Impact of Covid-19 Pandemic on Electricity Demand in the UK Based on Multivariate Time Series Forecasting with Bidirectional Long Short Term Memory

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Abstract

Due to lockdown measures taken by the UK government during the Coronavirus disease 2019 pandemic, the national electricity demand profile presented a notably different performance. The Coronavirus disease 2019 crisis has provided a unique opportunity to investigate how such a landscape-scale lockdown can influence the national electricity system. However, the impacts of social and economic restrictions on daily electricity demands are still poorly understood. This paper investigated how the UK-wide electricity demand was influenced during the Coronavirus disease 2019 crisis based on multivariate time series forecasting with Bidirectional Long Short Term Memory, to comprehend its correlations with containment measures, weather conditions, and renewable energy supplies. A deep-learning-based predictive model was established for daily electricity demand time series forecasting, which was trained by multiple features, including the number of coronavirus tests (smoothed), wind speed, ambient temperature, biomass, solar & wind power supplies, and historical electricity demand. Besides, the effects of Coronavirus disease 2019 pandemic on the Net-Zero target of 2050 were also studied through an interlinked approach.

Keywords: Coronavirus disease 2019; Electricity demand; Renewable power supplies; Bi-LSTM.

Nomenclature:

Latin symbols

$(M_{measured})_j$	Measured value of the j^{th} value from the met mast records
$(M_{predicted})_j$	Predicted value of the j^{th} value from the deep learning model
h	Cell state vector
U	Assigned weights

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W	Assigned weights
b	Bias
c	Cell state
f	Forget gate activation vectors
i	Input gate activation vectors
n	Number of tests
o	Output gate activation vectors
t	Time step
x	Input of neuron

Greek symbols

σ	Activation function

ABBREVIATION:

Adam	Adaptive moment estimation
Bi-LSTM	Bidirectional Long Short Term Memory
CECs	Constant Error Carousels
COVID-19	Coronavirus disease 2019
GDP	Gross Domestic Product
LSTM	Long Short Term Memory
MSE	Mean Square Error
MSLE	Mean Squared Logarithmic Error
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network

1. Introduction

The nationwide lockdown taken by the UK government not only controlled the spread of Coronavirus disease 2019 (COVID-19) but also significantly reduced the day-to-day social behaviours and economic activities, which are having an irreversible influence on the UK's electricity demand. Before COVID-19 pandemic, the electricity demand in the UK has kept declining for several years. As presented in **Fig. 1**, the net demand is only 324 TWh in 2019, which is 80% of its peak value in 2005. This occurred notwithstanding the UK population has increased by near 7.6 million during the past 14 years [1]. The continuous reduction of electricity demand in the UK was extensively impacted by a combination of energy efficiency enhancement, economic restructuring, consumer behaviours, and de-industrialisation [2].

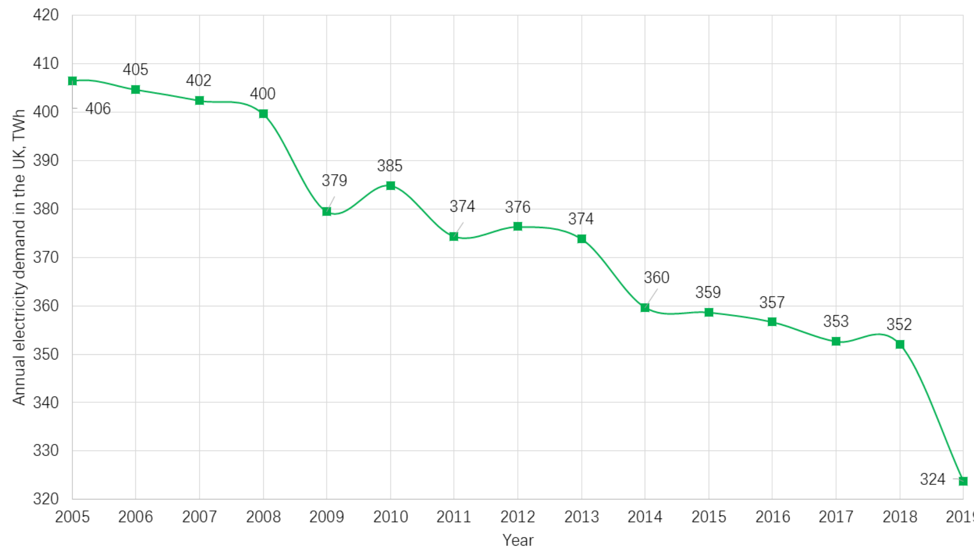

Fig. 1 – Variations of annual electricity demand from 2005 to 2019 in the UK [3].

It is expected that, due to the influence of lockdown and other restrictions of COVID-19, the national electricity demand will keep dropping in the future. A falling of such a scale will be unprecedented and give a significant long-term influence on the UK electricity industry. To control the spread of COVID-19, the UK government has taken various measures at different stages of the lockdown, which critically reduced daily social/economic activities and triggered disorder of day-to-day routines. As presented in **Fig. 2** (timeline in 2020), on 16th March, the government encouraged the public to keep social distancing, stop non-essential contacts, work from home, and avoid pubs, restaurants and travelling [4]. Then, more rigorous measures were taken in the evening of 23rd March, when the UK wide lockdown was announced by the Prime Minister, following the routes of Italy and Spain [5]. On 16th April, the national lockdown was further extended for three more weeks [6]. After that, the full lockdown was eased on 10th May across the UK [7]. Then, on 31st October, the Prime Minister has announced a second national lockdown for England due to the uprising of the second wave of COVID-19 [8].

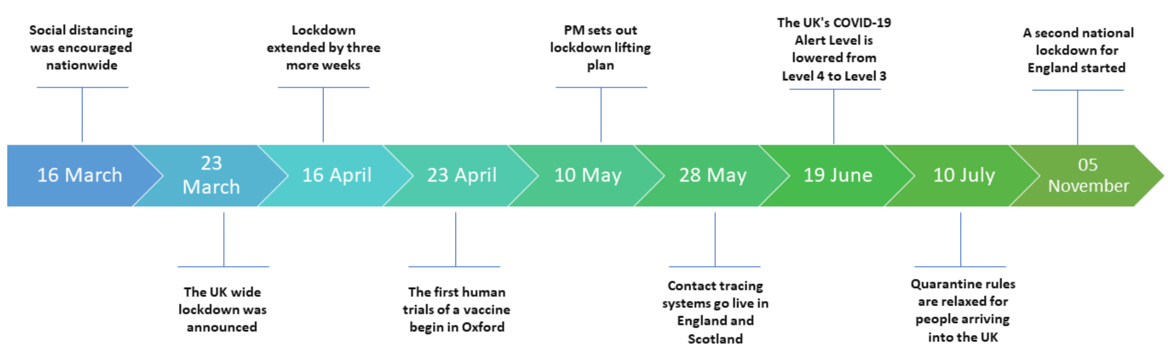

Fig. 2 – Timeline of the UK-wide COVID-19 pandemic in 2020 [9].

