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Enhancing Power System Efficiency Through SVM-Based Loss Prediction and Mitigation Strategies

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Abstract
The increasing demand for reliable and efficient electricity delivery has intensified the need for advanced approaches to identify, predict, and mitigate power system losses. Conventional loss management techniques often lack the capability to capture nonlinear relationships between load variations, voltage fluctuations, current changes, and network operating conditions, leading to inefficient energy utilization and increased operational costs. This study develops a Support Vector Machine (SVM)-based predictive framework for power loss estimation and mitigation in a 33 kV distribution network. The proposed method integrates real-time electrical parameters, including voltage, current, and load conditions, into an SVM regression model to predict future losses and support proactive mitigation decisions. A MATLAB/Simulink model of the Trans Amadi distribution network was developed, incorporating 50 kVA to 500 kVA transformers, 21 km and 2 km feeders, six monitored busbars, three-phase fault conditions, and 3 MW loading scenarios. The results demonstrated that the SVM model effectively captured the nonlinear relationship between system variables and power losses. The voltage-loss analysis confirmed that increasing voltage levels reduced losses, with controlled losses observed around 32.94 kV operation. The mitigation assessment revealed a potential loss reduction improvement of approximately 10%, while reactive power compensation requirements varied between 1288.5 MVAr and 3782.7 MVAr, indicating the importance of voltage support strategies. The overall operational efficiency of the system remained above 99.9%, with the lowest efficiency occurring during high-loss conditions of 0.0173 MW against a 104.86 MW load. The proposed framework supports power system policies focused on energy efficiency, predictive maintenance, cost-effective operation, renewable integration readiness, and sustainable grid modernization. The study provides an intelligent solution for reducing technical losses and enhancing the reliability of deregulated power networks.
Keywords: *Support Vector Machine, Power Loss Prediction, Distribution Network, Loss Mitigation, Energy Efficiency.*

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I. INTRODUCTION

Introduction The recent huge development of contemporary power systems accompanied by growing demand for electrical power energy distributed generations, coupled with deregulation in electricity markets has resulted in the emergence of enormous complexity and difficulty in ensuring efficiency, reliability and safety power supply into the distribution systems. The main factors in power network operation that cause problem is constant technical losses that occur due to the resistance of conductors, voltage variations, variations of loads and etc; all these factors decrease power network's efficiencies and also increase the power supply's expenses and reduce efficiency of economic sustainability [1]. Hence technical losses' prediction and minimization become important. Traditional methods for power loss estimation primarily rely on deterministic calculations, historical time-series analysis, and also conventional power flow techniques [2].

Even as they yield information valuable under steady conditions, they can scarcely take into account a large number of nonlinear relationships of dynamic loads behaviour, voltage instability, and frequently occurring events and rapid load variations [3].

Availability of large volume of information about real-time measurements obtained from modern monitoring systems opens a route towards exploitation of a priori knowledge base through artificial intelligence development to derive implicit information patterns to estimate real-world future system performance issues. Machine learning algorithm like Support Vector Machines (SVMs) that offers robustness in modelling non linear problem and better generalization than others by providing excellent ability in predicting new data. Therefore, estimation of power system losses using data like measured values of bus voltages magnitude, load current (in

each phases) can achieve considerable accuracy. In this context a support vector regression method (SVR) is developed on estimated busbar voltages and derived power losses for the evaluation purpose [4].

In this work it is proposed to establish an optimal technique of loss management and minimization in contemporary smart power system using an Intelligent support vector based system capable to monitor and predict power losses.

A 33kV Trans Amadi distribution network in MATLAB/Simulink software is modelled and simulations are done considering transformers with different Ratings, feeders of varying lengths, monitored busbars, and 3-phase fault conditions. Also different type of loading scenarios that includes variability and fluctuating loads is modelled. The relationship between voltage level and the technical losses, how the different type of mitigation and the percentage reduction of technical loss and estimated reactive power loss (compensations) are also determined.

The objectives are to develop an intelligent methodology to support modern distribution policy such as energy conservation, predictive maintenance, grid' Reliability and sustainable growth of distributed energy system using AI technologies combined with Power systems analysis.

