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A Data-Driven Support Vector Machine Framework for Loss Allocation in Deregulated Power Markets

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Abstract
Due to nonlinear grid behaviour, varying operation condition and availability of efficient settlement process. Traditional power loss allocation models often utilizes fixed percentage based methods and is incapable of capturing inherent loss contribution of market players which lead to disparity in the cost to be assigned and market efficiency. This study aims at an in-depth study that utilizes Support Vector machine based data driven approach to efficiently allocate, forecast and minimize the power losses that occurs in a deregulated power market. The network connectivity, market and equipment related data and the real-time network measurements are utilized along with past power losses data for developing the model that mimics the nonlinear loss behavior and allocate losses based on market and grid operational characteristics. The research proposes to use a Support Vector machine model developed using Radial Basis function (RBF) kernel for regression to model nonlinear relationship, while the loss allocation principles based on Optimization concept have been applied while integrating fairness index for developing better decision support system. A 33kV transmission network, which represented the transmission and sub-transmission of Trans Amadi, has been the benchmark for implementation and analysis of the model using MATAB Simulink. Feeder configuration and transformers ratings, fluctuating loads on the transmission line as well as some faults conditions were also used for carrying out simulation. Results from the simulation had clearly show up some level of current flowing along transmission lines. Max load was observed at 590.76 A corresponding to 0.0174 MW loss, while min current in line recorded was 210.89 A associated with loss of 0.0022 MW in the line. Total transmission loss during the 68 day simulated duration exceed over 0.6 MW .the proposed SVM model achieved a relatively good accuracy, with error below 0.001 MW using Mean Absolute Error (MAE) estimation method which implies improved energy market policies which encourages equity, fairness, cost reflective billing, loss accountability and enhanced operational efficiency in terms of reliability and performance of deregulated electricity system using artificial intelligence based tool.
Keyword: *Support Vector Machine, Deregulated Power Market, Loss Allocation, Artificial Intelligence, Transmission Loss Prediction.*

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I. INTRODUCTION

A shift of electricity sector from traditional vertically integrated utility systems to deregulation of power markets caused tremendous operational, economic, and regulatory impacts to utilities, independent power producers (IPPs) and consumers in recent years. The market is separated into transmission, distribution, and generation businesses to have a fair allocation mechanism for operational costs. One of the big problem in competitive electricity market is the allocation of transmission power losses. Transmission power loss is wasted electricity at the transmission system and cause direct financial losses. A fair loss allocation method based on user contribution to loss creation will alleviate billing problems, avoid market disputes, assure market invest-ability, and insure efficiency in the utilization of transmission system resources [1]. Conventional methods for loss allocation including; (1) proportional loss allocation; (2) marginal cost/participation methods for marginal loss; and (3) incremental transmission loss allocation based on different methods are developed and discussed in [2] and [3]. Most of these approaches have limitations as they are usually based on approximated DC load flow models or linearized system models, which ignore many significant phenomena occur in a typical power network. For example, losses are in general nonlinear functions of load, network topology, fault currents, and different dispatch orders of generators, due to the voltage dependency in RL load model [4]. Hence, intelligent loss allocation and estimation methodologies utilizing large-scale electrical measurement data and capturing the time-varying operational condition are of significant interest.

Recent advancements in intelligent systems and computational algorithms have opened new doors for developing data-driven tools for analyzing electrical power systems [8]. Machine learning algorithms like Support Vector Machine (SVM) have successfully been employed for various regression and classification tasks because of their ability to handle complex non-linear relations by using a number of kernel functions while ensuring a good generalization performance [5, 6]. Employing SVM to electrical losses allocation can potentially map high dimensional input variables to estimated losses directly by training the network on relevant recorded parameters that influencing losses to produce correct estimations [7].

Data-driven method requires large databases from actual and simulated results and therefore this study propose a data-driven approach to estimate and allocate transformer and line losses by utilizing the Support Vector Machine (SVM) tool [11][12][13].

The proposed framework aims to enhance the system accuracy, intelligibility, and fairness for all parties in a liberalized market. The model developed in this framework based on network parameters, measurement, historical losses, and market related inputs to estimate system losses. The framework is applied to the 33 KV Trans Amadi distribution network incorporating transmission line parameters, transformers, various load conditions and faults to estimate power system losses and provide a fair allocation among the network users in a deregulated market by simulating results in MATLAB/Simulink environment [9][10][14]. It facilitates transparent, unbiased cost recovery mechanisms, which contribute towards market viability and efficient grid operations in conformity with sound operational and environmental policies in modern electricity industry.

