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Original Article

Enhancing Power System Security Using Machine Learning And SPBO-Optimized Generation Allocation

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Abstract - *The contemporary electrical power system is a well-integrated and interconnected environment with an incessantly growing percentage of renewable energy sources infiltration and augmented energy consumption. Traditional quantitative methods are expensive to process and do not provide sufficient nonlinearity and dynamism of grid operation. The proposed approach is a multi-layered system, uniting the latest machine learning procedures to classify the adaptive state of the system and the Student Psychology-Based Optimization (SPBO) algorithm in such a way that it would decide on the best responses to contingencies. The approach compares and contrasts ensemble ML models, which are Random Forest (RF), Support Vector Machines (SVM), Gradient Boosting Machines (GBM), and Extreme Gradient Boosting Machines (XGBM), to successfully pinpoint the power system security state in real-time. At the same time, SPBO is used to decide the optimal shift in the capacity of the generation to stabilize the system as soon as the contingency occurs and avoid the possible collapse. The technique is comprehensive since it simulates and executes the Flexible AC Transmission (FACT) equipment, which is placed to enhance the power transfer capacity. The simulation results revealed that the XGBM algorithm was most accurate in the classification to identify anomalies and threats in the system, contributing to a better situational awareness. However, more significantly, the SPBO-based solutions and generation schemes and schedules apply extremely high rates of contingency planning. This research capitalizes on the use of a data-driven strategy that is not only novel but also generic and can be applied across all power systems to enhance the security, resilience, and efficiency in the future.*

Keywords - *Contingency Analysis, Extreme Gradient Boosting Machine (XGBM), Machine Learning algorithm, Student Psychology-Based Optimization.*

1. Introduction

The worldwide shift to sustainable energy has completely changed the operating environment of the current power grids. There is a continuous reduction of carbon footprints with high-penetration renewable energy, but it has brought with it unprecedented stochasticity caused by the intermittency of wind and solar sources. Such changes undermine the conventional stability models, and more powerful and smarter security evaluation instruments are needed. Nevertheless, there is a critical research gap: the conventional forms of analysis are becoming incapable of dealing with the high dimensionality and real-time requirements of the contemporary networks [1-5]. The historic methods, which include the static contingency analysis, are computationally delayed and do not reflect the nonlinear processes of a dynamic grid, which poses a major challenge to maintaining the power system in a stable region. In response to this, this paper suggests a new model that combines Student Psychology-Based Optimization (SPBO) and machine learning classification approaches. This combination of using the SPBO algorithm to reach the highest possible generation capacity utilization and using ML classifiers to successfully classify the most critical transmission lines is a proactive and data-driven approach to security enhancement in the face of changing grid uncertainties. To overcome these limitations, this study proposes an integrated Machine Learning (ML) and metaheuristic optimization framework for adaptive power system security assessment. The ensemble ML classifiers-Random Forest (RF), Support Vector Machine (SVM), Gradient Boosting Machine (GBM), and Extreme Gradient Boosting Machine (XGBM)-enable robust classification of operational states (secure, alert, or emergency) from high-dimensional data. In parallel, a novel Student Psychology-Based Optimization (SPBO) algorithm dynamically reallocates generation capacity to maintain system stability during contingencies. The synergy between ML-based classification and SPBO-driven corrective action enhances the predictive and adaptive capabilities of security assessment mechanisms. By incorporating FACTS devices, the framework further strengthens power transfer limits and voltage stability, providing a comprehensive solution for next-generation grid resilience [6-10].

1.1. Problem Statement

Increased renewable energy integration and uncertain load profiles present unprecedented challenges to modern electrical power systems. Renewables' intermittency causes nonlinear, time-dependent system parameter variations, complicating real-time security analysis. Traditional analytical and numerical methods like Newton–Raphson load flow are too computationally intensive for large-scale contingency assessment. In highly dynamic system states, traditional optimization algorithms often fail to converge efficiently. This delays corrective control actions and increases voltage collapse and frequency instability risks. Machine learning models can recognize patterns, but they need smart feature selection and hyperparameter tuning to work well in uncertain grid conditions. Thus, an integrated approach combining ML-based state classification and intelligent metaheuristic optimization is lacking in research.