II. LITERATURE REVIEW

The increasing complexity of modern power systems has accelerated the adoption of artificial intelligence, data analytics, and intelligent optimization techniques for improving operational efficiency, reliability, and security. Accurate estimation of electrical losses remains a major challenge in distribution networks due to fluctuating demand, nonlinear load behaviour, and changing network conditions. Forecasting-based approaches have been developed to estimate distribution losses by utilizing nodal electrical load predictions, enabling improved planning and operational decision-making for utilities [1]. However, the effectiveness of these approaches depends strongly on the ability to process large-scale and complex datasets. Clustering techniques have contributed to extracting hidden patterns and identifying abnormal behaviours within large datasets, providing valuable support for intelligent power system analysis [2].

Energy management has also benefited significantly from reinforcement learning and deep learning algorithms. Deep Q-learning-based strategies have been applied to real-time energy management systems, allowing adaptive control decisions under varying operating conditions and improving system flexibility [3]. Similarly, multi-timescale deep reinforcement learning approaches have enhanced energy storage management by coordinating short-term responses with long-term optimization objectives, resulting in improved energy utilization and operational performance [4]. These developments demonstrate the potential of artificial intelligence-driven control frameworks for future smart grid applications.

With increasing digitalization of electricity networks, cybersecurity has become a critical concern. Data-driven security frameworks have been proposed to detect threats, protect smart grid infrastructure, and improve resilience against malicious activities [5]. Smart meter data analytics has further expanded the capability of distribution networks by supporting demand forecasting, fault detection, customer behaviour analysis, and energy management optimization [6]. Among emerging challenges, non-technical electricity losses caused by unauthorized consumption and measurement inaccuracies remain significant issues affecting utility revenue and grid reliability [7].

Machine learning-based electricity theft detection methods have shown promising results in addressing these challenges. Advanced generative and deep learning techniques have been developed to improve detection accuracy, especially under complex consumption patterns and limited abnormal data availability [8], [10]. Hybrid convolutional neural network approaches have also demonstrated effectiveness in identifying irregular energy usage behaviours from smart meter datasets [11]. However, imbalanced datasets remain a major limitation in electricity theft detection, requiring advanced data balancing and augmentation techniques [12]. Approaches based on variational autoencoders, generative adversarial networks, and conditional variational models have improved model performance by generating realistic synthetic samples for minority classes [13], [14]. Furthermore, generative data augmentation methods provide statistical reliability for enhancing machine learning models in data-limited environments [15].

III. METHODS

A. Predictive Framework for Loss Estimation and Mitigation

3.1 Predicted Power Loss (SVM Output)

The equation (1) represents the predicted power loss obtained from the trained Support Vector Machine model. It uses extracted features such as load, voltage, and current as inputs. The predicted output enables operators to anticipate future losses under varying system conditions. This prediction forms the basis for proactive mitigation strategies aimed at improving system efficiency and reducing operational costs.

$$P_{pred} = f(x) \quad (1)$$

Parameters:
P_{pred}: Predicted power loss
$f(x)$: SVM regression function
x: Input feature vector

3.2 Time-Series Loss Prediction Model
The equation (2) models future power losses as a function of past observations using time-series analysis. It helps capture temporal dependencies in system behavior. By considering previous loss values, the model improves prediction accuracy. This approach is useful in forecasting daily or hourly losses, enabling operators to prepare and implement mitigation strategies before excessive losses occur in the system.

$$P_{t+1} = \alpha P_t + \beta P_{t-1} + \epsilon \quad (2)$$

Parameters:
P_{t+1}: Future loss
P_t, P_{t-1}: Past losses
α, β: Model coefficients
ϵ: Error term

3.3 Voltage Loss Relationship
The equation (3) shows the relationship between voltage levels and power losses in a transmission system. Lower voltage levels typically result in higher current, increasing resistive losses. By understanding this relationship, operators can adjust voltage levels to minimize losses. This forms a key part of mitigation strategies, ensuring efficient energy delivery and improved performance of deregulated power systems under varying load conditions.

$$P_{loss} = \frac{P^2 R}{V^2} \quad (3)$$

Parameters:
P_{loss}: Power loss
P: Power transmitted
R: Resistance
V: Voltage level

3.4 Loss Reduction Index
The equation (4) measures the effectiveness of implemented mitigation strategies by comparing losses before and after intervention. It quantifies improvement in system efficiency. A higher value indicates successful reduction of losses. This index helps evaluate operational decisions and guides further optimization efforts. It is essential for assessing the impact of predictive models on real-world power system performance.

