Energy Management in an Agile Workspace using AI-driven Forecasting and Anomaly Detection

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***Abstract*—Smart building technologies transform buildings into agile, sustainable, and health-conscious ecosystems by leveraging IoT platforms. In this regard, we have developed a Persuasive Energy Conscious Network (PECN) at the University of Glasgow to understand the user-centric energy consumption patterns in an agile workspace. PECN consists of desk-level energy monitoring sensors that enable us to develop user-centric models that characterizes the normal energy usage behavior of an office occupant. In this study, we make use of staked long short-term memory (LSTM) to forecast future energy demands. Moreover, we employed statistical techniques to automate the detection of anomalous power consumption patterns. Our experimental results indicate that post-anomaly resolution leads to 6.37% improvement in forecasting accuracy.**

***Index Terms*—LSTM, Short term load forecasting, Time series forecasting, Agile workplace, COVID-19.**

I. Introduction

Cheap and uninterrupted energy supply has a significant impact on the socio-economic development of a country. Various studies directly relate energy consumption with technological advancements, economic growth, and high living standards [1], [2]. Electrical energy is one of the main sources of energy whose demand is increasing at an exponential rate. Maintaining the ever increasing energy demand comes at the cost of higher carbon emissions caused by the sources to generate electricity. According to the report of the International Energy Agency (IEA), 63.1 % of global electricity generation comes from combustible fuels which are quite alarming, keeping the current environmental concerns in view [3]. Therefore, energy usage optimisation is essential to reduce the dependence on fossil fuels and contribute to meeting zero net emissions (ZNE) targets.

The interconnection of information communication technologies (ICT), advanced metering infrastructure (AMI), and the internet of things (IoT) is term as the smart grid. The overall electrical power system is quite complex, involving multiple stakeholders including energy producers, distributors, utilities and consumers [4]. Furthermore, the electricity energy market is highly competitive and deregulated which requires efficient energy management schemes to ensure reliability, operations and consumer satisfaction [5]. This task can be achieved by exploiting the data generated by different stakeholders using ICT and AMI. For instance, a historic load profile can be used for short-term load forecasting (STLF) at both the supply side and consumer level, enabling the real-time fine grain consumption monitoring [6]. On the supply side, STLF is used for obtaining the regional aggregated energy profile which helps in energy dispatch, schedule maintenance, and smooth operations. Furthermore, predicted load is also used to devise effective energy management schemes to ensure the demand and supply equilibrium and reduce the per-unit generation cost [3], [5]. STLF for individual consumers is very essential as it provides insights on their consumption patterns necessary for scheduling daily activities based on the time of use pricing mechanism. This is despite it being a very challenging task due to the random behaviour, residents' habits, and unusual seasonal variations. Furthermore, the consumers are getting more energy aware and conscious about their energy consumption behaviour. Moreover, the current building sector is also moving towards smart buildings to optimise the energy usage and promote efficient energy consumption practices which can be reinforced by real-time monitoring using STLF.

Building sector is one of the major electrical consumer with the global share of approximately 38-40%. According to IEA, the building energy consumption will kept on increasing on an average of approximately 1.3% annually [7]. The significant amount energy in smart building is consumed by heating and cooling system, security and surveillance system, water and lighting. With the global NZE policy, the current effects are more focused on fulfilling the requirements for energy-efficient buildings by guaranteeing the operative needs with minimum energy cost and more environment friendly sources [8]. The recent Covid-19 pandemic has caused the unprecedented changes in life style of individual, influencing the energy market as well, especially smart buildings. For instance, in big organisation and universities, individuals preferred to work from home due to restriction, results in drastic change in energy consumption patterns. Furthermore, in recent times, a new concept of agile work space has emerged where no specific space is allotted to individual to use work space efficiently [9]. The agile work space setup has introduced the additional complexity, resulting in more random energy consumption patterns which make STLF even more challenging.

