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Auto-Evaluation Model for the Prediction of Building Energy Consumption That Combines Modified Kalman Filtering and Long Short-Term Memory

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Abstract: As the world grapples with the challenges posed by climate change and depleting energy resources, achieving sustainability in the construction and operation of buildings has become a paramount concern. The construction and operation of buildings account for a substantial portion of global energy consumption and carbon emissions. Hence, the accurate prediction of building energy consumption is indispensable for reducing energy waste, minimizing greenhouse gas emissions, and fostering sustainable urban development. The aspiration to achieve predicted outcomes with remarkable accuracy has emerged as a pivotal objective, coinciding with the burgeoning popularity of deep learning techniques. This paper presents an auto-evaluation model for building energy consumption prediction via Long Short-Term Memory with modified Kalman filtering (LSTM-MKF). Results gleaned from data validation activities evince a notable transformation—a reduction of the maximal prediction error from an initial 83% to a markedly ameliorated 24% through the intervention of the proposed model. The LSTM-MKF model, a pioneering contribution within this paper, clearly exhibits a distinct advantage over the other models in terms of predictive accuracy, as underscored by its superior performance in all three key metrics, including mean absolute error, root mean square error, and mean square error. The model presents excellent potential as a valuable tool for enhancing the precision of predictions of building energy consumption, a pivotal aspect in energy efficiency, smart city development, and the formulation of informed energy policy.

Keywords: sustainability; Building Information Modeling; green building; energy consumption; deep learning; Kalman filter

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1. Introduction

Buildings substantially influence global CO_2 emissions, with estimates indicating their responsibility for approximately 40% of these emissions [1]. This significant contribution underscores their pivotal role in the overall carbon footprint, a role that continues to grow in significance as technology advances [2]. At the forefront of this endeavor lies the built environment, where buildings, from residential to commercial, act as energy behemoths, accounting for a significant share of global electricity consumption [3,4]. The prediction of building energy consumption constitutes a foundational element within intelligent construction [5,6]. Its significance lies in its capacity to facilitate proactive energy management, optimize the utilization of resources, and ultimately contribute to substantially reducing the environmental impact [7–9]. The prediction of building energy consumption has emerged as a linchpin in this transformative journey toward sustainability [10,11]. Designing, operating, and inhabiting buildings profoundly influences energy consumption patterns [12,13]. Therefore, accurately predicting building electricity consumption assumes paramount importance [14–16]. Accurate forecasts enable stakeholders, including building owners, facility managers, and policymakers, to make informed decisions, optimize resource allocation, and mitigate the environmental impacts of energy use [17,18]. The development and implementation of accurate algorithms for the prediction of building energy consumption emerge as indispensable tools in this endeavor, which is vital for the realization of sustainable, energy-efficient smart cities [19–22].

The prediction of building energy consumption encompasses a spectrum of methodologies, with prominent categories including Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), Gaussian Process Regression (GPR), and Long Short-Term Memory (LSTM), among others [19,23–26]. In a study conducted by Ziwei Li, an innovative approach was introduced for the swift prediction of building energy consumption in the early design phases of architecturally intricate structures [26]. This approach leverages Artificial Neural Networks (ANNs) to streamline the process of energy consumption prediction [26]. It effectively converts the formidable task of predicting energy consumption for a singular complex architectural form into a series of manageable tasks for multiple simpler building blocks [26]. Kent and Khoa Huynh effectively employed SVM to detect blockages in desk illuminance sensors, a critical aspect of closed-loop daylight harvesting systems [25]. Their research not only contributes to predicting electric lighting use in office spaces but also holds the potential to monitor the health of sensor performance, thereby facilitating the minimization of energy consumption [25]. Significant volumes of real-world data collected from building energy management systems were harnessed for the purpose of the online forecasting of energy consumption [27]. This system was tailored for optimized control, real-time fault detection, diagnosis, and abnormality alarms, as demonstrated in the work by Aaron Zeng [27]. Their findings affirm the reliability of GPR as a method capable of generating consistently accurate predictions, even when operating on large datasets with short time intervals [27]. Zheng's results affirm the proposition that the predictive performance of conventional stateful Long Short-Term Memory (LSTM) neural networks can be markedly enhanced by initially making predictions at the appliance level and subsequently aggregating them to obtain household-level predictions [28]. This diverse landscape of approaches has evolved in response to the necessity of energy analysis and optimization in building environments. Initially, Al-Homoud undertook a comprehensive review, surveying prevalent techniques for building energy analysis. His work illuminated the burgeoning role of computer technology in simulating and optimizing energy utilization within buildings [29]. Key considerations and criteria for predicting building energy consumption were elucidated, providing a foundational framework for subsequent research. Statistical methods constituted an early foray into the prediction of building energy consumption. These methods established relationships between energy consumption and various influencing factors, such as weather conditions and temperature [30]. However, they exhibited limitations, particularly when handling independent variables, often resulting in predictions characterized by considerable errors and discrepancies between the predicted energy consumption values generated by the previous models and the actual energy consumption. The magnitude of these errors varied depending on the model and dataset but could be as high as 50% or more [19,31]. Consequently, statistical approaches found more excellent utility in the retrospective analysis of historical consumption data. The advent of Artificial Neural Networks (ANNs) marked a pivotal juncture in the prediction of building energy. ANNs, with their capacity to tackle nonlinear challenges inherent in building energy dynamics, notably those driven by weather and temperature fluctuations, emerged as a potent tool [30]. Nevertheless, the efficacy of ANNs is contingent upon data quality, with low-quality data yielding less accurate predictions. To contend with scenarios characterized by low data quality, Support Vector Machines (SVMs) were introduced. SVMs exhibit superior performance by constraining the upper bounds of generalization training error, thereby enhancing prediction accuracy even in data-scarce conditions [32]. For short-term and real-time data training in building energy consumption modeling, Gaussian Process Regression (GPR) has been proposed, enabling notably precise predictions [33]. In machine learning, deep learning, exemplified by LSTM networks, offers distinctive advantages [34]. These architectures can accommodate and process a wealth of information, leading to more accurate predictions [34]. However, deep learning models are characterized by a high parameter count, rendering them complex to train. LSTM, designed to mitigate errors stemming from this complexity, introduces temporal and forgettable factors, enhancing predictive accuracy [35]. In summary, the prediction of building energy consumption is a multidisciplinary field featuring a range of methodologies [36,37]. While statistical methods and traditional machine learning approaches have their merits, deep learning, specifically LSTM networks, stands out for its capacity to leverage vast amounts of data, thereby offering the promise of more accurate predictions [36]. Nonetheless, it is essential to consider the complexity and resource requirements associated with deep learning approaches in practice [36,38].

Algorithms for the prediction of building energy consumption constitute a crucial segment of the overarching smart city ecosystem [39,40]. The precise prediction and management of building energy consumption are paramount for advancing green building practices and greatly reducing carbon emissions [19,39]. These algorithms draw upon historical energy consumption data, ambient environmental parameters, occupancy patterns, and an array of other contextual inputs to anticipate future energy usage trends within buildings [41,42]. By providing accurate insights into energy consumption patterns, these algorithms empower building managers, urban planners, and policymakers to devise informed strategies to minimize energy wastage, maximize operational efficiency, and foster a greener, more sustainable urban environment [43,44].

