Monitoring the impact of energy conservation measures with Artificial Neural Networks

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Abstract

Energy Conservation Measures are mandatory in order to improve buildings' energy performance by using upgraded technologies, systems and installations. However, the lack of accurate techniques for Measurement & Verification (M&V) imposes insurmountable barriers towards their extended financing. The development of precise M&V techniques to estimate energy savings is a critical issue that can be tackled through the adoption of predictive models for the adjusted baseline energy consumption in the reporting period.

The most commonly used M&V practices to date are reported in the International Performance Measurement and Verification Protocol (IPMVP), where the most widespread techniques per case for calculating energy savings are defined. More specifically, the IPMVP indicates the adoption of linear regression methods to predict the adjusted baseline energy consumption of a building, exploiting outdoor temperature and heating degree days.

In this paper, utilisation of Deep Learning for training energy consumption predictive models is examined, as vast amount of data from Internet of Things devices are available nowadays. Thus, the feedforward Artificial Neural Network (ANN) is proposed for predicting the adjusted baseline energy consumption, using the hour of the day, the day of the week and weather data as training features. The proposed models incorporate both linear and non-linear relationships, in contrast to linear regression methods.

To validate the proposed method, an experimental application is implemented, applying the developed models on an educational institution in Latvia. The building has been renovated regarding its heating supply and ventilation system, as well as its enclosing structures insulation. The predictions from the ANN models are compared with the ones from the traditional degree days method, indicating that ANN achieves higher accuracy in energy savings estimation for electricity and diesel fuel consumption.

Introduction

The building sector is critical for accomplishing the EU's energy and climate objectives, as buildings are responsible for 40 % of the Union's total energy usage (EC, 2020). Simultaneously, the inhabitants' quality of life would be essentially increased, transforming existing inappropriate buildings into energy efficient ones and consequently enabling in a way the tackling of energy poverty. Moreover, adopting energy retrofitting actions to renovate the building stock would realise the goal of carbon-neutrality by 2050, set by the European Green Deal (EC, 2019). Several countries have already developed strategy plans that focus on the renovation of buildings in the residential sector. At the same time, the EU has presented tools and schemes to inspect the progress in energy efficiency financing of buildings (Marinakis, 2020), such as the EU Building Stock Observatory (BSO)[1], which monitors the performance of buildings across many countries, and the Smart Readiness

1. https://ec.europa.eu/energy/eu-buildings-database_en

Indicator (SRI)[2], which is a methodology for rating a building's capacity to incorporate smart-ready services.

In this context, the EU has proposed a revision of the Energy Efficiency Directive (EED)[3] under Fit for 55 package, which requires the public sector to renovate 3 % of its building per year. The 2018 Directive on EED[4] still imposed, updates the 2012 Directive and the key element of it, is the energy efficiency target for 2030 of at least 32.5 %. The most significant components of the above-mentioned directives are the renovation of public buildings into nearly Zero-Energy Buildings nZEB (Annunziata et al., 2013), higher energy savings targets, energy performance certificates (EPCs) and long-term renovation plans for buildings in the EU, among others.

Additionally, numerous research and innovations projects have been financed towards this direction, with the scope of providing novel methodologies, frameworks and digital tools (Papapostolou et al., 2020, Sarmas et al., 2022) to assess and monitor the energy consumption of buildings. As a result of this initiative, different aspects of the performance of a building have been controlled, including the energy efficiency levels of buildings (Marinakis et al., 2013, Ferreira et al., 2016, Marinakis et al., 2020), the energy poverty levels across the countries of the union (Santamouris et al., 2016, Arsenopoulos et al., 2021) and the different proposed performance certification schemes (Olaussen et al., 2017).