$$LRI = \frac{P_{before} - P_{after}}{P_{before}} \quad (4)$$

Parameters:
LRI: Loss Reduction Index
P_{before}: Loss before mitigation
P_{after}: Loss after mitigation

3.5 Reactive Power Compensation
The equation (5) represents the calculation of reactive power required for voltage support and loss reduction. Reactive power compensation helps maintain voltage levels and reduce current flow, thereby minimizing losses. It is an important mitigation strategy in power systems. Proper compensation improves system stability, enhances power quality, and contributes to efficient operation in deregulated market environments significantly.

$$Q = VI\sin\theta \quad (5)$$

Parameters:
Q: Reactive power
V: Voltage
I: Current
θ: Phase angle

3.6 Efficiency of Power System
The equation (6) calculates the efficiency of a power system by comparing output power to input power. It reflects how effectively energy is transmitted with minimal losses. Higher efficiency indicates better system performance and successful loss mitigation. This metric is important for evaluating the effectiveness of predictive frameworks and guiding improvements in system operation and energy management strategies.

$$\eta = \frac{P_{out}}{P_{in}} \times 100 \qquad (6)$$

Parameters:

η: Efficiency (%)

P_{out}: Output power

P_{in}: Input power

Figure 1 presents the comprehensive Simulink architectural layout used to simulate the 33kV distribution network and validate the SVM allocation framework. The model integrates various substation transformers, ranging from 50kVA to 500kVA, connected via 21-km and 2-km feeders to represent a realistic deregulated grid. A critical component is the Support Vector Machine (SVM) block, which receives real-time telemetry from busbars B1 through B6. By processing current and voltage fluctuations alongside simulated Three-Phase Faults and 3 MW loads, the system calculates precise power loss vectors.