In pursuing these sustainability objectives, a diverse array of algorithms for the prediction of building energy consumption has emerged [45]. Ranging from physics-based models to data-driven machine learning approaches, these algorithms reflect the multifaceted nature of the dynamics of energy consumption [46]. They encompass models that factor in thermal characteristics, occupancy patterns, climatic variations, and energy-consuming equipment, among other variables [37]. The rich diversity of these algorithms reflects the complex interplay of factors influencing building energy consumption [47]. However, while these algorithms offer promising solutions, a significant gap prevails in the realm of evaluating their effectiveness in real-world scenarios [48]. The trained model is susceptible to substantial errors when confronted with data exhibiting variations, encompassing discrepancies in values, disparities in input features, and similar factors, in the majority of scenarios.

The challenge in evaluation arises from the intricate nature of assessing the performance of diverse prediction algorithms across many building types, climatic zones, occupancy behaviors, and more [49]. The absence of developing the auto-evaluation model of deep learning techniques for building energy consumption must be resolved [50,51]. Consequently, building managers, urban planners, and researchers encounter difficulties in selecting the most suitable algorithm for more accurate prediction results [52]. This, in turn, impedes the creation of a cohesive strategy for energy optimization across the spectrum of buildings within a smart city [53].

Addressing this critical gap, the present paper introduces a groundbreaking solution—an auto-evaluation model tailored explicitly for the optimization of building energy consumption. This novel model aims to optimize Long Short-Term Memory (LSTM) in a way that not only quantifies the predictive accuracy of algorithms but also delves deeper into the underlying factors influencing their performance. By offering a holistic understanding of the algorithm's strengths and limitations, this model bridges the chasm in the evaluation and improvement of the algorithm and contributes to refining and enhancing techniques for energy consumption prediction.

The conceptual underpinning of the proposed auto-evaluation and diagnostic model finds its instantiation through the utilization of Long Short-Term Memory (LSTM) networks. These recurrent neural networks, acclaimed for their adeptness in sequence-prediction endeavors, are pivotal in manifesting the model's predictive capabilities. Concurrently, the model's analytical foundation is fortified through the strategic infusion of the Kalman filtering method—a paradigm of optimization algorithms that find pertinence in addressing complex trust-related challenges. Utilizing LSTM networks combining Kalman filtering showcases the practical implementation of the model and highlights its efficacy in improving the accuracy of predictions of building energy consumption. Remarkably, the impact of this research extends beyond immediate energy-optimization goals and resonates with broader objectives, including smart city development and the integration of Building Information Modeling (BIM).

Within the context of sustainable urban development, the incorporation of precise energy prediction models becomes imperative. The auto-evaluation and diagnostic model introduced align seamlessly with these sustainability imperatives by enabling accurate assessment and the continuous enhancement of energy optimization algorithms. As smart cities strive to achieve greater energy efficiency and embrace environmentally responsible practices, this research offers a vital tool for decision makers, aiding them in selecting and deploying the most suitable algorithms within their unique urban contexts.

In conclusion, the present paper aims to develop an innovative auto-model to comprehensively evaluate building energy consumption optimization algorithms. By bridging the existing gap in evaluation practices, this model lays a robust foundation for enhanced accuracy, resilience, and applicability of energy prediction algorithms within the dynamic milieu of smart cities. As urban centers across the globe actively strive to achieve their sustainability objectives and green building practices, exemplified by the adoption of well-established sustainability certification programs like LEED (Leadership in Energy and Environmental Design), the integration of cutting-edge construction technologies, and unwavering commitment to eco-friendly building principles, our proposed model emerges as a crucial advancement. It is essential in guiding societies toward a future characterized by elevated energy efficiency and heightened environmental consciousness. Through its intrinsic link to smart city development and the integration of Building Information Modeling (BIM), this research underscores its significance in shaping the urban landscapes of tomorrow.

Within the framework of this paper, Section 2 inaugurates a comprehensive exposition of the auto-evaluation model tailored to address the prediction of building energy consumption; the experimental data are elaborated in detail. Section 3 navigates through the terrain of empirical results, unfurling a tapestry that illuminates the model's performance. Section 4 undertakes a judicious exploration of the intrinsic merits and limitations inherent in the model's approach as the discourse matures. In Section 5, the study attains its culmination through a distilled summary of research findings. Utilizing LSTM-MKF in this paper will contribute to developing more stable and accurate models for the prediction of energy consumption, ultimately benefiting green building and sustainability efforts. The following hypotheses will evaluate the system efficacy through mean square error (MSE), root mean square deviation (RMSE), and mean absolute error (MAE).

H1. *The integration of Long Short-Term Memory (LSTM) with modified Kalman filtering (MKF) will greatly enhance the accuracy of the prediction of building energy consumption.*

H2. *MKF is anticipated to greatly enhance the performance of LSTM by dynamically adjusting the Kalman gain in response to increasing prediction errors.*

H3. *The proposed LSTM-MKF model will outperform other existing models in terms of predictive accuracy, particularly in reducing the maximum prediction error.*

2. Method

2.1. Data Description

The building energy consumption data utilized in this study were sourced from Schneider Electric, comprising a curated selection of time series data about the energy consumption profiles of more than 260 distinct buildings. The dataset encompasses several vital attributes, including the building's surface area, a unique identifier for each building, the base temperature setting for the respective building, with indicators denoting whether a given day was classified as a working day, and a metric quantifying the energy consumption for each individual building.

Furthermore, the meteorological temperature data integrated into this dataset were acquired from an external weather station, ensuring that precise and relevant weather conditions were considered in the analysis. The dataset's diverse range of buildings and associated features form the basis for our research on the prediction of building energy consumption.

Within this intricate tapestry of data orchestration, a quintet of variables emerges as the input, each holding a unique note in the ensemble. These variables encapsulate a wealth of environmental insights, identified site number, and building surface (m^2). The thread interwoven in this narrative pertains to the occupancy type, influencing the predictions that ensue.

Table 1 presents a comprehensive compendium of pivotal knowledge encapsulating the spectrum of our input parameters. The range of data is derived from the raw dataset provided by Schneider Electric. Surface denotes the building's surface area, while temperature signifies the base temperature. For the sites encompassed within the dataset, weekdays are indicated by the steadfast label 0, whereas weekends are characterized by the symbol 1.

Table 1. Input variables and the values range.

Variable	Measurement	Range
Surface	m^2	100~20,000
Temperature	*Deg. C*	10~40
Day Type	Weekday, and weekend	Weekday is 0 and weekend is 1
Time	MM/DD/YYYY	15 October 2016 to 31 December 2016
SiteId	/	1~302

The output data, building energy consumption, signify the culmination of electricity utilization, intricately choreographed by various appliances and the heating, ventilation, and air conditioning (HVAC) system. Schneider Electric meticulously recorded these patterns of energy usage throughout the period from 15 October 2016 to 31 December 2016. This peak, a poignant testament to energy's ebb and flow, assumes different forms across the canvas of days. The value that this peak embodies for each precious day, resonates with the character of the day itself. With the passage of each day, the value of this peak shifts, ever so slightly, mirroring the nuances of each distinct day type.

2.2. Principles for Auto-Evaluation Model

Long Short-Term Memory

Long Short-Term Memory (LSTM) networks represent a significant departure from traditional Recurrent Neural Networks (RNNs), introducing distinct architectural innovations that overcome inherent limitations in RNNs' ability to process sequential data [54]. Unlike RNNs, which involve nodes, layers, and connections like those found in Feedforward Neural Networks (FNNs), LSTMs redefine the landscape of sequential modeling with their exceptional architecture [55].

