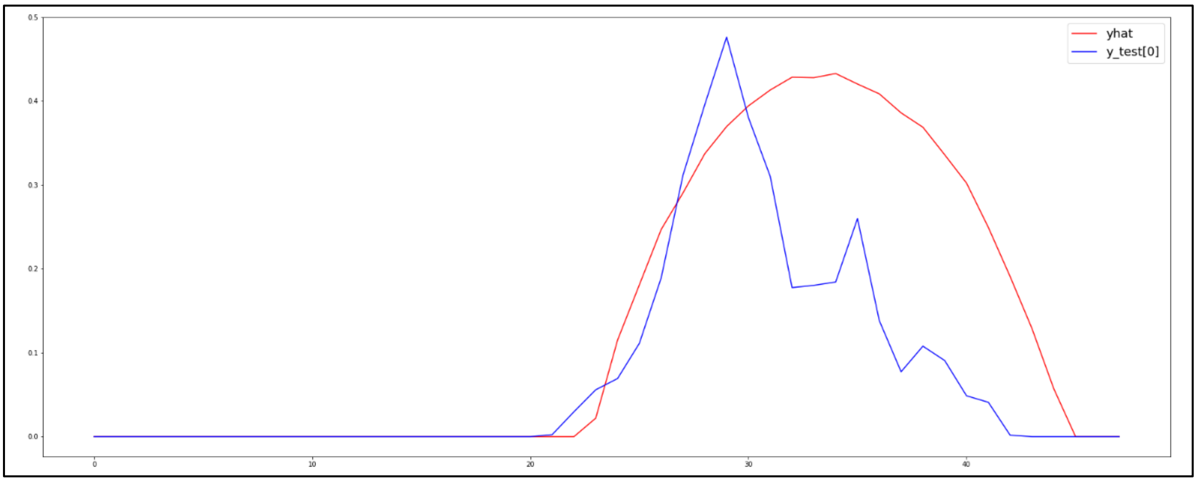
0.5
0
10
20
30
40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0.5
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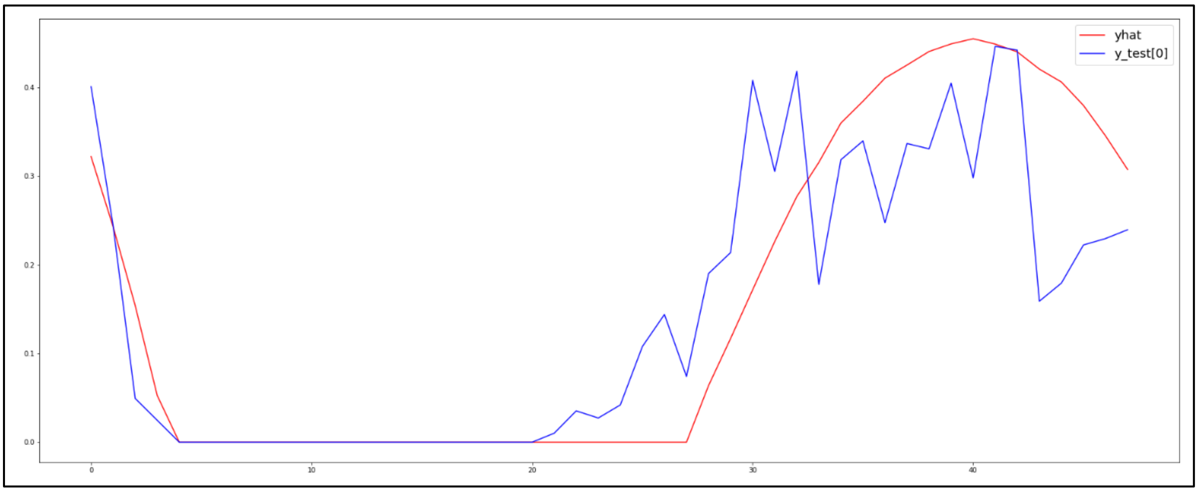
10
20
30
40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y_test[0]
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0.3
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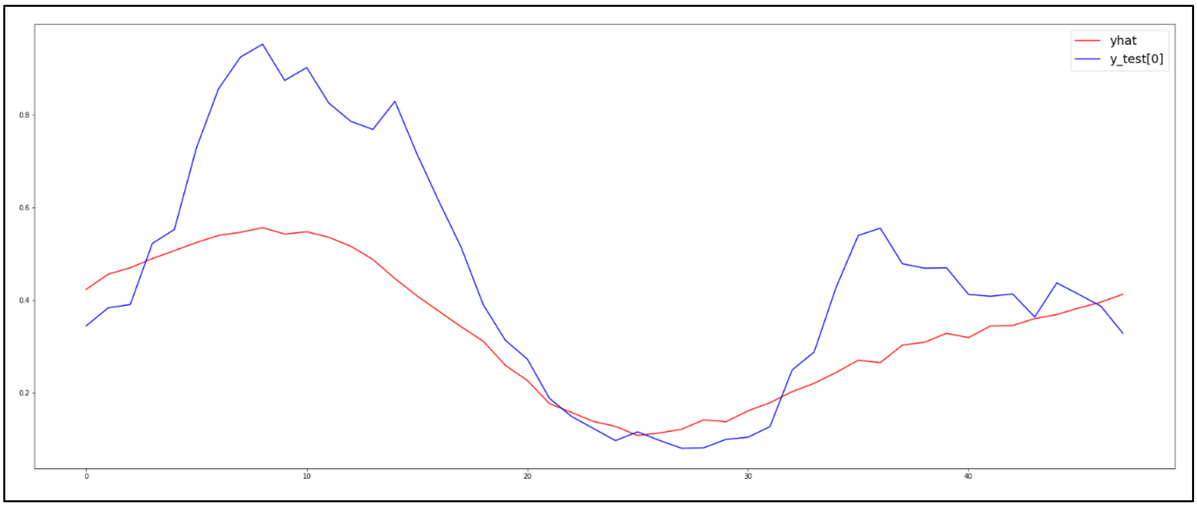
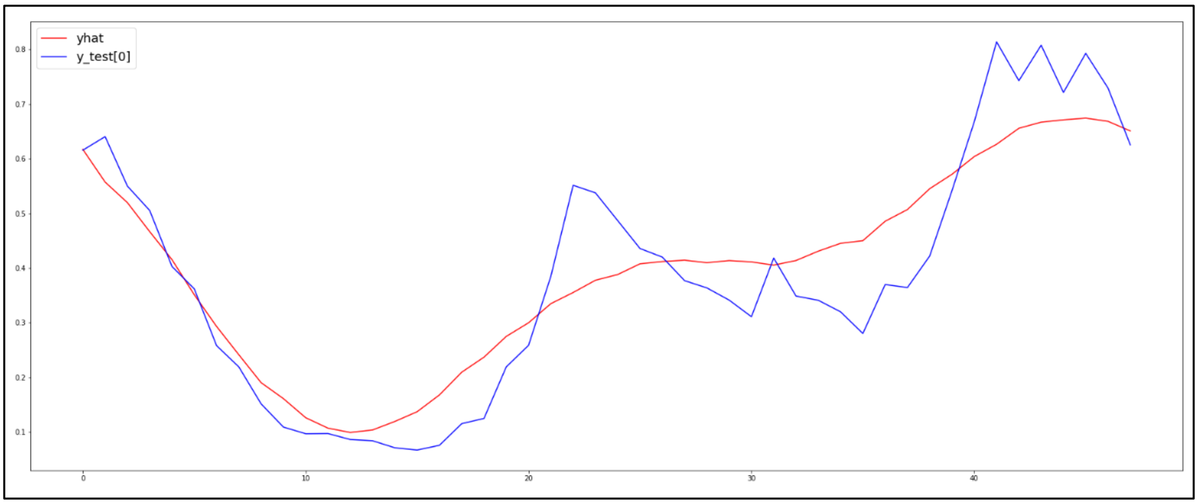
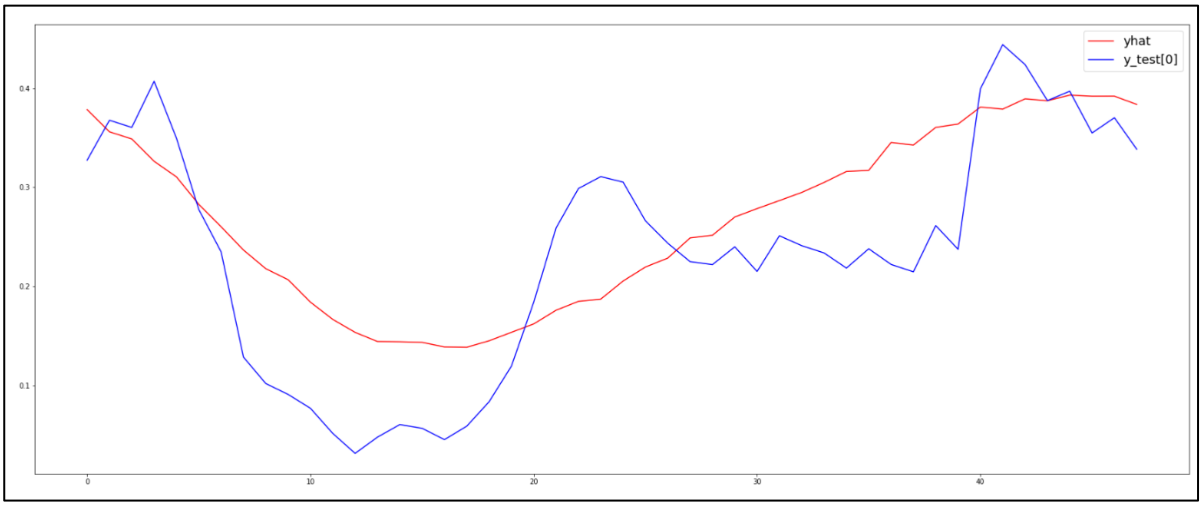
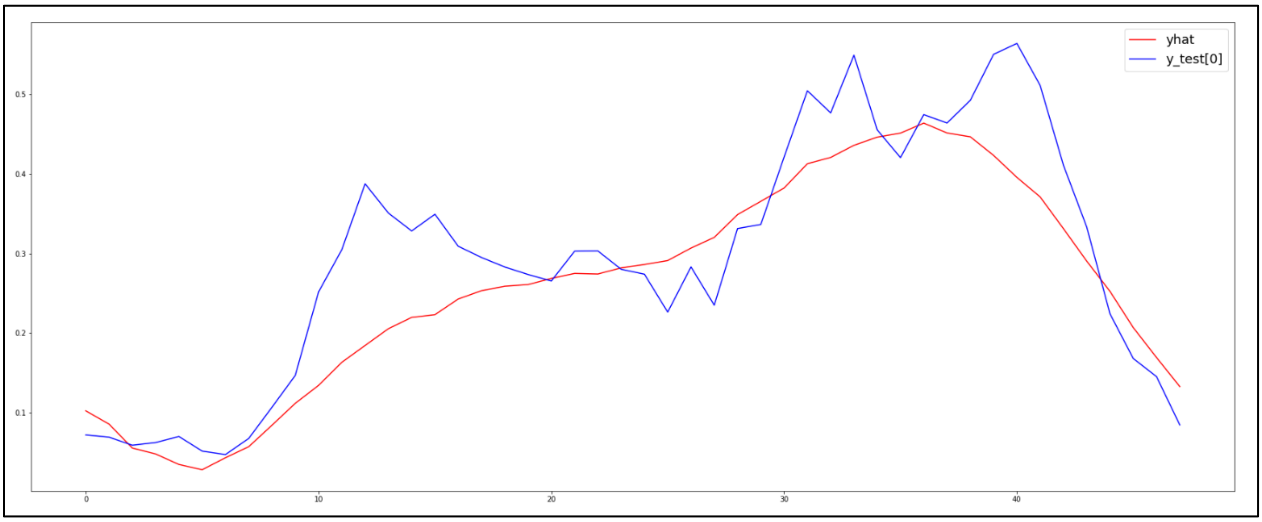
10
20
30
40

