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A Machine Learning Approach for Energy-Efficient IoT Systems

Mahmoud M. Ismail

Faculty of computers and Informatics, Zagazig University, Zagazig, 44519, Egypt
Email: mmsabe@zu.edu.eg

Abstract

The energy challenge in IoT refers to the significant energy consumption of IoT devices, which can lead to sustainability issues, shorter battery life, and increased operating costs. IoT devices are known for their high energy consumption, and optimizing their energy usage can have a significant impact on sustainability and cost. Machine learning (ML) can learn from data and patterns to predict and control energy consumption in IoT systems, making them more energy efficient. The main contribution of this paper is the establishment of a novel deep learning framework for enhanced predictive modeling of energy consumption in IoT networks to help realize Energy-efficient IoT systems. our framework applies recurrent processing to capture long-term relations in the energy consumption of IoT appliances. Then, the self-attention mechanism is devised to help the model to focus on important predictive features. Simulation experiments against the competing ML baselines demonstrate the predictive capability of our framework.

Keywords: Machine Learning; IoT; Energy Consumption, Sensors

1. Introduction:

The Internet of Things (IoT) is a technology that connects devices and objects to the internet, allowing them to collect and exchange data. IoT devices can range from simple sensors to complex systems such as smart homes, smart cities, and industrial automation [1]. The technology enables devices to communicate with each other and with humans, creating new opportunities for automation, efficiency, and innovation. IoT technology has the potential to revolutionize various industries, including healthcare, agriculture, transportation, and manufacturing. However, the widespread adoption of IoT also presents challenges related to power consumption, and energy management [2].

Energy consumption is a critical consideration in the design and deployment of IoT devices and systems. Many IoT devices are battery-powered or rely on energy harvesting, which places strict constraints on their energy consumption. Therefore, minimizing the energy consumption of IoT devices is essential to prolong their battery life, reduce maintenance costs, and lower the environmental impact of the technology. There are several techniques for reducing energy consumption in IoT, including optimizing hardware and software design, using low-power wireless communication protocols, and implementing energy-efficient algorithms for data processing and communication. Additionally, energy harvesting techniques, such as solar or kinetic energy harvesting, can be used to power IoT devices without relying on batteries [3]. Energy efficiency is especially crucial in large-scale IoT deployments, such as smart cities or industrial automation, where the energy consumption of thousands or even millions of devices can have a significant impact on overall energy usage. Therefore, optimizing energy consumption in IoT is not only beneficial for individual devices but also essential for the sustainable growth of the technology as a whole [4].

Machine learning (ML) algorithms have the potential to play a significant role in improving the energy efficiency of IoT devices and systems. As the number of IoT devices continues to grow, there is an increasing need for solutions that can reduce the energy consumption of these devices to conserve resources, reduce operating costs, and reduce

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carbon emissions. ML algorithms can be used to optimize the operation of IoT devices and systems by analyzing data collected from sensors, predicting future events, identifying patterns, and adapting to changes in the environment or user behavior. One of the primary benefits of using ML for IoT energy efficiency is that it allows for the development of energy-saving strategies that are tailored to specific devices and systems. For example, ML algorithms can analyze the energy consumption patterns of devices and determine the optimal times to activate or deactivate certain functions. By customizing energy-saving strategies for each device, ML algorithms can achieve greater energy savings than more general approaches [5-8].

However, there are several challenges associated with using ML for IoT energy efficiency. One of the biggest challenges is the need to balance the computational requirements of ML algorithms with the energy consumption of IoT devices [9]. To be effective, ML algorithms require significant computational resources, which can increase the energy consumption of IoT devices. Therefore, developing efficient ML algorithms that can run on low-power devices is critical for achieving energy savings without sacrificing performance. Additionally, ensuring the security and privacy of data collected by IoT devices is essential, as ML algorithms rely on access to large amounts of data to be effective [10-12]. Overall, the role of ML in improving the energy efficiency of IoT devices and systems is significant, but careful consideration of the challenges associated with its implementation is necessary for success [13-18].

To this end, this paper's contribution lies in developing a new deep-learning framework for improved predictive modeling of energy consumption in IoT networks. The prediction-generated framework is precise enough to guide the stockholders and decision maker about the future consummation of IoT appliances. Recurrent learning modules are applied to capture the historical dependencies in the IoT devices. attention mechanisms are also introduced to empower the predictive power of the model.

The upcoming sections of this work are outlined as follows: The literature on real-world uses of ML methods for IoT energy management is reviewed in Section 2. The approach of the suggested framework is discussed in Section 3. The experiments from this paper and associated settings are covered in Section 4. The main conclusions of this research are briefed in Section 5.

