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Neural Network Aided Extended Kalman Filter for Fault Detection and Isolation in Nonlinear Control System

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Abstract:

This article describes the presentation of neural networks for fault detection and isolation in nonlinear systems. Model-based fault detection schemes must include residual generation. The process of residual generation for nonlinear systems is often difficult because of the size of the issue or the absence of a suitable model from which the residual can be generated. To generate residuals for fault detection, this paper develops and applies neural network-based methods for nonlinear systems. Fault Detection and Isolation (FDI) is critical in many industries to ensure the safe operation of a process. Faults detection and Identification (FDI) methods are proposed to identify the type, size, position, and time of the fault. FDI are distinguished by their robustness, rapid detection, and isolation of faults. This paper compares the effectiveness of extended Kalman filters and neural network-based fault diagnosis systems. According to simulation results, the method has a faster convergence rate and a more accurate identification result than the traditional EKF algorithm.

Keywords: Neural networks; Fault detection and isolation (FDI); Non-linear systems; Extended Kalman filter (EKF); fault diagnosis.

1. INTRODUCTION

One of the critical steps in security and intelligent process control is fault diagnosis. Initial fault detection can prevent system shutdown, failure, and even disasters that cause property damage and fatalities. Even if it does not result in a physical breakdown or failure, a fault is to be comprehended as an unexpected development in how a system operates. An automatic system's normal operation can be hindered or disturbed by faults, which can result in a slowdown that is unacceptable or even dangerous operation. A fault diagnosis system is a surveillance or supervisory tool that is used to locate faults in a system, determine their type or qualities, and isolate them. As the two most crucial functions of a diagnosis system, fault detection, and isolation (FDI) are commonly used to refer to fault diagnosis [1].

The majority of methods used to identify major faults in the research are based on linear theory or precise models. Particularly, initial fault detection and diagnosis techniques are useful for carrying out safety precautions. The following conditions should be attached to these methods:

- ✓ quality and standard developments
- ✓ knowledge of the relationship between mistakes and diagnosis
- ✓ creation of innovative products and technologies that are profitable

The fundamental goal of this scheme is to produce signals that indicate discrepancies between detected and tested operating system parameters. Regretfully, a popular flaw in these methods is that an exact mathematical model of the diagnosed plant is necessary. The modeling process is frequently time-consuming for complex and nonlinear systems, and computational methods either cannot be computed or produce unreliable results [2].

Trying to deliver alarm systems in the event of faults is the purpose of fault detection. It is the purpose of fault diagnosis to identify the kind, size, and placement of faults. The observed system and our understanding of the process serve as the foundation for detection and diagnostic test methods. Therefore, measurements that have been noticed and process knowledge that is relevant to the fault are the input data of a knowledge-based fault diagnosis system. The diagnosis of valves, detectors, and components of the system can then be accomplished either using a municipal intelligence and identity method or a remote and supervisory diagnosis system. These fault detection and identity methods are widely used in a wide range of applications. The challenge with FDI is typically in making an early diagnosis. Even though algorithms with short delays are typically used for detection, diagnosis takes more time because it needs to gather data and analyze the background [3].

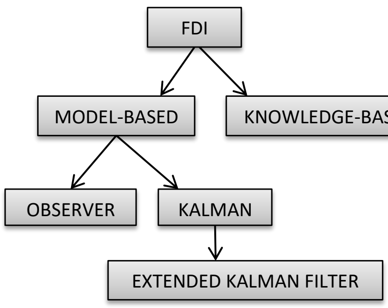


Figure 1.1. Classification of FDI

The major contribution of the proposed approach

- It performs better than the neural network approach.
- It performs similarly to the best filtering method, but with less computational complexity.
- Compared to the ideal filtering method, it is more reliable.

The paper is organised as follows: Section 2 discusses the related works; Section 3 Describes the method of fault diagnosis that uses the structures of neural networks; Section 4 Additionally reported comparisons with various Fault Detection and Isolation (FDI) approaches. Lastly, Section 5 takes the paper to a close by explaining the main points made and making some suggestions for additional scientific fields.

2. RELATED WORKS

Ene, M Donald el.al [4] introduced stochastic neural networks, which are four-layered radial basis neural networks. Through the use of a method based on the Bayes probabilistic rule, this specific type of neural network provides a solution for classification tasks.

Thirumarimurugan, el.al [5] the primary problems with hardware redundant systems include the extra machinery and construction expenditures, as well as the additional room required to store the tackle.. Diagnostic redundancy, based on residuals, overcomes the limitations of physical redundancy. A set of residuals must be produced to achieve FDI. The residual is the variation between the output response that has been measured and predicted. There are many two steps in the fault detection algorithm: residual generation and residual evaluation.

