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DYNAMIC DECISION MAKING SYSTEM FOR SMART GRIDS STABILITY USING HYBRID POLICY GRADIENT- REINFORCEMENT LEARNING WITH FUZZY LINEAR PROGRAMMING

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Abstract:

Smart grid operations need accurate decision-making structures which also adapt to changing circumstances for improved stability assessment. Traditional statistical models together with rule-based systems have difficulties in effectively processing sophisticated and uncertain data from the smart grid because this can result in incorrect stability assessments. The proposed system uses Policy Gradient Reinforcement Learning with Fuzzy linear Programming (PGRL-FLP) model by combining PGRL with FLP for establishing an adaptive smart grid stability classification system. Predictive modeling and pattern recognition systems achieve better discovery of important data relationships through the use of correlation-based feature extraction with smart grid stability datasets. The decision-making system benefits from fuzzy constraints because they allow FLP to manage unpredictable grid situations effectively. Through the combination of PGRL-FLP model, the accuracy improves alongside decreased misclassification errors and better smart grid management enabling better performance of resilient smart grid infrastructure. The proposed model achieves 98.6% accuracy, 97.5% precision, 94.5% recall and 97.4% F1-score.

Math. Subj. Classification: 03B52,39A26,94D05

Keywords: *Smart grids system***,** *Dynamic decision making system, Fuzzy linear programming, Reinforcement learning.*

1. Introduction

The modern power distribution system operates under smart grids which serve as important components since they provide efficient energy management and real-time monitoring capabilities [1].These intelligent systems combine safe communication platforms and controls which maximize the power transmission flow, decrease energy wasted and improve power network stability [2-5].Vast operational data resulted from smart grid technology implementation requires intelligent decision-making frameworks which ensure stability together with resilience of power systems [6-8].

The computation of grid stability through existing statistical models together with rule-based systems encounters severe difficulties when analyzing the multidimensional and unpredictable data of smart grids [9-11]. The evaluation methods prove inadequate at detecting the nonlinear power network behavior along with dynamic characteristics which results in inaccurate stability evaluations [12-15]. The flaws in conventional assessment

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methods worsen because of noise, missing values and imprecise measurements which may cause both incorrect classification and substandard power grid management [16-20].

- **Hybrid PGRL-FLP model:** The proposed work presents a decision-making system which unites FLP with PGRL to create adaptive smart grid stability classification.By leveraging correlation-based feature extraction, the proposed system automatically identifies key relationships within the smart grid stability dataset, improving predictive modeling and pattern recognition. The incorporation of fuzzy constraints allows FLP to effectively handle data uncertainty, while PGRL enhances adaptability by continuously optimizing decision-making strategies. By bringing these two approaches together the system achieves greater accuracy and reduces misclassifications which ensure better smart grid system reliability.

The research paper is structured as follows: Previous research on smart grid stability is described in Section 2.The mathematical background is given in Section 3. The mathematical formulation and analysis of Hybrid PGRL-FLP model is given in Section 4. Section 5offers a comprehensive discussion of performance evaluation. Section 6 concludes the analysis and provides some potential directions for further investigation.

2. Literature Review:

Deep reinforcement learning for voltage control in distribution networks is described in the research of Yuanyaun Shi et al. [1]. The research includes formal stability guarantees for the voltage system. The implementation of this method achieves stable voltages and minimizes transient controls. The system faces two principal drawbacks which lead to complex stability operations and need long training times. The smart grid received an intelligent scheduling control system through the deep LSTM method created by Zhanying Tong et al. [3]. The method achieves optimum coal usage while giving essential support to economic growth and environmental protection of power plants. This approach offers its main benefit in lower emission production. This method faces two main drawbacks because it demands large computational power and needs long training periods. Researchers Marian B. Gorzalczany et al. [4] developed Genetic algorithm with fuzzy rule based classifiers for explaining and precise smart grid stability prediction. This method achieves genetic optimization between accuracy and interpretability to enable transparent and accurate prediction of decentral smart grid control (DSGC) stability. High interpretability characterizes this method as its main benefit. This approach comes with two main disadvantages of high computational cost and need for expert knowledge. Esmeralda Lopez et al. [5] implemented fuzzy logic with fuzzy linear method to enhance economic dispatch on grids. The procedure enables decision-makers to determine hydropower and wind power generation ranges. The implementation of this method leads to efficient cost optimization alongside stability improvement. The method shows limitations when it comes to adjusting to changing grid conditions. Qiuling yang et al. [6] presented a deep reinforcement model which controls voltages in smart grid systems. The research explored traditional utility equipment control together with modern smart inverter voltage regulation through reactive power provision. This approach delivers a main advantage of maintaining stable voltages. The main drawback is the system's high complexity level.