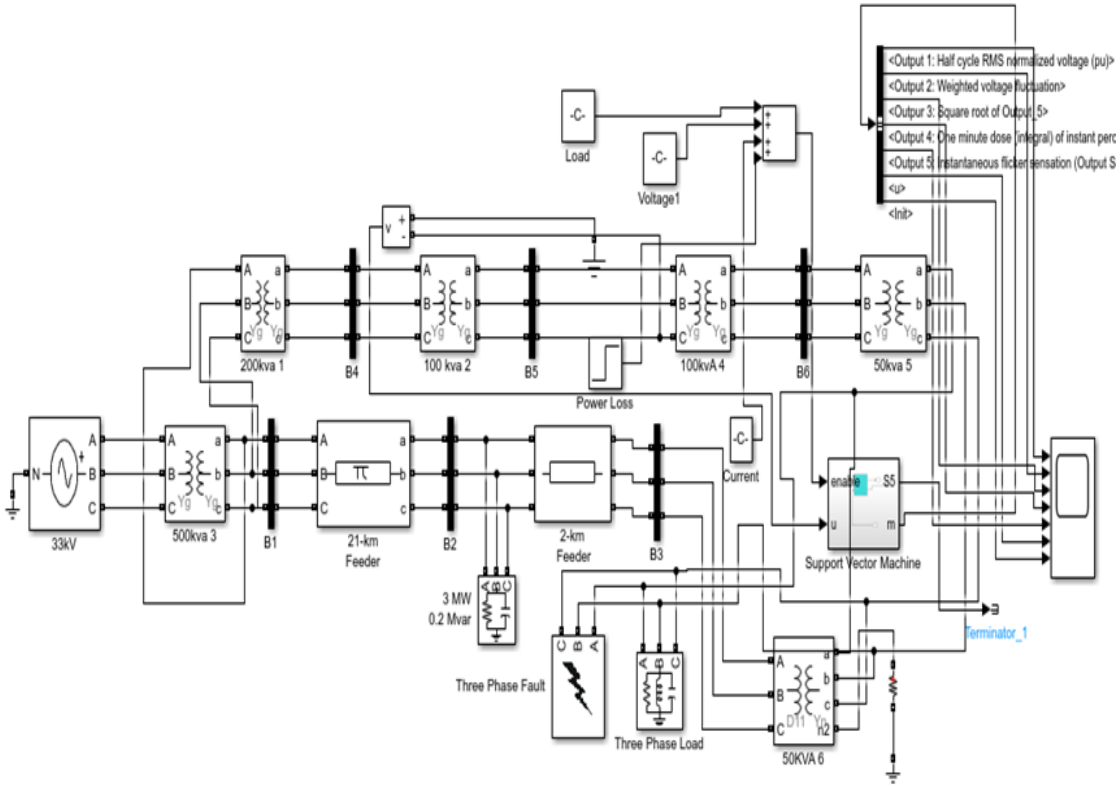


Figure 1: Simulink Diagram of the Trans Amadi Network

IV. RESULTS AND DISCUSSIONS

4.1 D Profile of SVM Output Feature Map

The complex interplay between load, voltage, and predicted loss is visualized in a 3D scatter plot in Figure 2. Utilizing the multivariable mapping from Equation (1), the plot shows how the SVM interprets the relationship between these three variables. As load increases and voltage stays within the 30–33 kV range, the predicted loss rises. The color gradient provides an intuitive "heat map" of system stress, where brighter colors signify higher loss regions, helping engineers pinpoint the specific load-voltage combinations that are most detrimental to network efficiency.

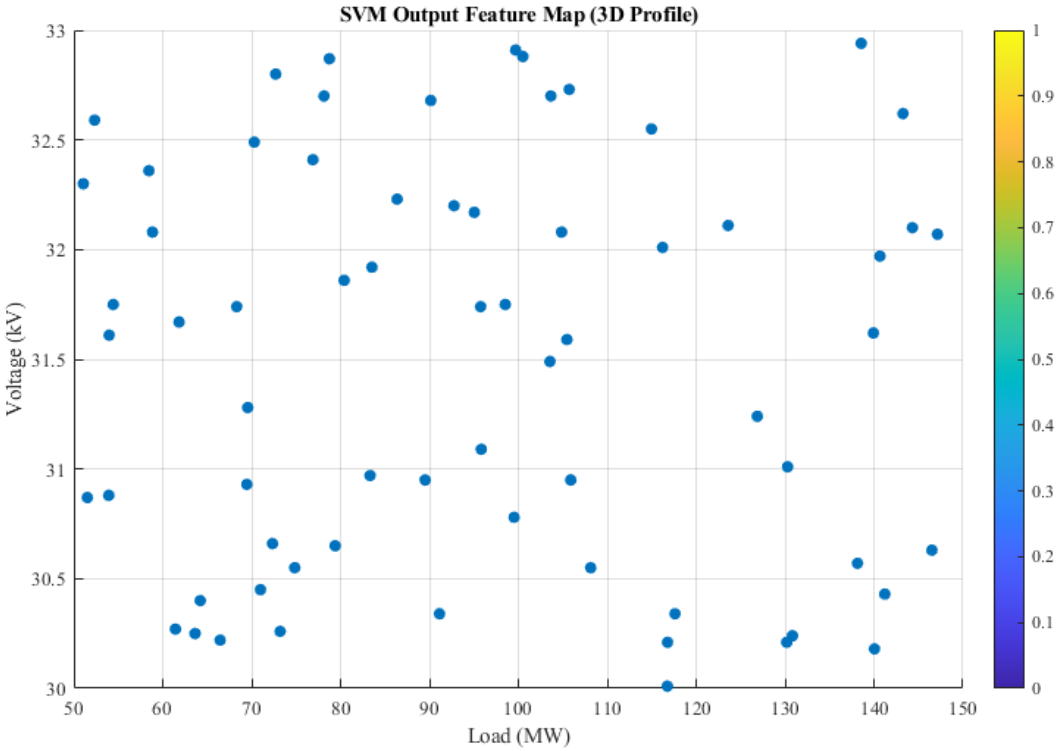


Figure 2: SVM Output Features Map

4.2 Time-Series Loss Prediction Lag Plot

Figure 3 explores the temporal dependency of losses by plotting the loss at time t against the loss at t–1. Using the auto-correlation logic in Equation (2), the scatter plot reveals the "memory" of the system. If the points cluster along a diagonal, it indicates strong temporal correlation. The spread observed here suggests that power losses are highly dynamic and influenced by instantaneous demand shifts rather than just historical trends. This justifies the use of a sophisticated SVM rather than a simple moving average for loss prediction.