Rahimi, A. el.al [6] the Kalman Filter (KF) is a design observer that generates predictions based on a system's stochastic characteristics. Due to its robustness against measurement and process noise, the KF is easy to use. KFs are most frequently used in fault diagnosis and identification (FDI), which was thoroughly researched in the literature.

Wu, X., & Wang el.al [7] although vibration limits the effectiveness of several methods for identification, modelling, prediction, and regulation of deterministic systems, it is present in the majority of real time series observations. Preservative tones can be handled by linear systems using Kalman filtering and its extensions, such as the extended Kalman filter (EKF).

Pebrianti, D., Samad el.al [8] the method of creating the variations between the ideal model and the actual system effectiveness is known as a residual generation. And once the residual is known, a different sub-system will determine how often the system experiences failures. The more advanced FDI method also will create the location of the failures.

Simani, S., & Turhan el.al [9] To complete the modelling and identity task, a collection of neural network prediction models is developed and given instructions to mimic the actions of the systems being studied.. The results are contrasted with other control strategies taken from the relevant literature. Additionally, a Monte Carlo analysis confirms the proposed solutions' resilience to common parameter disturbances and uncertainty.

Härter, F. P., & de Campos Velho el.al [10] the weights are adjusted during the training process so that the network performs optimally when establishing the mapping of numerous input/output vector pairs. The weights are fixed after training, and the network can then be presented with new inputs to determine the corresponding outputs predicated on the information it has learned.

Calderon-Mendoza el.al [11] in contrast to additional devices suggested in the works that perform detection over a predetermined amount of period falling space, the identification technique based on the Kalman Filter used in this experiment has the main benefit of enabling frequent sequential prediction through such an integrated platform processing structure. In fault diagnosis and navigation systems, it is common practice to employ the Kalman filter and the extended Kalman filter (EKF). The Kalman filter calculates instant provinces from loud information recorded in a recursive manner.

3. METHODS AND MATERIALS

This section is organised as follows. First, define the notation and provide a brief overview of the Identification and Fault Diagnosis, while asserting the links between our recently proposed model and the neural networks. The ideal architecture and approach for neural networks based on kalman filter arrangement will be looked into in this paper.

Identification and Fault Diagnosis:

Charges accumulate for a probe's mission life, and faults/failures, if they occur, add to it. The space-based attitude control method is the most likely position for a problem to develop. The majority of actuators are made up of moving metal devices that are susceptible to unanticipated responsibilities or failings, as when a frozen weld joint degrades device conductivity, when microscopic particle contaminate metal devices, or when there are rapid temperature fluctuations. To monitor and/or predict a few of these factors, FDI methods have been created. Fault diagnosis is the identification and isolation of faults, while identification is concerned with the nature of the fault and its intensity.

Greater space probes used to have device redundant information to handle faults and/or failures because they had more inbuilt space and needed more computational power online [6]. Numerical techniques can be used to identify and fix faults when they occur (s). Whenever a system's behaviour unexpectedly changes and degrades effectiveness or restricts even the appearance of normal operating conditions, the term "fault" is used to describe it.

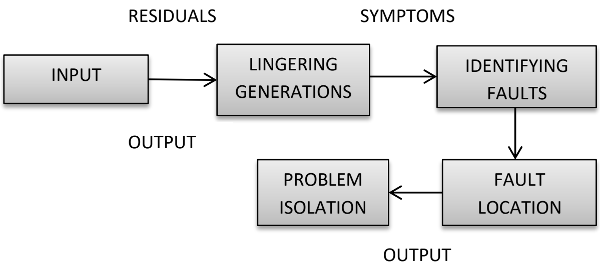


Figure 3.1. Fault diagnosis steps

As shown in Figure 3.1, the system must be able to detect the appearance of a mistake, pinpoint the location of the mistake and, for correctness, determine and which type of fault has occurred. All applications won't need these tasks; a few will only need fault detection, and others will also need isolation. Only when the corrective action is the same regardless of the fault's place or type would detection be necessary; In this case, the method or system would merely notify the operator that a fault has happened.

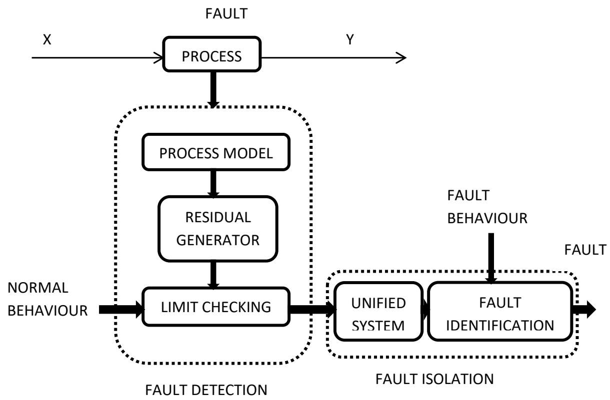


Figure 3.2. Block diagram of Fault isolation and detection methods

To determine whether a fault is present, the residual evaluator compares the residual with a criterion generated by the residual generator. Fault detection and isolation's general block diagram is displayed in Figure 3. 2.

