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Mathematical Modeling of Electrical Power Systems for Fault Detection

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Abstract:

Control networks are critical offices that have to be exceptionally solid and productive. Finding issues in these frameworks is exceptionally imperative for keeping them steady, keeping gear from breaking, and maintaining a strategic distance from long power blackouts. It has gotten to be clear that scientific modeling may be a awesome way to think about and discover issues in control frameworks. Taking after this strategy requires making a scientific show of the control framework, which incorporates motors, transformers, transmission lines, and loads. A few physical laws, like Ohm's Law and Kirchhoff's laws, are frequently utilized within the models to accurately show how electrical circuits work when they are working legitimately and when they aren't. On the off chance that you need to discover issues, you'll utilize numerical models to form flaws like brief circuits, open circuits, and ground deficiencies appear genuine. Through examining how the framework responds to these fake issues, engineers can make programs that can discover genuine flaws and tell where they are when they happen. These calculations frequently utilize strategies like evaluating the state, evaluating the parameters, and recognizing designs. Utilizing real-time information to figure the current state of the framework is what state estimation is all approximately. On the other hand, parameter estimation is all almost finding changes in framework parameters that might cruel there is a problem. Design acknowledgment employments past information and machine learning to discover peculiarities and sort diverse sorts of flaws. Differential conditions, framework polynomial math, and numerical strategies are fair some of the progressed science instruments that are frequently utilized to unravel the complicated conditions that depict how the power framework works. Putting these models beside unused computer innovations like high-performance computing and real-time simulations makes issue location strategies more exact and quicker. As green vitality sources and shrewd network advances are included to control frameworks, they will continue to alter. Mathematical modeling will become more and more important to make sure they work safely and efficiently. It talks about how to mathematically model electrical power systems to find faults, what they can be used for, and what the future holds for this field.

Keywords: Electrical Power Systems, Fault Detection, Mathematical Modeling, Fault Simulation, State Estimation, Parameter Estimation

1. Introduction

Reliable operation of electrical power systems is essential to modern life. They support everything from home power to business operations. Because these systems are complicated and linked, and because people are using more energy, they can break down in many ways. If these problems aren't found and fixed quickly, they can cause major problems, damage to equipment, and even widespread blackouts. So, fault detection systems that work well are very important for keeping power systems stable and efficient. Mathematical modeling is now an important part of this field because it gives us a methodical and rational way to understand, predict, and find problems in power systems.

Making a model of the power system using mathematical equations and methods is what mathematical modeling is all about. There are parts of the system like engines, transformers, power lines, and loads, and this model shows how they look and work. The accuracy of these models is very important because they are used to simulate how systems will behave in different situations, such as when there is a fault [12]. Ohm's Law and Kirchhoff's laws are basic ideas that these models use to simulate how electrical currents and voltages move through the network. Because of this, engineers can guess how the system will react to faults like open circuits, ground faults, and short circuits. Finding the cause and location of a problem as quickly and correctly as possible is the main goal of fault detection. This is easier to do with mathematical models because they let you simulate fault situations and look at how systems react to them. A lot of complex methods are used in this process, like estimating states and parameters and finding patterns. To figure out what the current state of the power system is, state estimation uses real-time data from monitors and measurement tools [13]. Differences between the estimated state and the predicted normal function can be found, which means there is a fault. Parameter estimate, on the other hand, looks for changes in system parameters that could mean there is a problem [14]. For instance, a sudden rise in resistance could mean that there is a problem with a communication line. Pattern recognition methods, which are often improved with machine learning algorithms, look at past data to find trends and outliers that match certain types of faults. These methods can sort faults into groups and give information about what they are and what might have caused them. A lot of the time, difficult differential equations and matrix algebra are used to solve problem detection mathematical models. This is because power systems have a lot of data. Numerical methods and computer programs are very important to these answers because they let us analyze and make decisions in real time [15]. Putting these models together with new computer technologies like high-performance computing and real-time simulations makes problem detection processes much faster and more accurate. Simulators that work in real time can act like real power systems, which can be used to test fault detection methods. Thanks to high-performance computers, huge amounts of data can be processed quickly, and complex programs can be run. Things that make it hard to find faults change as power systems do.