One of the most interesting issues in the field of energy efficiency, is the measurement of energy savings stemming from Energy Conservation Measures (ECMs) in buildings (Marinakis et al., 2018). The term ECM refers to any required activity which is performed to the building or to any of the building's subsystems after the initial building construction, such as thermal insulation, HVAC improvement or lighting reconstruction. ECM evaluation in buildings varies and depends on many factors which introduce a probabilistic aspect increasing the complexity of the problem. Therefore, estimating the uncertainties of ECMs energy savings is a critical issue, especially during risk analysis and evaluation for decision making purposes. The techniques which are deployed to assess the energy savings of ECMs are referred to as Measurement and Verification (M&V) protocols. The adoption of accurate M&V protocols is of great importance and can be achieved through the development of predictive models to estimate the adjusted baseline energy consumption in the reporting period. Several M&V practices have been proposed to measure the energy savings of ECMs, the most widely used being the International Performance Measurement and Verification Protocol (IPMVP), which was originally issued in 2000 with the scope to promote investments in energy and water efficiency (IPMVP, 2001).

In this study, a data-driven approach is presented aiming at determining the energy savings of a building refurbishment. The proposed approach is based on Deep Learning (DL) models, using the feedforward artificial neural network (ANN) composed of three layers, usually referred to as Multilayer Perceptron (MLP). The proposed models exploit the abundance of available data before and after the refurbishment takes place, in order to provide more accurate energy savings predictions compared to the traditional statistical models. The proposed models were implemented in Python programming language, and they were applied on a real case study.

The paper is organised as follows: Section 2 provides the description of the problem, as well as a review of relevant background literature. This is followed by a description of the methodology followed, in Section 3. Results of the case study are provided in Section 4. Finally, in Section 5 the outcomes and conclusions are summarised and key points for further research are proposed.

Problem Setting and Review

Energy savings can be estimated by comparing the energy used before and after the implementation of an energy efficiency renovation. Throughout this section we use the terminology as it has been applied by the Efficiency Valuation Organisation (EVO) (IPMVP, 2001), which develops, maintains and improves the IPMVP since 1997, and ASHRAE's Guideline 14 (ASHRAE, 2002). In this respect, the term baseline period is used to refer to the period before the ECM installation, while the term reporting period refers to the period after the ECM installation. The main idea is that energy savings due to an ECM cannot be directly calculated by comparing the measured energy consumption of a building before and after the ECM installation. This can be attributed to the different set of conditions that may affect the use of energy in the building between the two periods, such as weather conditions, building occupancy and other socioeconomic factors (Nikolaidis et al., 2009). A typical example is when there are different shifts in an office building between the baseline and the reporting period, resulting in diverse levels of equipment and building usage. Another common example can be considered when the calendar year of the baseline period is significantly warmer or colder than the one of the reporting period.

The method for estimating energy savings after the ECM installation is based on energy measurements before and after the retrofit takes place. The measurements before the ECM installation are used to calculate the baseline energy, while the measurements after the ECM installation are used to compute the reporting period energy. The adjusted baseline energy is the result of a normalisation process of the baseline energy against weather effects. Finally, energy savings can be estimated as the difference between the adjusted baseline energy and the reporting period measured energy. Figure 1 summarises the calculation of energy savings based on the IPMVP framework.

The IPMVP proposed four different options for M&V of building renovations depending on the availability of measures and on the extent of the ECM installation. More specifically, the energy consumption of a building can be measured with smart meters isolating a specific retrofit, with fuel and/or electricity supplier invoices or with computer simulations modelling the inspected facility. Moreover, the M&V process can be applied to a specific retrofit or to the whole building, depending on whether the ECM installation affects a specific sub-system of the facility The four options proposed by the IPMVP protocol (IPMVP, 2001) are presented in Table 1.

2. https://energy.ec.europa.eu/topics/energy-efficiency/energy-efficient-buildings/smart-readiness-indicator

3. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52021PC0558

4. https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32018L2002&rid=7

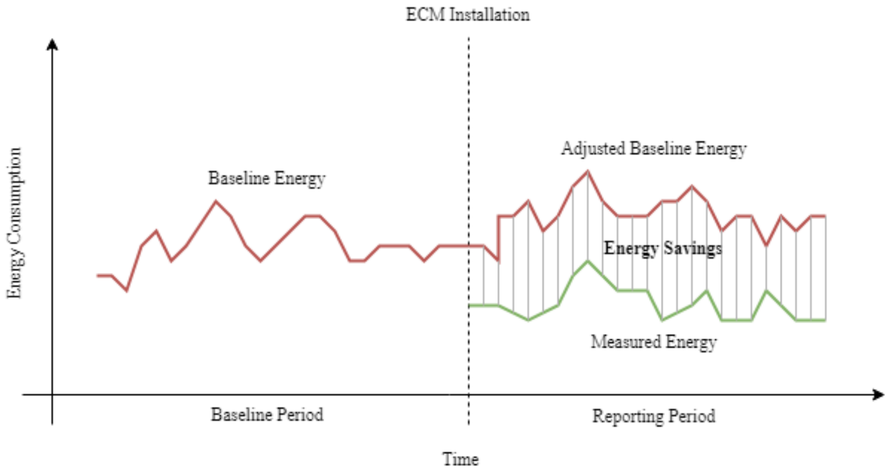

Figure 1. Energy savings calculation according to the IPMVP framework. Savings can be estimated with measurements before and after the ECM installation, but a normalisation of the baseline energy is also required to incorporate weather and other effects.

Table 1. The four M&V options according to the IPMVP.

Option	*Description*	*Calculation*
Option A: Partially Measured Retrofit Installation	Measurement of specific sub-systems of the building, when not all the parameters can be measured.	Engineering calculations using post-retrofit measurements.
Option B: Retrofit Installation	Measurement of specific sub-systems of the buildings, when all the parameters can be measured.	Engineering calculations using post-retrofit measurements.
Option C: Whole Facility	Measurement of energy use at the whole facility.	Regression analysis techniques using smart meters data.
Option D: Calibrated Simulation	Savings are determined by simulating certain sub-systems or the whole facility.	Energy use simulations using fuel and/or electricity invoices.

The presented framework has been widely adopted and many studies have been conducted focusing on finding the most appropriate regression methods and models to predict the adjusted baseline energy for the whole facility (Option C). One of the most common and simplest approaches for weather normalisation of energy consumption are the degree days, a relative measure of outdoor air temperature, as energy consumption is shows high correlation with the outdoor air temperature in heated/cooled buildings (Kaiser et al., 2010). Heating Degree Days (HDD) are used for periods that the building is heated, while Cooling Degree Days (CDD) are exploited for calculations related to the cooling of buildings. The application of this regression method is quite simple, requiring the selection of a base temperature which serves as comparison factor for the average temperature of each day. The degree days can be calculated, measuring how many degrees the outside temperature was lower than the base temperature for HDD (or higher for CDD) (Mokhtar, 2022). The utilisation of degree days for estimating the adjusted baseline energy has been promoted in several studies (Aris et al., 2015, Razali & Dahlan, 2015), mainly due to the ease of implementation and to the fact that weather is the main driving factor for energy use.

However, the degree days method is based on the daily average, thus failing to incorporate patterns across the day, as well as other influencing factors. In this context, there is a considerable amount of literature investigating different methods and models for energy consumption prediction. These methods include statistical techniques, machine learning (ML) and DL models such as the KNN algorithm and ANNs, as well as energy simulation software. A detailed review of these studies is presented in the following paragraphs.

A study which estimates the accuracy of automated M&V techniques for energy savings in commercial buildings and goes beyond the regression models has been conducted (Granderson et al, 2016). Nine different models, including Principal Component Analysis, Random Forests, ensemble approaches and nearest neighbors advanced regression among others, are tested, in order to measure energy savings calculations of whole buildings. A data-driven methodology has been proposed to estimate the achieved energy savings on synthetic and real-time datasets using the building energy simulation software EnergyPlus (Grillone et al., 2021). The methodology clusters the buildings using a Gaussian mixture model and a Bayesian Confirmation Criterion to estimate the optimal number of clusters aiming to extract typical consumption patterns of buildings.