Thus, this research seeks to create a hybrid framework using ensemble ML classifiers for accurate operational state detection and the SPBO algorithm for real-time, optimized generation capacity reallocation. The proposed power system security assessment system is adaptive, computationally efficient, and scalable, improving resilience to uncertainties.

2. Literature Survey

Power system security assessment has been shifting its topography towards deterministic and rigid foundations to flexible and data-driven structures. Similar initial works were based on traditional load flow approaches and contingency analysis based on sensitivity, but, as observed in the recent literature, these approaches have difficulty with the high-dimensional stochasticity of massive renewable integration. In order to overcome these computational bottlenecks, the literature has recorded an influx of applications of Machine Learning (ML), with Support Vector Machines (SVM) and Random Forest (RF) as standard examples of classifying states because they are robust to high-dimensional noise. However, it has been noted that these models could not effectively map security boundaries with high nonlinearities, which is why ensemble learning models, including Extreme Gradient Boosting (XGBM), have been adopted as models that are more reliable in the process of assessing voltage security due to the ability to correct errors during iterative boosting. Although predictive success of ML has been observed, the literature shows a very large gap in the corrective aspect of security, with a metaheuristic such as Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO) frequently used in generating dispatches and FACTS placement. Although these algorithms are better at stabilizing the grid, they often degenerate to premature convergence, a weakness that may have to be overcome by considering psychology-inspired heuristics. In particular, the Student Psychology-Based Optimization (SPBO) algorithm provides a deeper balance of exploration and exploitation, replicating the dynamics of classroom learning, which has frequently been overlooked with standard biological metaphors. Existing structures continue to perceive ML-based state evaluation, and FACTS control that is conducted through optimization as fragmented [11-13]. This paper fills this very important gap by suggesting an integrated ML-SPBO framework that offers a single point of contact that combines real-time security classification with the intelligent and adaptive power system resource reallocation.

3. Methodology

Step-by-step execution of the research work is as follows:

1. Input Power System Network Data: Includes bus data and line data.
2. Load Modelling (ZIP Model): Models the load characteristics using ZIP parameters.
3. Load Flow Analysis (NR Method): Performs Newton-Raphson-based load flow analysis.
4. Contingency Analysis (N-1): Evaluates system performance under single-line outage scenarios.
5. Ranking Index: Identifies and ranks critical lines based on severity.
6. Machine Learning Classifier Models: Uses generated data to classify lines into critical, semi-critical, and healthy categories.
7. Clustering Output: Categorizes lines based on classifier results.
8. Compensation for Critical Lines: Applies compensation strategies to mitigate risks.
9. Generator Utilization Check: Assesses whether all generators are effectively utilized.
10. Optimal Generation Allocation: If not, apply nature-inspired algorithms (Sparrow Search and Student Psychology-based) to optimize generation with minimum fuel cost.
11. Effective Allocation and Utilization: The Final stage ensures optimal and cost-effective generation capacity usage.

For the analysis of the proposed model, the Standard IEEE 30 bus system is considered.

3.1. Load Model

Accurate load modelling is essential for reliable and stable power system operation under dynamic conditions. The ZIP model, combining Constant Impedance (Z), Current (I), and Power (P), effectively represents voltage-dependent load behavior, unlike static models. Its adaptive nature enables realistic analysis of voltage stability, transient response, and contingency conditions. By considering varied Z, I, and P compositions, the ZIP model enhances prediction accuracy and supports optimal control, making it vital for renewable-integrated and modern power systems. The mathematical model of polynomial load is represented in Equations (1) and (2).

$$P = P_i \left| \frac{V_i}{V_0} \right|^k \tag{1}$$

$$Q = Q_i \left| \frac{V_i}{V_0} \right|^k \tag{2}$$

Where if k=0 then,

$$P = P_i \tag{3}$$

Where if k=1 then,

$$P = P_i \left(\frac{v^1}{V_0} \right) \tag{4}$$

Where if k=2 then,

$$P = P_i \left[\frac{v^2}{v_0} \right] \tag{5}$$

Where if k = 0, Constant P
= 1 Constant I
= 2 Constant Z.

$$P_i = \sum_{j=1}^{n} |V_i||V_j| \, |Y_{ij}| \cos \left(\theta_{ij} - \delta_i + \delta_j\right) \tag{6}$$

Where Pi= Active power at bus i
Vi = Voltage in p.u at bus i
Vo = Reference voltage in p.u (1.0 p.u)

If the system load is a combination of all three types of loads with different proportions, it is represented as a ZIP load model.