Keeping the agile working space in our mind, we have deployed a persuasive energy conscious network (PECN) at the James Watt School of Engineering, University of Glasgow

(UofG). The PECN consists of LoRaWan-enabled IoT nodes (smart energy sensors) that captures the desk level hourly load profile and store the data on a cloud server placed at UofG. The idea of PECN is to merge IoT and smart sensing technologies to capture the energy pattern in the agile workspace and use this data to influence user consumption behaviour. The first step is to develop a STLF model, generating proactive load curves for real-time monitoring. In this paper, we have exploited the PECN data and developed a STLF model using LSTM, and compared the results with feed forward network, convolutional, and bi-directional neural network. Furthermore, we have also developed an anomaly detection mechanism to filter the outliers, resulting in improved forecast results. The key contributions of this paper are highlighted below:

- We have developed an energy monitoring setup by merging the IoT and smart sensing technologies to collect the desk-level information in an agile work space.
- Developed a zone level anomaly detection mechanism for data filtering and LSTM based STLF model for hourly load prediction in agile work space.

II. Test bed and data acquisition

The PECN testbed is currently operational at the University of Glasgow, UK and it is monitoring and displaying the energy consumption habits of individuals to persuade them and alter their energy usage behaviours in ways that may be financially and environmentally beneficial. This testbed consists of twenty LoRaWan-enabled smart sensors installed in different studying desks in two zones, 12 sensors in zone 1 and 8 in zone 2, as illustrated in Fig.1. The sensors continuously report the electricity-related information to the multi-access edge computing (MEC) server through the LoRa WAN gateways. In addition, these sensors have actuating capability to perform remote controlling. Raw data is collected from smart nodes and transmitted through LoRaWAN to a LoRa Gateway provided by IoT Scotland, situated in the Communications, Sensing, and Imaging (CSI) lab. LoRa Gateway is connected to the IoT Boston server, also provided by IoT Scotland via 5G backhaul link. IoT Boston server is not being used to store any data, it is just a passageway of data packets to the MQTT public server. A topic (labeling of incoming data packets) is created at the MQTT server, and a corresponding URL is generated. Now data is pushed to MEC server where data is received by Node Red software, a java-based application. At Node Red the created topic is subscribed, and a flow is created. Then the following information is retrieved:

1) Active energy (Wh)
2) Reactive energy (VARh)
3) Voltage (V)
4) Frequency (Hz)
5) CO_2 footprint
6) Occupancy

The retrieved data set is then stored in tabular form in InfluxDB. Grafana Dashboard is then used to display the stored data. The data acquisition process is depicted graphically in Fig 2.

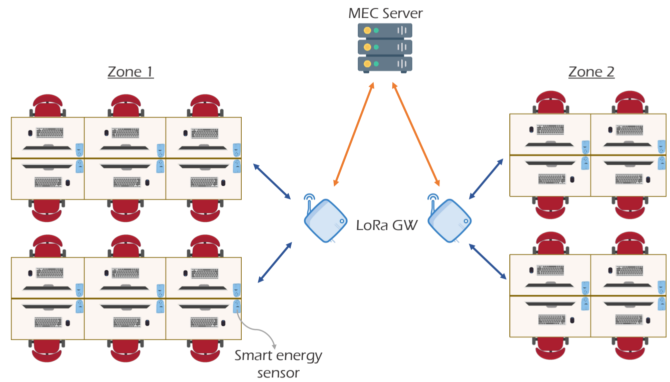

Fig. 1. Illustrative diagram of the PECN project and how the smart energy sensors are connected with the MEC server.

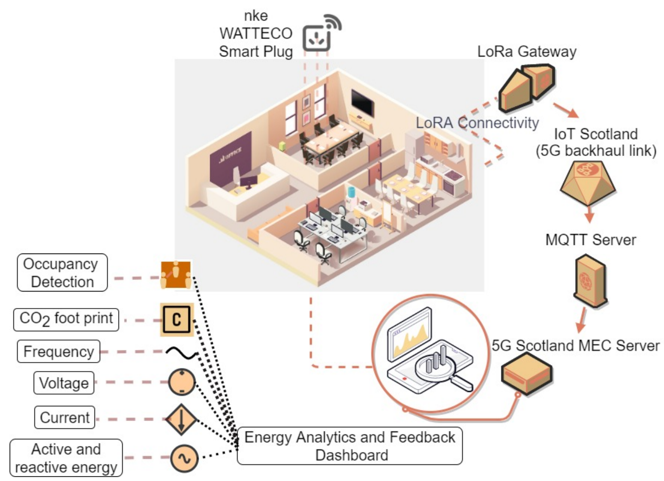

Fig. 2. Data acquisition in PECN testbed.

The two zones are considered agile workspace, which means the desks are not dedicated to a specific person. Therefore, this working mechanism will add more privacy to the collected data as usage habits can not be linked to specific individuals. In this work, we focus on STLF, thus the received data is accumulated in hourly time resolution and then fed to the ML algorithms to predict the energy consumption patterns.