In reality, the total primary energy consumption in the second quarter of 2020 is 29% less than in the same period of 2019 [10], which was directly caused by the Covid-19 lockdown measures that took effect from 23rd March (see **Fig. 2**), resulting in a considerable reduction in electricity demand for the main transport and other commercial business. The Department for Business Energy & Industrial Strategy often categorizes electricity end-users in the UK into domestic, services, industry, and transport sectors, as presented in **Fig. 3**. Until the second quarter of 2020, energy consumptions of the domestic sector have dropped by 4.5%, even more professionals started to work at home. Energy consumptions of the service and the industrial sectors have also decreased by 13% and 19%, respectively, as factories, shops, and schools were closed during the lockdown. Furthermore, the energy consumptions of the transport sector have significantly reduced by 52% because of strict restrictions on both domestic and international travelling. [11]

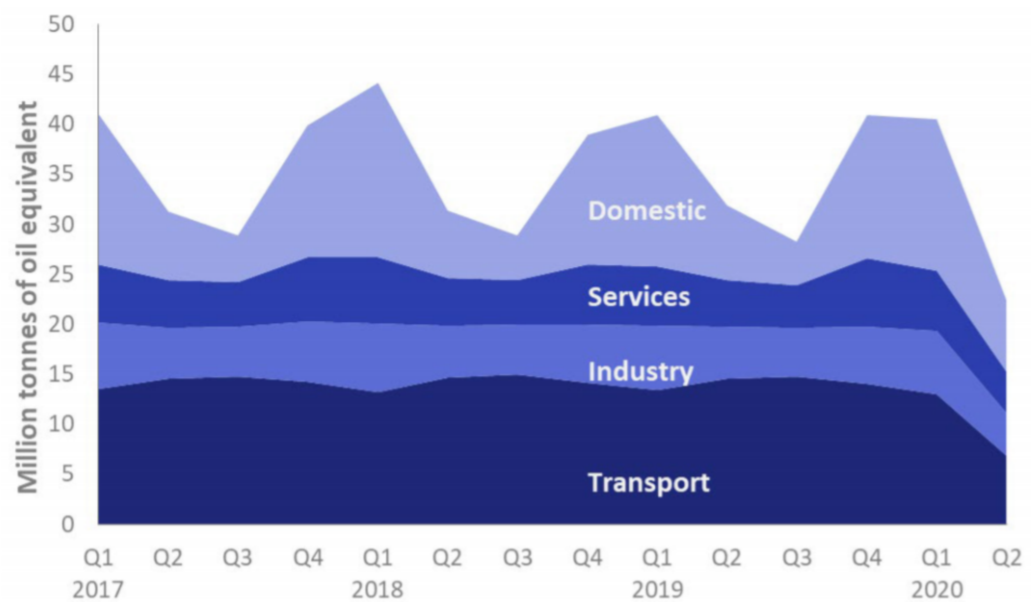

Fig. 3 – Statistics of final energy consumption by end-users in the UK from 2017 to 2020 [11].

Meanwhile, the UK has become the first major economy in the world to pass the Net-Zero law, ending its greenhouse gas emissions by 2050 [12]. Even the carbon emission reduction target has become harder and more complicated under COVID-19 pandemic, the Net-Zero 2050 program is still one of the key priorities for the UK government, where the renewable infeeds are playing an irreplaceable role. The COVID-19 pandemic has impact nearly every aspect of the Net-Zero 2050 program in the UK. For instance, the COP26 UN climate change conference, which is one of the flagship UN climate-related events, has been postponed to 2021 due to COVID-19 despite it was originally scheduled in Glasgow in November 2020 [13]. Even so, the UK government has announced a new transport decarbonisation plan during the COVID-19 outbreak [14].

As stated above, different factors have various influences on national electricity demand, including the COVID-19 measures. However, these impacts are difficult to be quantified. Many studies have investigated the correlations between electricity demand and its corresponding impact factors. For instance, Sinden [15] investigated the relationships between wind power generation and electricity demand levels through analysing 66 onshore weather measuring sites in the UK. The authors concluded that the growth of wind power supply can be observed during high electricity demand periods. Cassarino et al. [15] studied the European historical electricity demand to evaluate how social (such as human activities) and weather drivers (such as temperature, wind, humidity index solar irradiation, and temperature) can impact energy consumptions' variation. Rosenberg et al. [16] presented a long-term projection of Norwegian energy demand through energy system modelling, suggesting that if energy demand is decreasing, a higher renewable fraction will be triggered. Norouzi et al. [17] explored the influences of COVID-19 on electricity demand in China through a neural network model, where the authors released that the historical trends of electricity demand may become blurred during the global COVID-19 crisis. Bedi et al. [18] proposed a deep-learning-based approach through Long Short Term Memory (LSTM) to forecast electricity demand through the time interval defined by the user, which outperformed the algorithms of Recurrent Neural Network (RNN), Support Vector Machines (SVM) and Artificial Neural Network (ANN). Klemeš et al. [19] studied the additional demands of energy and resources in COVID-19 fighting measures during the pandemic. Most recently, Lu et al. [20] introduced a hybrid system for daily electricity demand prediction, considering the impacts from the pandemic, where both the accuracy and the stability of the proposed models were tested through an example based in US. However, based on the authors' knowledge, there have been no existing studies regarding how lockdown restrictions quantitatively influence the national electricity system, although this is vital for maintaining safe and normal application purposes. On this account, the present study introduces a deep-learning-Bidirectional-LSTM (Bi-LSTM) based multivariate time series forecasting model to investigate the correlations among containment measures, weather conditions, renewable energy supplies and the national electricity demand. This was realized in several phases defined by the adopted methodology (see **Fig. 4**), which involved identifying input features for electricity demand time series forecasting, designing Bi-LSTM neural networks, and tuning hyperparameters through grid and manual search. To the end, the levels of significance of each feature in the time series predictive model, especially for COVID-19 measures, were also identified by the proposed predictive model.