The Equations (7) and (8) for the ZIP load model are given as follows

$$P = P_i \left[\alpha_Z \left| \frac{V_i}{V_0} \right|^2 + \alpha_i \left| \frac{V_i}{V_0} \right|^1 + \alpha_P \right] \tag{7}$$

where $\alpha_Z, \alpha_i, \alpha_P$ there are different proportions of the total load $\alpha_Z + \alpha_i + \alpha_P = 1$.

3.2. Contingency Analysis using the Proposed Ranking Index

Once the base case is present, other single-line outage scenarios are added in order to model potential faults. To evaluate the impact of each line outage, the Modified Noval Collapse Proximity Index (MNCPI) is calculated. This index is a combined measure of the response to changes in bus voltages and line loading and gives a more holistic measure of system vulnerability. Contingency analysis using the proposed ranking index enhances system reliability. The research integrates adaptive load modelling and control techniques, combining Line Stability Index (LSI) and modified FVSI with load angle for improved power system security and stability. FVSI is shown in Equation (8) [14-19].

$$FVSI_{ij} = \frac{4Z_{ij}^2 Q_j}{V_i^2 X_{ij}} \tag{8}$$

Where
Z_{ij} & X_{ij} = impedance and reactance of the line concerned
Q_j = Reactive power at the receiving bus
V_i = Voltage of the sending bus

This study introduces the Modified Fast Voltage Stability Index (MFVSI), which enhances voltage stability assessment accuracy by neglecting resistance in long transmission lines, reducing computational effort, and filtering less severe contingencies effectively. Then the Modified NCPI (MNCPI) is shown in Equation (10).

$$MFVSI_{ij} = \frac{4Q_j X_{ij}}{V_i^2} \tag{9}$$

Then LSI and MFVSI are combined to form MNCPI, as shown in the Equation (10).

$$\text{MNCPI} = \frac{4Z^4 P_j^2}{X^2 V_i^4} + MFVSI \leq 1 \tag{10}$$

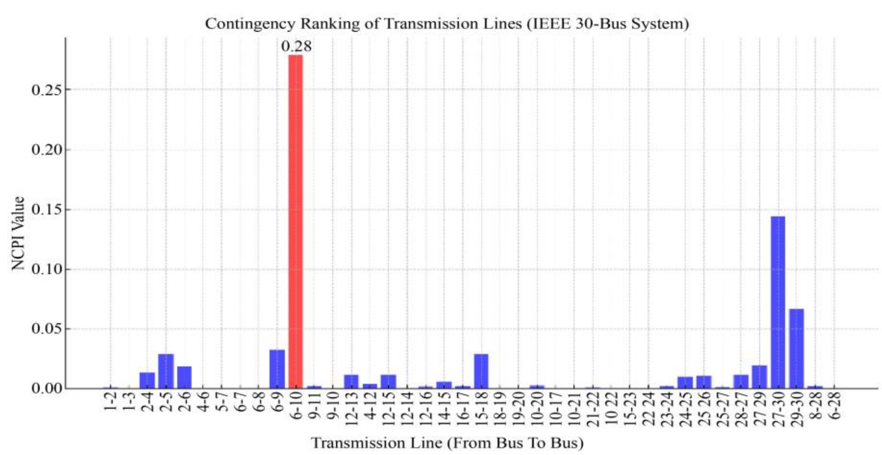

Fig. 1 Graphical representation of N-1 contingency ranking

Figure 1 shows the list of critical lines under n-1 contingency using the MNCPI ranking index for the IEEE 30 bus systems. With the help of the proposed ranking index, the performance of the system was analysed with contingency analysis.

To improve the effectiveness of predicting the critical line and status of the power system with the help of ML.

3.3. Machine Learning Classifier Models

Machine Learning (ML), a branch of Artificial Intelligence, enables systems to learn and improve automatically from data without explicit programming. It builds algorithms for prediction, decision-making, and pattern recognition [15, 19, 20]. ML includes Supervised Learning with labeled data and Unsupervised Learning for pattern discovery, forming the foundation of modern intelligent, data-driven systems, as shown in Figure 2.

