GENTE

PROJECT REPORT

Revision 0

SUMMARY

This document describes processes in achieving task deliverable in WP 6.1. This task deliverable focuses on developing forecast algorithms for both the electricity load, PV generation and heat demand to be used as inputs for the optimization of the local energy communities (LECs) building energy management systems (BEMSs).

Impressum

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Abstract

In this report, advanced forecasting algorithms for both the electricity load, PV generation and heat demand of the local energy communities (LECs) are described. The expected building energy management system for the LECs resources optimization would leverage this short term forecast for the management of all energy-related services. Accordingly, advanced AI based forecast algorithms with two different time steps of 1-hour ahead with 10-minutes resolution and 24-hours ahead with 1hour resolution are provided for the prediction of the PV generation, building loads and heat demands of the LEC demonstrated using HSB Living Lab (HSBLL), Chalmers University of Technology Sweden. In principle, observed weather conditions, and historical data (outputs of PV, Electricity, and heat loads), from previous hours were used to forecast for an hour and 24-hours ahead.

Developing the machine learning models for the prediction of stochastic entities such as load demand and PV production requires historical data for a period to provide trends and patterns. The measurement data for this project is collected from Chalmers HSBLL building, while weather related data are retrieved from a Numerical Weather Prediction (NWP) model. For each forecasting algorithm tested based on the stated data, an individual forecasting method and performance optimization concept applied for the prediction is presented. The forecast for short term and very short term (1-hour ahead with 10 minutes resolution) are based on Long Short-Term Memory (LSTM) architecture while the 24-hours ahead with 1hour resolution is on Gated Recurrent Unit (GRU) and ConvLSTM – a combination of convolutional neural networks and LSTM.

The results of the best performing model showed an accuracy of 97.29% when compared with the actual data. The models were further validated and compared with the other state-of-art methods, hence the justification for their selection for deployment in GENTE project. Furthermore, the realization and future exploitation of the forecast system is briefly described. The presented forecast methods utilized predictions on weather variables instead of their real-time measurements. Therefore, the accuracy of the weather predictions highly influenced the predictions made especially that of the PV. This implies that the results of this forecasts are more viable in real time exploitation where weather variables may not be required as factor.

List of Abbreviations

AR	Autoregressive Model
AI	Artificial Intelligence
ARMA	Autoregressive Moving average
ARIMA	Autoregressive Integrated Moving Average
BEMS	Building Energy Management System
CNN	Convolutional Neural Networks
ConvLSTM	Convolutional Long Short-Term Memory
DL	Deep Learning
BEM	Energy Management System
EV	Electric Vehicle
FC-LSTM	Fully Connected-Long Short-Term Memory
GRU	Gated recurrent units
HEMS	Home Energy Management Systems
IoE	Internet of Energy
IoT	Internet of Things
kWh	Kilowatt Hour
LOCF	Last Observation Carried Forward
LSTM	Long Short-Term Memory
LTLF	Long-Term Load Forecasting
MAD	Mean Absolute Deviation
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MTLF	Medium-Term Load Forecasting
ML	Machine Learning
NPL	Natural Language Processing
PCA	Principal Components Analysis
RF	Random Forest

ReLU	Rectified Linear Unit
RMSE	Root Mean Square Error
RNN	Recurrent Neutral Networks
SARIMA	Seasonal Autoregressive Integrated Moving Average
SGD	Stochastic Gradient Descent
STLF	Short-Term Load Forecasting

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1. Introduction

1.1 Scope of the report

One of the main objectives of GENTE is to develop forecast algorithms that support distributed control for optimal operation of buildings and LEC optimisation for flexibility and grid support services. These user-oriented solutions are geared towards communities and community managers` energy-resource management. Proper understanding of energy production and consumption behaviours has numerous advantages to participants in smart grids, such as manufacturers, renewable energy generators, utility companies, prosumers, and consumers especially. Part of the advantages range from tracking the loads relative to proper balancing, real-time energy pricing opportunity, and efficient energy management.

This report addresses forecasting both from the demand and supply point of view to provide required energy flexibility. The local energy community proposed by GENTE is expected to generate its own energy, preferably from renewable sources, and as well supply energy to the members of the community. So, energy generation and electricity/heat demand forecast are pivotal to proper planning and management of such a project. However, forecasting complex real-world problems like PV and electricity/heat demand with linear models like autoregressive (AR), autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA), as well as ARIMA with seasonality component (SARIMA) etc. is always difficult and yield less reliable results. Obviously, such types of models cannot determine non-linear relationships in complex data [1] like that of PV generation and power demand, therefore complex models [2, 3] with high computation and inference capacity like neural networks are advantageous in this type of problem.

In contrast to statistical models, neural network models formulate a model based on features learned from existing data and this dependency makes it data-driven, self-adaptive and a preferred choice as far as time series forecasting and Big Data is involved. Neural networks are preferable though not without their own inherent limitations. Importantly, learning of arbitrary complex mapping from inputs to outputs has become research focus recently with significant performance improvement recorded, yet a huge gap still exists between the methods of deployment and implementation environment. Some of these gaps include: the proper ways to capture dominant factors in the data to be learned; how to reduce the size of the model, and increase its computational speed; and finally, how to determine model parameters selection etc. Basically, these are the major areas this proposed forecast model aims to optimize.

The forecast results of this deliverable will be input to the building energy management system (BEMS) developed in Task 6.2 and 6.3 of the WP6 to achieve “building control as a service”, wherein forecasts would be relied upon for real-time controls in the building facilities, especially the heap pump. The reported forecast is for short-term operational planning of EMSs, i.e. 1 hour and daily. However, algorithms adjustment can be made according to the data availability and required complexity if the EMS is intended to be used for long term operation energy management or planning like yearly or triannual.

1.2 Purpose of forecasting

Research published so far has shown that having a prior knowledge of energy demand and production is instrumental in optimal energy management, especially as it relates to striking a balance between the energy produced at a given time and the energy consumed, resulting to a reduced cost of power reserve and battery storage. The emergence of smart energy technologies like artificial intelligence and Internet of Energy have made forecasting less complex. Forecasts performed using artificial intelligence algorithms can be easily integrated into Local Energy Communities (LECs) services like energy optimisation, and control strategies in the areas of peak load control through heat-pumps and other power consuming appliances in buildings. With accurate forecasts, there will reduction in both operational and maintenance costs, increase in reliability of power supply and delivery system, and an opportunity for future expansion on the part of energy suppliers. Based on this, forecasts reported here are on an hour with 10mins resolution and 24hrs with 1hour resolution. The chosen forecast horizon and resolution is best suited for real time control, ramp rate control, variability management as well as demand response scheduling.

1.3 Deliverable structure

This report is structured in five sections. In addition to this introduction, the outline of the sections is described as below.

Section 2 focuses on the PV generation forecast where first the data measurement accumulation and PV sites are described, then a literature review and description on methodologies, forecast horizon and algorithms of PV generation prediction is provided. Thereafter, the forecast models for short term, medium term and very short term are presented and the results of the proposed models are validated and compared with state-of-art forecasting techniques.

In section 3 the load forecast methodology for the three mentioned forecast horizons is described and a comparison with other forecasting techniques is presented.

Later, section 4 analyses and discusses extensively the results obtained from forecast methods applied in the project. It also outlines the challenges and approach that will be followed for the realization and exploitation of the forecasting in the optimization of building energy management systems of WP6.2.

Section 5 describes the model exploitation for the effective deployment, including the software requirements, dataset description, and model compilation and evaluation.

Finally, section 6 concludes the report with the main conclusion and suggests the future research focus.

2. Existing Forecast Efforts

2.1 PV generation forecast

Various methods [4-6] have been deployed in forecasting PV productions. A sizeable number of these models are state-of-the-art forecast models. While some of these methods are statistical based others are based on either a physical approach or artificial intelligence. Statistical approaches usually depend on time series data of measured parameters to learn its present trends or patterns. Physical approaches depend on satellite images and numerical weather predictions (NWP). [5] for instance, applied a stack of neural network models to predict solar irradiance values based on weather patterns.

Smart grid distributed networks, globally embraced in recent times for energy production, transmission, and distribution, come with challenges and opportunities. Part of the challenges is the inability to accommodate the voltage fluctuations resulting from large amounts of solar PV [7]. Solar PV generation is most often paired with energy storage system, but an inability to manage those storage systems poses a challenge, hence, need for accurate forecast to maximize their economic returns. Therefore, the forecast results in this study are used in the energy management system (EMS) optimization to achieve electricity load and heat flow balancing and control operations. For instance, set points for the charging/discharging of controllable loads such as energy storage (ES) can be fixed if the expected energy production and consumption for the building is known. More explanation on the contributions of energy forecasting within GENTE is made in chapter 5, where forecast models' integration to EMS is detailed. In energy markets, forecast horizon and resolution may change significantly from one application to the other, hence, the justification for short term (an hour and a day ahead) and medium-term (24hrs ahead) forecasting implemented using neural networks algorithm with multivariate time series dataset.

Renewable energy sources (RESs) like PV generation cannot be precisely planned beforehand due to their stochastic nature. This arises from the fact that PV generation is highly dependent on meteorological factors [8]. The power output of a PV plants fluctuates along with the intensity of solar radiation which has random characteristic based on the geographical location, weather conditions, solar hour angle and seasons. If these meteorological factors are collected over time across different seasons of the year as historical data and properly trained with an intelligent algorithm like neural networks, perhaps predictions of possible outputs ahead can be made. One major gap in the existing models addressed in the developed forecast model reported here is the adaptability of the model to different datasets. Figure 1 and 2 showed the PV production distribution in HSB Living Lab (HSBLL) used as a test site for this forecasting and its dependent variables distribution respectively. HSBLL is a 29-bed apartment in a student community of Chalmers University of Technology, Sweden equipped with 18kWp PV system. While Figure 1 shows the PV productions patterns across different seasons of the year, Figure 2 shows the variability of meteorological variables against the PV production.