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3. Mathematical Background:

The foundation of the proposed dynamic decision making for smart grid framework includes PGRL and FLP mathematical interpretation. The system uses PGRL to improve the decision making strategies and FLP is used to handle uncertainty and imprecision in the grid environment. By combining two models, it enhances the dataset based stability prediction accuracy.

3.1 Smart grid stability dataset:

Dataset Name: Smart grid stability.

Dataset Link: (https://www.kaggle.com/datasets/pcbreviglieri/smart-grid-stability)

The smart grid stability dataset contains power system stability-related parameters such as voltage levels together with frequency and power flows along with system inertia measurements. The set of parameters delivers critical information about power grid present operation which enables stability assessments in various operational scenarios. The stability assessment through analysis determines labels based on system dynamics, operational constraints and transient behavior. The synthesized data allows predictive model development for real-time stability management through frequency analysis of power flow inconsistencies and voltage level examination followed by measuring frequency deviations. The input is given as,

$$H = \sum_{a=1}^{n} S_B, \quad (1)$$

Where, S_B denotes the number of dataset with in the value ranges from 1to n.

3.2 Fuzzy Linear Programming:

It extends traditional linear programming by incorporating fuzzy parameters to handle the imprecision in medical data. It can be defined as,

$$\max Z = \frac{\sum c_j x_j}{\sum d_j x_j + \beta} \;, \quad (2)$$

Subjected to,

$$\sum a_{ij} \leq b_i, x_j \geq 0, \quad (3)$$

Where,

- x_j= decision variables (e.g., treatment decisions)
- c_j= benefit coefficients (e.g., effectiveness of treatment)
- d_j= risk coefficients (e.g., side effects of treatment)
- a_{ij}= constraints on resources
- b_i= available resources
- β= fuzzy factor for uncertainty handling

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In fuzzification the patient's parameters such as blood pressure, cholesterol, and heart rate are represented as fuzzy sets, it can be fuzzified as,

$$\mu_S(x) = \begin{cases} 0, x < a \\ \frac{x-a}{b-a}, a \le x \le b \\ 1, x > b \end{cases}, \tag{4}$$

The membership value μ between 0 and 1 assigned be this function.

3.3 Policy gradient reinforcement learning:

PGRL is a method used in smart grids for dynamic decision-making by directly optimizing the policy that governs the actions of grid agents, such as energy producers, consumers, or storage systems. It works by iteratively adjusting the policy to maximize a long-term cumulative reward, which can be energy efficiency, cost reduction, or grid stability. The policy is typically parameterized by a neural network, and the gradient of the expected reward with respect to the policy parameters is computed and used to update the policy. In mathematical terms, the policy gradient is computed using the following equation,

$$\theta_{t+1} = \theta_t + \alpha \nabla_\theta J(\theta), \tag{5}$$

Where,

- ✓ α denotes the learning rate,
- ✓ $\nabla_\theta J(\theta)$denotes the computed gradient used to improve the decision making.

To compute the gradient of the expected reward with respect to the policy parameters θ is calculated based on the policy gradient theorem. This gradient is then used to update the policy in the direction that improves performance. The expected cumulative rewardJ (θ) is defined as:

$$J(\theta) = \Delta\theta[\sum_{t=0}^{T} \beta^t R_t], \tag{6}$$

Where,

- ✓ β denotes the discount factor,
- ✓ R_t denotes the reward received at time step t,
- ✓ Tbe the total time horizon.