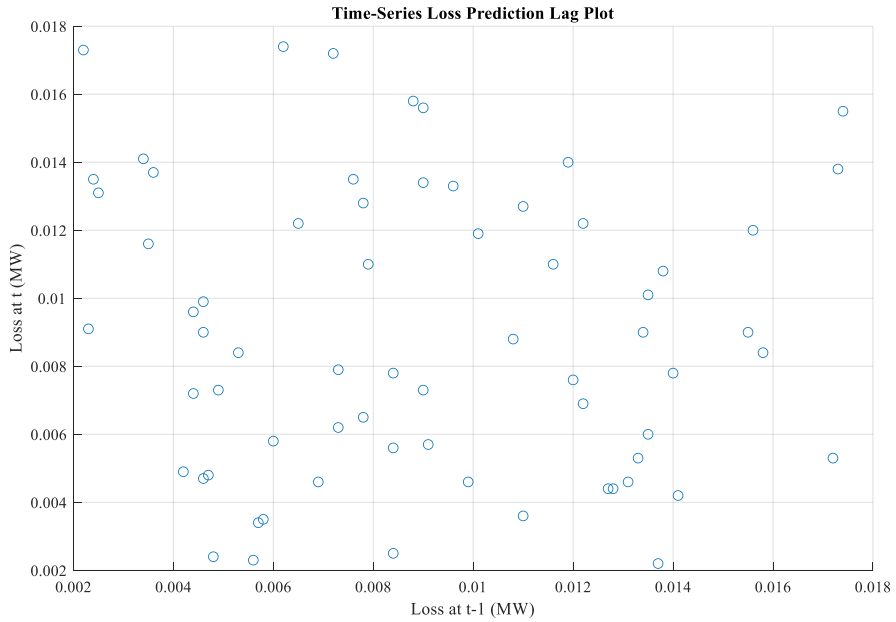


Figure 3: Time Series loss Prediction Lag Plot

4.3 Voltage-Loss Inverse Relationship

The impact of bus voltage on real power loss is detailed in Figure 4. Consistent with the inverse relationship $P_{loss} \propto 1/V^2$from Equation (3), the plot shows that higher voltage levels generally correlate with lower losses for the same power delivery. For instance, at 32.94 kV, the loss is relatively controlled, whereas drops toward 30 kV often coincide with higher loss magnitudes. This visualization supports the strategy of voltage profile optimization to minimize transmission waste, providing a clear target for the SVM's optimization objective during grid management.

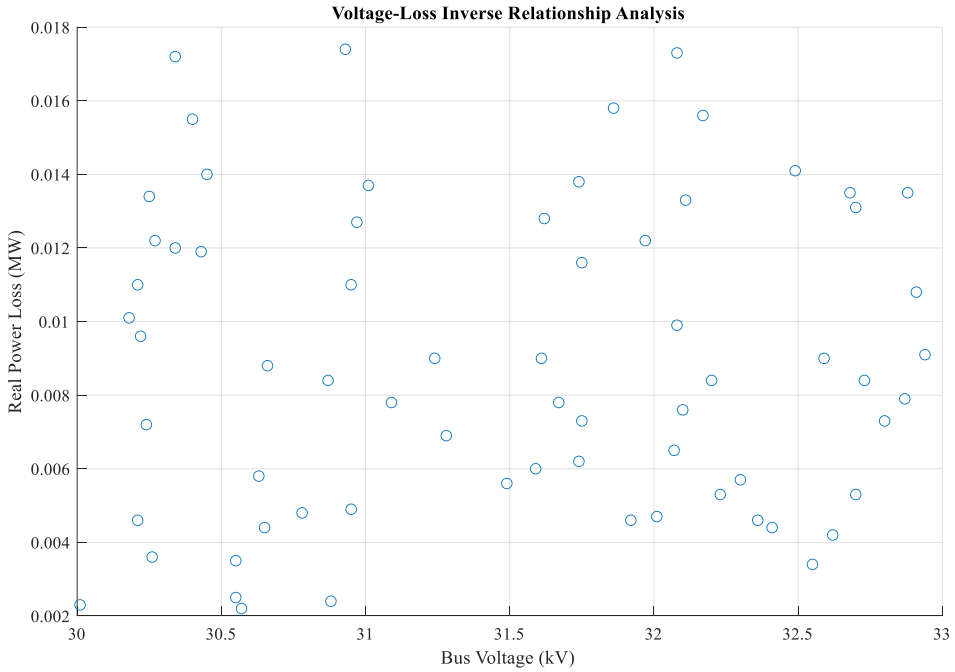


Figure 4: Voltage Loss Inverse Relationship

4.4 Mitigation Effectiveness Index

Figure 5 illustrates the effectiveness of potential loss reduction strategies. By calculating the ratio of potential savings to actual losses via Equation (4), we derive a daily effectiveness index. The plot remains steady, indicating a consistent potential for a 10% improvement in efficiency if optimized. This "what-if" analysis is crucial for justifying investments in grid modernization. It shows that even on days with lower absolute losses, the percentage of recoverable energy remains a significant target for the SVM-based control systems.