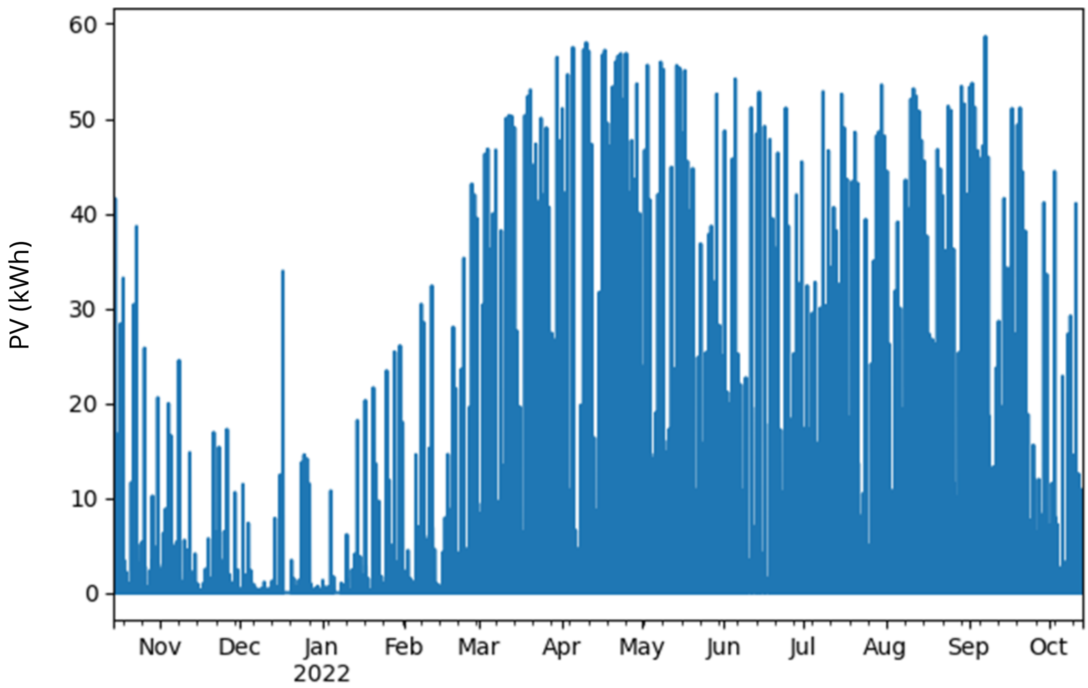

Figure 1. PV Output structure sampled over an hour in a 1-year period

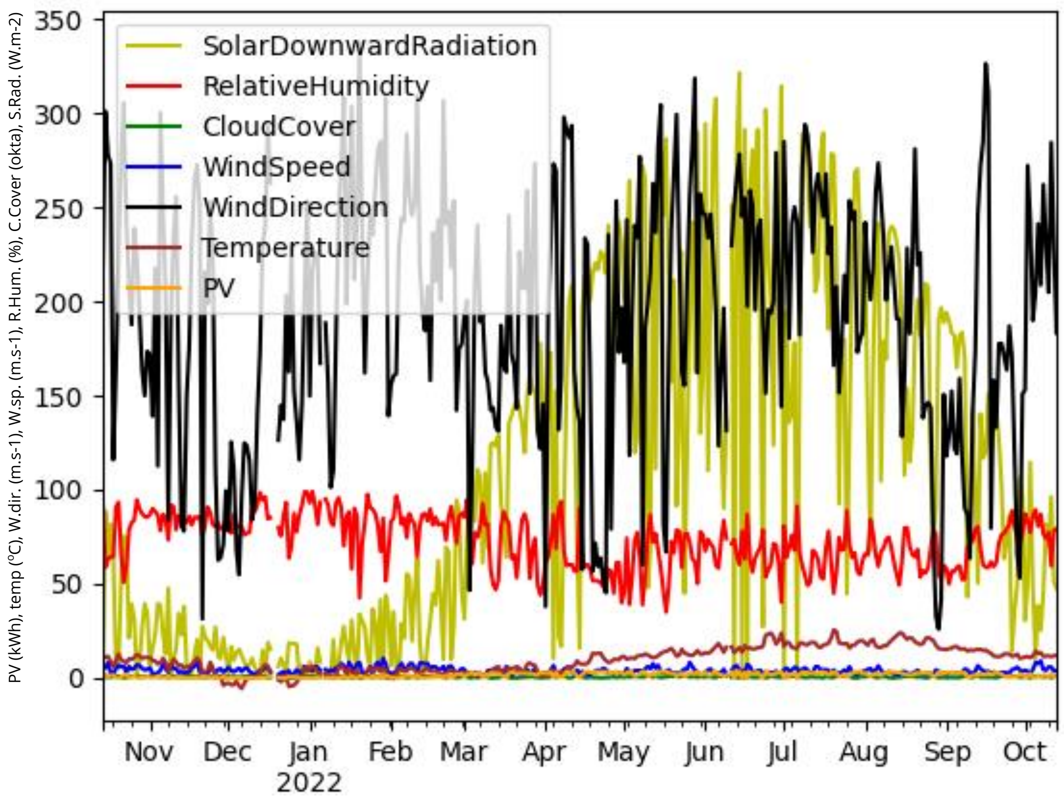

Figure 2. Distribution of the input variables over a period of 1 year

2.2 Electricity Load demand forecast

Rapid technological growth in the energy industry has made energy management an interesting research area due to the insight it provides in terms of individual loads i.e., on a per-customer level. Proper planning and management of energy requires understanding of energy consumption behaviours to keep track of consumers' load. Though electricity demand behaviour at any given instance is perceived to be dynamic and nonlinear, hence, keeping track of consumption profile over time can be extremely helpful in terms of energy planning on the part of suppliers and consumers alike. It will make the amount of energy delivered per unit generated to be easily managed in smart grid context. This will in turn reduce the fuel needs and carbon emissions on the part of energy suppliers. Interestingly, energy generation follows the consumption demands, which is a time-varying factor, and one prerequisite of grid stability is consumption and generation balancing. This implies that both generation and consumption should be observed from time to time to ensure proper balancing. Consequently, historical load data is leveraged in making load demand projections for integrated resource planning and optimization. Figure 3 shows the correlation between the targeted variable (electricity load) and some variables including calendar variables that influences electricity consumption. This correlation test result showed that load is strongly correlated with the previous 24hrs and 168hrs loads, then followed by the hour of the day.

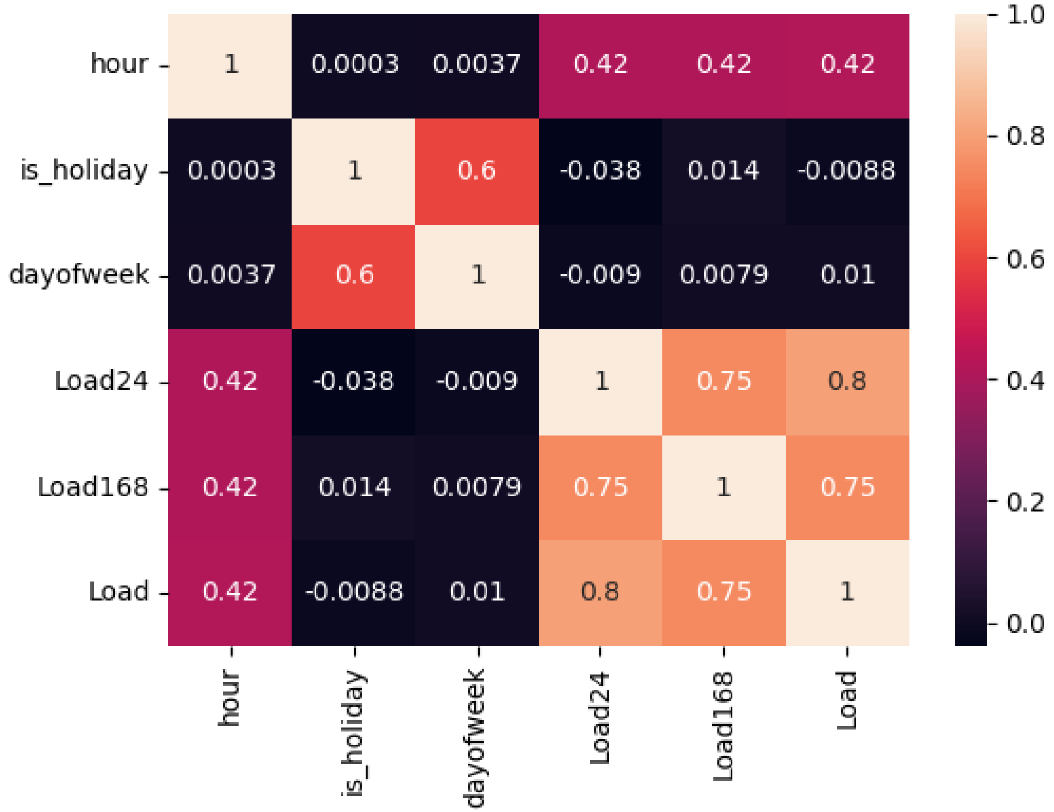

Figure 3. Heat Map of Correlation Test on Load Demand

To achieve a state-of-art power consumption forecast model, numerous deep learning techniques [2, 3, 9] had been deployed in the processes of problem formulation, data transformation to supervised learning, and neural networks architecture building. [10] used feature encoding method on a deep reinforcement learning algorithm for inputting of data into the neural network layers. Nonlinear transformation defined by this encoder and decoder method can be viewed as an advanced feature extractor capable of preserving the hidden abstractions and invariant structures in input.

2.3 Thermal Load demand forecast

Building heating forecast research is very popular these days considering its importance for optimal energy planning and management. Several efforts are being made to address the flexibility gap between the use of district heating systems and heat pumps in buildings. These efforts are majorly centred on making forecasts and using the results of these forecasts in managing the heat demands. However, data-driven forecast methods are becoming a fulcrum of buildings thermal load forecasting and short-term forecasting have shown high performance in many cases. To achieve a model with high performance, some previous research efforts have paired both linear and nonlinear models. For instance, [11] integrated machine learning models for improved training mechanisms, higher accuracy, and short learning time. Some important variables such as seasonality (calendar), occupancy, weather, and consumption behaviours can be co-opted while making forecasts in a district heating system.

2.4 Data Collection/Measurement

Table 1 showed the PV data structure from the demonstration site located at Chalmers campus shown in Figure 4. The HSBLL building has dishwasher, washing machines, tumbler dryer, EV charging stations, two air-to-water heat pumps (Energy Save AWH 9kW-V6), and 18 kW of solar PV capacity, installed on the rooftop of the building. Observations on both the electricity load, heat load and PV production were made on hourly basis and the output captured the consumption behaviour and PV production pattern across different seasons of the year at different weather conditions. Chalmers campus is equipped with a central mini-SCADA system which can measure and store the PV output power at each of the PV sites and store such data in servers which can be accessed through the communication system.

However, the fact that atmospheric climate changes across locations have significant effect on power consumption necessitated the collection of data from Alingsas HEM, which is considerably far away from HSBLL to investigate the effect of the climatic changes to the model performance.

The forecasts are performed for the demonstration sites where historical data were collected, however, to better illustrate the results, this report presents the PV generation, load and heat demand forecast results of HSBLL, Chalmers.

