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

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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.

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Abstract

Inspired by Imitation Learning, this dissertation 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 dissertation 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 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 dissertation 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 dissertation 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 dissertation 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 applied neural network purely to predict key features related to electricity industry, such as energy demands, weather condition and electricity prices. These predictions can be used to support operator's decision making, but not directly provide operation actions on the electricity equipment or systems. In Ref [2], a next-value prediction and a sequence-to-sequence LSTM networks were built to estimate building electricity load. These networks receive time/date indicator and load data from previous time steps as input and then it outputs an estimation of future load. Another LSTM networks created in Ref [3] forecasts the energy consumption at a target time, taking past energy consumptions data of individual residential households, indicators of each hour in a day, indicators of each day in a week and a binary indicator of whether it is a holiday as input. Ref [4] developed a DNN that takes more input features, including weather features of the target date (temperature, humidity, wind speed, solar radiation, and cloud cover), past electricity consumptions and time/date/month/season indicators. It forecasts the energy loads of the target date, divided into 24 hours intervals. In Ref [5], LSTM networks was trained by hourly data of past prices and loads to predict day ahead and week ahead electricity price and load in a smart grid. In a similar way, Ref [6] trained RNNs, LSTM and GRU networks with multiple input features for conducting electricity price forecast. Performance of these networks were compared with single and multi-layer neural networks and statistical methods. Ref [7] compared the performance of many machine learning and statistical approaches for electricity price forecasting, including DNN, LSTM, GRU, SVR, MLP, fARX-EN, fARX-Lasso, etc.

LSTM has also been widely adopted in weather forecasting. Two sequence-to-sequence LSTM networks were built in Ref [8]. These networks receive values of a feature of previous n hours to predict values of the same features of next n hours. Features studied in Ref [8] includes temperature, humidity and wind speed with n equal to 24 or 72. In contrast to using only the same feature of output as input, Ref [9] created LSTM networks to forecast future solar irradiance with previous local data of solar irradiance and exogenous features, including wind speed, wind direction and solar irradiance of each neighbouring locations. It showed that input data from multi-location improves the performance of LSTM predictors. With input and output of the same hours, Ref [10] created another kind of LSTM networks to predict solar irradiance of 24 hours in a day, using different features of the same 24 hours in that day as input, including time/date/month indicators, temperature, dew point, humidity, visibility, wind speed and weather types.

The main difference between each model mentioned above is the feature selection and the architecture of those networks. It is obvious that this difference could influence accuracy of each network. Many researchers have worked on improving the performance of their networks by introducing novel/hybrid networks or feature engineering. Ref [11] built a sequence-to-sequence CNN to predict energy load with historic data of past load. The output sequence of this CNN, along with time/date indicators, are then fed into fully connected layers to make a final prediction of future energy load. In Ref [12], wrapper and embedded feature selection methods were adopted to determine the best feature set for training a LSTM network that forecasts energy load. Genetic algorithm was also used in Ref [12] to figure out an effective number of hidden layers and an effective number of time lag between input and output sequences. Introducing the idea of encoder-decoder architecture, Ref [13] combined LSTM and multi-layered perceptron layers for load prediction. The LSTM layer provides variables that represents the pattern of an input sequence. The variables then were concatenated with the original input sequence for the following multi-layered perceptron network. For short-term building energy load, Ref [14] analysed RNN, LSTM and GRU with different architectures and systematically tested the effectiveness of each network.

To increase the accuracy of electricity price forecast, Ref [15] implemented Decision Tree, Recursive Feature Elimination and Random Forest for feature selection. In addition, Grid Search was also used for tuning parameters of a network. Ref [16] combined CNN and LSTM that the CNN extract important convolution features from the input sequence, and the LSTM receives these features to make a prediction of electricity price. Ref [17] built a similar network that conducts a feature selection by CNN and then a solar radiation prediction by LSTM. Stack on this CNN+LSTM architecture, Ref [18] further applied wavelet decomposition on raw data of solar irradiance sequence.

Statistical methods were also adopted by researches. Ref [19] used Pearson coefficient to extract main features that affect photovoltaic power (PV). Ref [20] used least absolute shrinkage and selection operator (LASSO) to represent linear relationship and LSTM to learn the nonlinear. K-means++ was also used in Ref [20] to cluster historic data for training different networks.

Researches, such as Ref [3, 4, 6, 10, 12, 13, 14, 16, 17, 19], consider that increasing the accuracy of prediction for features that cause uncertainty in a system can improve the operation of that system. Therefore, these researches adopted neural networks as predictors and focused on improving the accuracy of neural networks. In this dissertation, this approach is called the standard model or the conventional way in which the predictors are only used to support the operation strategy. Ref [21] developed a control strategy for thermal storage electric boiler. This strategy uses the predictive load curve of a LSTM network to determine how to operate the boiler. Similarly, Ref [22] introduced control strategies of operating energy storage and then implemented this strategy based on the predictive load of a LSTM network.

In the field of sewer system operation, Zhang (2017, 2018) [23, 24] proposed operation strategies for water managements, and then pointed out key uncertainty in these strategies. LSTM networks were implemented only to predict the uncertainty, such as future inflow of each wastewater treatment plant or sewer. Similarly, LSTM predictions made in [23, 24] have no connection to their proposed strategies, but only provide better information to operators who use those strategies.

In Chapter 2, we introduced a solar energy community distribution system that has five operation features: PV generation, electricity demand, heat demand, System Sell Price (SSP) and System Buy Price (SBP). The five features are all with uncertainty which means that future values of each feature are unknown. As showed in Figure 1.1, the Standard Model, a conventional way of implementing LSTM predictors, includes five different predictors for each feature. It's obvious that the accuracy of each predictor is critical to the performance of the operation strategy. As discussed later, we expected the occurrence of significant error with SSP and SBP predictors since too many factors have influence on electricity price and it is hard to forecast future prices only by historical data of prices. Therefore, we had expected the performance of the Standard Model would be compromised.

As showed in Figure 1.2, we proposed a novel way to utilise the potential of LSTM. A mock-up expert was created by executing the operation strategy with historical data in advance. The mock-up expert provides the training pair of historical sequences and the target heat level for operation a heat storage. Thus, the Proposed Model of this dissertation fundamentally changes how a LSTM predictor can be used in system operation.

By examining the simulation results of the Standard Model and the Proposed Model, we aimed to answer that in a system where all features have uncertainty, and part of which would cause significant errors of prediction, can reconstructing the relationship between inputs and outputs of the predictors improve the performance of operating that system?

Figure 1.1 Structure of Standard Model

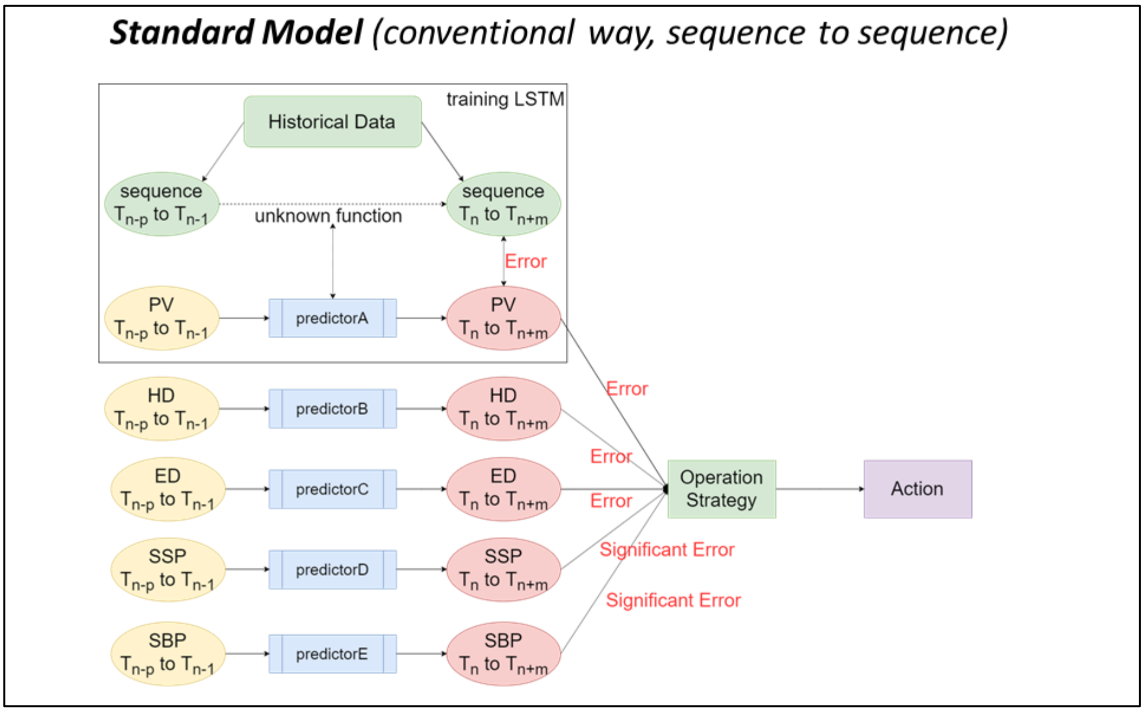
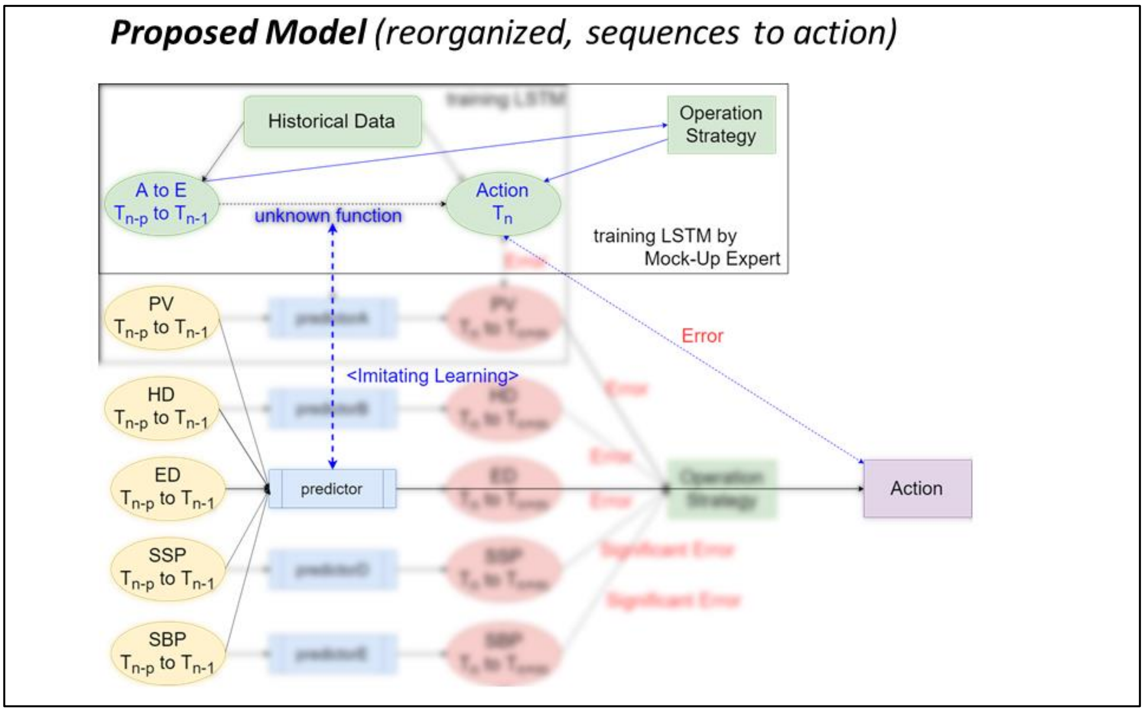


Figure 1.2 Structure of Proposed Model (compared with Standard Model)



In this dissertation, we built three models to compare the performance of conventional and our proposed method. The Standard Model adopted the idea discussed above that forecast only serves as a reference in operating a 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 needs 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 heat storage always starts at fixed times to be charged and to be discharged.

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

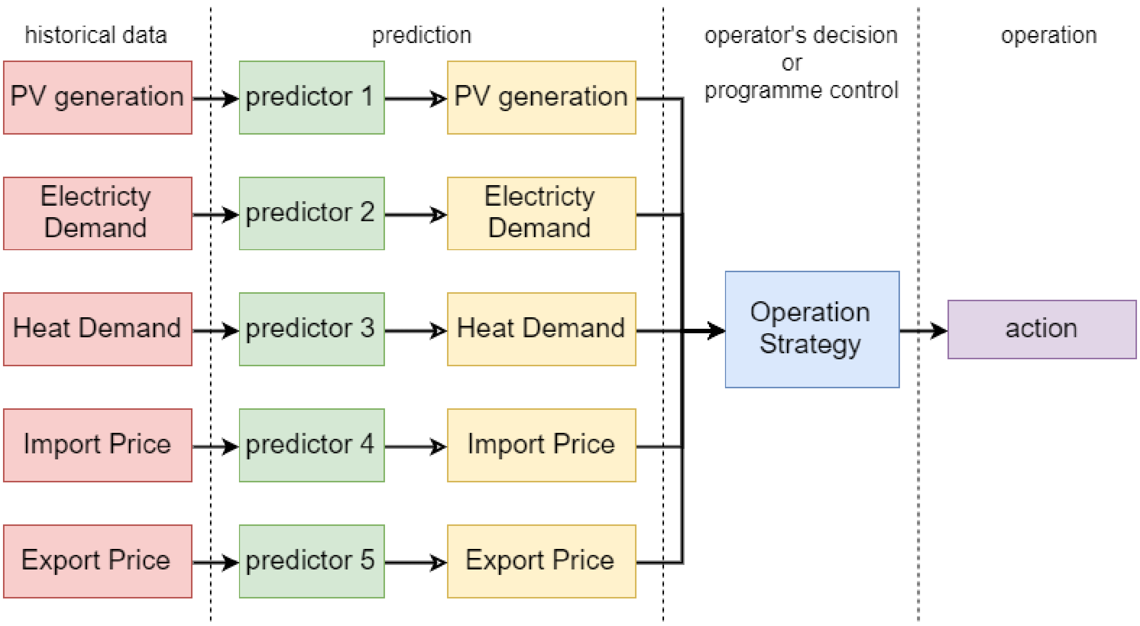
In addition, in this dissertation, the Standard Model, the Propose Model and the Vanilla Model refer to the ‘methods’ or ‘framework’ of operating the solar energy community distribution system, as shown in Figure 1.1 and Figure 1.2. The word, ‘predictor,’ is used to refer to the LSTM networks in the Standard Model and in the Proposed Model.

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 for operation of systems with uncertainty and has been adopted by many researches.

