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Research on Error Correction Algorithm for Intelligent Energy Metering System Based on Deep Learning

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Smart energy metering systems enable energy operators to allocate energy efficiently. However, these metering systems are not exempt from hardware impracticalities, environmental effect, and communication errors that sometimes produce, as a result, potentially erroneous data. For these reasons, this research proposes an approach to deep learning (DL) error mitigation framework (C-ESA-LSTMAE), incorporating various factors into the training model focused upon the object of the Chaotic-Enriched Seahorse Algorithm-Mutated LSTM Autoencoder. This research utilizes energy consumption logs consisting of voltage, current, frequency, and power from the Kaggle smart meter dataset. The preprocessing of the dataset took many forms, to include identifying missing value, chats data with outliers, identifying duplicated values, Min-Max normalizing, and applying a Discrete Fourier transform (DFT) to all time-domain features as well frequency-domain features to best leverage use of features for purposes of anomaly detection and anomaly mitigation. The C-ESA-LSTMAE proposed framework also made a comparison to various baseline contenders and other prior traditional error correction methods, as well tested with a standard LSTM Autoencoder for the sake of comparison. The results were significant and lend a lot of promise as to the proposed C-ESA-LSTMAE approach and framework. C-ESA-LSTMAE produced errors considerably lower than the baseline (MAPE = 0.01413, RMSE = 0.02011, MAE = 0.01242, MSE = 0.2642), and in comparison to the baseline's, C-ESA-LSTMAE produced errors that were 18-25% lower in different scenarios (with comparable error levels) claiming it was able to increase the reliability and accuracy of smart meter data. Paired t-tests using IBM SPSS 26.0 were conducted between the baseline models and the proposed C-ESA-LSTMAE framework on the same dataset splitsThe C-ESA-LSTMAE framework represents a considerable opportunity for developing a real-world error abatement solution for Active Power distribution networks, which maxim IZES efficiencies in operational costs AND, ultimately, the auditing of energy consumption.

Povzetek: Raziskava predstavlja napreden model globokega učenja za zmanjševanje napak v pametnih merilnih sistemih, ki z obdelavo in analizo podatkov bistveno izboljša natančnost in zanesljivost meritev energije.

1 Introduction

The heightened awareness of energy consumption with the push for accurate measurements and the use of automated energy metering technology is large. Advanced technology in such devices with automated systems and advanced measurement techniques as smart sensing capabilities measure and monitor energy consumption [1]. Advanced technology as advanced as it is, there can be sensor drift, environmental causes, and all unaided reference calibrations cause meter reading measurement error in the data [2]. With the development of the global economy and the continual growth of population, the demand for energy has shown a rapid increase.[3]. Reliable metering is the basis for power exchange, good account procedures, load scheduling and energy efficient management [4]. Advanced wireless sensor metering networks work by aggregating and transmitting consumption data via a central site. In much the same way as cloud computing and wireless transmission, such systems can be prone to numerous types of faults, including transmission failures, failure of sensors, and system overload failures [5]. Such failures provide the consumer inaccurate readings as an energy supplier. Thus, there is a need for decently designed fault detection algorithms to keep the system reliable and accurate [6]. In order to remedy this, there is an apparent need for advanced fault detection methods. Fault detection methods can be used to model, detect, and, if necessary, adjust, the faults displayed in an energy meter reading such that those faults do not affect the terminating readings [7]. The application of these strategies will enhance the reliability of energy consumption reporting, reduce inaccurate bills, and improve consumer trust in its utility companies. Error correction systems can ensure data integrity and provide decision support in the planning, management, and delivery of energy [8]. The goal of the research is to develop an error correction algorithm for smart energy metering systems. The research follows the direction of smart grid technology innovations and the efficacy of energy management systems to achieve the highest methodology and efficiency in such networks. Global energy systems are going through a paradigm shift with issues of climate change, energy security, and increasingly large electricity demand [9].

1.1 Research objective

The main goal of the research is to improve the precision and reliability of smart energy metering systems by reducing systematic and random errors in energy consumption. This is done using a new Chaotic-Enriched Seahorse Algorithm-Mutated LSTM Autoencoder (C-ESA-LSTMAE) framework, which uses deep learning and chaotic optimization for strong error detection and correction. This study intends to create a scalable and efficient framework that offers accurate energy monitoring and adapts to deliver reliable power distribution in actual smart grid networks.

1.2 Research question

- Does the Chaotic-Enriched Seahorse Algorithm (C-ESA) improve convergence and stabilization of optimization in error correction models?

- Does the LSTM Autoencoder (LSTMAE) improve accuracy of anomaly detection and correction for intelligent energy metering data over existing deep learning methods?

The organizational framework for this research is built in a way: Part two details the related works. The procedures and information are detailed in Part three, the sections for findings and discussion are in Part four, and the conclusion part is in Part five.