Illustrated in Figure 1 is the intricate architecture characterizing an LSTM unit, which starkly contrasts the relatively uncomplicated structure of a standard RNN unit [54]. Initially, the metrological data about building energy consumption undergo a pre-processing stage, transforming them into input features. Subsequently, a deep learning model is employed, comprising three LSTM layers, each housing 64 neurons, to train the prepared input data. The LSTM's architecture is notably distinguished by the incorporation of memory blocks, each endowed with three vital gates: the quantity of temporal input features. S, the input gate. i_t, the output gate o_t, and the forget gate f_t. This departure from the RNN paradigm is rooted in the LSTM's robustness against the vanishing gradient problem. This predicament becomes pronounced, especially in scenarios housing a plethora of environmental variables [56].

$$i_t = \sigma(W_t x_t + U_i h_{t-1} + b_i) \tag{1}$$

$$f_t = \sigma\left(W_f x_t + U_f h_{t-1} + b_f\right) \tag{2}$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o) \tag{3}$$

$$C_t^{\sim} = tanh(W_C x_t + U_C h_{t-1} + b_C) \tag{4}$$

$$C_t = f_t \otimes C_{t-1} + i_t \otimes C_t^{\sim} \tag{5}$$

$$h_t = \mathrm{o}_t \otimes \tan\mathrm{h}(C_t) \tag{6}$$

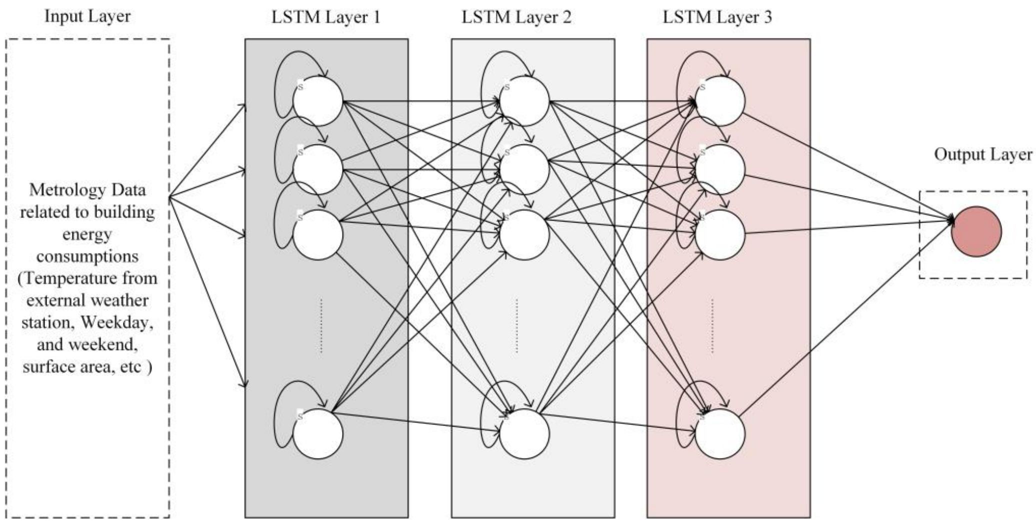


Figure 1. Long Short-Term Memory (LSTM) Schematic.

Within the mathematical expressions delineated earlier, the symbols i_t, f_t, and o_t encapsulate the triumvirate of fundamental gates—the input, forget, and output gates respective—at the given temporal instance. These gates manifest as pivotal conduits through which critical information flows, orchestrating the intricate dynamics of LSTM computations [55].

b_i, b_f, b_o represent the bias, and the symbols U_i, U_f, and U_o emerge as sentinels of connectivity, embodying the linkages between the gates and the hidden layer, with each gate extending its tendrils to the hidden realms. σ represents the logistic sigmoid function [56].

x_t graces the stage as a vector gracefully positioned in the input layer. h_t, a splendid output vector of the hidden domain, emerges as the protagonist housed within the LSTM's domain at the temporal juncture, t. Lending their presence, C_t and $C_t^{\sim}$ are unfurled as pivotal actors in this narrative [56]. C_t, the current cell state, waltzes hand in hand with its counterpart $C_t^{\sim}$, which emerges as a prospective candidate for the forthcoming cell state, propelling the LSTM's narrative forward [56].

The LSTM model in this paper, an epitome of computational intricacy, was methodically trained to utilize a comprehensive input suite encompassing eight distinct features. These features encompassed an amalgamation of environmental variables and a solitary external variable, each pivotal in shaping the model's perception of the underlying dynamics. At the nucleus of this model architecture lay an output layer, diligently constructed to encapsulate the predictions for the energy usage variable.

2.3. Auto-Evaluation Model Based on Modified Kalman Filtering (MKF) Algorithm Combining LSTM

The Kalman filter algorithm emerges as a recursive marvel, employing the state space methodology as its compass for filter design [57]. This methodology particularly lends itself to the intricate task of estimating multidimensional stochastic processes [58]. The crux of the approach rests in articulating the metamorphosis of the estimator's dynamics through the vessel of state equations [58]. In this choreographed symphony, the statistical attributes of the estimator emerge as a harmonious interplay of excited white noise and the alchemical equations of state [59]. In this intricate ballet, excited white noise dances as a stationary entity, while the equations of state assert their dominance in orchestrating the estimator's statistical panorama [60]. A captivating dichotomy surfaces: the estimator, fueled by a stationary process and anchored by known equations, can weave narratives of stability or tumultuous unpredictability [61]. The core functions of the Kalman filtering method are as follows:

The status matrix is

$$x_{k/k-1} = \boldsymbol{A_{k-1}} x_{k-1/k-1} + \boldsymbol{B_{k-1}} u_{k-1} \tag{7}$$

The update of the covariance matrix is

$$P_{k/k-1} = \boldsymbol{A_{k-1}} P_{k-1/k-1} \boldsymbol{A_{k-1}^T} + \boldsymbol{\Gamma_{k-1}} Q_{k-1} \boldsymbol{\Gamma_{k-1}^T} \tag{8}$$

The Kalman gains matrix is

$$K_{\ k} = P_{k/k-1} \boldsymbol{C_{k-1}^T} \left(\boldsymbol{C_k} P_{k/k-1} \boldsymbol{C_k^T} + R_k \right)^{-1} \tag{9}$$

The measurement update of the status matrix is

$$x_{k/k} = x_{k/k-1} + K_k (\mathrm{y_k} - \boldsymbol{C_k} x_{k/k-1} - \boldsymbol{D_k} u_k) \tag{10}$$

The measurement update of the covariance matrix is

$$P_{k/k} = (\mathrm{I} - K_k \boldsymbol{C_k}) P_{k/k-1} \tag{11}$$

The Kalman gain matrix was proposed to be auto-modified every time the big error occurred as follows:

$$K_k = T_k K_{k-1} \tag{12}$$

$x_{k/k-1}$ is the forecast value of status, $x_{k/k}$ is the filtering value of status, K_k is the Kalman filtering gains matrix, $P_{k/k}$ is the value of the filtering covariance matrix, $P_{k/k-1}$ is the forecast covariance matrix, and I is the unit matrix. T_k is the diagonal matrix for the adjustment of Kalman gain. The output value estimated by LSTM will be auto-evaluated using the modified Kalman filtering (MKF) for more accurate prediction results.