3.4 Hybrid policy gradient Reinforcement Learningwith Fuzzy linear model:

The Hybrid PGRL-FLP model used to optimize dynamic decision-making in uncertain environments, such as smart grids. The policy gradient method is used to iteratively update the decision-making policy based on feedback from the environment, while fuzzy linear handles uncertainty in system parameters like energy demand and supply. The hybrid model enhances decision-making by considering both precise rewards from PGRL and fuzzy rewards based on uncertain inputs. The combined model can be expressed as,

$H = Z + \theta_{t+1}$, (7)

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Where Z denotes the FLP adjusted score accounting for fuzzy constraints, and θ_{t+1} be the policy gradient based reinforcement learning.

3.5 Performance Matrices:

The performance matrices such as accuracy, precision, recall and f1-score are calculated by,

Accuracy: It measures the overall correctness of the model.

$$Accurcy = \frac{TP+TN}{TP+TN+FP+FN}, \quad (8)$$

Precision: It evaluates positive cases predicted are actually positive.

$$Precision = \frac{TP}{TP+FP}, \quad (9)$$

Recall: It measures how many actual positive cases are correctly identified.

$$Recall = \frac{TP}{TP+FN}, \quad (10)$$

F1-score: It balances both precision and recall.

$$F1 = 2 \times \frac{Precision \times Recall}{Precision+Recall}, \quad (11)$$

4. Mathematical Formulation and analysis:

The system employs a PGRL to carry out structured classification processes. The first step of data processing involves data preprocessing to normalize data, address missing values, and outliers for achieving quality data. Prior to classification feature extraction implements ICA and statistical method. At the fuzzification stage the extracted features receive fuzzy membership value transformation to enhance the decision making ability through uncertainty handling. A PGRL model operates in the classification step to analyze the fuzzified features before generating final class predictions. This method improves classification accuracy through combination of preprocessing techniques and feature enhancement methods with fuzzy linear algorithms for secure decision operations.

4.1 Input and Preprocessing:

The input is collected from Smart grid stability dataset and the input is denoted as H, then the input is given to the preprocessor for handling missing data, and normalization. A raw dataset H with m number of samples and n number of features are represented as,

$$H = \sum_{a=1}^{n} S_B, (12)$$

Where, S_B denotes the number of dataset with in the value ranges from 1to n.

In the preprocessing method the input H are preprocessed with missing value handle and normalization. For handling missing data, it fills all the missing values using mean imputation.

$$M_{ij} = \frac{1}{N}\sum_{a=1}^{n} S_B, \text{ if } M_{ij} \text{ is missing} \quad (13)$$

Where,

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- ✓ M_{ij} be the missing value in the dataset,
- ✓ S_B represent the values in the dataset,
- ✓ The missing value M_{ij} is replaced with the mean of all available values.

Normalization method ensures all the features and it can be calculated by,

$$N = \frac{M_{ij} - M_{min}}{M_{max} - M_{min}}, \quad (14)$$

Where,

- ➢ Nbe the normalized value.
- ➢ M_{ij}be the original value in the dataset.
- ➢ M_{min}denotes the minimum value.
- ➢ M_{max}denotes the maximum value.

Then the preprocessed output be,

$$P = N, \quad (15)$$

4.2 Feature extraction:

Independent Component Analysis (ICA) and Statistical feature (SF) method is used for extracting the features of the preprocessed data. ICA accepts the preprocessed data as its main input.

4.2.1 Independent Component Analysis:

The preprocessed data$P = N,$ is used as the input for the ICA. ICA separates mixed signals into independent components. It performs data representation step, whitening step and ICT transformation step. The input is taken from equation (13),

$$P = N,$$

Data representation can be calculated as,

$$D = AP, \quad (16)$$

Where,

- D denotes the data representation,
- A denotes the mixing matrix,
- Pre denotes the independent source matrix.

The whitening step can be calculated by using D as an input,

$$WS = E1^{\frac{-1}{2}} E2^T D, \quad (17)$$

Here W be the whitened data, E1and E2 are the Eigenvalues and Eigenvectors of the covariance matrix.

To calculate the ICA transformation, the input is given by the WS,

$$C = W.WS, \quad (18)$$

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Here WS denotes the whitened data.