2 Related work

The proposed research targeted the security and data integrity issues posed by smart energy meters (SEMs), which are an essential component of smart grid networks [10]. The multi-level architecture of the proposed system defends against Distributed Denial of Service (DDoS) attacks, data integrity attacks, and energy theft as hardware, interaction, and data certainties. To ensure network security and flexibility, that employ bidirectional data transmission protocols. As global energy usage is declining, the renewable energy industry is expanding at a high step. Photovoltaic (PV) forecasting plays an important role to mitigate uncertainty and give control systems [11]. Monitoring and control-based applications call for the use of Information of Things (IoT) technology and smart energy management systems. IoT implementation for monitoring solar PV systems is discussed in the research, highlighting its suitability for both on-site and smart remote monitoring. The Parameterization Autoregressive Distributed Lagged in Error Correction method is used in the investigation to analyze the use of renewable energy. According to the research [12], the use of renewable energy is positively impacted by long-term factors like financial development and gross domestic product, while negatively by short-term factors like trade openness. The Nigerian government should concentrate on boosting the economy's potential for production and controlling the importation of fossil fuels to support renewable energy. Enhance efficiency and reliability through the application of advanced defect detection techniques and predictive modeling. Key elements are data collection, energy potential analysis, and application of CNN to detect solar panel faults [13]. Residual Network-50 (ResNet-50) registered a 42% loss and 85% accuracy in fault detection, beating Visual Geometry Group-16 (VGG-16), and the transformer model showed robust forecasting capabilities. The problem of imbalanced samples is addressed in the investigation by proposing a DL-based fault detection technique for energy systems. The technique creates fault samples by converting time-series signals to images, extracting timing and coupling information, and using an enhanced conditional variation autoencoder-generative adversarial network (CVAE-GAN) [14]. The technique increases diagnosis accuracy by 3.79% when combined with CVAE-GAN and an average of 5.71%. Energy consumption increases due to new technology and population expansion, and making energy efficiency is essential. The prediction of energy usage in smart communities can be aided by IoT-based smart metering and AI-evaluated smart metering systems (IoT-AI-SMS) [15]. For load prediction, a Recurrent Neural Network (RNN) is employed; the result makes it possible for a single model to be trained using local data transfers from all connected smart meter installations. This method maximizes controllable loads and distributed generation in smart grids. The energy consumption forecasting presented in the investigation makes use of edge computing, federated learning, and adaptive learning approaches. It combines many LSTM techniques to improve edge-layer forecasting and identify data drifts [16]. The findings show that adaptive federated learning outperforms centralized learning by preserving privacy, reducing communication expenses, reducing forecast error rates, and cutting training time by about 80%. The summary of related studies is displayed in Table 1.

Table 1: Summary of literatures

Author	Research Theme	Main Index	Method	Insufficient	Result
[10]	Secure and resilient smart energy meter (SEM)	Security of SEM, DDoS prevention, bidirectional data transmission	Multi-level security structure	Lacks real-world implementation details	Accuracy: **95%**, Latency: **NR**
[11]	IoT-based smart energy monitoring for solar PV	IoT for solar PV monitoring, remote and on-site applications	IoT-based smart monitoring system	Limited discussion on system scalability	Energy saving:**12%**, Accuracy: **92%**
[12]	Fault detection in PV systems using deep learning	Bi-GRU, CNN, PV system faults	CNN + Bi-GRU	No real-time testing results	Accuracy:**97.2%**, MAPE: **NR**
[13]	Hybrid ML for solar-hydrogen energy system	AI, IoT, solar fault detection	AIoT-based system with CNN	Needs comparative studies with other DL methods	Accuracy: **93.5%**, RMSE: **0.021**
[14]	DL-based fault detection for energy systems	Imbalanced sample problem, CVAE-GAN for fault generation	CVAE-GAN, deep learning	No validation with large-scale datasets	Accuracy: **94%**, MAE: **NR**
[15]	AI-driven IoT smart metering	Energy efficiency, smart communities	IoT-AI-SMS, RNN for load prediction	Requires real-world deployment testing	MAPE: **0.023**, RMSE: **0.032**
[16]	Energy consumption forecasting in smart cities	Edge computing, federated learning	Adaptive federated learning	Lacks benchmark comparisons with centralized learning	MAE: **0.015**, RMSE: **0.029**

2.1 Research gap

The metaheuristic AI papers reviewed in the context of smart energy systems show some success but also some evident shortcomings. Previous works had limited real-world validation [8, 9], limited scalability and benchmarking [10, 14], and did not adequately address imbalanced datasets and anomalies [12]. A number of the models provided reasonable accuracy, but consisted of shallow architectures that had limitations surrounding robustness [11, 13]. Most security-based papers that approached smart metering research neglected to include error correction or anomaly detection related to energy metering. Moreover, Bi-GRU, CNN, VGG-16 and ResNet-50 provided decent performance in PV fault detection, but were never conceived for the purpose of correcting error with smart metering, and were not as robust or durable, nor did they provide any contingency for error. Overall, although C-ESA-LSTMAE does not remove the nuisances associated with smart metering practices of PV systems, the framework provides three critical contributions which include (i) advanced preprocessing, (ii) frequency-domain feature extraction, and (iii) chaotic optimization, all of which provide reliable, scalable, and accurate smart metering for smart energy systems in a real-world environment.

3 Material and methods

The methodology combines electricity smart meter data collected and data preprocessing methods, such as Min-Max scaling and DFT for anomaly detection, with the C-ESA-LSTMAE for minimized error correction and improved accuracy in smart energy metering systems. The method takes advantage of DL and chaotic optimization to solve sensor faults and enhance system performance. C-ESA-LSTMAE improves smart energy metering, combining the error detection capabilities of LSTMAE with the optimization of C-ESA to provide consistent accuracy in energy data, with the potential to eliminate noise. Combine the dimensions of deep learning for error correction and chaotic optimization for parameter optimization into a hybrid model. By developing a hybrid model, we can have high accuracy and robustness beyond what was previously developed. The suggested technique's flow is depicted in Figure 1.