KALMAN FILTER:

The extended Kalman filter is the method for applying the Kalman filter to a nonlinear model [10]. The Kalman filter is the finest linear unbiased estimator. A state-space illustration with the following structure can be used to define a dynamic system's statistical equation:

$$q(m+2) = b * p(m) + s(m) \qquad (1)$$

$$p(m) = d * q(m) + p(m) \qquad (2)$$

Where $p(m)$ is the reasoned output, $s(m)$ is the progression state vector, a is the transfer matrix, $q(m)$ is the procedure matrix, d is the production matrix, and $q(m)$ is the parameters are estimated structure.

A series of curving faults in the energy section with an unidentified energetic is effectively linked to the sounds s (m). The sound presented by the current source is primarily related to the measurement noise matrix $q(m)$, both are taken to be zero-mean, non-correlated white noise processes. When developing the Kalman filter, correlation coefficient variables from $p(m)$ and $q(m)$ are taken into consideration. These settings represent a compromise between improved filter estimates and a quicker filter reaction. The definition of synchronous covariance is

$$x = e[s^t\, s] and\ y = e[t^t t] \qquad (3)$$

The separate element present the estimation and filter method of the Kalman filter. In a typical circuit, the current signal is expressed by two phases, one of which has an initial phase of 1 degree and the second of which has an 80-degree shift.

$$i(n) = a1 * (\cos s_0\, t) - a2 * (sin s_0 t) \qquad (4)$$

Where the imaginary and the real components are represented by $a1$ and $a2$, two separate, zero-mean. A two-state model created during this project serves as the ideal estimator Kalman filter.

$$\begin{pmatrix} a1(n+1) \\ a2(n+2 \end{pmatrix} = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} \begin{pmatrix} a1(n) \\ a2(n) \end{pmatrix} + [s(n)] \qquad (5)$$

$$i(n) = [\cos s_0 \Delta t - sin s_0 \Delta t] \begin{pmatrix} a1(n) \\ a2(n) \end{pmatrix} + [t(n)] \quad (6)$$

In the case of measurement vibration, the setup of $a1$ and $a2$ using original standards and a prior allocation of the fault covariance matrix $q(n-2) = 0$ comes first.

$$p(m) = ap(m-2) \quad (7)$$

$$g(m) = ag(m-2)a^t + y \quad (8)$$

$$g(k) = x(m)c^t inv(cgc^t + y) \quad (9)$$

$$inno = j(m) - cp(m) \quad (10)$$

$$p(m+2) = q(m) + gk * inno \quad (11)$$

$$[x(m+1)] = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} * [x(m)] - [gk * c * x(m)] \quad (12)$$

$$i_{estimates} = px(m+1) \quad (13)$$

The adjustment mechanism calculates the fault covariance, the corrected state vector, and the advancement. using Eqs. (10) through (12). At last, Eq is used to obtain the approximate output signal (13). The Kalman filter interaction can also be displayed for consistency analytical purposes by undue. (7) and (11).

$$p(m+1) = (a - gk * t)e(m) \quad (14)$$

The model $a - gk * t$ eigenvalues must always be contained within the unification circular pattern for the Kalman filter to be nearly constant. The method described in for tuning the Kalman filter is the foundation for [11].

To keep the filters are consistent, initialize x and y with the identity matrix. The x matrix tests are then adjusted while keeping y constant. Whenever a fault event is generated, this same procedure's objective is to generate approximate state the values with little noise. Reducing values of matrix x can fulfill this condition. Consequently, following some MATLAB tests, the ideal matrix are

$$x = \begin{pmatrix} 0.002 & 0 \\ 0 & 0.002 \end{pmatrix} \; y = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} \quad (15)$$

The above matrix values enable an approximation stable solution to Equation (15). Once the model is chosen, predictions or simulation models can be made, which was the case with the neural network model [12].