4.2.2 Statistical Feature:

The SF is calculated by using the input as $P = N$. The statistical features are calculated by using mean, variance, skewness, and kurtosis also the equation for calculating the mean be given as,

$$\mu = \frac{1}{n} P, \qquad (19)$$

Here μ denotes the mean if the extracted features using ICA.

The variance is calculated by using the formula,

$$\sigma^2 = \frac{1}{n} \sum_{a=1}^{n} (P - \mu)^2, \qquad (20)$$

The input for skewness is given by mean, variance and preprocessed output,

$$Q = \frac{1}{n} \sum_{a=1}^{n} (\frac{P-\mu}{\sigma})^2, \qquad (21)$$

The input for Kurtosis is given by mean, variance, skewness and preprocessed output,

$$K = \frac{1}{n} \sum_{a=1}^{n} (\frac{P-\mu}{Q})^4 - 3, \quad (22)$$

The final output for calculating Statistical feature are,

$$F_{SF} = \mu + \sigma^2 + Q + K, \qquad (23)$$

The combined feature extraction output be,

$$F_{fin} = C + F_{SF}, \qquad (24)$$

4.3 Fuzzification:

Decision making relies on the process of converting extracted features to fuzzy representation during this step. The input for fuzzification step is taken from equation (24) of the feature extraction.

$$F_{fin} = C + F_{SF}$$

Each feature $F_j$in F_{fin} is assigned a fuzzy membership value using,

$$\mu_S(F_j) = \begin{cases} 0, F_j < a \\ \frac{x-a}{b-a}, a \le F_j \le b \\ 1 \quad , F_j > b \end{cases}, \qquad (25)$$

- If F_j is low the membership value is 0,
- If F_j is in the defined range it gets a value between 0 and 1 ,
- If F_j us high the membership value is 1.

After the fuzzification the fuzzified output will be mentioned as,

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- The mean (μ) be changed into μ_f,
- Variance (σ^2) be turned into $\sigma^2{}_f$,
- Skewness (Q) be turned into Q_f,
- Kurtosis (K) be changed intoK_f.

Then the final output for fuzzification is,

$$F_{fuzzy} = \mu_S(F_j), \tag{26}$$

After the fuzzification the FLP optimization function is used to optimize the decision-making by handling fuzzified inputs.

The FLP optimization function can be calculated as,

$$Z = \sum c_j \ \mu_S(F_j), \tag{27}$$

The final output for FLP is

$$\boldsymbol{F_{final} = Z}, \tag{28}$$

4.3 Classification using Policy Gradient reinforcement learning:

The FLP output is used as an input for calculating the PGRL. This model plays a crucial role in optimizing decision making strategies by iteratively refining policy parameters. The equation for calculating PGRL are,

$$\theta_{t+1} = \theta_t + \alpha \nabla_\theta J(\theta), \tag{29}$$

Where,

- ✓ α denotes the learning rate,
- ✓ $\nabla_\theta J(\theta)$denotes the computed gradient used to improve the decision making.

To compute the gradient of the expected reward with respect to the policy parameters θ is calculated based on the policy gradient theorem. This gradient is then used to update the policy in the direction that improves performance. The expected cumulative rewardJ (θ) is defined as:

$$J(\theta) = \Delta\theta\left[\sum_{t=0}^{T} \beta^t R_t \ F_{final}\right], \tag{30}$$

Where,

- ✓ β denotes the discount factor,
- ✓ R_t denotes the reward received at time step t,
- ✓ Tbe the total time horizon.

4.4 Proposed Hybrid PGRL-FLP model:

Hybrid policy gradient with fuzzy linear model integrates the PGRL and FLP to get refined decision making, the inputs are taken from,

$F_{final} = Z$, from (27)

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$\theta_{t+1} = \theta_t + \alpha \nabla_\theta J(\theta)$, from (28)

The final equation for calculating hybrid PGRL-FLP model is,

$$H = Z + \theta_{t+1}, \qquad (31)$$

Where Z denotes the FLP adjusted score accounting for fuzzy constraints, and θ_{t+1} be the policy gradient based reinforcement learning.

5. Result:

The Hybrid PGRL-FLP model provides a strong framework for accurate classification by recognizing different stability states in smart grids. Its improved predictive capabilities enhance performance, minimize classification errors, and support reliable decision-making. As a valuable asset to smart grids, the system efficiently manages unpredictable grid conditions while maintaining operational stability.