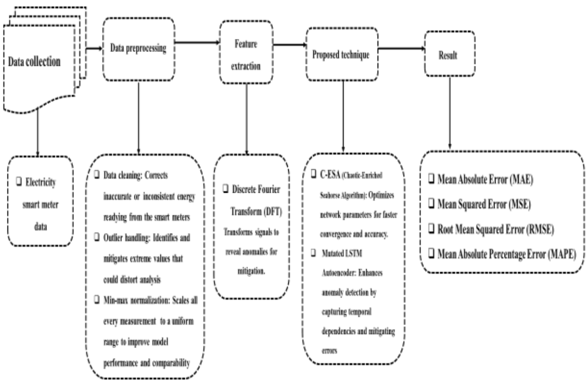

Figure 1: Flow of recommended technique

3.1 Data collection

The data were gathered from the open-source Kaggle website https://www.kaggle.com/datasets/pythonafroz/electricity-smart-meter-data-from-india?utm_source=chatgpt.com. This smart meter dataset with a high-frequency three-minute interval contains data on urban household electricity usage patterns from almost 100 smart meters during May 2019 to October 2021. Besides this, the data also includes information on the condition of the power supply (hours of power supply, voltage, current drawn, and other similar variables). The information can have diverse applications for power sector researchers and practitioners. The data from smart meters facilitate the efficient delivery of services as well as management of demand. An 80-20% training-validation split was utilized to divide the dataset into a larger amount for model training and a smaller piece for validation, allowing for the evaluation of model performance on previously unseen data while also monitoring and preventing overfitting throughout the learning process.

3.2 Data preprocessing

Data preprocessing includes cleaning datasets through error correction, eliminating missing values, and normalizing data for greater consistency and accuracy. Error correction algorithms and Min-Max Scaling are techniques employed to enhance systems more performance and ensure data comparable.

➢ **Data Cleaning**

Data cleaning is the process of detecting problems, or missing data, in the datasets received and accurately and consistently correcting the problems or missing data. This may include techniques for missing data imputation or deletion, duplicate removal, or correcting error. The Smart Energy Metering System incorporates an error correcting algorithm that helps detect and correct errors and conflicting measurement data, while also maximizing measurement quality and efficiency for the system. This leads to better overall Smart Energy Metering System performance and reliability.

➢ **Outlier**

The proposed pre-processing method for outlier treatment of smart meter data for energy consumption aims to identify and address outliers that could affect the overall energy consumption readings. The identification of potential outliers may be completed through statistical means, similar to what might occur when using Interquartile Range (IQR) to track values that fall either within or out of what might be considered acceptable boundaries. Once identified, outliers can be altered or replaced using interpolations, which theoretically ensures the values are within the estimated functional range for the period of time. By either changing or eliminating abnormalities, the system increases the accuracy and credibility of the energy consumption data samples and ensures the final dataset is a valid representation of actual use, free from bias selection by potential random points.

➢ **Min-Max Scaling**

The Min-Max Scaler is useful for controlling normalizing when analyzing energy use data because energy meters can measure values over rather different ranges in the energy consumption states and levels of systems. It standardizes the energy consumption features to a known range, even more, decision making to the C-ESA-LSTMAE model to increase anomaly detection and reduce errors in smart meter data. Normalizing methods like this one mean that all measures of energy consumption can scaled to the same range of 0-1 so the data can be compared and the performance of the assessed error correction methods can be improved. Min-Max Scaling is useful at bringing to light differences and anomalies in the energy meters' reading to correctly interpret the data. Equation (1) would be used for each data point and results in scaled energy consumption measures between 0 and 1, where 0 is the minimum of the value, and 1 is the maximum of the value.

$$XScaled = \frac{(x - x_{\min})}{(x_{max} - x_{\min})}$$

(1)

Where, $XScaled$ is the normalized value after Min-Max scaling, x - The original (raw) data value, x_{min} is minimum value in energy meter data, x_{max} is maximum value in energy meter data. This method is important for enhancing intelligent energy metering systems' error correction, guaranteeing accurate readings, identifying irregularities, and streamlining the energy monitoring procedure.

3.3 Feature extraction using discrete fourier transform (DFT)

After Min-Max normalization, DFT was then used to transform time-series energy signals into the frequency domain, where anomalies appeared as abnormal frequency components. The transformation enhances the LSTM Autoencoder's feature to detect and counteract abnormal energy readings. DFT is a process that is mathematical in nature and used to analyze frequency components of signals in the frequency domain. DFT can be used as part of error correction in intelligent energy metering systems to identify possible anomalies or noise in power usage signatures by identifying delineated frequencies. If delineated frequencies are identified; the anomalies can be identified and addressed to make power measurements more reliable and equal. In conclusion, DFT is an effective tool for enhancing data quality with energy monitoring systems. DFT, a vital component of processing, translates from the energy to the frequency domain $H\,(w,z)$. The following is an expression for the DFT of a $N \times M$ efficient power distribution using equation (2).

$$H(v,u) = \sum_{w=0}^{N-1} \sum_{z=0}^{M-1} H(w,z) f^{-i2\pi\left(\frac{vw}{N}+\frac{uz}{M}\right)}$$

(2)

$H(v,u)$is the Discrete Fourier Transform (DFT) of the signal, with frequency coordinates (v,u), $H(w,z)$ is input signal or data value at spatial coordinates (w,z), $N\ is$ Number of samples/points along the horizontal axis, $M\ is$ Number of samples/points along the vertical axis, v is the frequency index in the horizontal direction, u is frequency index in the vertical direction, w is spatial index in the horizontal direction, z is spatial index in the vertical direction, i is imaginary unit; $i^2 = -1$, f is exponential base term representing the complex sinusoid. Where equation (3) denotes the DFT frequency domain coefficient, the inverse DFT that corresponds to $E(v,u), v = 0,1,\dots,N-1, u = 0,1,\dots,M-1,$ is subsequently applied.