Figure 1.3 depicts the Standard Model of using LSTM predictors to aid operators in operation of a solar energy distribution system. The energy distribution system is shown in Figure 2.1 and detailed in Chapter 2. Each predictor (green square) in Figure 1.3 is a LSTM network. In the beginning of every half hour, each predictor 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 1.3 Concept of Standard Model

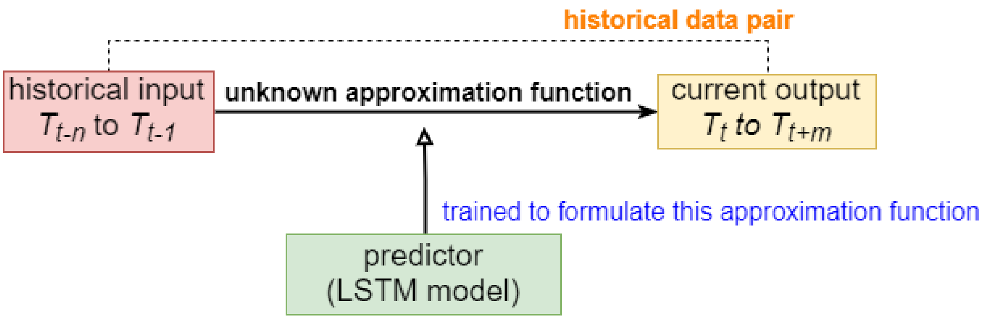


Note that predictors of the Standard Model can be more complicated, taking more features as input to increase its accuracy. However, since the Proposed Model in this dissertation only use the five input features, we set predictors of the Standard Model only take its own feature as input for a fair comparison of the two models.

Figure 1.4 shows the training method of each predictor of the Standard Model. The LSTM predictors 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 1.4 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 at the end of 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 1.3 is the same as our proposed operating strategy of heat storage in Figure 1.5. Note that the operation strategy (blue square) in Figure 1.5 is not actually executed during online operation. The Proposed Model executes this operation strategy during the preparation of training pairs, discussed in Chapter 4.

To utilise the proposed strategy, uncertainties of the five input features must be eliminated. Instead of training five LSTM predictors that predict these features, the

Proposed Model trained only one LSTM predictor that takes these five features as inputs to directly output a target level of heat storage at the end of every half hour.

We applied the principle behind Imitation Learning, of which a network learns from expert's behaviours. For example, when learning self-driving cars, a network is shown 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 a heat storage, we can create a mock-up expert from historical data. This mock-up expert follows the proposed strategy in simulations of operating a system. The expert's behaviours are then used as the training pairs for the LSTM predictor in the Proposed Model.

The training method of the predictor in Proposed Model is shown in Figure 1.6. In contrast to the training pairs for the Standard Model in

Figure 1.4, the predictor in the Proposed Model learns to interpret the relationship between time sequences and one output value. The training pairs in Figure 1.6 are 'handcrafted' by following the proposed strategy. Consequently, the predictor in the Proposed Model is connected to the proposed strategy itself, and it directly outputs the target level of heat storage at the end of next half hour.

The working process of the Proposed Model is depicted in Figure 1.5. Compared with the Standard Model depicted in Figure 1.3, 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 every half hour when it receives new forecasts from its five predictors.

Figure 1.5 Concept of Proposed Model

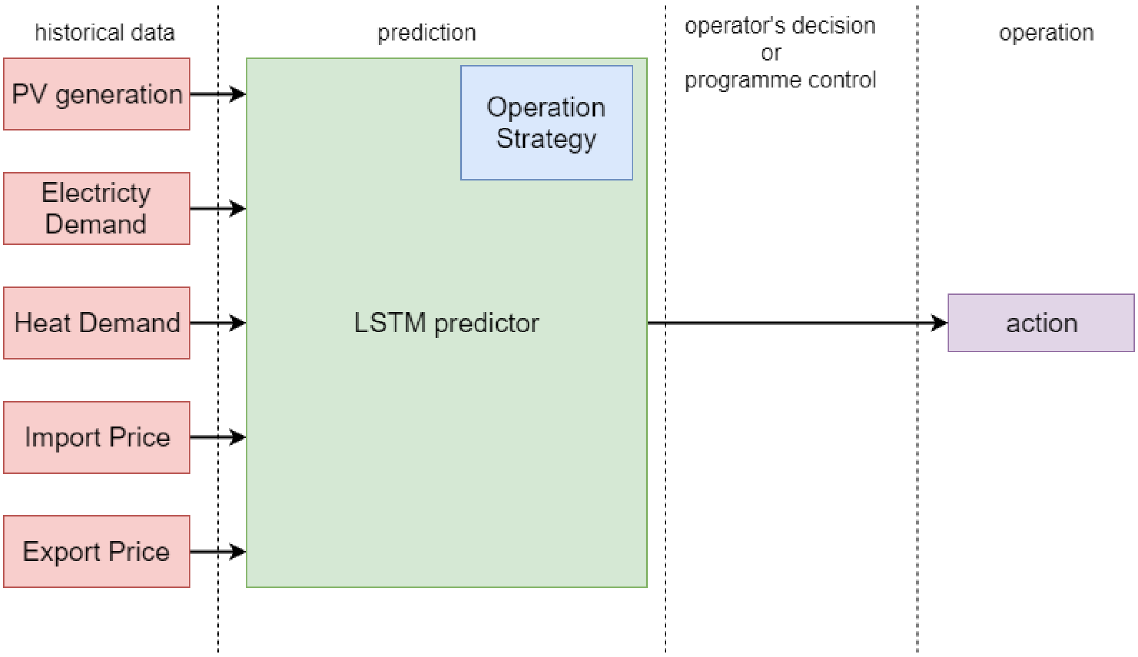
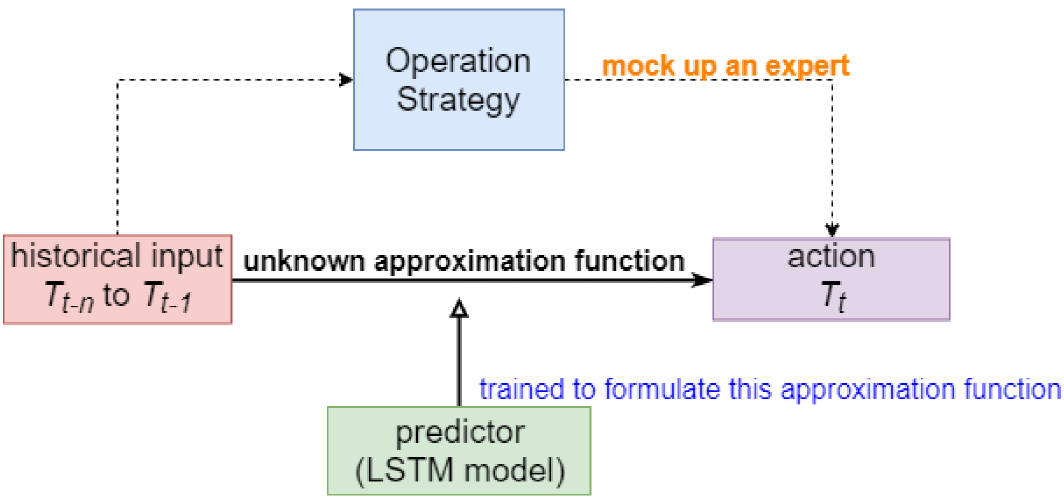


Figure 1.6 Training of Proposed Model



1.3 Vanilla Model

A common strategy is to charge and to 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 that the Vanilla Model always charges and discharges 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.

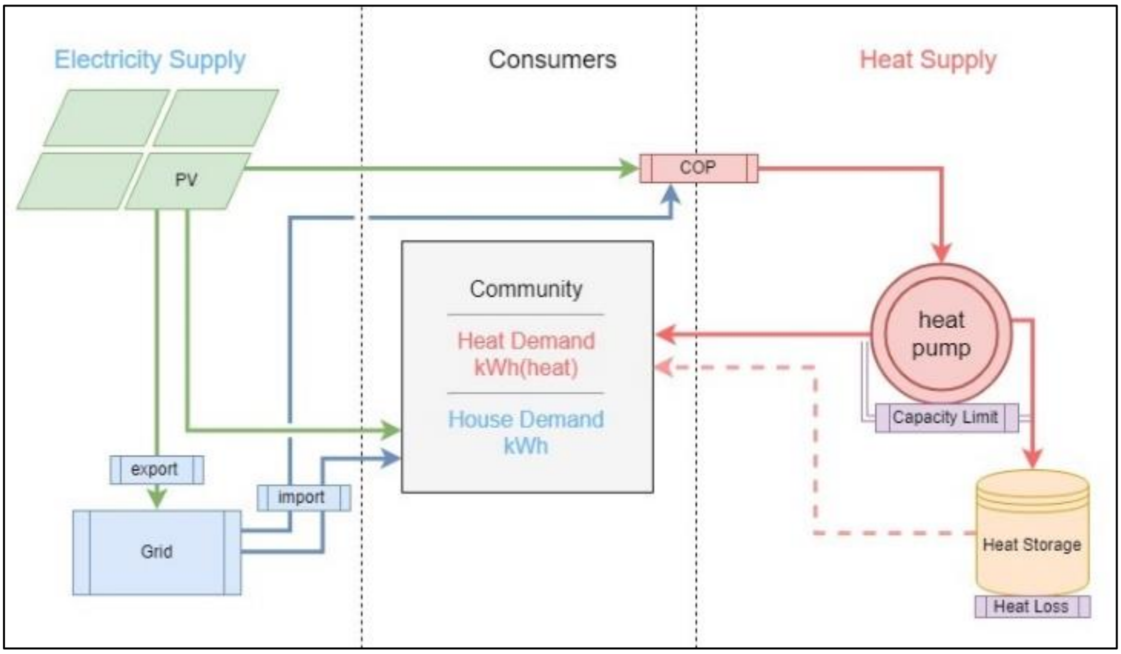
The remainder of this dissertation is organized in the following way: Chapter 2 details the components of the solar energy community distribution system and the objective of its operation. Chapter 3 introduces the proposed strategy for operation of this community distribution system and describes how 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

Shown 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 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 dissertation, 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 for heat demand is always more economical than selling to the grid. In other word, System Buy Price (SBP) is always higher than System Sell Price (SSP) of the same half hour.

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 operator when the operator exports 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 changes 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:

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

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

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 or importing electricity:

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

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

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

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 advance. 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 than future SBP.

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:

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

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:

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

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

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

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

$$\boldsymbol{income = 0}$$

$$\boldsymbol{expenditure = 0}$$

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

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

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

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

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

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

, 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.

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

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

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

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

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

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

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

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

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

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

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

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

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:

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

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.

In summary, the objectives of operating the solar energy community distribution system are:

- Reduce the operation cost of the system by decreasing expenditure of importing electricity.
- 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. This is called $PV\ Surplus$.
- Store an exact amount of $PV\ Surplus$ needed to meet an expected heat demand in the future if importing electricity in the future costs more than not exporting currrent $PV\ Surplus$ to the grid.
- Store an amount of imported electricity needed to meet an expected heat demand in the future if importing electricity in the future costs more than importing electricity currently from the grid.

In this dissertation, the Models predict a target level at the start of every half hour, attempting to achieve the objectives mentioned above. The heat storage compares its current heat level with the target level to determine whether to be charged or discharged during that half hour.

3 Operation Strategy for the Community System

With historical data, we can pretend that there is an expert who knows all information we need in next 24 hours, which is divided equally into t_0 to t_{47}. In this way an operation strategy was developed with omniscient knowledge of PV surplus, Shortage, SSP and SBP each half hour of a day, t_0 to t_{47}. By analysing the information of next 24 hours, a daily optimal operation curve, i.e., the optimal heat level of heat storage at the end of each half hour, can be determined.

In this section, the operation strategy is introduced. Its pseudo code is showed in Table 3.1 as Algorithm 1. Feeding information of each day into Algorithm 1, we obtain the daily optimal operation curves. These curves serve as a benchmark of which operation cost is the lowest, as discussed later.

In the Standard Model, five conventional LSTM predictors forecast future information by historical data, and then the operation strategy is executed with this predictive information to determine an optimal heat level of heat storage at the end of each half hour.

For the Proposed Model, we first prepared the training set by pairing the historical data with the optimal heat level of heat storage based on the benchmark shown by the mock-up expert, and then trained the one LSTM predictor of the Proposed Model. Thus, in the Proposed Model the predictor receives historical data and output an optimal heat level of heat storage at the end of each half hour directly.

Only with perfect knowledge of future information, the operation strategy can be realised. Following the strategy, a mock-up expert analyses 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 mock-up expert holds the values of PV surplus, Shortage, SSP and SBP at t_0 to t_{47}. Following the operation strategy, the mock-up expert creates a profit table, in which each entry is called a 'profit number':

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

, 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 mock-up expert distributes all available electricity source to all Shortage, starting from the smallest $pf_{p,n}$. The mock-up 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 mock-up 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 mock-up 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, accordingly.

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 $t_p \le t_x \le t_n$ 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 mock-up 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. Finally the mock-up expert obtain an optimal operation curve, such as shown in Figure 3.1 and Figure 3.2.

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 shown 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 shown by the mock-up expert in Figure 3.1 and Figure 3.2 demonstrate several behaviours that the predictor of the 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 the mock-up 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 mock-up 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 mock-up expert’s capability of operating the storage optimally by knowing PV generation and heat demand in advance.

B. Charge the storage economically:

Knowing how much amount of heat needs to be prepared is not enough. The mock-up expert must figure out how to charge the storage in a cost-effective way. In Figure 3.1, the mock-up 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 mock-up 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 modified prices at these times are relatively low during the period of PV generation between t_{18} and t_{33}.

In Figure 3.1, from t_{18} to t_{32}, the mock-up expert has several different electricity sources from PV generation or from the grid for meeting the target level at t_{33}. The mock-up 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