2. Literature review

The IoT has turned out to be a prevailing technology in recent times, enabling the connection of various devices and the exchange of data between them. However, this rapid growth has led to concerns about its impact on energy consumption. Many studies have been conducted to evaluate the energy consumption of IoT devices and networks and to identify potential ways to reduce it. These studies have employed various methods, including simulation-based studies, empirical measurements, and analytical models, to investigate the energy consumption of different IoT applications and technologies. The findings of these studies suggest that there is considerable scope for improving the energy efficiency of IoT devices and networks through the development of energy-efficient protocols, hardware optimization, and smart scheduling techniques. However, more research is needed to optimize IoT energy consumption in the context of emerging applications and technologies and to ensure sustainable and environmentally friendly IoT growth.

In [1], The authors created a LoRa (a long-range, low-power wireless platform)–based smart regulator for an HVAC (heating, ventilation, and air conditioning) system in a residential building and contrasted it to narrow Radio transmission in a controlled environment. In [2], the authors established a RESTful framework for assisting Internet-connected appliances in making more informed decisions about how to cut down on energy consumption. They concentrated on coffee machines found in public places, such as workplaces, where most people do not give much thought to reducing their carbon footprint. According to the suggested method, such devices can report on their usage patterns and have their data processed in the cloud using ARIMA forecasting models. The goal of such forecasting was to restore the appliances' usage forecast for the following week so that they can run independently and as efficiently as possible. In [3], the authors introduced the ML technique for keeping tabs on an Android device's battery life in order to spot ransomware threats. To distinguish malicious software from benign programs, their proposed approach was applied to track how much power each one uses. The work [4], provided a comprehensive overview of the use of ML for IoT data analysis and highlights the potential of ML to address some of the key challenges associated with IoT data analysis. it also identifies several opportunities for future research, including the development of new ML algorithms that are specifically designed for IoT data analysis and the integration of ML algorithms with other IoT technologies, such as edge computing and blockchain. In [7], the

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authors discussed how to effectively regulate HVAC energy use in smart networks where the cost of electricity fluctuates. They presented an approach for energy planning and control that takes into account the power prices and a set of comfy constrictions is, a range of temperatures according to usage patterns for a given room—and finds the optimal solution that minimises the cost of energy consumption during a given time interval. Then, they suggested a scheduler for energy consumption in which the client may decide whether or not to enforce strict temperature limits, hence maximising energy savings. Furthermore, the IoT paradigm enabled remote user interaction with the HVAC management system, in which the user could set the ideal temperature from afar while receiving updates on their energy consumption and temperature via the internet on their end device. In [8], the authors presented a comprehensive overview of the energy consumption challenges associated with IoT devices and systems and provides practical recommendations for software developers to optimize energy consumption in IoT systems. The authors argued that a software-centric approach to energy optimization is essential for addressing the energy consumption challenges associated with the IoT and that developers must take a proactive approach to energy efficiency in IoT system design. In [11], the authors debated the importance of energy consumption evaluation and analysis for reducing the environmental impact of products. They argued that IoT and cloud-based technologies can provide a cost-effective and scalable solution for energy consumption evaluation and analysis. they presented a case study on the use of IoT and cloud-based technologies to evaluate the energy consumption of a water heater. They argued the development of an IoT system that collects real-time energy consumption data from the water heater and sends the data to a cloud-based platform for analysis. In [14], the authors reviewed the main ML techniques that are commonly used in smart city microgrids, including deep learning, and reinforcement learning. They presented several case studies that demonstrate the use of ML in smart city microgrids in different domains, including renewable energy integration, demand response management, and energy storage optimization. Their work also identified several opportunities for future research, including the development of ML algorithms that are specifically designed for smart city microgrids and the integration of AI with other smart city technologies, such as blockchain and IoT devices. In [15], the authors provided a high-level summary of the issues and opportunities around smart city energy management. Next, they presented a unified architecture for planning and optimization of IoT-based smart cities with a focus on minimising energy use. In addition, they debated the opportunities and difficulties of energy harvesting in smart cities, a possible approach for prolonging the usable lifetime of low-power gadgets. They discussed the specifics of two examples. Smart household energy management is the focus of the first, while in the second, wireless transmission of electricity for Internet of Things devices is discussed in the context of smart cities.