(2) Electricity Demand Prediction





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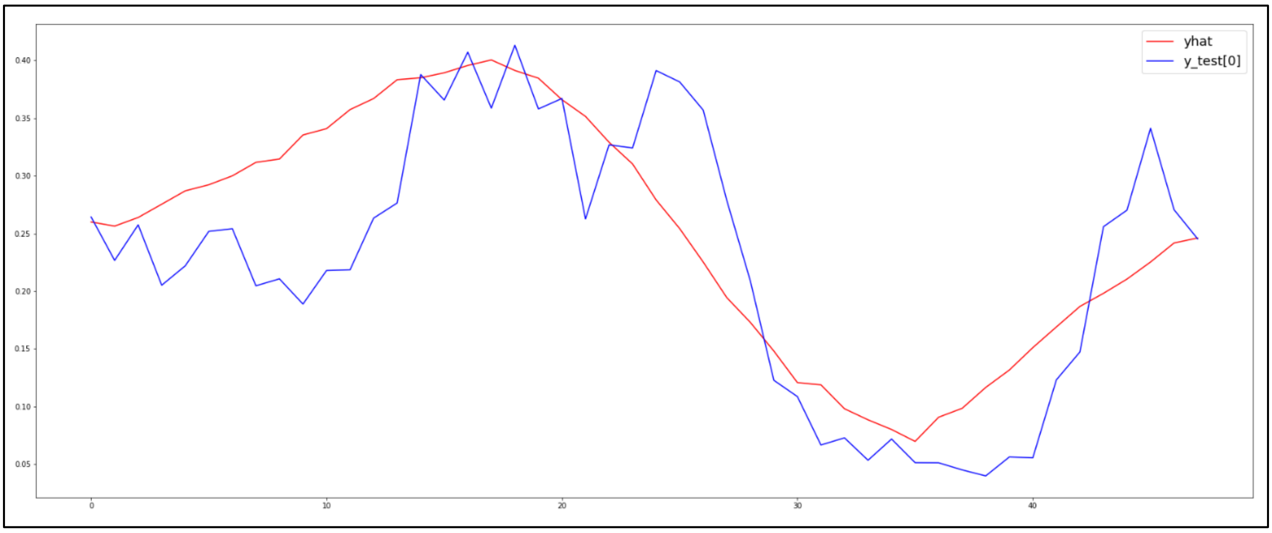
0
10
20
30
40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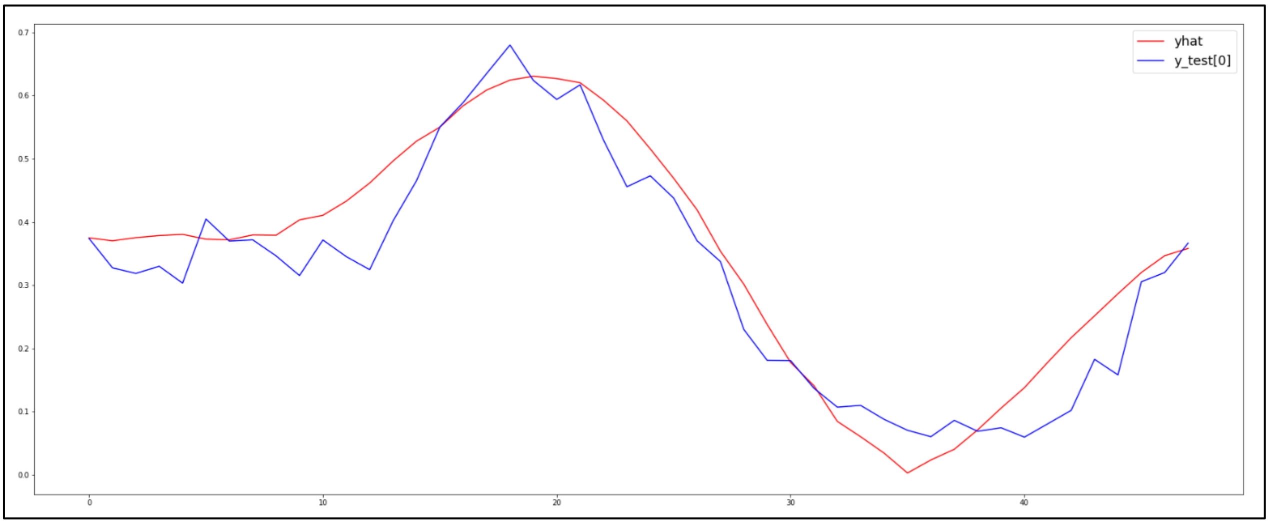
0.05
0
10
20
30
40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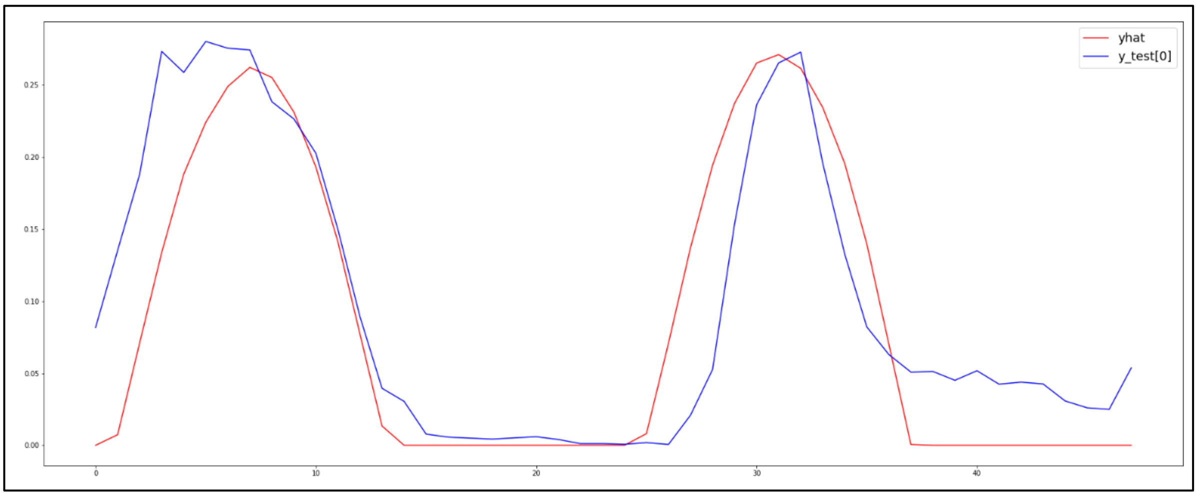
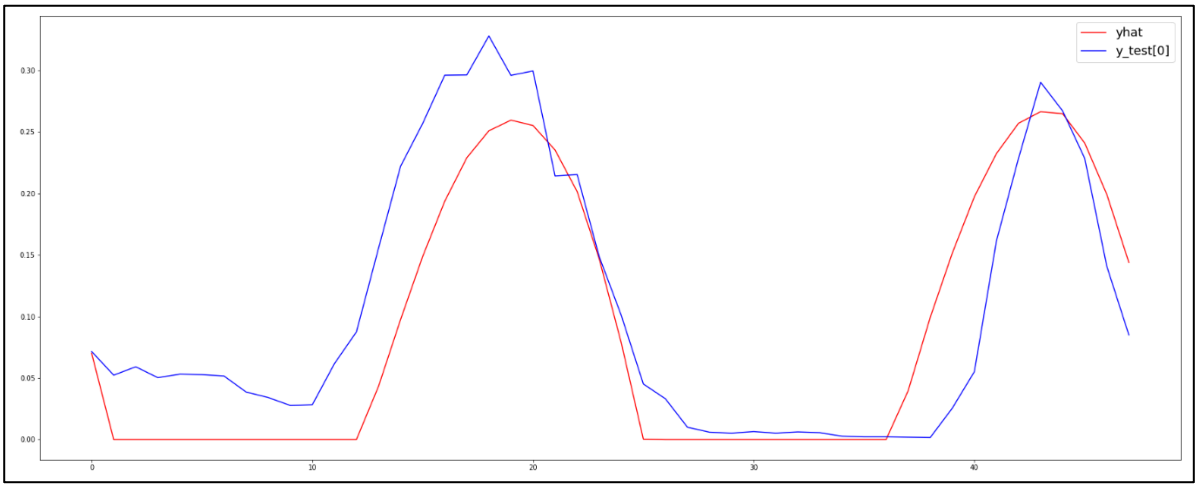
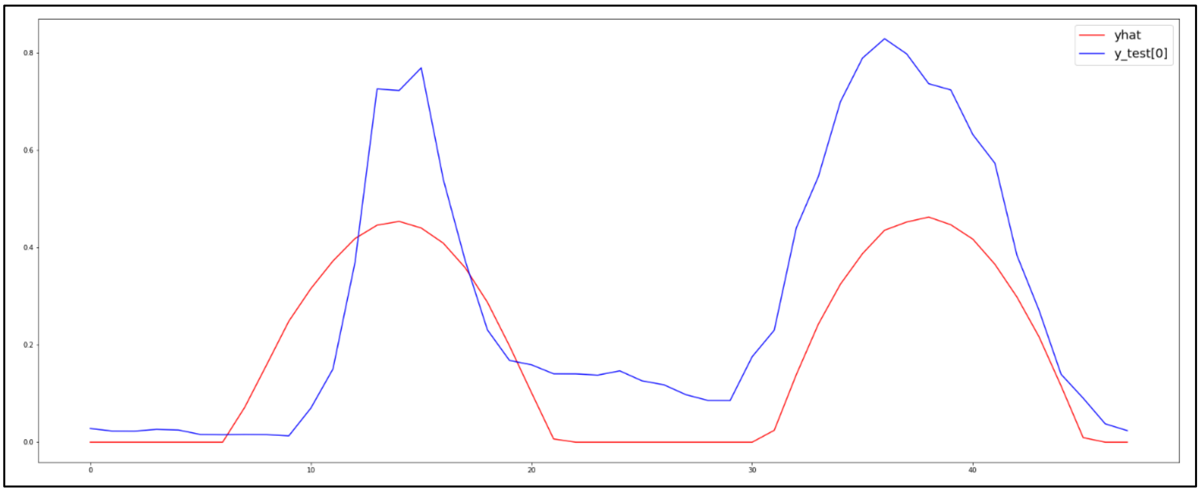
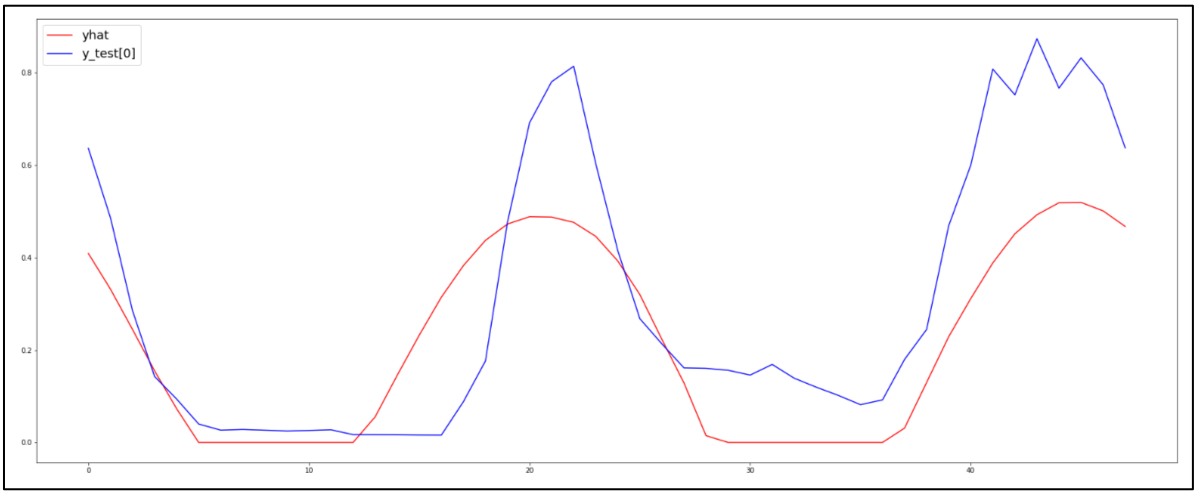
0
10
20
30
40