Table 1. PV data shape and structure

```
(8516, 7)
            DateAndTime  Day  Hour  ...  RelativeHumidity  CloudCover   PV
0  15-Oct-2021 00:00:00    6     0  ...             92.56        1.00  0.0
1  15-Oct-2021 01:00:00    6     1  ...             91.59        1.00  0.0
2  15-Oct-2021 02:00:00    6     2  ...             83.05        0.95  0.0
3  15-Oct-2021 03:00:00    6     3  ...             79.68        1.00  0.0
4  15-Oct-2021 04:00:00    6     4  ...             71.28        1.00  0.0

[5 rows x 7 columns]
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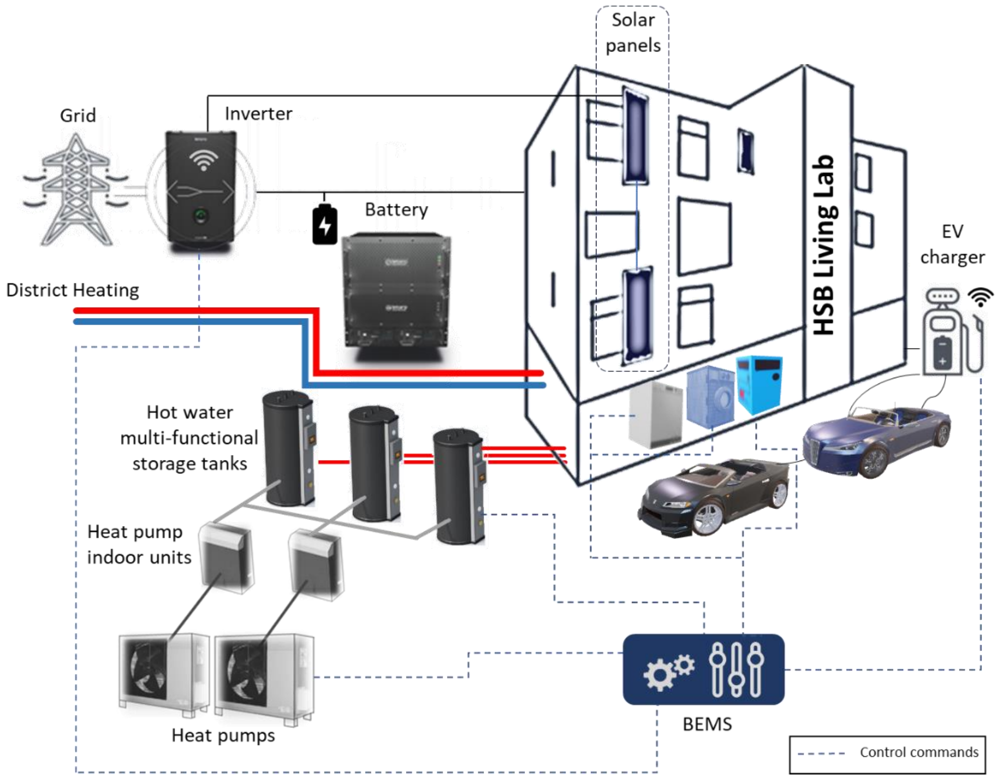


Figure 4. HSBLL and data collection sources

2.4.1 Thermal load data

Heat demand profile from small-scale energy system in HSBLL is used in training thermal demand forecast model. External and internal factors affecting the heat consumption of the buildings were considered as inputs to the model. Heat demand in HSB Living Lab emanating from hot water, floor, and space heating is provided by both district heating system and heat pumps. Heat demand in the context of this modelling is a direct function of the outdoor temperature, sun, and wind. Heating systems in HSBLL include: Two Air-to-water heat pumps (Energy Save AWH 9kW-V6), and three hot water storage tanks (MWT 500C.1). The heat historical data (psh) used for modelling the heat demand pattern is obtained from a log data from the GE meter at the HSB Living Lab.

From the heat transfer analysis carried out on this data as part of pre-modelling procedure, it was discovered that three major factors affect heat transfer in a building. These includes mass of the building, its specific heat capacity considering the heating systems, and variation in temperature. The first two factors can be easily determined except temperature variation. A test was further conducted to examine how these variables variations affects the heat transfer in the building. The analysis result shown in the Figure 5 showed that temperature variations followed a seasonality trend within the period of 365days i.e., 8760hours analysed. And the heat demand is lowest between 3130hours to 5020hours because of significant increase in temperature. Further probe showed these hours fall within the summer period.

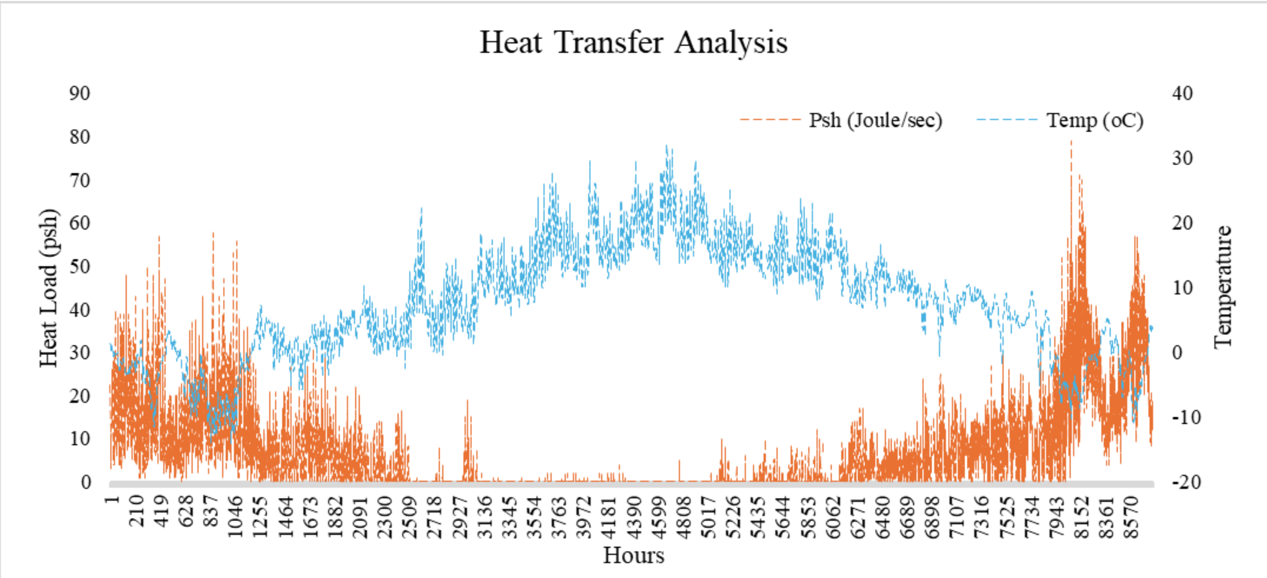


Figure 5. Temperature Variations in HSBLL over the period of 430days

2.4.2 Weather Variables

The meteorological data used for the PV forecasting is acquired from an API of Rebase Energy [12]. These 6 post-processed variables are described below:

- Cloud Cover: the fraction of the sky obscured by clouds on average when observed from a particular location. It is measured in Okta. On the average, the global is around 0.68 on clouds optical depth larger than 0.1, and lower than 0.56 with optical depth larger than 2. Cloud cover fraction (0-1) derived from Total cloud cover (CLCT) in percent (%).
- Pressure Reduced MSL: Pressure at mean sea level pressure in Pascals (Pa) derived from Pressure in Pascals (Pa) reduced to mean sea level (PMSL).
- Relative Humidity: Relative humidity in percent (%) at 2 meters above the surface
- Solar Downward Radiation: Surface solar radiation in Watts per square meter (W.m-2) derived from Net short wave radiation flux (m) (at the surface) in Watt per square meter (W.m-2).
- Temperature: Temperature at 2m in degrees Celsius (°C) derived from Temperature.

- Wind Direction: Wind direction at 10m (°) in degrees (°) derived from Zonal wind in meters per second (m.s-1), at several heights (U) and Meridional wind in meters per second (m.s-1), at several heights (V).
- Wind Speed: Wind speed at 10m in meters per second (m.s-1) derived from Zonal wind in meters per second (m.s-1), at several heights (U) and Meridional wind in meters per second (m.s-1), at several heights (V).

2.5 PV generation forecast approach

The two major approaches for PV plant output forecast are indirect and direct forecasts. Indirect forecast approaches predict the solar radiation of different scales and then joined it with other associated data to forecast the PV output power using the performance model of the plant while direct approaches directly forecast the PV output power using historical data such as PV output and associated meteorological data. Both methods directly or indirectly depend on weather related factors like solar irradiance, temperature, wind speed and direction etc. In recent times, PV forecast has focused on using solar irradiance for the prediction of PV power plant output and have also been applied in the areas of agriculture and climate change research [13, 14]. However, in this report, a holistic review of other meteorological factors was made and integrated in the forecast. GENTE aims to embed the solar generation forecast and other similar forecasts of the work package 6.1 in the EMS's optimization and control strategies being developed for LECs, therefore, the PV power output of the PV plants are forecasted directly to make it as an applicable input to the EMS.

Direct PV generation forecasting methods learn the behaviour of the PV output timeseries using historical data of the PV output itself and exogenous inputs and implement the acquired knowledge to predict future values. Many papers have proposed techniques for PV generation forecasting which can be broadly divided into three subgroups; mathematical based models, machine learning (ML) based techniques, and hybrid methods [15]. Most often, hybrid models combine a decomposition technique, an ML regression model, a feature selection method, and sometimes a meta-heuristic algorithm for optimization purposes. Mathematical based models are based on statistical approaches such as ARMA (Autoregressive moving average model) [16], ARIMA (Autoregressive integrated moving average model) and regression techniques i.e., regression trees [17] and identification-based model [18]. Mathematical based models have limitations in dealing with non-linear systems, therefore, machine learning based model such as Artificial Neural networks, support Vector machine (SVM), have been applied to PV generation forecasting. These methods have shown competent ability in predicting non-stationary data patterns, albeit large data sets are required for training stage. Some researchers have focused on combination of machine learning and indirect models, while others applied hybrid methods composed of mathematical and ML methods, ML based models and optimization algorithms. The latter uses optimization algorithms to optimize/tune the ML parameters. Generally, hybrid methods improve the prediction accuracy compared to single methods, however, impose higher computational complexity.

2.6 Artificial Intelligence Models

Over the years, several machine learning models have been developed to solve real-world problems including regression problems like forecasting. These models leverage different methods and techniques for performance improvement. Unfortunately, as high performance is achieved in some of these models, the size of their trainable parameters increases, making them unsuitable for low-memory low-storage devices. However, several efforts are being made to reduce the size of models' trainable parameters without necessarily reducing their performance. In the model reported in Table 2, efforts were made not only in reducing their size so it can be deployed in low-energy low-memory devices but ensure their inference time is significantly reduced. This concept of model size reduction should be an interesting one to GENTE project since there is likelihood of deployment in low-energy low-memory devices for the LECs. Juxtaposing the percentage of error of these state-of-the-art models as shown in Table 3 to their sizes, it is obvious that additional efforts is required to further reduce both the model size and error. This is part of the significant achievements of the developed forecast model reported here.

Table 2 State-of-the-art Artificial Intelligence Models

Model	Parameters	Size	Error-5 (%)	Training Time	Inference Time
ENet [19]	0.37 M	0.7 MB	-	15mins	383ms
LEDNet [20]	1.856 M	3.8 MB	-	-	-
SegNet [21]	29.46 M	56.2 MB	-	37mins	286ms
AlexNet [22]	60 M	232 MB	19.7	7,920mins	-
VGG16 [23]	138 M	528 MB	10.4	-	-
SqueezNet [24]	0.66 M	4.8 MB	19.7	-	-
ResNet152 [25]	232 M	60 MB	6.7	-	-