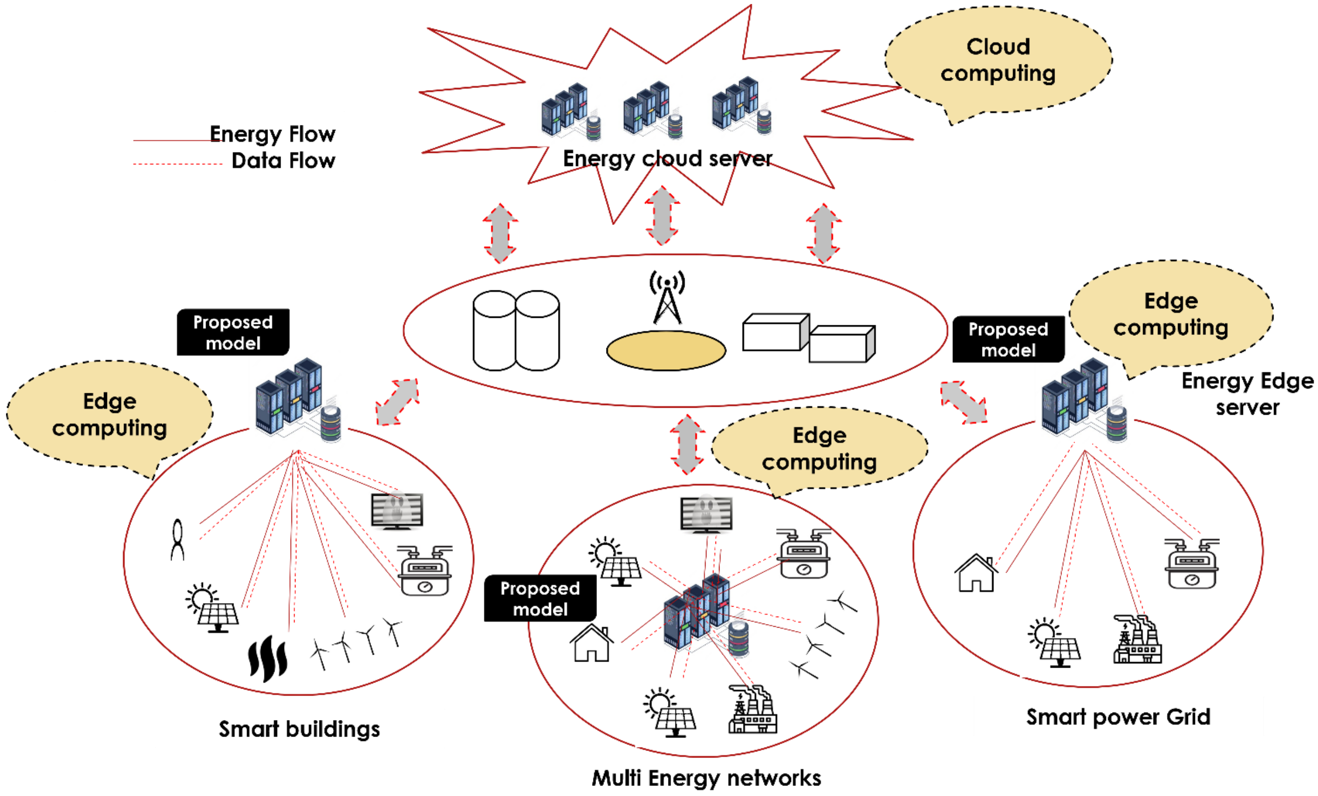

Figure 1. General illustration of energy consumption in IoT environment.

3. Machine learning for IoT energy optimization.

This section provides an in-depth discussion of the methodology of the proposed framework for predictive modeling of energy consumption in complex IoT environments. The general architecture of energy management is shown in Figure 3. As visualized, our framework can be deployed to predict the energy consumption at either cloud or edge computing layer of the network.

LSTM (Long Short-Term Memory) is a popular type of recurrent neural network (RNN) that is often used for time series forecasting, including energy consumption predictions. Thus, we propose an LSTM model for energy consumption predictions. We collected historical energy consumption data and preprocessed it by normalizing the data and selecting relevant features such as temperature, time of day, day of the week, and seasonality. We created an LSTM model with multiple LSTM layers. The LSTM process receives time-series information through the following gating computations:

$$\text{input gate} \rightarrow \; i_t = \sigma(W_i([x_t, y_{t-1}])) \tag{1}$$

$$\text{forget gate} \rightarrow f_t = \sigma(W_f([x_t, y_{t-1}])) \tag{2}$$

$$\text{output gate} \rightarrow o_t = \sigma(W_o([x_t, y_{t-1}])) \tag{3}$$

$$g_t = tanh(W_g([x_t, y_{t-1}])) \tag{4}$$

$$\text{input modulation gate} \rightarrow c_t = f \odot c_{t-1} + i \odot g \tag{5}$$

$$y_t = o \odot tanh(c_t) \tag{6}$$

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Self-attention (SA) is a type of attention mechanism that can be used for time series forecasting, including energy consumption predictions. Unlike traditional attention mechanisms that focus on input features, SA allows the model to attend to different parts of the input sequence and weigh them according to their relevance to the prediction task.