(3) Heat Demand Prediction





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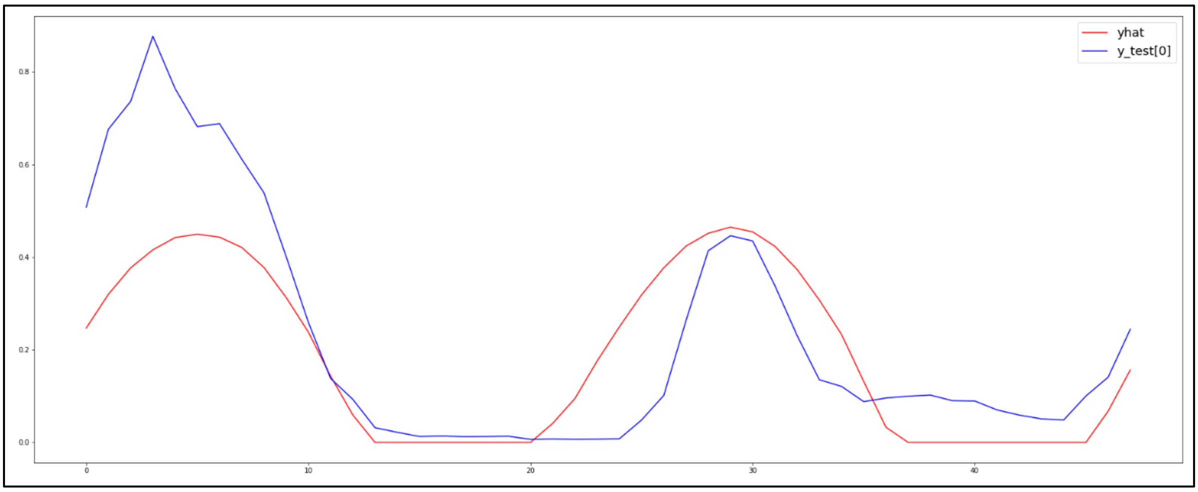
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0
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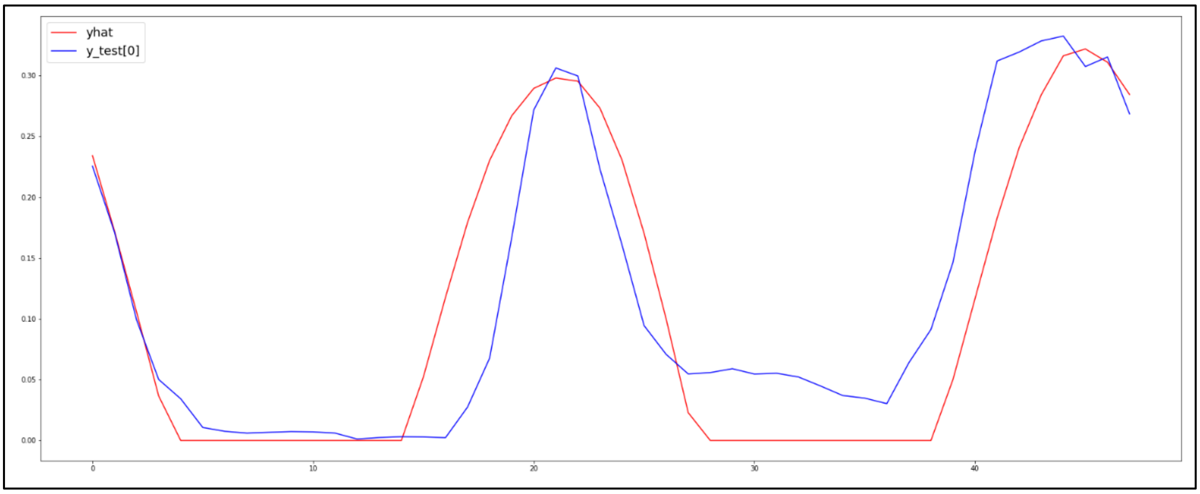
20
30
40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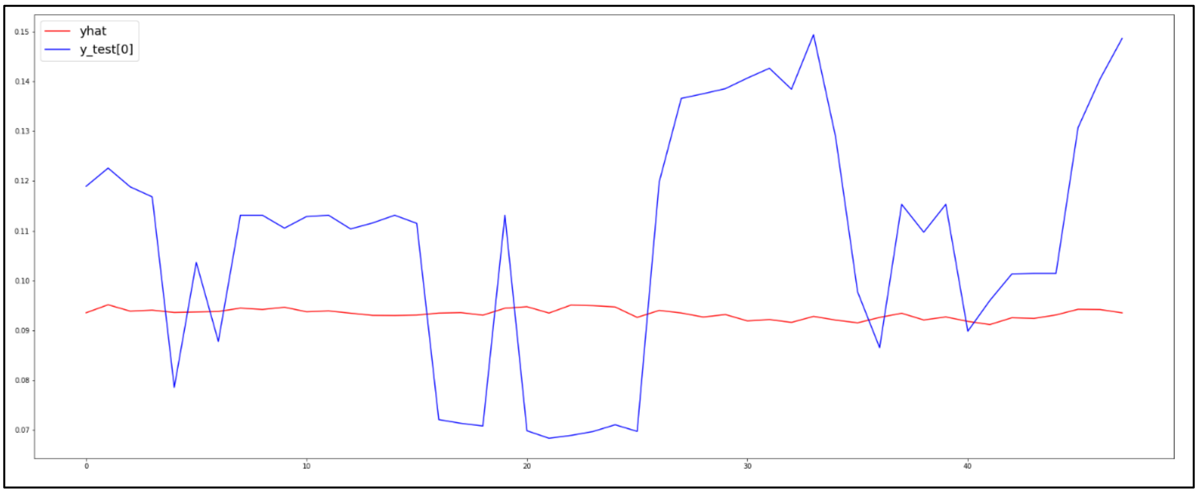
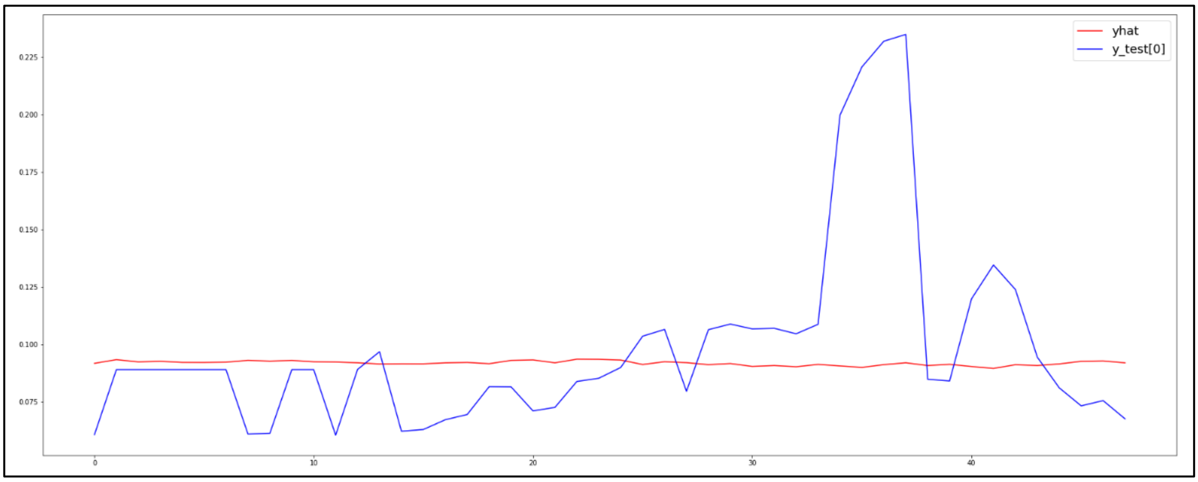
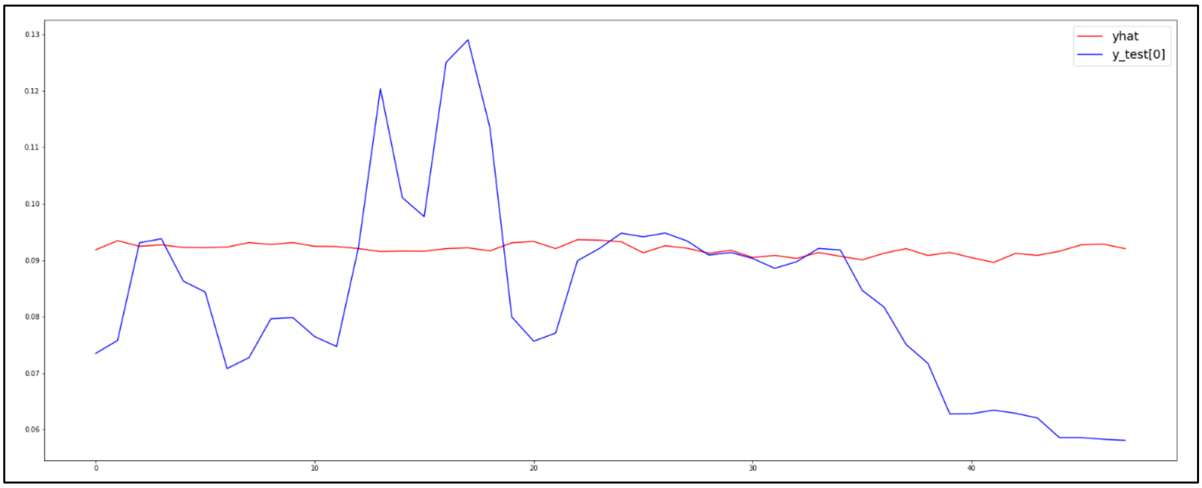
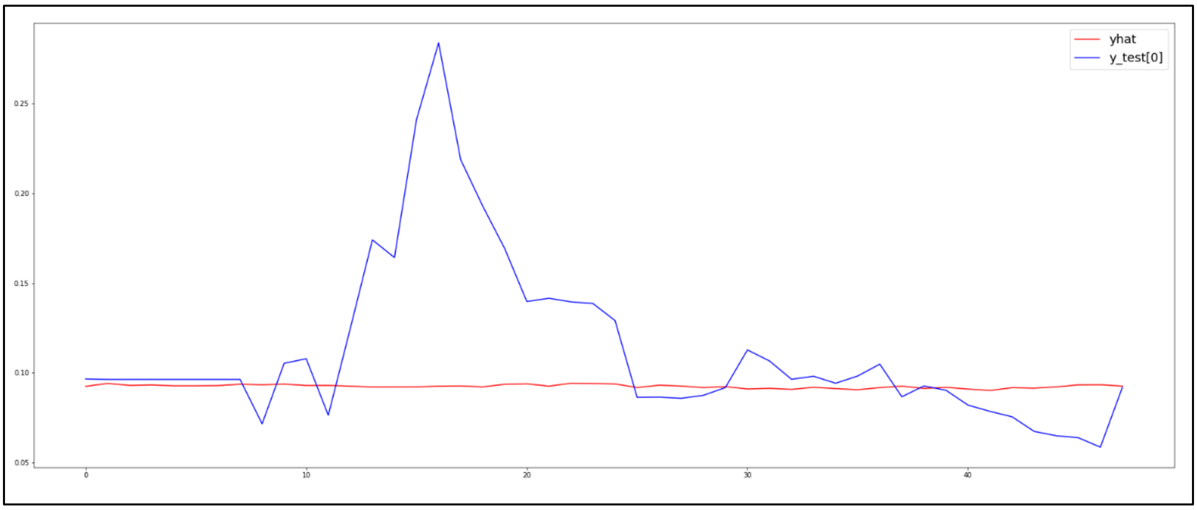
0.05
0.00
0
10
20
30
40