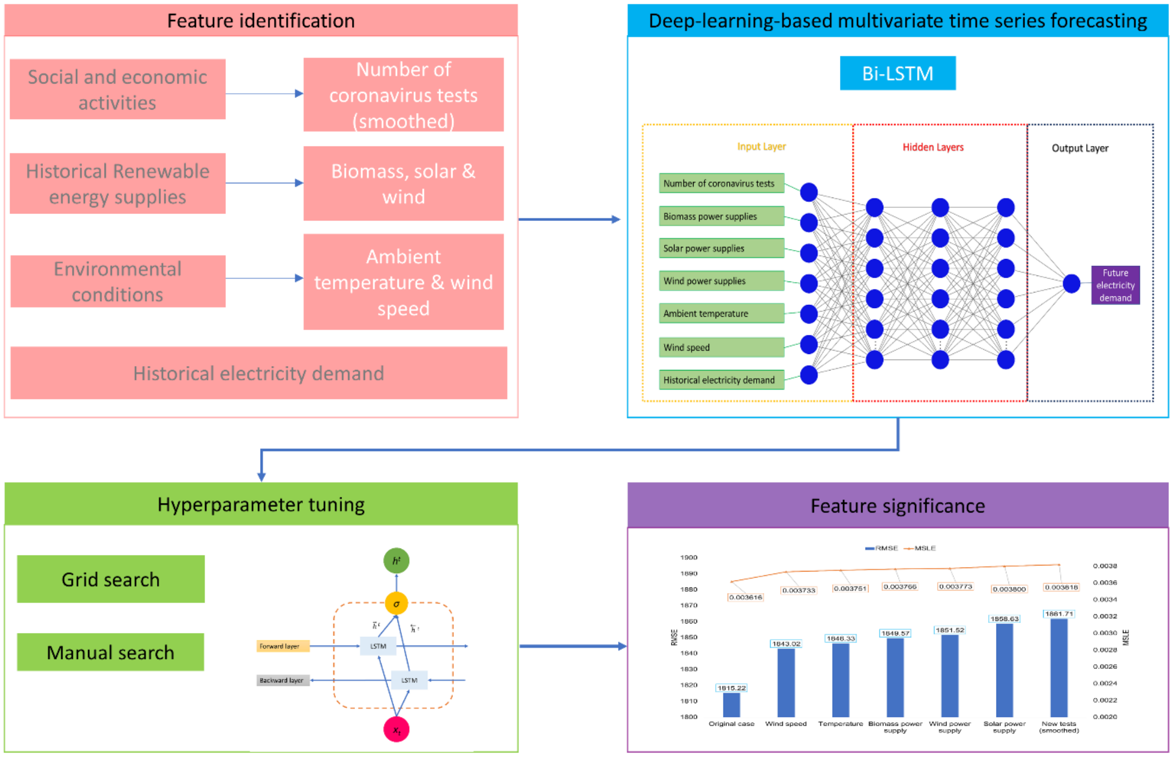

Fig. 4 – Diagram of applied methodology.

The remnants of this paper are introduced as follows: Section 2 described how features were selected in this investigation, covering social and economic activities (focusing on impacts from COVID-19 lockdown), renewable energy supplies (including biomass, wind, and solar power), and environmental conditions (represented by ambient temperature and wind speed). Section 3 depicted the methodologies of Bi-LSTM time series forecasting, which were used to build deep-learning-based neural networks. After that, the Bi-LSTM predictive model was trained and validated for daily electricity demand prediction in section 4. Besides, in this section, the feature importance was quantitatively identified between inputs and the target output by ranking the level of significance of each feature. To summarize, section 5 described a series of key conclusions in this paper.

2. Feature identification

A country's electricity demand can be impacted by various factors, including population, Gross Domestic Product (GDP), social behaviours, economic activities, and environmental conditions [21]. All those features regulate daily electricity consumption in the UK. Currently, as the COVID-19 pandemic is still in the time scale of months, the factor of the population and GDP can be roughly treated as constants. Besides, historical renewable power supplies (such as wind, biomass, and solar) were also involved in the electricity demand time series forecasting. In the UK, the National Grid balanced electricity demand and supply by matching them in real-time, indicating when national electricity is over-supplied, certain power plants in some supply sectors would be turned off. Currently, near half of the UK's electricity generation comes from the renewable energy sector [22], performing a strong correlation between historical electricity demand and historical renewable power supply. In addition, some authors have concluded that a higher renewable proportion would be observed while the overall electricity demand is declining [16], which is the case in the global COVID-19 crisis [11]. Therefore, in this study, four groups of features were used as inputs to develop a multivariate time series forecasting model for the UK-wide electricity demand, including historical electricity demand (represented by the daily electricity consumption in the UK), social/economic activities (represented by lockdown measures, see section 2.1), environmental conditions (represented by ambience temperature and wind speed, see section 2.2), and renewable supplies (represented by wind, biomass, and solar power; see section 2.3). Notice that, as this investigation used multivariate time series modelling for forecasting, all input features mentioned above will only be employed in the training phase while creating the predictive model. In the validation phase, where actual predictions are carried out, only time index is required as arguments.

2.1 Social and economic activities

Social behaviours and economic activities have been considered as fundamental drivers in energy consumptions [23]. Under normal circumstances, social activities were strongly influenced by cultural customs, which are often repeatedly presented in specific patterns during a certain period. However, because of COVID-19 measures, human activities have been dramatically changed and extremely limited at home, at work and elsewhere for holidays, schooling, shopping, etc. The decreasing of social and economic activities can be treated as the pre-indicator of electricity demand reductions, which can be used for forecasting purpose. This fact can be further proved through a comparison of daily electricity demand profiles under the conditions with and without lockdown restrictions in the same period of a year. In **Fig. 5**, the electricity demand profile of the fifth week during the lockdown (13th ~ 19th April 2020) was compared with the corresponding demand variations in the same week of 2019 (15th ~ 21st April 2019). It can be observed that the electricity load of every single day in 2019 is higher than that in the following year, when all pubs, restaurants, factories, and shops were closed in public. More specifically, in 2020, the weekly electricity demand was reduced by near 15% during the corresponding week of lockdown. This phenomenon occurred more obviously during the working days (Monday ~ Friday) than the weekends (Saturday and Sunday) as greater demand gaps were developed. The public, who were forced to stay at home, couldn't attend schools, commute, go to offices, or do any routines during a working day, flat out the daily electricity demand and make it closer to a weekend day. As displayed in **Fig. 5**, even the demand gaps still existed on Saturday and Sunday, the power usage on the weekend of 2020 performed similarly to that of 2019.

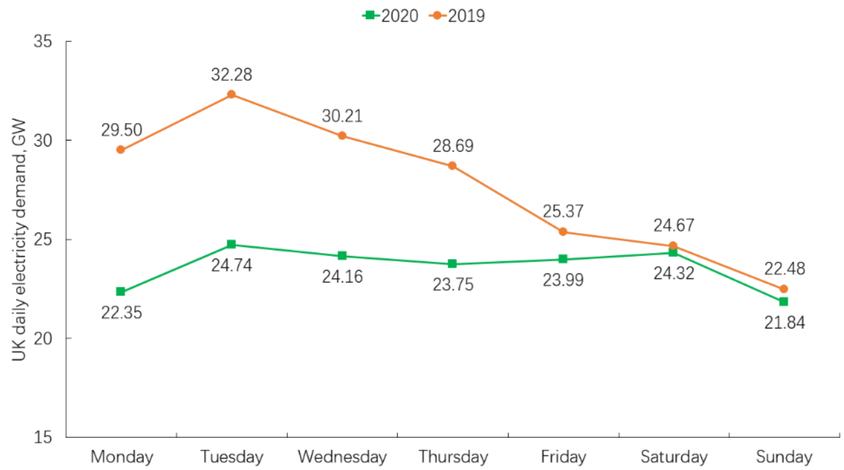

Fig. 5 – Comparison of electricity demand profiles in the third week of April between 2019 and 2020.