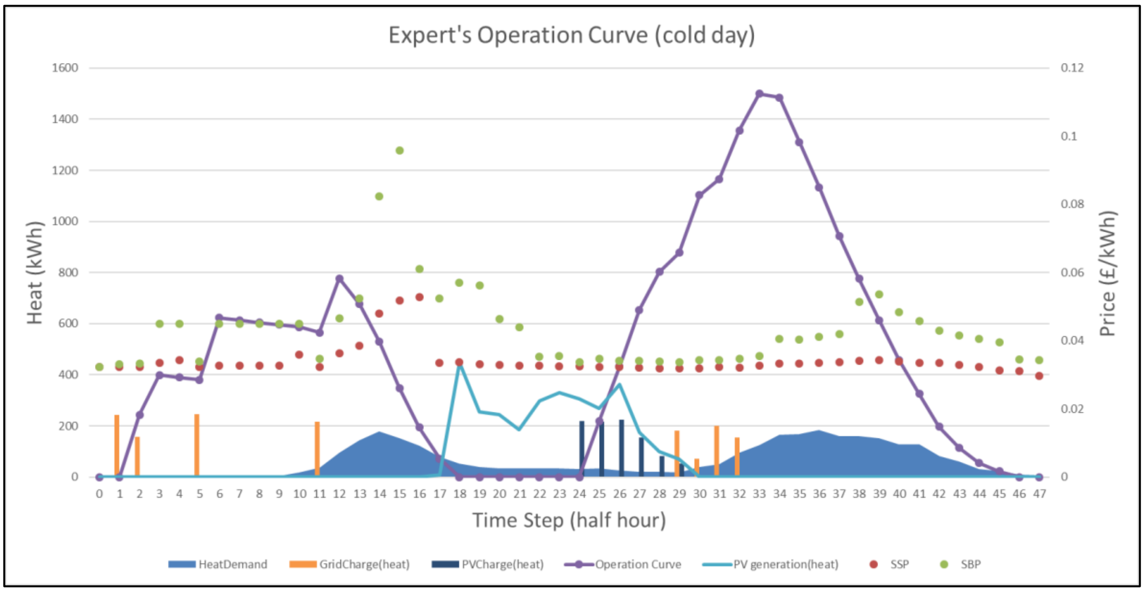


Figure 3.2 Expert's Operation Curve on a warm day

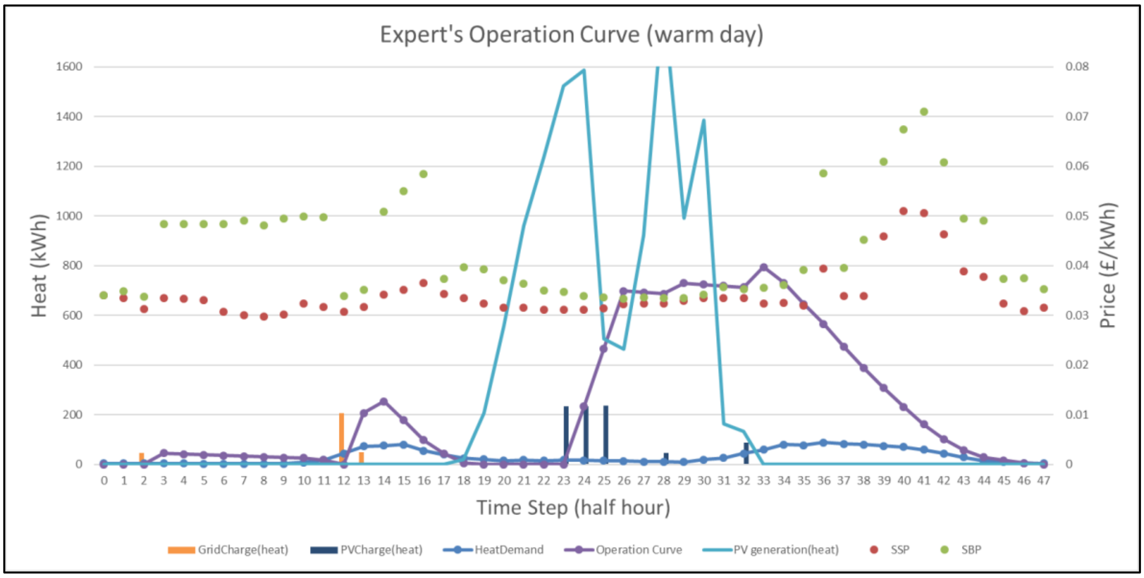


Table 3.1 Pseudo Code: Operation strategy for optimal operation curve

Feeding historical data of five features into Algorithm 1, we obtain the daily optimal operation curves, i.e., the optimal heat level of heat storage at the end of each half hour, t_0 *and* t_{47}*. Detailed discussion can be found at the beginning of Chapter 3.*

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 simulation environment and the predictors in the Standard Model and the Proposed Models. The implement of LSTM networks is constructed by Keras, a neural networks API of Python [25].

Note that in this dissertation, the Standard Model, the Propose Model and the Vanilla Model refers to the 'methods' or 'framework' of operating the solar energy community distribution system, as shown in Figure 1.1 and Figure 1.2. The word, 'predictor,' is used to refer to the LSTM networks in the Standard Model and the Proposed Model.

4.1 Simulation Environment

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. This data was repeated four times to match the length of PV generation data. Random noises were introduced to add ±3% to the original data point of the second, third and fourth repeat. These random noises have a normal distribution.

C. Heat demand per dwelling is set to be 4500 kWh. Heat demand curve is based on a one-year estimated data. This data was repeated four times to match the length of PV generation data. Random noises were introduced to add ±3% to the original data point of the second, third and fourth repeat. These random noises have a normal distribution.

D. SBP and SSP are based on a one-year real data. This data was repeated four times to match the length of PV generation 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.

This four-year database has a resolution of 30 minutes, from t_0 to t_{70079} (48 half-hours x 365 days x 4 years = 70080 time intervals). It consists of the five features mentioned above. Each data point is denoted by $F_{k,t}$, where k = {1: PV generation, 2: Heat Demand, 3: Electricity Demand, 4: SSP, 5: SBP} and t = {0, 1, 2, 3, ……, 70079}.

In the Standard Model , the training pair of each predictor for feature k is prepared as {input: ($F_{k,u}$, $F_{k,u+1}$, $F_{k,u+2}$, ……, $F_{k,u+47}$), output: ($F_{k,u+48}$, $F_{k,u+49}$, $F_{k,u+50}$, ……, $F_{k,u+95}$)}, where u = {0, 1, 2, 3, ……, 69984}. The total number of pairs in a training set for a feature k is 69985. For each feature k, the order of the first three years data pairs was randomised and divided into two parts: training set and validation set with the ratio of 2:1. The training pairs of the last year is used as the testing set.

The training pair of the only one predictor in the Proposed Model is {input: ($F_{1,u}$, $F_{1,u+1}$, $F_{1,u+2}$, ……, $F_{1,u+47}$, $F_{2,u}$, $F_{2,u+1}$, $F_{2,u+2}$, ……, $F_{2,u+47}$, $F_{3,u}$, $F_{3,u+1}$, $F_{3,u+2}$, ……, $F_{3,u+47}$, $F_{4,u}$, $F_{4,u+1}$, $F_{4,u+2}$, ……, $F_{4,u+47}$, $F_{5,u}$, $F_{5,u+1}$, $F_{5,u+2}$, ……, $F_{5,u+47}$), output: H_{u+48}}, where u = {0, 1, 2, 3, ……, 70031} and H is the optimal heat level of heat storage calculated by executing the operation strategy (Algorithm 1 discussed in Section 3). The total number of pairs in this training set is 70032. The order of the first three years data pairs was randomised and divided into two parts:

training set and validation set with the ratio of 2:1. The data pairs of the last year is used as the testing set.

The pseudo code of simulation environment (Algorithm 2) is shown in Table 4.1. After picking a day from the testing set, Algorithm 2 conducts a daily simulation for each Model. The purpose of each simulation is to record the daily operation curve of heat storage if implementing one of the Models as the operator. With the operation curve and the historical data of the five features (PV generation, Heat Demand, Electricity Demand, SSP and SBP), the operation cost of that day can be calculated by Equation (3). Summing the cost of 365 simulations of each Model, annual cost of implementing each Model can be obtained separately.

Algorithm 2 first conducts the simulation of the Standard model. With $u = 0\ to\ 47\ and\ F_{k,48} = value\ of\ F\ at$ 12:00 AM of chosen day, each predictor in the Standard model receives a historical sequence of ($F_{k,u}$, $F_{k,u+1}$, $F_{k,u+2}$, ……, $F_{k,u+47}$), prepared by Algorithm 2, to forecast the sequence of ($F_{k,u+48}$, $F_{k,u+49}$, $F_{k,u+50}$, ……, $F_{k,u+95}$), as shown in

Figure 1.4, in which $n = u + 48, p = 48$ and $m = 47$. The operator then put these predicted sequences into Algorithm 1 (Table 3.1) to determine the target level of heat storage at H_{u+48}. The pseudo code of these predictors (Algorithm 3) is shown in Table 4.2. The output of this simulation in Algorithm 2 is a daily operation curve of the Standard Model between $u + 48$ and $u + 95$, and the total operation cost of that day.

Next, Algorithm 2 conducts the simulation of the Proposed model. With $u = 0\ to\ 47\ and\ F_{k,48} = value\ of\ F\ at$ 12:00 AM of chosen day, the predictor in the Proposed model receives a historical sequence of ($F_{k,u}$, $F_{k,u+1}$, $F_{k,u+2}$, ……,

$F_{k,u+47}$), prepared by Algorithm 2, to determine the target level of heat storage at H_{u+48}, as shown in Figure 1.6, in which $n = u + 48$ and $p = 48$. The pseudo code of the predictor (Algorithm 4) is shown in Table 4.3. The output of this simulation in Algorithm 2 is a daily operation curve of the Proposed Model between $u + 48$ and $u + 95$, and the total operation cost of that day.

Finally, the daily operation curve of the Vanilla Model is determined by the predefined charging and discharging time. Algorithm 2 uses these fix times to simulate the daily operation curve of the Vanilla Model between $u + 48$ and $u + 95$, and the total operation cost of that day.

4.2 Proposed Model

In the Proposed Model, we trained only one predictor. This predictor receives five sequences of t_{n-48} to t_{n-1} to forecast one value: the target heat level for t_n, as shown in Figure 1.6, in which $p = 48$. The operator has no need to run Algorithm 1 (Table 3.1) repeatedly. The pseudo code of the predictor in the Proposed Model is shown in Table 4.3.

The first layer of the predictor in the Proposed Model 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. Both the common sigmoid function and the hard-sigmoid function have been implemented, and both demonstrated similar performance, yet the training time with hard-sigmoid function is less. The output of the sigmoid function ranges from 0 to 1, which is suitable for the database since the five features are always positive. Implementing the dropout layer can mitigate the problem of overfitting [26]. The cost function of the predictor 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 database. This is because normalization can make learning process faster.

Several sets of training parameters and network settings have been examined:

- optimiser: adam or nadam
- learning rate: 0.001 or 0.002
- epochs: 10 or 20
- batch: 72
- number of time steps: 48 (as 48 half hours of a day)
- units (latent_dim) of the LSTM: 48, 64 or 96
- dropout: 0.3 or 0.5

Results shown that there is no significant difference with different sets of training parameters and network settings. The losses were around 0.0048 to 0.0058, and the validation losses were around 0.0044 to 0.0056. Consequently, the final training set of parameters and network settings was picked because of its shorter training time: optimiser=adam, learning rate=0.001, epochs=10 and batches=72. The chosen LSTM layer has units=64 and the dropout layer has a fraction of 0.5.

4.3 Standard Model

In Standard Model, we trained five predictors to predict each feature (PV generation, heat demand, electricity demand, SSP and SBP). Each predictor receives a value sequence of t_{n-48} to t_{n-1} to forecast the sequence of t_n to t_{n+47}, as shown in

Figure 1.4, 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 heat level of heat storage at t_n. The pseudo code of the predictors in the Standard Model is shown in Table 4.2.

The figuration of these five predictors in the Standard Model were set to be the same as the predictor in the Proposed Model because we attempted to demonstrate the influence of simply changing the relationship of the input and output, discussed in Chapter 1:" can reconstructing the relationship between inputs and outputs of the predictors improve the performance of operating that system?"

The first layer of these predictors in the Standard Model 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 of the predictor 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 data set. This is because normalization can make learning process faster.

The training set of parameters includes: optimiser=adam, learning rate=0.001, epochs=10 and batches=72. The LSTM layer has units=64 and the dropout layer has a fraction of 0.5.

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 predictors in Standard Model. The predictors that forecast PV generation, electricity and heat demands show the ability to match a rough pattern to the curve of true values. However, these predictors 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 SBP and SSP predictors are not trained enough, resulting in a bad approximation that sticks around average number to bring a smaller MSE.

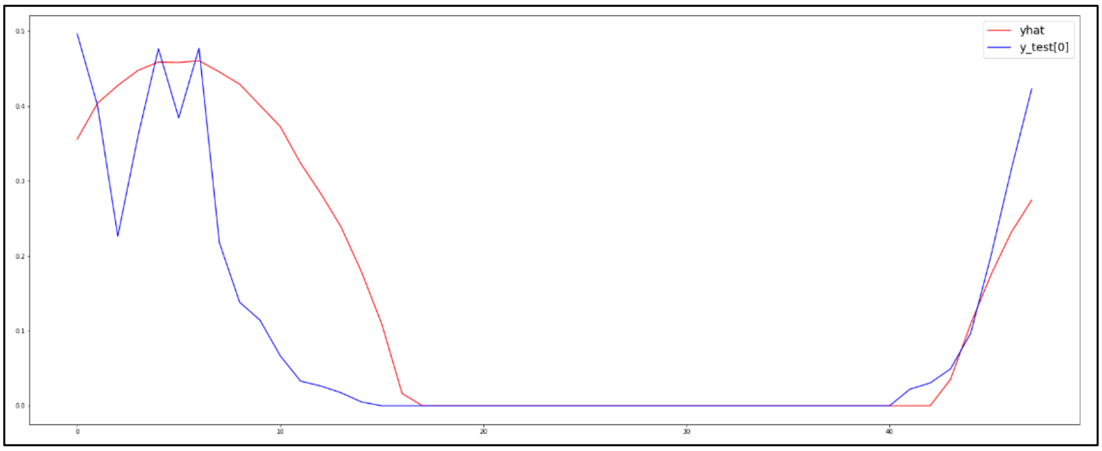
One reason could be that the SBP and SSP predictors need more features to better define an approximation between input and output of the prices. Many factors influence the variations of SBP and SSP, such as real-time changes of generation and consumption, unexpected shutdowns of some units and grid imbalance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

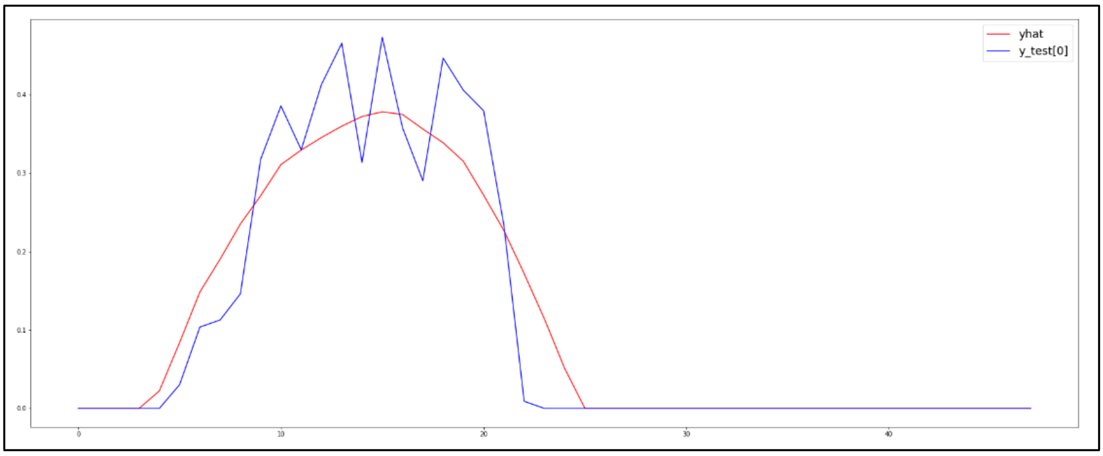
In our study, we did not improve the SBP and SSP predictors of the Standard Model because we aim to demonstrate the difference of performance between the Standard Model and the Proposed Model. Therefore, the five predictors in the Standard Model can only receive the same five features as used in the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

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

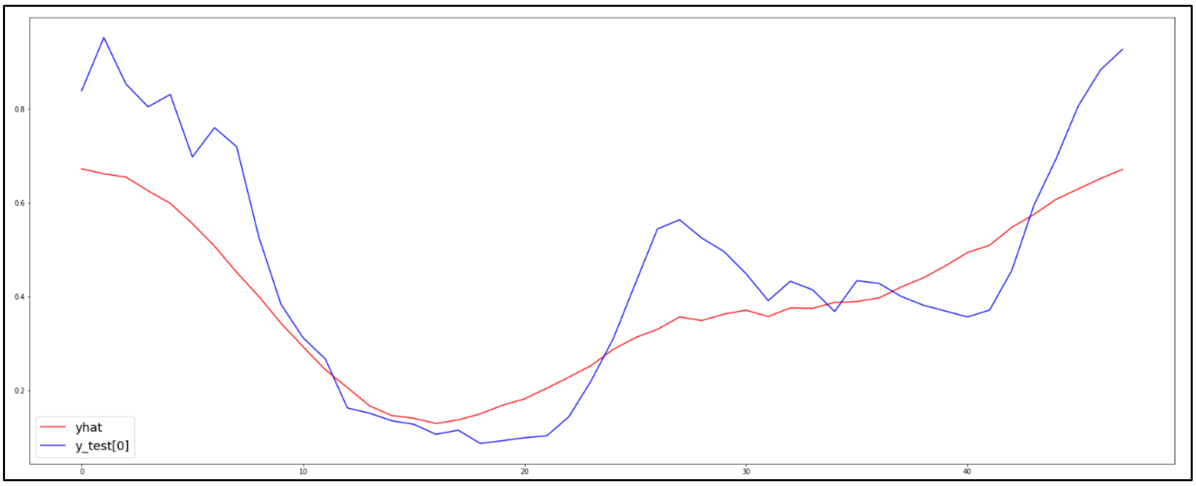
(1) PV Generation

The x-axis shows feature values (PV generation in this figure), 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.