(4) SBP Prediction





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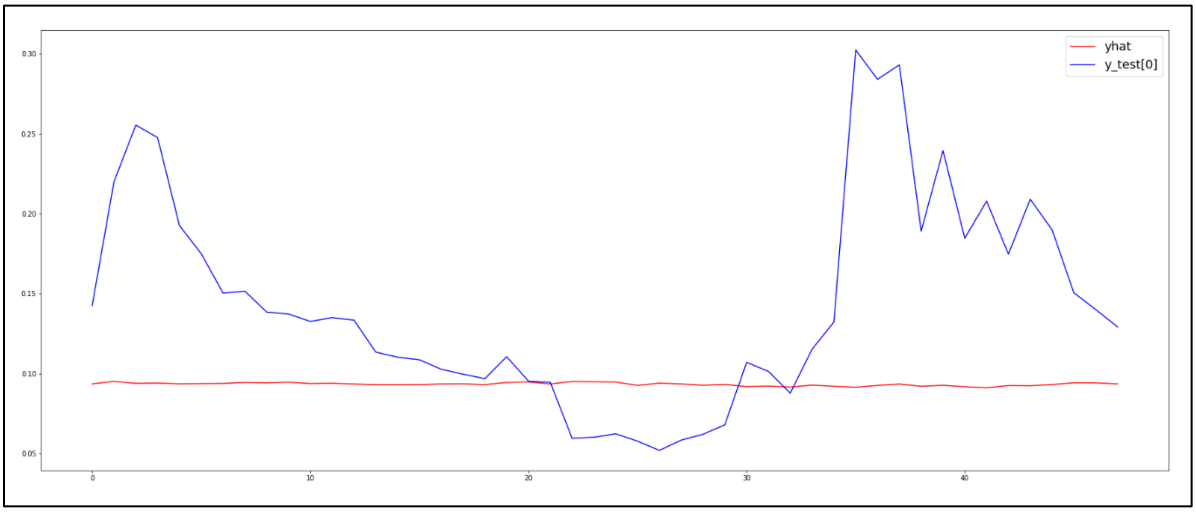
30
40


yhat
y_test[0]
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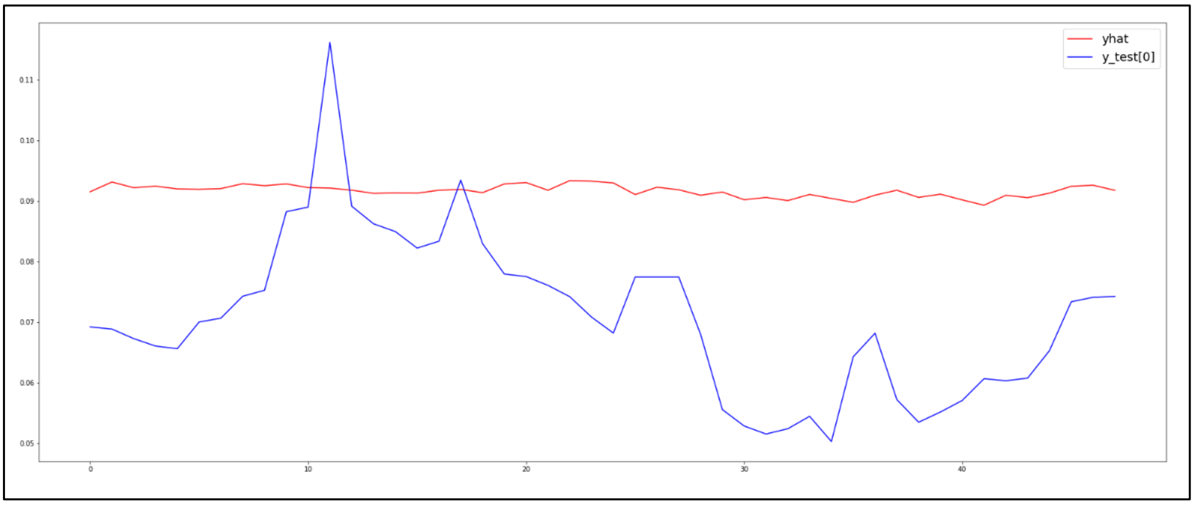
0.10
0.05
0
10
20
30
40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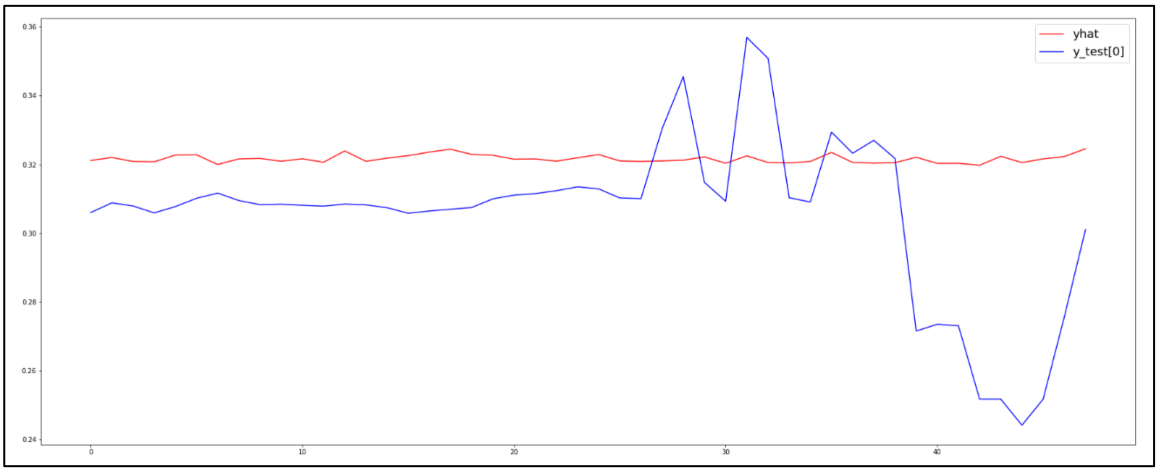
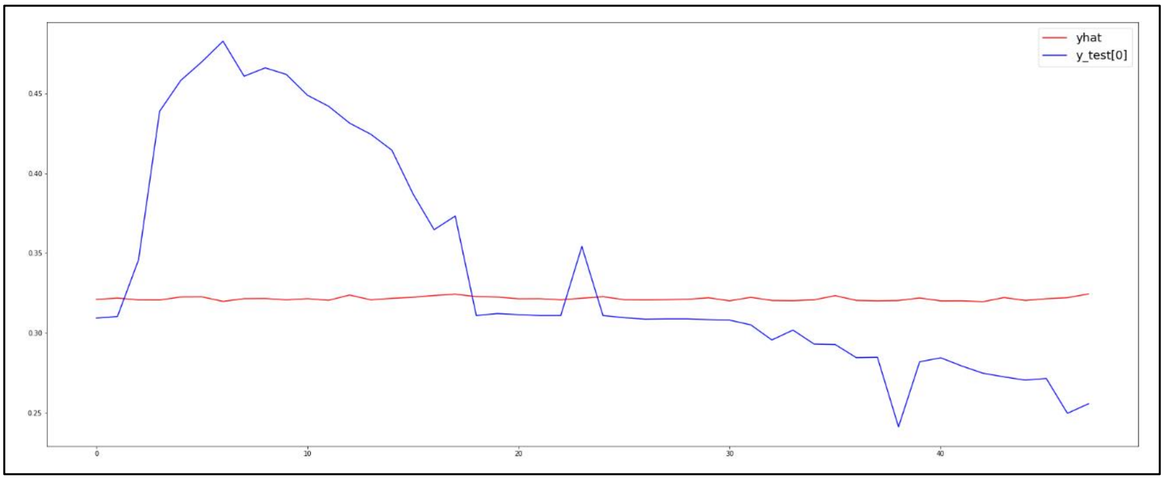
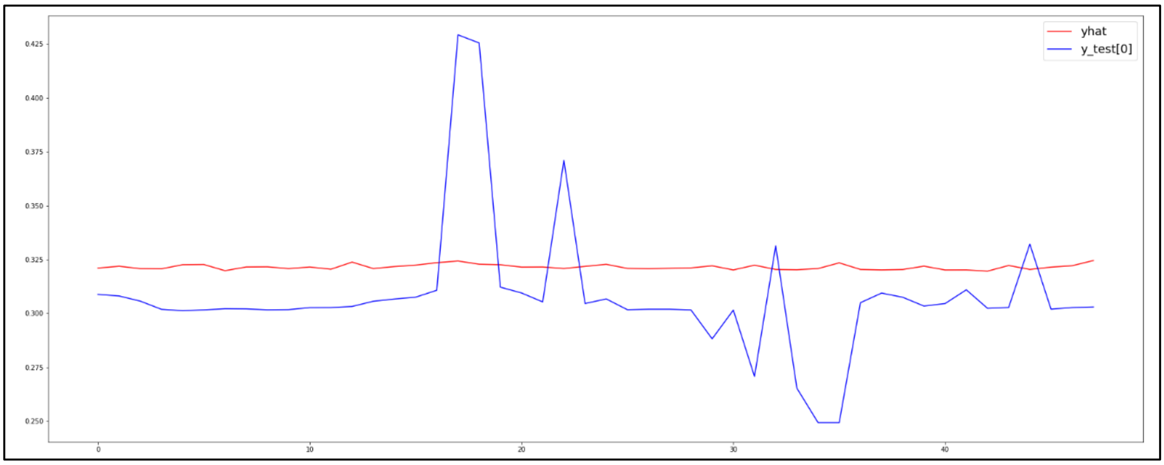
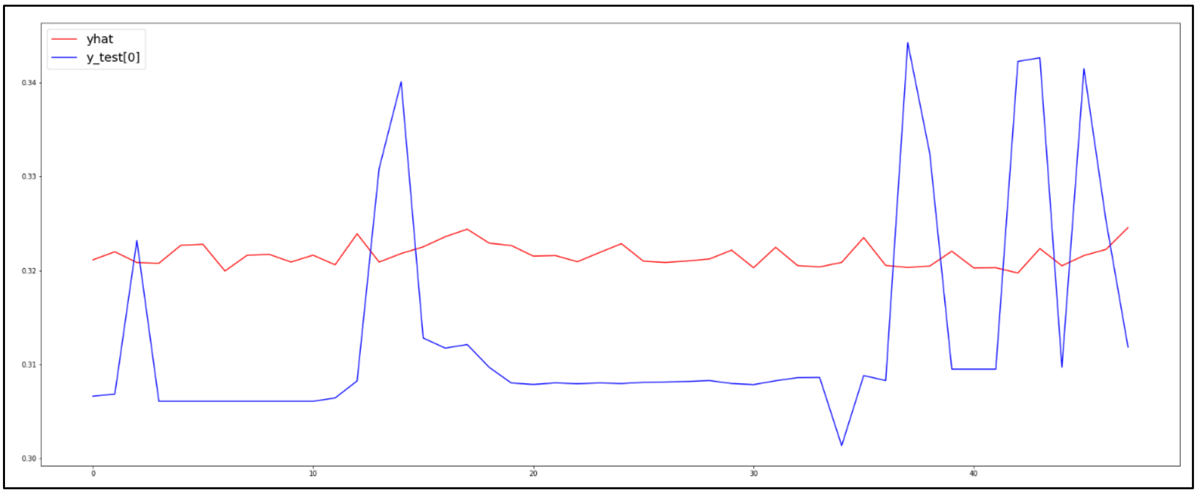
0.05
0
10
20
30
40