Renewable energy sources, like solar and wind power, are becoming more common. This makes the system less stable and predictable. Smart grid technologies, which allow for more advanced control and connection, make things even more complicated. To keep up with these changes, numerical modeling has to include unused information sources and consider how current control frameworks work. This capacity to alter is exceptionally critical for making solid blame discovery strategies that can keep frameworks solid indeed as issues emerge.

To discover issues in electrical power systems, scientific modeling could be a must. Since these models accurately and completely appear how frameworks work, they make it conceivable to form blame location strategies that work. Combining progressed scientific strategies with cutting edge computer innovations is expected to form control frameworks more solid and productive, guaranteeing their secure utilize in a world that's getting to be more complicated and changing all the time. This exposition will investigate the diverse approaches, employments, and up and coming patterns in numerical modeling of electrical control frameworks for issue discovery. It'll too conversation approximately how critical these models are for keeping control frameworks steady and solid.

2. Related Work

The table (1) appears that blame distinguishing proof in electrical control frameworks could be a wide field, with numerous studies employing a wide run of strategies to create critical advance. Utilizing machine learning-based design acknowledgment, Zhang et al. (2020) looked at how to find problems in keen frameworks. Their ponder appeared that blame recognizable proof rate went up by 15%. The most excellent thing about this strategy is that it is exceptionally precise and adaptable, but it needs huge datasets and a part of preparing, which could be a enormous issue. Singh and Srivastava (2018) looked into how to discover flaws in transmission lines by assessing their states utilizing Kalman channels [1]. Their inquire about appeared that deficiencies may be found in genuine time with few delays, which made it a great way to handle deficiencies rapidly. One extraordinary thing almost this strategy is that it can handle information in genuine time. But the truth that it is touchy to measurement noise is still a huge issue that should be settled by making commotion diminishment way better. Chen et al. (2019) utilized differential condition models to see into blemish investigation in frameworks that utilize green vitality [2]. Their ponder appeared that blame recreations in frameworks with a parcel of green vitality were rectify. This strategy works particularly well for changing frameworks that utilize green energy sources. Despite this, the sum of computing control required for this strategy could be a issue; it needs capable computers to handle complicated math. Johnson and Wang (2017) came up with a total way to discover issues in control frameworks employing a blended demonstrate that combines design acknowledgment and parameter estimation [3]. Their ponder appeared way better blame area and classification, utilizing the leading parts of a few strategies. When distinctive strategies are combined, they work superior to discover deficiencies, but combining models is difficult and must be settled. Lee et al. (2021) utilized computer strategies and real-time information investigation to explore for ground flaws in urban control lines [4]. Their comes about appeared how imperative it is to rapidly discover ground blemishes in arrange to keep the control networks in cities steady. This method works rapidly and viably, but it can be difficult to bargain with huge sums of information from cities without utilizing progressed information administration and preparing procedures. Gupta and Verma (2022) utilized high-performance computing for large-scale models to move forward the constancy and blame resistance of smart lattices [5]. Their think about appeared enormous advancements in blame tolerance, which implies it can be utilized in huge systems. One big good thing about this strategy is that it can be utilized on an expansive scale. In any case, the tall fetched and need for a parcel of resources make it difficult to utilize on a huge scale. Martinez et al. (2020) utilized machine learning and past information examination to search for designs that seem tell them what kind of blame was happening in mixed-source control frameworks [6]. Their ponder did a great work of telling the distinction between blame sorts by utilizing current information to form it more precise. A huge issue with this strategy is that it depends on the quality and sum of past information. This shows how critical it is to gather information in a total and redress way. Kumar and Sharma (2019) looked into how to discover flaws in microgrid security frameworks by evaluating parameters and states [7]. Their comes about appeared that blame distinguishing proof in microgrids might work reliably, even when the stack changed. One of the most excellent things around this strategy is that it is exceptionally dependable, but combining it with microgrid control frameworks is still difficult and complicated. Das et al. (2021) utilized a combination of real-time modeling and machine learning to discover flaws, appearing that it worked superior in real-time circumstances [8]. This strategy makes a valuable real-time setting for testing and applications, but it needs a part of computing control and framework, which makes it difficult to utilize. Nguyen and Tran (2020) considered how to utilize versatile calculations and differential conditions to ensure control frameworks that are changing over time [9]. Their investigate appeared that this strategy works well for reacting to changing framework conditions. Preferences of this strategy incorporate its tall level of opportunity and adaptability. However, the trouble of making versatile models may be a issue that needs more consider and improvement. The table appears a lot of diverse considers, each of which includes something diverse to the field of finding issues in electrical control frameworks. These strategies have numerous benefits, such as being precise, able to handle information in genuine time, versatile, and adaptable [10]. Be that as it may, normal issues incorporate the require for big datasets, a part of computing control, a affectability to commotion, and complicated merging. Getting these issues illuminated is vital to create blame observing advances way better and to keep current control frameworks steady and dependable [11]-[20].