GoogleNet [26]	6.8 M	28 MB	6.7	-	-

3. Methodology

3.1 Data Pre-processing

The historical data from HSBLL acquired over the period 1year was cleaned, and imputation method used to fill all missing and corrupted values using a day-wise Last Observation Carried Forward (LOCF) technique. This simply means carrying an observation from the same time the previous day. In a time-series data of this nature with seasonality trend, other methods like linear interpolation, seasonal adjustment + linear interpolation could also be applied.

From Figure 6, it can be noticed that solar downward radiation seems to have a somewhat gaussian distribution look whereas the rest of the variables considered were completely skewed (i.e., non-symmetric), necessitating thorough cleaning, adequate data normalization and standardization before modelling. Exploratory analysis shown in heatmap of Figure 6 further showed that PV output expected to be predicted has strongest correlation with Solar downward radiation with a factor of 0.9, followed by relative humidity and cloud cover respectively. Therefore, further investigation was carried out to determine the extent each input variable affects the outcome of the prediction result of the PV output.

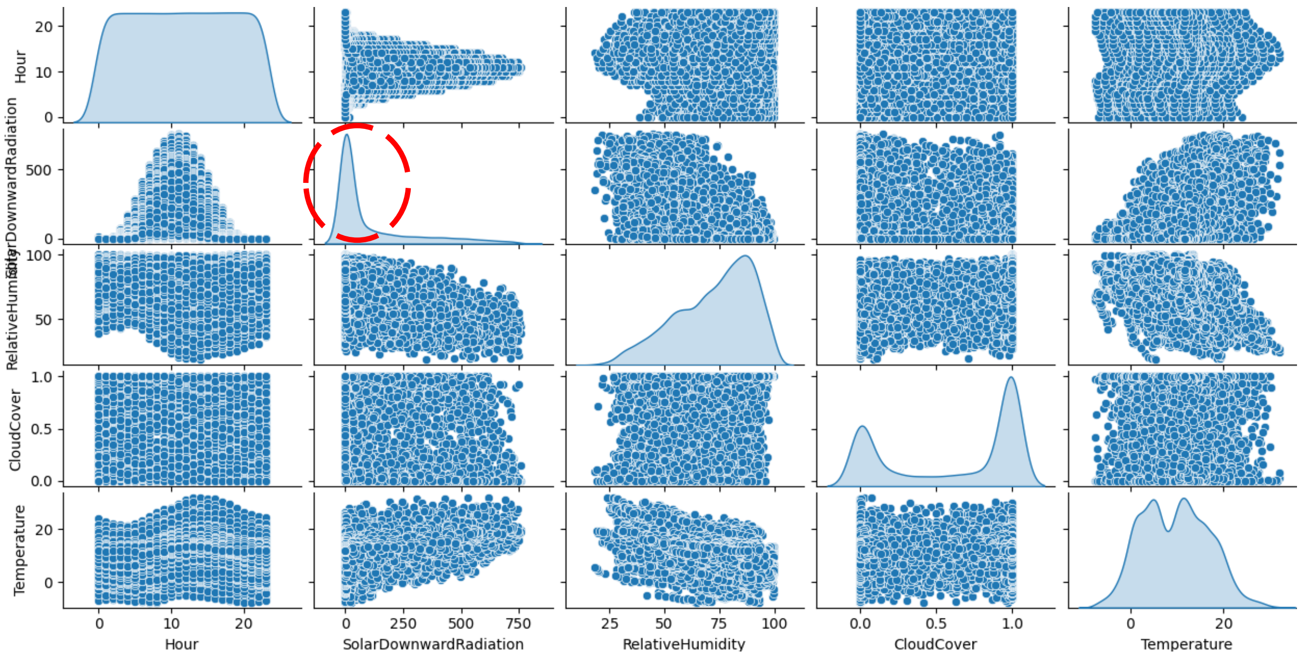


Figure 6. Correlation Distribution of PV Forecast Variables

Data preprocessing stage is an important stage of AI-based modelling because it transforms the raw data into efficient format to enhance the performance of ML algorithms. Our data preprocessing involves two steps of data cleaning and normalization. The cleaning step involves handling of missing data and noisy data. There were large intervals of missing data in the dataset, thus, they were handled by replacing them with *NaN* values which the algorithm would ignore, rather than interpolating. The noisy data and outliers are handled by omitting data larger than the maximum production. Furthermore, in some intervals the data were repetitive or oscillating in a small interval, these data were replaced with *NaN* values as well. To complete the data preprocessing, the time series were scaled between -1 and 1with the equation (2) and then the output of the neural networks is scaled back.

$$x_{scaled} = 2\frac{x - x_{min}}{x_{max} - x_{min}} - 1 \tag{1}$$

where, x_{max} and x_{min} are the maximum and minimum points of the time series, respectively.

3.1.1 Data Normalization

The fact that power generation and consumption is purely a stochastic process, predicting their patterns or modelling them is often a herculean task but not impossible. These type of timeseries have some hidden patterns which can be predicted. The variables in the dataset used for the modelling have difference scales and can sometimes go beyond zero like the meteorological data that constitutes about 80% of the dataset. This called for data normalization carried out. In the implementation of these models, each n-sized window of training/testing data is normalized (i.e., making data at point *i* = 0 to always be 0) to reflect percentage changes the start of that window. However, for PV variables, the normalization range is -1 to +1.

$$\text{Normalization } (N_i) = \left(\frac{Pi}{Po}\right) - 1, \tag{2}$$

$$\text{De-Normalization } (P_i) = Po(ni + 1), \tag{3}$$

where N is normalized data and P is raw data.

3.2 Data-driven approach

For proper energy flexibility modelling, modelling of different spatial-temporal resolutions data of multiple energy carriers (heating, electricity) and energy generating system (PV) was carried out and their forecast results reported. A data-driven method was adopted where a persistence model was developed and used as a performance reference, and other neural networks approaches compared against this baseline model. Furthermore, comparative analysis of the performance of the models against state-of-the-art models was performed. Data-driven models like neural network models formulate a model based on features learned from existing data making them most appropriate for time series forecasting. They are popular because of their high performance. The research gap in neural networks is centred on capturing the dominant factors in the data that need to be learned, as well as reducing the size of the model, increasing its inference time. Applying neural networks solution usually require training of large amounts of data. Given this, the resulting model size is usually big, requiring lengthy processing time.

Problem of large number of trainable parameters sometimes makes neural networks models consume much computer resources and unimplementable in low-processing devices. For an instance, [27] utilized 539,001 trainable parameters for LSTM network for 24hours energy consumption forecast. It is not enough to have an accurate prediction model without the ability to operate on resource-constrained low-power devices without latency problem. Experimentally illustrated facts have shown that the model size affects its inference time, so the smaller the model size the faster the computational speed [28, 29]. The availability of high-speed Graphics Processing Units (GPUs) in labs gives greater performance for models with larger trainable parameters, but these models are unusable in many real-world applications especially when implemented on resource-constrained devices.

3.3 Machine learning models

Aggregated Deep Belief Networks (DBNs) outputs using the Support Vector Machine (SVM) algorithm, reported in [7], outperformed benchmark methods such as Support Vector Regression (SVR), feedforward Neural Networks (FFNN), DBN and ensemble feedforward Neural Networks. The model compression algorithm implemented in the current work addresses the challenges of cost, power, heat, and other related issues, all of which will be elaborated in the methodology discussion.

3.3.1 Horizon of forecasting

Different categories of forecasting horizon are applicable to the 3 components of forecasts in this report. There are three major standards of forecasting: short-term forecasting (STF), medium-term forecasting (MTF) and long-term forecasting (LTF), though the fourth leg which is very-short-term forecasting is now added. However, the forecast reported here is based on short-term forecasting (STF) and medium-term forecasting (MTF). In short-term forecasting, forecast has a prediction period ranging from minutes to hour. Short-term forecasting is used in real/near real time dispatch and control of power systems [30]. Short term forecasting time horizon is between 30-minutes to 360- minutes [8], however, one to several hours is regarded as a short-term forecasting horizon in some literature [8]. The prediction with this horizon is highly beneficial to economic load dispatch and energy management of power systems. Medium-term time horizon spans from 6 to 24-hours and is suitable for dispatch and planning of power systems [8, 30] [31]. Long term forecasting corresponds to prediction time intervals with more than 24-hours [30]. Such forecasts are essential for long term planning.

In GENTE, PV forecasts as well as load and heat forecasts will be used for both long term planning and short-term management of the resources of the LEC. It will aid in building of a demonstrator with load control with optimized environmental footprint, enabled by advanced control of heat pumps, and energy storage that can match a building's energy demand with local generation and energy storage devices in near real-time. Considering the different type of storages (thermal energy storages and battery energy resources) with different dynamics, near-real time and day-ahead energy management is developed. Consequently, based on the available data, PV generation, heat and load forecasts is performed for short-term i.e., 1-hour, and medium term i.e., 24-hours in advance. According to these forecast horizons, relevant features are identified and the associated measured historical data or predicted weather data are collected for the development of the machine learning based forecasting algorithms.

3.3.2 Short-term (1 hour ahead) prediction