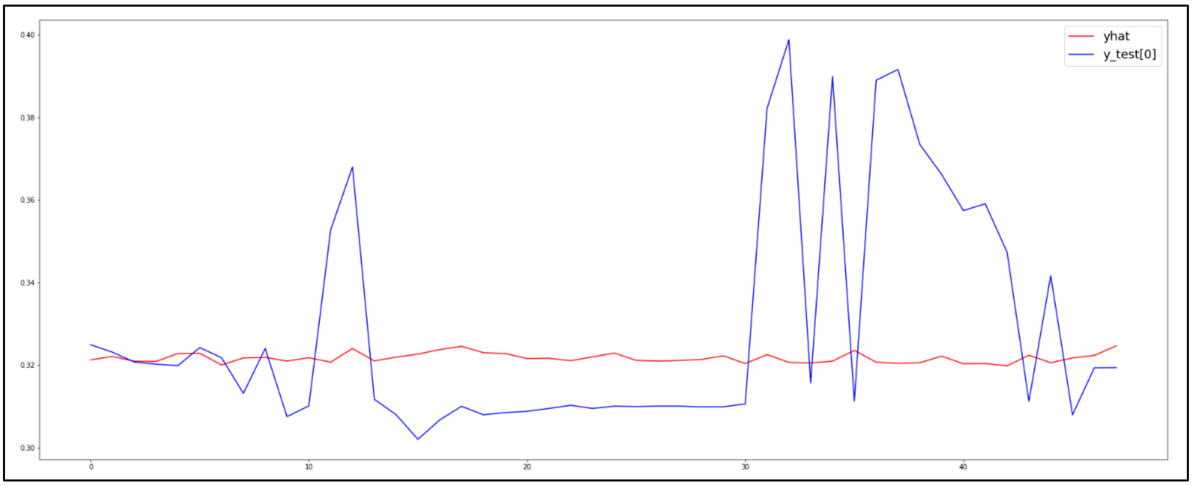
(5) SSP Prediction

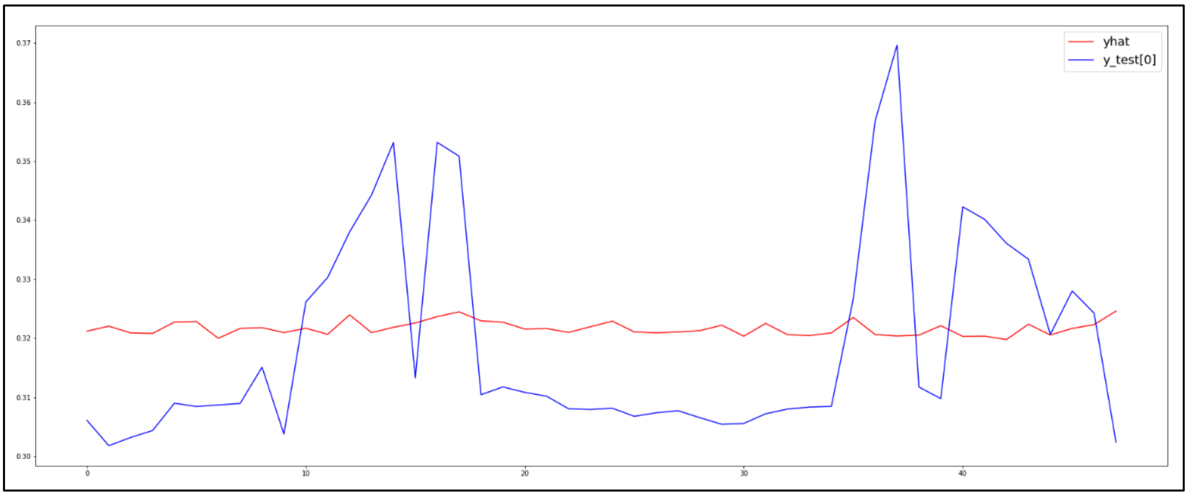







yhat
y_test[0]


yhat
y_test[0]


yhat
y_test[0]

Appendix 2 Python Code

```python

import os
import pandas as pd
import numpy as np
import time
import math

class GridParameter():
    def __init__(self):
        self.HP_CAPACITY = 250.0
        self.HP_COP = 3.667
        self.MAX_DISCHARGE_ABS = 250.0
        self.DATA_FILENAME = 'Historical_Data.pkl'
## Historical_Data.pkl is a pd.Dataframe with six columns:
##        DateTime            PV     ElecDemand  HeatDemand   SSP      SBP
## 0  2014-09-17 00:00:00  0.000000  18.059080  2.998558  0.033500  0.039760
## 1  2014-09-17 00:30:00  0.000000  15.479212  2.998558  0.036650  0.037740
## 2  2014-09-17 01:00:00  0.000000  13.544310  2.998558  0.037390  0.038200
## ... ... ... ... ... ... ...

        self.TIME_INTERVAL_PER_DAY = 48
        self.TANK_CAPACITY = 1500.0
        self.TANK_LOSS_PER_DAY  = 0.7
        self.TANK_LOSS_PER_T = pow(self.TANK_LOSS_PER_DAY,
                                   1/self.TIME_INTERVAL_PER_DAY)

        self.BENEFIT_THRESHOLD = 1.0
        ## a thresold of the ratio(of cost)
        ## = [stored heat from other time / import electricity right now]
        ## only ratio smaller than BENEFIT_THRESOLD would be taken into
        ## consideration. Thus, we can avoid storing heat(namely occupying
        ## tank capacity) that doesn't bring much benefit

        self.DECISION_TIME = 1
        ## if set to be 24, the storage would only be charged after
        ## 12:00 AM everyday
        self.PRIME_PV = 7


class Expert(GridParameter):
    def __init__(self):
        GridParameter.__init__(self)
        self.Data = pd.read_pickle(self.DATA_FILENAME)
        self.Data_len = self.Data.shape[0]
        self.DAYS = self.Data_len / self.TIME_INTERVAL_PER_DAY

        np.random.seed(4944)
        noise = 1 + np.random.normal(0, 1, self.Data_len)*0.03
        self.Data.loc[:, 'ElecDemand']=self.Data.loc[:, 'ElecDemand']*noise

        np.random.seed(4944)
        noise = 1 + np.random.normal(0, 1, self.Data_len)*0.05
        self.Data.loc[:, 'HeatDemand']=self.Data.loc[:, 'HeatDemand']*noise

        self.reset_dataframe()

    def reset_dataframe(self):
        self.Data['Tank']  = 0.0
        self.Data['Prediction'] = 0.0