To obtain a more detailed insight, the daily electricity demand profile of a normal working day (04/05/2020, Monday) during the COVID-19 crisis was directly compared with the corresponding working day (06/05/2019, Monday) from 2019 and its contiguous weekend day (05/05/2019, Sunday) in **Fig. 6**. As can be seen, for most of the day, the national electricity demand in the UK remained at a relatively low level during the global pandemic, even when compared a Sunday in 2019. More specifically, the morning peak in a weekday of 2020 is nearly overlapped with that in a Sunday of 2019 as most of the professionals are now working at home with no need for commuting along with their children who couldn't go to school, which dramatically reduced the normal morning electricity peak. Similar patterns can also be observed in other countries in Europe (see **Fig. 7**, using electricity demands in Spain as an example). Based on the facts above, the daily smoothed number of COVID-19 tests across the UK is used as the feature to represent the impact of lockdown measures. The number of newly confirmed cases per day is not considered because this parameter only becomes meaningful when the country is testing enough cases [24].

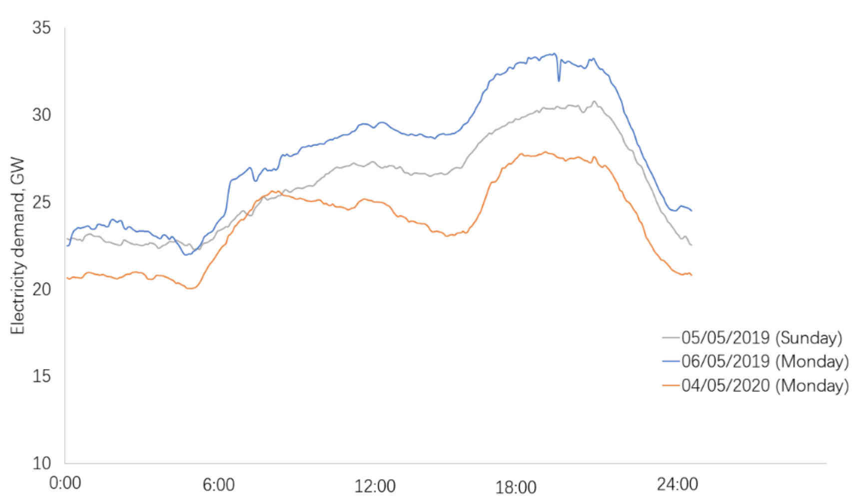

Fig. 6 – Comparisons of daily electricity demand profiles before and after the COVID-19 pandemic in the UK.

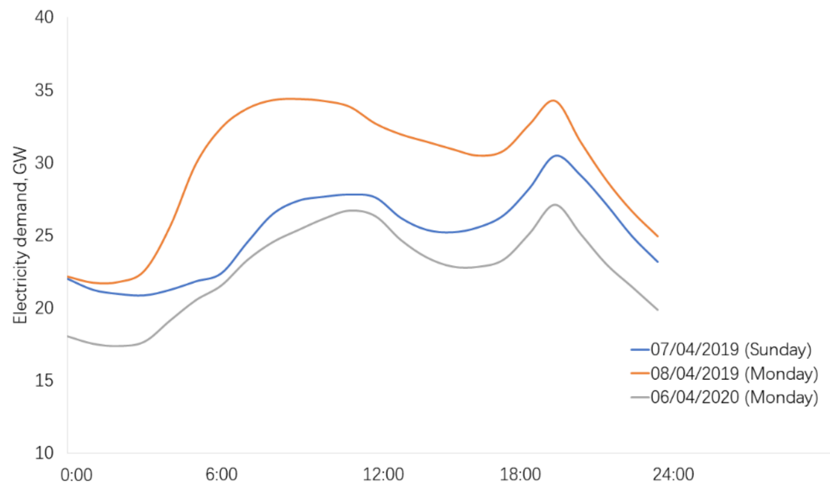

Fig. 7 – Comparisons of daily electricity demand profiles before and after the COVID-19 pandemic in Spain.

2.2 Renewable energy supplies

In the UK, renewable energy is continuously accounting for a larger share of the market [25], leading to a less carbon-intensive grid mix. As displayed in **Fig. 8**, of total electricity generation in the second quarter of 2020, renewables (wind, solar and bioenergy) accounted for 44.6%, which is near half of this season's electricity generation in the UK, whilst conventional coal only accounted for 0.5%, driving fossil fuels to a record low share of the mix. On the other hand, compared with the electricity generation on a year earlier (the second quarter of 2019), a 9% increase of low carbon generation was observed due to the sizable growth in the renewable generation [10]. Due to the continuous recession of national electricity demand, the renewables may play a more significant role in the energy market in the post-epidemic era of the UK.

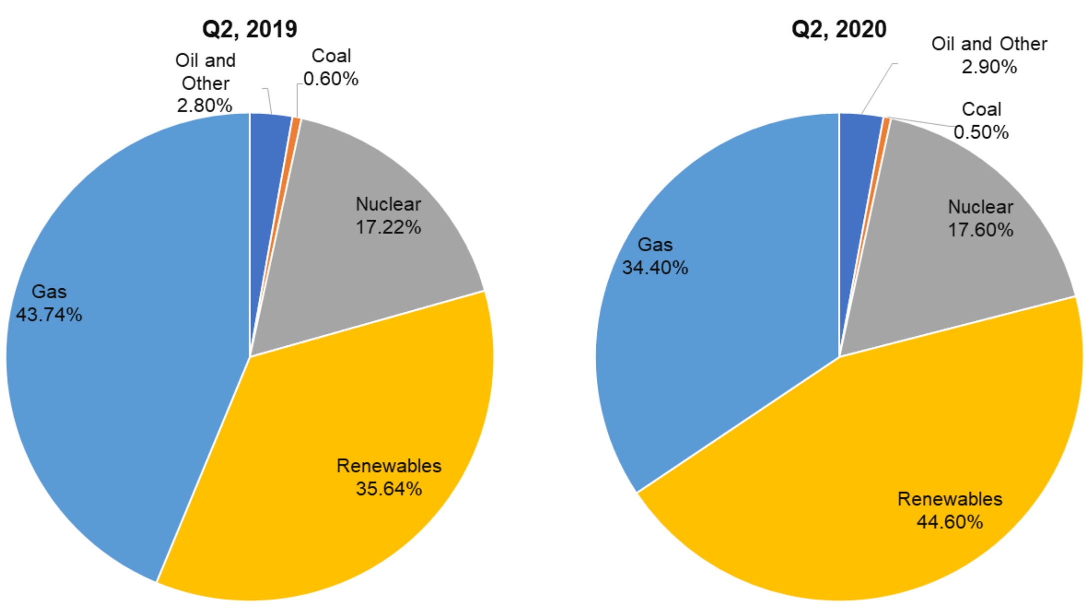

Fig. 8 – Variations of generated electricity shares in the UK between the second quarters of 2019 and 2020 [22].

