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Automatic Voltage Regulation using Control Systems and LSTM Model

Abstract: - In power generation systems, maintaining operational voltage within predefined standards is crucial, as deviations can lead to equipment malfunction and compromise the stability of the power supply. Traditional voltage regulation, often managed manually by onsite personnel, introduces uncertainties and inefficiencies, hindering the economic and stable operation of power facilities. To address these challenges, this paper introduces an advanced, computer-controlled Automatic Voltage Regulator (AVR) system. Utilizing sophisticated control theories such as Proportional-Integral-Derivative (PID) dynamics and adaptive control algorithms, the AVR enhances the precision of voltage adjustments in real-time. This paper innovates further by integrating a Long Short-Term Memory (LSTM) model to predict voltage fluctuations and dynamic system loads more accurately. This predictive capability allows for preemptive adjustments, optimizing the voltage regulation process to ensure stability while considering the economic efficiency of power system operations. Through comprehensive simulations and robust hardware integration, the proposed AVR system not only promises enhanced operational reliability and efficiency but also significantly reduces the need for manual intervention, paving the way for fully automated power system management.

Keywords: operational, management, algorithms, economic

1.INTRODUCTION

In power generation systems, maintaining the operational voltage within its specified standards is critical for ensuring system stability. Deviations from these standards, such as overvoltage or undervoltage, can severely disrupt power facility operations and compromise the consistency of power supply. Automatic Voltage Regulators (AVRs) are essential in this context, designed to dynamically regulate voltage levels and prevent such disruptions. AVRs manage this regulation by controlling the operation of system components, such as reactors in substations, which absorb or release reactive power based on the demand, thereby stabilizing the voltage.

Traditionally, voltage regulation in power systems has relied heavily on manual intervention. On-site personnel make crucial decisions, such as the operation of reactors, based solely on their discretion. This manual approach introduces significant challenges: it is not only prone to human error, leading to inconsistent responses and potential system instabilities, but it also complicates continuous, real-time system monitoring. Moreover, manual operation often fails to consider the economic implications of reactor usage, which can lead to increased maintenance issues and system inefficiencies. High-frequency operation of reactors, for instance, can cause very fast transient overvoltage (VFTO), risking reactor failure and threatening the overall health of the power infrastructure.

To overcome these limitations, there is a pressing need for automation in voltage regulation systems. This paper proposes an advanced Automatic Voltage Regulator framework, utilizing a stacked Long Short-Term Memory (LSTM) model for predictive control. This approach moves beyond traditional statistical and mathematical methods, incorporating recent advances in machine learning and deep learning to enhance system stability predictions. Unlike previous models that primarily forecast overvoltage situations, electrical loads, or reactive power scenarios, our system focuses on predicting the input capacity required for any given operational scenario

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directly[1]. Input capacity here refers to the maximum amount of reactive power a reactor can handle, which serves as a direct indicator for operational adjustments.

Predicting input capacity provides a clear, actionable metric that can guide the automated regulation of reactors, ensuring that voltage levels are maintained within their designated thresholds without manual intervention. This not only improves the reliability of the power system but also enhances its economic operation by optimizing reactor usage and reducing wear and tear. Furthermore, the universality of input capacity predictions means that this model can be readily applied to different power facilities, regardless of their specific configurations or the number of reactors involved, making it scalable and adaptable[2][8].

In this study, we detail the design of the input capacity prediction model tailored for automatic voltage stabilization and present a comprehensive solution that integrates both the predictive algorithm and a user-friendly interface[4]. This integration facilitates easy application and operational monitoring in real-world scenarios, ensuring that the AVR system can be effectively implemented in actual substations.