The dataset used in this study covers the time period from 15 October 2021 to 2 March 2022 consisting of 138 days. Fig. 3 shows more details about the energy dataset for different time resolutions. Fig. 3(a), shows the raw data which we feed to the ML model. It contains 3033 samples collected on an hourly basis. The average energy consumption throughout the days is plotted in Fig. 3(b). It can be seen that zone 1 consumed more energy than zone 2. Daily aggregated and average monthly consumed energy is illustrated in Figs. 3(c) and (d), respectively.

It is worth noticing that zone 1 has high valued outliers than zone 2. The augmented ducky fuller test showed that p-values for zone 1 and zone 2 are 0.000040 and zero, respectively. Since the p-value is less than 0.05, it means that both collected datasets of zone 1 and zone 2 are stationary and have no time

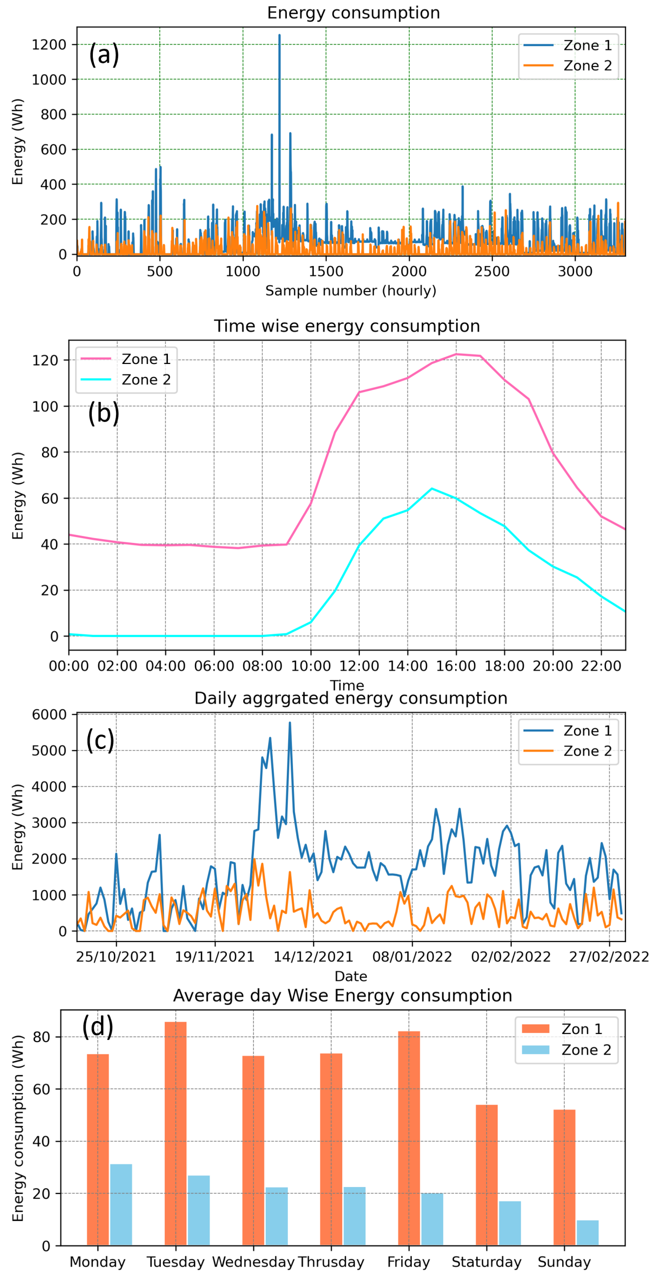

Fig. 3. Data characteristics for different time resolutions. (a) Hourly aggregated energy data samples, (b) average energy consumption for one day, (c) daily aggregated energy consumption, (d) average energy consumption for each weekday.

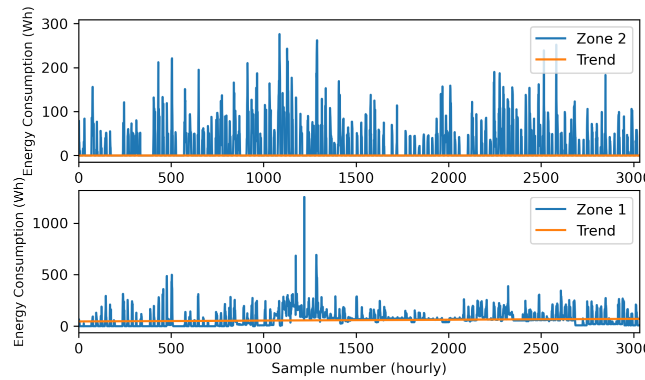

Fig. 4. Trend of zone 1 and zone 2.