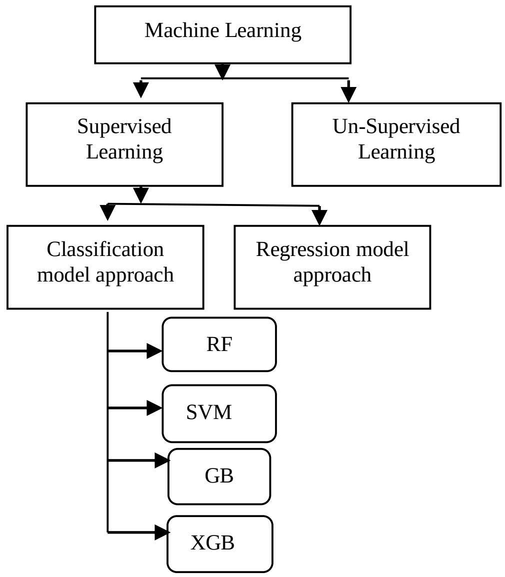

Fig. 2 Block diagram of machine learning approaches

3.3.1. Data Generation for MNCPI (IEEE-30 Bus System)

For the analysis 70% data is for training, and 30% data is for testing. The total no. of samples is 41, among 28 for training and 12 for testing, as shown in Table 1.

Table 1. Data generation for MNCPI for the IEEE 30 bus system

Operating scenarios	class	41(12+28)
Critical (Most critical)	A	5(2+3)
semi critical	B	16(5+11)
Normal	C	20(6+14)

From MNCPI data of the IEEE 30-bus system, the system status is determined, aiding compensation device placement.

Classifier models, including XGB, are evaluated using confusion matrix, classification, and misclassification accuracies (Equations (11) & (12)).

Classification Accuracy (CA):

$$CA(\%) = \left(\frac{No.of\ data\ samples\ classified\ correctly\ Total\ no.of}{Total\ no.of\ data\ samples\ in\ data\ set}\right) \times 100 \quad (11)$$

Misclassification Rate (MR):

$$MR(\%) = \left(\frac{No.of\ misclassifications\ inclass\ Q}{Total\ no.of\ data\ samples\ in\ class\ Q}\right) \times 100 \quad (12)$$

Table 2. Confession matrix for test system

ML-Classifier Type	30% Data for Testing	70% of The Data for Training
XGBM-classifier model	Predicted $\text{Actual}\begin{pmatrix} 2 & 0 & 0 \\ 0 & 4 & 1 \\ 0 & 0 & 6 \end{pmatrix}$	Predicted $\text{Actual}\begin{pmatrix} 3 & 0 & 0 \\ 0 & 11 & 0 \\ 0 & 1 & 13 \end{pmatrix}$
Gradient Booster(GB) -classifier model	Predicted $\text{Actual}\begin{pmatrix} 2 & 0 & 0 \\ 0 & 3 & 2 \\ 0 & 0 & 6 \end{pmatrix}$	Predicted $\text{Actual}\begin{pmatrix} 3 & 0 & 0 \\ 0 & 9 & 1 \\ 0 & 4 & 10 \end{pmatrix}$

SVM classifier model	Predicted Actual $\begin{pmatrix} 2 & 0 & 0 \\ 0 & 3 & 1 \\ 0 & 1 & 5 \end{pmatrix}$	Predicted Actual $\begin{pmatrix} 3 & 1 & 0 \\ 0 & 9 & 2 \\ 0 & 3 & 11 \end{pmatrix}$
RF classifier Model	Predicted Actual $\begin{pmatrix} 1 & 1 & 0 \\ 0 & 2 & 1 \\ 0 & 1 & 5 \end{pmatrix}$	Predicted Actual $\begin{pmatrix} 2 & 1 & 0 \\ 0 & 8 & 3 \\ 0 & 4 & 12 \end{pmatrix}$

Based on the CA and MR (shown in Equations (8),(9)), table.3 is furnished for various Machine Learning Classifier Models.