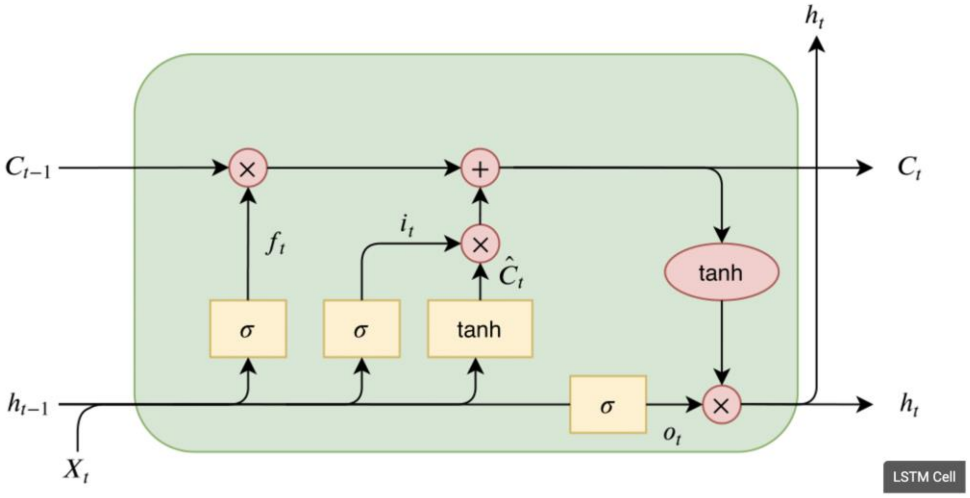


Figure 1: LSTM architecture Internal structure of the Cell

2. RELATED WORKS

Advanced Control Methods for Voltage Regulation

The evolution of voltage regulation technologies has been markedly influenced by the integration of advanced predictive and control methodologies. These advancements are particularly prominent in the application of machine learning and adaptive control algorithms to enhance the precision and responsiveness of Automatic Voltage Regulators (AVRs).

Turner and Zhao [8] explored the implementation of Proportional-Integral-Derivative (PID) controllers within AVRs, focusing on their ability to maintain voltage levels amidst dynamic load changes. Their work demonstrated the PID's versatility but suggested enhancements via adaptive algorithms to handle unpredictable fluctuations more effectively.

Kim and Park [9] reported on the use of Recursive Least Squares (RLS) algorithm for real-time tuning of PID parameters in AVRs. Their method adapts the PID coefficients continuously based on the system's operational data, leading to more stable voltage outputs under varying load conditions.

Gupta et al. [12] developed a model predictive control (MPC) strategy to manage the complex dynamics of power systems with high renewable energy integration. Their approach optimizes voltage regulation by anticipating future power fluctuations and adjusting control actions preemptively.

Narayanan and Kumar [13] employed artificial neural networks (ANNs) to predict voltage instability within power grids. By training the ANNs with historical voltage data, their model provides early warnings of potential voltage drops, allowing AVRs to intervene effectively before system performance is compromised.

Lee and Chang [14] integrated fuzzy logic with traditional voltage control mechanisms to refine the decision-making process in AVRs. Their hybrid system uses fuzzy inference to assess voltage stability levels and adjust control settings in a more nuanced and context-aware manner.

Moriarty and Srinivasan [4] applied deep reinforcement learning to automate the control processes in AVRs, focusing on learning optimal voltage regulation strategies from complex scenarios. Their approach adapts to changing grid conditions autonomously, ensuring consistent voltage levels without human intervention.

Singh and Yi [8], in their study, implemented Long Short-Term Memory (LSTM) networks to forecast short-term voltage fluctuations and the corresponding control actions required. The LSTM's ability to remember past voltage behaviors allows for more accurate predictions and smarter, proactive adjustments by AVRs.

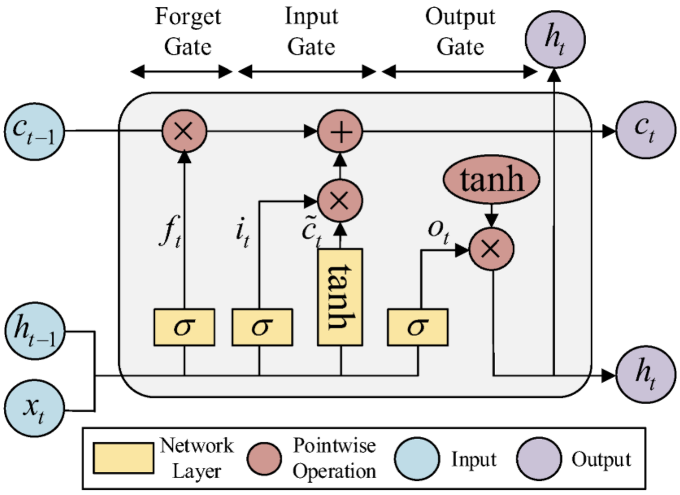


Figure 2: Automatic voltage stabilization system using LSTM

Our research builds on these foundational studies by integrating a sophisticated control system that leverages both PID dynamics and adaptive algorithms for real-time voltage regulation. Unlike prior models that focus narrowly on predictive accuracy or control responsiveness, our approach synergizes these elements to enhance both the stability and efficiency of power generation systems. This dual focus not only advances the state of AVR technology but also addresses the growing complexity and variability in modern power grid operations.