5.1 Confusion matrix for Hybrid PGRL-FLP model:

The Hybrid PGRL-FLP model demonstrates its classification outcomes for Normal, Fluctuating, and Extreme grid conditions through Table 1 using a confusion matrix. Each diagonal entry in the matrix shows the number of correctly identified cases belonging to True Positive (TP) categories. The off-diagonal confusion matrix elements represent incorrect predictions as the model assigns an inaccurate classification to instances that should belong to different groups. The incorrect classifications exist in two forms: False Positives (FP) and False Negatives (FN). FP condition arises when the model identifies a different condition from the actual one creating artificial warnings and incorrect stability measurements. The classification of actual unstable conditions as stable conditions represents the most critical issue for smart grid management because these false negative cases present a significant risk. True Negatives (TN) refer to correct identifications of non-occurring specific conditions. The confusion matrix serves as a systematic approach to evaluate model classification performance which enables the calculation of accuracy, precision, recall and F1-score metrics. The evaluation of these values enables us to assess how well the model separates different grid stability conditions for effective performance in real-world applications. The confusion matrix for Hybrid PGRL-FLP model appears in Figure 1.

Table 1: Confusion matrix for Hybrid PGRL-FLP model.

Actual/predicted	Normal	Fluctuating	Extreme
Normal	60	2	1
Fluctuating	3	72	2

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Extreme	2	4	50

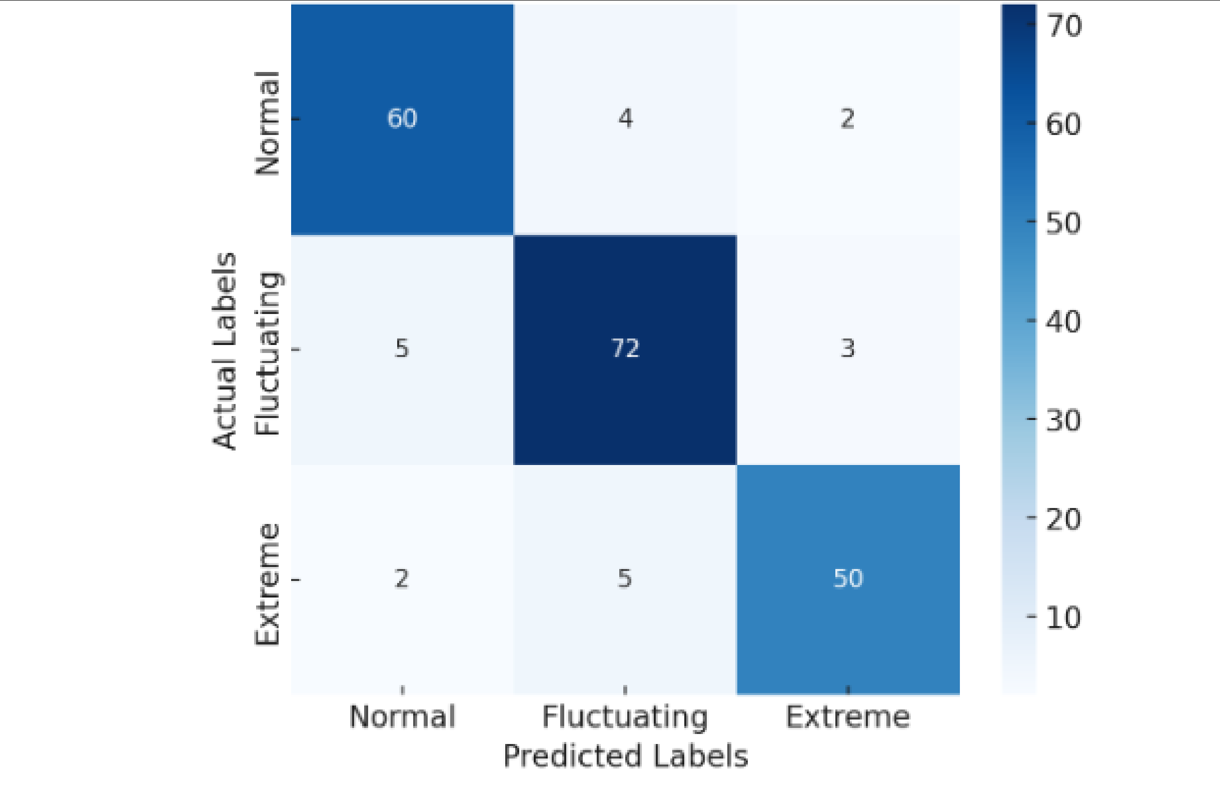

Figure 1: Confusion matrix for Hybrid PGRL-FLP model.

5.2 Performance Analysis of Hybrid PGRL-FLP model:

The Hybrid PGRL-FLP model demonstrates the remarkable performance in smart grid stability classification by progressively improving across multiple evolution metrics at the training percentage of 90 with epoch's ranges from 100 to 500. Figure 2a shows that the accuracy levels for these epochs reached 70.45%, 83.1%, 89.75%, 94.20%, and 97.85%. Figure 2b displays precision results which peaked at 77.67%, 89.37%, 93.24%, 89.55% and 98.1%. Figure 2c shows recall measurement outcomes for the identical epochs where the highest rates reached 76.55% and 95.56% and 88.67% and 89.66% and 91.79%. Figure 2d presents the f1-score results of Hybrid PGLR-FLP model, which reached its highest levels at 77.45%, 93%, 90%, 86.55% and 96.94%.

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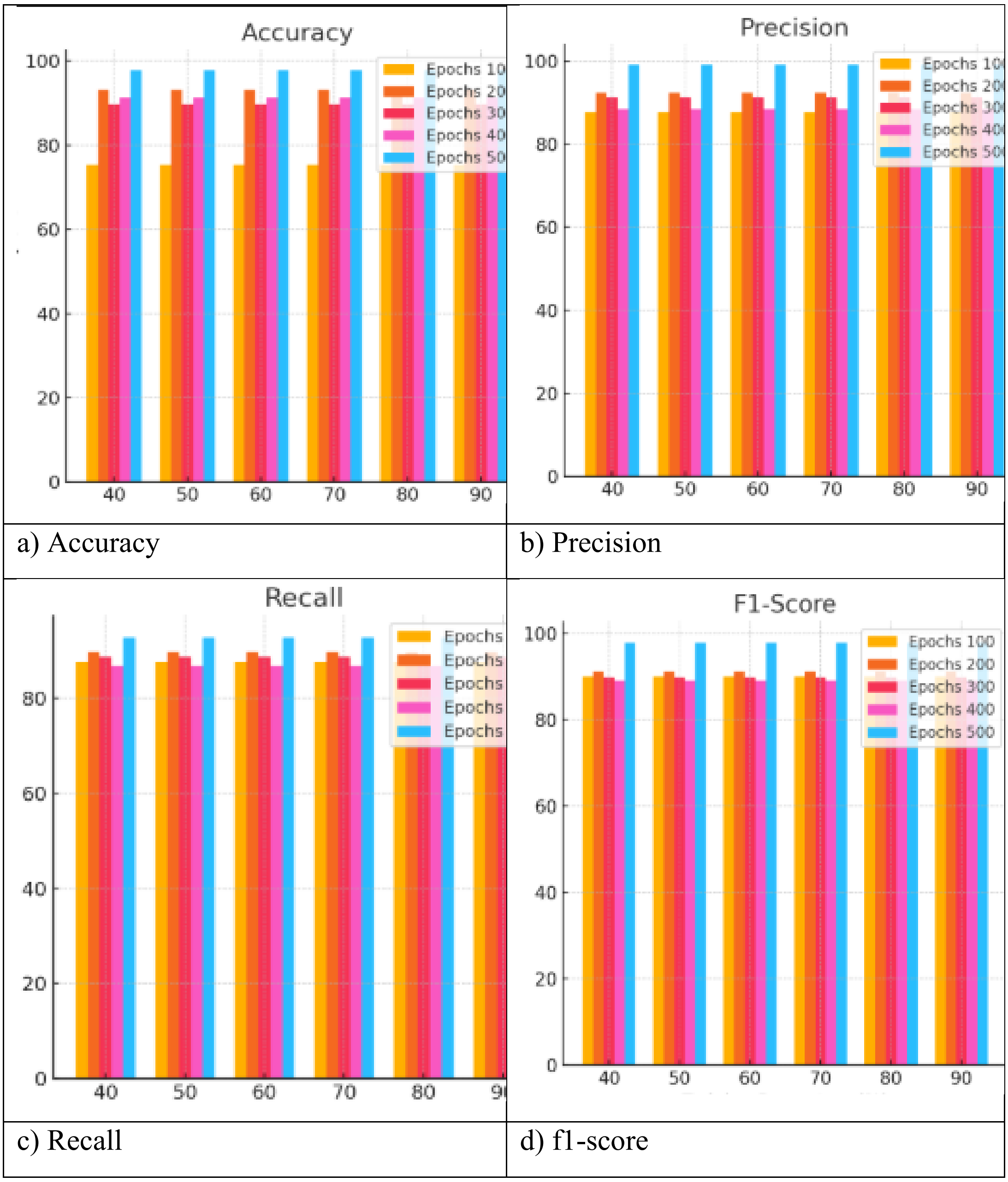