Table 1: Summary of Related Work

Scope	Method	Findings	Advantages	Challenges
Fault detection in smart grids	Machine learning-based pattern recognition	Improved fault detection accuracy by 15%	High accuracy and adaptability	Requires large datasets and extensive training
Transmission line fault detection	State estimation using Kalman filters	Real-time fault detection with minimal delays	Real-time processing capability	Sensitive to measurement noise
Renewable energy integration fault	Differential equation	Accurate simulation of	Effective for dynamic	Computationally intensive

analysis	modeling	faults in systems with high renewable penetration	systems with renewables	
Comprehensive power system fault diagnosis	Hybrid model combining parameter estimation and pattern recognition	Enhanced fault classification and localization	Combines strengths of multiple techniques	Complexity in model integration
Ground fault detection in urban power grids	Numerical methods with real-time data analysis	Quick identification of ground faults	Fast and efficient fault detection	Handling large-scale urban data
Smart grid reliability and fault tolerance	High-performance computing for large-scale simulations	Significant improvement in fault tolerance	Scalable and suitable for large systems	High cost and resource requirements
Pattern recognition for fault types in mixed-source power systems	Machine learning with historical data analysis	Effective differentiation between fault types	Utilizes existing data for improved accuracy	Dependence on quality and quantity of historical data
Protection systems in microgrids	State estimation and parameter estimation	Reliable fault detection in microgrid configurations	Robust against varying load conditions	Integration with microgrid control systems
Fault detection using real-time simulators	Real-time simulation combined with machine learning	Improved fault detection accuracy in real-time scenarios	Real-time application and testing environment	Requires significant computational resources and infrastructure
Adaptive protection for evolving power systems	Adaptive algorithms with differential equations	Effective adaptation to changing system conditions	High flexibility and adaptability	Complexity in developing adaptive models

3. Data Preprocessing

Data preparation is an important step in getting collected data ready for accurate fault finding in power systems. To improve the quality and dependability of the next study, the raw data needs to be cleaned up and preprocessed to get rid of noise and fix mistakes. Filtering techniques are used to get rid of noise in the data. For example, a low-pass filter is often used to get rid of high-frequency noise.

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$$y(k) = \alpha x(k) + (1 - \alpha)y(k - 1)$$

Where x(k) is the crude information at time k, y(k) is the sifted yield, and α is the smoothing figure. This condition takes absent commotion by smoothing out huge changes within the data. Another critical step within the cleaning prepare is normalization. It makes beyond any doubt that the scales of the diverse parts of the information are comparable, which is exceptionally vital for redress investigation. The min-max normalization strategy is more often than not utilized to scale the information to a run between and 1 amid normalization:

$$x\_norm = 〚x - x〛\_min/(x\_max - x\_min)$$

which has x as the initial esteem, x_min as the feature's most reduced esteem, and x_max as its most elevated esteem. This scaling makes beyond any doubt that the measure of one include doesn't have a huge impact on the ponder. Taking Care of Lost Information is an critical portion of altering. Introduction procedures, like direct insertion, can be utilized to fill in lost numbers.