Presenting a pioneering leap in the prediction of building energy consumption, an innovative auto-evaluation model emerges, seamlessly integrating the prowess of Modified Kalman Filters (MKFs) and Long Short-Term Memory (LSTM). Within this hybrid marvel, MKF stands tall as a luminary, harnessing its power to bestow high-precision estimations by adeptly recalibrating its Kalman gain wherever the tentacles of estimation error dare to extend. The model proposed in this paper aims to elevate the prediction accuracy of LSTM models through the incorporation of a modified Kalman filtering approach. This symbiotic amalgamation of MKF and LSTM heralds a groundbreaking step toward the auto-evaluation of the prediction of building energy consumption.

The heart of this ingenuity lies within the unique interplay of MKF and LSTM. Like masterful performers, they join forces to orchestrate a harmonious duet, each bringing its remarkable prowess to the stage. The refined agility of MKF steps forward to meticulously navigate the seas of estimation, its ability to adapt the Kalman gain in response to the surges of error bestowing upon it the crown of precision. This interlaced synergy forms the backbone of an auto-evaluation model poised to redefine the landscape of the prediction of building energy consumption.

The significance of this auto-evaluation model echoes with relevance, particularly in the context of the burgeoning era of artificial intelligence. As the digital symphony of AI surges forth, orchestrating advancements in every domain, the auto-evaluation model emerges as an essential protagonist in the narrative of green building. Amidst the backdrop of environmental consciousness and sustainability imperatives, this model steps in as a guiding light, illuminating the path toward optimized energy consumption predictions. With AI's ascendance in full swing, the auto-evaluation model stands poised to empower green building practices, steering it toward new heights of efficiency and conservation.

3. Results

3.1. Auto-Evaluation Model Validation

For the validation of the proposed auto-evaluation model based on MKF combining LSTM, the electricity usage of the building during 2016 was devoted to training. A symphony of meticulous steps orchestrated the training of the trio of predictive models. The initial training unfurled as the training and validation datasets were divided. Eighty-nine percent of the total datasets were set for training. The remaining 11% offered itself for validation.

The instantiation and execution of the LSTM model were executed by utilizing the deep learning framework within Keras. A carefully defined set of LSTM parameters was adopted, an outline meticulously documented in Table 2, serving as a guiding blueprint for the model's architecture [34]. During the training process, a total of eight distinct features were utilized, sourced from the Schneider Electric dataset. These features include the building's identification number, building surface area, base temperature of the building, workday identification (as presented in Table 1), and time. The parameters of forecasting energy consumption through utilizing GPR facilitated by the Kernel are as follows [27]. The RBF (1.0, (1×10^{-2}, 1×10^{2})) part of the code represents an RBF kernel with an initial length scale of 1.0 and a range constraint for the length scale hyperparameter; the (1×10^{-2}, 1×10^{2}) specifies that the length scale hyperparameter should be searched within the range from 0.01 (1×10^{-2}) to 100 (1×10^{2}).

Table 2. Forecasting energy consumption through the utilization of an LSTM architecture facilitated by the Keras.

```
model = Sequential()
model.add(LSTM(64, input_shape = (1, 8))
model.add(Dense(1))
model.compile(loss = 'mean_squared_error', optimize = 'adam')
history = model.fit(train_X, train_Y, epochs = 200, batch_size = 1)
validation_data = (test_X, test_Y))
```

An essential juncture within this endeavor manifested in the meticulous pursuit of optimal hyperparameters. This pursuit was animated by the delicate interplay of variables encompassing the number of epochs, the batch size, and the count of hidden neurons. With an acute focus on performance enhancement, a systematic exploration and interpretation of these variables unfolded, identifying optimal hyperparameters.

Emerging from this analytical crucible, the optimized configuration for the LSTM model crystallized. An epoch count of 200 was decided on as the optimal threshold for model convergence and learning refinement. The hidden layer was graced with 64 neurons, each akin to a conductor of information flow, orchestrating the model's insights. Furthermore, the pivotal aspect of batch processing was honed, with a batch size of one chosen to harmonize the trade-off between computational efficiency and model convergence.

The LSTM model's architecture and configuration became a product of reasonable deliberation and empirical insight in this meticulous ballet of model instantiation, parameter tuning, and performance refinement. This orchestration, a testament to the academic rigor driving the endeavor, stood as a beacon of computational prowess poised to illuminate the domain of the prediction of building energy consumption.

Figure 2 shows the temporal trajectory of building energy consumption spanning the interval from 15 October 2016 to 31 December 2016, sourced from the Schneider Electric dataset. Meanwhile, Figure 3 encapsulates the anticipated energy consumption of the building, predicted via LSTM, over the period from 15 November 2016 to 21 November 2016. Actual energy consumption encapsulates the quantified energy utilization, laying bare the zenith of electricity usage. This consumptive profile is orchestrated by the interplay of electrical appliances and the operation of the heating, ventilation, and air conditioning (HVAC) system, meticulously documented and curated by Schneider Electric. This visual exploration unveils a pattern where energy consumption escalates during the course of Monday through Thursday and Saturday. In contrast, discernible reductions manifest on Friday and Sunday. Moreover, this narrative unravels an intriguing partition of the day into three temporal segments (0, 1, and 2). Notably, it becomes apparent that energy consumption is most pronounced within the segment labeled as 1.

Proceeding to Figure 4, a profound narrative of improvement unfolds. Figure 4a compares the predicted energy consumption of the LSTM and the auto-evaluation model of the building from 15 November 2016 to 21 November 2016. The "Measurements" represent the predicted building energy consumption obtained through LSTM, which is further subjected to the MKF process. Notably, the results of this process exhibit enhanced stability and reduced error compared to the actual building energy consumption as predicted by the LSTM-MKF model. Figure 4b is the error of the auto-evaluation model. The graph chronicles the transformation of predictive accuracy, presenting a journey from a maximum error magnitude of 83% to a notably lessened 24%. In parallel, the nadir of error minimality undergoes refinement, experiencing a transition from 5% to a commendable 3%. These empirical revelations underscore the profound efficacy of the auto-evaluation model in realizing results of conspicuous precision.

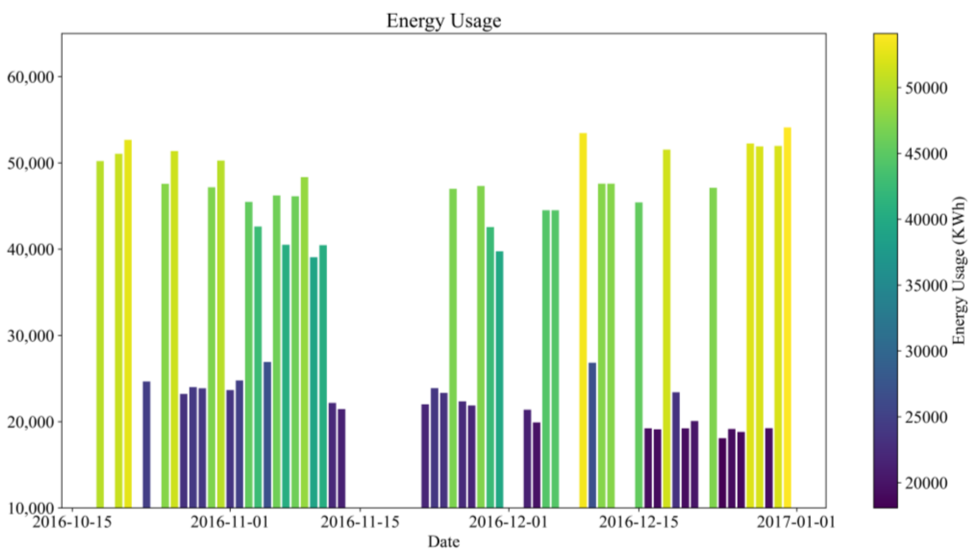


Figure 2. The energy consumption of the building from 15 October 2016 to 31 December 2016.