In SA, the input sequence is transformed into three vectors: query, key, and value. The query vector represents the current time step, while the key and value vectors represent all the time steps in the input sequence. The dot product between the query and key vectors is computed to obtain a weight for each time step, which is then used to compute a weighted sum of the value vectors. The resulting vector is the output of the SA layer.SA can be integrated into a neural network model for energy consumption predictions, such as a feedforward neural network or a transformer. The SA layer can be placed before or after the LSTM layer, depending on the architecture of the model. The SA mechanism can help the model capture long-term dependencies in the input sequence and improve the prediction accuracy, especially for complex time series with nonlinear patterns and seasonality.

After the LSTM layers, we propose an attention mechanism for energy consumption predictions. The self-attention mechanism is integrated into the LSTM model to enhance its ability to capture long-term dependencies and selectively focus on relevant features. The calculation of this layer is given bellows:

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{7}$$

The training process of our model needs to optimize some objective that maximizes the predictivity of our model. thus, the log-cosh loss is used in this work.

$$\text{Logcosh:}\, l = \frac{1}{n}\sum_{i=1}^{n} log(\cosh(Y_i - \hat{Y}_i))^2 \tag{8}$$

with $Y_i$and$\hat{Y}_i$ denote the actual data element and predicted value, respectively.

4. Experimental Results and Discussion

In our experiments, we use the IoT dataset [10] to evaluate the proposed model. For around 4.5 months, the data was captured over 10-minute intervals. ZigBee wireless sensors were deployed to track indoor measurements including temperature and moisture. Around every 3.3 minutes, each wireless node broadcasted the current temperature and humidity. 10-minute moving averages were calculated for the wireless data. Using m-bus energy meters, the consumption data was recorded every 10 minutes. The experimental data sets were combined with the weather data from the closest airport weather station utilizing the time attributes from a publicly available data set from Reliable Prognosis (rp5.ru). To put the prediction methods to the test and eliminate irrelevant attributes, 2 variables were added to the dataset. Summary statistics are provided for the dataset in Table 1. It could be noted that the features of data belong to scale, which might complicate the gradient computations during the learning process. To this end, min-m-ax normalization was applied as follows:

$$v' = \frac{v - min_A}{max_A - min_A}\left(new_{max_A} - new_{min_A}\right) + new\_min_A \tag{9}$$

where v' denote the normalized value of the original v.

Table 1. Summary of statistics of the IoT appliance dataset.

	COUNT	MEAN	STD	MIN	25%	**50%**	**75%**	**MAX**
APPLIANCES	19735	97.695	102.525	10.000	50.000	60.000	100.000	1080.000
LIGHTS	19735	3.802	7.936	0.000	0.000	0.000	0.000	70.000
T1	19735	21.687	1.606	16.790	20.760	21.600	22.600	26.260
RH_1	19735	40.260	3.979	27.023	37.333	39.657	43.067	63.360
T2	19735	20.341	2.193	16.100	18.790	20.000	21.500	29.857
RH_2	19735	40.420	4.070	20.463	37.900	40.500	43.260	56.027
T3	19735	22.268	2.006	17.200	20.790	22.100	23.290	29.236
RH_3	19735	39.243	3.255	28.767	36.900	38.530	41.760	50.163
T4	19735	20.855	2.043	15.100	19.530	20.667	22.100	26.200

RH_4	19735	39.027	4.341	27.660	35.530	38.400	42.157	51.090
T5	19735	19.592	1.845	15.330	18.278	19.390	20.620	25.795
RH_5	19735	50.949	9.022	29.815	45.400	49.090	53.663	96.322
T6	19735	7.911	6.090	-6.065	3.627	7.300	11.256	28.290
RH_6	19735	54.609	31.150	1.000	30.025	55.290	83.227	99.900
T7	19735	20.267	2.110	15.390	18.700	20.033	21.600	26.000
RH_7	19735	35.388	5.114	23.200	31.500	34.863	39.000	51.400
T8	19735	22.029	1.956	16.307	20.790	22.100	23.390	27.230
RH_8	19735	42.936	5.224	29.600	39.067	42.375	46.536	58.780
T9	19735	19.486	2.015	14.890	18.000	19.390	20.600	24.500
RH_9	19735	41.552	4.151	29.167	38.500	40.900	44.338	53.327
T_OUT	19735	7.412	5.317	-5.000	3.667	6.917	10.408	26.100
PRESS_MM_HG	19735	755.523	7.399	729.300	750.933	756.100	760.933	772.300
RH_OUT	19735	79.750	14.901	24.000	70.333	83.667	91.667	100.000
WINDSPEED	19735	4.040	2.451	0.000	2.000	3.667	5.500	14.000
VISIBILITY	19735	38.331	11.795	1.000	29.000	40.000	40.000	66.000
TDEWPOINT	19735	3.761	4.195	-6.600	0.900	3.433	6.567	15.500
RV1	19735	24.988	14.497	0.005	12.498	24.898	37.584	49.997
RV2	19735	24.988	14.497	0.005	12.498	24.898	37.584	49.997