```

```
        self.Data['HP'] = self.HP_CAPACITY - self.Data['HeatDemand']
        self.Data['PVOutput_h'] =\
            (self.Data['PV']-self.Data['ElecDemand']) * self.HP_COP
        updateby = self.Data[self.Data['PVOutput_h'] < 0].copy()
        updateby.loc[:, 'PVOutput_h'] = 0.0
        self.Data.update(updateby)

        self.Data['PVSurplus_h'] = \
                    self.Data['PVOutput_h'] - self.Data['HeatDemand']
        self.Data['Shortage_h']  = -self.Data['PVSurplus_h']
        updateby = self.Data[self.Data['PVSurplus_h'] < 0].copy()
        updateby.loc[:, 'PVSurplus_h'] = 0.0
        self.Data.update(updateby)
        updateby = self.Data[self.Data['Shortage_h'] < 0].copy()
        updateby.loc[:, 'Shortage_h'] = 0.0
        self.Data.update(updateby)

        self.Data['GridCharge_h'] = 0.0
        ## how much heat generated by imported electricity
        ## for charging the storage
        self.Data['PVCharge_h']   = 0.0
        ## how much heat generated by PV electricity for charging the stroage

    def create_train_data(self):
        self.reset_dataframe()

        for index in range(0, self.Data_len, self.TIME_INTERVAL_PER_DAY):
            self.generate_episode(index)
            print('day:', index/self.TIME_INTERVAL_PER_DAY, end='\r')

            if index%(500*48) == 0:
                filename = 'Historical_Data_expert_done_checkpoint.pkl'
                self.Data.to_pickle(filename)
                print('checkpoint at ', filename)
                print(' ')

        filename = 'Historical_Data_expert_done.pkl'
        self.Data.to_pickle(filename)
        print('pickle as ', filename)
        print(' ')

    def generate_episode(self, t):
        episode = self.Data[t : t + self.TIME_INTERVAL_PER_DAY].copy()
        episode.reset_index(inplace=True)
        self.tank_cp = self.TANK_CAPACITY

        Profit = self.CreateProfitTable(episode)


        ## ---- filling the episode, according to Profit table

        for _ in range(Profit.shape[0]):            ## --works like a while-loop,
            try:                                    ## --try to pick up first row
                Profit.index[0]
            except:                     ## --if there's no first row, all is done
                #print('All entries in Profit table are done.')
                break
            else:
                t_curr = Profit.loc[Profit.index[0], 't_curr']
                t_past = Profit.loc[Profit.index[0], 't_past']
```

```
                source = Profit.loc[Profit.index[0], 'source']

                Profit, trimmed = self.DistributeEnergy(t_curr, t_past,
                                                        source, episode, Profit)

                if trimmed == False:
                    Profit = Profit.drop(Profit.index[0])
                    ## --delete first row because it's done.

        episode.set_index('index', inplace=True)
        self.Data.update(episode)


    def CreateProfitTable(self, episode):

        ## profit = stored price / current import price, smaller better
        ## t_curr = current time
        ## t_past = between t_0 and t_curr
        ## source should be a string, either "PV" or "Grid"

        list1 = ['profit', 't_curr', 't_past', 'source']
        Profit = pd.DataFrame(columns = list1)
        rows = 0


        for t_curr in range(self.DECISION_TIME, self.TIME_INTERVAL_PER_DAY):
            if episode.loc[t_curr, 'Shortage_h'] <= 0:
                pass   ## no need to 'buy' heat, no need to calculate profit
            else:
                denominator = episode.loc[t_curr, 'SBP']

                t_past = t_curr

                while t_past >= self.DECISION_TIME:
                    ## (1) importing electricity at t_past to charge tank
                    ##     for later use at t_curr
                    numerator=episode.loc[t_past,'SBP']/  \
                                        (self.TANK_LOSS_PER_T**(t_curr-t_past))

                    ratio = numerator / denominator
                    ## alternative source / importing right now
                    if ratio < self.BENEFIT_THRESHOLD:
                        Profit.loc[rows] = [ratio, t_curr, t_past, 'Grid']
                        rows += 1

                    ## (2) using PV surplus at t_past to charge tank
                    ##     for later use at t_curr
                    if episode.loc[t_past, 'PVSurplus_h'] > 0:
                        numerator=episode.loc[t_past, 'SSP'] / \
                                    ( self.TANK_LOSS_PER_T**(t_curr - t_past) )

                        ratio = numerator / denominator
                        if ratio < self.BENEFIT_THRESHOLD:
                            Profit.loc[rows] = [ratio, t_curr, t_past, 'PV']
                            rows += 1

                    t_past -= 1

        ## break tie by t_curr, we deal with the energy distribution
        ## at early time first. This would probably reduce the occurence of
```

```
        ## occupying tank capacity for too long
        Profit = Profit.sort_values(by = ['profit', 't_curr'])
        Profit = Profit.reset_index(drop = True)


        ## this prime number is for sorting and deleting specific data
        ## PV = 7, a prime number, making any [label = t * 7] unique
        ## whenever the solar surplus runs out, or whenerer the solar surplus is
        ## still available but HP capacity or tank capacity runs out
        ## we can use this unique label to delete all related entries in profit
        ## table at once.
        ## If we delete entries that are no longer feasible,
        ## overall calculation will be more efficient
        for index in range(Profit.shape[0]):
            if Profit.loc[index, 'source'] == 'PV':
                Profit.loc[index, 'PV_label'] = \
                Profit.loc[index, 't_past'] * self.PRIME_PV

        return Profit


    def DistributeEnergy(self, t_curr, t_past, source, episode, Profit):
        trimmed = False
        ## if Profit has been altered in this function,
        ## its first rows would have been deleted before being return.
        ## Consequently, its first two rows would be deleted in one main loop.
        ## (one happens in this function, another in the main loop)

        ## Shortage should be positive
        if episode.loc[t_curr, 'Shortage_h'] < 0.0:
            raise ValueError('Shortage should be positive at ', t_curr)


        ## toTake = how much we "aim" to take at t_past.
        ## Tank loss must be considered.
        toTake = \
        episode.loc[t_curr,'Shortage_h']/(self.TANK_LOSS_PER_T**(t_curr-t_past))


    ##---- checking feasibility -----------------------------------

        ## Grid is unlimited, but PV is not.
        if source == 'PV':
            if episode.loc[t_past, 'PVSurplus_h'] < 0.0:
                raise ValueError('PVSurplus should be positive at ', t_past)

            if episode.loc[t_past, 'PVSurplus_h'] < toTake:
                ## PV surplus at t_past is less than we aim to take
                toTake = episode.loc[t_past, 'PVSurplus_h']
                ## so we can only aim to take all the PV surplus
                ## else, we can keep our original aim

        ## HP capacity has a limit
        if episode.loc[t_past, "HP"] < toTake:
            ## HP capacity at t_past is less than our aim
            toTake = episode.loc[t_past, "HP"]
            ## so we can only aim to take all the PV surplus
            ## else, we can keep our original aim

## now, check all the Tank capacity from t_past+1 to t_curr
```

```
## Note: any change to the heat level of storage at t reflects on 'Tank' at t+1
## for example, 'storage' at t=0 is a result from all events happened before t=0,
## which means 'storage' at t represents the status of tank "at the start of t"
## Thus, if we charge tank at time t_past,
## we check tank capacity from t_past+1 to t_curr

        t = t_past + 1
        toStore = toTake

        while t <= t_curr:
            toStore = toStore * self.TANK_LOSS_PER_T
            EmptyTank = self.tank_cp - episode.loc[t, 'Tank']
            if EmptyTank < toStore:
                ## Tank capacity at t is less than our aim
                toStore = EmptyTank
                ## so we can only aim to use all the remaining capacity
                ## else, we can keep our original aim for t

            t += 1

        ## after all above,
        ## now toStore =
        ## a feasible amount of heat that can be stored at the start of t_curr





    ##---- updating episode data -----------------------------------

## let 'Shortage_h' at t_curr consumes the heat we stored for it
## note that this doesn't means HeatDemand at t has consumed the stored heat yet,
## nor the number of 'storage' at t_curr need to be decreased.
## We can see that HeatDemand at t has been fulfilled only at the data of t+1 on
## the final episode table.
## 'Shortage_h' is just a variable for calculation of how to distribute available
## energy.
        episode.loc[t_curr, 'Shortage_h'] -= toStore


        if abs(episode.loc[t_curr, 'Shortage_h'])  < 1e-6:
            trimmed = True
            episode.loc[t_curr, 'Shortage_h'] = 0.0
            Profit = Profit[Profit.t_curr != t_curr]
            ## delete all entries of t_curr in profit table
            ## because Shortage at t_curr has been fulfilled


        ## put toStore into storage at (the start of) t_curr
        episode.loc[t_curr, 'Tank'] += toStore

        if abs(self.tank_cp - episode.loc[t_curr, 'Tank']) < 1e-6:
            trimmed = True
            episode.loc[t_curr, 'Tank'] = self.tank_cp
            Profit = Profit[ np.logical_or(\
                np.logical_and(Profit.t_curr < t_curr, Profit.t_past < t_curr ),
                np.logical_and(Profit.t_curr > t_curr, Profit.t_past > t_curr ))]
    ## because storage is full at this t,
    ## any attempt from profit table that tries to "cross" t would fail
    ## "cross" means storing heat at time<t and reserving it until another time>t
```

```
    ## put toStore into storage in each t, retrospectively
    ## (TANK_LOSS_PER_T should be considered)

        t = t_curr - 1

        while t > t_past:
        ## charging storage at time t_past only affects tank from
        ## t_past+1 to t_curr
            toStore = toStore / self.TANK_LOSS_PER_T
            episode.loc[t, 'Tank'] += toStore

            if abs(self.tank_cp - episode.loc[t, 'Tank']) < 1e-6:
                trimmed = True
                episode.loc[t, 'Tank'] = self.tank_cp
                Profit = Profit[ np.logical_or(\
                        np.logical_and(Profit.t_curr < t, Profit.t_past < t ),
                        np.logical_and(Profit.t_curr > t, Profit.t_past > t )  )]
            ## because storage is full at t,
            ## Any attempt from profit table that tries to "cross" t would fail.
            ## "Cross" means storing heat at time < t and reserving it until
            ## another time > t.
            t -= 1

         ## after above,
        ## now toStore = the amount of heat would be stored at the end of t_past


        ## use HP capacity at t_past to generate toStore
        episode.loc[t_past, 'HP'] -= toStore
        if abs(episode.loc[t_past, 'HP']) < 1e-6:
            trimmed = True
            episode.loc[t_past, 'HP'] = 0.0
            Profit = Profit[Profit.t_past != t_past]
            ## because HP can no long generate heat at t_past,
            ## any attempt from profit table that tries to
            ## charge storage at t_past would fail

        ## spend and record the source
        if source == 'PV':
            episode.loc[t_past, 'PVSurplus_h'] -= toStore
            episode.loc[t_past, 'PVCharge_h']  += toStore
            if abs(episode.loc[t_past, 'PVSurplus_h']) < 1e-4:
                trimmed = True
                episode.loc[t_past, 'PVSurplus_h'] = 0.0
                PV_label = t_past * self.PRIME_PV
                Profit = Profit[Profit.PV_label != PV_label]
                ## because there is no PV surplus at t_past,
                ## any attempt from profit table that tries to
                ## charge tank by PV at t_past would fail
        else:
            episode.loc[t_past, 'GridCharge_h'] += toStore


        return Profit, trimmed



########## Object: predictors ##########
```

```
from keras.models import load_model
from sklearn.preprocessing import MinMaxScaler

class FORECASTER():
    def __init__(self):
        self.agent_PV = self.PV_AGENT()
        self.agent_HD = self.HD_AGENT()
        self.agent_ED = self.ED_AGENT()
        self.agent_SSP = self.SSP_AGENT()
        self.agent_SBP = self.SBP_AGENT()
        self.expert_4forecast = self.EXPERT_FOR_FORECAST()
        self.TIME_INTERVAL_PER_DAY = 48   ## should have avoided 'magic number'
        self.set_cutoff()

    def produce_yhat(self, ndarray, agent):
        ndarray = ndarray.reshape([ndarray.shape[0], ndarray.shape[1], 1])
        return agent.predict(ndarray)

    def set_cutoff(self, start_from = 24):
        self.start_from = start_from

    def _forecast_each(self, input_arr):

        self.tank_target = []
        ## this should be a np.array with shape of (336, 1), this is yhat
        self.SBPhat = []
        self.SSPhat = []


        for i in range(input_arr.shape[0]):
            half_hour = i%self.TIME_INTERVAL_PER_DAY

            if half_hour == 0:
                dataframe = pd.DataFrame(columns=\
                                ['PV', 'ElecDemand', 'HeatDemand' ,'SSP' ,'SBP'])
                dataframe.loc[:, 'PV']          = self.hatPV[i]
                dataframe.loc[:, 'ElecDemand'] = self.hatED[i]
                dataframe.loc[:, 'HeatDemand'] = self.hatHD[i]
                dataframe.loc[:, 'SSP']       = self.hatSSP[i]
                dataframe.loc[:, 'SBP']       = self.hatSBP[i]

                self.tank_target.append(0.0)

            else:
                dataframe.loc[:half_hour-1, 'PV']= self.re_inputPV[i][-half_hour:]
                dataframe.loc[half_hour:, 'PV']= self.hatPV[i][:-half_hour]

                dataframe.loc[:half_hour-1, 'ElecDemand'] =\
                                                self.re_inputED[i][-half_hour:]
                dataframe.loc[half_hour:,'ElecDemand']=self.hatED[i][:-half_hour]

                dataframe.loc[:half_hour-1, 'HeatDemand'] =\
                                                self.re_inputHD[i][-half_hour:]
                dataframe.loc[half_hour:,'HeatDemand']=self.hatHD[i][:-half_hour]

                dataframe.loc[:half_hour-1,'SSP']=self.re_inputSSP[i][-half_hour:]
                dataframe.loc[half_hour:, 'SSP']= self.hatSSP[i][:-half_hour]

                dataframe.loc[:half_hour-1,'SBP']=self.re_inputSBP[i][-half_hour:]
                dataframe.loc[half_hour:, 'SBP']= self.hatSBP[i][:-half_hour]
```

```python


            if half_hour < self.start_from:
                self.tank_target.append(0.0)
            else:
                self.expert_4forecast.generate_episode(dataframe)
                self.tank_target.append(dataframe.loc[half_hour, 'Tank'])

        self.SBPhat.append(dataframe.loc[half_hour, 'SBP'])
        self.SSPhat.append(dataframe.loc[half_hour, 'SSP'])

    self.yhat = np.asarray(self.tank_target)
    self.yhat = self.yhat.reshape(input_arr.shape[0], 1)

    return self.yhat

def forecast(self, input_arr):
    # PLZ check columns=['PV','ED','HD','SSP','SBP']
    self.inputPV = input_arr[:, :, 0]  ## scaled value
    self.inputHD = input_arr[:, :, 2]
    self.inputED = input_arr[:, :, 1]
    self.inputSSP = input_arr[:, :, 3]
    self.inputSBP = input_arr[:, :, 4]

    self.re_inputPV = self.agent_PV.rescaler.inverse_transform(self.inputPV)
    self.re_inputHD = self.agent_HD.rescaler.inverse_transform(self.inputHD)
    self.re_inputED = self.agent_ED.rescaler.inverse_transform(self.inputED)
    self.re_inputSSP = \
            self.agent_SSP.rescaler.inverse_transform(self.inputSSP)
    self.re_inputSBP = \
            self.agent_SBP.rescaler.inverse_transform(self.inputSBP)


    self.hatPV = self.produce_yhat(input_arr[:, :, 0], self.agent_PV)
    self.hatHD = self.produce_yhat(input_arr[:, :, 2], self.agent_HD)
    self.hatED = self.produce_yhat(input_arr[:, :, 1], self.agent_ED)
    self.hatSSP = self.produce_yhat(input_arr[:, :, 3], self.agent_SSP)
    self.hatSBP = self.produce_yhat(input_arr[:, :, 4], self.agent_SBP)

    self.yhat = self._forecast_each(input_arr)

    return self.yhat




class PV_AGENT():
    def __init__(self):
        self.model = load_model('lstm_model_PV.h5')
        self.scale_base = pd.read_pickle('PV_scale_base.pkl')
        ## PV_scale_base.pkl is a pd.DataFrame, which is the training set used
        ## to train lstm_model_PV.h5 (a trained keras.model in Standard Model)
        ## columns = ['DateTime', 'feature'], here feature = PV generation
        try:
            self.scale_base.drop(columns=['DateTime'], inplace=True)
        except:
            pass
        self.rescaler= MinMaxScaler()
        self.rescaler.fit(self.scale_base)