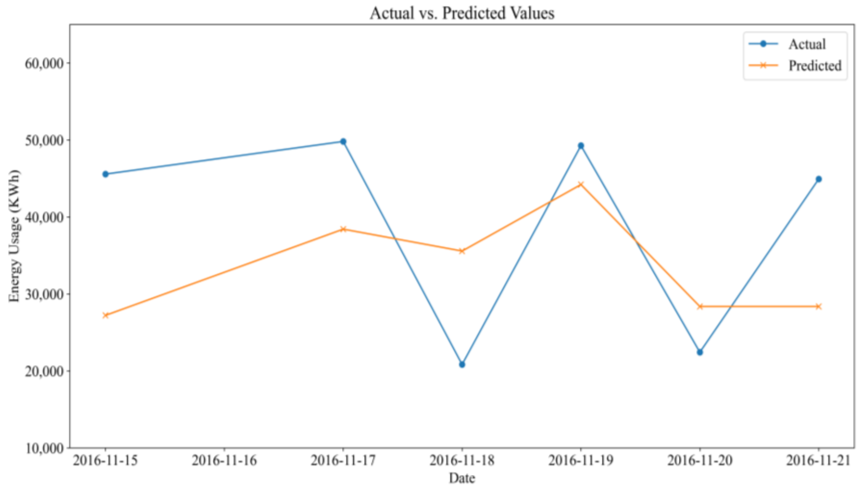
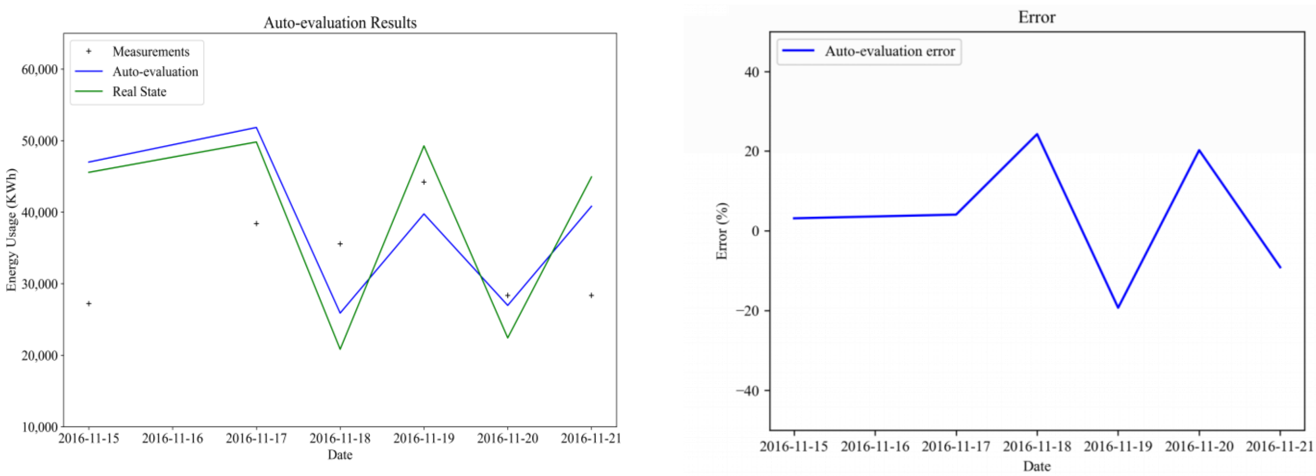


Figure 3. The predicted energy consumption of the building from 15 November 2016 to 21 November 2016 by LSTM.



(**a**) (**b**)

Figure 4. (**a**) The comparison between the energy consumption predicted by the LSTM and the auto-evaluation model of the building from 15 November 2016 to 21 November 2016. (**b**) Error of the auto-evaluation model.

The unveiled panorama bears testament to the potency of the auto-evaluation model in transcending the thresholds of accuracy. Amidst the symphony of data and predictions, this model emerges as a beacon of excellence, traversing the intricate terrain of the prediction of energy consumption with insight and discernment.

3.2. Comparison between Different Models

To compare the performance of the prediction of building energy consumption by different algorithms and models, mean square error (MSE), root mean square deviation (RMSE), and mean absolute error (MAE) were used to judge the effectiveness of different models.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|y_{predicted} - y_{actual}\right| \tag{13}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(y_{predicted} - y_{actual}\right)^2 \tag{14}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_{predicted} - y_{actual}\right)^2} \quad (15)$$

Here, N represents the size of the test datasets, $y_{predicted}$ denotes the predicted values, and y_{actual} represents the actual values.

The mean absolute error (MAE) is a widely recognized statistical metric employed to assess models' performance [62]. It quantifies their accuracy by determining the average magnitude of the absolute errors between predicted and actual values. In contrast, the root mean square error (RMSE) is a statistical measure representing the sample standard deviation of the predicted and actual values [62]. It is important to note that RMSE tends to amplify errors, mainly due to its mathematical characteristics, which include squaring the errors before averaging [62]. In statistical analysis, the objective is to minimize both MAE, MSE, and RMSE, as smaller values of these metrics indicate superior predictive modeling and a closer alignment between predicted and actual values [62,63].

Table 3 presents a comprehensive assessment of three distinct predictive models, each evaluated based on three critical performance metrics. Gaussian Process Regression (GPR) is a probabilistic machine learning technique used for regression and probabilistic classification tasks [64]. It provides a non-parametric, flexible approach to modeling data by estimating the probability distribution over functions. In the context of our study, we employed GPR to predict building energy consumption using the same dataset that was utilized to validate the feasibility and performance of our LSTM-MKF model. This allowed us to compare the effectiveness of different approaches, MAE, MSE, and RMSE, for the prediction of building energy consumption. The LSTM-MKF model demonstrates a substantially lower MAE (4445) in comparison to the baseline LSTM model (13,821) and the Gaussian Process Regression model (19,187). This substantial reduction signifies that the LSTM-MKF model exhibits superior accuracy in predicting building energy consumption, outperforming both the baseline and the alternative model. The LSTM-MKF model boasts a greatly reduced MSE (26,604,400), further reinforcing its prowess in minimizing prediction errors. In contrast, the LSTM and GPR models exhibit considerably larger MSE values (169,802,000 and 461,862,000, respectively), signifying less accurate predictions than LSTM-MKF. The LSTM-MKF model's RMSE (5157) emerges as notably lower than that of both the LSTM model (13,030) and the GPR model (6796). This underscores the LSTM-MKF model's ability to provide more precise estimations of building energy consumption, thus reducing the margin of error in its predictions.

Table 3. Comparative Performance Evaluation of Predictive Models for Building Energy Consumption.