a) Accuracy

b) Precision

c) Recall

d) f1-score

Figure 2: Performance analysis based on TP 90 a) accuracy, b) precision, c) recall, and d) f1-score.

5.3 Comparative methods: To highlight the achievements of hybrid PGRL-FLP model the comparison are made by using existing methods. Several methods are used in this analysis including Deep RL [1], Deep LSTM [3], GA-Fuzzy rule [4], and Fuzzy Logic-Fuzzy Linear.

5.4 Comparative analysis based on TP:

The Hybrid PGRL-FLP model demonstrates the superior performance compared to fuzzy logic +fuzzy linear model for smart grid stability during a TP of 90, marked by a notable improvement of 15.15% and achieving a peak accuracy of 98.6 % as depicted in figure 3a.

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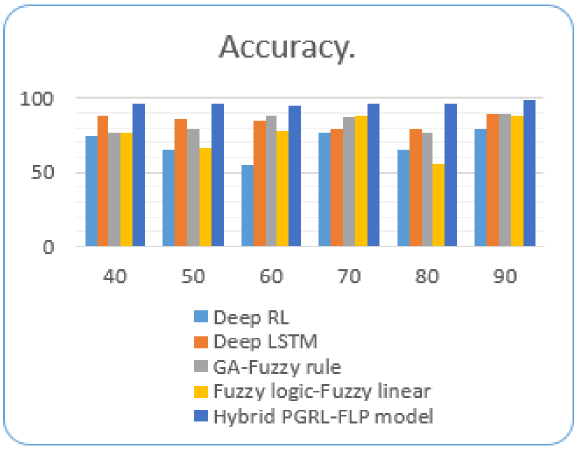
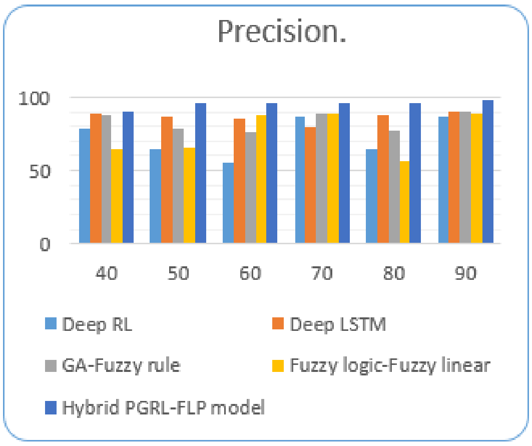
In figure 3b, the Hybrid PGRL-FLP model exhibits enhanced predictive capabilities for smart grid stability compared to the fuzzy logic +fuzzy linear model, outperforming it by 10.34% and attaining a maximum precision of 97.5% with a TP of 90.

According to figure 3c, the Hybrid PGRL-FLP model exceeds the fuzzy logic +fuzzy linear model by 14.34% in its predictions for smart grid stability, achieving a top recall of 94.5% with a TP of 90, thus surpassing previously established methods.