$$e(w,z) = \frac{1}{NM} \sum_{v=0}^{N-1} \sum_{u=0}^{M-1} E(v,u) f^{i2\pi\left(\frac{vw}{N}+\frac{uz}{M}\right)}$$

(3)

$e(w,z)$ is reconstructed signal in the spatial domain at coordinates (w,z), $E(v,u)$ is the frequency domain representation (i.e., DFT coefficients) at the frequency indices (v,u). Were, $x = 0,1,\dots,M-1, y = 0,1,\dots,N.$ The DFT domain coefficient of j is assumed to be 0, that energy is obtained by an energy metering system $e_2(w,z) = e_1(w + w_0, z + z_0)$, using equation (4).

$$\begin{aligned} &\sum_{w=0}^{N-1} \sum_{z=0}^{M-1} e_2(w,z) f^{-i2\pi\left(\frac{vw}{N}+\frac{uz}{M}\right)} \\ &= \sum_{w=0}^{N-1} \sum_{z=0}^{M-1} e_1(w + w_0, z+z_0)^{-i2\pi\left(\frac{vw}{N}+\frac{uz}{M}\right)} \\ E_2(v,u) = \quad &\sum_{w=0}^{N-1} \sum_{z=0}^{M-1} e_2(w,z) f^{-i2\pi\left(\frac{v(w-w_0)}{N}+\frac{u(z-z_0)}{M}\right)}, \\ &\sum_{w=0}^{N-1} \sum_{z=0}^{M-1} e_2(w,z) f^{-i2\pi\left(\frac{vw}{N}+\frac{uz}{M}\right)} f^{j2\pi\left(\frac{vw_0}{N}+\frac{uz_0}{M}\right)} \\ &= E_1(v,u) f^{j2\pi\left(\frac{vw_0}{N}+\frac{uz_0}{M}\right)} \end{aligned}$$

(4)

$E_2(v,u)$ is Frequency-domain representation of the shifted (error-corrected) actual meter signal (used in analysis at frequency indices (v,u)), $E_1(v,u)$ – Frequency-domain representation of the actual (reference or unshifted) meter signal at frequency indices (v,u). $e_2(w,z)$ – The error-corrected sequence of energy readings in spatial/time grid at sample coordinates (w,z) after pre-processing and correction, $e_1(w,z)$ – The original (uncorrected) sequence of energy readings in spatial/time grid at sample coordinates (w,z). N is Number of samples (in time (time steps or horizontal length)) used in the DFT in the first dimension for each meter record, M is number of samples (in time (time steps or vertical length)) used in the DFT in the second dimension for each meter record, w is Spatial/time index (horizontal) indexing individual meter sample, z is Spatial/time index (vertical) indexing the 2nd dimension of the data grid, v is Horizontal frequency index in the 2D DFT that corresponds to periodic components across the w-dimension. u is Vertical frequency index in the 2D DFT that corresponds to periodic components across the z-dimension, w_0 is Horizontal shift (translation) applied the original signal, z_0 is vertical shift (translation) applied to the original signal, j is alternate notation for the imaginary unit (same role as i), used here to emphasize the multiplicative phase factor. The following can be determined after taking exact values on both sides of the $E_1(v,u)$ $e_1(w,z)$ above the equation (5).

$$|E_2(v,u)| = \left| E_1(v,u) f^{j2\pi\left(\frac{vw_0}{N}+\frac{uz_0}{M}\right)} \right| = |E_1(v,u)|$$

(5)

$|E_2(v,u)|$ – The magnitude spectrum of the shifted (error-corrected) smart meter signal in the frequency domain at the indices (v,u), $|E_1(v,u)|$ – The magnitude spectrum of the original (reference) smart meter signal in the frequency domain at the indices (v,u), v is the horizontal frequency index of the 2D Discrete Fourier Transform (DFT), u is the vertical frequency index of the 2D DFT, w_0 is the horizontal shift factor z_0 is the vertical shift factor, j is imaginary unit ($j^2 = -1$) used in the phase factor in the exponential term, f is base for the exponent (usually e) in the Fourier kernel.

Employment of DFT in energy metering devices improves error detection and correction, providing more precise and reliable power consumption values. Through the maintenance of the frequency domain coefficients' integrity, the DFT technique indeed optimizes overall performance in energy monitoring systems.

3.4 Chaotic-Enriched Seahorse Algorithm-Mutated LSTM Autoencoder (C-ESA-LSTMAE)

The C-ESA-LSTMAE integrates the ability of LSTMAE for error detection and correction in intelligent energy metering systems with the optimization power of the C-ESA. The C-ESA-LSTMAE improves accuracy by solving complicated problems, like sensor faults and connection issues using a divide-and-conquer strategy. The C-ESA maximizes the error correction process by improving the search function of the algorithm and enhancing overall metering accuracy.