Then, weather dependent analysis was performed to identify the temperature dependence of the building, by calculating the change-point temperature of the building. A Gaussian Process modelling framework has been proposed (Heo & Zavala, 2012) to determine energy savings and uncertainty level in M&V practices. The methodology can capture complex behaviour, including nonlinearities, multivariable interactions, and time correlations as opposed to existing modelling practices. This approach has been applied to two case studies, one considering a simulated scenario of a predictive control system deployed in a typical office building and another to verify energy savings of a retrofitted building. An approach to calculate building energy consumption in commercial buildings by using gradient boosting machine (GBM) has been proposed (Touzani et al, 2018). By using k-fold-blocks cross validation and the grid search method to tune the hype-parameters of the model, the algorithm is applied to predict the electricity consumption in real data commercial buildings. The underlying algorithm used is the XGBoost algorithm and the results were compared against to a Random Forest baseline and Time-of-Week-and-Temperature model, showcasing a much greater accuracy. A generalised approach to predict retrofit effects, by demonstrating a data-driven approach using cumulative data of previous implemented retrofit projects has also been proposed (Xu et al., 2021). By applying the Causal Forest method, in measured data (energy use, weather historical information, retrofit records, building characteristics), energy savings were predicted in six retrofit actions and sub-actions (advanced metering, building envelope, commissioning, GSALing, HVAC and lighting).

ANNs have also been extensively deployed for energy consumption prediction. ANN models based on the Levenberg-Marquardt algorithms using as features the hour of the day, day of the week, outdoor temperature, wind speed and direction, relative humidity and indoor temperature have been proposed (Ye et al., 2020). The method was compared to the linear and quadratic regression methods following the IPMVP protocol in air-source heat pump retrofit in residential housing. The energy savings of an ECM program at one floor of a university building were determined (Mustapa et al., 2020), using Non-Linear autoregressive with Exogenous inputs Artificial Neural Network (NARX-ANN). The quantified energy savings estimated by the NARX-ANN model was then compared with the Multiple Linear Regression results. A baseline model of a building's energy consumption using a hybrid ANN-cross validation technique has been developed (Adnan et al., 2020) to predict a building's monthly energy consumption. The baseline model used limited data, consisting of the working days, class days and cooling degree days. By creating the baseline energy model with the hybrid neural network, the post retrofit energy savings can be predicted with high accuracy for option C of IPMVP method.

Finally, comparisons among different algorithms have been developed attempting to compare the accuracy of different approaches. An automated method has been developed (Agenis-Nevers et al., 2021) to select the most relevant baseline model to capture energy savings for buildings. New explanatory variables were introduced, and 11 different algorithms were tested, classified in three categories based on their ability to compute IPMVP indicators: class 1 models (Linear Regression), class 2 models with non-parametric regression methods (LARS2, RLM, BAYES, GPR) and class 3 models with non-linear Machine Learning Algorithms (KNN, SVML, GAMLOESS, CUBIST, RF). Moreover, four inversed modelling approaches have been compared (Zhang et al., 2015) in order to estimate the energy performance of a building's subsystem (HVAC hot water energy consumption) pre-retrofit. The data-driven energy prediction models (change-point regression model, Gaussian Process Regression, Gaussian Mixture Regression and ANN model) were trained with pre-retrofit building data in order to be used as baseline models in a retrofit project.

Proposed Methodology

In this study we propose the MLP for estimating the adjusted baseline energy consumption for a facility as a whole (Option C of the IPMVP) during the reporting period breaking the analysis into two heating subsystems: electric and diesel fuel. The MLP can be described as a feedforward ANN that connects a set of input data with a set of output labels (Gardner & Dorling, 1998). The typical MLP structure is composed of multiple layers of interconnected nodes. The first layer is called input layer, the last one is called output layer, while the middle ones are called the hidden layers of the network. Each layer is fully connected to both the preceding and the succeeding ones (Atkinson & Tatnall, 1997). The architecture of MLPs and the usage of a non-linear activation function enables them to deal with non-linear separable problems (Zou et al., 2008). The training process of MLPs is based on a backpropagation algorithm which consists of two steps (Mas & Flores, 2008, Haykin, 1999): the feedforward step, where the input vector crosses forward the network, and the backpropagation step, where the predicted output is compared to the real value, causing weight adjustment based on an error-correction rule. The architecture of a typical MLP network with fully connected layers is depicted in Figure 2.