II. LITERATURE REVIEW

Abstract The complex structure of power systems, especially of the present ones in distributed power, in intelligent power and for market models, the advanced models for acquisition of information, intelligent processing and management. Studies of behaviour of electric loads, analysis of power loss, of electric service safety and their operations have become indispensable. Research is done in building models for various elements of electric power system and in applying these to predict their behaviour. Thus mathematical models were applied for investigation of operation behaviour of the transformer [1], and to characterize in dynamics wave behaviours and changes of magnetic flow, to ensure more reliable operation in the industrial application and for DC architecture with renewable resources, for power management [2]. Distributed electric generation, based on integration of power from renewable sources, require robust network analyses and specific models. Analysis tools were created for estimating behavior of network using different levels of penetration of generation [4]. Application of models for accurate assessment of energy consumption during transit, for electric vehicles, in relation with operational parameters and topology of roads, was addressed using an adaptable method and support for electrified mobility in small business [3]. Prediction techniques were made for energy load forecasting [6], and applied for estimation of power loss. Artificial intelligence techniques and data-based method were successfully presented in studies as a very suitable for power systems challenges. Usage of deep neural network techniques in electric fraud detection based on real time unusual load patterns, helps improving safety conditions for the grid, especially smart grids [5]. Smart meters have allowed vast capabilities related to observation, fault analysis and forecasting of power consumptions through big data and machine learning techniques in distribution networks [11]. Use of density-based clusters to find patterns and data anomalies provided basis for future intelligent applications of any system [7]. Modern energy management systems have shown increased adoption of advanced machine learning techniques such as reinforcement learning and deep learning for improved performance, e.g., adaptive learning through reinforcement deep Q-learning, for real-time decision-making with greater accuracy in flexible power systems [8]. Multi-timescale deep reinforcement learning approaches have also been developed to improve real-time energy storage optimization considering both short-term and long-term operational strategies [9]. The widespread digitization in electrical grids necessitates advanced techniques in protection against cyber-security threats, whereas data-driven solutions, fraud analysis techniques in general, and specifically prediction methods for non-technical losses continue to improve the protection of revenue, while strengthening operational safety for electrified distribution grids [10]. This suggests that hybrid AI models based on data-driven approach combined with monitoring frameworks and predictive analytics holds a great promise for efficient, secure and smart electrical systems of the future.

III. METHODS

3.6 SVM-Based Loss Allocation Model

3.6.1 Power Loss in Transmission Line

This equation represents the fundamental calculation of real power loss in a transmission line based on current flow and conductor resistance. It forms the foundation for loss allocation modeling by quantifying how electrical energy dissipates as heat during transmission. Accurate estimation of this loss is essential for assigning responsibility among market participants in deregulated power systems effectively and fairly.

$$P_{loss} = I^2R \quad (1)$$

Parameters:
P_{loss}: Power loss (W)
I: Line current (A)
R: Line resistance (Ω)

3.6.2 Total Network Loss

This equation computes the total power loss across an entire network by summing individual line losses. It is crucial in deregulated markets where system-wide losses must be distributed among multiple participants. By aggregating losses, the model provides a basis for proportional allocation, ensuring that each participant is assigned losses based on their contribution to overall system usage patterns.

$$P_{total} = \sum_{k=1}^{n} I_k^2 R_k \quad (2)$$

Parameters:
P_{total}: Total network loss
I_k: Current in line k
R_k: Resistance of line k
n: Number of transmission lines

3.6.3 SVM Regression Function

This equation defines the Support Vector Machine regression function used to predict power losses based on system input variables. It maps input features into a higher-dimensional space using kernel functions, allowing nonlinear relationships to be captured. The function combines weighted support vectors and bias to produce accurate predictions essential for fair and data-driven loss allocation decisions in deregulated markets.

$$f(x) = \sum_{i=1}^{n} \alpha_i K(x_i, x) + b \quad (3)$$

Parameters:
$f(x)$: Predicted loss
α_i: Lagrange multipliers
$K(x_i, x)$: Kernel function
b: Bias term
x: Input vector

3.6.4 SVM Optimization Problem

This equation represents the optimization objective of the Support Vector Machine model. It minimizes the model complexity while penalizing prediction errors using slack variables. The balance between margin maximization and error tolerance ensures robust performance. This formulation is critical for achieving accurate loss prediction, which directly supports equitable allocation among participants in deregulated power systems under varying operating conditions.

$$\min \frac{1}{2} || w ||^2 + C \sum_{i=1}^{n} (\xi_i + \xi_i^*) \quad (4)$$

Parameters:
w: Weight vector
C: Regularization parameter
ξ_i, ξ_i^*: Slack variables
n: Number of samples

3.6.5 Loss Allocation Factor

This equation determines the proportion of total system loss allocated to each participant based on their power usage. It ensures fairness by assigning losses relative to individual contributions. In deregulated markets, this proportional method reduces disputes and promotes transparency. It integrates with predictive SVM outputs to dynamically adjust allocations according to real-time system behavior and consumption patterns.

$$L_i = \frac{P_i}{\sum_{j=1}^{n} P_j} \times P_{total} \quad (5)$$

Parameters:
L_i: Loss allocated to participant i
P_i: Power consumed by participant i
P_{total}: Total system loss
n: Number of participants