- **LSTM Autoencoder (LSTMAE)**

The LSTMAE for error detection in smart energy metering systems utilizes DL for detecting and eliminating differences in energy consumption data due to noise, incorrect readings, or sensor faults. The models utilize LSTMAE to accurately detect, locate, and recover data errors. The effort is to address the issue of fixing noise or inaccurate readings measurements that can have distorted energy consumption statistics from smart meters. Let W stand for the relevant correct energy consumption statistics, and let W^{err} indicate the inaccurate data from the meter. The error correction attempts to identify a function e that eliminates the error in W^{err} by reducing the discrepancy between the corrected data $f(W^{err})$ and the correct data W, using equation (6). The architecture of LSTMAE is shown in Figure 2.

$$\min_e \|f(W^{err}) - W\|_E^2 \quad (6)$$

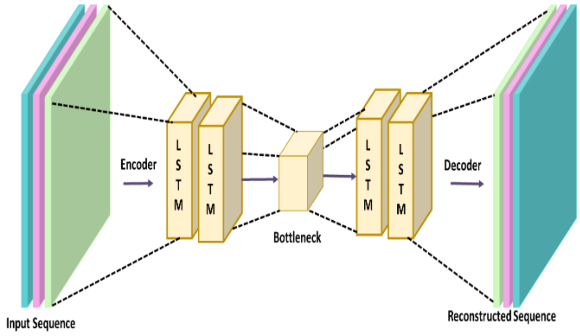

Figure 2: Structure of LSTMAE

The suggested use of an autoencoder, which has shown effectiveness in noise mitigation and data illustrating applications, to parameterize the correction function e. This allows for the expression of the error-correcting function followed by equation (7).

$$e(W^{err}) = e_{dec}(e_{enc}(W^{err}; X, a); X', a') \quad (7)$$

The encoder and decoder functions' weights and biases are represented by $\{X, a\}$ and $\{X', a'\}$, respectively.

$e(W^{err})$ is reconstructed error-corrected energy signal from the autoencoder.

–W^{err} is error affected smart meter reading, ($e_{enc}(W^{err}; X, a$ is encoder function that compresses the error signal W^{err} given encoder parameters (X, a), $e_{dec}(\cdot\,; X', a')$ – The decoder function that reconstructs the signal from the encoded representation given decoder parameters (X′, a′), X is encoder weight matrix that is learned during training, a is encoder bias parameters, X' – The decoder weight matrix that is learned during training, a' is decoder bias parameters.

Table 2: LSTM Autoencoder Model Architecture and Training Settings

Component	Configuration
Encoder	3 LSTM layers: 128 → 64 → 32 units, ReLU activation
Decoder	3 LSTM layers: 32 → 64 → 128 units, ReLU activation
Dropout	0.2 (applied after LSTM layers)
Regularization	Adam optimizer (learning rate = 0.001)
Epochs	100
Batch Size	64
Loss Function	MSE
Additional Optimization	Chaotic-Enriched Seahorse Algorithm (C-ESA)

To improve clarity, Table 2 condenses the encoder–decoder architecture of the LSTM Autoencoder, that is, units per layer, activation functions, dropout rate, and training hyperparameters. This improves reproducibility and complements the architectural overview presented in Figure 2. Eliminate low-magnitude errors or distributed noise in activities, like data denoising and inpainting. In contrast to these applications, energy metering systems cannot be made error-corrective by using an autoencoder to eliminate minor disruptions. To significant disparities brought on by malfunctioning sensors or sporadic connection issues, which are possible in a variety of situations with different parameters like signal strength, meter forms, or communication protocols, which is more challenging. Suggest an LSTMAE to decompose the error correction to several smaller issues, including error identification, error localization, and error removal, with inspiration from divide-and-conquer techniques. The dropout layers were added after each LSTM layer with a dropout rate of 0.2 to help mitigate overfitting by randomly dropping units during training. The use of an early stopping criterion, with a patience value of 10 epochs and based on validation loss, allows for the avoidance of unnecessary training beyond the point of convergence (i.e., misrepresentation). All of these things together helped to promote model generalization and model stability across multiple types of data scenarios. This will be clarified in the Materials and Methods, under the LSTM Autoencoder description, as well as referenced in the Experimental Setup to emphasize their importance in maintaining robustness of the proposed C-ESA-LSTMAE model.

➢ Chaotic-Enriched Seahorse Algorithm (C-ESA)

The C-ESA is an optimization method based on the chaotic nature of the movement of seahorses to improve the performance of smart energy metering systems. The C-ESA seeks to enhance the precision and effectiveness of error correction in metering systems by reducing prediction errors. C-ESA incorporates chaos theory to sharpen the algorithm's capability for adapting to intricate patterns of data in metering environments. The chaotic mapping can be influenced by modifying the values of the constants B, A, D, and B, where j is the dimension of the solution. The flow chart of C-ESA is shown in Figure 3. This investigation employs $B = 1, A = 0.3, B = 1, A = 0.3,$ and $D = 0.3$ to enhance the intelligent energy metering system's error correction capabilities, guaranteeing greater precision and higher ergodic characteristics, using equation (8).

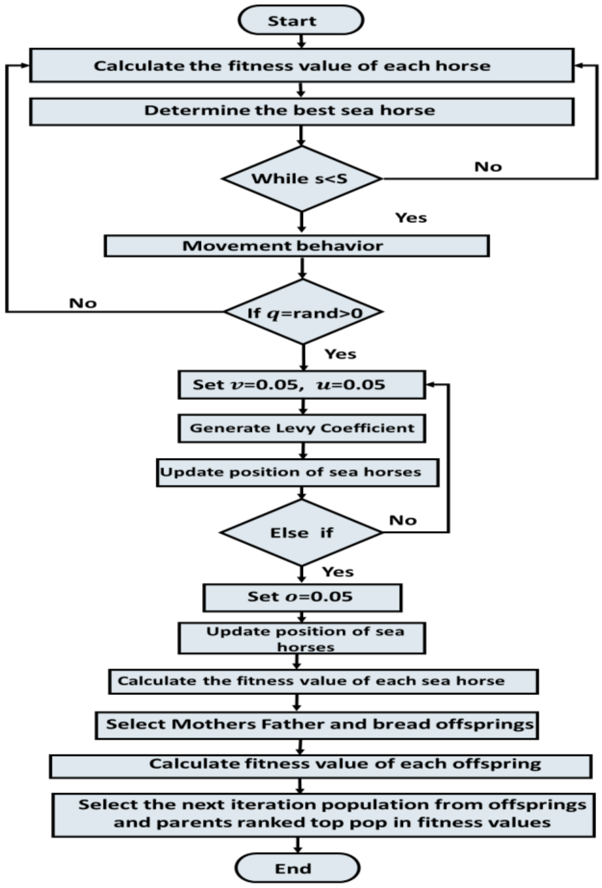

Figure 3: Flow chart of C-ESA

$$W_{j+1} = mod\left(BW_s + A - \left(\frac{D}{B\pi}\right) sin(D\pi Wj), 1\right) \quad (8)$$