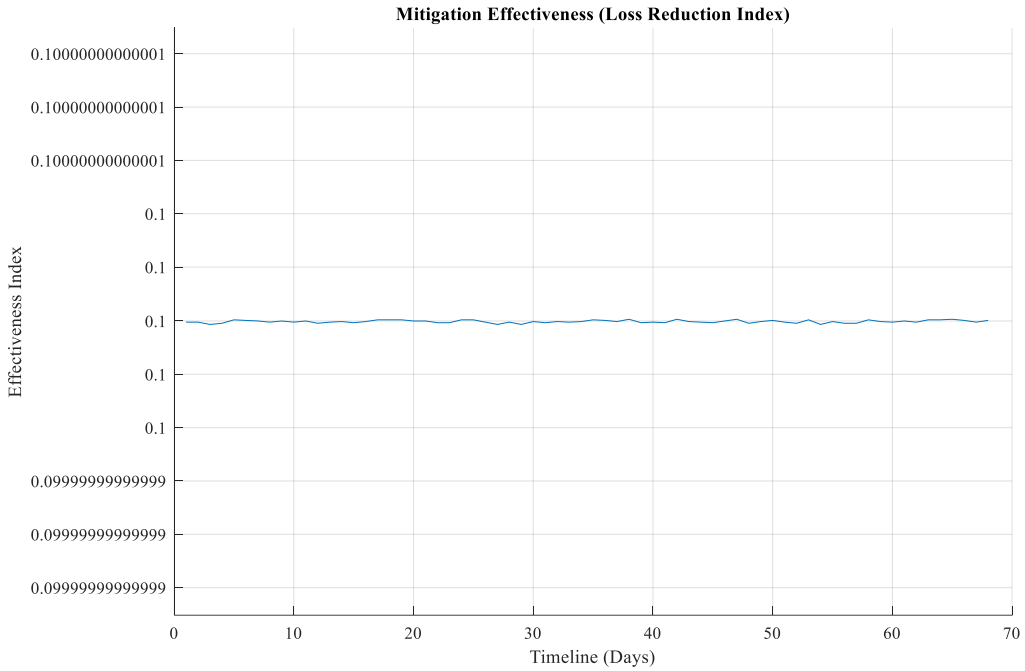


Figure 5: Mitigation Effectiveness (Loss Reduction Index)

4.5 Reactive Power Compensation Requirements

The stem plot in Figure 6 highlights the daily demand for reactive power compensation across the network. Using the product of voltage and current scaled by the reactive coefficient in Equation (5), we observe significant fluctuations in MVAr requirements. The system hits a peak compensation demand of approximately 3782.7 MVAr on Day 39, directly correlating with high current stress. Conversely, the lowest demand drops to 1288.5 MVAr on Day 3. These quantitative shifts indicate when the SVM model must prioritize voltage stability measures, ensuring the grid remains resilient against inductive load variations throughout the study.