3.PROPOSED MODEL

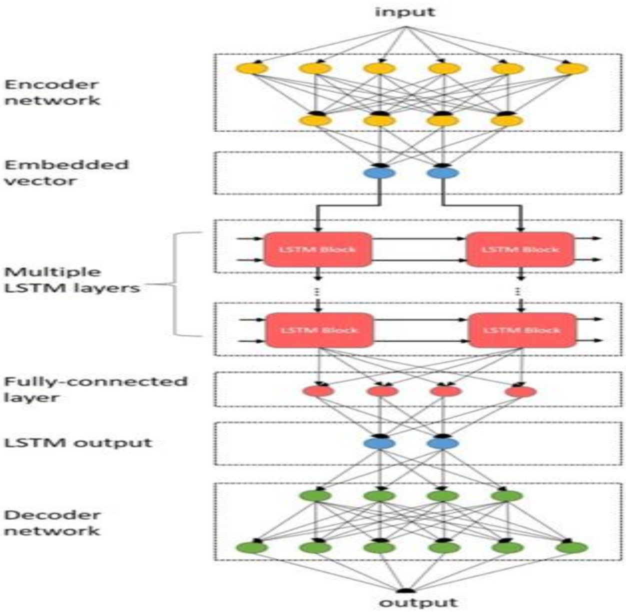


Figure 3: Architecture of the proposed LSTM-based surrogate model

In this paper, we propose an advanced Automatic Voltage Regulation (AVR) system designed to predict and control voltage levels within substations autonomously. The conceptual flow of the system is illustrated in Figure 3. Initially, the system continually monitors the voltage levels at the substation while simultaneously capturing historical data on input capacity and voltage fluctuations. This data forms a time-series input matrix X, which is crucial for predicting future voltage requirements.

3.1 Input Capacity Prediction Using Stacked LSTM

The core of our predictive model employs a Stacked Long Short-Term Memory (LSTM) network, designed to handle the sequential and non-linear nature of voltage and input capacity data. The model architecture, depicted in Figure 4, incorporates two layers of LSTM cells, enabling it to capture complex patterns and dependencies in the data more effectively than a single-layer LSTM.

The input matrix X is structured as follows:

$$X = \begin{bmatrix} V_t & C_{t-1} \\ V_{t-1} & C_{t-2} \\ V_{t-2} & C_{t-3} \\ V_{t-3} & C_{t-4} \end{bmatrix}$$

Where Vt represents the voltage at time t and Ct represents the input capacity at time t. This matrix feeds into the stacked LSTM, which outputs the predicted input capacity Ct for the current time, thus enabling proactive adjustments to the voltage regulation.