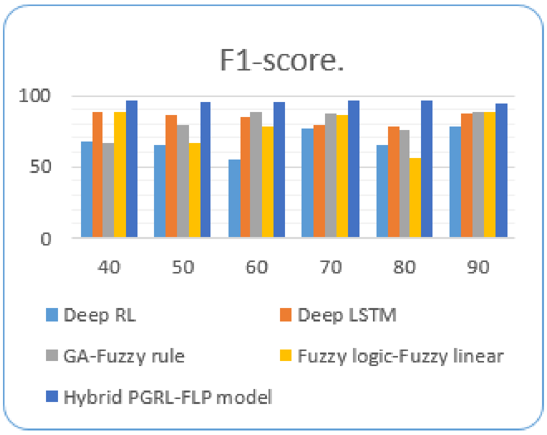
Figure 3d illustrates the Hybrid PGRL-FLP model exceeds the fuzzy logic +fuzzy linear model for smart grid stability by achieving an f1-score of 97.4%, with a TP of 90, which is 13.25% higher than that of the fuzzy logic +fuzzy linear model.

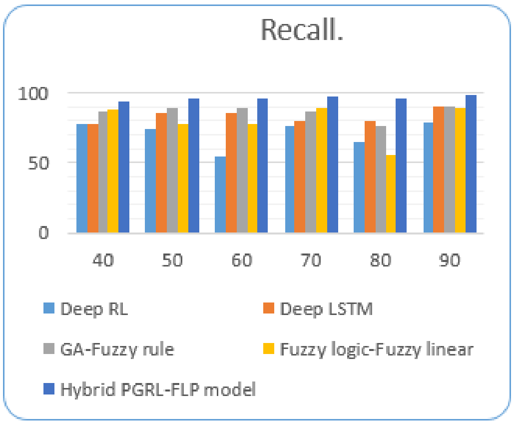




a) Accuracy

b) Precision





c) Recall

d) F1-score

Figure 3: Comparative analysis based on TP 90 a) Accuracy b) precision c) Recall d) F1-score.

5.5 Comparative discussion table for TP 90:

Table 2 illustrates the comparative discussion table for TP 90 with existing methods. The Deep RL model demonstratedperformance at all categories with 74.3% accuracy, 77%

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precision and 80.5% recall along with 89.6% F1-score. Deep LSTM model performed at a superior level through its achievement of 79% accuracy together with 86.4% precision, 89.7% recall and 88.67% F1-score. The GA-Fuzzy rule approach delivered 85.6% accuracy together with 77.6% precision, 86.5% recall and 87.3% F1-score. The Fuzzy logic – Fuzzy Linear model achieved evaluation results of accuracy 76.4%, precision 79.6% along with recall 80.6% and F1-score 88.65%. The Proposed Hybrid PGRL-FLP model proved most effective with its 98.6% accuracy rating, 97.5% precision rate along with 94.5% recall and 97.4% F1-score which established its superiority over other models.

Table2: Comparative discussion table for TP 90:

Model	Accuracy	Precision	Recall	F1-score
Deep RL model	74.3%	77%	80.5%	89.6%
Deep LSTM model	79%	86.4%	89.7%	88.67%
GA-Fuzzy rule	85.6%	77.6%	86.5%	87.3%
Fuzzy logic – Fuzzy Linear model	76.4%	79.6%	80.6%	88.65%
Proposed Hybrid PGRL-FLP model	98.6%	97.5%	94.5%	97.4%

6. Conclusion:

The Hybrid PGRL-FLPModel delivers smart grid stability assessment through its effective solutions for dynamic decision-making challenges, uncertainty management and classification accuracy enhancement. The model achieves superior performance compared to traditional methods with 98.6% accuracy, 97.5% precision, 94.5% recall and 97.4% F1-score at TP 90 through its optimization of real-time decision strategies which combines reinforcement learning with fuzzy constraints. The system improves the electrical network's resilience and decreases classification errors through adaptive energy control measures. The Hybrid PGRL-FLP Model proves itself as a scalable and efficient solution for modern smart grids because it improves stability and operational efficiency.

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Conflicts of interest

The authors declare that they have no conflict of interest.

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