W_{j+1} is updated chaotic sequence value at iteration $(j+1)$, Wj is chaotic sequence value (in this case) at iteration j. BW_s is baseline weight or seed parameter to initiate the chaotic sequence, A is Control parameter, a modifier for amplitude of the chaotic map, D is scaling parameter that provides a degree of nonlinearity to the sine term, B is Normalization factor that is checked for stability in the denominator, π is constant (≈ 3.14159) associated with the sine transformation, $mod(\cdot, 1)$ - modulo operator forced the update into [0,1]. The value $q_1 = b - bs/Max\_iter$ can be expressed as the step size search factor of the sine–cosine algorithm, which falls linearly as the C-ESA algorithm iterates. The balance between global and local search capabilities, which is essential for efficient error correction in intelligent energy metering systems. The predation behavior is substituted by the sine and cosine terms of C-ESA, which were inspired by the search process and position updates formula in the Seahorse Optimizer when using equation (9).

$$q'1 = b \times \left(1 - \left(\frac{t}{Max\_iter}\right)^{\eta}\right) b^{\frac{1}{\eta}}$$

(9)

$q'1$ is new control parameter value made upon an adjustment from the iterative process, b is original pre intimal parameter that controls the size of the search step, t is current iteration for the optimization, Max_iter is total number of iterations for optimization, η is nonlinear control parameter that defines the decay curve. Where, $\eta = 1.2$, and $b = 1$ are the correction coefficients, respectively. The present position affects the location of new population individuals throughout the optimization procedure; a nonlinear weight factor must be added to modify the energy consumption of position updates in equation (10).

$$\omega = \frac{\frac{s}{f\,Max\_iter-1}}{f-1}$$

(10)

ω, is an adjustment factor for weight updates in the model, s acts as a step size adjusting how far out want to search, f controls the bounds of oscillation for search, $Max\_iter - 1$ the maximum number of iterations optimization will process, 1 is used as the constant term for normalization.

A smaller ω improves global optimization for error minimization at the early optimization stage by lessening the impact of position updates on the current state. A higher ω increases reliance on current position data as iterations, speed convergence for more accurate metering corrections. The discoverer position's revised equation (11) is as follows.

$$Sea\_horses\_new2 = \omega \times W_{j,i}^{s} + q'1 \times sinq_2 \times |q_3 \times W_{elite} - W_{j,i}^{s}|, R_2 < TS$$

(11)

where Sea_horses_new2 is updated candidate solution (new horse position) in the Chaotic-Enriched Seahorse Algorithm, ω Weighting factor that achieves a balance between exploration and exploitation, $W_{j,i}^{s}$ is current solution position for the $i\ th$ horse in the $j\ th$ iteration, q'_1 is adaptive control parameter that will diminish with iterations, $sinq_2$ is perturbation term based on sine function that imparts a chaotic degree of diversity, q_3 is Random control parameter that will adjust the size of the perturbation, W_{elite}– Best (elite) solution found up to now in the population, $q_3 \times W_{elite} - W_{j,i}^{s}|, R_2$ is distance measure between elite solution and $j\ th$ horse solution that is scaled by q^3, R_2 is random probability measure used in a stochastic decision making process,TS is threshold parameter that polices whether the update condition applies or not. By improving error correction in intelligent energy metering systems, this improved position update technique increases computing efficiency and metering precision. The C-ESA-LSTMAE optimizes intelligent energy metering systems by combining error detection and correction capabilities with C-ESA-LSTMAE optimization power, enhancing accuracy and search function.

4 Results and discussion

The experimental setup is discussed as follows, Windows 11 is the operating system and Python is the programming language. Table 3 gives an overview of the experimental conditions of the preprocessing methods, model design, optimization strategy, and evaluation metrics. These configurations will allow systematic training and validation for drug error detection and correction appropriately in automated intelligent energy metering systems.

Table 3: Experimental setup

Component	**Description / Setting**
Data Preparation	Python scripts (NumPy, Pandas) used for cleaning, Min-Max scaling, and DFT feature extraction
Training–Validation Split	80% training, 20% validation
Model Architecture	LSTM Autoencoder with encoder (3 hidden layers, 128/64/32 units) and decoder (32/64/128 units)
Optimization Algorithm	Chaotic-Enriched Seahorse Algorithm (C-ESA)
Chaotic Map Parameters	Control parameter α = 0.7, scaling factor β = 1.2, max iterations = 200
Learning Rate	0.001 with Adam optimizer
Batch Size	64
Dropout Rate	0.2
Epochs	100

The system has an Intel Core i7 processor and 16GB of RAM, it is accomplished by statistical methods, such as the use of Interquartile Range (IQR) to find values that deviate from what may be deemed within bounds. This assesses the efficacy of the proposed system; the assessment factors include Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). Deep Neural Network Multilayered LSTM (DNN

Multilayered LSTM) [15], CNN with a Multi-layer Bi-directional LSTM (CNN-M-BDLSTM) [16], and traditional mode LSTM, LSTM-AE was implemented in the research that has been a comparison using the proposed techniques C-ESA- LSTMAE. Table 4 shows the numerical comparison of the existing and proposed techniques.