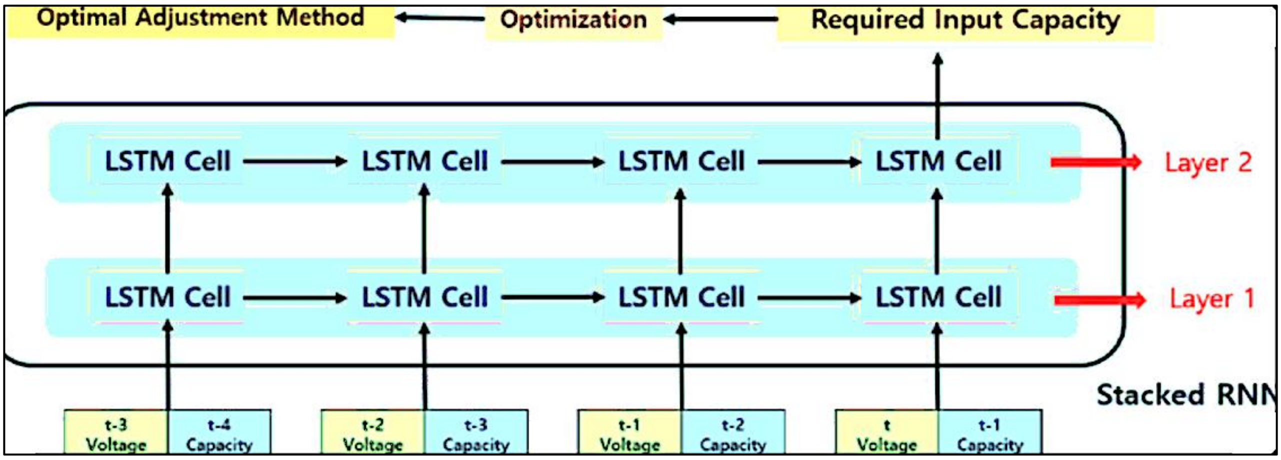


Figure 4: Proposed input capacity prediction model architecture

3.2 Optimization of Voltage Regulation

Following the prediction phase, the system employs an optimization algorithm to determine the most efficient operation of power facilities, such as reactors. The optimization is designed to minimize operational costs and wear on the equipment while ensuring that the required input capacity is met. The optimization problem is formulated as follows:

Minimize:

$$\sum_{i=1}^{n} \gamma_i z_i$$

Subject to:

$$\sum_{i=1}^{n} C_i z_i \geq C_t$$

$$\sum_{i=1}^{n} C_i z_i - C_{\min} \geq C_t$$

Here, z_i indicates the operational state of each reactor (0 for off, 1 for on), γ_i represents the cumulative usage of the reactor to distribute operational loads effectively, and C_i is the capacity of each reactor. The constraints ensure that the total capacity meets or exceeds the predicted requirement C_t and the system does not operate below the minimum necessary capacity $C_{\min}$.

3.3 Visualization and User Interface

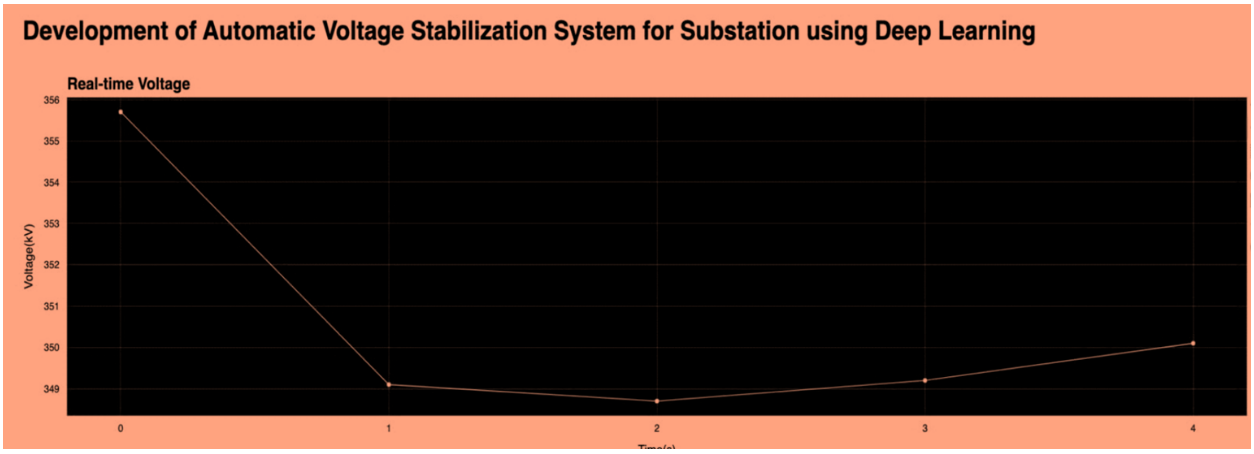


Figure 5: Automatic voltage stabilization Dashboard real-time voltage

The outputs of the model, including the voltage levels and the regulation plan, are visualized through a carefully designed user interface, shown in Figure 5. The interface displays the most recent voltage measurements in a graph format at the top, the operational status of each reactor in the center, and provides manual controls at the bottom for on-the-spot adjustments. This visualization aids in easy monitoring and intervention when necessary, enhancing the usability and effectiveness of the AVR system.