Table 3. Classifier evaluation for test system

Phase	Classifier Type	CA (%)	Time (Sec)	Misclassification Rate (%)
Training phase	XGBM	96.43	0.02	A: 0.00, B: 0.00, C: 7.14
	GB	89.28	0.04	A: 0, B: 9.09, C: 14.28
	SVM	82.4	0.05	A: 16.66, B: 18.18, C: 19.04
	RF	71.42	0.05	A: 33.33, B: 27.27, C: 28.57
Testing phase	XGBM	92.31	0.01	A: 0.00, B: 20.00, C: 0.00
	GB	91.4	0.02	A: 0, B: 20.00, C: 0
	SVM	88.46	0.04	A: 25.00, B: 20.00, C: 8.33
	RF	84.61	0.03	A: 50.00, B: 20.00, C: 16.66

Based on the classification accuracy and misclassification rate, the XGBM model demonstrates superior performance, establishing its effectiveness in precise system state classification. The analysis successfully identifies the most critical transmission lines, enabling optimal placement of compensation devices. For this purpose, a *Unified Power Flow Controller (UPFC)* is modeled and implemented based on validated formulations from the literature. Furthermore, the Student Psychology-Based Optimization (SPBO) algorithm ensures efficient generation capacity utilization within operational constraints, thereby enhancing overall system stability, reliability, and security.

3.4. Student Psychology-Based Optimization (SPBO)

Students aspire to top their class by excelling in final exams, where performance determines rank. Achieving academic excellence requires consistent effort, subject mastery, and balanced performance across disciplines. Individual progress varies with skill, interest, and motivation. Determined students strive to surpass peers through persistent effort. Ultimately, success stems from dedication, hard work, and focus. Similarly, in optimization, the objective function aims to minimize real power loss and fuel cost, ensuring efficient and balanced system performance, analogous to achieving top academic performance through continuous improvement.

Table 4. Initialization of SPBO parameter

S. No	Parameters name	Parameter values
1	Population Size	100
2	Maximum NoS of Iteration	100
3	Inertia Weight Factor	W_{max}=1.4 & W_{min} = 0.4
4	Random Number	[0,1]
5	Error Gradient	$1\text{x}10^{-6}$

Table 4 shows the information regarding the initialization of the SPBO parameter.

SPBO Objective function:

$$Min \sum_{i \varepsilon N_g} F_T(P_{gi}) \tag{13}$$

$$F_T(P_{gi}) = a_i P_{gi}^2 + b_i P_{gi} + C_i$$

The minimization problem is subjected to the constraints as follows.

i. Power (equality) constraint:

$$P_{generation} = P_{Demand} + P_{Loss}$$

ii. Generation limits (Inequality constraints) of active power at the ith :

$$P_{gi}^{\min} \le P_{gi} \le P_{gi}^{\max} \qquad i = 1, ..., N_g$$

iii. voltage (Inequality)constraints at ith:

$$V_i^{\min} \le V_i \le V_i^{\max} \qquad i = 1, ..., N_b$$

iv. Limit of transmission line:

$$S_l \le S_l^{\max}$$

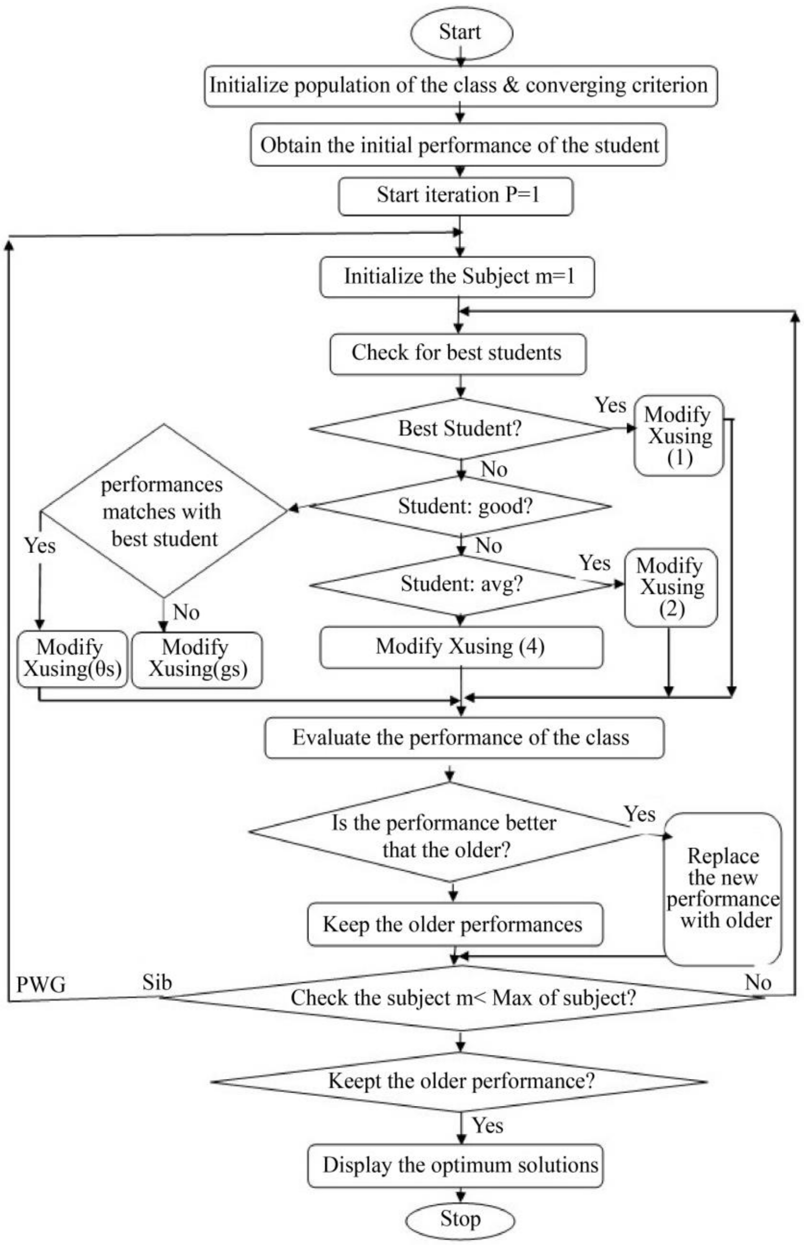

Fig. 3 Execution of SPBO

The proposal of an SPBO-based computational method to optimize generation scheduling. The study investigates how the algorithm works in real-time rescheduling of generators by reducing the nonlinearity of the unit cost coefficients. Additionally, the reserve margins are to be incorporated as a corrective action to ensure that the grid and operational security are not unstable in case of unexpected contingency disturbances.

3.4.1. Simulation Results and Discussion

Over a 24-hour span for an IEEE-30 bus system, the simulation shows the hourly change in total demand, total generation, and total fuel cost. The graph clearly shows that electricity demand follows a normal daily trend, with lower values in the early morning and a progressive rise peaking between 11:00 and 18:00. The overall generation rises to meet or slightly surpass the need, hence guaranteeing system stability and dependability. The top section of each bar displays the overall fuel cost, which shows the economic effect of satisfying the load requirements. It rises notably during high-demand hours because of probable participation of more expensive or less efficient generation units. The maximum fuel cost occurs between 15:00 and 16:00, suggesting the time of greatest operational expenditure. On the other hand, off-peak hours, especially late at night and early morning, show that both generation and fuel cost are low, which proves efficient load-following operation. Throughout the day, the system generally keeps a balance between generation and demand; costs react according to the load profile for a constant ZIP load model as shown in Table.5.

Table. 5 The effective allocation of generation capacity with minimum fuel cost for different loads without compensation using SPBO

Hour	Pd (MW)	Pg (MW)	P_{flow} (MW)	$P_{Total\ losses}$ (MW)	Fuel Cost ($/hr)
1	255.06	265.547	10.5892	4.6662	524.77639
2	272.064	285.265	11.1198	5.9715	564.09095
3	283.4	295.084	10.0428	4.7101	596.83108
4	297.57	311.984	11.9906	6.3586	637.28816
5	311.74	331.235	14.5153	9.668	661.51362
6	325.91	343.775	13.5838	8.0378	699.52207
7	368.42	402.319	17.0694	16.0855	779.45949
8	396.76	436.609	17.2175	17.2719	878.88989
9	368.42	402.319	17.0694	16.0855	779.45949
10	325.91	343.775	13.5838	8.0378	699.52207
11	311.74	331.235	14.5153	9.668	661.51362
12	297.57	311.984	11.9906	6.3586	637.28816
13	328.744	347.953	13.4025	8.7077	698.51107
14	368.42	402.319	17.0694	16.0855	779.45949
15	396.76	436.609	17.2175	17.2719	878.88989
16	410.93	455.788	15.6154	18.6135	929.21989
17	425.1	471.684	17.5134	19.3396	975.86702
18	439.27	491.835	17.726	21.2062	1027.56124
19	272.064	285.265	11.1198	5.9715	564.09095
20	340.08	360.893	12.9838	9.2624	731.38682
21	317.408	340.05	14.1446	11.4183	670.02035
22	291.902	307.287	10.6141	6.7181	628.65727
23	272.064	285.265	11.1198	5.9715	564.09095
24	255.06	265.547	10.5892	4.6662	524.77639