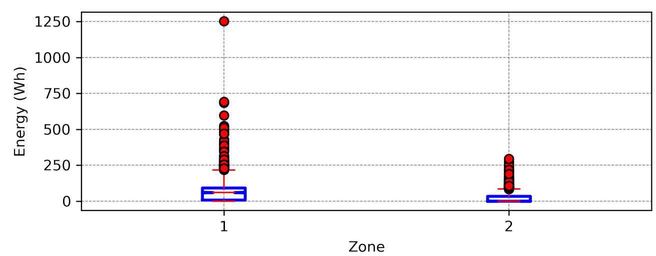

Fig. 5. Outlier visualisation in zone 1 and zone 2.

decencies. To check the randomness of collated data Ljung-Box test was performed, results showed that the data does contain an autocorrelation. The trend of collected data was checked with the Mann-Kendall test using pyMannKendall package [10], and results are depicted in 4, where energy consumption is represented with blue color and trend is shown with orange color. The test results showed that the trend slop and intercept of zone 2 are zero while the trend slop of zone 1 is 0.008 and the intercept is 46.16. To observe outliers in both zones, the boxplot is resented in Fig. 5 . It can be clearly seen that zone 1 has the high number of outliers.

Hence, it is clear that the collected samples have no trends, and the randomness exists, which is attributed to the fact that few students were visiting these zones at irregular times due to the situation of the COVID-19 pandemic. Accordingly, energy forecasting will be more challenging and require careful ML model selection and hyperparameter tuning.

III. Short-term Load Forecasting

A time series is described as a succession of values that are arranged sequentially and observed across time [11]. For a long time, linear statistical approaches such as ARIMA models have had an impact on time series forecasting. However, by the 1980s, it had become evident that linear models could not forecast time series for real applications [12]. In the meantime multiple new models started to emerge such as bilinear model [13], the threshold auto regressive [14], auto regressive conditional heteroscedastic (ARCH) model [15]. ML techniques have gained traction in the forecasting community during the last two decades and have established themselves as genuine competitors to traditional statistical models [12]. The results of Werbos' studies show that Artificial Neural Networks (ANNs) outperform classical statistical methods like linear regression and Box-Jenkins analysis [16].

In neural network time series forecasting a specific number of samples, known as call back window, are fed to the model, and the model predicts future values. A simplest example can be, feeding the past two values to the model and predicting a future value. Recurrent neural networks (RNNs) have historically been used in time series problems [17]. The network's delay recursion property of an RNN allows it to represent the dynamic performance of systems [18]. Furthermore, RNNs save a vector of activations for each time step, making the RNN an extraordinarily deep neural network [19]. However, because of the exploding and vanishing gradient problems, it is generally difficult to train RNNs to learn long-term relationships in time series data. [20] [21]. LSTM was developed to tackle this problem by improving gradient flow in the network. It is achieved by introducing a block in the cell that retains long-term memory [22]. The input gate, output gate, forget gate, and self-recurrent neuron are the four gates (or units) that make up an LSTM memory cell. The input gate determines whether the input signal can influence the result of the memory cell. The output gate, on the other hand, selects whether it can change the state of other memory cells. The forget gate, has the flexibility of remembering (or forgetting) its previous condition [23] [24].

In this paper, an LSTM network was used for short-term energy prediction. Research studies have demonstrated that increasing the depth of a neural network can improve its performance [25], hence a stacked LSTM network containing three LSTM layers, one dropout layer, and one output layer was created, as shown in Fig. 6.

For the construction of the LSTM network, the Keras library was used [26]. The first LSTM layers had 100 units, followed by a dropout layer, used to tackle the problems of overfitting. The dropout layer was further connected to the LSTM layer of 50 units and then to another LSTM layer of 32 units. In the end, a dense layer was added as the output layer. The performance of the created neural network was evaluated based on Mean Absolute Percentage Error (MAPE), which can be calculated as:

$$MAPE = \frac{1}{n} \sum_{n}^{t=1} \left| \frac{A_t - F_t}{A_t} \right| \tag{1}$$

where A_t is actual value, F_t is foretasted value and n is total number of iterations. It is worth mentioning that the MAPE is independent of system capacity and the unit of measurement, it may be the only error metric that can be used to compare forecasting performance between various utilities [27].