	MAE	**MSE**	**RMSE**
LSTM	13,821	169,802,000	13,030
LSTM_MKF	4445	26,604,400	5157
Gaussian Process Regression (GPR)	19,187	461,862,000	6796

In essence, the LSTM-MKF model, a pioneering contribution within this paper, clearly exhibits a distinct advantage over the other models regarding predictive accuracy, as underscored by its superior performance in all three key metrics (MAE, MSE, and RMSE). This highlights its potential as a valuable tool for enhancing the precision of predictions of building energy consumption, a pivotal aspect in energy efficiency, smart city development, and informed energy policy formulation.

4. Discussion

Drawing upon an exhaustive survey of prevailing prognostic methodologies within the expansive purview of deep learning, an innovative paradigm, underpinned by the foundations of MKF, has been conceptualized and subsequently validated. In stark contrast to the conventional Long Short-Term Memory (LSTM) frameworks, the articulated approach proffers a distinctive constellation of merits, which are enumerated below.

A conspicuously diminished count of requisite training epochs to attain an optimal model configuration stands out as the primary hallmark of the proposed MKF-based auto-evaluation model. This characteristic imparts a palpable acceleration to the predictive modeling process in building energy consumption. Machine learning techniques, including random forest models, and the utilization of Building Information Modeling (BIM) were integrated into a novel tool for the early assessment of design window view satisfaction, as demonstrated by Jaeha Kim [65]. This integrated approach showed exceptional predictive capabilities across various response variables. The LSTM-MKF model, characterized by its high prediction accuracy, holds significant promise for synergizing with BIM applications, particularly in the context of assessing factors like occupant view satisfaction in residential buildings. This synergy offers numerous advantages, extending its transformative potential across BIM, intelligent building infrastructure, and the overarching principles of sustainable construction practices.

The discerning attribute of augmented precision in predicting building energy consumption represents a cornerstone achievement of the proposed model. Indeed, the imperative augmentation in the stability of the model predictions becomes evident when assessing the comparative metrics of MAE, MSE, and RMSE. These evaluation metrics serve as critical indicators of the model's performance. While it is essential to minimize these metrics to enhance the predictive accuracy of the LSTM-MKF model, it is important to note that the extent of improvement should be analyzed in the context of the specific application. Generally, lower MAE, MSE, and RMSE values indicate a better model performance, showcasing its capacity to predict building energy consumption more accurately and with higher stability. The superior performance of the LSTM_MKF model in terms of lower RMSE can be attributed to the unique synergy of Long Short-Term Memory (LSTM) and the modified Kalman filtering method within our algorithm. For the Modified Kalman Filtering for Error Correction, the modified Kalman filtering method introduces a dynamic error-correction mechanism into the model. When discrepancies arise between predicted and observed values, the Kalman gain is adjusted to reduce these errors. This self-correction capability is pivotal in mitigating prediction inaccuracies, contributing to the lower RMSE. As for Model Fusion, the combination of LSTM and Kalman filtering creates a symbiotic relationship, where LSTM captures long-term dependencies, while Kalman filtering excels in real-time error correction. This fusion of strengths from both methods allows our model to produce more precise and consistent predictions. In summary, the LSTM_MKF model's superior performance in terms of RMSE results from its dual capability to comprehend temporal intricacies through LSTM and dynamically correct errors using modified Kalman filtering. This combination empowers the model to provide more accurate and reliable predictions, as reflected in the lower RMSE compared to other methods. By unraveling the intricate tapestry of energy dynamics with heightened fidelity, this model engenders a tangible reduction in carbon emissions, thereby bolstering the foundations of urban energy planning through informed decision making.

While these metrics provide valuable insights into the model's accuracy, it is essential to acknowledge their limitations. One limitation arises from the contextual interpretation of error rates. MAE, MSE, and RMSE are reported in the original units of the data, making it challenging to determine whether the error rates are high or low without a comprehensive understanding of the specific domain. This context dependency implies that the acceptable error thresholds may vary across different applications. To address this limitation, future studies could explore the establishment of domain-specific benchmarks or normalized error metrics that facilitate a more universal assessment of model performance. Another limitation is the relatively limited timeframe for predicting building energy consumption. The dataset covers a period of two months, which may not fully capture the seasonal variations and long-term trends in energy consumption. Extended data collection over multiple seasons or years could provide a more comprehensive understanding of the model's performance under diverse conditions. Additionally, it would be beneficial to investigate how the LSTM-MKF model adapts to changes in the external environment over time. Addressing these limitations by developing domain-specific benchmarks and conducting long-term assessments could enhance the robustness and applicability of future research in this field.

It is prudent to acknowledge that despite the demonstrated accomplishments, the stability of the proposed algorithm is not devoid of nuances. The algorithm's resilience to external influences, such as the perturbations introduced by humidity fluctuations, remains a pertinent area for enhancement. Addressing this aspect necessitates a conscientious augmentation of data dimensions and considerations, cultivating a more robust algorithmic bedrock.

Concomitantly, the avenue of future inquiry is envisaged to be illuminated by the confluence of diverse factors. The orchestration of enhanced algorithmic strategies, in tandem with the assimilation of additional feature variables, constitutes a focal axis for forthcoming explorations. Through these endeavors, the horizon of predictive excellence is poised for perpetual expansion, concurrent with the ever-evolving landscape of deep learning and its intricate applications within the prognostication of energy consumption.

5. Conclusions

In this paper, a groundbreaking advancement emerges in the prediction of building energy consumption by introducing an innovative auto-evaluation model. Distinctly underpinned by Long Short-Term Memory (LSTM), this model harmoniously integrates multifaceted features and judicious data pre-processing techniques, culminating in a cohesive framework that resonates with the inherent intricacies of the data. Evident from empirical exploration, the model demonstrates an exceptional capacity to attain convergence within a markedly abbreviated epoch count—a distinctive attribute poised to invigorate the landscape of endeavors for the prediction of building energy.

A notable facet of this novel paradigm lies in its assimilation of Modified Kalman Filtering (MKF), a strategic augmentation designed to amplify the model's predictive accuracy. The outcomes underscore the model's enhanced prowess in delineating energy consumption dynamics with heightened precision. This achievement is paramount, resonating particularly within the purview of green building principles and the ethos of Building Information Modeling (BIM), both emblematic of conscientious environmental stewardship.

However, it remains imperative to acknowledge the complexities inherent to real-world testing conditions, wherein the auto-evaluation model might encounter challenges in extrapolating uncertainties under specific extreme scenarios. Therefore, the trajectory of future inquiry converges upon extracting discerning features and cultivating an enhanced capacity to traverse diverse contextual nuances. The realm of the prediction of building energy consumption is teeming with prospects for developmental strides, particularly in conjunction with the ever-evolving landscape of deep learning applications.

In summation, this scholarly venture illuminates an epochal stride in the prediction of energy consumption. The confluence of LSTM architecture, meticulous feature curation, and the fortification afforded by MKF confers a potent tool, poised to recalibrate predictive horizons. The LSTM-MKF model, introduced for the first time in this paper, is a promising advancement in the prediction of building energy consumption. Its demonstrated superiority in predictive accuracy, as evident across all key metrics (MAE, MSE, and RMSE), underscores its potential as a valuable tool for refining the precision of building energy consumption forecasts. Such accuracy holds significant implications for energy efficiency, smart city development, and the formulation of well-informed energy policies, contributing to a more sustainable and environmentally conscious urban landscape.