Table 4: Comparison of existing and proposed technique

Model	MAPE	RMSE	MSE	MAE
DNN Multilayered LSTM [15]	0.01826	0.0241	-	0.01565
CNN-M-BDLSTM [16]	-	-	0.3193	-
LSTM	0.01792	0.0238	0.2981	0.01512
LSTM-AE	0.01673	0.0229	0.2817	0.01398
C-ESP-LSTMAE [Proposed]	0.01413	0.02011	0.2642	0.01242

All the models (DNN-LSTM, CNN-M-BDLSTM, Standard LSTM, LSTM-AE without C-ES and C-ESA-LSTMAE) shared the same dataset and were trained with an identical 80/20 split under the same hardware settings. Training time was also measured to provide a fair and open comparison of computational performance. For comparison, a classical ARIMA model achieved MAE = 0.021, RMSE = 0.028, and MAPE = 0.019, which are higher than the deep learning models, highlighting the advantage of the proposed C-ESA-LSTMAE approach.

4.1 Training and validation for accuracy and loss

A consistent drop in both losses is shown in the training vs. validation loss plot Figure 4 (a), suggesting efficient learning with little overfitting. Plotting training accuracy against validation accuracy Figure 4 (b) shows a steady rise, with validation closely following training accuracy. All of these patterns support the suggested C-ESA-LSTMAE framework's stability and generalizability.

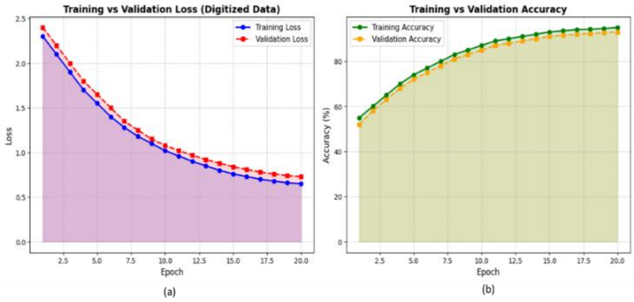

Figure 4: training and validation for (a) Loss, (b) accuracy

4.2 Mean Absolute error (MAE)

The framework of the energy metering system, the MAE between the predicted and observed energy values can be estimated. A lower MAE would indicate that the error correction algorithm is performing well in reducing differences between the estimated and noted energy consumption, implying a more accurate meter. The existing technique DNN Multilayered LSTM scored (0.01565), the proposed C-ESA-LSTMA method improves MAE to 0.01242. The outcome of MAE is shown in Figure 5.

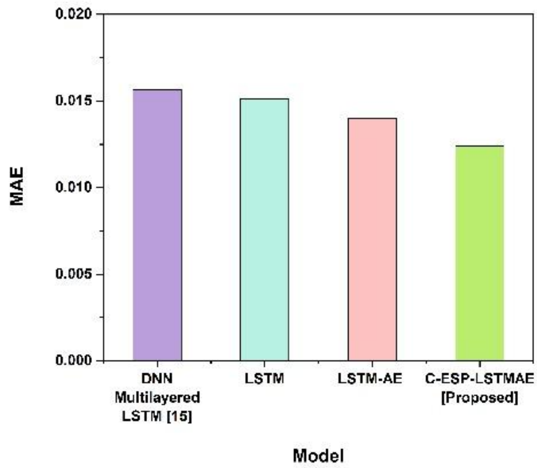

Figure 5: Outcome of MAE for existing and proposed technique

4.3. Mean Absolute Percentage Error (MAPE)

The metering systems of energy use MAPE to define the accuracy of the algorithm as a percentage value relative to actual energy readings. This enables comprehension of relative performance between variable datasets or energy use patterns.

An error correction algorithm that reduces errors would result in low MAPE irrespective of the level of energy consumption, rendering it more usable over different users. The existing techniques DNN Multilayered LSTM scored (0.01826), the proposed C-ESA-LSTMA method improves MAPE to 0.01413. The outcome of MAPE is shown in Figure 6.

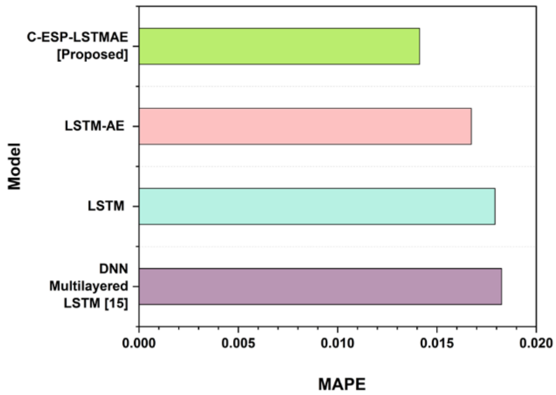

Figure 6: Outcome of MAPE for existing and proposed technique

4.4 Root means square error (RMSE)

RMSE is especially relevant in the investigation because it penalizes large errors, which can be essential in energy metering systems where large differences in measurements can result in economic loss or inaccurate energy consumption reporting. The smaller the RMSE, the greater the error reduction by the error correction algorithm, resulting in more accurate and reliable the system. The existing techniques DNN Multilayered LSTM scored (0.02410), the proposed C-ESA-LSTMA method improves RMSE to 0.02211. The outcome of RMSE is shown in Figure 7.