The data set consists of Wh energy values is used, as graphically illustrated in Fig. 3(a). During the experimentation call-back window of 2 to 24 previous values was considered to forecast one future value, however, optimal results were obtained using the past two values.

To perform cross-validation the train-test split method was implemented where seventy percent of the data was used as training and thirty percent used as testing. Experiment results showed that a MAPE of 13.77% was achieved from zone 1 and 12.30% from zone 2. The predicted and original curves for zone 1 and zone 2 are drawn in Fig. 7 and 8, respectively. Our experimental results showed energy curves of zone 2 can be foretasted with a lower MAPE, of 12.30%, because we have observed that zone 1 has a higher number of outliers and anomalies as compared to zone 2 (Fig. 3(a).

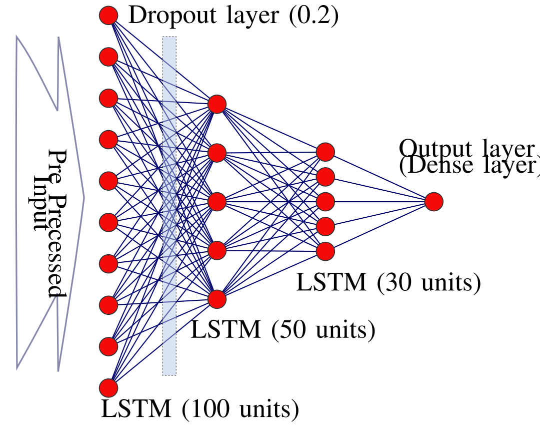

Fig. 6. Designed neural network

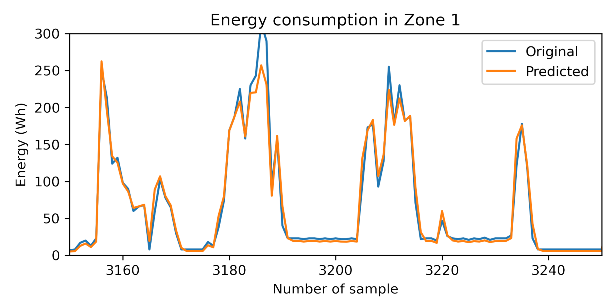

Fig. 7. Energy forecasting of zone 1.

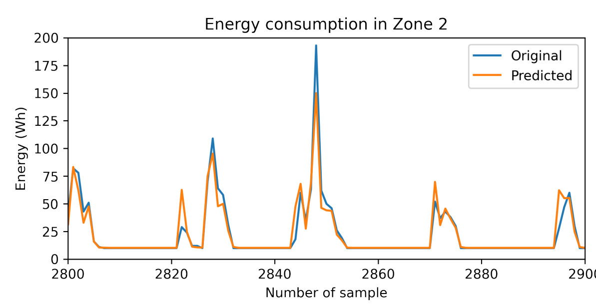

Fig. 8. Energy forecasting of zone 2.

The results of the LSTM neural network were compared with feed forward, convolutional and bi-directional LSTM neural networks. After an exhaustive set of simulations, it was found that the feed forward neural network provided a MAPE of 41.94% and 37.3% for zone 1 and zone 2, respectively. The convolutional neural network surpassed the feed forward network, with MAPE of 28.08% and 34.27% for zones 1 and 2, respectively. The bidirectional neural network did not outperform the convolutional neural network; it only generated a MAPE of 42% and 35% for zone 1 and zone 2, respectively.

IV. Anomaly identification

An anomaly can be defined as anything inconsistent from the rest of the data set [28]. Anomaly detection is performed in many applications such as energy forecasting [29] [30], grouping of load patterns [31], load data cleaning [32] and gas demand forecasting [33]. The anomalies in zone 1 and zone 2 can be categorised as point anomalies, also known as outliers [34]. Since the collected data falls under the category of stationary time series, non-regressive approaches [35] such as z-score can be used [36]. This method has been utilised in detection of anomalies in many applications such as [37], [38], [39]. Z-score can be calculated as:

$$Z = \frac{x_i - \mu}{\sigma} \tag{2}$$

where Z stands for z-score, x_i is data value at ith point and σ represents standard deviation. Given the random nature of the data Z of 5 was considered. After passing the data through anomaly removal criteria, described above, 14 and 30 anomalous points were detected from zone 1 and zone 2, respectively. Anomalous points from zone 1 and zone 2 are presented in Fig. 9 and in Fig. 10, respectively, here red dots represent anomalies and a black dotted line is drawn to separate train and test data.