Several studies have suggested that shrank energy demand can give rise to a higher renewable proportion [16]. Under COVID-19 measures, this phenomenon becomes more pronounced because of the declining of total energy consumption and the increasing of renewable generations. In the countries' future energy system, it can be expected that the UK's electricity demand will be filled by more renewable sources because of the stated Net-Zero 2050 target. It is important to consider the historical correlations between renewable energy supplies and national electricity demand during the COVID-19 pandemic. In the UK, the top three renewable contributions came from biomass, wind, and solar energy. For instance, around 40% of electricity was generated from renewables in the third quarter of 2019, which consists of 20% wind, 12% biomass and 6% solar [26]. Therefore, in this paper, the daily renewable supplies from biomass, wind, and solar are selected as input features in the designed time series forecasting model.

2.3 Environmental conditions

Electricity demands are also intensely impacted by the state of the weather, such as ambient temperature and wind speed. It can be observed that the energy consumptions of space heating rise while ambient temperature drops, and vice versa. Similarly, hot water demand from boilers upsurges as supply temperatures of water reduces, which were correlated with ground temperature. Besides, the rapid developments of both wind farms and solar PV across the UK have shaped the power supply system more dependent on weather conditions. In this study, meteorological parameters of ambient temperature and wind speed were considered as input features in the developed electricity demand time series predictive model.

2.4 Dataset description

The statistical description of count, mean, percentile and standard deviation of the used features were presented in **Table 1**. As the smoothed numbers of COVID-19 tests were announced daily since 08/04/2020 [27], the historical datasets between 08/04/2020 ~ 26/09/2020 (one hundred and seventy-two days) were extracted to be used in the designed time series predictive model, including electricity demand, number of new tests (smoothed), ambient temperature, wind speed, and wind, biomass & solar power supplies. Note that, in **Table 1**, electricity demand and renewable power supplies were recorded in gigawatts (GW), representing the rate of energy transfer. The meteorological parameters were collected from the records in London city airport station [28]. The standard deviation of the number of new tests (smoothed) was 57654, which presented the variability of this set of data, indicating the testing capability of COVID-19 has raised considerably during the target period. On the other hand, the standard deviations of other features were relatively small, suggesting the dispersions of those values are relatively low from their mean and median.

Table 1 – Statistical descriptions of the used datasets.

	Count	Mean	Standard deviation	Minimum	25%	Median	75%	Maximum

Number of new tests (smoothed)	172	111228	57654	15713	77983	94953	155665	231257
Electricity demand, GW	172	24.63	2.30	19.52	22.97	24.42	26.60	29.91
Ambient temperature, °C	172	17.17	3.90	8.20	14.45	17.45	19.23	26.70
Wind speed, m/s	172	14.76	5.31	5.30	11.00	13.95	17.93	33.00
Wind power supply, GW	172	4.61	2.71	0.28	2.57	4.10	6.79	11.04
Biomass power supply, GW	172	1.98	0.72	0.42	1.31	1.93	2.66	3.14
Solar power supply, GW	172	1.92	0.63	0.56	1.44	1.98	2.36	3.19

3. Methodology

As described in section 2.4, the electricity demand is varying in a relatively small range over time horizons, but the magnitudes of new tests (smoothed) are changing notably. Therefore, the long-established RNN and LSTM may not have their best performance on this occasion. In this paper, a deep-learning-based Bi-LSTM time series predictive model was proposed to forecast the daily electricity demand in the UK, which can better handle long-term dependencies and safer solved the vanishing gradient problem compared with RNN and LSTM.

3.1 Bidirectional Long Short Term Memory (Bi-LSTM)

Bi-LSTM admits cells to learn the sequence data both forward and backward with two individual hidden layers that serve the same output layer. A classic architecture of the Bi-LSTM cell is displayed in **Fig. 9**.

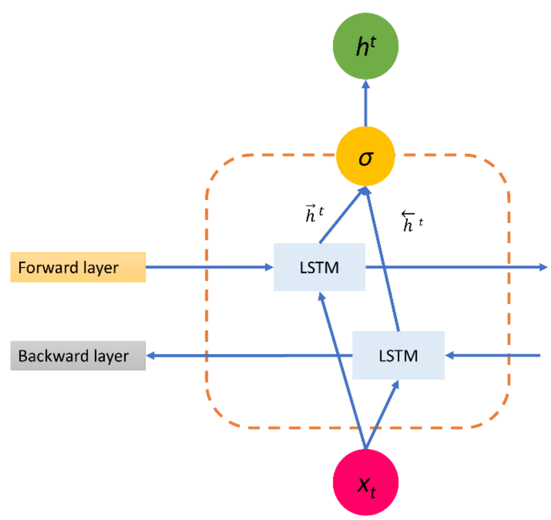

Fig. 9 – Architecture of a Bi-LSTM unit.

The corresponding forward hidden layer functions were identified in **Eqs. (1)** ~ **(6)** (note that the → is representing the forward process). In **Eqs. (1)** ~ **(3)**, input, forget and output gate activation vectors of $\vec{\imath}^{\,t}$, $\vec{f}^{\,t}$ and $\vec{o}^{\,t}$ were calculated through the assigned weights of $\vec{W}$ and $\vec{U}$, and the bias $\vec{b}$ along with corresponding activation functions σ. $\vec{x}^{\,t}$ is the input of neuron at time step t and $\vec{h}^{t-1}$ is the cell state vector for time step $t-1$.

$$\vec{\imath}^{\,t} = \sigma\left(\vec{W}^{\,i}\,\vec{x}^{\,t} + \vec{U}^{i}\,\vec{h}^{t-1} + \vec{b}^{i}\right) \tag{1}$$

$$\vec{f}^{\,t} = \sigma\left(\vec{W}^{f}\,\vec{x}^{\,t} + \vec{U}^{f}\,\vec{h}^{t-1} + \vec{b}^{f}\right) \tag{2}$$

$$\vec{o}^{\,t} = \sigma\left(\vec{W}^{\,o}\,\vec{x}^{\,t} + \vec{U}^{o}\,\vec{h}^{t-1} + \vec{b}^{o}\right) \tag{3}$$

In **Eq. (4)**, the newly assessed value of state $\vec{\tilde{c}}^{\,t}$ is calculated in a similar mothed along with corresponding activation functions $tanh$.