```

```
    def predict(self, array):
        yhat = self.model.predict(array, verbose=0)
        yhat = self.rescaler.inverse_transform(yhat)
        return yhat

class HD_AGENT():
    def __init__(self):
        self.model = load_model('lstm_model_HD.h5')
        self.scale_base = pd.read_pickle('HD_scale_base.pkl')
        try:
            self.scale_base.drop(columns=['DateTime'], inplace=True)
        except:
            pass
        self.rescaler= MinMaxScaler()
        self.rescaler.fit(self.scale_base)

    def predict(self, array):
        yhat = self.model.predict(array, verbose=0)
        yhat = self.rescaler.inverse_transform(yhat)
        return yhat

class ED_AGENT():
    def __init__(self):
        self.model = load_model('lstm_model_ED.h5')
        self.scale_base = pd.read_pickle('ED_scale_base.pkl')
        try:
            self.scale_base.drop(columns=['DateTime'], inplace=True)
        except:
            pass
        self.rescaler= MinMaxScaler()
        self.rescaler.fit(self.scale_base)

    def predict(self, array):
        yhat = self.model.predict(array, verbose=0)
        yhat = self.rescaler.inverse_transform(yhat)
        return yhat

class SSP_AGENT():
    def __init__(self):
        self.model = load_model('lstm_model_SSP.h5')
        self.scale_base = pd.read_pickle('SSP_scale_base.pkl')
        try:
            self.scale_base.drop(columns=['DateTime'], inplace=True)
        except:
            pass
        self.rescaler= MinMaxScaler()
        self.rescaler.fit(self.scale_base)

    def predict(self, array):
        yhat = self.model.predict(array, verbose=0)
        yhat = self.rescaler.inverse_transform(yhat)
        return yhat

class SBP_AGENT():
    def __init__(self):
        self.model = load_model('lstm_model_SBP.h5')
        self.scale_base = pd.read_pickle('SBP_scale_base.pkl')
        try:
            self.scale_base.drop(columns=['DateTime'], inplace=True)
        except:
```

```
                pass
            self.rescaler= MinMaxScaler()
            self.rescaler.fit(self.scale_base)

        def predict(self, array):
            yhat = self.model.predict(array, verbose=0)
            yhat = self.rescaler.inverse_transform(yhat)
            return yhat



    class EXPERT_FOR_FORECAST(Expert):
        def __init__(self):
            GridParameter.__init__(self)

        def reset_episode(self, episode):
            episode['Tank']  = 0.0
            episode['HP'] = self.HP_CAPACITY - episode['HeatDemand']

            episode['PVOutput_h'] =\
                             (episode['PV'] - episode['ElecDemand']) * self.HP_COP
            updateby = episode[episode['PVOutput_h'] < 0].copy()
            updateby.loc[:, 'PVOutput_h'] = 0.0
            episode.update(updateby)


            episode['PVSurplus_h'] = episode['PVOutput_h'] - episode['HeatDemand']
            episode['Shortage_h']  = -episode['PVSurplus_h']

            updateby = episode[episode['PVSurplus_h'] < 0].copy()
            updateby.loc[:, 'PVSurplus_h'] = 0.0
            episode.update(updateby)

            updateby = episode[episode['Shortage_h'] < 0].copy()
            updateby.loc[:, 'Shortage_h'] = 0.0
            episode.update(updateby)

            episode['GridCharge_h'] = 0.0
            ## how much heat generated by imported elec for charging tank
            episode['PVCharge_h']    = 0.0
            ## how much heat generated by PV elec for charging tank


        def generate_episode(self, episode):
            self.tank_cp = self.TANK_CAPACITY
            self.reset_episode(episode)

            Profit = self.CreateProfitTable(episode)



            ## ---- filling the episode, according to Profit table

            for _ in range(Profit.shape[0]):
                ## --works like a while-loop,
                try:
                    ## --try to pick up first row
                    Profit.index[0]
                except:
                    ## --if there's no first row, all is done
```

```
                    ## print('All entries in Profit table are done.')
                    break
                else:
                    t_curr = Profit.loc[Profit.index[0], 't_curr']
                    t_past = Profit.loc[Profit.index[0], 't_past']
                    source = Profit.loc[Profit.index[0], 'source']

                    Profit, trimmed =\
                     self.DistributeEnergy(t_curr, t_past,
                                           source, episode, Profit)

                    if trimmed == False:
                        Profit = Profit.drop(Profit.index[0])
                        ## --delete first row because it's done.



            return episode.loc[0, 'Tank']


########## Object: simulator ##########

import pickle
import os
import pandas as pd
import numpy as np
import time
import math
from matplotlib import pyplot

from sklearn.preprocessing import MinMaxScaler
from keras.models import load_model
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM
from keras.layers import Dropout



class Simulator(GridParameter):
    def __init__(self, model, forecaster,
                 environment='Historical_Data_expert_done.pkl'):
## Historical_Data_expert_done.pkl = Historical_Data.pkl + expert's operation
## columns = ['DateTime', 'PV', 'ElecDemand', 'HeatDemand', 'SSP', 'SBP', 'Tank',
##              'Prediction', 'HP', 'PVOutput_h', 'PVSurplus_h', 'Shortage_h',
##              'GridCharge_h', 'PVCharge_h']
## Note that we didn't delete the column 'Prediction' even though in our actual
## implementation we never use this column.

        GridParameter.__init__(self)
        self.MODEL = model
        self.FORECASTER = forecaster
        self.HISTORY = pd.read_pickle(environment)
        self.EPISODE_LEN = 7*self.TIME_INTERVAL_PER_DAY

        self.rescaler = MinMaxScaler()
        drops = ['DateTime', 'Tank', 'Prediction', 'HP', 'PVOutput_h',
                 'PVSurplus_h', 'Shortage_h', 'GridCharge_h', 'PVCharge_h']
        self.rscd_history = \
                  self.rescaler.fit_transform(self.HISTORY.drop(columns=drops))
```

```
        self.rscd_history = pd.DataFrame(self.rscd_history)
        self.rscd_history.columns = \
                  self.HISTORY.drop(columns=drops).columns.tolist()

        ## vanilla strategy
        self.VANI_CHARGE = 25
        self.VANI_DISCHARGE = 34
        self.VANI_MAX_TARGET = 1200.0

    def run(self, start, figure=False, network=True, forecast=True,
            vanilla=True, no_tank=True, day=1):
        self.EPISODE_LEN = day*self.TIME_INTERVAL_PER_DAY
        curve_expert, cost_expert = self.expert_perform(start)
        print('expert ', curve_expert.shape, cost_expert)

        if network:
            curve_network, cost_network = \
                         self.network_perform(start, self.MODEL, scaled=True)
            print('network operation ', curve_network.shape, cost_network)

        if forecast:
            curve_forecast, cost_forecast = \
                   self.network_perform(start, self.FORECASTER, scaled=False)
            print('forecaster operation', curve_forecast.shape, cost_forecast)

        if vanilla:
            curve_vanilla, cost_vanilla = self.vanilla_perform(start)
            print('vanilla operation[25,43] ', cost_vanilla)

        if no_tank:
            cost_no_tank = self.no_tank_perform(start)
            print('no Tank ', cost_no_tank)


##################################
        if figure == True:
            duration = self.EPISODE_LEN

            curve_pv_output_heat = \
                 self.HISTORY[start:start+duration]['PVOutput_h'].values
            curve_heat_demand = \
                 self.HISTORY[start:start+duration]['HeatDemand'].values
            point_SBP = self.HISTORY[start:start+duration]['SBP'].values
            point_SSP = self.HISTORY[start:start+duration]['SSP'].values



            fig, ax1 = pyplot.subplots()


            ax1.set_xlabel('time (half hour)')
            ax1.set_ylabel('heat(kW))')
            ax1.plot(curve_heat_demand, 'm:', label='curve_heat_demand')
            ax1.plot(curve_pv_output_heat, 'g:', label='curve_pv_output_heat')
            ax1.plot(curve_expert,'b', label='curve_expert')
            try:
                ax1.plot(curve_network, 'r', label='curve_network')
            except:
                pass
            try:
```

```
                ax1.plot(curve_forecast, 'c', label='curve_forecast')
            except:
                pass
            try:
                ax1.plot(curve_vanilla, 'y', label='curve_vanilla')
            except:
                pass

            pyplot.legend(loc='upper left', prop={'size': 18})

            ax2 = ax1.twinx()
            # instantiate a second axes that shares the same x-axis
            ax2.set_ylabel('price(pound/kW)')
            ax2.plot(point_SBP, 'rD', label='point_SBP')
            ax2.plot(point_SSP, 'b+', label='point_SSP')

            fig.tight_layout() # otherwise the right y-label is slightly clipped
            fig.set_size_inches(30, 12, forward=True)
            pyplot.legend(prop={'size': 18})

            pyplot.savefig('output.png')
            pyplot.show()

##################################


    def _provide(self, need, have):
        assert need >= 0
        assert have >= 0

        if need >= have:
            need -= have
            provide = have
            have = 0.0
        else:
            have -= need
            provide = need
            need = 0.0

        return need, have, provide

############################################

    def network_perform(self, start, agent, scaled=True, confident=True):
        episode = self.HISTORY[start:start+simulator.EPISODE_LEN].copy()
        episode['Tank'] = 0.0
        episode['HP'] = self.HP_CAPACITY - episode['HeatDemand']

        episode['PVSurplus_h'] = episode['PVOutput_h'] - episode['HeatDemand']
        updated = episode[episode['PVSurplus_h'] < 0].copy()
        updated['PVSurplus_h'] = 0.0
        episode.update(updated)
        del updated

        episode['Shortage_h']  = episode['HeatDemand'] - episode['PVOutput_h']
        updated = episode[episode['Shortage_h'] < 0].copy()
        updated['Shortage_h'] = 0.0
        episode.update(updated)
        del updated