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References

1. Nejat, P.; Jomehzadeh, F.; Taheri, M.M.; Gohari, M.; Majid, M.Z.A. A global review of energy consumption, CO_2 emissions and policy in the residential sector (with an overview of the top ten CO_2 emitting countries). *Renew. Sustain. Energy Rev.* **2015**, *43*, 843–862. [CrossRef]
2. Cao, X.; Dai, X.; Liu, J. Building energy-consumption status worldwide and the state-of-the-art technologies for zero-energy buildings during the past decade. *Energy Build.* **2016**, *128*, 198–213. [CrossRef]
3. Hassan, J.; Zin, R.; Majid, M.; Balubaid, S.; Hainin, M. Building energy consumption in Malaysia: An overview. *J. Teknol.* **2014**, *70*, 33–38. [CrossRef]
4. Zhang, Y.; Wang, H.; Gao, W.; Wang, F.; Zhou, N.; Kammen, D.M.; Ying, X. A survey of the status and challenges of green building development in various countries. *Sustainability* **2019**, *11*, 5385. [CrossRef]
5. Ma, Y.X.; Yu, C. Impact of meteorological factors on high-rise office building energy consumption in Hong Kong: From a spatiotemporal perspective. *Energy Build.* **2020**, *228*, 110468. [CrossRef]
6. Xiang, Y.; Chen, Y.; Xu, J.; Chen, Z. Research on sustainability evaluation of green building engineering based on artificial intelligence and energy consumption. *Energy Rep.* **2022**, *8*, 11378–11391. [CrossRef]
7. Zhao, D.; McCoy, A.; Du, J. An empirical study on the energy consumption in residential buildings after adopting green building standards. *Procedia Eng.* **2016**, *145*, 766–773. [CrossRef]
8. Liang, R.; Le-Hung, T.; Nguyen-Thoi, T. Energy consumption prediction of air-conditioning systems in eco-buildings using hunger games search optimization-based artificial neural network model. *J. Build. Eng.* **2022**, *59*, 105087. [CrossRef]
9. Fumo, N. A review on the basics of building energy estimation. *Renew. Sustain. Energy Rev.* **2014**, *31*, 53–60. [CrossRef]
10. Lombardi, P.; Giordano, S.; Farouh, H.; Yousef, W. Modelling the smart city performance. *Innov. Eur. J. Soc. Sci. Res.* **2012**, *25*, 137–149. [CrossRef]
11. Chen, X.; Yang, H.; Lu, L. A comprehensive review on passive design approaches in green building rating tools. *Renew. Sustain. Energy Rev.* **2015**, *50*, 1425–1436. [CrossRef]
12. Camero, A.; Alba, E. Smart City and information technology: A review. *Cities* **2019**, *93*, 84–94. [CrossRef]
13. Holcomb, D.; Li, W.; Seshia, S.A. *Algorithms for Green Buildings: Learning-Based Techniques for Energy Prediction and Fault Diagnosis*; University of California at Berkeley: Berkeley, CA, USA, 2009.
14. Dameri, R.P. *Smart City Implementation*; Progress in IS; Springer: Genoa, Italy, 2017.
15. Meijer, A.; Bolívar, M.P.R. Governing the smart city: A review of the literature on smart urban governance. *Int. Rev. Adm. Sci.* **2016**, *82*, 392–408. [CrossRef]
16. Geng, Y.; Ji, W.; Wang, Z.; Lin, B.; Zhu, Y. A review of operating performance in green buildings: Energy use, indoor environmental quality and occupant satisfaction. *Energy Build.* **2019**, *183*, 500–514. [CrossRef]
17. Tushar, W.; Wijerathne, N.; Li, W.-T.; Yuen, C.; Poor, H.V.; Saha, T.K.; Wood, K.L. Internet of things for green building management: Disruptive innovations through low-cost sensor technology and artificial intelligence. *IEEE Signal Process. Mag.* **2018**, *35*, 100–110. [CrossRef]
18. Alshboul, O.; Shehadeh, A.; Almasabha, G.; Mamlook, R.E.A.; Almuflih, A.S. Evaluating the impact of external support on green building construction cost: A hybrid mathematical and machine learning prediction approach. *Buildings* **2022**, *12*, 1256. [CrossRef]
19. Amasyali, K.; El-Gohary, N.M. A review of data-driven building energy consumption prediction studies. *Renew. Sustain. Energy Rev.* **2018**, *81*, 1192–1205. [CrossRef]
20. Fang, P. Short-term carbon emission prediction method of green building based on IPAT model. *Int. J. Glob. Energy Issues* **2023**, *45*, 1–13.
21. Goudarzi, S.; Anisi, M.H.; Soleymani, S.A.; Ayob, M.; Zeadally, S. An IoT-based prediction technique for efficient energy consumption in buildings. *IEEE Trans. Green Commun. Netw.* **2021**, *5*, 2076–2088. [CrossRef]
22. Papamichael, K. Green building performance prediction/assessment. *Build. Res. Inf.* **2000**, *28*, 394–402. [CrossRef]