Each single output is calculated by the MLP from multiple inputs of the preceding layer with the method of linear combination with respect to the input weights. Then, the output is determined through a non-linear activation function (Bishop, 1995). This process is represented by the following equation:

$$y = f\left(\sum_{i=1}^{n} w_i x_i + b\right)$$

where y is the output, x_i is the input vector (i = 1, 2, …, n), w_i is the weighting factor, b is the bias factor and f is the activation function.

MLPs have been extensively used in various regression problems in the energy sector, offering high predictive accuracy for both energy supply and energy demand problems. Although there are several differences between these two types of problems, they are closely related because the nature of the problem is the same (time-series forecasting problems) and there is high degree of similarity between the features of these problems, such as weather features and seasonal variables. Several studies, for example (Soofastaei et al., 2016, Ehteram et al., 2021, Ekonomou, 2010), have been carried out focusing on energy consumption prediction both in building level and in national level, in various forecast horizons. Additionally, feedforward ANNs have been successfully applied on energy production prediction problems, either from photovoltaic panels (Ehsan et

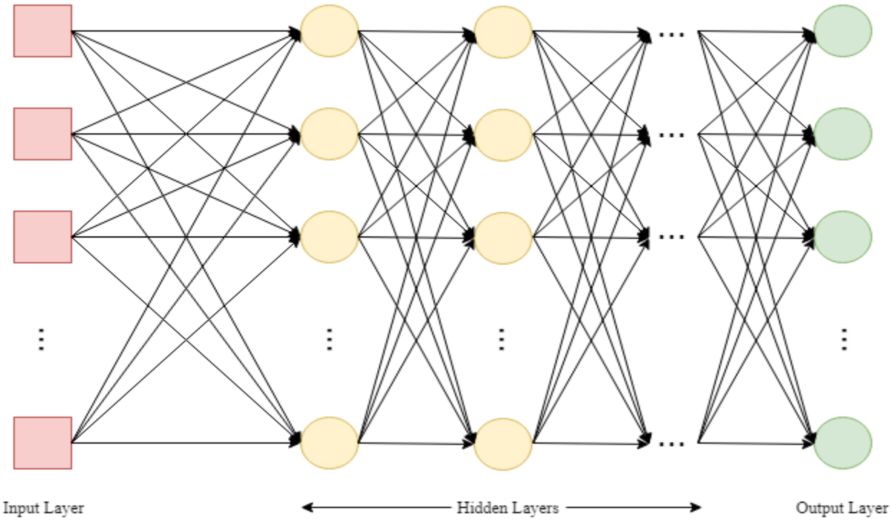

Figure 2. The multilayer perceptron (MLP). The architecture of the MLP includes an input layer, one or more hidden layers, and an output layer.0§1 The typical MLP network is fully connected.

al., 2017, Azimi et al., 2016), or from wind turbines (Velo et al., 2014, Yeh et al., 2014). In the proposed models, the linear activation function has been selected for the output layer because it produces a continuous interval of activation values, which is necessary in this regression problem. However, the derivative of the linear activation function is fixed, thus it cannot be utilised in the hidden layers (Agostinelli et al., 2014). On the contrary, the rectified Linear Activation Function (ReLU) was deployed for the hidden layers, as it is not limited by a fixed derivative and it is computationally inexpensive (Schmidt-Hieber, 2020). The formula of the ReLU activation function is represented by the following equation:

$$y = \max\{0, x\} = f(x) = \begin{cases} 0, & x < 0 \\ x, & x \geq 0 \end{cases}$$