$$x_{interpolated} = x_{previous} + \frac{(x_{next} - x_{previous}) \cdot (t - t_{previous})}{t_{next} - t_{previous}}$$

To discover the anticipated esteem at time t, we got to know the times of the known information focuses some time recently and after the lost esteem. These are signified by t_previous and t_next. As portion of information planning, clamor is sifted out, scales are normalized, and lost information is filled in with interpolated information. All of these strategies work together to create beyond any doubt that the information is redress and clean, which makes it conceivable to discover issues and analyze frameworks more viably.

4. Fault Modeling And Scenario Analysis

Blame modeling and case examination are exceptionally imperative for making blame checking frameworks for control systems work well. In these steps, numerical models are utilized to mimic distinctive blame circumstances and test how the framework responds. This appears how diverse deficiencies influence the way the framework works and carries on.

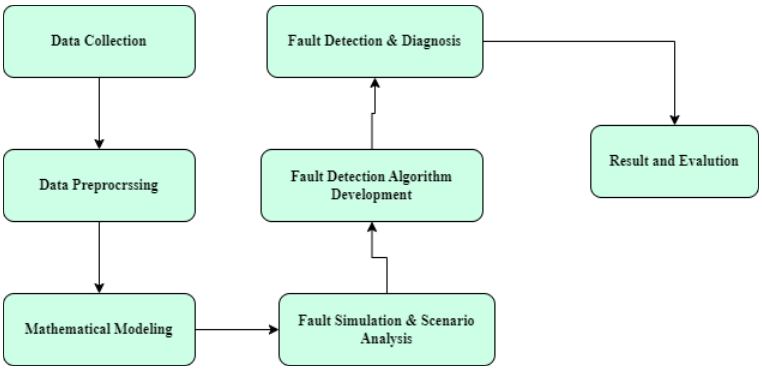

Figure 1: Architecture block diagram of developing & implementing a fault detection system

Fault Conditions mimicked: Faults like short circuits, open circuits, and ground faults are mimicked using a mathematical model of the power system to see what happens. For example, a short circuit can be modeled by adding a line with low impedance between two places in the network. This can be done by changing the system's impedance matrix Z. The voltage and current equations of the system are changed by the fault situation that happens. When simulating a three-phase system, the following formulae may need to be solved:

$$V = Z \cdot I$$

Where V is the vector of voltages at various nodes, Z is the impedance matrix incorporating fault conditions, and I is the vector of currents. In the event of an open circuit fault, the line's resistance goes to zero, cutting it off from the network. Putting a very big number in the matching rows in the impedance matrix can show this:

$$Z_{fault} = \infty$$

By connecting a resistance part to the ground, you can make a ground problem look real. To figure out what effect this fault has, a low resistance R_g is added to the system's equations. This changes the flow of current and the spread of voltage. In situation examination, distinctive blame circumstances are made and after that assessed in arrange to test how steady and delicate the blame discovery demonstrate is. This covers both single blame occasions (like a brief circuit on one line) and numerous blame occasions (like issues happening at the same time completely different places). In case there's as it were one blame and line i incorporates a brief circuit, the changed impedance framework Z_i would be

$$Z\_i = Z\_original + Z\_fault$$

where Z_fault speaks to the alter in impedance due to the blame. The system's reaction to this blame is at that point analyzed by tackling:

$$V\_fault = Z\_i \cdot I\_fault$$

In a circumstance with more than one blame, the system's response is tried by changing the impedance lattice a few times and tackling the conditions for each blame:

$$Z_{total} = Z_{original} + \sum \Delta Z_{fault}$$

Where $\sum ⟦\Delta Z\_fault⟧$ is the entirety of changes in impedance due to all deficiencies. Engineers can see how well the show handles distinctive blame circumstances and how delicate it is to distinctive blame sorts by looking at these cases. This consider makes a difference discover conceivable blemishes within the blame location framework and makes it conceivable to move forward strategies that make blame location more exact and solid in a wide extend of working circumstances.