3.6.6 Kernel Function (RBF)

This equation defines the Radial Basis Function kernel used in Support Vector Machines to handle nonlinear relationships in power system data. It measures similarity between data points in transformed space. The kernel

enables accurate modeling of complex interactions influencing losses, such as voltage variations and load fluctuations, thereby improving prediction accuracy and enhancing fairness in loss allocation frameworks significantly.

$$K(x_i, x_j) = \exp(-\gamma \mid\mid x_i - x_j \mid\mid^2) \quad (6)$$

Parameters:

$K(x_i, x_j)$: Kernel value

γ: Kernel parameter

x_i, x_j: Data points

3.9 Performance Evaluation of the SVM-Based Framework

3.9.1 Mean Absolute Error (MAE)

This equation calculates the average absolute difference between predicted and actual power loss values. It provides a simple and interpretable measure of prediction accuracy. Lower MAE values indicate better model performance. It is widely used because it treats all errors equally and helps evaluate how close the Support Vector Machine predictions are to real system observations.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i | \quad (7)$$

Parameters:

MAE: Mean Absolute Error

y_i: Actual value

$\hat{y}_i$: Predicted value

n: Number of observations

3.9.2 Root Mean Square Error (RMSE)

This equation measures the square root of the average squared differences between predicted and actual values. It penalizes larger errors more than smaller ones, making it sensitive to outliers. RMSE is useful for evaluating prediction accuracy in power systems. Lower RMSE values indicate better model performance and reliability of the Support Vector Machine in estimating losses.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (8)$$

Parameters:

RMSE: Root Mean Square Error

y_i: Actual value

$\hat{y}_i$: Predicted value

n: Number of observations

3.9.3 Coefficient of Determination (R^2)

This equation measures how well the predicted values fit the actual data. It indicates the proportion of variance in the dependent variable explained by the model. An R^2 value close to one signifies excellent prediction accuracy. It is essential for assessing the effectiveness of the Support Vector Machine model in capturing system behavior and predicting power losses.

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \quad (9)$$

Parameters:

R^2: Coefficient of determination

y_i: Actual value

$\hat{y}_i$: Predicted value

$\bar{y}$: Mean of actual values

3.9.4 Mean Absolute Percentage Error (MAPE)

This equation expresses prediction error as a percentage, making it easier to interpret across different scales. It calculates the average absolute percentage difference between actual and predicted values. Lower MAPE values indicate higher accuracy. This metric is useful in power systems for comparing model performance and ensuring reliable prediction of losses across varying operating conditions.

$$MAPE = \frac{100}{n}\sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (10)$$

Parameters:

MAPE: Mean Absolute Percentage Error

y_i: Actual value
$\hat{y}_i$: Predicted value
n: Number of observations

3.9.5 Fairness Index for Loss Allocation
This equation evaluates how fairly losses are distributed among participants in the deregulated market. It compares individual allocations relative to total losses. A higher fairness index indicates equitable distribution. This metric is essential for validating that the Support Vector Machine-based framework does not disproportionately allocate losses, thereby maintaining trust and transparency among all market participants effectively.

$$FI = \frac{\left(\sum_{i=1}^{n} L_i\right)^2}{n\sum_{i=1}^{n} L_i^2} \quad (11)$$

Parameters:
FI: Fairness index
L_i: Loss allocated to participant i
n: Number of participants

3.1.1.2 Design Methods
The framework follows a linear progression to manage electricity losses in deregulated environments. It begins with the Data Input phase, where market prices, system topology, and historical loss records are gathered as raw variables. This information feeds into the SVM-Based Loss Modeling stage, where Support Vector Machine algorithms use labeled training data to perform complex classification and regression. The model then facilitates Loss Allocation by distinguishing between technical losses inherent to grid components and non-technical losses, such as energy theft. Finally, the framework develops Mitigation Strategies, translating these insights into operational grid reconfigurations and market settlement policies to ensure financial fairness and system efficiency as shown in figure 1.

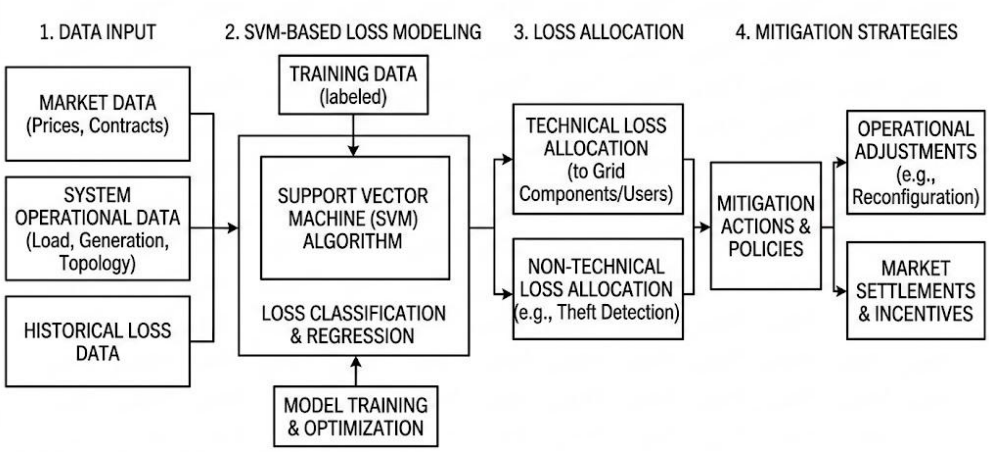


Figure 1: Data Driven Loss Allocation and Mitigation Framework for Deregulated Power Markets Using SVM