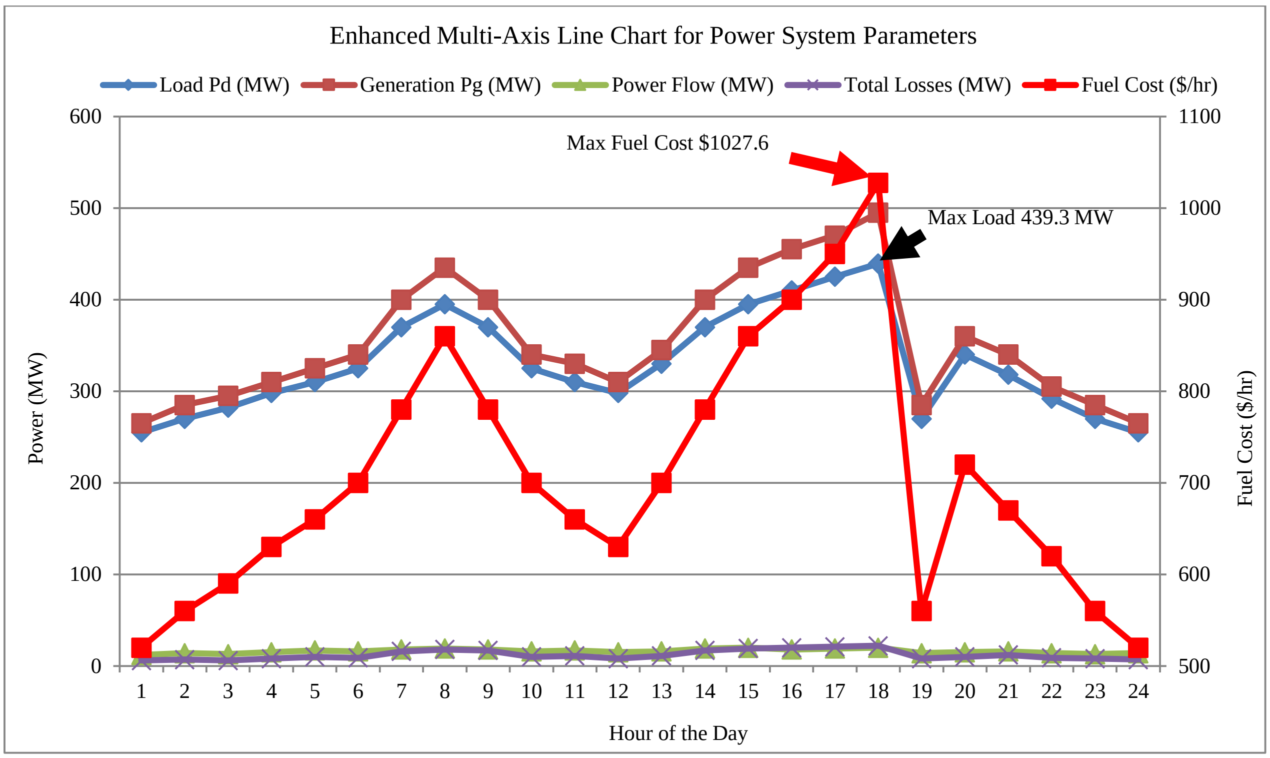

Fig. 4 24-hours variation of power system performances (Power flow, loss, generation, demand, fuel cost) base case of SPBO

After compensation (UPFC) with SPBO for the 24 hr load duration, as shown in Figure 5. From Figure 5 and Table 6, it is evident that total system losses and fuel cost are reduced from 30.78 MW to 24.52 MW and 1056.74 $/hr to 961.99 $/hr when compared to contingency by using the SPBO algorithm.