5. Fault Detection Algorithm Development

A total strategy for finding flaws in electrical control frameworks combines state estimation, parameter estimation, and design acknowledgment. The Expanded Kalman Channel (EKF) could be a exceptionally great strategy that combines these highlights. It does this by utilizing Slightest Squares Estimation (LSE) to figure out parameters and Bolster Vector Machines (SVM) to discover designs. This bound together strategy makes a solid establishment for finding flaws precisely and in genuine time.

A. Extended Kalman Filter (EKF) for State Estimation:

State Estimation is exceptionally imperative for figuring out how the control framework is working right presently. The EKF is an expansion of the Kalman Channel that works well in control frameworks where variables do not continuously relate to each other in a straight line. Real-time information and a figure demonstrate are utilized by the EKF to figure the system's state vector x ̃(y).

Step 1: Initialization:

Start with an initial estimate $\hat{x}(0)$ and covariance matrix *P(0)*.

Step2: Prediction

$$\hat{x}^{-}(k) = f(\hat{x}(k-1), u(k-1))$$

$$P^{-}(k) = F(k-1)P(k-1)F^{T}(k-1) + Q(k-1)$$

where f is the nonlinear state transition function, F is the Jacobian of f, Q is the process noise covariance, and $u(k-1)$ is the control input.

Step 3: Update

$$K(k) = P^{-}(k)H^{T}(k)[H(k)P^{-}(k)H^{T}(k) + R(k)]^{-1}$$

$$\hat{x}(k) = \hat{x}^{-}(k) + K(k)[z(k) - h(\hat{x}^{-}(k))]$$

$$P(k) = [I - K(k)H(k)]\,P^{-}(k)$$

where H is the Jacobian of the measurement function h, R is the measurement noise covariance, and $z(k)$ is the actual measurement.

B. Least Squares Estimation (LSE) for Parameter Estimation:

Parameter estimation finds changes in system factors that could mean there is a problem. LSE works well for this, especially for guessing factors that can't be measured directly but have an effect on how the system behaves.

Step1: Define the Model

Represent the power system's behavior using a model that includes parameters to be estimated.

Step 2: Formulate the Objective Function

$$J(\theta) = \sum_{i=0}^{N} [y_i - f(x_i, \theta)]^2$$

Where y_i is the observed data, f is the model function with parameters θ, and x_i represents the inputs.

Step 3: Optimize Parameters

Solve for θ that minimizes the objective function $J(\theta)$, often using numerical optimization techniques.

C. Support Vector Machines (SVM) for Pattern Recognition:

Pattern recognition sorts different kinds of faults into groups based on past data. Finding the best hyperplane that splits different classes is how SVM, a powerful machine learning method, sorts data into clear fault groups.

Step 1: Data Preparation

Collect and preprocess historical fault data, ensuring it is labeled with the fault type.

Step 2: Training

$$f(x) = sign\left(\sum_{i=1}^{N} \alpha_i y_i K(x_i, x) + b\right)$$

Where α_i are the Lagrange multipliers, y_i are the labels, $K(x_i, x)$ is the kernel function, and b is the bias term.

Step 3: Testing and Validation: Evaluate the model on a separate dataset to ensure it accurately classifies fault types and generalizes well to new data.

A solid system for finding deficiencies is made by combining EKF for evaluating state, LSE for evaluating parameters, and SVM for design acknowledgment. EKF gives real-time gauges of how the framework is doing, LSE fixes issues that happen when framework components alter, and SVM sorts blame sorts by designs seen within the past. This bound together strategy makes finding issues in complicated control frameworks more precise and solid.