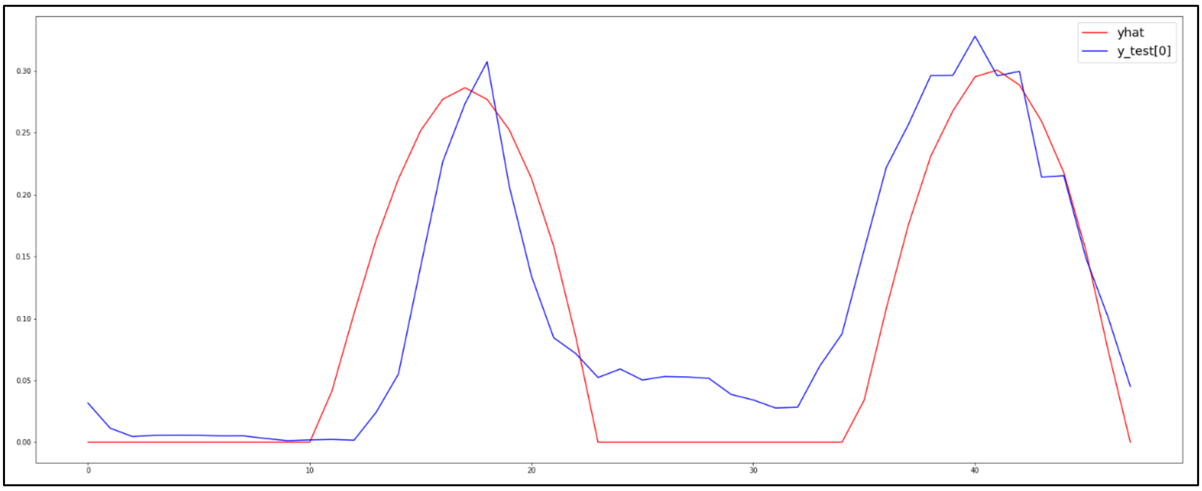




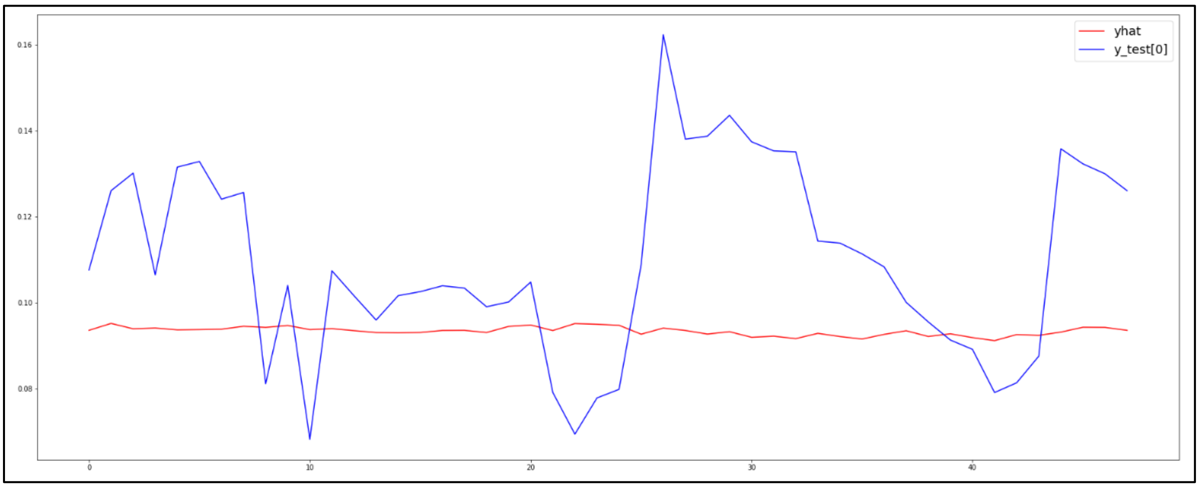
(2) Electricity Demand Prediction



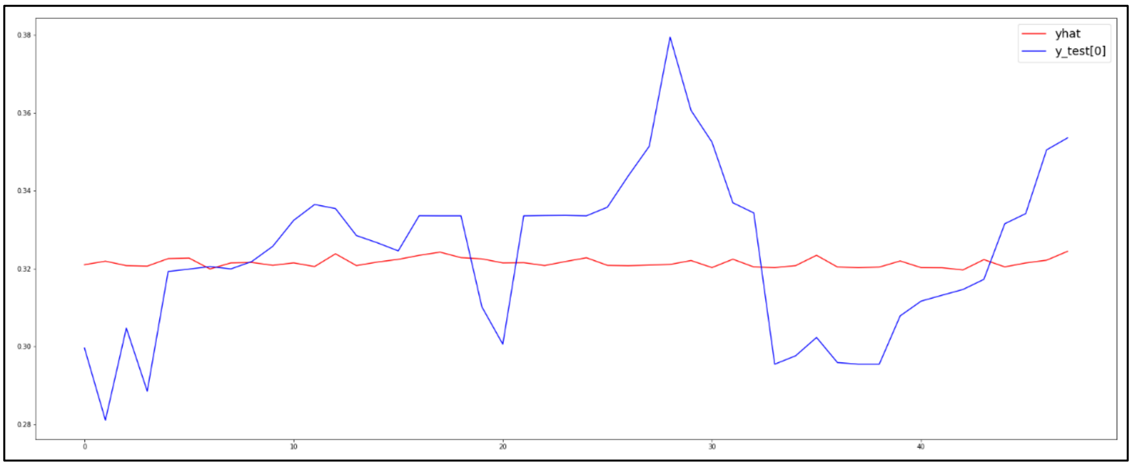
(3) Heat Demand Prediction



(4) SBP Prediction



(5) SSP Prediction



5.2 Operation Performance

Figure 5.2 shown the simulation results of Algorithm 2, which are the heat storage daily operation curves of implementing each Model and the optimal curve demonstrate by the mock-up expert. Daily operation curves of the Standard Model and the Proposed Model exhibit a similar behaviour of the mock-up 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.

Note that in this dissertation, the Standard Model, the Propose Model and the Vanilla Model refer to the ‘methods’ or ‘framework’ of operating the solar energy community distribution system, as shown in Figure 1.1 and Figure 1.2. The word, ‘predictor,’ is used to refer to the LSTM networks in the Standard Model and the Proposed Model.

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 predictor in 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 predictor in 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 shown 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 mock-up expert starts to charge the storage in the morning.

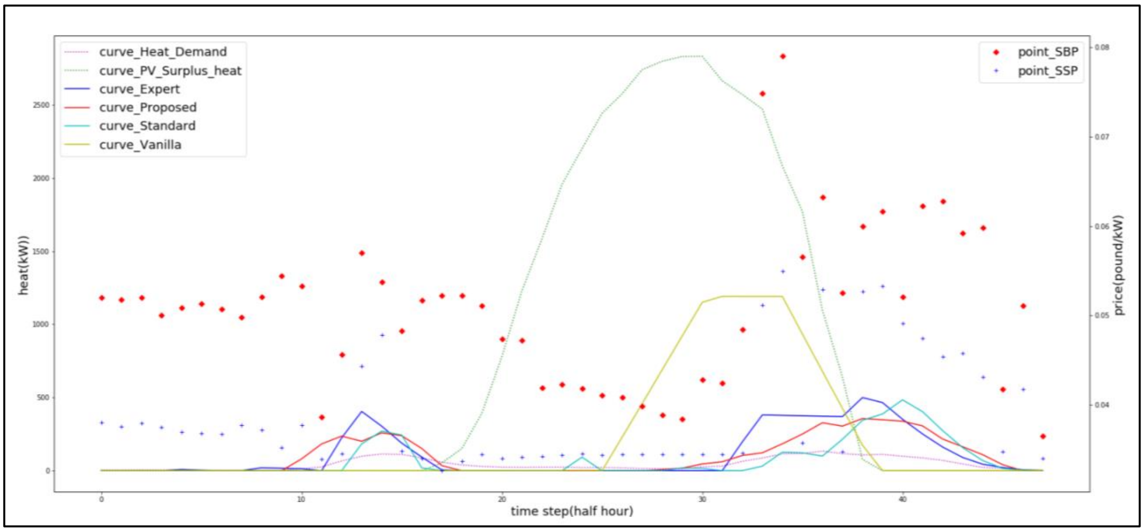
The same behaviour of the Standard Model can be seen in Figure 5.5 during the morning. Since outputs of the unreliable SBP predictor in the Standard Model are stuck around the average of SBPs, it's hard for the Standard Model to notice the sudden drop of SBP at t_{10} in Figure 5.5.

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 mock-up expert, the Standard Model charges no heat into the storage during the peak at t_{29} because its predictor does not expect this PV generation peak. The Standard Model 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 mock-up 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 tho 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}, 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 mock-up 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 predictor 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 heat storage operation curves of the mock-up 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)

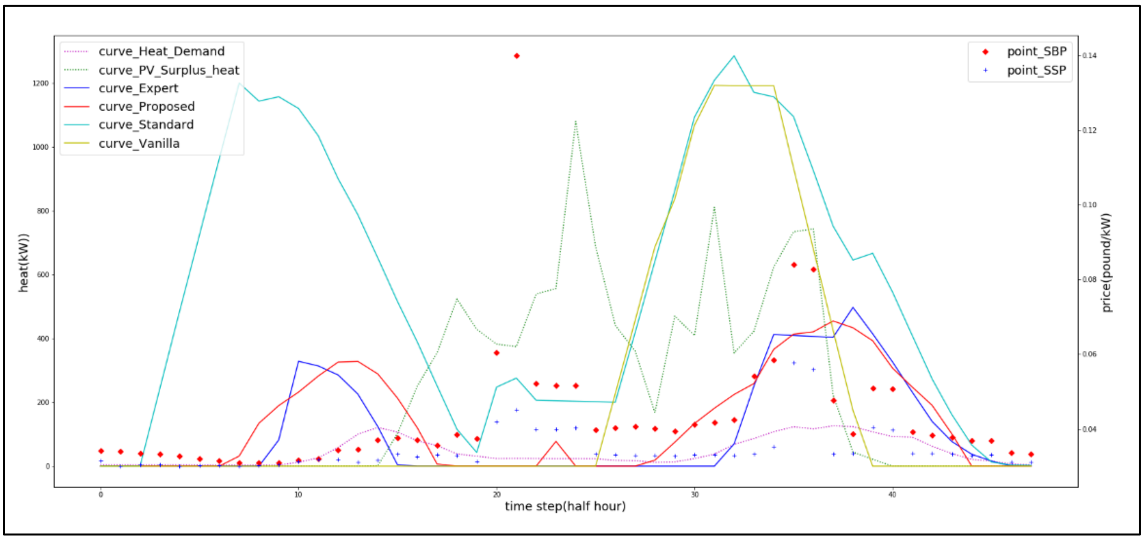


Figure 5.4 One-day simulation (Result 3)

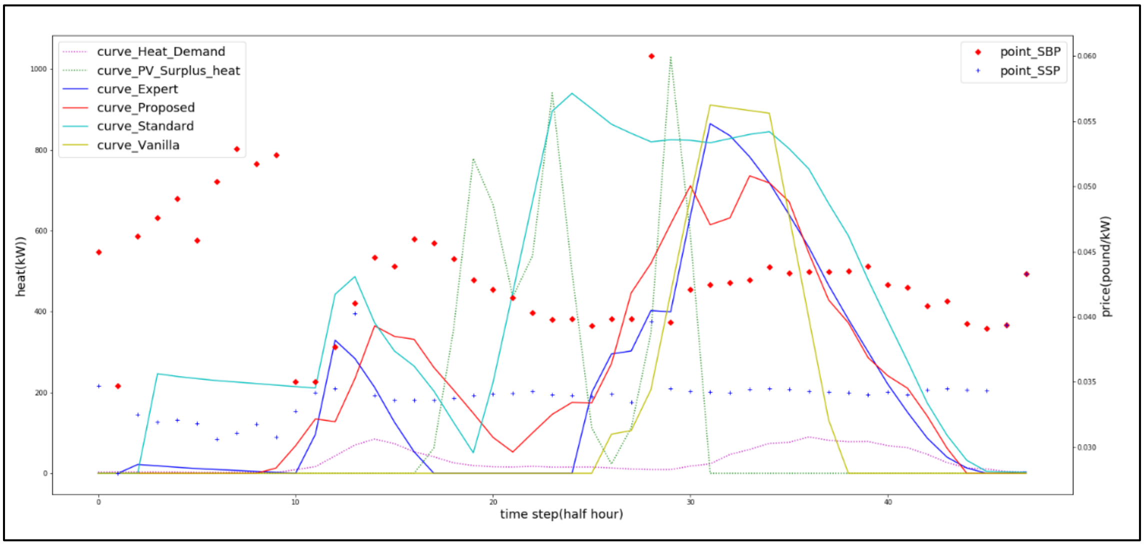
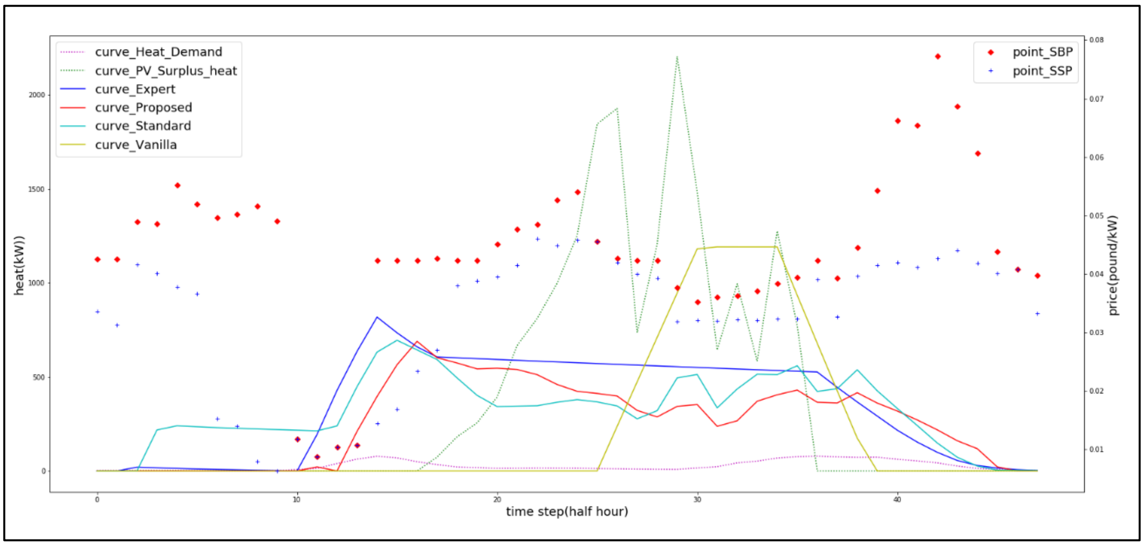


Figure 5.5 One-day simulation (Result 4)



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 all the Models and summed the daily operation cost according to Equation (3). The results are shown in Table 5.1. Note that the last entry in the table, Model without storage, sells all PV Surplus to the grid, and whenever there is a Shortage, it imports electricity.