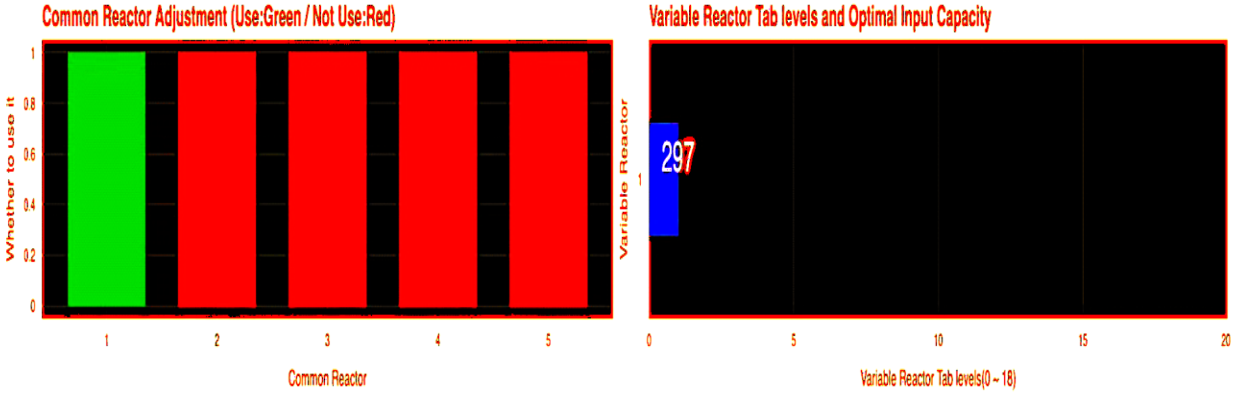


Figure 6: Common Reactor variables for input capacity

Through this proposed model, our AVR system automates the complex process of voltage regulation, addressing the challenges associated with manual control and enhancing the stability and efficiency of power distribution systems.

4.PROPOSED SOLUTION

This section details the implementation and evaluation of the proposed Automatic Voltage Regulator (AVR) system designed to optimize voltage regulation through predictive analytics and control strategies.