$$\vec{\tilde{c}}^{\,t} = tanh(\vec{W}^{c}\,\vec{x}^{\,t} + \vec{U}^{c}\,\vec{h}^{t-1} + \vec{b}^{c}) \tag{4}$$

In **Eq. (5)**, the cell state $\vec{c}^{\,t}$is obtained from the previous cell state $\vec{c}^{\,t-1}$ and the newly assessed value of state $\vec{\tilde{c}}^{\,t}$.

$$\vec{c}^{\,t} = \vec{f}^{\,t} \circ \vec{c}^{\,t-1} + \vec{\imath}^{\,t} \circ \vec{\tilde{c}}^{\,t} \tag{5}$$

In **Eq. (6)**, the forward output $\vec{h}^{\,t}$ is generated from the Hadamard product ($\circ$) of the output gate control signal $\vec{o}^{\,t}$ and the cell state $\vec{c}^{\,t}$ of the unit across the activation function $tanh$.

$$\vec{h}^{\,t} = \vec{o}^{\,t} \circ tanh\,(\vec{c}^{\,t}) \tag{6}$$

Similarly, **Eqs. (7)** ~ **(12)** defined the corresponding backward hidden layer functions (note that, the → is representing the backward process).

$$\overleftarrow{\imath}^{\,t} = \sigma\left(\overleftarrow{w}^{\,i}\,\overleftarrow{x}^{\,t} + \overleftarrow{u}^{\,i}\,\overleftarrow{h}^{\,t+1} + \overleftarrow{b}^{\,i}\right) \tag{7}$$

$$\overleftarrow{f}^{\,t} = \sigma\left(\overleftarrow{w}^{\,f}\,\overleftarrow{x}^{\,t} + \overleftarrow{u}^{f}\,\overleftarrow{h}^{\,t+1} + \overleftarrow{b}^{\,f}\right) \tag{8}$$

$$\overleftarrow{o}^{\,t} = \sigma\left(\overleftarrow{w}^{\,o}\,\overleftarrow{x}^{\,t} + \overleftarrow{u}^{\,o}\,\overleftarrow{h}^{\,t+1} + \overleftarrow{b}^{o}\right) \tag{9}$$

$$\overleftarrow{\tilde{c}}^{\,t} = tanh\left(\overleftarrow{w}^{\,c}\,\overleftarrow{x}^{\,t} + \overleftarrow{u}^{\,c}\,\overleftarrow{h}^{\,t+1} + \overleftarrow{b}^{c}\right) \tag{10}$$

$$\overleftarrow{c}^{\,t} = \overleftarrow{f}^{\,t} \circ \overleftarrow{c}^{\,t+1} + \overleftarrow{\imath}^{\,t} \circ \vec{\tilde{c}}^{\,t} \tag{11}$$

$$\overleftarrow{h}^{\,t} = \overleftarrow{o}^{\,t} \circ \tanh\,(\overleftarrow{c}^{\,t}) \tag{12}$$

Finally, the hidden element representation h^t can be expressed in **Eq. (13)** as the concatenated vector of the outputs of forwards and backwards processes [29]:

$$h^t = \overline{\vec{h}^t} \oplus \overline{\overleftarrow{h}^t} \tag{13}$$

3.2 Model configuration

To further explain the details of the neural network configuration, a visualised process of the proposed deep-learning-based Bi-LSTM structure is described in **Fig.10**. For any newly proposed neural network configuration, it is essential to maintain a high degree of forecasting accuracy through manual and grid search. In this study, this is realised through assessing a variety of neural network structures, adjusting the trials with various layer numbers and different neuron numbers in each layer. The evaluation results have suggested a deep learning neural network consists of a three-layer structure (see **Fig. 10**, Hidden layers), creating a strong relationship between inputs (number of new coronavirus tests, wind speed, ambient temperature, biomass, solar & wind power supplies, and historical electricity demand; see **Fig. 10** Input layer) and the output (future electricity demand, see **Fig. 10**, Output layer). Besides, the first and the third hidden layers consist of 10 neurons, while the remaining layer has 20 neurons.

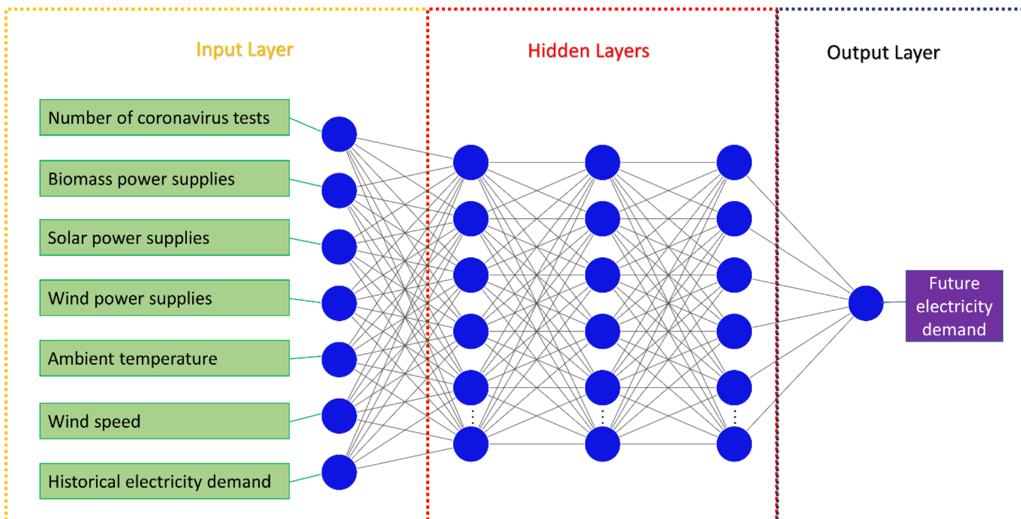

Fig. 10 – Visualization of the deep-learning-based Bi-LSTM configuration.

Before entering into the deep learning model, input data were transformed into a matrix with three dimensions of *batch*, *input*, and *shape*, where *batch* is the number of independent observations in the time series; *input* is the sequence length of the given observation; *shape* is the number of features at the observation time. More specifically, in the current deep learning neural networks, the used multivariate sequences were converted into multiple samples. Each sample contains only one-time step that is used to output a single future step. Similar to other machine learning models, Bi-LSTM models can only work well whereas the involved time series data are on the scale of a certain range. In this study, all inputs were scaled between 0 and 1 before feeding into the deep learning layers. Besides, the Bi-LSTM deep learning neural networks were also validated through the walk-forward rolling prediction, indicating each time step in electricity demand forecasting will be rolled at a time. After the time series predictive model developed a prediction for one-time step, the recorded electricity demand will be grasped and further used in predictions for the next time step.