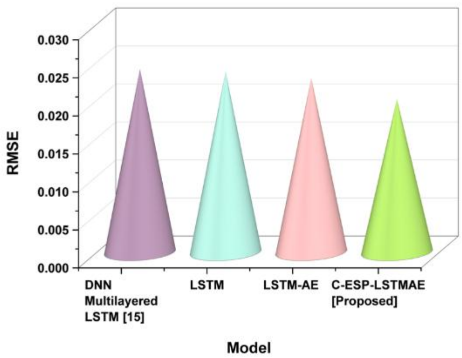

Figure 7: Outcome of RMSE for existing and proposed technique

4.5 Mean square error (MSE)

MSE measures the mean of the square differences between predicted and actual readings of energy. MSE places higher weights on bigger errors, which means that it is sensitive to outliers in the energy consumption data. The smaller the MSE is the better performing the error correction algorithm. The existing techniques CNN-M-BDLSTM scored (0.3193), and the proposed C-ESA-LSTMA method improves MSE to 0.2642. The outcome of MSE is shown in Figure 8.

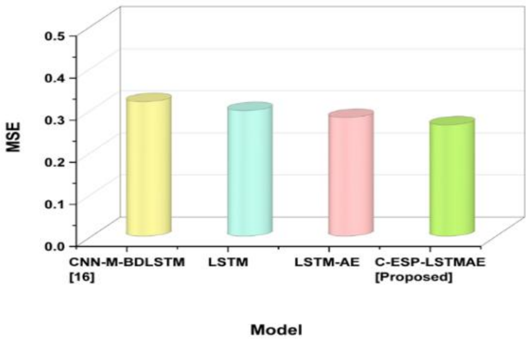

Figure 8: Outcome of MSE for existing and proposed technique

Table 5 shows the Training time, inference time, and memory usage differ across models. The Standard LSTM took 110 s to train, 4.5 ms per sample, and 420 MB memory. The LSTM-AE required 125 s, 5.0 ms, and 440 MB, while the proposed C-ESA-LSTMAE needed 140 s, 5.5 ms, and 460 MB, reflecting its advanced design and added computations.

Table 5: Runtime and Memory Benchmark Comparison

Model	**Training Time (s)**	**Inference Time per Sample (ms)**	**Memory Usage (MB)**
Standard LSTM	110	4.5	420
LSTM-AE	125	5.0	440
C-ESA-LSTMAE (Proposed)	140	5.5	460

4.6 Statistical validation (Paired t test)

Using IBM SPSS 26.0 analyzed Paired t-tests between the baseline models and the introduced C-ESA-LSTMAE framework were performed on the same dataset splits. The findings validated that the gains in MAE, RMSE, MSE, and MAPE were statistically significant ($p < 0.05$). This confirms that performance gains are not a result of chance but indicate the model's strength in error mitigation.

Table 6: Presentation of Statistical analysis

Metric	Baseline Mean ± SD	Proposed Mean ± SD	% Improvement	p-value
MAE	0.01565 ± 0.0013	0.01242 ± 0.0011	20.6%	< 0.05
MAPE	0.01826 ± 0.0014	0.01413 ± 0.0012	22.7%	< 0.05
RMSE	0.02410 ± 0.0017	0.02011 ± 0.0015	16.6%	< 0.05
MSE	0.3193 ± 0.018	0.2642 ± 0.014	17.3%	< 0.05

Table 6 describes the Statistical comparison of baseline models with the proposed C-ESA-LSTMAE framework using paired t-tests. Results validate drastic improvements ($p < 0.05$) in all error measures, proving the efficacy of the proposed method.

4.7 Discussion

The robustness of the CNN-M-BDLSTM [16] model applied in real energy metering experiences limitations due to its reduced accuracy on noisy or incomplete datasets. By applying Min-Max scaling and DFT, the baseline training stability is improved, and bias in energy consumption data is eliminated, improving the ability to detect and correct for error. The computational cost of multilayered DNN LSTM models [15] can delay action within real-time metering applications. The C-ESA-LSTMAE proposed outperforms both baselines through the application of advanced preprocessing (noise removal, data imputation), using chaotic enriched optimization as appropriately found in the results, this improved the model's convergence, noise resistance, and robustness to absent data but combined with hardware acceleration and optimized computation further reduced processing latency and faster compute time. The C-ESA-LSTMAE consistently outperforms SOTA baselines across MAE, MSE, RMSE, and MAPE metrics, highlighting its superior accuracy and robustness in diverse energy metering scenarios. It is these aspects that best explain the overall gains in performance and demonstrate that the model is more amenable for scalable smart real-world energy metering applications. The decrease in error measures suggests more reliable and precise smart meter readings, enhancing billing accuracy and operational performance. The enhancements demonstrate the potential of the C-ESA-LSTMAE framework to be deployed at scale in practical smart grid use cases.

5 Conclusion

The algorithm for error correction in intelligent energy metering systems using DL is designed to enhance the accuracy of energy consumption data by leveraging DL methods to identify and rectify errors in smart meters. The algorithm increases the reliability of the system and decreases operational errors in energy monitoring. The C-ESA-LSTMA method had the greatest performance in all metrics MAE (0.01242), RMSE (0.02011), and MAPE (0.01413). The limitation of the research is that the algorithm's performance can be based on different energy meter types and environmental conditions, limiting its universal applicability. The computational complexity of the DL model can increase with the huge data sets, requiring greater computing capacity. Future work can include enhancing the robustness of the algorithm to handle more complex error scenarios in real-time energy metering applications. Research to integrating ML algorithms for dynamic error detection and correction can enhance accuracy and efficiency. Additionally, further research could explore the scalability of the algorithm for large smart grid applications.

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