Based on the feature engineering analysis conducted on variables influential to both energy generation and consumption using Pearson correlation coefficient test, the best features based on their coefficient factor were selected among the potential features as presented in Table 3. This prediction is based on two-step modelling chain, where the first step is the prediction of meteorological variables using Numerical Weather Predictions (NWP) [15].

Table 3. Features selected for 1-hour ahead PV generation prediction

Feature	Description
Hour of day	Numbers presenting the hour of the day
Month of year	Numbers presenting the month of the year
Direct solar radiation	Surface Solar radiation (W.m-2)
Humidity	Relative humidity at 2m (%)
$\boldsymbol{y_{t-1}}$	Last hour PV generation

For the 1 hour ahead prediction various methods including neural networks like LSTM, ConvLSTM, and GRU were implemented, and the neural networks were selected as the ML algorithms. The random forest regression (RF) method was selected rather than linear regression methods such as ARIMAX for comparison since it models the PV power generation as a multi-input-single-output system and can catch the nonlinearity of the PV generation.

$$\begin{aligned} x_{n+1} &= Ax_n + Bu_n + Ke_n \\ y_n &= Cx_n + Du_n \end{aligned} \tag{4}$$

Where, u_n is input vector, y_n is the output vector, and x_n is the state vector. To forecast the PV power generation in n-step head, the vectors of A, B, C, D, and K should be identified [32].

3.3.1 Medium-term (24 hours ahead) prediction

It is expected that a day-ahead prediction could be a useful input for scheduling of energy management systems, hence, predictions made from time step t+1 to t+24, at t = 1hr. To achieve this type of prediction, two approaches can be used: use of previous 24hour data by resampling a minute-wise or hourly data to daily or doing a multistep hourly prediction for 24hours. The training data was resampled to daily, and a day previous PV output used as an input time series for t+1 prediction. Unfortunately, the historical data of the previous hours actual values are not always available for all timesteps of the 24-hour horizon. Similarly for the last hour of the horizon i.e., t+24 only the last predicted values are accessible, and no previous time step actual value is available.

Consequently, a multi-step ahead approach was followed in framing 24-hours ahead prediction problem. The input to Machine Learning algorithm is a time series which the forecasted values of the ML itself is used as the input for the next timesteps

3.3.2 Algorithms and modelling

As mentioned earlier, short term i.e., 1-hour, and medium term i.e., 24-hour is forecasts is performed in this GENTE work package. Since the available data/features in the realization of the forecast algorithm for each forecasting horizon is different, the most suitable Machine Learning method for forecasting them must be selected uniquely for every forecast horizon and time-step. Importantly, several machine learning algorithms were tried using different supervised learning methods before settling for the selected ones used in the models for each forecast horizon presented in this report.

3.3.3 Feature selection

In this section initially potential features for the Machine Learning methods are identified and then the approach toward selecting them is described. The determining features for the outputs of forecasts reported here can be categorized in three groups: calendar features, meteorological features, and historical features. Calendar or time features including hour of day and month reflect the seasonality and the daily pattern of the PV output. Meteorological features such as downward solar radiation, temperature, humidity, wind direction and speed, affect the output power of the PV plant. Similarly, the previous timestep data of the PV output has shown to have high level correlation with the predicted sample, hence, the choice of imputation technique leveraged during data cleaning.

In this project, the weather features are retrieved from rebase energy weather API (Application program interface) [12]. The API serves endpoints from different numerical weather predictions (NWPs) and reanalysis models. Based on the geographical coverage and resolution the MEPS NWPs are selected to retrieve the weather features. It should be noted that due to limited access and proximity of the PV sites to each other, the weather features are collected for a location in center of Chalmers University of Technology and used for all PV sites. Eight weather features including cloud cover, pressure, relative humidity, solar downward radiation, temperature, total perception, wind direction and wind speed are obtained by the NWP model and can be potential candidates for the neural networks. To determine the relationship between PV generation and the individual weather features, Pearson Correlation Analysis (PCA) were employed. PCA method evaluates the linear relationship between two variables by computing the correlation coefficient by (1) [33]:

Pearson's linear correlation coefficient two variables, x and y is defined as:

$$r_{x,y} = \frac{\sum_{i=1}^{n}(x_i - \overline{x_i})\,(y_i - \overline{y_i})}{\left[\sum_{i=1}^{n}(x_i - \overline{x_i})^2 \sum_{i=1}^{n}(y_i - \overline{y_i})^2\right]^{1/2}} \tag{5}$$

Where $\overline{x_i}$, $\overline{y_i}$ and n are the mean and sample size, respectively, x_i and y_i are the individual sample points indexed by i. Values of the correlation coefficient can range from –1 to +1. A value of –1 indicates perfect negative correlation, while a value of +1 indicates perfect positive correlation. A value of 0 indicates no correlation between the variables. The heat map of Figure 7 provides the correlation between PV generation and weather features.

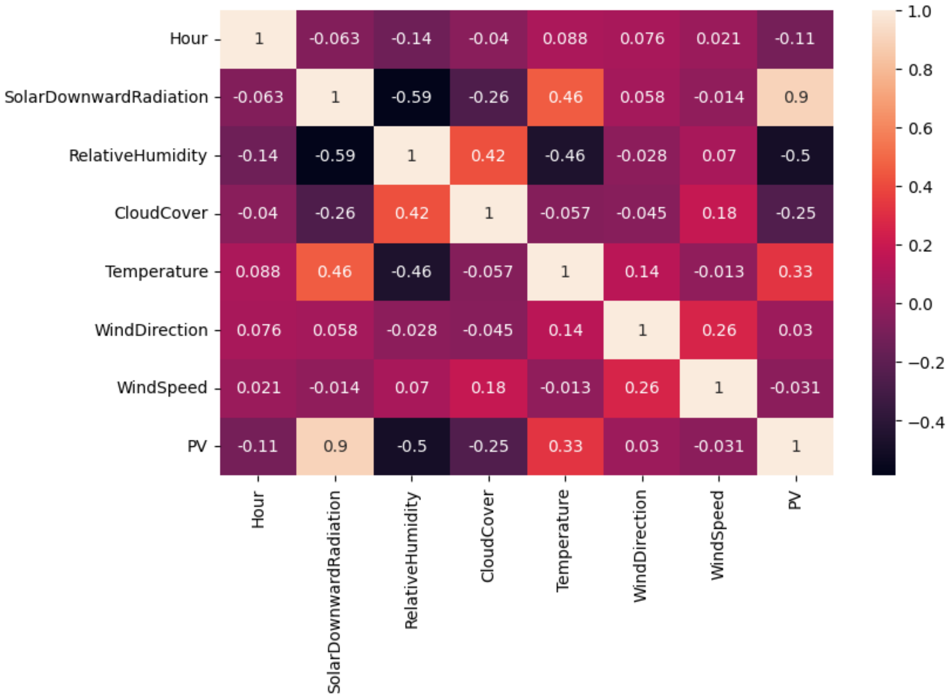


Figure 7. correlation heat map of the data variables

The heatmap clearly showed that solar radiation has the highest correlation followed by relative humidity. This pre-processing analysis is important because it changed the null hypothesis that cloud cover, wind speed and direction have greater correlations PV generation. From the autocorrelation analysis, it was noticed that the highest correlation of PV generation with solar irradiance occurred between the current time step and the 1-hour and 2-hour lagged points in time. Implying that these two-time delays (1 hour and two hour) can be potential features for the prediction. However, 24 hour and 48 hours were also considered based on the result of feature engineering carried out using Grid Search method to determine how these variables changes with PV output. Hour and month were selected as calendar features to show both daily and season patterns.

From the Pearson correlation analysis, Table 4 showed the variables with their importance values and Figure 10 showed the bar chart. The result showed that wind direction and wind speed have little or no significance, hence, they were dropped in the modelling stage.

Table 4. Correlation Feature Selection

Hour Feature: 0	S. Radiation Feature: 1	R. Humidity Feature: 2	CloudCover Feature: 3	Temp. Feature: 4	W. Direction Feature: 5	WindSpeed Feature: 6
82.3590	28810.7816	2276.7948	442.3754	774.2654	6.7311	5.8159

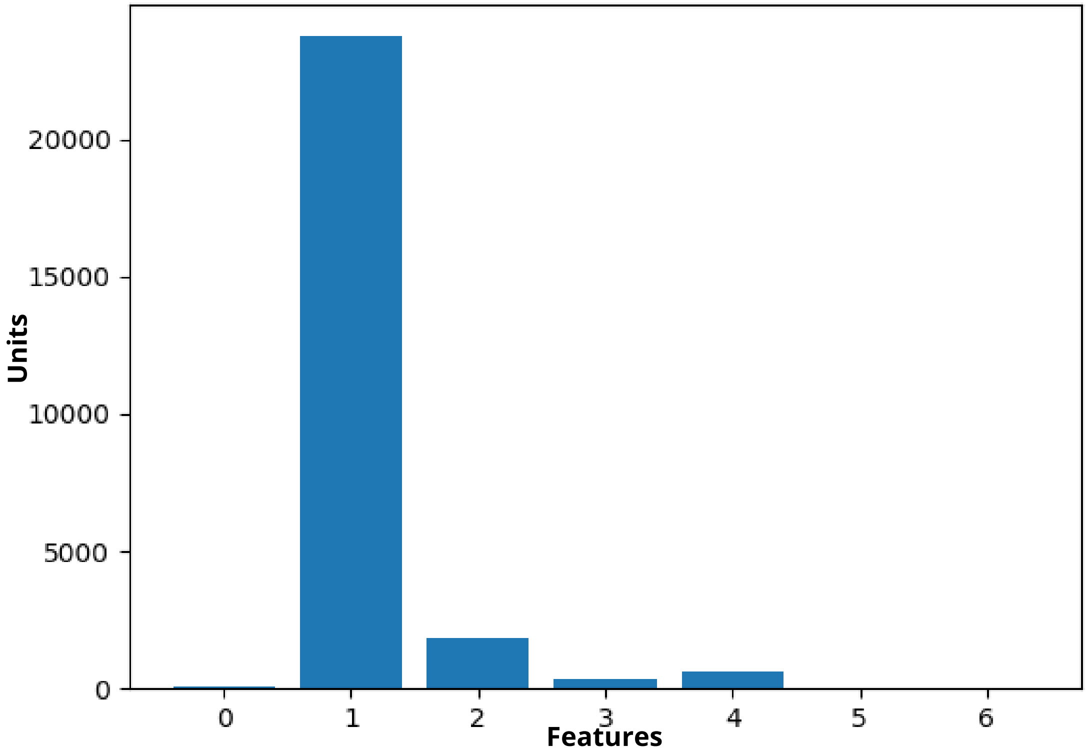


Figure 8. Bar Chart of the Input Features (x) vs. Correlation Feature Importance (y)

The plot in figure 8 clearly shows 1, 2, 3 and 4 features are a lot more important than the other features. Consequently, 5 and 6 features were dropped because of their insignificance, since the larger the positive value, the larger the relationship, and, more likely, the feature should be selected for modelling.

3.4 Model Configuration