```

```
        episode['GridCharge_h'] = 0.0
        episode['PVCharge_h']   = 0.0


        index_start       = start - self.TIME_INTERVAL_PER_DAY
        index_end_exclude = start + self.EPISODE_LEN
        rscd_episode = self.rscd_history[index_start:index_end_exclude].copy()

        input_arr = np.zeros((self.EPISODE_LEN, 48, 5))


        for i in range(0, self.EPISODE_LEN):
            input_arr[i] = rscd_episode[i:i+self.TIME_INTERVAL_PER_DAY].values

        if scaled:
            self.yhat = agent.predict(input_arr, verbose=0) * self.TANK_CAPACITY
            keyword = 'proposed'
        else:
            self.yhat = agent.forecast(input_arr)
            keyword = 'standard'

        for i in range(self.EPISODE_LEN):
            index = i + start
            if confident:
                episode = self.step_confident(episode, index, self.yhat[i][0])
            else:
                episode = self.step(episode, index, self.yhat[i][0])

        ## record how much PV-generated electricity remains
        ## that can be exported at time t
        episode['Export_e']       = episode['PVSurplus_h'] / self.HP_COP
        ## record how much shortage of electricity remains
        ## that we need to import for it at time t
        episode['Import_e']       = episode['Shortage_h']  / self.HP_COP
        ## record how much electricity imported to charge
        ## the tank at time t
        episode['Import_forTank'] = episode['GridCharge_h']  / self.HP_COP

        Export        = -episode['SSP'] * episode['Export_e']
        Import        = episode['SBP']  * episode['Import_e']
        Import_charge = episode['SBP']  * episode['Import_forTank']

        curve_network  = episode['Tank'].values
        cost_network   = \
           Export.values.sum() + Import.values.sum() + Import_charge.values.sum()

        return curve_network, cost_network


    def step_confident(self, episode, index, target):
        ## always fulfill the targer value requested,
        ## no matter using PV generation or imported electricity
        ## to charge heat storage

        ## during good weather, step_naive() shows better performance than step(),
        ## because there are less time that the system need to import electricity
        ## for charging.
        ## Also, there are more oppotunities for the system to

        assert target >= 0
```

```
        assert target <= self.TANK_CAPACITY

        tank_curr = episode.loc[index, 'Tank']
        action = target - tank_curr

        if action > episode.loc[index, 'HP']:
            action = episode.loc[index, 'HP']

        ## charge
        if action >= 0 and episode.loc[index, 'PVSurplus_h'] > 0:
            tank_next = tank_curr * self.TANK_LOSS_PER_T + action
            action, episode.loc[index, 'PVSurplus_h'], episode.loc[index, \
            'PVCharge_h'] = self._provide(action,
                                          episode.loc[index, 'PVSurplus_h'])
            if action > 0:
                episode.loc[index, 'GridCharge_h'] = action

        elif action >= 0 and episode.loc[index, 'Shortage_h'] >= 0:
            tank_next = tank_curr * self.TANK_LOSS_PER_T + action
            episode.loc[index, 'GridCharge_h'] = action

        ## discharge
        elif action < 0 and episode.loc[index, 'PVSurplus_h'] > 0:
            action = abs(action)
            if action > self.MAX_DISCHARGE_ABS:
                action = self.MAX_DISCHARGE_ABS

            tank_next = (tank_curr - action) * self.TANK_LOSS_PER_T


        elif action < 0 and episode.loc[index, 'Shortage_h'] >= 0:
            action = abs(action)
            if action > self.MAX_DISCHARGE_ABS:
                action = self.MAX_DISCHARGE_ABS

            tank_next = (tank_curr - action) * self.TANK_LOSS_PER_T

            episode.loc[index, 'Shortage_h'], _, _ = \
            self._provide(episode.loc[index, 'Shortage_h'], action)

        else:
            raise ValueError('Error')


        if index+1 > episode.index[-1]:
            pass
        else:
            episode.loc[index+1, 'Tank'] = tank_next


        return episode

    def step(self, episode, index, target):
        assert target >= 0
        assert target <= self.TANK_CAPACITY

        tank_curr = episode.loc[index, 'Tank']
        action = target - tank_curr

        ## charge
```

```
        if action >= 0 and episode.loc[index, 'PVSurplus_h'] > 0:

            action, episode.loc[index, 'PVSurplus_h'], episode.loc[index, \
            'PVCharge_h']=self._provide(action, episode.loc[index, 'PVSurplus_h'])

            tank_next = \
                tank_curr*self.TANK_LOSS_PER_T + episode.loc[index, 'PVCharge_h']


        elif action >= 0 and episode.loc[index, 'Shortage_h'] >= 0:
            tank_next = tank_curr * self.TANK_LOSS_PER_T #+ action
            #episode.loc[index, 'GridCharge_h'] = action

        ## discharge
        elif action < 0 and episode.loc[index, 'PVSurplus_h'] > 0:
            action = abs(action)
            if action > self.MAX_DISCHARGE_ABS:
                action = self.MAX_DISCHARGE_ABS

            tank_next = (tank_curr - action) * self.TANK_LOSS_PER_T


        elif action < 0 and episode.loc[index, 'Shortage_h'] >= 0:
            action = abs(action)
            if action > self.MAX_DISCHARGE_ABS:
                action = self.MAX_DISCHARGE_ABS

            tank_next = (tank_curr - action) * self.TANK_LOSS_PER_T

            episode.loc[index, 'Shortage_h'], _, _ = \
            self._provide(episode.loc[index, 'Shortage_h'], action)

        else:
            raise ValueError('Error')


        if index+1 > episode.index[-1]:
            pass
        else:
            episode.loc[index+1, 'Tank'] = tank_next


        return episode

############################################

    def expert_perform(self, start):
        episode = self.HISTORY[start:start+self.EPISODE_LEN].copy()
        print(episode.loc[start, 'DateTime'])

        ## record how much PV-generated electricity remains
        ## that can be exported at time t
        episode['Export_e']       = episode['PVSurplus_h'] / self.HP_COP
        ## record how much shortage of electricity remains
        ##that we need to import for it at time t
        episode['Import_e']       = episode['Shortage_h']  / self.HP_COP
        ## record how much electricity imported to charge
        ##the tank at time t
        episode['Import_forTank'] = episode['GridCharge_h']  / self.HP_COP

```

```
        Export        = -episode['SSP'] * episode['Export_e']
        Import        = episode['SBP']  * episode['Import_e']
        Import_charge = episode['SBP']  * episode['Import_forTank']

        curve_expert  = episode['Tank'].values
        cost_expert = \
           Export.values.sum() + Import.values.sum() + Import_charge.values.sum()


        return curve_expert, cost_expert

############################################

    def vanilla_perform(self, start):
        episode = self.HISTORY[start:start+simulator.EPISODE_LEN].copy()
        episode['Tank'] = 0.0
        episode['HP'] = self.HP_CAPACITY - episode['HeatDemand']

        episode['PVSurplus_h'] = episode['PVOutput_h'] - episode['HeatDemand']
        updated = episode[episode['PVSurplus_h'] < 0].copy()
        updated['PVSurplus_h'] = 0.0
        episode.update(updated)
        del updated

        episode['Shortage_h']  = episode['HeatDemand'] - episode['PVOutput_h']
        updated = episode[episode['Shortage_h'] < 0].copy()
        updated['Shortage_h'] = 0.0
        episode.update(updated)
        del updated

        episode['GridCharge_h'] = 0.0
        episode['PVCharge_h']   = 0.0

        for i in range(self.EPISODE_LEN):
            index = i + start
            episode = self.step_vanilla(episode, index)


        ## record how much PV-generated electricity remains
        ## that can be exported at time t
        episode['Export_e']       = episode['PVSurplus_h'] / self.HP_COP
        ## record how much shortage of electricity remains
        ## that we need to import for it at time t
        episode['Import_e']       = episode['Shortage_h']  / self.HP_COP
        ## record how much electricity imported to charge
        ## the tank at time t
        episode['Import_forTank'] = episode['GridCharge_h']  / self.HP_COP

        Export        = -episode['SSP'] * episode['Export_e']
        Import        = episode['SBP']  * episode['Import_e']
        Import_charge = episode['SBP']  * episode['Import_forTank']


        curve_vanilla  = episode['Tank'].values
        cost_vanilla  = \
            Export.values.sum() + Import.values.sum() + Import_charge.values.sum()

        return curve_vanilla, cost_vanilla

    def step_vanilla(self, episode, index):
```

```
        tank_curr = episode.loc[index, 'Tank']

        if index%self.TIME_INTERVAL_PER_DAY < self.VANI_CHARGE:
            action = 0.0
        elif index%self.TIME_INTERVAL_PER_DAY < self.VANI_DISCHARGE:
            action = self.VANI_MAX_TARGET - tank_curr
            if action > episode.loc[index, 'HP']:
                action = episode.loc[index, 'HP']
        else:
            target = tank_curr - self.MAX_DISCHARGE_ABS
            if target < 0:
                target = 0
            action = target - tank_curr

        ## charge
        if action >= 0 and episode.loc[index, 'PVSurplus_h'] > 0:

            action, episode.loc[index, 'PVSurplus_h'], episode.loc[index, \
            'PVCharge_h'] = self._provide(action,
                                          episode.loc[index, 'PVSurplus_h'])

            tank_next = \
                tank_curr * self.TANK_LOSS_PER_T + episode.loc[index,'PVCharge_h']


        elif action >= 0 and episode.loc[index, 'Shortage_h'] >= 0:
            tank_next = tank_curr * self.TANK_LOSS_PER_T #+ action (Disabled line)
            #episode.loc[index, 'GridCharge_h'] = action          (Disabled line)
            ## Disable two lines above in order to avoid
            ## incorrect prediction that costs extra expenditure


        ## discharge
        elif action < 0 and episode.loc[index, 'PVSurplus_h'] > 0:
            action = abs(action)
            if action > self.MAX_DISCHARGE_ABS:
                action = self.MAX_DISCHARGE_ABS

            tank_next = (tank_curr - action) * self.TANK_LOSS_PER_T


        elif action < 0 and episode.loc[index, 'Shortage_h'] >= 0:
            action = abs(action)
            if action > self.MAX_DISCHARGE_ABS:
                action = self.MAX_DISCHARGE_ABS

            tank_next = (tank_curr - action) * self.TANK_LOSS_PER_T

            episode.loc[index, 'Shortage_h'], _, _ = \
            self._provide(episode.loc[index, 'Shortage_h'], action)

        else:
            raise ValueError('Error')


        if index+1 > episode.index[-1]:
            pass
        else:
            episode.loc[index+1, 'Tank'] = tank_next

```

```

        return episode

################################################

    def no_tank_perform(self, start):
        episode = self.HISTORY[start:start+self.EPISODE_LEN].copy()

        ## record how much PV-generated electricity remains
        ## that can be exported at time t
        episode['Export_e']  = \
                   (episode['PVOutput_h'] - episode['HeatDemand'])/ self.HP_COP
        pick_positive_export = episode[episode['Export_e'] > 0].copy()

        ## record how much shortage of electricity remains
        ## that we need to import for it at time t
        episode['Import_e']        = episode['Export_e'] * -1
        pick_positive_import = episode[episode['Import_e'] > 0].copy()


        Export = -pick_positive_export['SSP'] * pick_positive_export['Export_e']
        Import = pick_positive_import['SBP']  * pick_positive_import['Import_e']

        cost_no_tank = Export.values.sum() + Import.values.sum()

        return cost_no_tank


expert_history = 'Historical_Data_expert_done.pkl'
model = load_model('lstm_model_Proposed_Model.h5')

forecaster_for_simu = FORECASTER()

simulator = Simulator(model, forecaster_for_simu, expert_history)
simulator.FORECASTER.set_cutoff(start_from=simulator.DECISION_TIME)

simulator.run(1918*48, figure=True,network=True,
              forecast=True,vanilla=True,no_tank=False, day=1)
```