Due to the limit of available data, only the simulation Result 1 was unseen by the trained LSTM, namely the fourth-year data mentioned in Section 4.1.

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 shown in Column (A) in Table 5.1.

Expenditure of importing in Equation (3) can be further separated depending on its purpose, as shown 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 mock-up 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 shown 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). According to the definition of e_{op} as Equation (11), 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. It is profitable to implement a Model only if the e_{op} of that Model is larger than 1.

$$\boldsymbol{E_{PV} = Expenditure\ of\ PV\ Surplus\ for\ charging\ the\ storage}$$

$$= (\boldsymbol{Revenue\ of\ a\ Model}) - (\boldsymbol{Revenue\ of\ the\ Model\ without\ storage}) \tag{8}$$

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

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

$$= (\boldsymbol{Expenditure\ of\ the\ Model\ without\ storage}) - (\boldsymbol{Expenditure\ of\ a\ Model}) \tag{10}$$

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

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 mock-up expert has the highest e_{op} around 1.55. The 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 shown 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 advance. 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, the Standard Model and the Vanilla Model is greater than 1 during the cold 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 other Models 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 future price. 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
Mock-up 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	(D) Operation Cost (£) (D)=(A)+(B)+(C)	(A) Sell to the Grid	(B) Buy for Heat Demand	(C) Buy for Charging
Mock-up 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	(D) Operation Cost (£) (D)=(A)+(B)+(C)	(A) Sell to the Grid	(B) Buy for Heat Demand	(C) Buy for Charging
Mock-up 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, $\boldsymbol{e_{op}}$

Model	Result 1	Result 2	Result 3
Mock-up 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	Mock-up 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
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

	Mock-up Expert	Proposed Model	Standard Model	Vanilla Model
Week 1				
e_{op}	1.74	1.32	1.16	1.54
R	462	197	106	65
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 shown in Figure 1.3, Figure 1.4, Figure 1.5 and Figure 1.6, 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 the 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 predictor in the Proposed Model due to the computation caused by running Algorithm 1 for a three-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/variables is different in each Model. In addition, the training time can also be influenced by the complexity of the dataset, which is different in the two Models.

5.4.3 Computation Efficiency

For a one-day simulation, it took approx. 0.8 second for the Proposed Model to make decision, while the Standard Model 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 1.3, Figure 1.4, Figure 1.5 and Figure 1.6.

6 Conclusion

In this dissertation we proposed a LSTM network 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 network that are only used to predict features for supporting an operator or a control programme to make a decision, in our proposed model, the operation strategy was integrated into the LSTM network, and thus the network provides an operation action directly.

With historical data, we created a mock-up expert who can perfectly predict future. This mock-up expert follows the operation strategy we proposed in this dissertation, and then the operation behaviours of the mock-up 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 dissertation 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 directly without executing the operation strategy.

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 mock-up 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 relatively low. We defined a number, e_{op}, to describe the operation effectiveness of a Model:

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

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

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

The results of one-year simulations show that the mock-up 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, the Standard Model and the 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 effectiveness and less computation time in simulation than the Standard Model which follows the conventional way of implementing LSTM networks.

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 [27] 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 dissertation. We can also consider how carbon tax or subsidy for solar energy influences the operation strategy and the performance of our Proposed Model.

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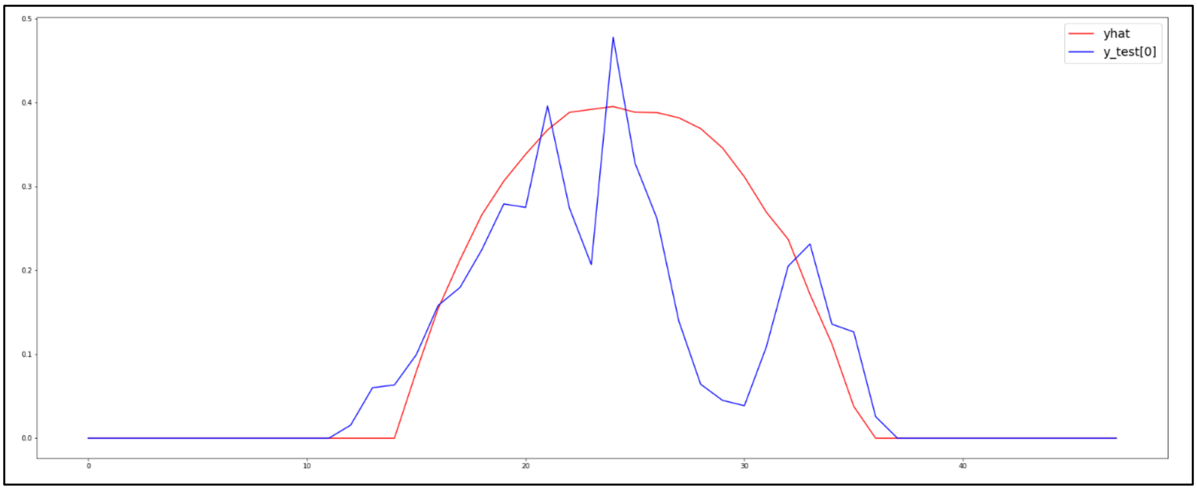
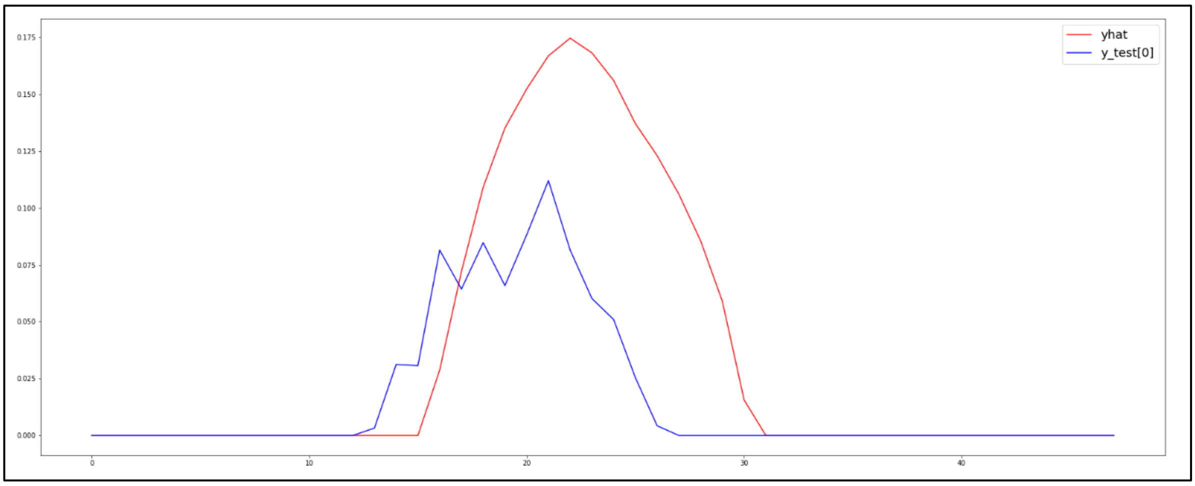
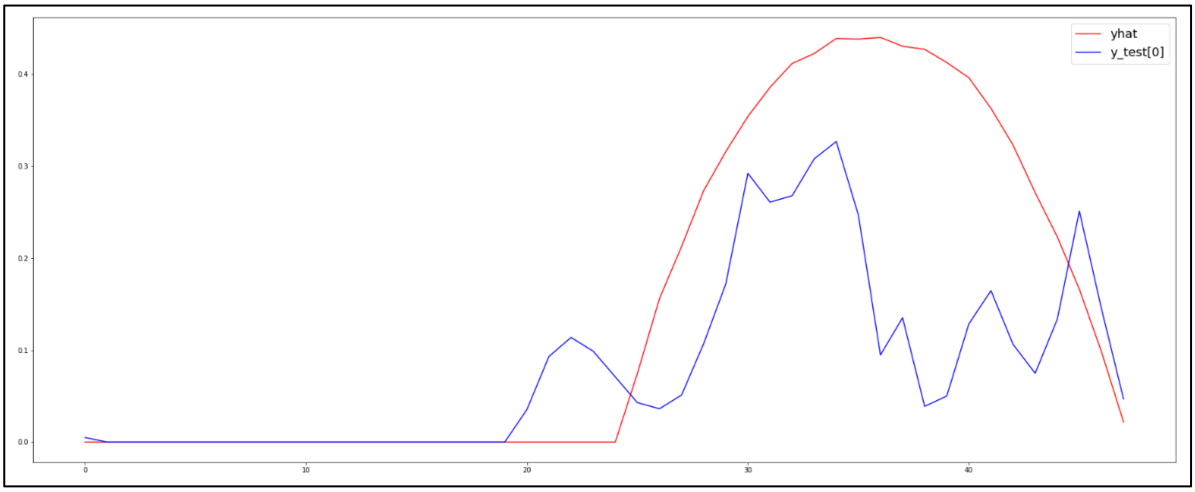
8 Appendices

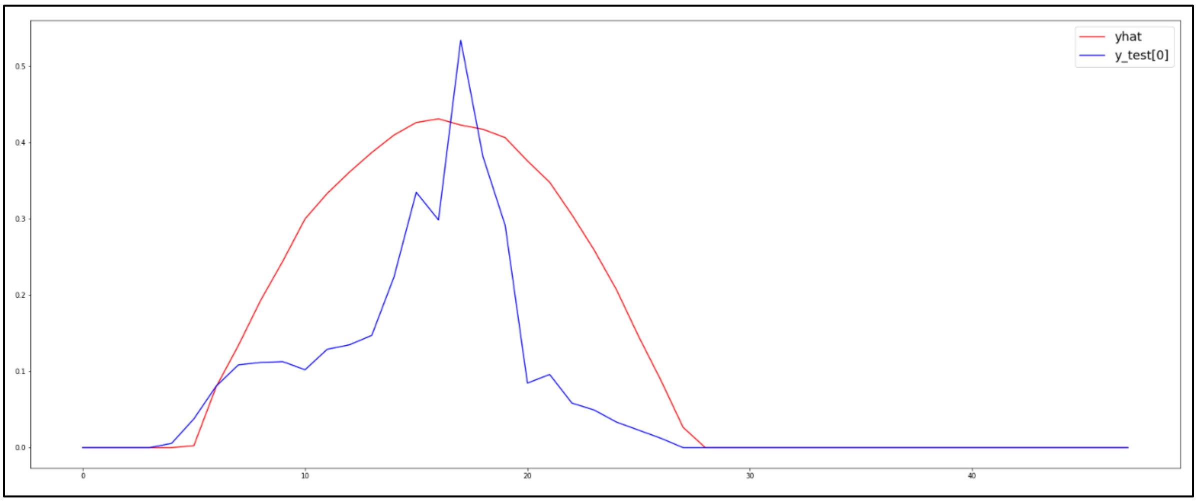
Appendix 1 Comparisons of predictive and true values in the Standard Model