Designing a model to solve a regression problem like forecasting requires series of considerations like deployment environment, the size of dataset and how to make the model adaptable to a new dataset. Based on success recorded by neural networks algorithms in the past, LSTM, GRU and ConvLSTM became the choice. The next step after putting appropriate considerations onboard is the process of scanning the data to configure optimal parameters for the proposed model. This process can be done automatically (grid searching) or manually (hyperparameter or optimization tuning). The architecture of the best performing network (LSTM) as shown in table 5 has 8 input dimensions with 1 output layer, 3 hidden layers. Also, the architecture of the combination of Convolutional Neural Network (CNN) and Long Sort-Term Memory (LSTM) has similar configurations. While the input transformations and feature map extraction take place in the convolutional layers, the resulting out is convolve and read into LSTM units. Because the input data is a 1-D sequence, it was easy for the interpretation over the number of time steps. The LSTM has 3 hidden layers with 4 gates that handles updates and memory functions of the network. As the gates receives both the input (output from the last convolutional or hidden layer) obtained at previous time step (h_{t-1}) and the related current time step (x_t), they are concatenated to be used as input to the next time step. For the GRU, additional gate called reset gate is included and it regulates the relevance of past recollections, and the update gate.

Table 5. Model Configuration and its parameters

Models	**Configurations**		
	Layer (type)	**Output Shape**	**Parameters**
LSTM	LSTM, Dropout, dense and call-back	8 input dimensions with 1 output layer	**43200**
GRU	Module wrapper, dropout, dense	8 input dimensions with 1 output layer	124200
ConvLSTM	ConvLSTM2D, Flatten, LSTM, RepeatVector	8 input dimensions with 1 output layer	50176

3.4.1 Feature Learning process

Neural networks normally learn its features using either forward or backword propagation. But for the models implemented, backword propagation was used because it enabled error committed in the prediction (forward) phase to be injected into the network and the parameters (*W* and *b*) updated so they can perform better on the next iteration as shown in Figure 9. Once these parameters which can be regarded as the model coefficients are initialized using the activation function (ReLU), the algorithms will start learning the features in the data sequentially. While learning, it periodically optimizes these coefficients and return arrays of parameters which minimizes the error.

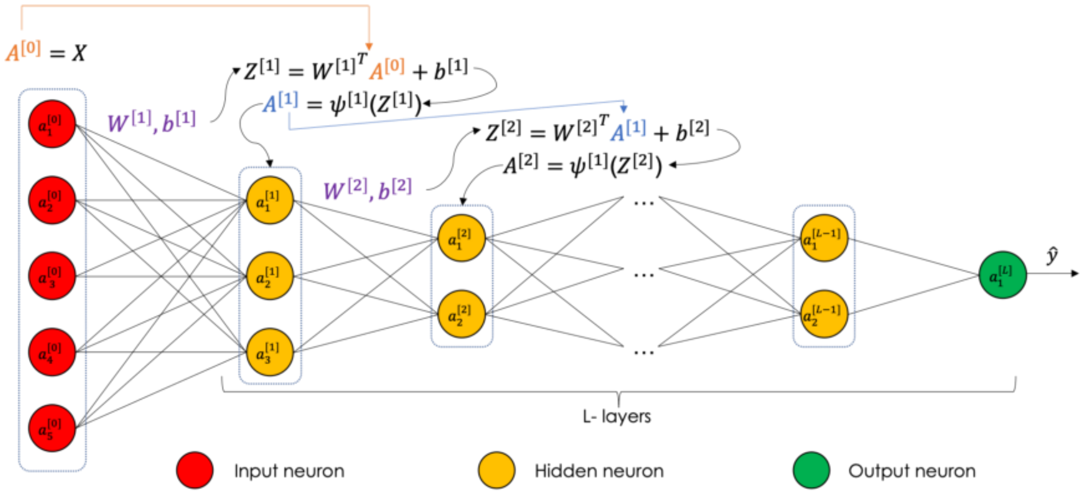


Figure 9. Structure of Neural Networks and its layers

3.4.2 Model Regularization

The need for regularization is to address challenges of overfitting and error generalization inherent in time domain neural networks. Problem with learned features is that they can be too specialized to the training data or overfit, and not generalize well to new examples. Dropout which has been a common technique in deep learning helps to block out random set of unit cells during model training. Network structure optimization and parameters tuning is carried out instead of grid searching because of the large dataset. A rectified linear unit (ReLU) is used for activation. ReLU is one of the most notable non-saturated activation functions. The ReLU activation function is defined as: ai, j, k = max (zi, j, k, 0), where zi, j, k is the input of the activation function at location (i, j) on the k-th channel. ReLU is a piecewise linear function that output the input directly if it is positive but prunes the negative part to zero if otherwise.

On the hand, addressing the problems emanating from the non-stationarity of the variables used in the model necessitated data standardization and normalization. For the PV, the data was scaled between -1 to 1 because the meteorological variables change rapidly with time, while electricity and heat load are scaled between 0 to 1 even though some of their variables are weather variables.

3.4.3 Model Parameters

Google Colab TPU and Keras® (one of the finest neural network APIs) with its backend TensorFlow were used as the development environment and programming language is python. Based on validation result, the model for each of the area of forecast carried out significantly outperformed the baseline model. As stated earlier, 3 neural networks algorithms with different model configurations and parameters were used for the 3 areas of forecasting carried out. For the LSTM model, a total of 250 neurons (100 at first layer, and 50 neurons at each hidden layer) and 1 in the output layer used for predicting PV generation, electricity load, and heat load in HSBLL. The first layer of the ConvLSTM architecture consists of a network with filter output size of 64, kernel size of (1, 3), Dropout of 50% of the layers, Input shape of 2 time-steps with 8 features, Mean Square Error loss function and Adam version of stochastic optimization gradient. The model was fit for 20 training epochs at batch size of 64.

3.5 Model Validation and Evaluation

In this work, the final model is made to make predictions for new data with unknown outcome. The model employs a novel moving Walk-forward validation approach as shown in Figure 10, (where the model makes a forecast for each observation in the test dataset one at a time by adding up the true observation for the current time step as part of the input for making prediction on the next time step) is used. Actual input data from previous hour and a day timesteps were used to make an hour and 24hrs ahead predictions respectively. This type of validation is crucial to enable model performance to be assessed by recursively augmenting the training data with recent observations and re-evaluating the model over extended horizon [34]. It is can as well be applied even when test data is not a representative sample of the entire dataset and are significantly different from data used for model training.

During model training, it is expected that the error for the current state of the model must be estimated repeatedly. Adam version of stochastic gradient descent was used to optimize the mean squared error ('MSE') loss function by estimating the training loss so that the weights can be updated to reduce the loss on the next evaluation. MSE is the default loss function for regression problems, and it is preferred mathematically under the inference framework of maximum likelihood if the target variable has Gaussian distribution. This type of models' loss function makes the larger mistakes result into more error than smaller mistakes, meaning that the model is punished for making larger mistakes.

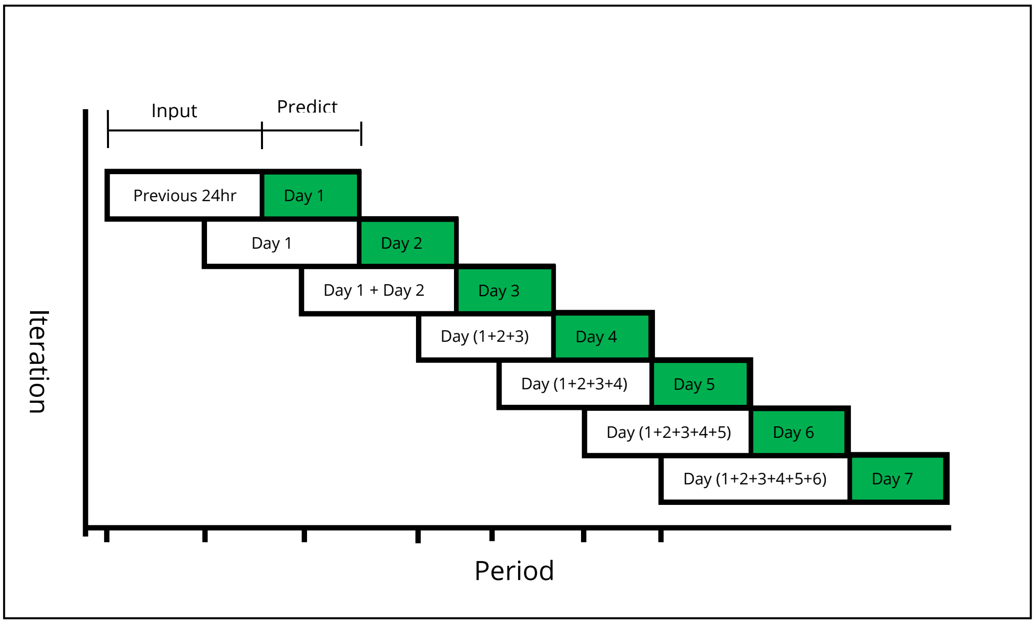


Figure 10. Walk-forward Validation

4. PV, Load and Thermal Heat Demand at HSBLL

4.1 Forecast Result Analysis on HSBLL Datasets

As mentioned earlier, the forecasting reported here is demonstrated using two different datasets emanating from different locations. It is imperative to note that the result analysed so far only contain the testing done using HSBLL dataset. That of Alingsas HEM will be included in the comprehensive report. The performance evaluation metric for assessing forecasts is based on five major standard error measurements: Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Coefficient of Determination (R^2). These error metrics are the most suitable and commonly used metrics for PV, electricity, and heat load forecasting, and they are also widely applied in neural networks models evaluation. Secondly, both error metrics use the same scale as the measured data, which implies that the error is of the same unit with the predictions and can range from 0 to ∞.

4.1.1 Root Mean Square Error (RMSE)

Root Mean Square Error (RMSE) is a popular quadratic scoring rule that measures the average magnitude of the error. It is the square root of the average of squared differences between prediction and actual observation.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2}, \qquad (6)$$

where x_i is the observed data, y_i denotes the predicted data, e_i is the arithmetic average of the absolute error, and n is the number of observations. This takes the variation between the predicted and actual values, square it up due to positive and negative difference that may arise, and obtain the means to aggregate all the unseen data and finally square root it to counterbalance the square operations.

4.1.2 Mean Absolute Error (MAE)

This type of error metrics also measures the average magnitude of errors in each set of predictions, without necessarily considering their direction. MAE is sometimes termed Mean Absolute Deviation (MAD) and it shows the magnitude of overall error in data points, in the cause of the forecast. It is the average over the test sample of the absolute differences between prediction and actual observation where all individual differences have equal weight.