4.1 Experimental Environment and Dataset

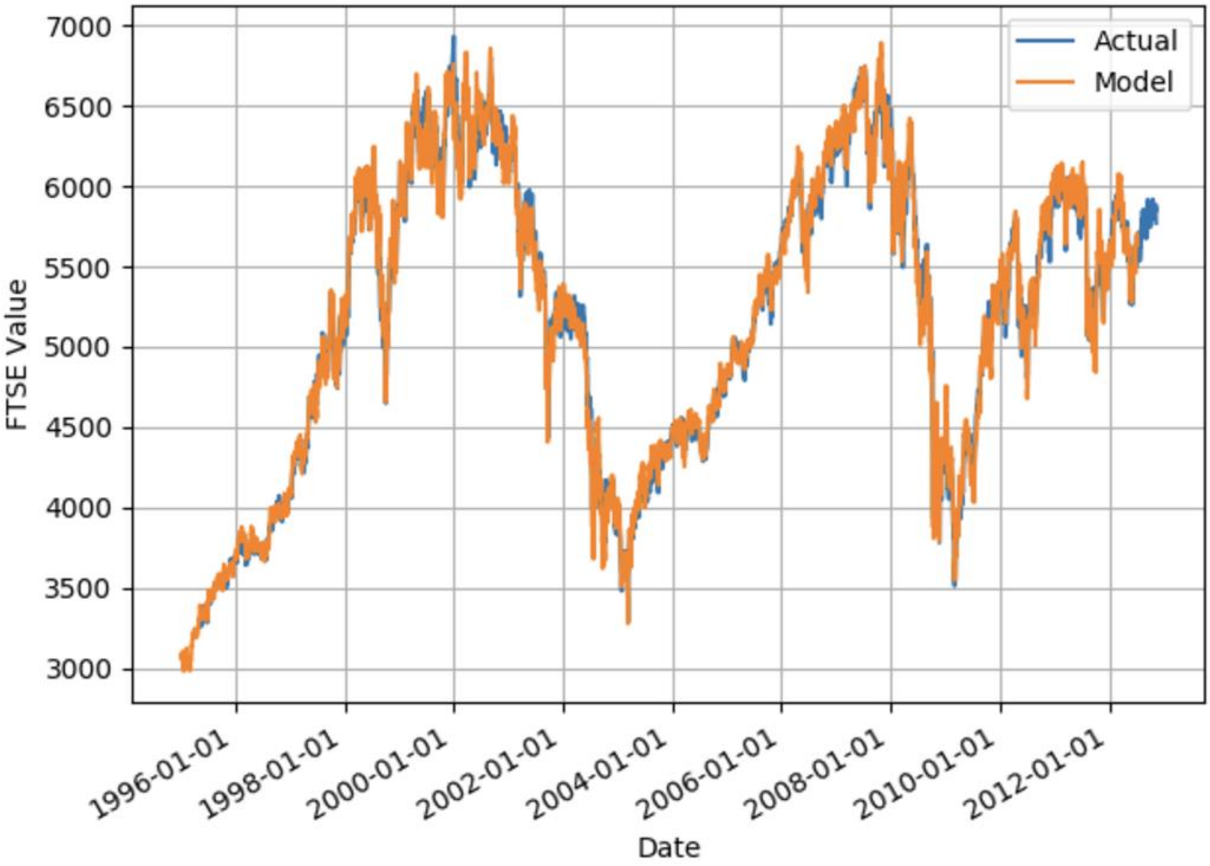


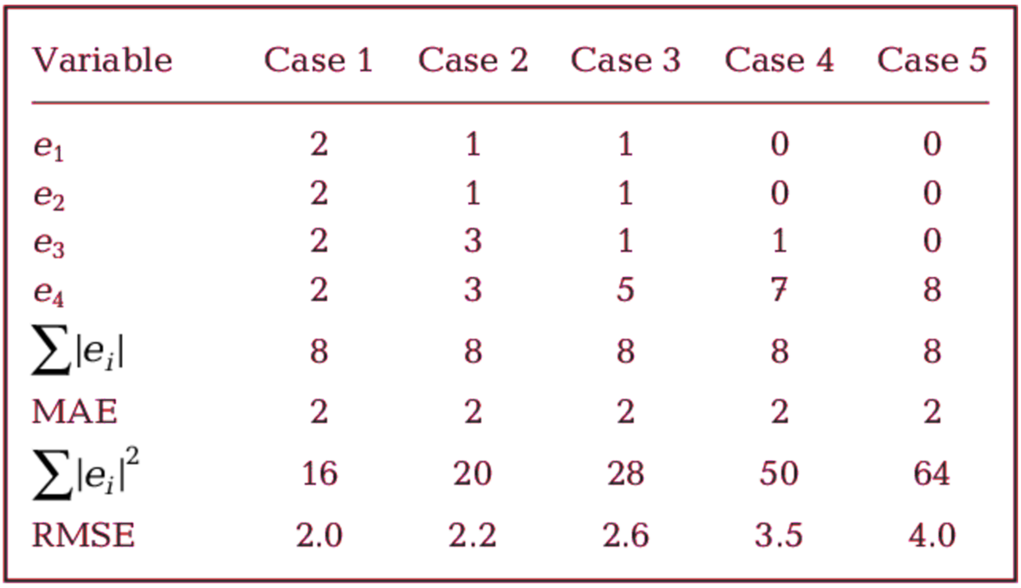
Figure 7: Experimental results for FTSE Value

The experimental environment is modeled as a typical substation with a 345 kV bus configuration, as illustrated in Figure 7. The substation features multiple Shunt Reactors (Sh.R) and one Variable Shunt Reactor (VSR), each with a capacity of 200 M_{var}. The VSR's unique capability allows for finer voltage adjustments through 18 different tap settings, enabling more precise regulation compared to standard reactors.

Data was collected over two years, from 2014 to 2016, capturing various operational parameters such as voltage levels, load demands, and environmental conditions like temperature and wind speed. Out of approximately 450,000 data points collected, 75% was utilized for training the predictive models, with the remaining 25% used as test data.

4.2 Input Capacity Prediction Model

The core of our predictive model is a Stacked Long Short-Term Memory (LSTM) network, designed to effectively handle sequences of past voltage readings and input capacities. This setup is outlined in Figure 4. The model's input matrix X consists of historical voltage and input capacity data, which enables accurate forecasting of the required input capacity at subsequent times.