(1) PV generation Prediction





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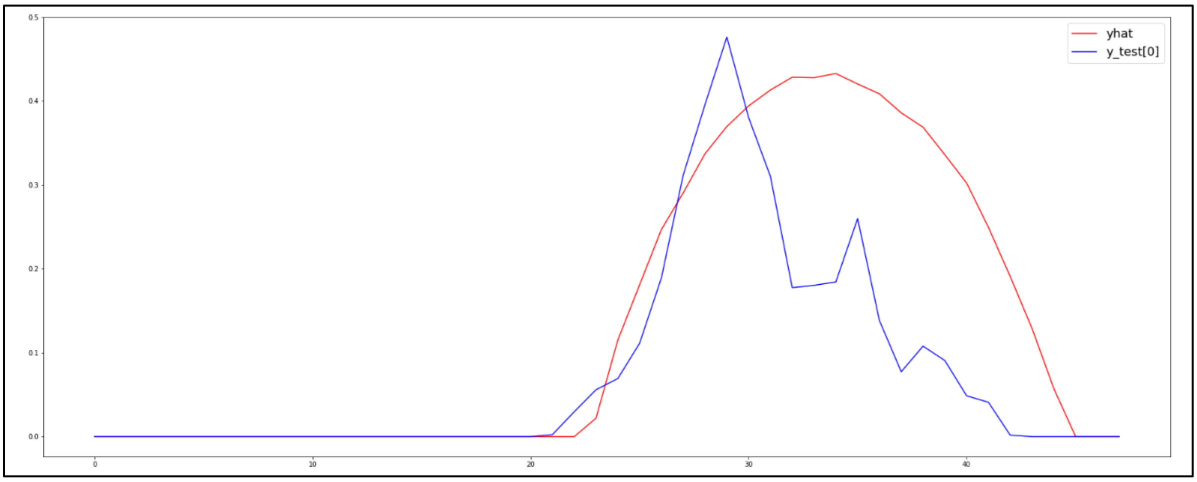
20
30
40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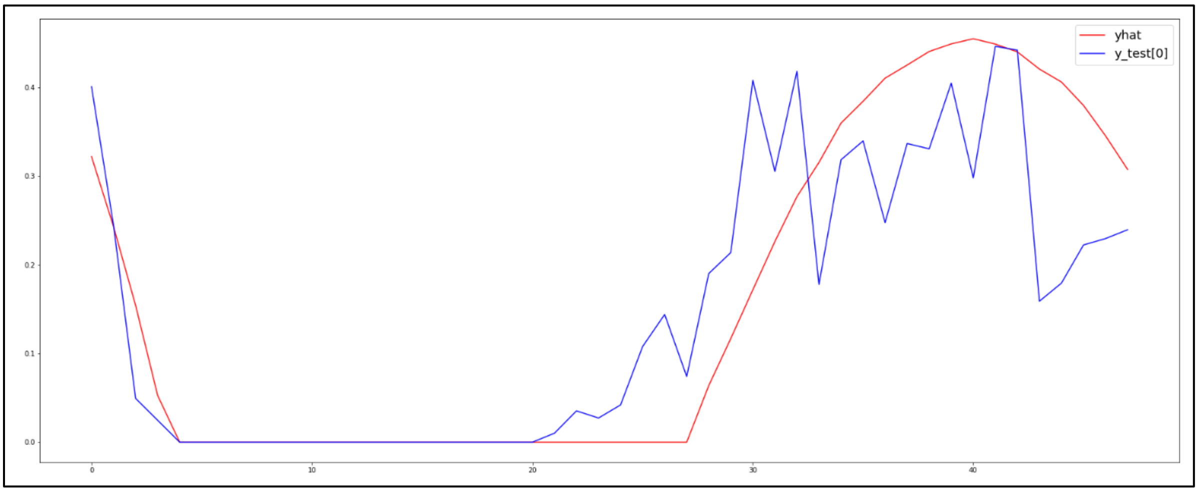
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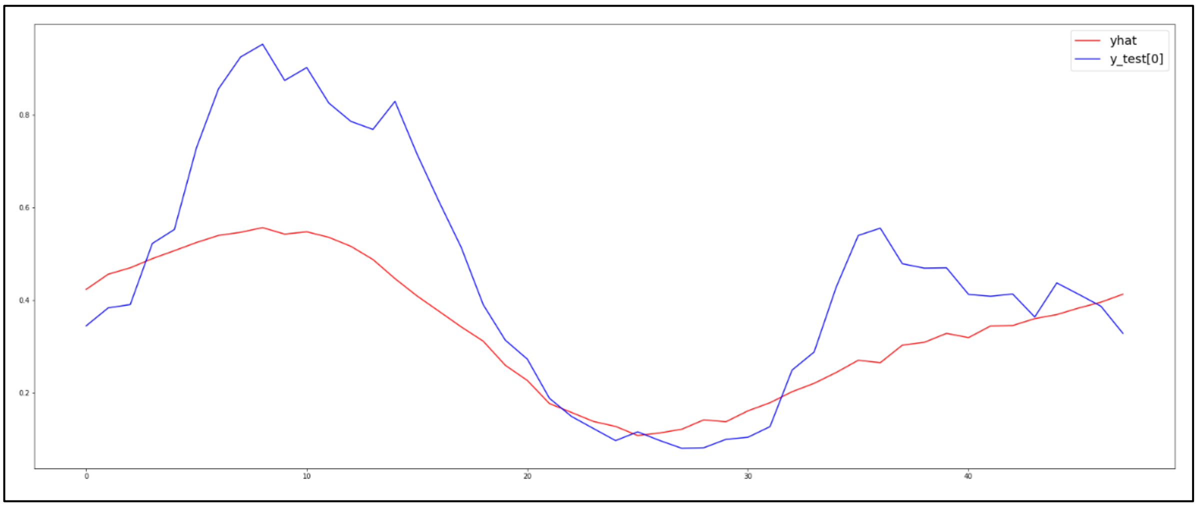
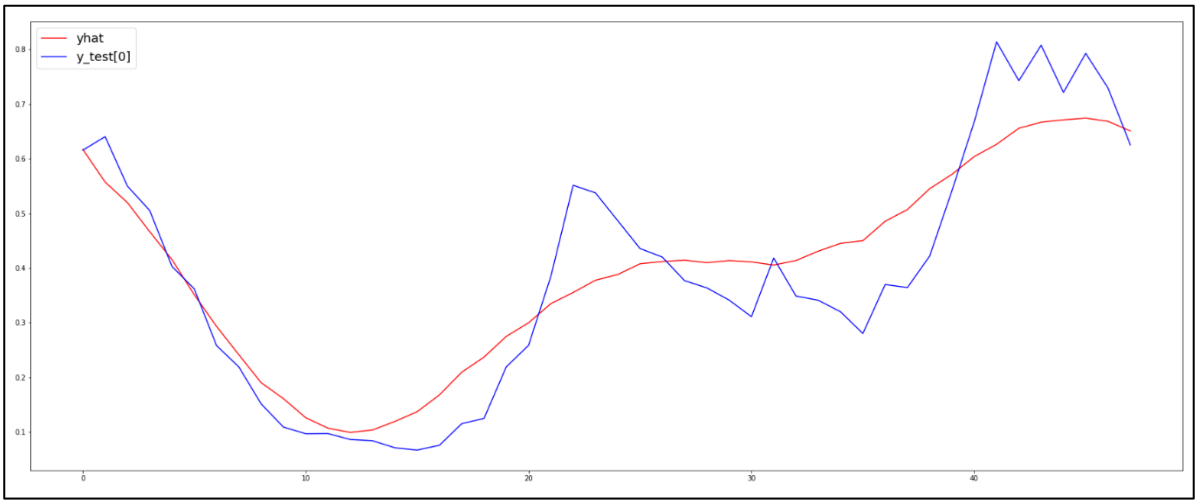
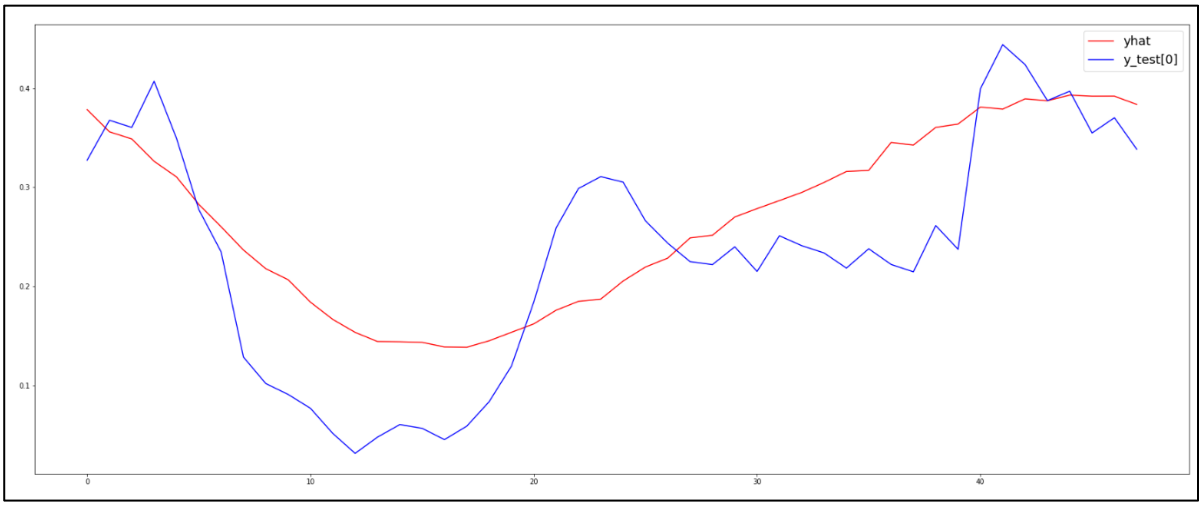
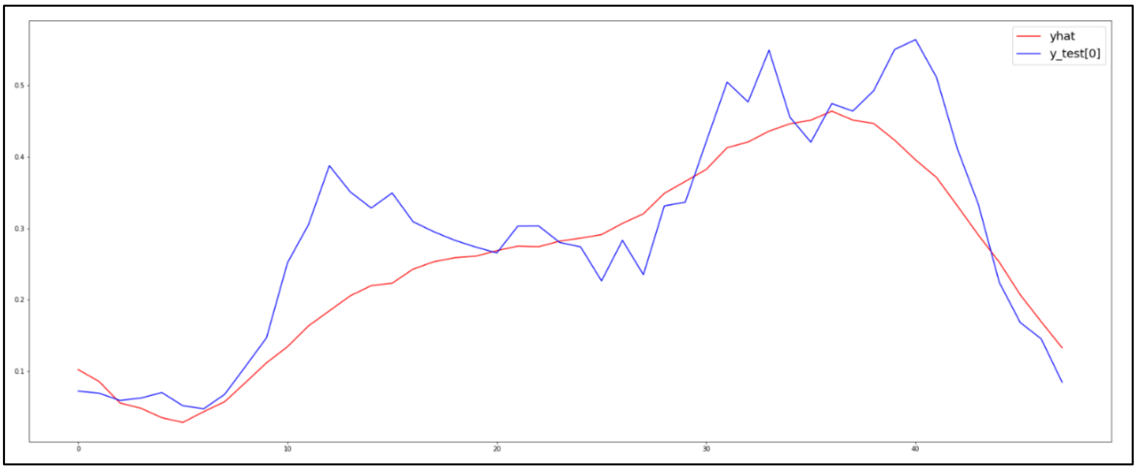
40

(2) Electricity Demand Prediction





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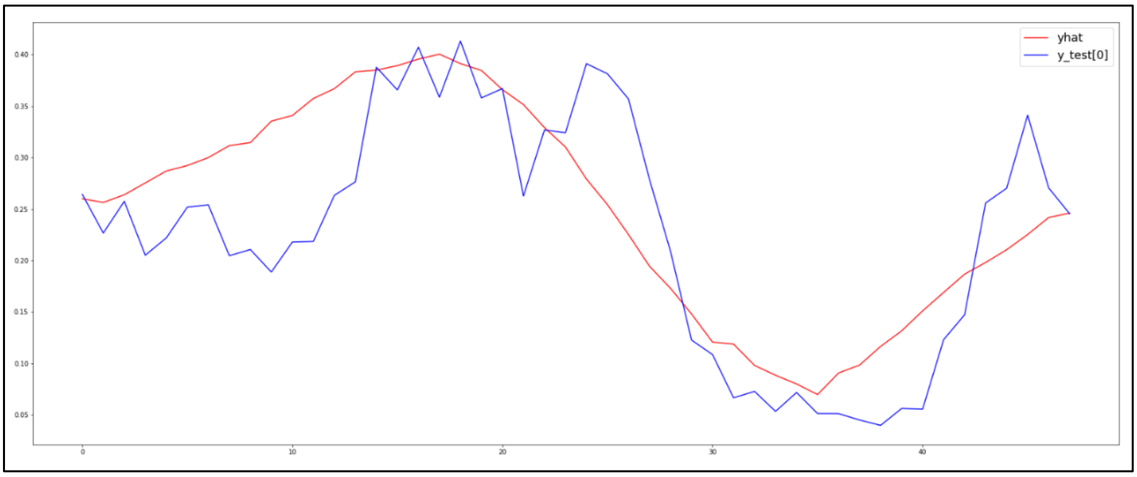
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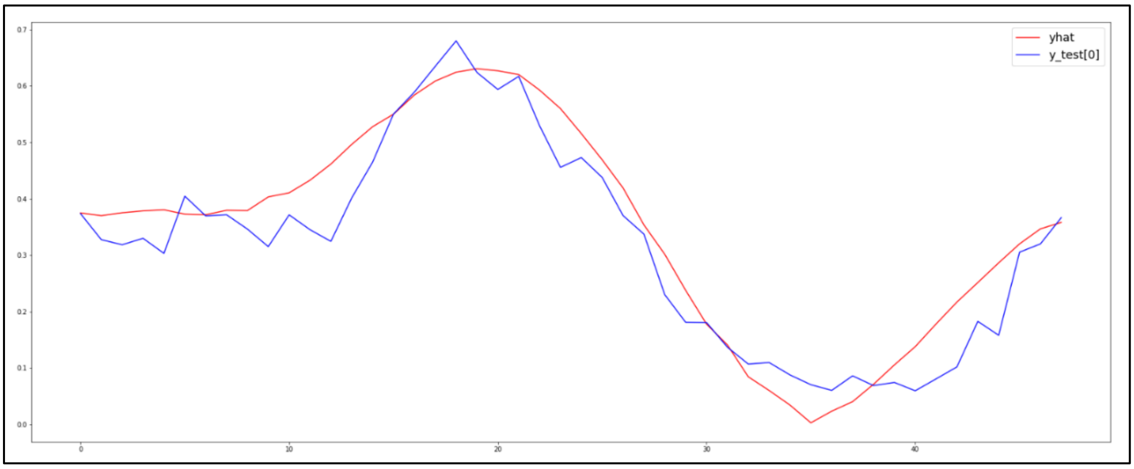
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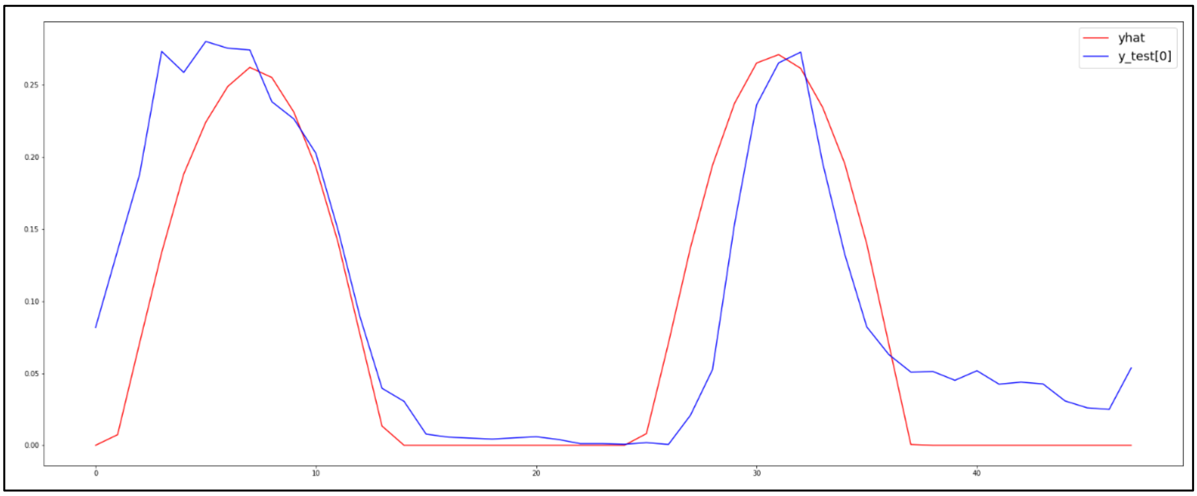
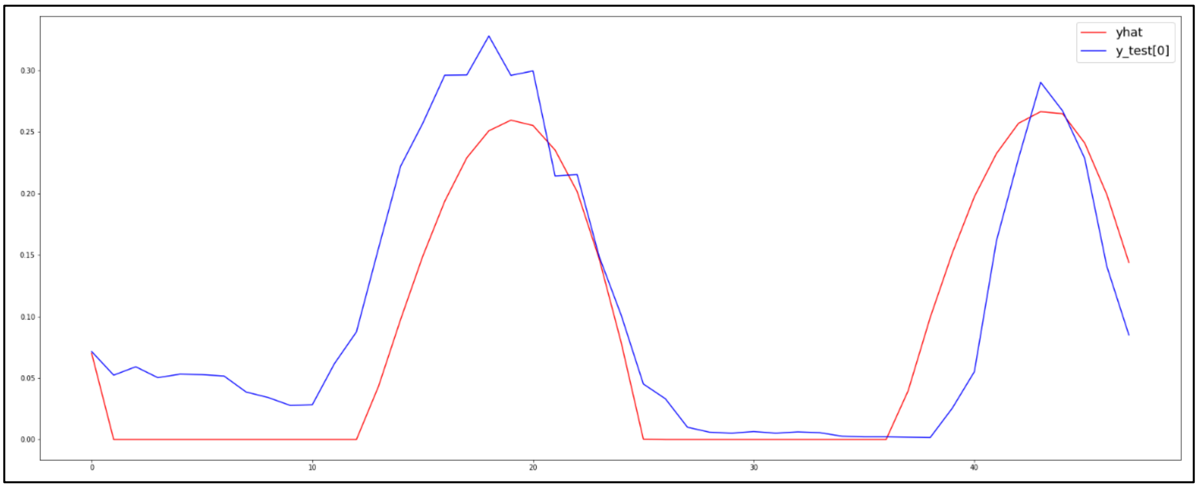
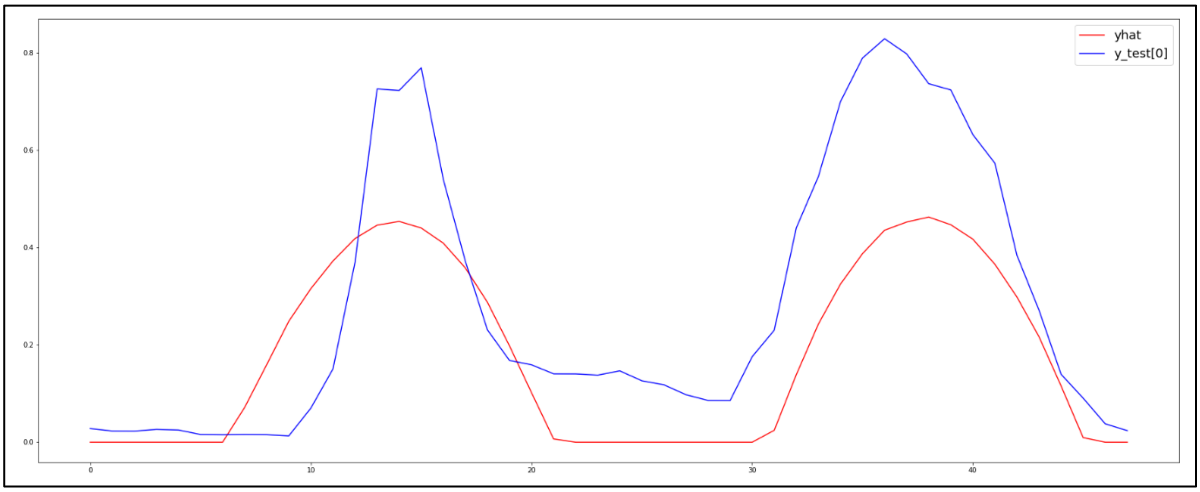
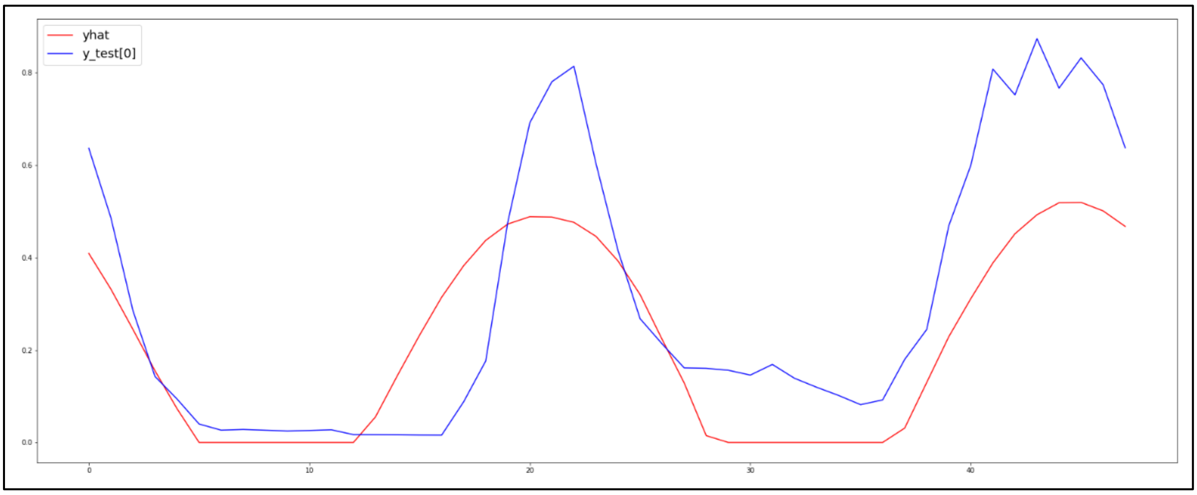
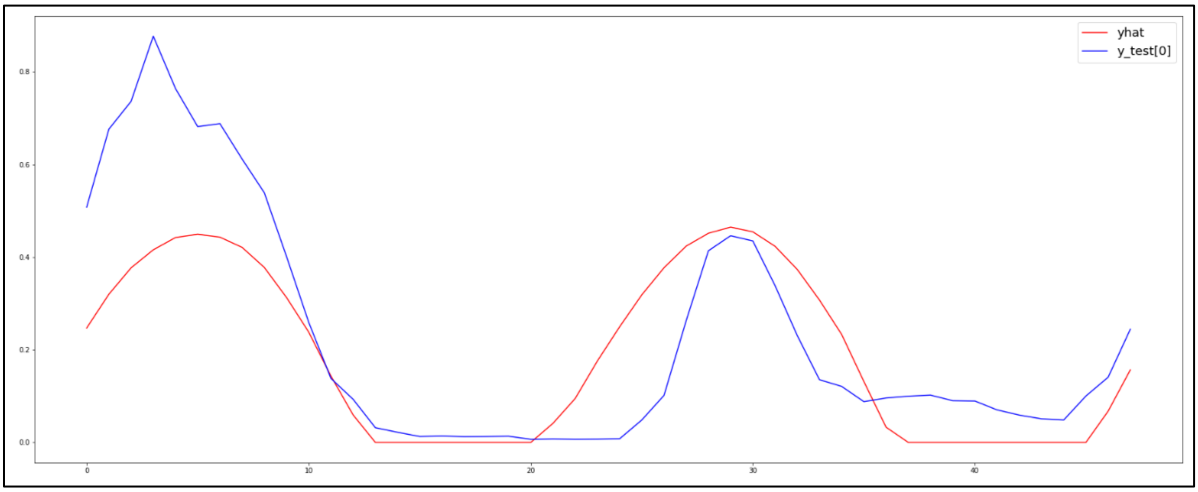
(3) Heat Demand Prediction