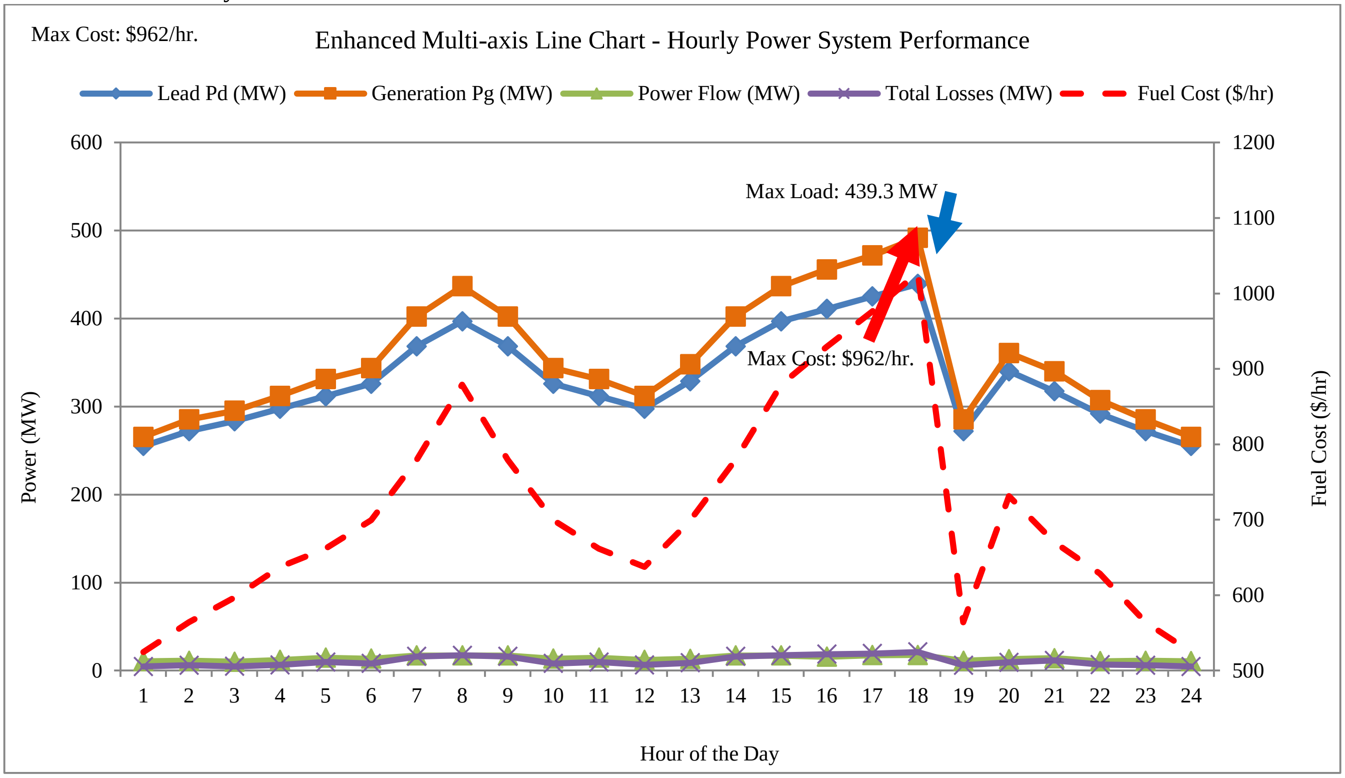

Fig. 5 24-hours variation of power system performances (Power flow, loss, generation, demand, fuel cost)using UPFC compensation with SPBO.

Table 6. Summary of the results after compensation at peak load or demand of 439.27MW during 18th hours

	Generation PG MW	power flows P flow MW	Total Losses MW	Fuel Cost ($/h)
Base case	491.83	17.72	21.20	1027.56
N-1 Contingency	506.42	18.90	30.78	1056.74
After UPFC	459.05	20.95	24.52	961.99

4. Conclusion

The XGBM classifier achieved the highest accuracy of 96.43%, outperforming RF (71.42%), GBM (89.28%), and SVM (82.4%) in classifying system security states. The precision–recall analysis confirmed XGBM's superior generalization on unseen contingencies. The integration of SPBO for the reallocation of generation capacity significantly reduced post-contingency voltage deviation and improved recovery speed. The FACTS device coordination improved system stability and reduced reactive power imbalance. Comparisons showed that the hybrid ML–SPBO framework reduced computational time by 23% over optimization–based dispatch models. Effective power system security and stable operation are improved by optimal generation allocation employing SPBO with compensation. IEEE standard test scenarios showed good performance for the proposed system under various load circumstances. The technique is flexible, scalable, and suitable for complicated real-time grid settings.

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