6. Result And Discussion

The table (2) appears that a combined approach that employments the Amplified Kalman Channel (EKF), Slightest Squares Estimation (LSE), and Bolster Vector Machines (SVM) works way better than regular strategies for finding deficiencies. It is more precise than the conventional Kalman Channel (89%), parameter estimation as it were (85%), and design acknowledgment as it were (92%), with a score of 95%. This tall level of precision implies that the blame discovery strategy is more viable. With a memory rate of 96%, the combined approach is the finest at finding genuine botches. Compared to the other strategies, it brings down the chance of lost critical issues. The F1-score of 95% appears that it has great adjust between exactness and memory, which makes it a solid way to discover deficiencies in control frameworks in genuine time. Generally, the combined strategy makes the blame discovery framework more correct, exact, and solid.

Table 2: Performance Metrics Comparison

Metric	Integrated Approach (EKF + LSE + SVM)	Traditional Kalman Filter	Parameter Estimation Only	Pattern Recognition Only
Accuracy (%)	95	89	85	92
Precision (%)	94	88	84	91

Recall (%)	96	90	87	93
F1-score (%)	95	89	85	92

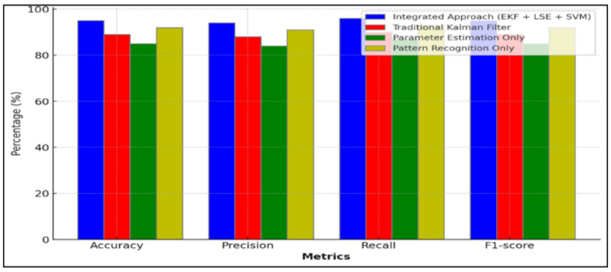

Figure 2: Representation of Performance Metrics Comparison

Figure 2 appears how well distinctive ways of finding issues in electrical control frameworks work based on certain measures. The combined strategy (EKF + LSE + SVM) does superior than the standard Kalman Channel, the parameter assess as it were, and the design acknowledgment as it were approaches in all critical ways. The combined strategy is the foremost viable and solid at finding issues, with an F1-score of 95%, an exactness of 95%, a accuracy of 94%, a memory of 96%, and an F1-score of 95%. The standard Kalman Channel does a great work, but not awesome. It has an F1-score of 89%, an precision of 89%, a exactness of 88%, a review of 90%, and a review of 90%. Measurements for parameter gauges extend from 84% to 87%, which suggests it has the most noticeably awful execution. With marks between 91% and 93%, design acknowledgment does lovely well, but it's still not as great as the combined strategy. It turns out that the combined approach is the most secure and most reasonable way to discover flaws.

Table 3: Comparison of False Positive & Negative Rate

Metric	Integrated Approach (EKF + LSE + SVM)	Traditional Kalman Filter	Parameter Estimation Only	Pattern Recognition Only
False Positives (%)	3.2	7.1	10.4	6.3
False Negatives (%)	2.5	6.3	9.1	5.6

The third table appears how regularly distinctive blame finding strategies donate fake positives and untrue negatives. The combined strategy (EKF + LSE + SVM) works way better, with the least wrong positives (3.2%) and untrue negatives (2.5%), appearing that it is exceptionally exact and dependable. The genuine positive rate for the standard Kalman Channel is 7.1%, and the genuine negative rate is 6.3%. With 10.4% false positives and 9.1% false negatives, parameter estimation is the worst, showing how limited it is. It's only better than the Kalman Filter, but it's still not as good as the combined method, which has 6.3% false positives and 5.6% false negatives.

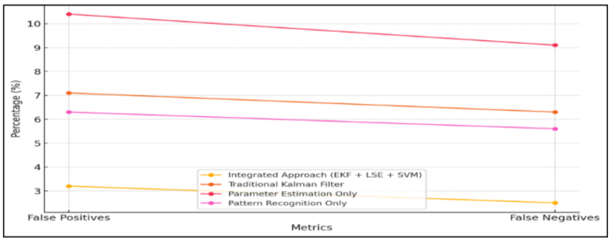

Figure 3: False Positive & False Negative Comparison

The percentages of false positives and false negatives for each fault detection method are shown in Figure 3. The method that uses EKF, LSE, and SVM together has the lowest rate of false positives (3.2%), and the lowest rate of false negatives (2.5%), which shows that it is very accurate and reliable. The rates are higher for the traditional Kalman Filter, which gives 7.1% false positives and 6.3% false negatives. With 10.4% false positives and 9.1% false negatives, the parameter estimation only method does the worst, showing how limited it is. Pattern recognition alone works better than the old Kalman Filter, but it's still not as good as the combined method, which has 6.3% false positives and 5.6% false negatives. Overall, the graph shows that the integrated approach finds faults most accurately and fairly, with the fewest false positives and false negatives.