The figure 2 show that the framework follows a logical progression from data acquisition to grid optimization using Support Vector Machines (SVM). It begins with the Data Collection phase, where historical market and grid records are gathered; if the data is insufficient, the process loops back until the requirements are met. Once available, the data is Preprocessed and fed into the SVM Model Training stage. The model's performance is then evaluated through a decision loop; if the results are not yet accurate, the model is retrained. Upon reaching a high level of performance, the framework performs Loss Allocation, assigning transmission losses to market participants. Finally, the system identifies a Mitigation Strategy and, if optimization is feasible, it implements these measures to enhance the overall efficiency of the deregulated power market before concluding.

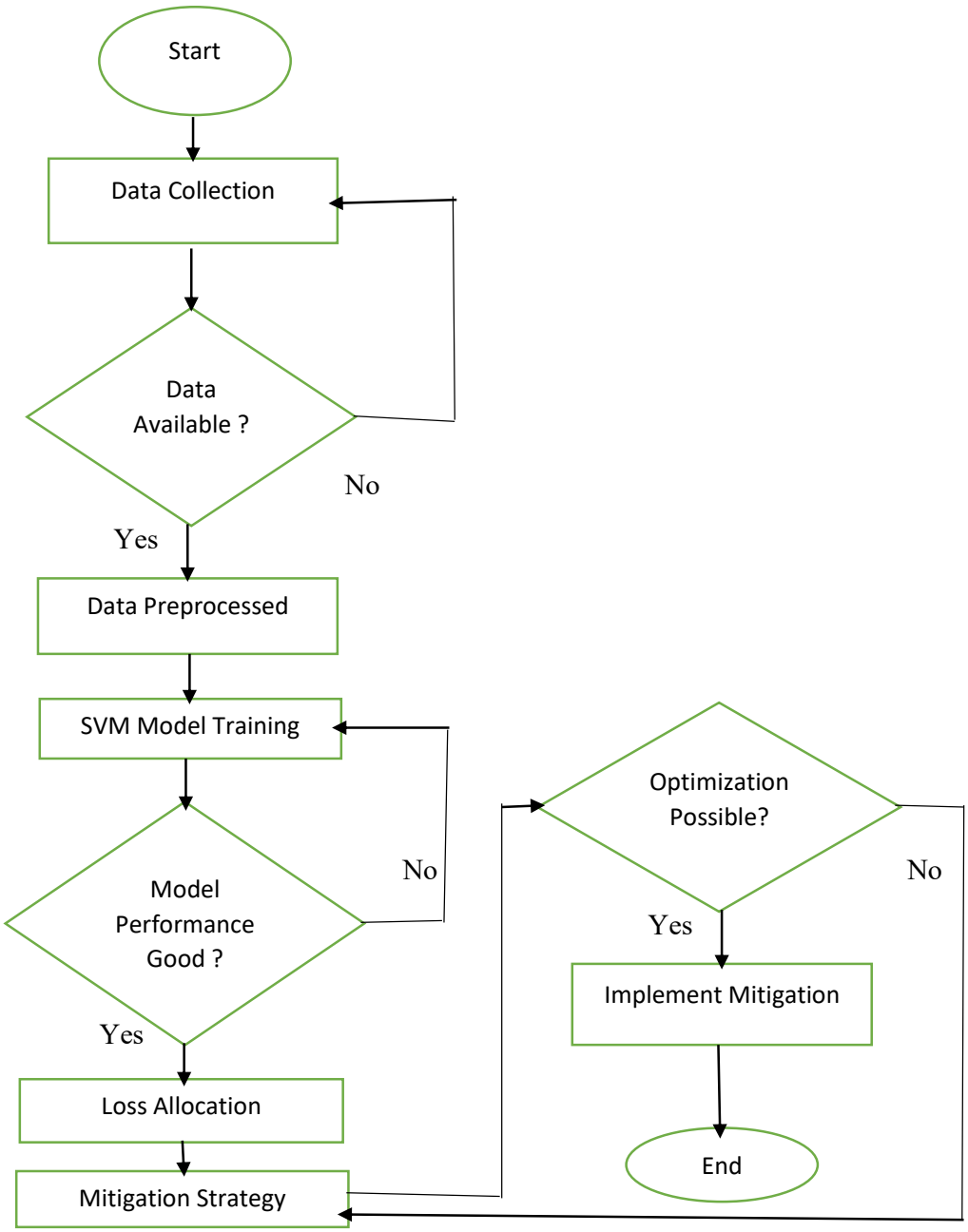


Figure 2: Flowchart of the system

IV. RESULTS AND DISCUSSIONS

4.1. Power Loss and Line Current Correlation