To improve the reproducibility of our work, the hyperparameters of our model are given in Table 2.

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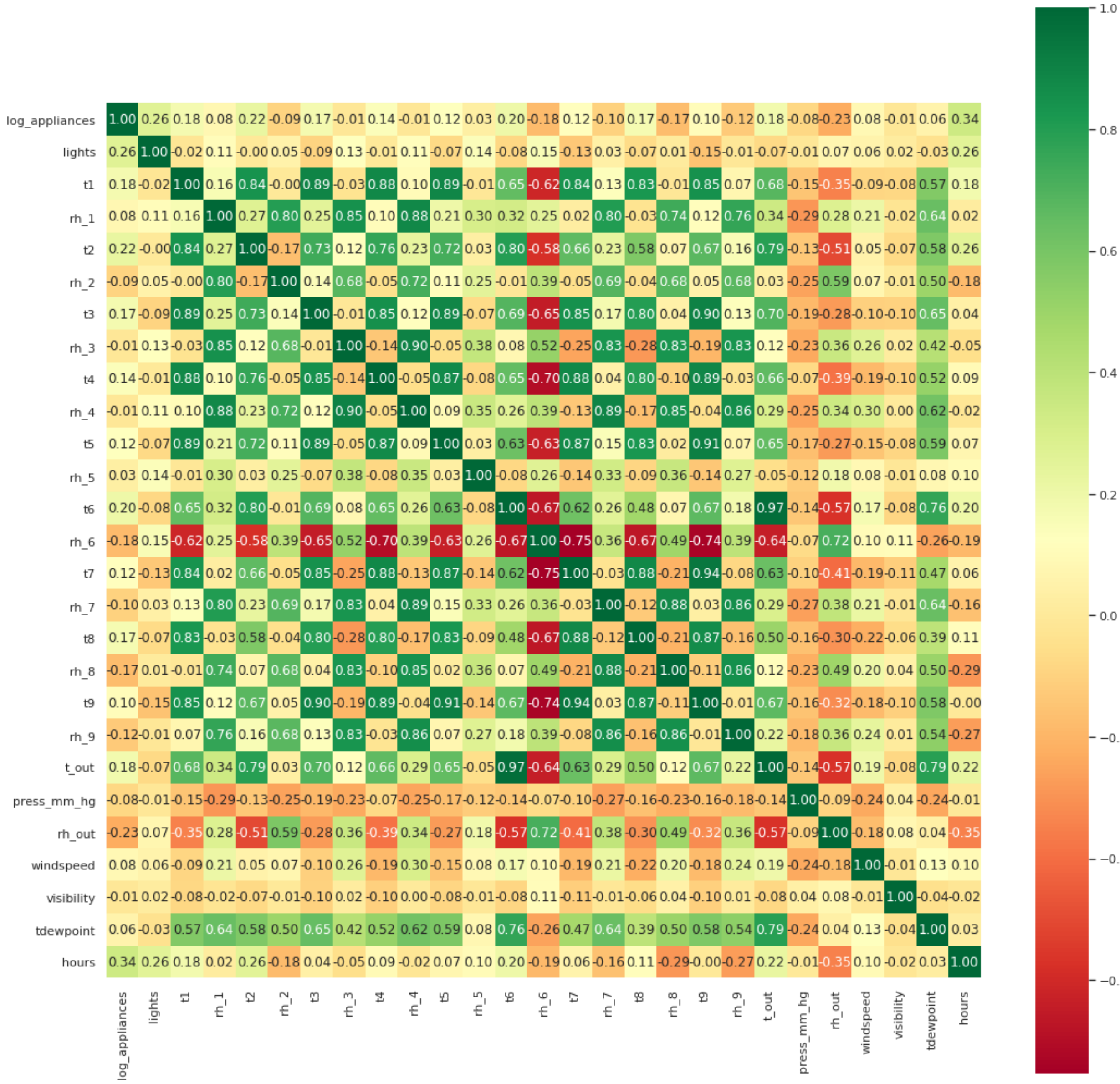