23. Zhao, H.-X.; Magoulès, F. A review on the prediction of building energy consumption. *Renew. Sustain. Energy Rev.* **2012**, *16*, 3586–3592. [CrossRef]
24. Qiao, Q.; Yunusa-Kaltungo, A.; Edwards, R.E. Towards developing a systematic knowledge trend for building energy consumption prediction. *J. Build. Eng.* **2021**, *35*, 101967. [CrossRef]
25. Kent, M.; Huynh, N.K.; Schiavon, S.; Selkowitz, S. Using support vector machine to detect desk illuminance sensor blockage for closed-loop daylight harvesting. *Energy Build.* **2022**, *274*, 112443. [CrossRef]
26. Li, Z.; Dai, J.; Chen, H.; Lin, B. An ANN-based fast building energy consumption prediction method for complex architectural form at the early design stage. *Build. Simul.* **2019**, *12*, 665–681. [CrossRef]
27. Zeng, A.; Ho, H.; Yu, Y. Prediction of building electricity usage using Gaussian Process Regression. *J. Build. Eng.* **2020**, *28*, 101054. [CrossRef]
28. Zheng, Z.; Chen, H.; Luo, X. Spatial granularity analysis on electricity consumption prediction using LSTM recurrent neural network. *Energy Procedia* **2019**, *158*, 2713–2718. [CrossRef]
29. Al-Homoud, M.S. Computer-aided building energy analysis techniques. *Build. Environ.* **2001**, *36*, 421–433. [CrossRef]
30. Kalogirou, S.A. Artificial neural networks in energy applications in buildings. *Int. J. Low-Carbon Technol.* **2006**, *1*, 201–216. [CrossRef]
31. Yun, K.; Luck, R.; Mago, P.J.; Cho, H. Building hourly thermal load prediction using an indexed ARX model. *Energy Build.* **2012**, *54*, 225–233. [CrossRef]
32. Dong, B.; Cao, C.; Lee, S.E. Applying support vector machines to predict building energy consumption in tropical region. *Energy Build.* **2005**, *37*, 545–553. [CrossRef]
33. Carpenter, J.; Woodbury, K.A.; O'Neill, Z. Using change-point and Gaussian process models to create baseline energy models in industrial facilities: A comparison. *Appl. Energy* **2018**, *213*, 415–425. [CrossRef]
34. Somu, N.; Gauthama Raman, M.R.; Ramamritham, K. A deep learning framework for building energy consumption forecast. *Renew. Sustain. Energy Rev.* **2021**, *137*, 110591. [CrossRef]
35. Karijadi, I.; Chou, S.-Y. A hybrid RF-LSTM based on CEEMDAN for improving the accuracy of building energy consumption prediction. *Energy Build.* **2022**, *259*, 111908. [CrossRef]
36. Marino, D.L.; Amarasinghe, K.; Manic, M. Building energy load forecasting using deep neural networks. In Proceedings of the IECON 2016 42nd Annual Conference of the IEEE Industrial Electronics Society, Florence, Italy, 23–26 October 2016; pp. 7046–7051.
37. Luo, X.; Oyedele, L.O. Forecasting building energy consumption: Adaptive long-short term memory neural networks driven by genetic algorithm. *Adv. Eng. Inform.* **2021**, *50*, 101357. [CrossRef]
38. Li, Y.; Tong, Z.; Tong, S.; Westerdahl, D. A data-driven interval forecasting model for building energy prediction using attention-based LSTM and fuzzy information granulation. *Sustain. Cities Soc.* **2022**, *76*, 103481. [CrossRef]
39. Luo, X.; Oyedele, L.O.; Ajayi, A.O.; Akinade, O.O.; Owolabi, H.A.; Ahmed, A. Feature extraction and genetic algorithm enhanced adaptive deep neural network for energy consumption prediction in buildings. *Renew. Sustain. Energy Rev.* **2020**, *131*, 109980. [CrossRef]
40. Ve, S.; Shin, C.; Cho, Y. Efficient energy consumption prediction model for a data analytic-enabled industry building in a smart city. *Build. Res. Inf.* **2021**, *49*, 127–143. [CrossRef]
41. Lei, L.; Chen, W.; Wu, B.; Chen, C.; Liu, W. A building energy consumption prediction model based on rough set theory and deep learning algorithms. *Energy Build.* **2021**, *240*, 110886. [CrossRef]
42. Pérez-Chacón, R.; Luna-Romera, J.M.; Troncoso, A.; Martínez-Álvarez, F.; Riquelme, J.C. Big data analytics for discovering electricity consumption patterns in smart cities. *Energies* **2018**, *11*, 683. [CrossRef]
43. Wang, Z.; Srinivasan, R.S. A review of artificial intelligence based building energy use prediction: Contrasting the capabilities of single and ensemble prediction models. *Renew. Sustain. Energy Rev.* **2017**, *75*, 796–808. [CrossRef]
44. Tiwari, S.; Jain, A.; Ahmed, N.M.O.S.; Charu; Alkwai, L.M.; Dafhalla, A.K.Y.; Hamad, S.A.S. Machine learning-based model for prediction of power consumption in smart grid-smart way towards smart city. *Expert Syst.* **2022**, *39*, e12832. [CrossRef]
45. Wang, R.; Lu, S.; Feng, W. A novel improved model for building energy consumption prediction based on model integration. *Appl. Energy* **2020**, *262*, 114561. [CrossRef]
46. Zeng, A.; Liu, S.; Yu, Y. Comparative study of data driven methods in building electricity use prediction. *Energy Build.* **2019**, *194*, 289–300. [CrossRef]
47. Afzal, S.; Ziapour, B.M.; Shokri, A.; Shakibi, H.; Sobhani, B. Building energy consumption prediction using multilayer perceptron neural network-assisted models; comparison of different optimization algorithms. *Energy* **2023**, *282*, 128446. [CrossRef]
48. Wang, Z.; Wang, Y.; Srinivasan, R.S. A novel ensemble learning approach to support building energy use prediction. *Energy Build.* **2018**, *159*, 109–122. [CrossRef]
49. Liu, T.; Tan, Z.; Xu, C.; Chen, H.; Li, Z. Study on deep reinforcement learning techniques for building energy consumption forecasting. *Energy Build.* **2020**, *208*, 109675. [CrossRef]
50. Yang, J.; Ning, C.; Deb, C.; Zhang, F.; Cheong, D.; Lee, S.E.; Sekhar, C.; Tham, K.W. k-Shape clustering algorithm for building energy usage patterns analysis and forecasting model accuracy improvement. *Energy Build.* **2017**, *146*, 27–37. [CrossRef]
51. Deng, H.; Fannon, D.; Eckelman, M.J. Predictive modeling for US commercial building energy use: A comparison of existing statistical and machine learning algorithms using CBECS microdata. *Energy Build.* **2018**, *163*, 34–43. [CrossRef]

52. Wenninger, S.; Kaymakci, C.; Wiethe, C. Explainable long-term building energy consumption prediction using QLattice. *Appl. Energy* **2022**, *308*, 118300. [CrossRef]
53. Jiao, Y.; Tan, Z.; Zhang, D.; Zheng, Q. Short-term building energy consumption prediction strategy based on modal decomposition and reconstruction algorithm. *Energy Build.* **2023**, *290*, 113074. [CrossRef]
54. Yu, Y.; Si, X.; Hu, C.; Zhang, J. A review of recurrent neural networks: LSTM cells and network architectures. *Neural Comput.* **2019**, *31*, 1235–1270. [CrossRef] [PubMed]
55. Staudemeyer, R.C.; Morris, E.R. Understanding LSTM—A tutorial into long short-term memory recurrent neural networks. *arXiv* **2019**, arXiv:1909.09586.
56. Sherstinsky, A. Fundamentals of recurrent neural network (RNN) and long short-term memory (LSTM) network. *Phys. D Nonlinear Phenom.* **2020**, *404*, 132306. [CrossRef]
57. Welch, G.F. Kalman filter. In *Computer Vision: A Reference Guide*; Springer: Cham, Switzerland, 2020; pp. 1–3.
58. Welch, G.; Bishop, G. *An Introduction to the Kalman Filter*; University of North Carolina: Chapel Hill, NC, USA, 1995.
59. Li, Q.; Li, R.; Ji, K.; Dai, W. Kalman filter and its application. In Proceedings of the 2015 8th International Conference on Intelligent Networks and Intelligent Systems (ICINIS), Tianjin, China, 1–3 November 2015; pp. 74–77.
60. Chen, B.; Dang, L.; Zheng, N.; Principe, J.C. Kalman filtering. In *Kalman Filtering Under Information Theoretic Criteria*; Springer: Berlin/Heidelberg, Germany, 2023; pp. 11–51.
61. Maybeck, P.S. The Kalman filter: An introduction to concepts. In *Autonomous Robot Vehicles*; Springer: Berlin/Heidelberg, Germany, 1990; pp. 194–204.
62. Chai, T.; Draxler, R.R. Root mean square error (RMSE) or mean absolute error (MAE). *Geosci. Model Dev. Discuss.* **2014**, *7*, 1525–1534.
63. Willmott, C.J.; Matsuura, K. Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance. *Clim. Res.* **2005**, *30*, 79–82. [CrossRef]
64. Taki, M.; Rohani, A.; Soheili-Fard, F.; Abdeshahi, A. Assessment of energy consumption and modeling of output energy for wheat production by neural network (MLP and RBF) and Gaussian process regression (GPR) models. *J. Clean. Prod.* **2018**, *172*, 3028–3041. [CrossRef]
65. Kim, J.; Kent, M.; Kral, K.; Dogan, T. Seemo: A new tool for early design window view satisfaction evaluation in residential buildings. *Build. Environ.* **2022**, *214*, 108909. [CrossRef]