$$MAE = \frac{\sum_{i}^{n} | x_i - y_i |}{n} = \frac{\sum_{i}^{n} | e_i |}{n} \qquad (7)$$

where e_i denotes the arithmetic average of the absolute error. This is also known as a scale-dependent accuracy measure, so it will be illogical to make comparisons between this metric and other series using different scales. The mean absolute error is commonly used for the measurement of forecast error in a time series analysis. It is less susceptible to outliers compared to MAPE and RMSE.

4.1.3 Mean Absolute Percentage Error (MAPE)

The mean absolute percentage error is the measure of the level of accuracy of a forecast system in terms of percentage. Mean absolute percentage error (MAPE) is commonly used as a loss function for regression tasks and model evaluation because of its interpretation in terms of relative error. It measures the forecast error and performs optimally if there are no extremes to the data (and no zeros). It can be calculated as the average absolute percent error for each time-period minus actual values divided by actual values.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right| \text{ x } 100 \qquad (8)$$

where n is the number of fitted points, and A_t is the actual value, while F_t is the forecast value. The summation for the absolute value is done for every forecasted point in time and divided by the number of fitted points n. This performance metric is independent of the scale of measurement, yet it is affected by data transformation.

4.2 PV Hourly Forecast Analysis

In analyzing the PV, all evaluation metrics were not utilized because several PV output time-steps have zero values at night hours, therefore normalized index such as MAPE was not included in the metrics of evaluation to avoid infinite values. From the models training loss shown in figure 11 (a), unstable training trajectory was experienced immediately after initialization of the model for training, which could be likened to overfitting in the training data, but the overall performance is good based on validation as highlighted in figure 11 (b). The model was validated with 7day i.e., 168hrs test dataset. The plots showed that the training error decreases sharply after commencement of training before it became almost linear because of the model's complexity. From the result shown in Table 6, LSTM model outperformed others virtually in all metrics considered with least error, and with highest correlation between predicted and actual values.

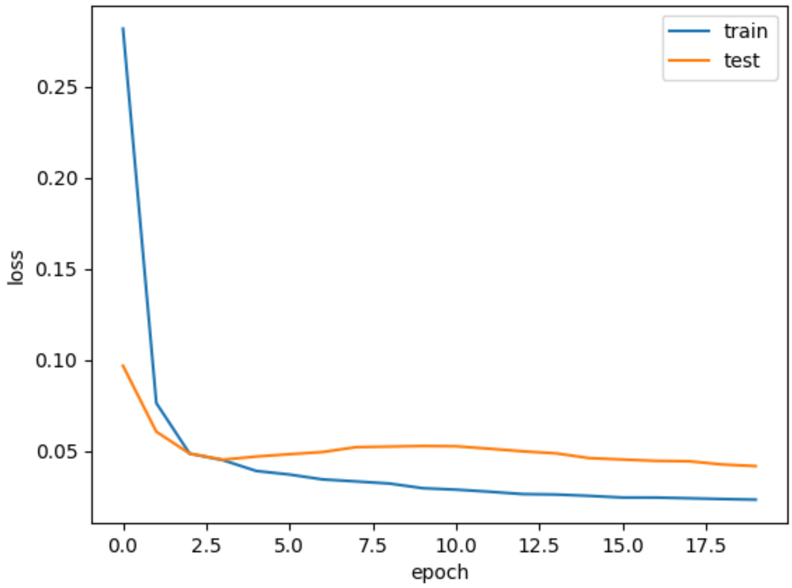
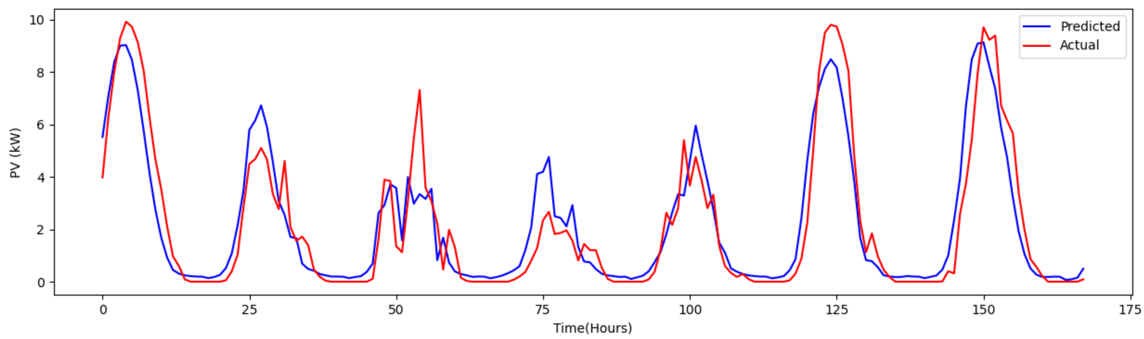


Figure 11. (a) Training Loss on PV forecast



(b) Model Prediction Error on PV forecast

Table 6. Result of PV Forecast Evaluation across different metrics

Models and their performances on PV Generation data			
	LSTM	**GRU**	**ConvLSTM**
MAE (kWh)	**0.6662**	0.6677	0.6409
MSE (kWh)	**1.1572**	1.3364	1.2936
RSME (kWh)	**1.0757**	1.1560	1.1374
MAPE	**-**	-	-
R^2	**0.9267**	0.9148	0.9230

4.3 Electricity Hourly Load Forecast Analysis

Since all time-steps of the electricity load have a value greater than zero, normalized index such as MAPE was included in the metrics of evaluation. From the models training loss shown in fig 12 (a), sharp training loss and instability was experienced during training, but the performance is good as highlighted in figure 12 (b). The gap between training and test loss is so insignificant. The plots showed that the training error decreases sharply after commencement of training before it became linear because of the model's complexity, likewise the validation error. To validate this model, 168hrs (7days) data was used and the result showed increased test set does not necessarily affect the model performance. Table 7 showed that LSTM is considered a better model for electricity load since it has the least percentage error.

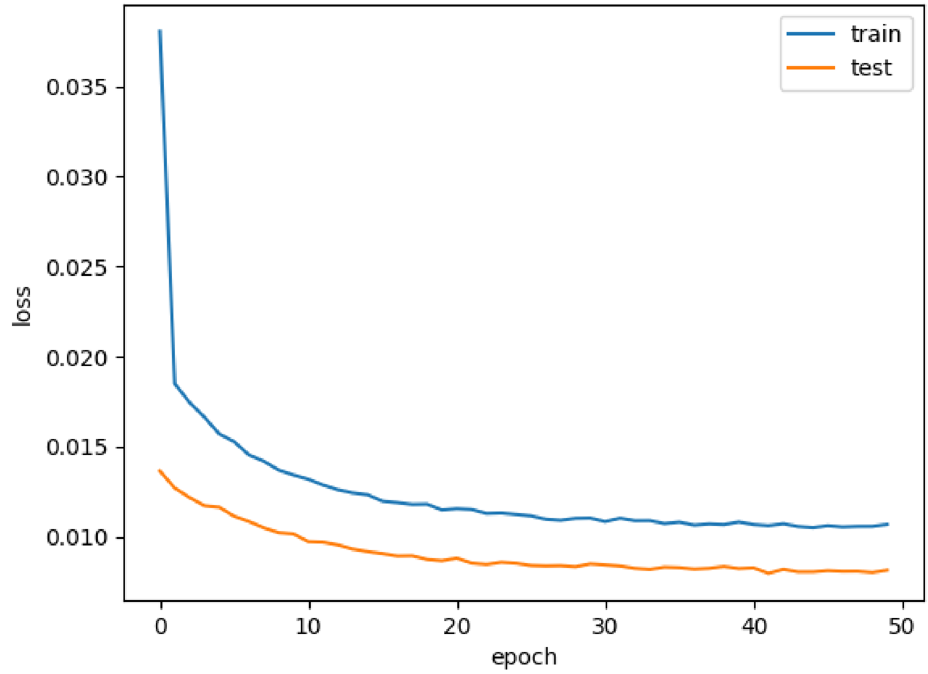
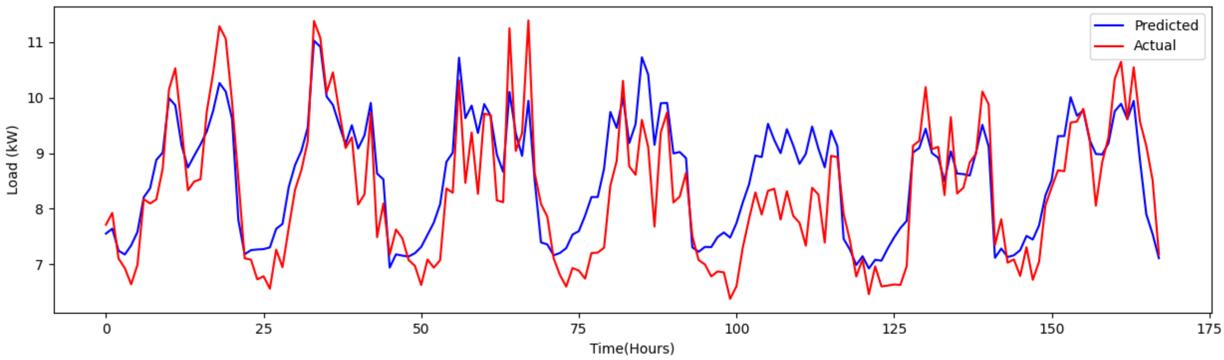


Figure 12. (a) Training Loss on Electricity Load



(b) Model Prediction Error on Electricity Load

Table 7. Result of Electricity Load Forecast Evaluation across different metrics

Models and their performances on Electricity Load data			
	LSTM	**GRU**	**ConvLSTM**
MAE (kWh)	**0.8417**	0.8693	0. 8615
MSE (kWh)	**1.4487**	1.4305	1. 5281
RSME (kWh)	**1.2036**	1.1960	1. 2361
MAPE	**7.8306**	8.4633	7.9883
R^2	**0.8505**	0.8543	0. 8434

4.4 Heat Hourly Load Forecast Analysis

In analyzing the Heat Load, MAPE was not included in the metrics of evaluation to avoid infinite values brought about by zero or near zero values especially from the weather variables used in the model. As shown earlier in Figure 5 of the heat transfer analysis, temperature and heat load can at some certain periods have zero values due to seasonality. From the models training loss shown in fig 13 (a), training loss experienced a sharp drop immediately after initialization and tends towards linearity as the training progressed down the epochs. The model performance was validation with 168hrs test dataset as shown in Figure 13 (b). The evaluation report of Table 8 showed that GRU model outperformed others in all the metrics evaluated.

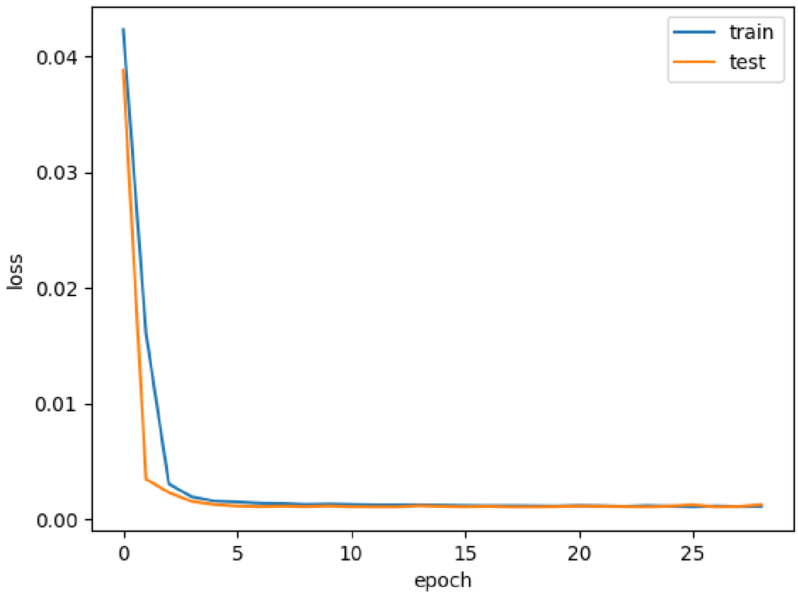
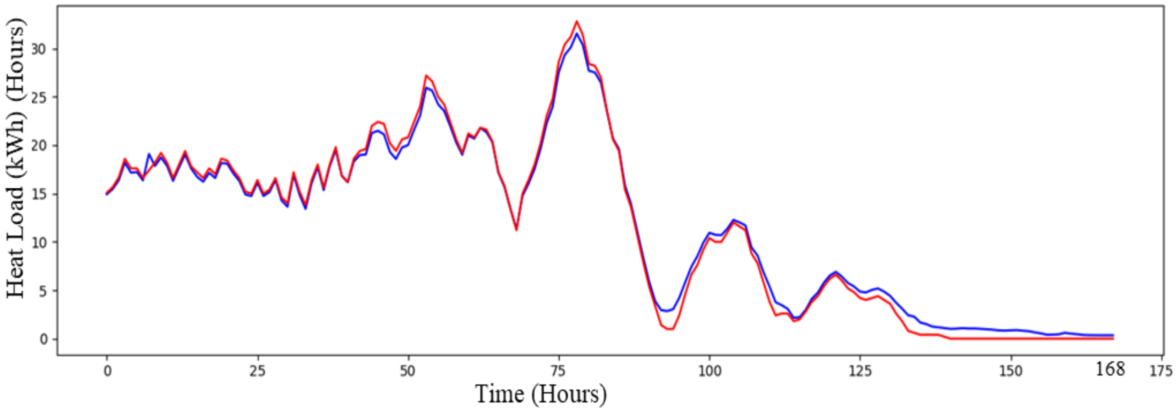


Figure 13. (a) Training Loss on Heat Load



(b) Model Prediction Error on Heat Load

Table 8. Result of Heat Load Forecast Evaluation across different metrics

Models and their performances on Heat Load data			
	LSTM	**GRU**	**ConvLSTM**
MAE (kWh)	1. 4312	**1.1852**	1.6240
MSE (kWh)	3. 8943	**2.3926**	4.6223
RSME (kWh)	1. 9734	**1.5468**	1.8327
MAPE	-	-	-
R^2	0. 9769	**0.9772**	0.9642

4.5 24-Hours ahead PV Forecast Analysis

For the 24hrs ahead forecast horizon, the last 24-hour historical data as well as the previous data before that i.e., $y_{t-24}, y_{t-25,..}$ were combined with the predicted weather data and fed to the neural network algorithm as input. Figure 14 showed the PV predictions for the period of 24hours against the real PV output generated. To further investigate the effect of the timesteps in the model performance, a 60hrs prediction was made using previous t+1 to t+60 as shown in Figure 15 and subsequently a 150hrs prediction as shown in Figure 16. It was discovered that model accuracy was reducing instead of increasing as the timestep increases. Juxtaposing this to the hourly forecast performance, the justification for best performance hourly predictions is made.

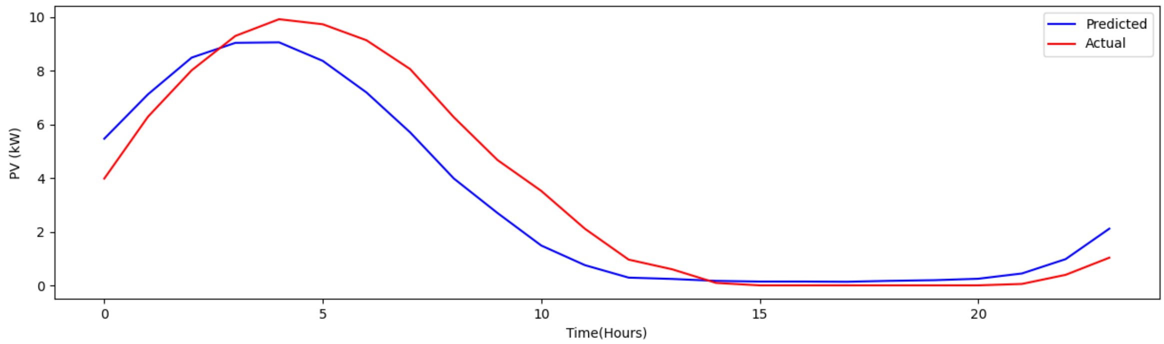


Figure 14. 24-hours ahead PV Prediction

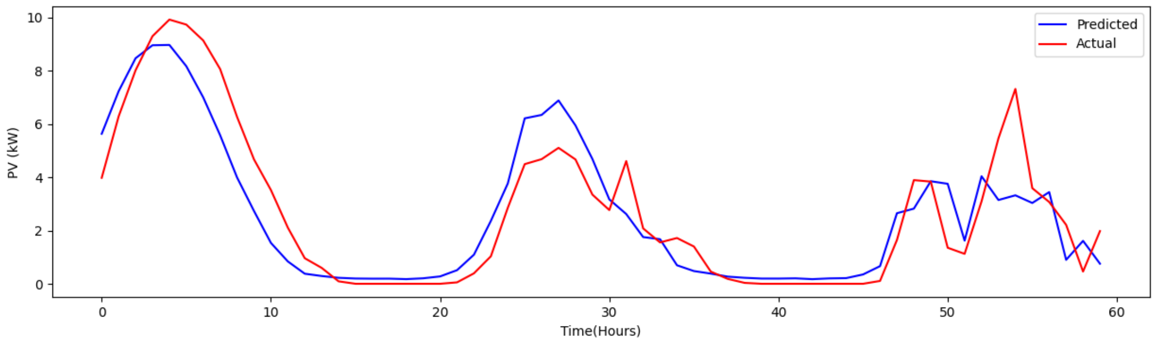


Figure 15. 60-hours ahead PV Prediction

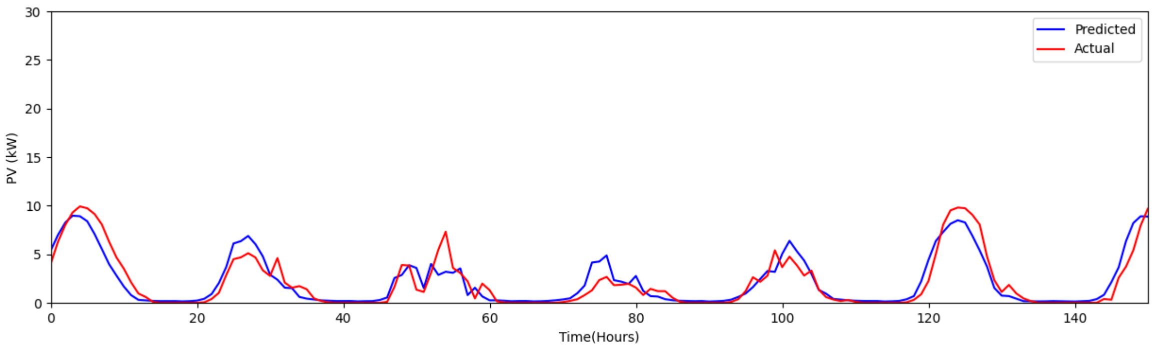


Figure 16. 150-hours ahead PV Prediction

From the overall result analysis across the two horizons forecasted, it was discovered that LSTM performed best in PV and electricity load forecasting followed by ConvLSTM, while GRU outperformed all the tested models in Heat Load forecasting. Our forecast approach achieved error improvement of 12% over statistical time series models. Aside the performance improvement of the model's prediction, it also demonstrated scalability, fast to train and can be augmented to provide outputs that are interpretable without considerable loss in accuracy.

To further confirm the accuracy of the model, 24 hours ahead PV and Electricity Load forecast was made, and the predicted values were plotted against the real values upon their availability a day after as shown in Figures 17 and 18. And an average of **97.29%** accuracy was achieved.

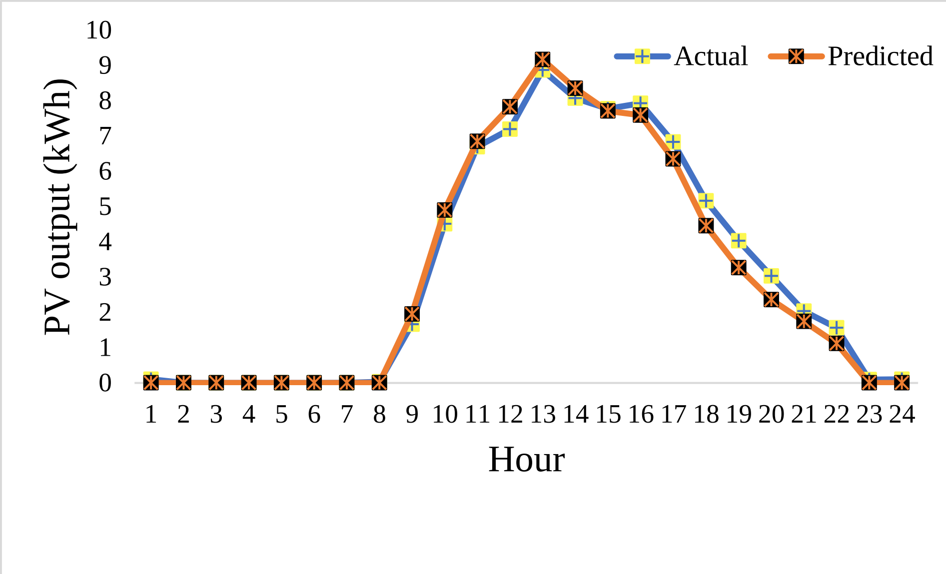


Figure 17. Predicted PV Output Vs real Load (24hrs) – 28/05/23 to – 29/05/23

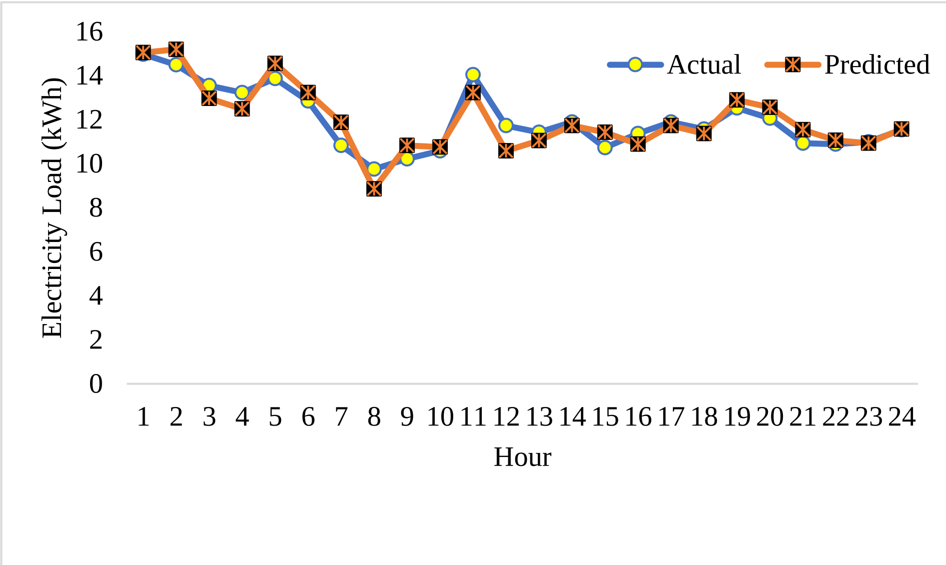


Figure 18. Predicted Electricity Load Vs Real Load (24hrs) – 28/05/23 to 29/05/23

4.6 Model Optimization

To further consolidate the best performing model adaption to lag hours and features variation in predictions, the weather variables for the hour to be predicted (t) was removed from the last 24 hours used as lag variables. The supervised learning was framed with 4 lag hours and 8 features. A neural network with three hidden layers comprising of 120 nodes in the first layer, 160 nodes in the second layer and 120 nodes in the third layer is designed for training of the model. From the validation loss of Figure 19, instability in training and testing was observed but the overall error did not increase rather reduced significantly. This showed the model robustness in learning the training data and accuracy in prediction.