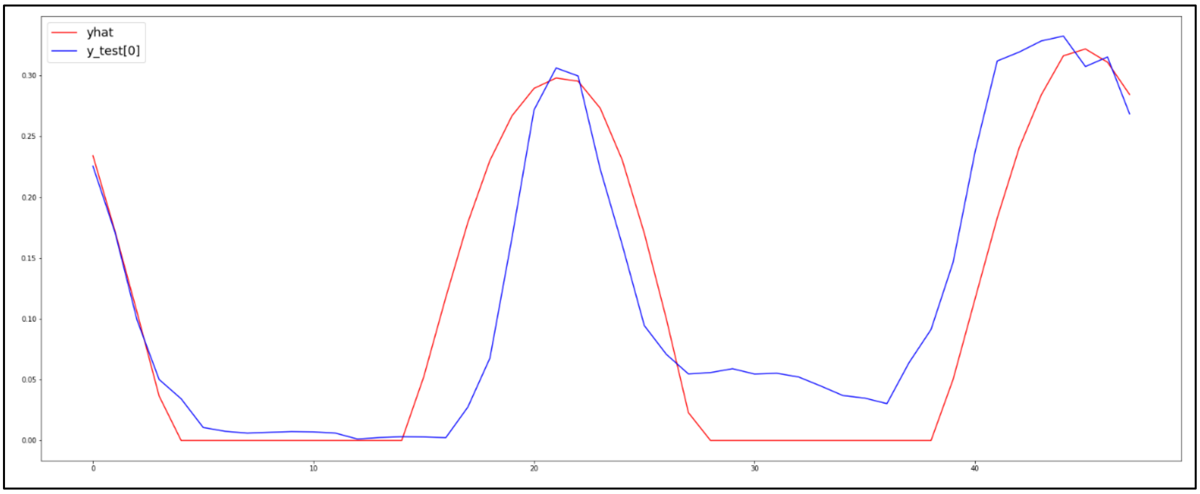




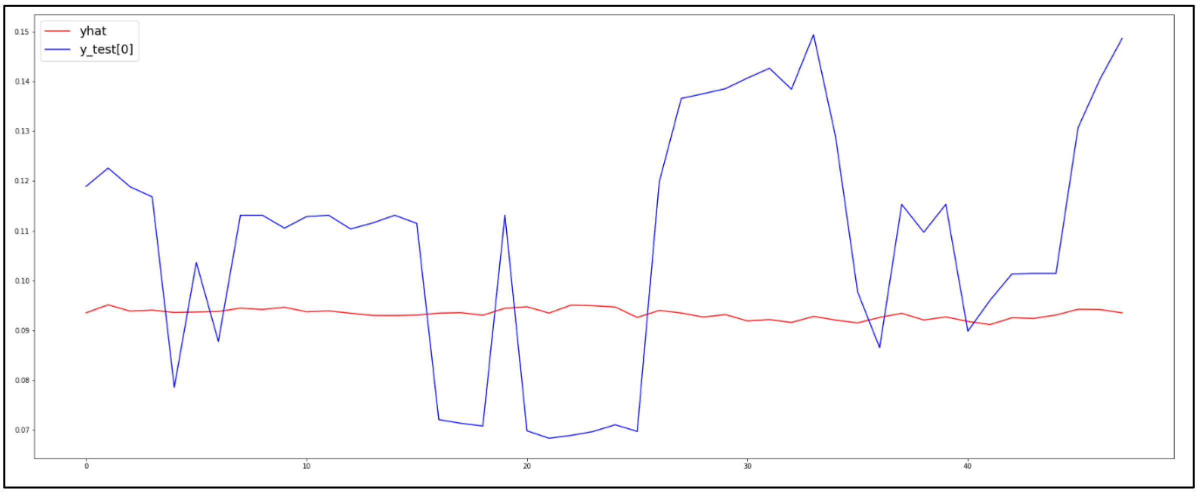


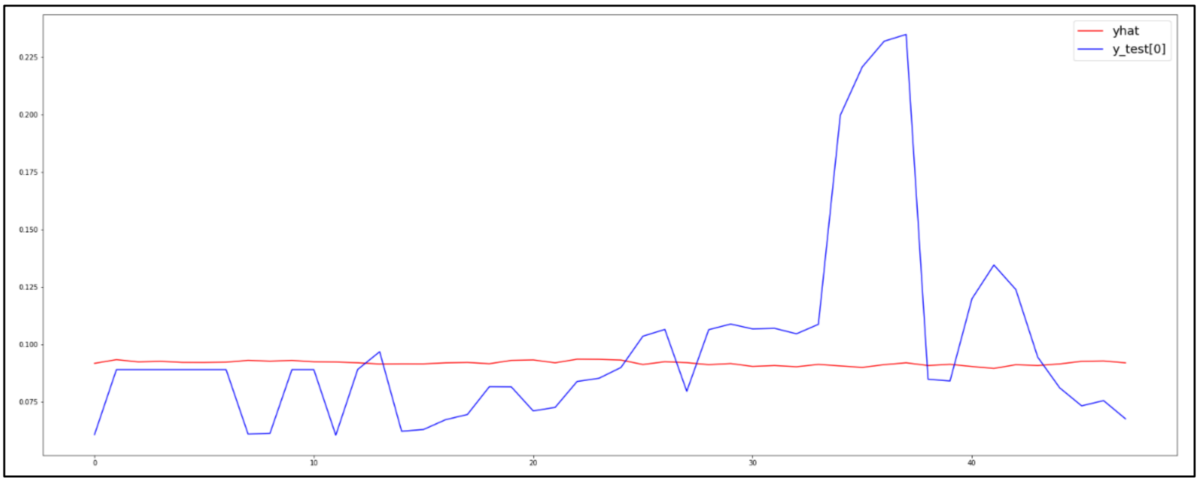

yhat
y_test[0]
0.0
0.2
0.4
0.6
0.8
0
10
20
30
40

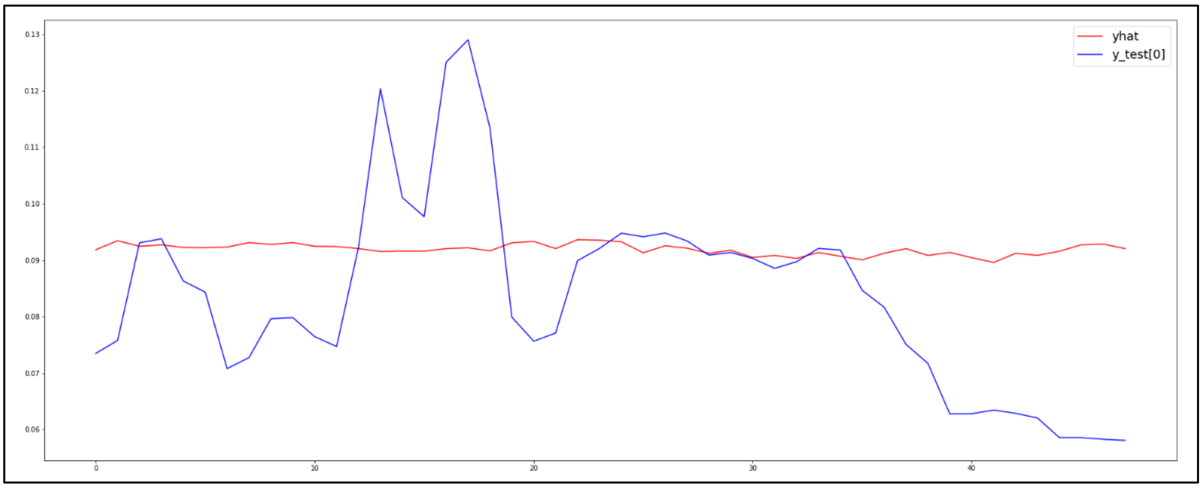

yhat
y_test[0]
0.0
0.2
0.4
0.6
0.8
0
10
20
30
40

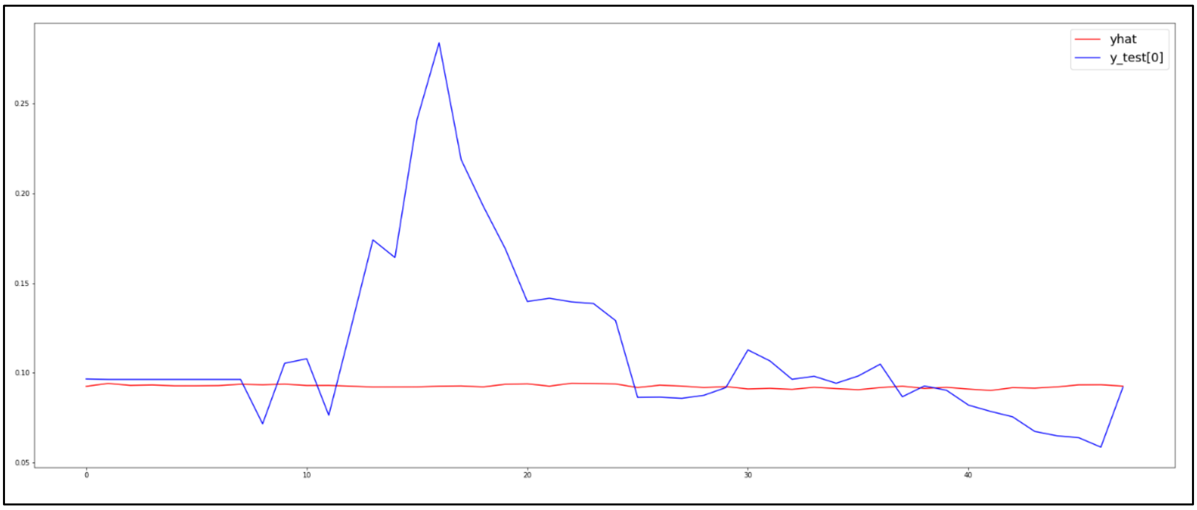

yhat
y_test[0]
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0
10
20
30
40