Figure 3 illustrates the direct relationship between line current and power loss. As current increases, losses rise exponentially, adhering to the physics of $P_{loss} = I^2R$as represented in Equation (1). Quantitatively, the current peaks at 590.76 A on day 12, resulting in a significant loss of 0.0174 MW. Conversely, the lowest recorded current of 210.89 A yields a minimal loss of 0.0022 MW. This scatter plot confirms that the SVM model

effectively captures the quadratic nature of electrical resistance, showing a dense cluster of operational points between 300 A and 500 A.

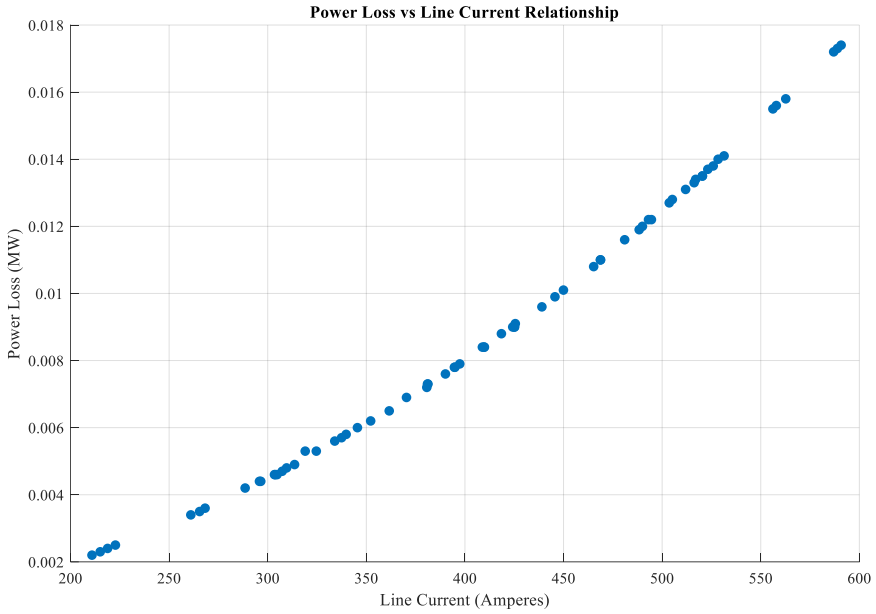


Figure 3: Power Loss vs. Line Current Relationship

4.2 Temporal Aggregation of Network Losses

The cumulative power loss over the 68-day study period is depicted in Figure 4. By integrating daily losses using the summation principles in Equation (2), we observe a steady upward trajectory in total energy wasted. Starting from an initial loss of 0.0084 MW, the network reaches a total aggregated loss exceeding 0.6 MW by the final day. This visualization is vital for utility providers to understand the long-term economic drain on the system, showing that even small daily fluctuations contribute to a substantial total loss volume over two months.