4. Results and Discussions

In this section, the developed deep-learning-based Bi-LSTM time series predictive model was used to explore the intensity of key features in electricity demand forecasting and to identify the quantitative impacts of COVID-19 measures. The obtained datasets were divided into two groups – the training group (08/04/2020 ~ 05/09/2020) and the validation group (06/09/2020 ~ 26/09/2020). The built Bi-LSTM neural network follows the train-validation framework. More specifically, in the training phase, both input and output features were presented to the forecasting model while Bi-LSTM learns the patterns to produce accurate electricity demand forecasting. After that, the independent validation dataset was used to validate its forecasting ability.

4.1 Training phase

The selected features were trained in the designed Bi-LSTM deep learning configuration, where the activation function of "sigmoid" was used to engage all the neuron units for learning the patterns between input features and the targeted electricity demand. Also, the loss function of Mean Square Error (MSE) was applied to maximise the performance of the predictive model concerning its desired accuracy. Additionally, the effective optimizer of adaptive moment estimation (adam) was directed to support the loss function to achieve its convergence with minimum delay. During the training phase, the MSE profile has dropped rapidly once the first one-hundred of epochs were achieved, showing convergency after around 150 iterations (see **Fig. 11**).

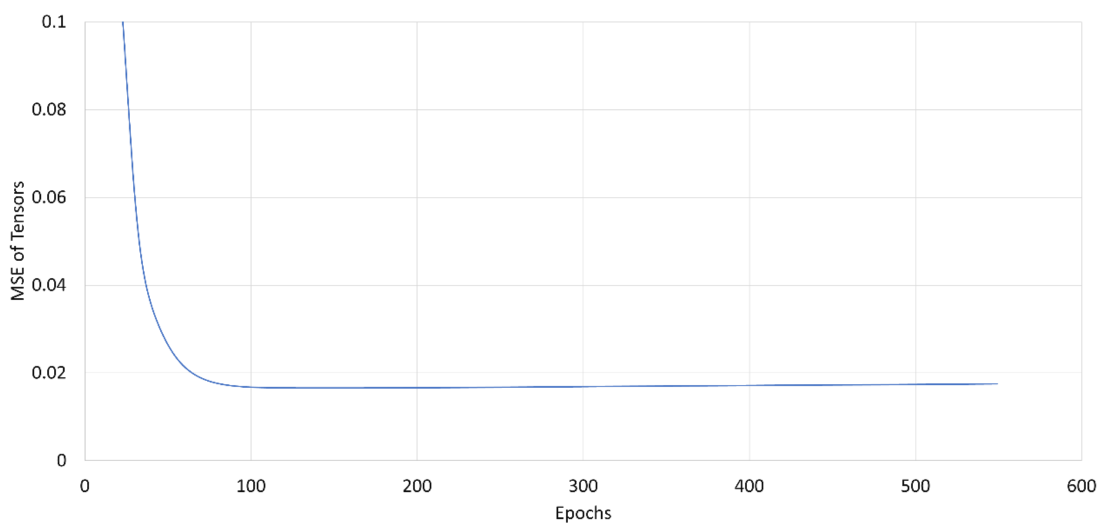

Fig. 11 – Variations of MSE profile in the Bi-LSTM time series forecasting model during the training phase.

4.2 Validation phase

The daily electricity demand predicted in the validation loop was compared with the recorded observations in **Fig. 12**, where a good agreement was achieved for a duration of 20 days (06/09/2020 ~ 20/09/2020). During the validation phase, the accuracy of the designed Bi-LSTM neural network was quantified through Root Mean Square Error (*RMSE*) [30] and Mean Squared Logarithmic Error (*MSLE*) [31], which were stated in **Eqs. (14)** and **(15)**, respectively. In the validation loop, the final values of *RMSE* and *MSLE* were 1815.22 and 0.003616, respectively (see **Fig. 12**).

RMSE is one of the most widely used metrics for measuring the discrepancy between forecasting values and actual observations. Generally, the lower the *RMSE* value is, the more accurate the forecasting models are. Its definition can be expressed as:

$$RMSE = \sqrt{\frac{\sum_{j=1}^{n}\left[(M_{predicted})_j - (M_{measured})_j\right]^2}{n}} \tag{14}$$

The metric of *MSLE* is corresponding to the assessed value of squared logarithmic errors, which can be stated as:

$$MSLE = \frac{1}{n}\sum_{j=0}^{n-1}(\log_e(1 + (M_{measured})_j) - \log_e(1 + (M_{predicted})_j))^2 \tag{15}$$

Logarithms give MSLE unique properties of its own. The major difference between RMSE and MSLE is their sensitivities to outliers in the datasets. In the case of MSLE, the impacts from the outliers can be scaled down, because MSLE reflects relative errors between the forecasted and the actual values, where influences from the absolute scale of error terms were considerably reduced. On the other hand, RMSE is more sensitive for exceptional data points. Therefore, MSLE is more robust when outliers were contained in the assessed datasets.

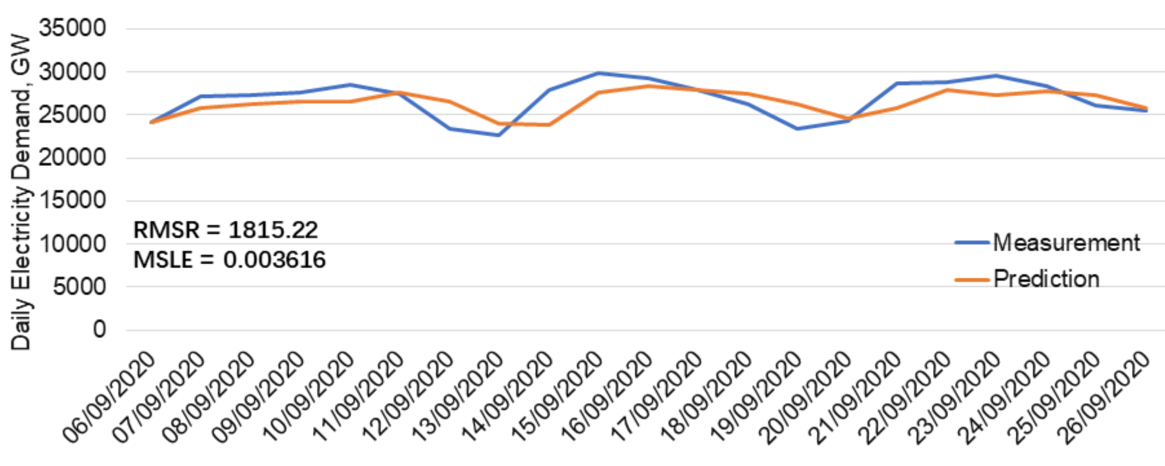

Fig. 12 – Comparisons of daily electricity demands between the designed forecasting model (prediction) and the actual records (measurement).