After anomaly detection of zone 1 and zone 2, data was again fed to the designed neural network to forecast future values. Since the best results were obtained from LSTM networks, so here only LSTM is considered. Post anomaly forecasting of zone 1 showed that MAPE decreased from 13.77% to 10.92% and in zone 2 MAPE decreased from 12.30% to 5.93%. Post anomaly original and foretasted for zone 1 and zone 2 curves are presented in Fig. 11 and Fig. 12, respectively. The experimental results are summarized in Table I, here feed forwarded, convolutional, and bidirectional LSTM neural networks are represented by FF, Conv, and Bi-LSTM, respectively.

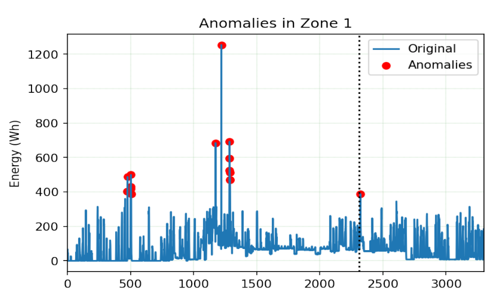

Fig. 9. Anomaly detection in Zone 1.

V. Conclusions

Energy forecasting is a difficult task in an agile environment. To obtain user-centric information on energy consumption Persuasive Energy Conscious Network (PECN) testbed was created during the pandemic at the University of Glasgow, UK. The PECN testbed collects energy consumption from

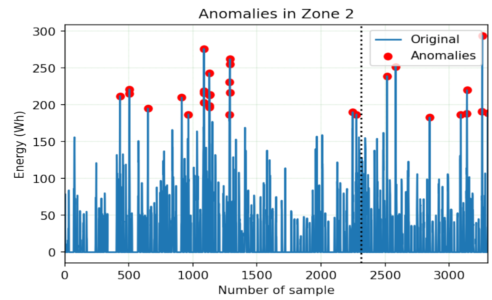

Fig. 10. Anomaly detection in Zone 2.

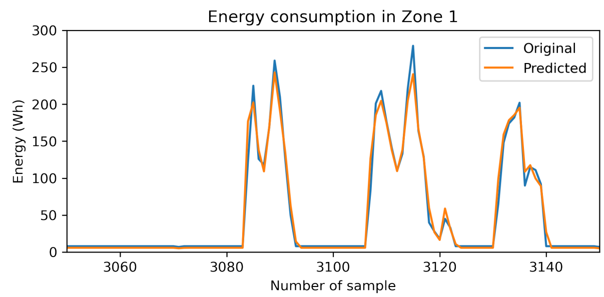

Fig. 11. Post anomaly STL forecasting of Zone 1.

two different zones operating as agile workspace meaning that anyone can sit anywhere throughout the day. In this paper, we performed short-term energy forecasting and anomaly detection. A stacked LSTM neural network with three LSTM layers was used for energy forecasting. The result of the designed LSTM network was compared with feed forward, convolutional and bidirectional LSTM networks. The results of a comprehensive set of simulations showed that LSTM outperformed all other neural networks. Results indicated that

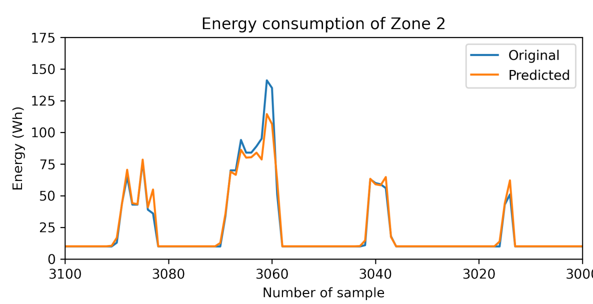

Fig. 12. Post anomaly STL forecasting of Zone 2.