	log_appliances	lights	t1	rh_1	t2	rh_2	t3	rh_3	t4	rh_4	t5	rh_5	t6	rh_6	t7	rh_7	t8	rh_8	t9	rh_9	t_out	press_mm_hg	rh_out	windspeed	visibility	tdewpoint	hours
log_appliances	1.00	0.26	0.18	0.08	0.22	-0.09	0.17	-0.01	0.14	-0.01	0.12	0.03	0.20	-0.18	0.12	-0.10	0.17	-0.17	0.10	-0.12	0.18	-0.08	-0.23	0.08	-0.01	0.06	0.34
lights	0.26	1.00	-0.02	0.11	-0.00	0.05	-0.09	0.13	-0.01	0.11	-0.07	0.14	-0.08	0.15	-0.13	0.03	-0.07	0.01	-0.15	-0.01	-0.07	-0.01	0.07	0.06	0.02	-0.03	0.26
t1	0.18	-0.02	1.00	0.16	0.84	-0.00	0.89	-0.03	0.88	0.10	0.89	-0.01	0.65	-0.62	0.84	0.13	0.83	-0.01	0.85	0.07	0.68	-0.15	-0.35	-0.09	-0.08	0.57	0.18
rh_1	0.08	0.11	0.16	1.00	0.27	0.80	0.25	0.85	0.10	0.88	0.21	0.30	0.32	0.25	0.02	0.80	-0.03	0.74	0.12	0.76	0.34	-0.29	0.28	0.21	-0.02	0.64	0.02
t2	0.22	-0.00	0.84	0.27	1.00	-0.17	0.73	0.12	0.76	0.23	0.72	0.03	0.80	-0.58	0.66	0.23	0.58	0.07	0.67	0.16	0.79	-0.13	-0.51	0.05	-0.07	0.58	0.26
rh_2	-0.09	0.05	-0.00	0.80	-0.17	1.00	0.14	0.68	-0.05	0.72	0.11	0.25	-0.01	0.39	-0.05	0.69	-0.04	0.68	0.05	0.68	0.03	-0.25	0.59	0.07	-0.01	0.50	-0.18
t3	0.17	-0.09	0.89	0.25	0.73	0.14	1.00	-0.01	0.85	0.12	0.89	-0.07	0.69	-0.65	0.85	0.17	0.80	0.04	0.90	0.13	0.70	-0.19	-0.28	-0.10	-0.10	0.65	0.04
rh_3	-0.01	0.13	-0.03	0.85	0.12	0.68	-0.01	1.00	-0.14	0.90	-0.05	0.38	0.08	0.52	-0.25	0.83	-0.28	0.83	-0.19	0.83	0.12	-0.23	0.36	0.26	0.02	0.42	-0.05
t4	0.14	-0.01	0.88	0.10	0.76	-0.05	0.85	-0.14	1.00	-0.05	0.87	-0.08	0.65	-0.70	0.88	0.04	0.80	-0.10	0.89	-0.03	0.66	-0.07	-0.39	-0.19	-0.10	0.52	0.09
rh_4	-0.01	0.11	0.10	0.88	0.23	0.72	0.12	0.90	-0.05	1.00	0.09	0.35	0.26	0.39	-0.13	0.89	-0.17	0.85	-0.04	0.86	0.29	-0.25	0.34	0.30	0.00	0.62	-0.02
t5	0.12	-0.07	0.89	0.21	0.72	0.11	0.89	-0.05	0.87	0.09	1.00	0.03	0.63	-0.63	0.87	0.15	0.83	0.02	0.91	0.07	0.65	-0.17	-0.27	-0.15	-0.08	0.59	0.07
rh_5	0.03	0.14	-0.01	0.30	0.03	0.25	-0.07	0.38	-0.08	0.35	0.03	1.00	-0.08	0.26	-0.14	0.33	-0.09	0.36	-0.14	0.27	-0.05	-0.12	0.18	0.08	-0.01	0.08	0.10
t6	0.20	-0.08	0.65	0.32	0.80	-0.01	0.69	0.08	0.65	0.26	0.63	-0.08	1.00	-0.67	0.62	0.26	0.48	0.07	0.67	0.18	0.97	-0.14	-0.57	0.17	-0.08	0.76	0.20