Two separate MLP models have been developed to address the problem of electricity and diesel fuel consumption forecasting. The need for separate models is justified by the fact that the available data for each consumption series have different granularity; electricity consumption data are hourly, while diesel fuel consumption data are daily. The architecture of the proposed MLP model for electricity consumption includes three hidden layers (the first one includes 32 units, the second one includes 64 units and the third one includes 16 units). The corresponding MLP model for diesel fuel consumption includes three hidden layers (the first one includes 16 units, the second one includes 16 units and the third one includes 8 units). The optimal number of layers and units per layer were selected after applying a grid search method on a sample of data which were used as validation set. Both networks were optimised with the adam optimiser (Zhang, 2018) based on the mean absolute error criterion, and the remaining hyperparameters were determined as follows, for the electricity consumption model: batch size=32, number of training epochs=32 and validation split=0.2, and for the diesel fuel consumption model: batch size=16, number of training epochs=32 and validation split=0.2. The implementation of the proposed MLP models was designed with Keras (Keras, 2015), which is one of the most used Python DL APIs.

The electricity consumption forecasting model is designed to provide hourly predictions for the energy consumption of the selected target. The choice for hourly output data has been made in order to secure aligned point forecasts for the adjusted baseline energy and the reporting period measured energy, as most smart meters can provide reliable hourly measurements of electricity consumption. The features of the model are both weather and seasonal features. More specifically, the proposed MLP includes the following features: (a) outdoor air temperature, (b) hour of the day, (c) day of the week, (d) weekday or weekend (binary variable), (e) month of the year, (f) vacation period or not (binary variable). The last feature is of great importance for buildings which are utilised as offices, as in vacation period they are vacant, thus being less energy costly. August and Christmas were considered as the only vacation periods in the context of this study.

The diesel fuel consumption forecasting model is developed to provide daily predictions. Daily heating forecasting models instead of hourly, can allow the generalisation of them, especially under IPMVP Option C, where the building-as-a-whole is considered. The daily amount of diesel fuel consumption of a building is aggregated and does not incorporate the fluctuations in the consumption, based on its tenants' actions (heating scheduling, occupancy, etc.) that occurs in day-to-day activities and could affect the hourly diesel fuel consumption models. The features of the proposed diesel fuel forecasting model are the following: (a) average daily outdoor air temperature, (b) day of the week, (d) weekday or weekend (binary variable), (e) month of the year, (f) vacation period or not (binary variable).

Results

The proposed methodology has been evaluated on a real building and the predictions of the MLP models have been compared with the results that the traditional degree days method has given. The evaluated building is a secondary education school in north-eastern Latvia, and more specifically in the town of Gulbene. The building has undergone a series of major renovations including insulation of the entire exterior wall with mineral wool of 120mm, building cap insulation with expanded polystyrene, modernisation of the rainwater drainage system, replacement of wooden doors and windows with PVC profile ones and restoration of the heating system's pipe insulation.

The dataset of the experimental application consists of two years of electricity and diesel fuel data. Electricity data have been provided with hourly frequency from smart meters installed in the building, while diesel fuel data have been provided with daily frequency. The starting date of data recording is March 2019, and the ending date is February 2021. Weather data in an hourly interval were also gathered from the meteorological station of Aluksne, which is a nearby town to Gulbene. In this 2-year period no renovations have been made to the building in order to test the prediction accuracy of the proposed MLP model. In this respect, the first year of data were exploited to train the model, while the second year of data were used as test set.

The selected data have been pre-processed to extract outliers and replace missing data with the method of linear interpolation using data of the same hour from previous and next days. The summer months were marked as vacation period because the school was closed and same applies for the Christmas vacation period. Finally, dates that school was closed due to COVID-19 were also taken into consideration and were marked as outliers. The last step before applying the MLP models was the data standardisation process. For the standardisation of data, the standard scaler of the Scikit-Learn library was exploited (Pedregosa et al., 2017), which performs scaling of all the features by removing the mean and scaling to unit variance. A comparative plot of the electricity consumption time-series showing one month of hourly data (720 hours) is depicted in Figure 3. The solid line represents the real consumption of the building, while the dashed line represents the predicted consumption by the MLP model. The corresponding comparative plot for diesel fuel consumption, including three months of daily data (30 daily forecasts) is presented in Figure 4. The first forecasts of Figure 4 correspond to a three-week interval that the school was closed due to COVID-19, which inevitably affects the accuracy of the model.