TABLE I
Percentage MAPE

Neural Net. / Zone	FF	Conv	LSTM	Bi-LSTM	Post anomaly LSTM
Zone 1	41.49	28.08	13.77	42	10.92
Zone 2	37.3	34.27	12.30	35	5.93

the designed neural network was better able to forecast energy in zone 2 with MAPE of 12.30 % compared to zone 1 with MAPE of 13.77 % because zone 1 contained outliers with high energy consumption points. To overcome this problem, anomaly detection was done using a z-score model. Z-score > 5 indicated 14 and 30 anomalous points in zone 1 and zone 2, respectively. After anomaly reduction, the MAPE of zone 1 and zone 2 was reduced to 10.92% from 5.93%, respectively. In our future work, we plan to expand this work and exploit federated learning; a decentralised model training mechanism without sharing the data. Furthermore, our idea is to introduce a feedback mechanism in one of the zones to intervene in the inefficient energy consumption behaviour. Moreover, as the pandemic restriction is relaxing and we expect full capacity in both zones which provides us the opportunity to study the energy consumption behaviour of individuals post Covid-19.

REFERENCES

[1] W. Tao, H. Guang-shun, G. Jing, Y. Yue, and L. Lin-lin, "Energy consumption and economic growth in china's marine economic zones-an estimation based on partial linear model," *Energy*, vol. 205, p. 118028, 2020.

[2] G. Gozgor, C. K. M. Lau, and Z. Lu, "Energy consumption and economic growth: New evidence from the oecd countries," *Energy*, vol. 153, pp. 27–34, 2018.

[3] "Electricity - fuels amp; technologies," IEA, [Accessed: 28-Mar-2022] Jan, 2022. [Online]. Available: https://www.iea.org/fuels-and-technologies/electricity

[4] Z. Alavikia and M. Shabro, "A comprehensive layered approach for implementing internet of things-enabled smart grid: A survey," *Digital Communications and Networks*, 2022.

[5] H. J. Jabir, J. Teh, D. Ishak, and H. Abunima, "Impacts of demand-side management on electrical power systems: A review," *Energies*, vol. 11, no. 5, p. 1050, 2018.

[6] S. K. Mohapatra, S. Mishra, H. K. Tripathy, A. K. Bhoi, and P. Barsocchi, "A pragmatic investigation of energy consumption and utilization models in the urban sector using predictive intelligence approaches," *Energies*, vol. 14, no. 13, p. 3900, 2021.

[7] D. Mariano-Hernández, L. Hernández-Callejo, A. Zorita-Lamadrid, O. Duque-Pérez, and F. S. García, "A review of strategies for building energy management system: Model predictive control, demand side management, optimization, and fault detect & diagnosis," *Journal of Building Engineering*, vol. 33, p. 101692, 2021.

[8] J. Li, C. Zhang, Y. Zhao, W. Qiu, Q. Chen, and X. Zhang, "Federated learning-based short-term building energy consumption prediction method for solving the data silos problem," in *Building Simulation*. Springer, 2021, pp. 1–15.

[9] T. Keeling, D. Clements-Croome, and E. Roesch, "The effect of agile workspace and remote working on experiences of privacy, crowding and satisfaction," *Buildings*, vol. 5, no. 3, pp. 880–898, 2015.

[10] M. Hussain and I. Mahmud, "pymannkendall: a python package for non parametric mann kendall family of trend tests." *Journal of Open Source Software*, vol. 4, no. 39, p. 1556, 7 2019. [Online]. Available: http://dx.doi.org/10.21105/joss.01556

[11] J. F. Torres, D. Hadjout, A. Sebaa, F. Martínez-Álvarez, and A. Troncoso, "Deep learning for time series forecasting: a survey," *Big Data*, vol. 9, no. 1, pp. 3–21, 2021.

[12] J. G. De Gooijer and R. J. Hyndman, "25 years of time series forecasting," *International journal of forecasting*, vol. 22, no. 3, pp. 443–473, 2006.

[13] S. Price, "Mining the past to determine the future: Comments," *International Journal of Forecasting*, vol. 25, no. 3, pp. 452–455, 2009.

[14] H. Tong, *Non-linear time series: a dynamical system approach*. Oxford university press, 1990.

[15] R. F. Engle, "Autoregressive conditional heteroscedasticity with estimates of the variance of united kingdom inflation," *Econometrica: Journal of the econometric society*, pp. 987–1007, 1982.

[16] P. J. Werbos, "Generalization of backpropagation with application to a recurrent gas market model," *Neural networks*, vol. 1, no. 4, pp. 339–356, 1988.