rh_6	-0.18	0.15	-0.62	0.25	-0.58	0.39	-0.65	0.52	-0.70	0.39	-0.63	0.26	-0.67	1.00	-0.75	0.36	-0.67	0.49	-0.74	0.39	-0.64	-0.07	0.72	0.10	0.11	-0.26	-0.19
t7	0.12	-0.13	0.84	0.02	0.66	-0.05	0.85	-0.25	0.88	-0.13	0.87	-0.14	0.62	-0.75	1.00	-0.03	0.88	-0.21	0.94	-0.08	0.63	-0.10	-0.41	-0.19	-0.11	0.47	0.06
rh_7	-0.10	0.03	0.13	0.80	0.23	0.69	0.17	0.83	0.04	0.89	0.15	0.33	0.26	0.36	-0.03	1.00	-0.12	0.88	0.03	0.86	0.29	-0.27	0.38	0.21	-0.01	0.64	-0.16
t8	0.17	-0.07	0.83	-0.03	0.58	-0.04	0.80	-0.28	0.80	-0.17	0.83	-0.09	0.48	-0.67	0.88	-0.12	1.00	-0.21	0.87	-0.16	0.50	-0.16	-0.30	-0.22	-0.06	0.39	0.11
rh_8	-0.17	0.01	-0.01	0.74	0.07	0.68	0.04	0.83	-0.10	0.85	0.02	0.36	0.07	0.49	-0.21	0.88	-0.21	1.00	-0.11	0.86	0.12	-0.23	0.49	0.20	0.04	0.50	-0.29
t9	0.10	-0.15	0.85	0.12	0.67	0.05	0.90	-0.19	0.89	-0.04	0.91	-0.14	0.67	-0.74	0.94	0.03	0.87	-0.11	1.00	-0.01	0.67	-0.16	-0.32	-0.18	-0.10	0.58	-0.00
rh_9	-0.12	-0.01	0.07	0.76	0.16	0.68	0.13	0.83	-0.03	0.86	0.07	0.27	0.18	0.39	-0.08	0.86	-0.16	0.86	-0.01	1.00	0.22	-0.18	0.36	0.24	0.01	0.54	-0.27
t_out	0.18	-0.07	0.68	0.34	0.79	0.03	0.70	0.12	0.66	0.29	0.65	-0.05	0.97	-0.64	0.63	0.29	0.50	0.12	0.67	0.22	1.00	-0.14	-0.57	0.19	-0.08	0.79	0.22
press_mm_hg	-0.08	-0.01	-0.15	-0.29	-0.13	-0.25	-0.19	-0.23	-0.07	-0.25	-0.17	-0.12	-0.14	-0.07	-0.10	-0.27	-0.16	-0.23	-0.16	-0.18	-0.14	1.00	-0.09	-0.24	0.04	-0.24	-0.01
rh_out	-0.23	0.07	-0.35	0.28	-0.51	0.59	-0.28	0.36	-0.39	0.34	-0.27	0.18	-0.57	0.72	-0.41	0.38	-0.30	0.49	-0.32	0.36	-0.57	-0.09	1.00	-0.18	0.08	0.04	-0.35
windspeed	0.08	0.06	-0.09	0.21	0.05	0.07	-0.10	0.26	-0.19	0.30	-0.15	0.08	0.17	0.10	-0.19	0.21	-0.22	0.20	-0.18	0.24	0.19	-0.24	-0.18	1.00	-0.01	0.13	0.10
visibility	-0.01	0.02	-0.08	-0.02	-0.07	-0.01	-0.10	0.02	-0.10	0.00	-0.08	-0.01	-0.08	0.11	-0.11	-0.01	-0.06	0.04	-0.10	0.01	-0.08	0.04	0.08	-0.01	1.00	-0.04	-0.02
tdewpoint	0.06	-0.03	0.57	0.64	0.58	0.50	0.65	0.42	0.52	0.62	0.59	0.08	0.76	-0.26	0.47	0.64	0.39	0.50	0.58	0.54	0.79	-0.24	0.04	0.13	-0.04	1.00	0.03
hours	0.34	0.26	0.18	0.02	0.26	-0.18	0.04	-0.05	0.09	-0.02	0.07	0.10	0.20	-0.19	0.06	-0.16	0.11	-0.29	-0.00	-0.27	0.22	-0.01	-0.35	0.10	-0.02	0.03	1.00