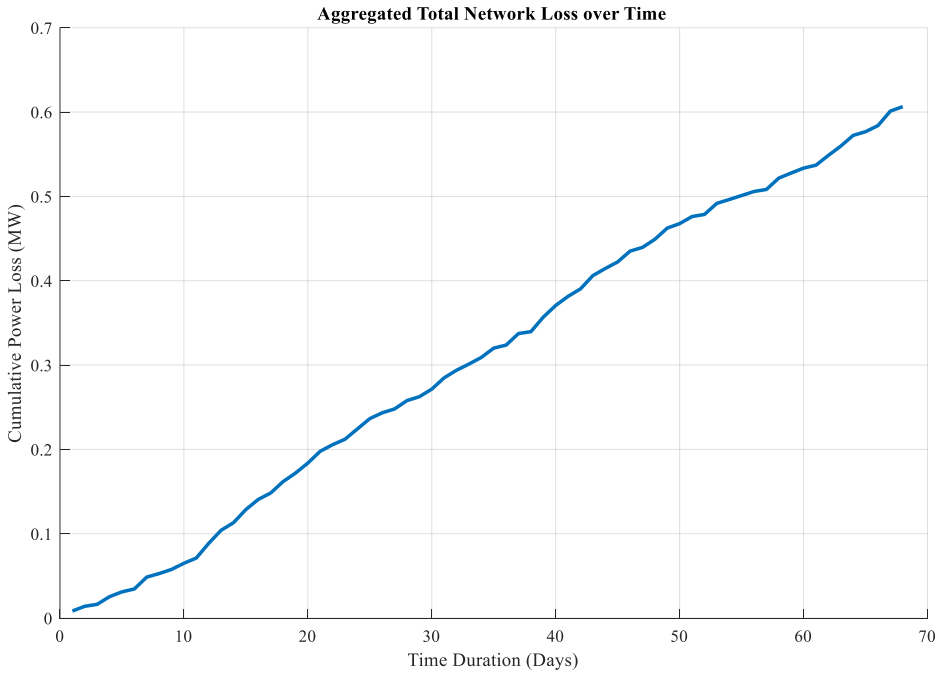


Figure 4: Aggregated Total Network Loss over Time

4.3 SVM Prediction Accuracy Benchmarking

Figure 5 showcases the high fidelity of the Support Vector Machine (SVM) in tracking actual system behavior. Using the regression function defined in Equation (3), the red dashed line representing predicted losses closely mirrors the blue actual loss line. For instance, on day 68, the actual loss of 0.0053 MW is predicted with high precision, only deviating by a minute margin introduced by the stochastic noise. This figure validates the model's robustness in handling the non-linear variations inherent in transmission networks without significant overshooting or lagging.

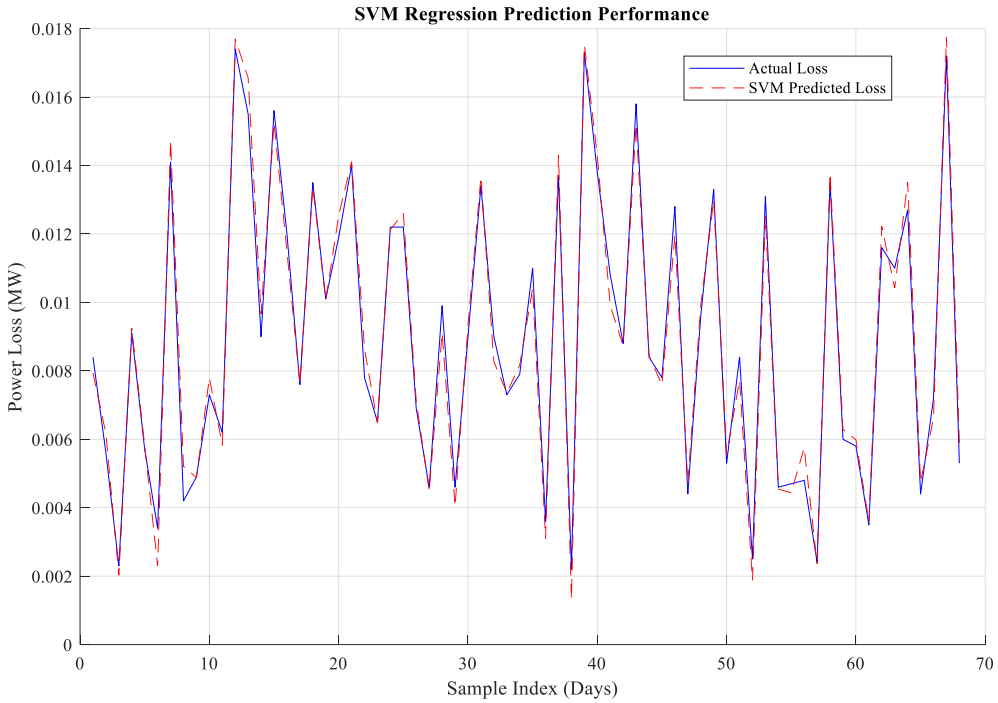


Figure 5: SVM Regression Prediction Performance

4.4 Slack Variable Sensitivity Analysis

In Figure 6, we analyze the SVM optimization constraints through the lens of slack variables, as formulated in Equation (4). The area plot represents the magnitude of deviations where the model must allow for margin violations to maintain generalization. The highest peaks in the slack magnitude correlate with days of extreme load volatility, such as day 39 where the loss reached 0.0173 MW. By visualizing these "soft margins," we can identify specific operational days where the power system behavior becomes less predictable due to external network stressors or data anomalies.