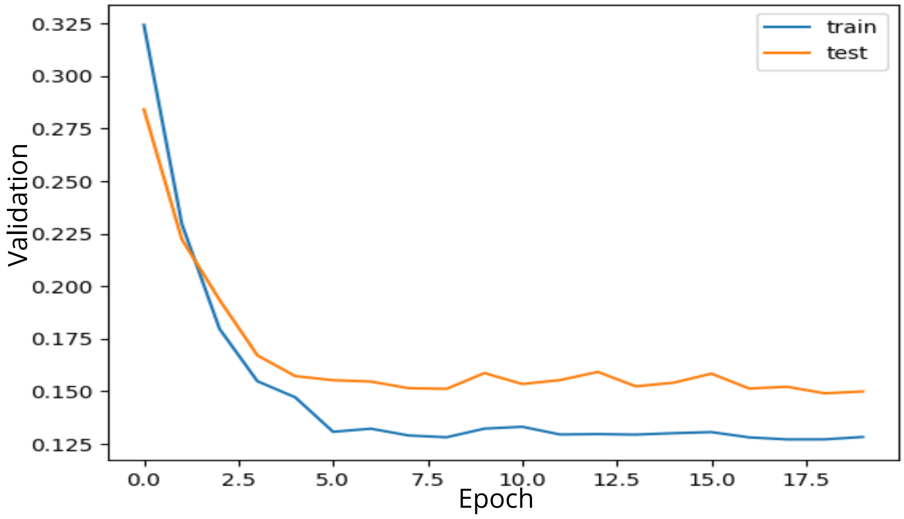


Figure 19. Loss for hourly prediction without weather variables for the hour to be predicted (t)

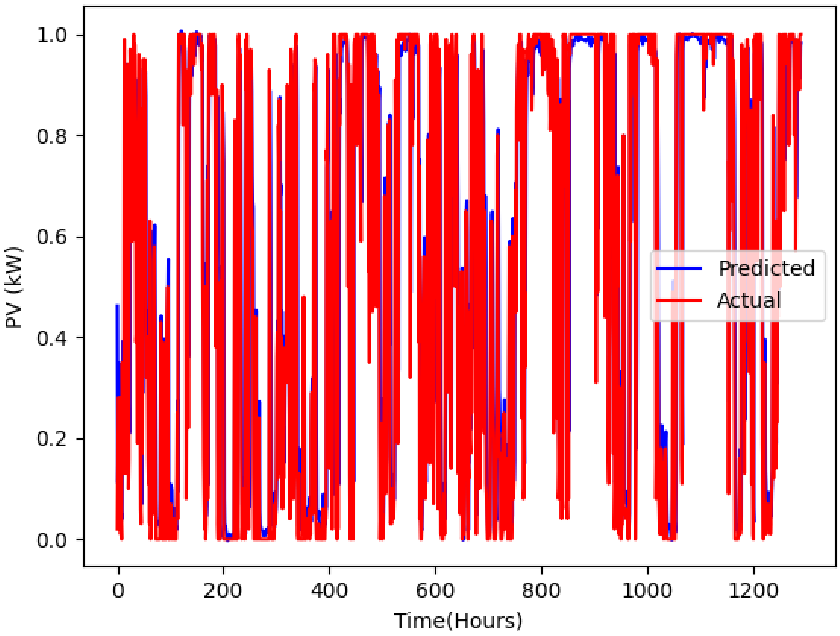


Figure 20. Actual vs Predicted values using 1280 hours test data

5. Model Exploitation

Flowchart for the effective deployment of the models is shown in Figure 21. Exploitation of these model required some software requirements' satisfaction as Figure 21 block 1. It is expected that computer resources like Python SciPy development environment is installed, ideally the Python 3. Also, it is required that Keras (2.2 or higher) is installed with either the TensorFlow or Theano backend. This high-level TensorFlow API provides interface for machine learning with focus on deep learning specifically in the areas of computation, scalability, and cross-platform capabilities. This forecast is implemented using a famous Google cloud service for artificial intelligence developers and researchers called Google *Colab* with python 3 as the runtime type and TensorFlow processing unit (TPU) as the hardware accelerator. It can as well be implemented on on-premises as well as web-based interactive computing platform called *Jupyter* notebook.

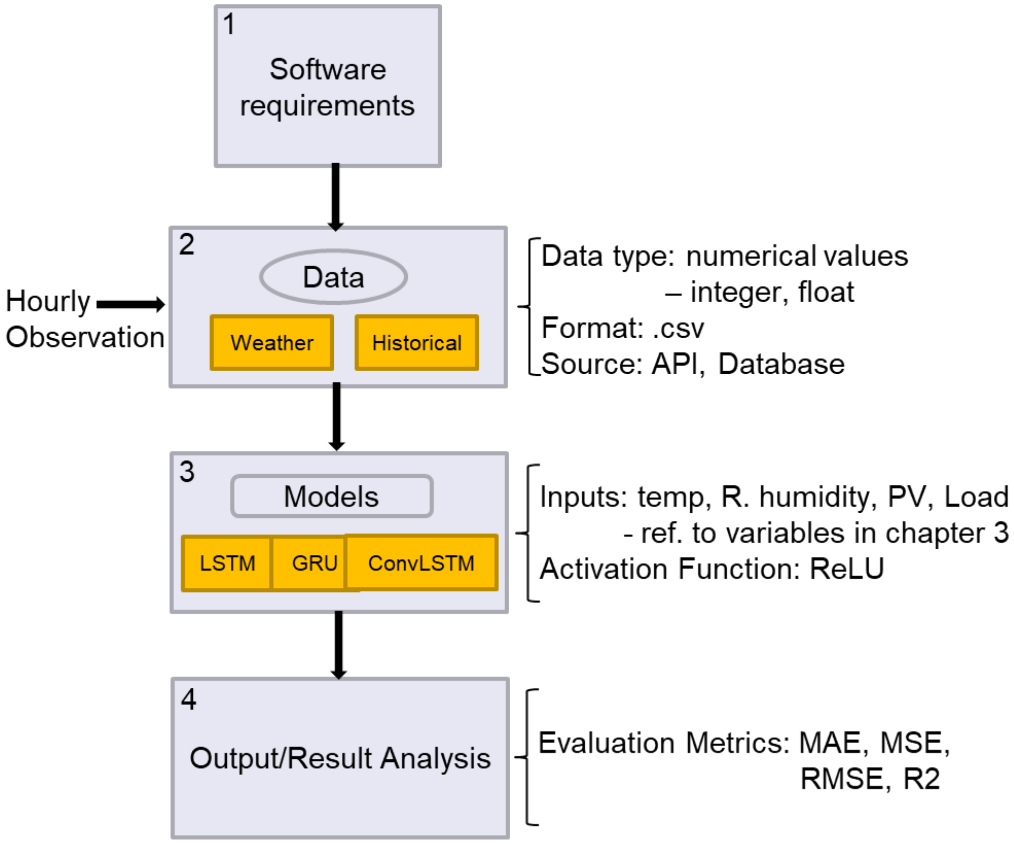


Figure 21. Model Exploitation

Block 2 showed the data used for model training, their type, format, and source. Meteorological data was acquired from Rebase Energy API between 15/10/21 to 13/10/22. Historical data was collated from HSBLL database within the same period. This dataset is available for Chalmers use but can be made available to other partners with some discussions. Three deep learning algorithms were used as shown in block 3, and some input variables from both weather and historical data were used in the training of the model with rectified linear unit as activation function. Finally, block 4 showed the model evaluation metrics and the forecast results emanating from this model is used as inputs for EMS optimization. The models can be provided to interested partners upon request.

5.1 Forecast Model Integration to EMS

For GENTE work package 6.2, optimisation of building energy is focused on smart buildings control especially on the heat pumps control. Three of the following test cases were considered in the demonstration sites for heat pump control: case 1 – provision of local flexibility, case 2 – provision of optimal dispatch, case 3 – provision of other ancillary services. Therefore, the energy optimization technique leverages forecasted results from AI-based forecast models as inputs to the EMS optimization model. The forecast models are integrated in such a way that 24hours ahead forecasts with hourly timestamps are made to solve rolling horizon optimization problem and effect peak load control/reduction. The basic building block of the EMS optimization algorithm is the load balancing equation computed from the forecast results that shows the variation between energy expected to be produced and consumed in the next 24hours in the building at each timestamp.

The outputs of the EMS optimization model based on the load balancing computation results set the charging/discharging set points for controllable loads such as energy storage (ES) and electric vehicle (EV) as well as operational start time for non-interruptible loads like washing machines and the dishwashers in the building to reduce the peak demands and minimize the total energy procurement costs. For the optimal dispatch of heat pump, BEMS control algorithm is combined with building demand forecast algorithm to provide cost minimization model. Figure 22 shows various components of the EMS and the objectives achieved on both controllable and non-interruptible loads in the demo sites using EMS. While Figure 23 shows how the optimization parameters used are combined for control operations.

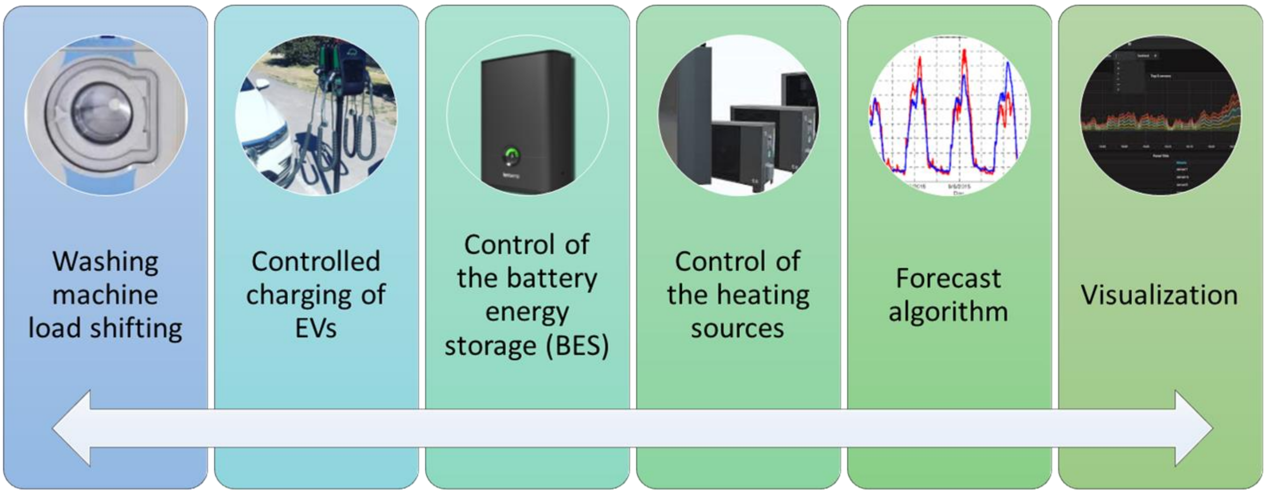


Figure 22. Building Energy Management Systems Components

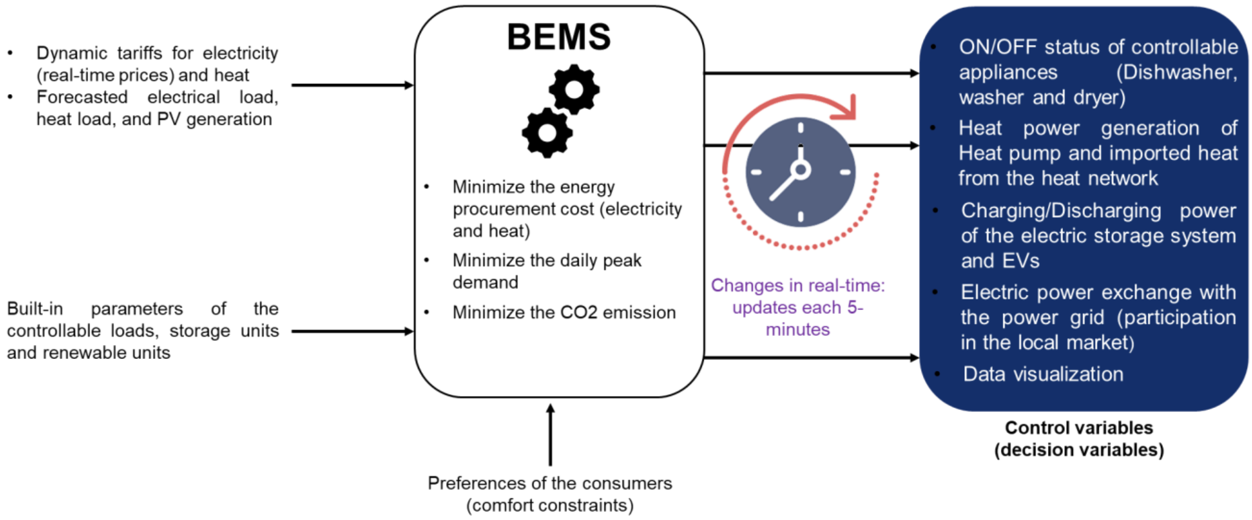


Figure 23. Building Energy Management Optimization System

5.2 Forecast Model Adaptability to New Dataset

To ensure these models generalize well across different data sources or domains, some adaptive strategies like the use of domain-independent data pattern capturing, transfer learning, dropout, data augmentation and hyperparameter tuning were incorporated in their development stage, training, and testing. For instance, feature engineering strategy deployed was able to learn both temporal and spatial features in the data. However, when the developed model was tested on a data collected from another demo location (Alingsas hem) with slightly variation in climatic conditions compared to the HSBLL Chalmers, the results showed that the overall models' performance remained consistence with slight variation. This variation can be ascribed to presence of noise or inconsistency in the data. It was discovered that discrepancies in the school holidays within the year under review brought about inconsistency in PV production and electricity load demand. There are also cases where PV production is higher that electricity load, resulting to negative values. So, proper data cleaning and augmentation is required to improve the quality of the data.

6. Conclusion

In this deliverable, PV generation, load and heat forecast were performed in short term i.e., 1-hour, and medium term i.e., 24-hour horizons using machine learning algorithms and mathematical identification-based models. The forecasting leveraged real-time data from HSBLL, Chalmers University of technology PV generation, electricity load and heat demand and the results were compared with other state-of-art forecasting methods.

For the 1-hour ahead PV generation and load demand forecasts, weather, calendar, and historical data were used as input to the neural network algorithms. The forecasts for this horizon illustrated high precision across different neural architectures. In 24-hour ahead PV generation horizon the best performance was achieved by the LSTM, however, the accuracy of the forecast decreases compared to one-time step prediction in 1-hour ahead prediction since the forecasting horizon is longer. Moreso, the model proved that it is not susceptible to weather variables variation when used in predicting a specific hour without including weather variables for that hour. This implies that the model is adaptive, hence, can be tested on any dataset.

The load and heat demand data showed low correlation with weather features necessitating the use of only historical and calendar features in their modelling. Different models were developed with the electricity load and heat load data, however, PV generation forecast has the best performance due to the similarity of attributes. Therefore, in the 1-hour ahead and in the 24-hour ahead horizons, the LSTM model and GRU model is selected, respectively. In both PV generation and electricity load demand forecast short term forecasts, the LSTM model illustrated high accuracy making it a possible choice for exploitation in WP6. On the hand, GRU is a better choice for Heat load prediction.

It was shown in the PV generation forecast that the weather feature predictions' accuracy can highly affect the forecast results, therefore, weather features from different NWP models including MetNo, ERA5, and ICON were also investigated in the PCA and feature engineering. All the NWP models resulted in the same weather features, however, the accuracy of the results differed. In the realization of the forecasts system either of these NWP models can be utilized with respect to their update cycle and delay delivery, this aspect will be further investigated in the demonstration of WP6.

The use of spatial data from sky images either captured with cameras or from satellite images other than historical and meteorological data is the next direction for future PV forecasting. The reason is to model the movement of the clouds in 2D or 3D and then predict their evolution and consequently the PV plant power output for the very short term

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