[17] I. Goodfellow, Y. Bengio, and A. Courville, *Deep learning*. MIT press, 2016.

[18] I. Sutskever, *Training recurrent neural networks*. University of Toronto Toronto, ON, Canada, 2013.

[19] R. Jozefowicz, W. Zaremba, and I. Sutskever, "An empirical exploration of recurrent network architectures," in *International conference on machine learning*. PMLR, 2015, pp. 2342–2350.

[20] S. Hochreiter, Y. Bengio, P. Frasconi, J. Schmidhuber *et al.*, "Gradient flow in recurrent nets: the difficulty of learning long-term dependencies," 2001.

[21] R. Pascanu, T. Mikolov, and Y. Bengio, "On the difficulty of training recurrent neural networks," in *International conference on machine learning*. PMLR, 2013, pp. 1310–1318.

[22] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural computation*, vol. 9, no. 8, pp. 1735–1780, 1997.

[23] A. Graves, "Generating sequences with recurrent neural networks," *arXiv preprint arXiv:1308.0850*, 2013.

[24] F. A. Gers, J. Schmidhuber, and F. Cummins, "Learning to forget: Continual prediction with lstm," *Neural computation*, vol. 12, no. 10, pp. 2451–2471, 2000.

[25] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *nature*, vol. 521, no. 7553, pp. 436–444, 2015.

[26] N. Ketkar, "Introduction to keras," in *Deep learning with Python*. Springer, 2017, pp. 97–111.

[27] A. Candelieri, "Clustering and support vector regression for water demand forecasting and anomaly detection," *Water*, vol. 9, no. 3, p. 224, 2017.

[28] V. Barnett and T. Lewis, "Outliers in statistical data," *Wiley Series in Probability and Mathematical Statistics. Applied Probability and Statistics*, 1984.

[29] C. Guan, P. B. Luh, L. D. Michel, Y. Wang, and P. B. Friedland, "Very short-term load forecasting: wavelet neural networks with data pre-filtering," *IEEE Transactions on Power Systems*, vol. 28, no. 1, pp. 30–41, 2012.

[30] X. Chen, C. Kang, X. Tong, Q. Xia, and J. Yang, "Improving the accuracy of bus load forecasting by a two-stage bad data identification method," *IEEE transactions on power systems*, vol. 29, no. 4, pp. 1634–1641, 2014.

[31] G. Chicco, "Overview and performance assessment of the clustering methods for electrical load pattern grouping," *Energy*, vol. 42, no. 1, pp. 68–80, 2012.

[32] Z. Guo, W. Li, A. Lau, T. Inga-Rojas, and K. Wang, "Detecting x-outliers in load curve data in power systems," *IEEE Transactions on Power Systems*, vol. 27, no. 2, pp. 875–884, 2011.

[33] H. N. Akouemo and R. J. Povinelli, "Probabilistic anomaly detection in natural gas time series data," *International Journal of Forecasting*, vol. 32, no. 3, pp. 948–956, 2016.

[34] D. M. Hawkins, *Identification of outliers*. Springer, 1980, vol. 11.

[35] A. A. Cook, G. Mısırlı, and Z. Fan, "Anomaly detection for iot time-series data: A survey," *IEEE Internet of Things Journal*, vol. 7, no. 7, pp. 6481–6494, 2019.

[36] V. Aggarwal, V. Gupta, P. Singh, K. Sharma, and N. Sharma, "Detection of spatial outlier by using improved z-score test," in *2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI)*. IEEE, 2019, pp. 788–790.

[37] G. Pang, C. Shen, and A. van den Hengel, "Deep anomaly detection with deviation networks," in *Proceedings of the 25th ACM SIGKDD international conference on knowledge discovery & data mining*, 2019, pp. 353–362.

[38] Z.-G. Zhou and P. Tang, "Continuous anomaly detection in satellite image time series based on z-scores of season-trend model residuals," in *2016 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*. IEEE, 2016, pp. 3410–3413.

[39] J. Kornak, J. Fields, W. Kremers, S. Farmer, H. W. Heuer, L. Forsberg, D. Brushaber, A. Rindels, H. Dodge, S. Weintraub *et al.*, "Nonlinear z-score modeling for improved detection of cognitive abnormality," *Alzheimer's & Dementia: Diagnosis, Assessment & Disease Monitoring*, vol. 11, no. 1, pp. 797–808, 2019.