The developed forecasting models are evaluated using the Mean Absolute Error (MAE) and the Coefficient of Variation of the Root Mean Squared Error (CVRMSE). MAE serves as an error index that measures the individual differences between the real and the predicted values. The formula for MAE is given as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

CVRMSE is an index recommended by ASHRAE 14 (Ashrae, 2020) which serves as a normalised version of the Root Mean Squared Error (RMSE) index, as it is divided by the average consumption value. CVRMSE is calculated by the following equation:

$$CVRMSE = \frac{1}{\bar{y}}\sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}}$$

The developed MLP model for electricity consumption has shown a MAE index of 4.678 kWh (corresponding to 32.59 % normalised value) and the CVRMSE of the model is 47.17 %. These indexes indicate a quite good performance of the MLP model, taking into account the short training period of only 1 year and the fluctuations in building occupancy due to COVID-19. More specifically, the CVRMSE value is higher than the proposed value of ASHRAE Guideline 14, but this is because the testing period of the MLP model's performance coincides with the outbreak of the pandemic, resulting in some school classes kept closed for some days because of COVID-19 active cases, affecting the occupancy and consequently the energy consumption of the building.

Nevertheless, a comparison with the traditional method of degree days would emphasise the advantages of the proposed model. In this respect, the consumption of the building has also been estimated applying the HDD method as follows: A baseline temperature of 15 °C was selected and heating degree days were calculated as the difference between the mean daily temperature and the baseline temperature. Then, a linear regression model was performed using the first year of the dataset as training set and the second year of the dataset as test set. Both training and test sets were aggregated in daily format by summing 24-hourly electricity values for each day. The selection of 15 °C as baseline temperature was based on minimizing the error on the fit against baseline data. Eventually, the average HDD for the training period was 8.019 °C, while for the testing period it was 7.983 °C. It is important to mention that no electrical cooling system operates in the building; therefore, the analysis is performed based only on HDDs and CDDs are not calculated, as well.

The MLP model for diesel fuel consumption has even better accuracy resulting in a MAE index of 0.280 MWh (corresponds to a 23.45 % normalised value) and a 37.35 % CVRMSE index. The respective error metrics for the HDD method regarding the diesel fuel consumption of the building are 0.337 MWh for MAE (28.22 %) and 42.29 % for CVRMSE. Finally, the differences between the MLP method and the HDD method in yearly level are presented in Table 2.

Summing up the daily forecasts of the linear regression HDD method, electricity consumption during the second year was estimated 134,654 kWh. On the other hand, summing up the hourly forecasts of the MLP model the cumulative predicted electricity consumption has been found 131,549 kWh. Given that the real cumulative electricity consumption during the test period has been measured 125,706 KWh, it is evident that the MLP significantly outperforms the HDD method. Same applies for the heating consumption model which has a deviation percentage of 1.358 %, in comparison to the HDD method that performs worse having a deviation percentage of 1.836 %.

Conclusions

The deployment of DL models for predicting energy consumption in buildings has the potential to provide enhanced results compared to the traditional regression methods in terms of accuracy, because DL models exploit not only the outdoor air temperature measurements but also several factors to provide the forecasts. However, great emphasis must be placed on data quality, as occupancy data in a building tend to be less reliable