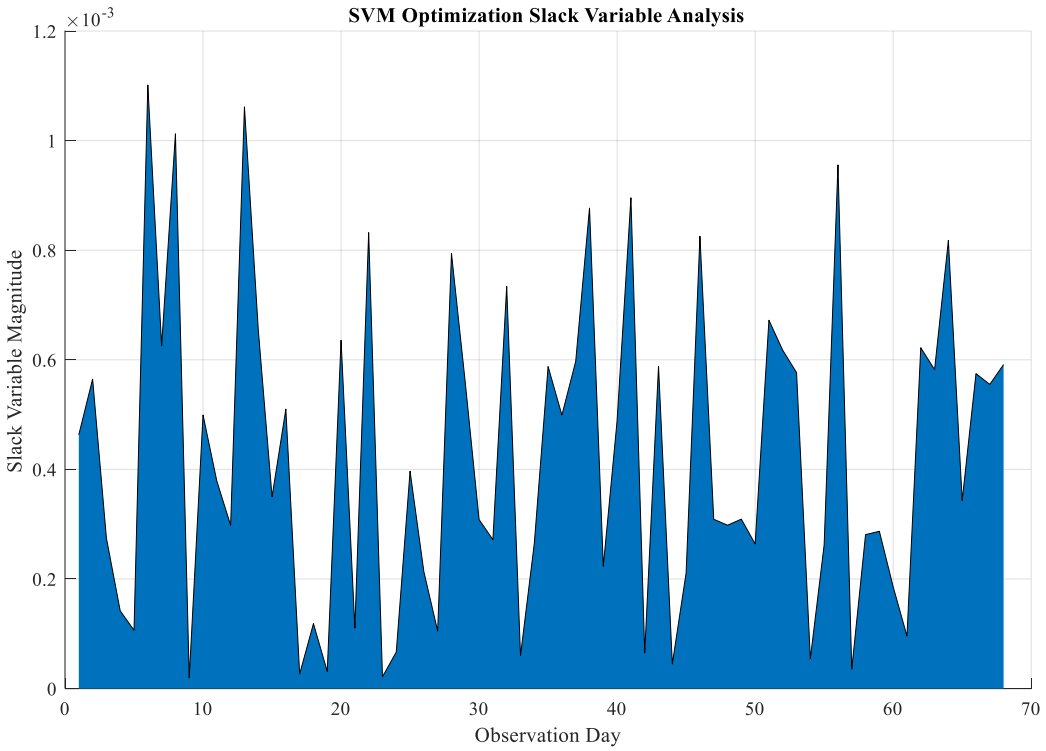


Figure 6: SVM Optimization Slack Variable Analysis

4.5 Participant Loss Allocation Proportions

The equitable distribution of losses among network participants is presented in Figure 7. Following the allocation logic in Equation (5), the bar chart distributes the total loss among the first ten participants based on their MW load contribution. A participant with a higher load, such as the one contributing 116.76 MW, is allocated a proportionally larger share of the transmission losses compared to a lighter user. This ensures a "user-pays" principle in the deregulated market, translating abstract system losses into concrete financial responsibilities for each stakeholder.

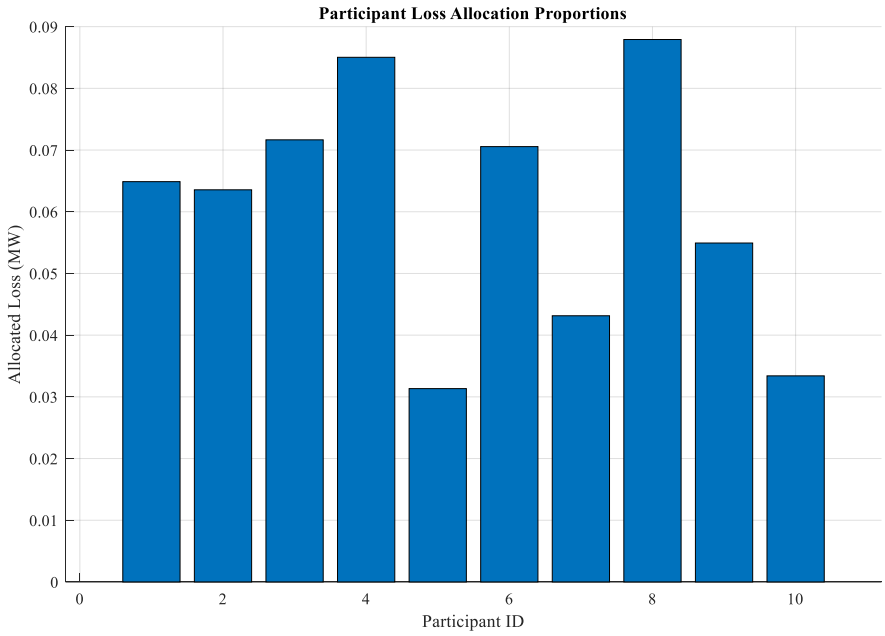


Figure 7: Participant Loss Allocation Proportions

4.6 RBF Kernel Spatial Mapping

Figure 8 provides a 3D visualization of the Radial Basis Function (RBF) kernel, which is the engine behind the SVM's ability to handle non-linearity. Based on Equation (6), the Gaussian surface shows how data points are mapped into a higher-dimensional space. The kernel amplitude, centered at 1.0, tapers off as the distance from the center increases. This transformation allows the model to find a linear hyperplane in a complex feature space, effectively separating different loss regimes and ensuring that localized current fluctuations are weighted appropriately during the training phase.