Figure 2. illustration of the correlation maps for the variable of IoT energy consumption dataset.

Table 2. summary of the hyper-parameters of our model

HYPER PARAMETERS	**VALUE**
BATCH SIZE	64
OPTIMIZER	Adam
INIT LEARNING RATE	0.001
EPOCHS	30
DEPTH	6
CALLBACKS	Early stopping

Correlation analysis is a useful tool in regressive ML for identifying relationships between variables. In regression problems, correlation analysis can be used to determine how strongly the independent variables are related to the dependent variable. The correlation coefficient is a measure of the strength of the linear relationship between two variables. It ranges from -1 to 1, with 0 indicating no correlation and -1 or 1 indicating a perfect negative or positive

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correlation, respectively. To perform correlation analysis for ML regressors, you can calculate the correlation coefficients between each independent variable and the dependent variable. You can use a scatter plot to visualize the relationship between each pair of variables. Figure 3 shows the correlation plot in which the correlation values are computed between every pair of values. It is notable that Random variables have no role to play, while the humidity, Visibility, Tdewpoint, and Press_mm_hg attributes show limited relations. For temperature variables from T1-T9, we note that all t6, and t9 show high positive correlations with many other temperature variables. Thus, T6 & T9 are removed from training data since the information supplied by them could be supplied by another variable.

The predictivity performance was evaluated using four metrics that estimate the difference between the model's predictions, $\hat{Y}$, and real traffic information Y. These metrics can be expressed as follows:

$$Mean\ Square\ Erro(MSE) = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2 \tag{10}$$

$$Root\ MSE(RMSE) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2} \tag{11}$$

$$Mean\ Absolute\ Error\ (MAE) = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - \hat{Y}_i\right| \tag{12}$$

$$MAPE = \frac{1}{n}\left(\sum_{i=1}^{24}\frac{\left|Y_i - \hat{Y}_i\right|}{Y_i}\right) \times 100\% \tag{13}$$

Experimental comparisons involve conducting experiments to test the predictive modeling performance of different ML methods. The aim is to compare the results of different approaches to determine which one is better or more suitable for a specific application or problem. Experimental comparisons are conducted on this work, and the corresponding results are presented in Table 3. To ensure the validity of experimental comparisons, we carefully design and conduct these experiments under the same conditions. it is notable that the proposed model can achieve significant performance improvements over the competing methods. this in turn reflects our claims that combining attention and recurrent model in our model is beneficial for improving the predictivity of the model.

Table 3. Numerical comparison of the performance of the proposed model against the competing methods.

	MSE	**RMSE**	**MAE**	**MAPE**
LR	0.8780	0.9370	0.7246	0.8273
SVR	0.7885	0.8880	0.5289	0.7326
RF	0.4706	0.6860	0.4914	0.5937
LGBM	0.7430	0.8620	0.2583	0.4690
XGBR	0.7586	0.8710	0.2417	0.3685
PROPOSED	0.0520	0.2280	0.1640	0.2130

Figure 3 shows the training loss curves to enable diagnosing the stability of learning behavior. It could be noted that the proposed model can reach the low loss value after only a few numbers of epochs, which reflect the rapid convergence, and show smoothed learning behaviors.

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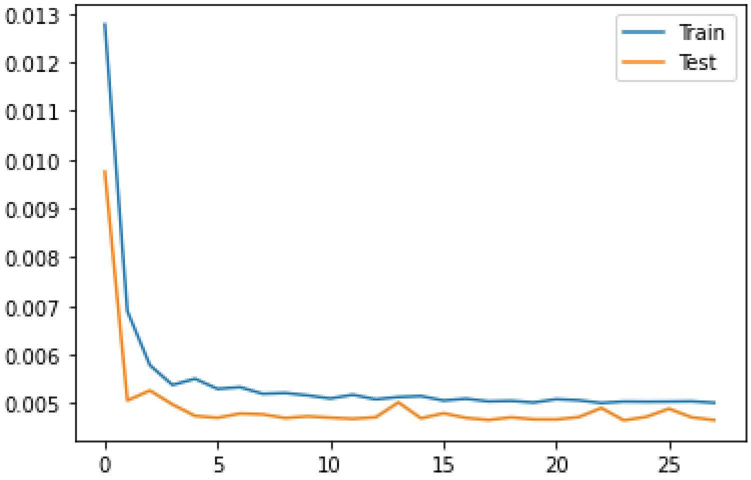

Figure 3. loss curves of the proposed method.

5- Conclusion

This work proposed a promising approach for predicting energy consumption in IoT devices. This model combines the power of LSTM networks to capture long-term dependencies in time series data with the attention mechanism to focus on the most important features and improve model performance. The use of IoT devices is rapidly growing, and accurate energy consumption prediction is crucial for optimizing their performance and minimizing energy waste. The LSTM-attention model has shown promising results in predicting energy consumption in various IoT applications, including smart homes and industrial IoT. Proven effectiveness and competitiveness in experimental validations against state-of-the-art methods support the suggested strategy. Our approach is a viable tool for implementation in an energy management system since it can precisely predict energy consumption in IoT network.

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