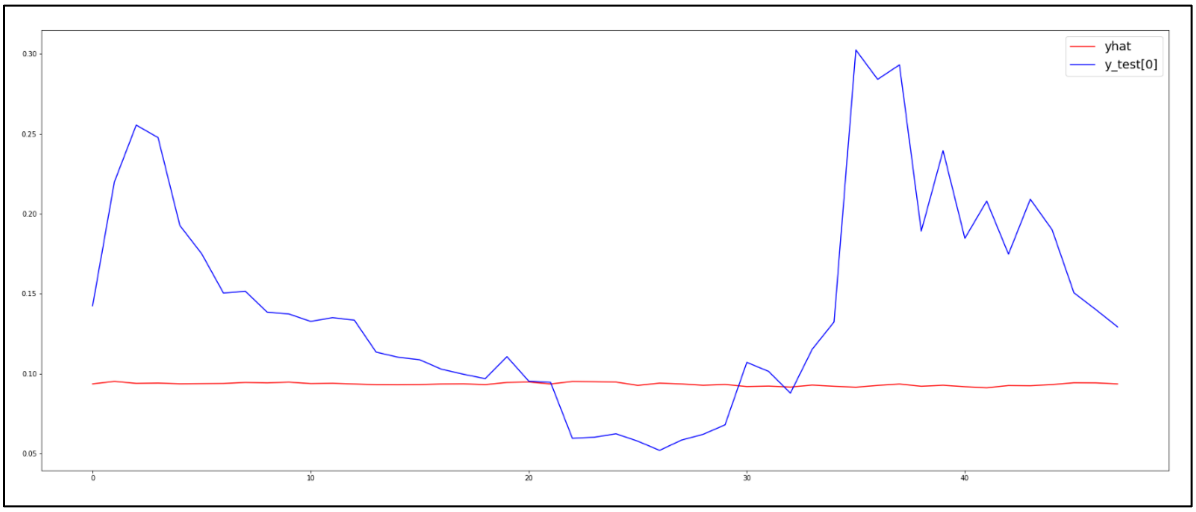
(4) SBP Prediction

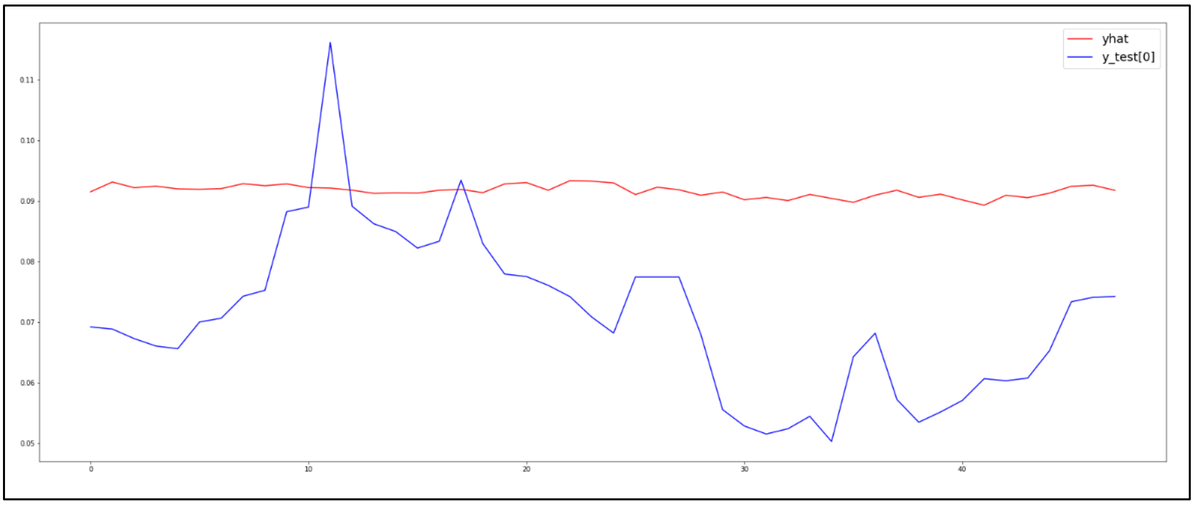




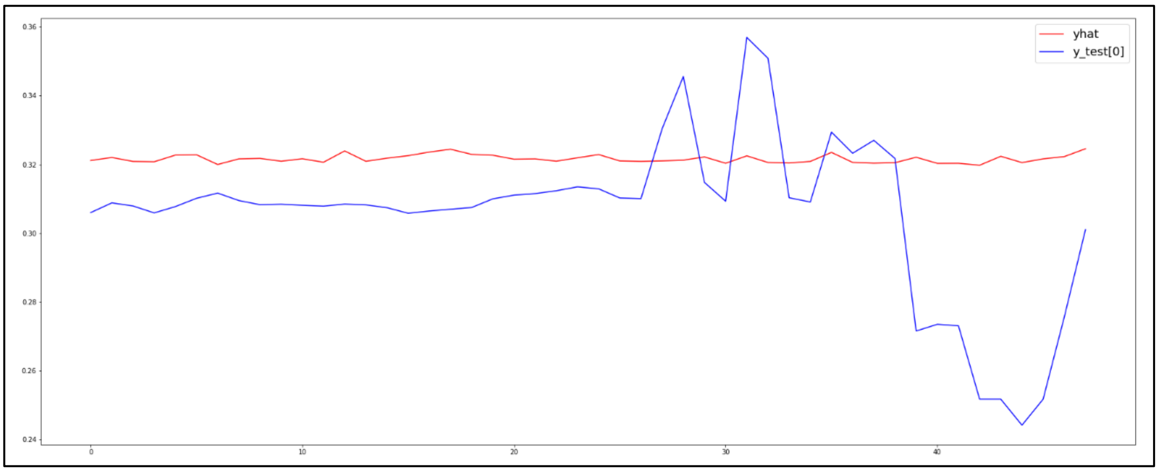


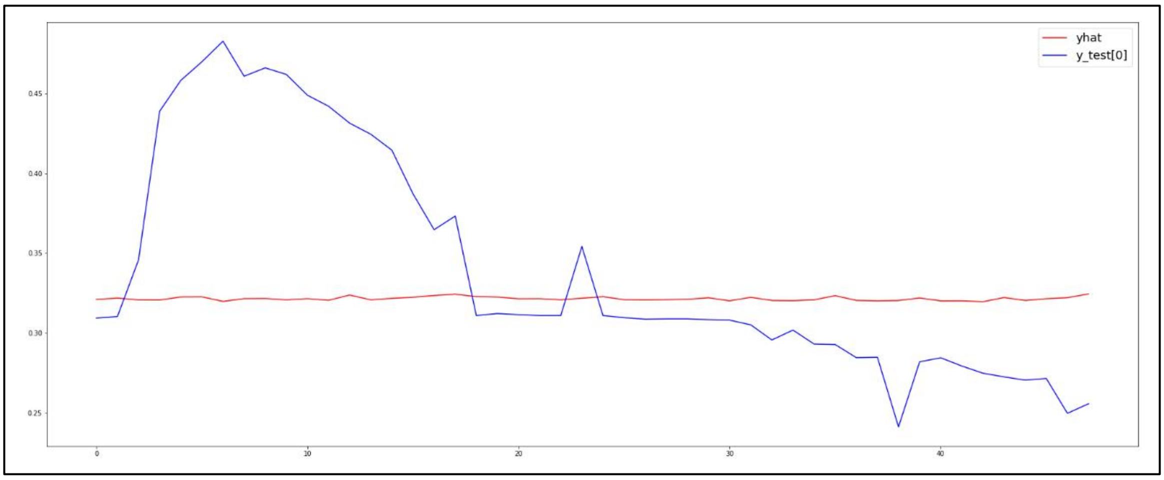

yhat
y_test[0]
0.25
0.20
0.15
0.10
0.05
0
10
20
30
40

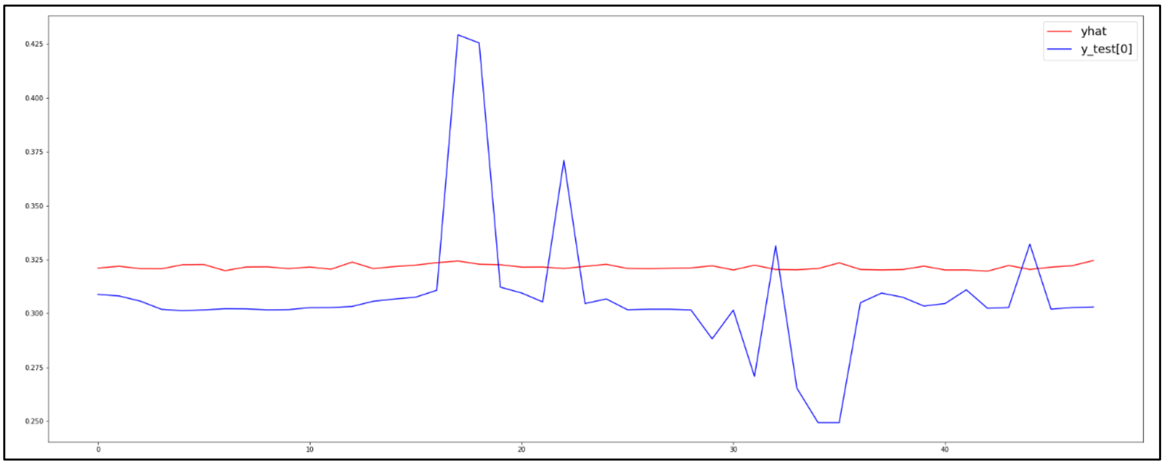

yhat
y_test[0]
0.30
0.25
0.20
0.15
0.10
0.05
0
10
20
30
40

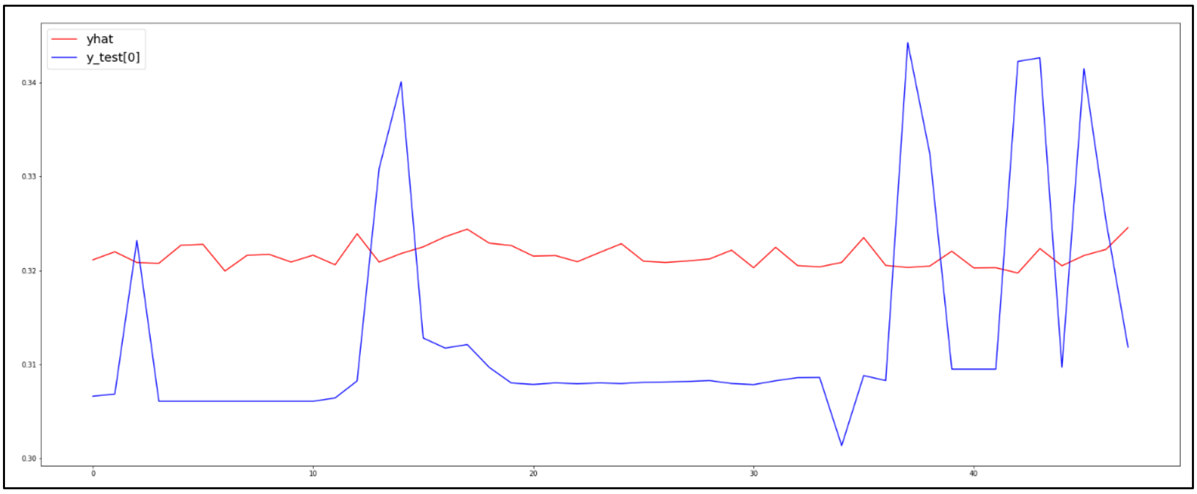

yhat
y_test[0]
0.11
0.10
0.09
0.08
0.07
0.06
0.05
0
10
20
30
40

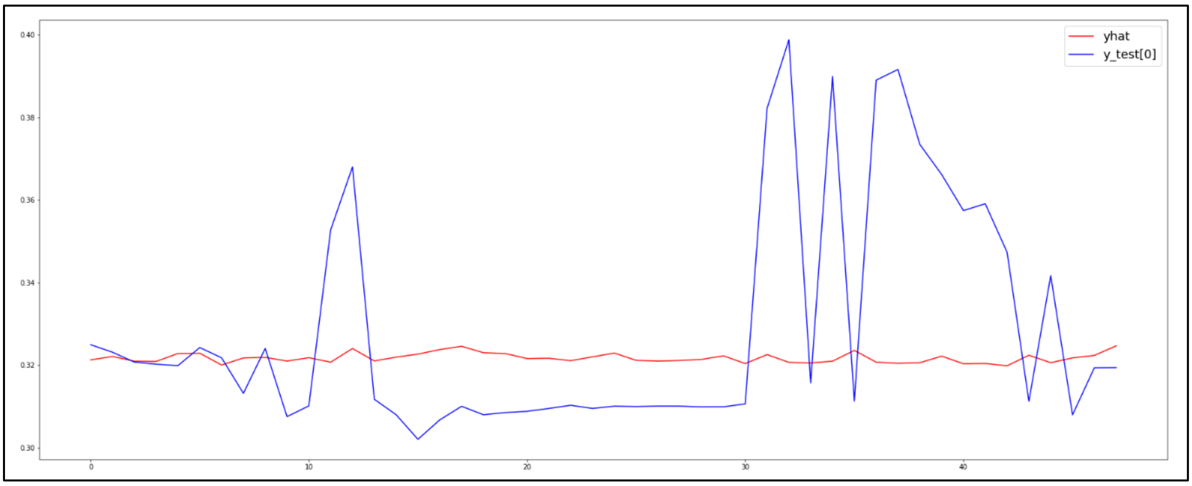
(5) SSP Prediction

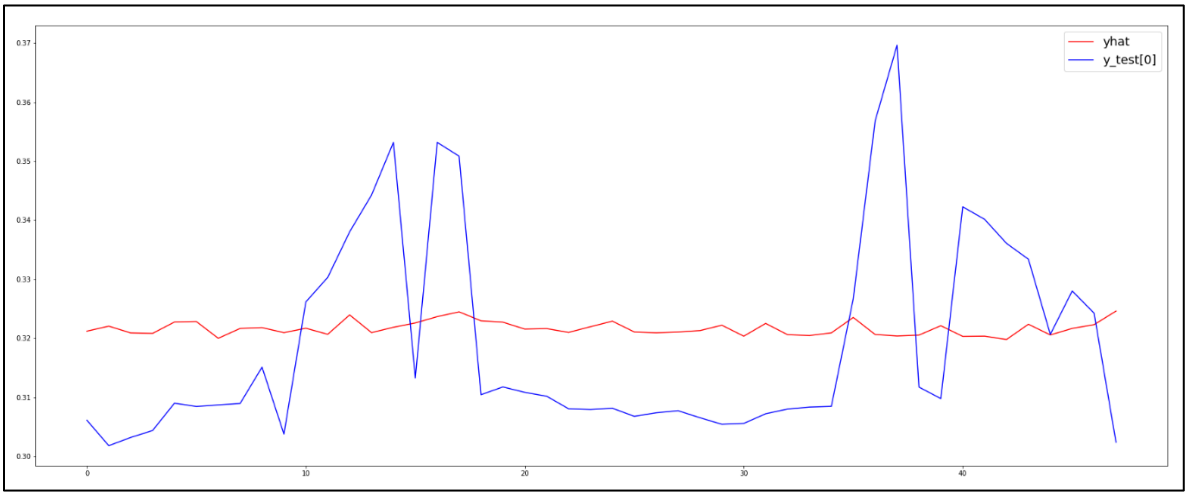







yhat
y_test[0]
0.34
0.33
0.32
0.31
0.30
0
10
20
30
40


yhat
y_test[0]
0.40
0.38
0.36
0.34
0.32
0.30
0
10
20
30
40


yhat
y_test[0]
0.37
0.36
0.35
0.34
0.33
0.32
0.31
0.30
0
10
20
30
40