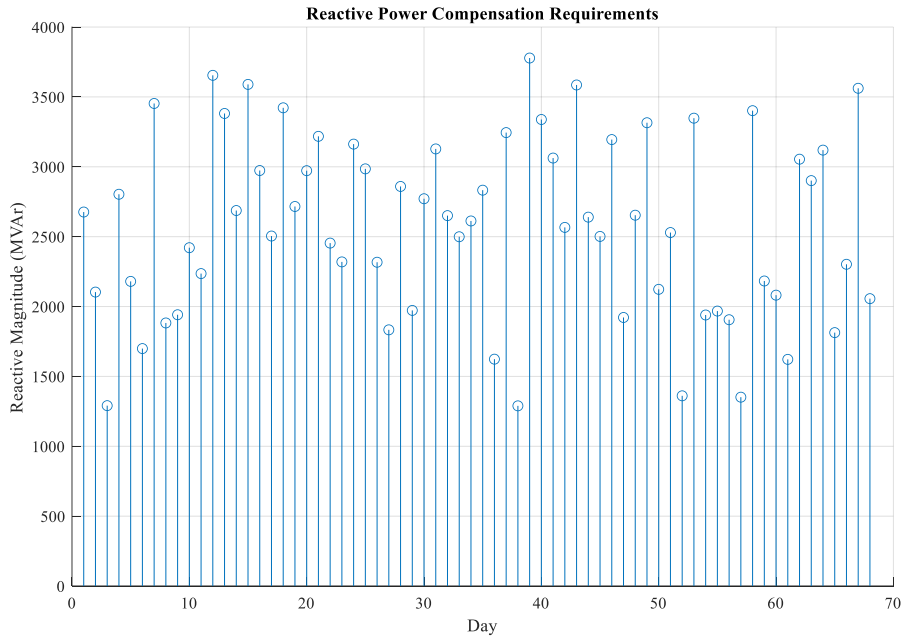


Figure 6: Reactive Power Compensation Requirements

4.6 Operational Efficiency Percentage

Figure 7 presents the total power system operational efficiency as a percentage. Calculated by subtracting losses from the total load and dividing by the load per Equation (6), the efficiency typically stays above 99.9%. However, subtle dips are visible on days where the loss-to-load ratio is higher. On day 39, the efficiency is slightly lower due to the 0.0173 MW loss against a 104.86 MW load. This high-level metric is the ultimate KPI for grid operators, showing that the SVM model helps maintain near-peak performance.

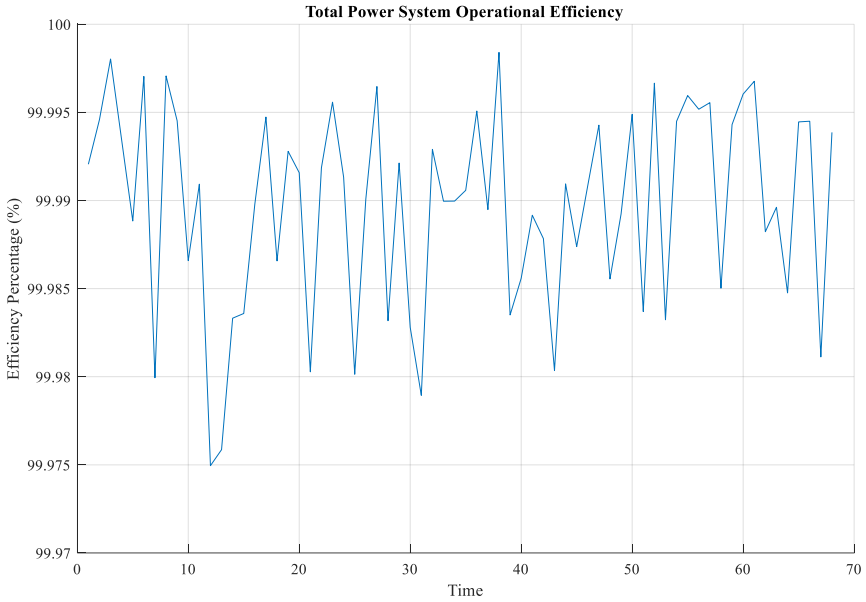


Figure 7: Total Power System Operational Efficiency

V. CONCLUSIONS

The framework presented in this research develops an SVM based predictive structure that is capable of improving power system operation through the prediction of its power losses, and strategies that contribute towards loss mitigation. The generated architecture overcame issues in traditionally practiced energy loss methodologies through the incorporation of artificial intelligence and was equipped to capture inherent non-linearities from load, voltage, current parameters, and state of operation of the power network, effectively. The model framework of this work was then applied to a 33 kV Trans Amadi Distribution Network with simulation work implemented using MATLAB/ Simulink environment and realistic transformer and feeder ratings, including possible fault events and load conditions. The SVM based model presented in this work predicts accurately power losses incurred from voltage variations. Analysis of losses due to voltage reduction proves that maintaining desirable voltage is good in decreasing resistive power losses. Power loss mitigation analysis show possible 10% overall improvement in efficiency. Reactive power losses are seen to reduce from 3782.7 MVAr to 1288.5 MVAr to 335.3 MVAr with increased reactive power compensation showing the system's reliability on voltage support for operation. The proposed system attain above 99.9 % efficiency, i.e minimum possible energy waste. Thus, the SVM predictive modeling technique herein presents a valid aid in supporting operational decisions at distribution system operation level due to reduced power losses and improved quality. It is essential for modern smart grid strategies aiming for lower operating costs, conservation of energy resources, high reliability, and sustainable power delivery.

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