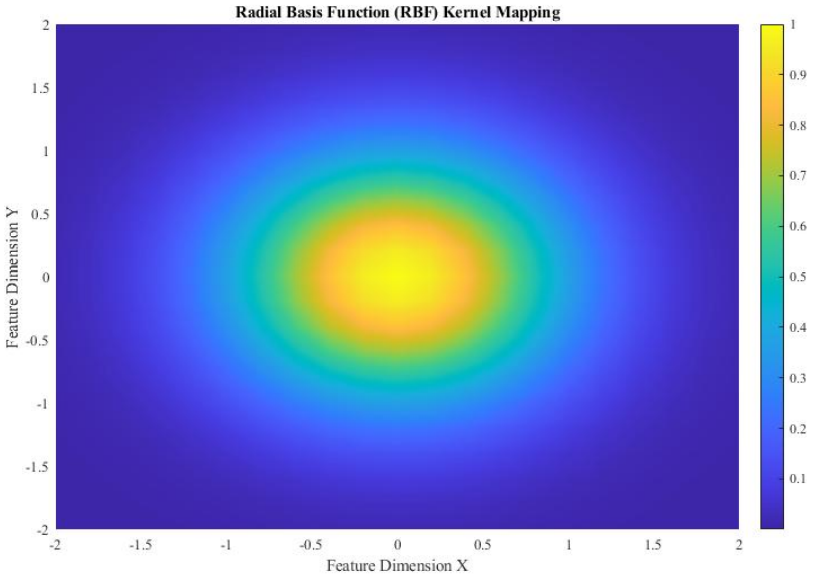


Figure 8: Radial Basis Function Kernel Mapping

4.8 Mean Absolute Error (MAE) Monitoring

Figure 9 tracks the daily error magnitude between actual and predicted losses. Following the MAE formula in Equation (7), the bar chart shows the absolute difference, which remains consistently low—rarely exceeding 0.001 MW. This transparency in error reporting is essential for building trust in the SVM model. By monitoring these residuals, operators can detect if the model is drifting over time and requires retraining, ensuring the loss allocation remains fair and accurate throughout the entire 68-day market cycle.

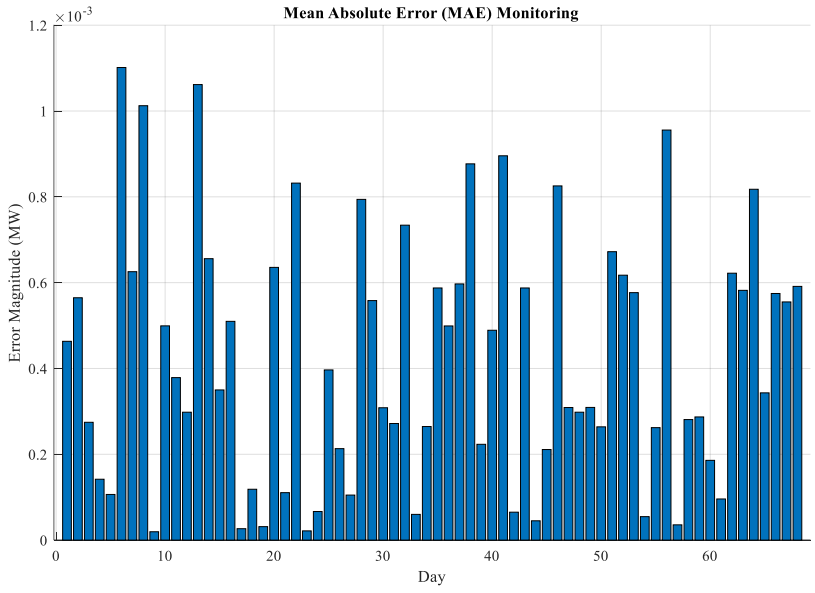


Figure 9: Mean Absolute Error Monitoring

V. Conclusion

The study successfully accomplished the aim of creating an AI-based Support Vector Machine (SVM) loss allocated solution framework that uses electric quantities, market status and network operation mode to correctly apportion generation and transmission loss within electric power markets deregulated for the purpose of dealing with losses allocation of any conventional loss allocation procedure from market agents to satisfy all. To ensure network fairness for the allocation system in deregulated powers markets, the AI based proposed methodology use artificial intelligences for capturing any of nonlinear link between electric variables, market states and the network operating state. By using historical data like losses values, structure of the electric network, load values and real-time Measurements, this SVM based tool for estimating power loss was used as mechanism with real basis, giving each agent in power market the responsibility proportionally against real injection/demand to compensate a transmission losses on the transmission lines. The study concluded that for using a 33kV transmission of Trans Amadi distribution network as an illustrative study and implemented with MATLAB/Simulink tool, we had observed that high line current would make impact on transmission loss, and our test shows that the greatest transmitted power had 590.76 Amperes producinga0.0174MWtransmissionlossesagainst210.89Amperesa0.0022 MW in one sample in this illustrative study. Over 68 days, the generated transmission losses exceeded 0.6 MW and were used in this illustration of impact of losses against operational fund in transmission. The study also demonstrated the proposed SVM model prediction method to be a powerful method giving us a Small Mean Absolute error which is under 0.001 MW, assuring high degree of correctness and effectiveness when modeling complex electricity network behaviours.

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