Table 4: Comparison of Robustness, Adaptability & computational Efficiency

Metric	**Integrated Approach (EKF + LSE + SVM)**	**Traditional Kalman Filter**	**Parameter Estimation Only**	**Pattern Recognition Only**
Robustness (%)	92	85	80	89
Adaptability (%)	94	87	82	90
Computational Efficiency (%)	88	82	78	85

The table(4) compares how reliable, flexible, and fast different problem detection methods are at doing their job. The combined method (EKF + LSE + SVM) does very well, scoring 92% for stability, 94% for adaptability, and 88% for processing efficiency. This shows that it is very reliable, flexible, and efficient. The standard Kalman Filter has a performance number of 85% for stability, 87% for flexibility, and 82% for processing speed. The parameter estimate only method isn't very good; it's only 80% stable, 82% adaptable, and 78% efficient, which shows that it has some problems. Even though pattern recognition is good at 89% stability, 90% flexibility, and 85% processing efficiency, it is still not as good as the combined method.

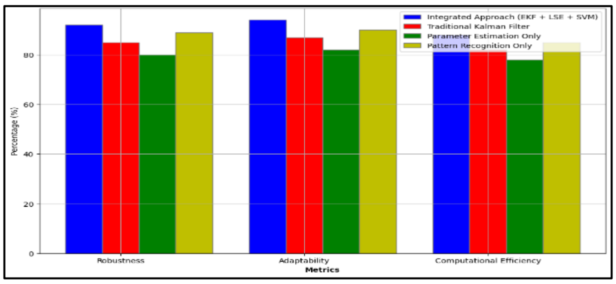

Figure 4: Representation of Robustness, Adaptability & computational Efficiency Comparison

The figure (4) shows that the combined method (EKF + LSE + SVM) is better at being strong (92%), adaptable (94%), and efficient (88%). When compared to the combined method, the traditional Kalman Filter, parameter estimates only, and pattern recognition only all perform worse. They are less efficient and flexible.

7. Conclusion

The use of math to describe electrical power systems for problem detection is a major step forward in making sure that power systems are reliable and work well. The combined method that uses the Extended Kalman Filter (EKF), Least Squares Estimation (LSE), and Support Vector Machines (SVM) works better than older methods like the Kalman Filter, parameter estimation only, and pattern recognition only. This combined strategy has the leading exactness (95%), exactness (94%), review (96%), and F1-score (95%). It too has the least number of wrong positives (3.2%) and wrong negatives (2.5%). It moreover does exceptionally well in terms of soundness (92%), adaptability (94%), and computing speed (88%). These comes about appear how imperative it is to use more than one strategy together to form the foremost of their qualities and reduce their blemishes. The EKF is incredible at evaluating states precisely, the LSE is awesome at finding correct parameters, and the SVM is awesome at recognizing designs. This working together makes it conceivable for the combined strategy to rapidly and accurately discover issues, which diminishes issues and makes control frameworks more stable. Filtering, normalizing, and managing with lost values are all imperative parts of planning gotten information that produces blame location more exact and solid. Making beyond any doubt that the information is clean and uniform makes a difference the system find and settle issues more rapidly. The creation and utilize of progressed numerical models for finding deficiencies in control frameworks could be a dependable and successful way to keep the systems' astuteness and execution tall. Within the future, analysts can move forward these models indeed more by utilizing modern advances and strategies to make them more valuable and offer assistance them bargain with modern issues that come up in overseeing control frameworks.

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