4.3 Feature significance

In the built multivariate Bi-LSTM time series predictive model, level of significance of each feature to the predicted daily electricity demand was put forward through a ranking of the six features. The top-ranked feature was determined using the variations of the final accuracy in the validation loop of the forecasting model. At each validation loop, one feature was swapped by its average value, while other parameters/structures remained the same in the deep-learning-based configuration. As only one feature is displaced at one time, this appraisal will be reiterated on all the six inputs one by one, including the number of new coronavirus tests (smoothed), wind speed, ambient temperature, and biomass, solar & wind power supplies.

Variations of *RMSEs* and *MSLEs* along validation loops over each feature are presented in **Fig. 13**. Comparing with the initial case, the values of the final *RMSEs* kept decreasing in a certain order. Therefore, the level of importance of features in electricity demand forecasting can be ranked in the order of new tests (smoothed) (*RMSE* = 1861.71), solar power supply (*RMSE* = 1858.63), wind power supply (*RMSE* = 1851.52), biomass power supply (*RMSE* = 1849.57), temperature (*RMSE* = 1846.33), and wind speed (*RMSE* = 1843.02). Similar to *RMSE*, the values of the final *MSLE* kept growing in the identical order, which indicated that the same correlations were observed between input features and electricity demand.

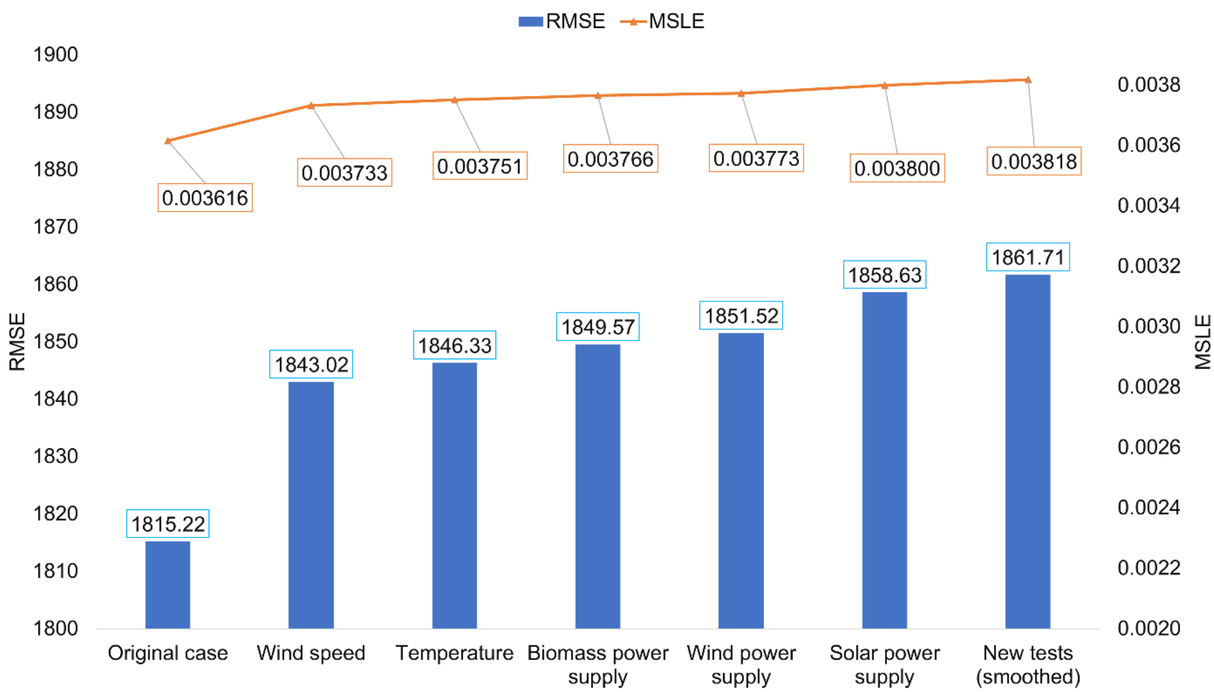

Fig. 13 – Variations of *RMSE* and *MSLE* scores in the deep-learning-based Bi-LSTM time series forecasting model under varying input features.

The influence of new coronavirus tests (smoothed) tops the bill in terms of feature significance, indicating that they are playing an essential role in the variations of daily electricity demand in the UK. While most companies, schools and supermarkets were forced to be closed, the nationwide electricity demand of transmission system has been significantly impacted by the lockdown measures, where the overall electricity demand in the UK was dramatically reduced due to the economic downturn of commercial and industrial businesses. It can be concluded that COVID-19 measures have a strong negative impact on daily electricity demand. On the other hand, solar, wind, and biomass power supplies took the 2nd, the 3rd, and the 4th places of all the features, indicating renewable powers also present a strong effect on the accuracy of the designed predictive model. Lower electricity demand indicates that a larger proportion of the UK transmission system can be occupied by renewable generators, such as solar and wind when meteorological conditions are advantageous, while less fossil fuel generators are required, such as gas and coal. The impact of ambient temperature on electricity demand is ranked as the 5th as the temperature has an integrated influence on electricity demand because it is a function of electricity in heating and cooling. Wind speed took the last place in the rank, representing that it provided the lowest impact on the daily electricity demand.

5. Conclusions

This work contributed to the knowledge gaps in electricity demand forecasting by considering the impacts of COVID-19 measures. A deep-learning-based multivariate time series Bi-LSTM model was trained and validated through a set of selected features. The key conclusions from this study were summarised as follows:

- This research has demonstrated and quantified, for the first time, the level of significance of various features to evaluate their impacts on electricity demand via a deep-learning-based Bi-LSTM model, including the number of new coronavirus tests (smoothed), ambient temperature, wind speed, and renewable power supplies (wind, biomass and solar). This approach facilitates our understanding of how COVID-19 measures will determine the reduction of electricity demand through a multivariate neural network configuration, showing quantifiable results. Compared to other common impact factors, the COVID-19 measures (represented by the number of new coronavirus tests) have a strong influence on the electricity system in the UK, which was ranked as the top among the involved features.
- The annual electricity demand in the UK has kept reducing long before the COVID-19 pandemic. The strict lockdown restrictions taken by the government make this phenomenon much severer, as most of the national population have been subjected to lockdowns since the 23rd March, following a sharp drop in social and economic activities. The falling in demand made the everyday electricity profile looks like a Sunday's. The recovery of nationwide electricity demand will be very gentle as the lockdown was lifted in stages. Besides, the second wave of the pandemic has come in the winter, representing a management challenge for grid network operators.
- Based on the deep-learning-based Bi-LSTM model, historical renewable power supplies of solar, wind, and biomass were ranked as the 2nd, the 3rd, and the 4th significant features, indicating their crucial correlations with electricity demand during the pandemic. One of the reasons could be the demand decreasing during the COVID-19 crisis, which raised the proportion of low-carbon energy. This may be one of the very few positive influences that COVID-19 has brought to the target of Net-Zero 2050. It can be expected that renewable supplies will keep growing in electricity generations of the UK, due to lower energy demands in future.

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