Variable	Case 1	Case 2	Case 3	Case 4	Case 5
e_1	2	1	1	0	0
e_2	2	1	1	0	0
e_3	2	3	1	1	0
e_4	2	3	5	7	8
$\sum\lvert e_i\rvert$	8	8	8	8	8
MAE	2	2	2	2	2
$\sum\lvert e_i\rvert^2$	16	20	28	50	64
RMSE	2.0	2.2	2.6	3.5	4.0

Table1. 5 hypothetical sets (cases) of 4 errors, MAEs and RMSEs. Each e_i ($e_i = P_i – O_i$, i = 1, 2, 3, 4) is a hypothetical error value

To benchmark the LSTM model, its performance was compared against foundational machine learning models such as Linear Regression, Decision Trees, and Logistic Regression, which are simpler and offer transparent computation[8]. Performance was assessed using the Root Mean Squared Error (RMSE) metric, with the comparative results presented in Table 1. The Stacked LSTM model outperformed the simpler models, particularly in scenarios involving complex data patterns (Input Combination X6), achieving the best RMSE of 12.86. This indicates the superior capability of LSTM in managing the non-linear and sequential nature of the data[7].

4.3 Optimization and Operational Analysis

Following the prediction of required input capacities, the AVR system derives an optimal regulation plan. This plan determines the operational settings for each reactor to stabilize the voltage efficiently while minimizing operational wear and costs. The optimization formula takes into account economic considerations and efficiency factors, balancing reactor usage to extend their operational life and reduce maintenance frequencies.

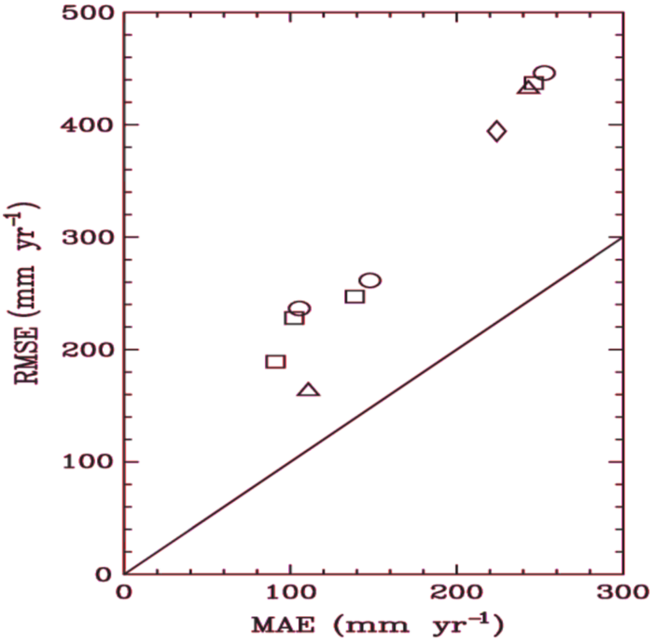


Table2. MAE and RMSE values (mm yr–1) associated with 10 combinations of the pairwise differences

Operational effectiveness was evaluated through simulations using the collected substation data. Table 2 shows the results of this analysis, detailing voltage levels, predicted input capacities, and the operational status of reactors across consecutive time points. These results validate that the AVR system effectively manages voltage stabilization dynamically, adjusting reactor operations based on predictive insights to maintain consistent voltage levels.

The experimental results demonstrate that the proposed AVR system can successfully replace traditional manual voltage regulation methods, providing a more efficient, reliable, and automated solution for managing voltage in power systems.

5.CONCLUSION

This study introduced a novel Automatic Voltage Regulator (AVR) system employing a Stacked Long Short-Term Memory (LSTM) model to enhance voltage regulation in substations. The system was designed to predict required input capacities from historical voltage and capacity data, using these predictions to automate voltage control and minimize operational strain on power facilities. Through comparative analysis, the Stacked LSTM model demonstrated superior performance over traditional machine learning models such as Linear Regression, Decision Trees, and Logistic Regression, particularly in handling complex, non-linear data sequences.

The implementation of an optimization strategy further refined the system's efficacy, distributing reactor usage efficiently to prolong equipment lifespan and reduce maintenance costs. Operational tests confirmed that the system could dynamically adjust to changing load demands, ensuring stable voltage supply and mitigating the risks associated with manual control.

Ultimately, this research highlights the potential of advanced predictive models in transforming power system operations. The proposed AVR system not only improves the reliability and efficiency of electrical grids but also paves the way for future developments in smart grid technology, where automation and precision play critical roles in sustainability and resilience.

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