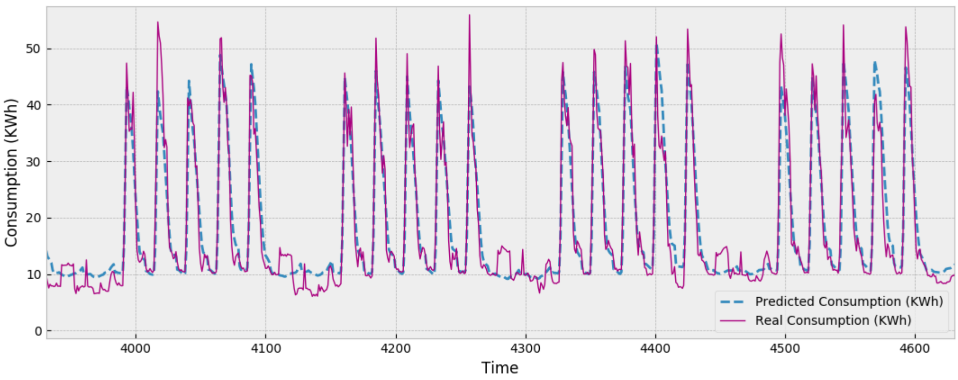

Figure 3. Example illustrating how the MLP electricity forecasting model performs. This example refers to a randomly selected period (2020-10-05 to 2020-11-03, 720 hourly point forecasts in total) of the evaluation period. The dashed line refers to the predicted consumption, while the solid line to the measured values.

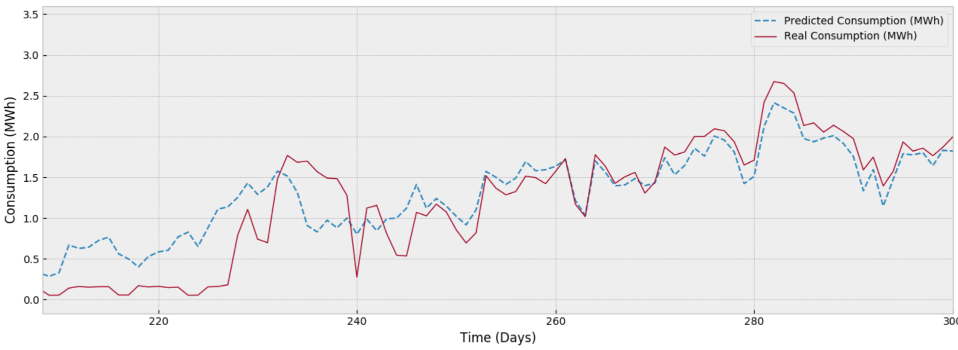

Figure 4. Example illustrating how the MLP diesel fuel forecasting model performs. This example refers to a randomly selected period (from October 2020 until December 2020, 90 daily point forecasts in total) of the evaluation period. The dashed line refers to the predicted consumption, while the solid line to the measured values.

Table 2. Comparison of the MLP model and the HDD method based on the predicted annual cumulative electricity and diesel fuel consumption.

Metric	*Real Value*	*MLP method*	*HDD method*
Annual Electricity Consumption (KWh)	125,706	131,549	134,654
Deviation Percentage of Electricity Consumption (%)	-	4.647	7.118
Annual Diesel Fuel Consumption (KWh)	435,810	441,730	443,811
Deviation Percentage of Diesel Fuel Consumption (%)	-	1.358	1.836

than meteorological data used by traditional methods, while it is also common for such data to be unavailable. In this paper, two feed-forward neural network models were presented for electricity and diesel fuel consumption prediction in buildings, aiming to calculate the adjusted baseline energy of renovated buildings during the reporting period. The developed MLP models, having both weather and seasonal features, outperform the traditional degree days method when applied to a real case study, involving an institutional building in Latvia. The case study was based on a 2-year dataset with hourly frequency electricity data and daily frequency diesel fuel data, where both methods were applied.

It should be noted, though, that the use of ANN includes significant limitations, as the training process of such models requires the existence of large datasets. More specifically, at least a whole calendar year of data must be given as input to the model in order to learn data patterns and provide precise forecasts. Another drawback of deep learning is the low degree of interpretability of the model results, in contrast to linear degree-day regressions which provide useful explanatory variables through their slope and intercept. The overwhelming advances in data processing and data sharing, as well as the evolution of Internet-of-Things (IoT) devices and the digitisation impact of this era enable the existence of large volume datasets that can be fed to DL models. However, alternative approaches must be investigated, such as transfer learning which could enable transferring knowledge from a building to another even if those buildings are in different locations. Finally, future research could focus on further exploring how the most appropriate features that affect a building's energy consumption could be incorporated in DL models to increase the forecasting accuracy, resulting in a more precise estimation of the energy savings of ECMs.

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