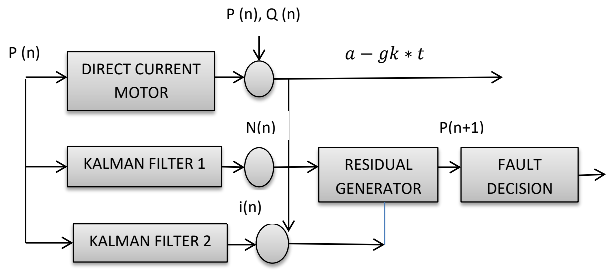


Figure 3.3. Kalman filter for defect detection

EXTENDED KALMAN FILTER:

The Kalman filtering method employs a sequence of measurements with random variation to provide estimates of unknown factors. This method of operation is recursive, suitable for inline real-time processing, and processes new data as it comes in. Once the system being considered is changing, the EKF is used because the Kalman filter could only operate with systems of equations. Suggest a nonlinear system that can be explained by the two equations below:

$$m_{t+1} = x(y_t) + v_t \qquad (16)$$

$$n_t = y(y_t) + s_t \qquad (17)$$

Where x is a variational function that delivers the program's procedure and y is the observation (nonlinear) function, and Y_t is a route that explains the system's current state. The Kalman filter offers a technique for recursively estimating the unidentified state y using monitoring value y up to time t [13].

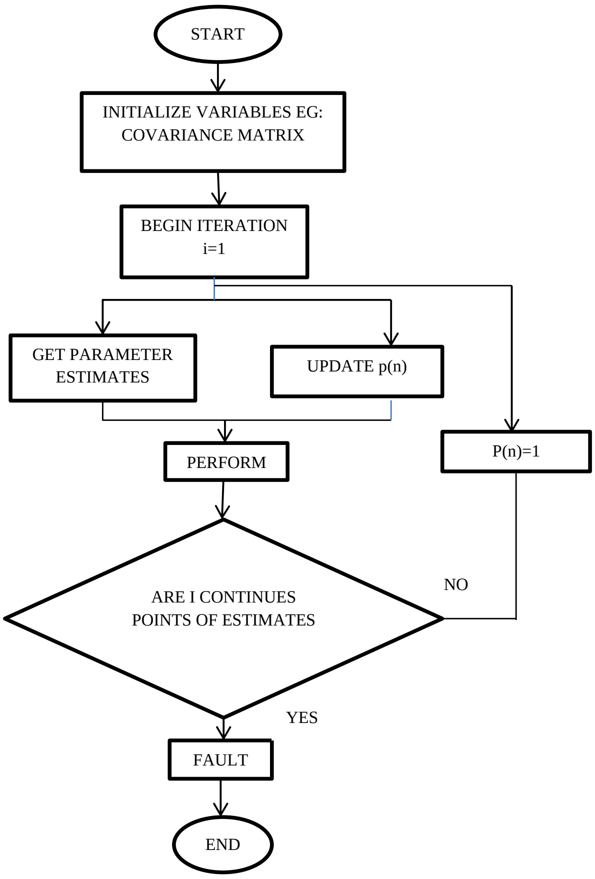


Figure 3.4. Flowchart of extended kalman filter

1. Initialization:

$m_t^a = m_0$ Where q_0 is the structure of fault covariance.

2. Next estimator step (T) th:

$$m_t^a = g(m_{t-1}^a) \qquad (18)$$

$q_t^q = l_f(m_{t-1}^a).q_{t-1}.l_s^k(m_{t-1}^a) + p_{t=1}$ Wherever $p_t = s[v_t.v_{t-1}^k]$ is the structure of procedure interference covariance.

3. The T th reparative step:

$$m_t^a = m_t^p + l_t.(n_t - y(m_t^p)), \qquad (19)$$

$l_t = q_k^q.l_h^k.(l_h(m_t^p).q_t^q.l_h^k(m_t^p) + s_t)$ Wherever $s_t = e[s_t, s_t^k]$,

$$q_t = \left(j - l_t.l_h(m_t^p)\right).q_t^p \qquad (20)$$

Where a represents the variable's real value, q its prediction, l_h its Jacobian matrix, l_f its Jacobian matrix, and l_t its Kalman gain matrix, which determines how quickly the filter adapts to new potential situations or variations of the type of data.

NEURAL NETWORK:

An input layer, a hidden layer, and an output layer are all present in this network. The mapping function and the weight training of the values that enter and exit the system connect them. Following the network's computation of the EKF, the state vectors, observation data vectors, and estimate forecasts of the filter are modified using the same weights.

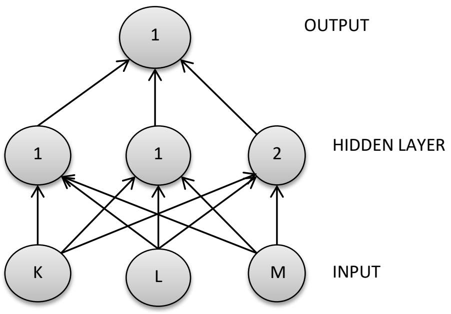


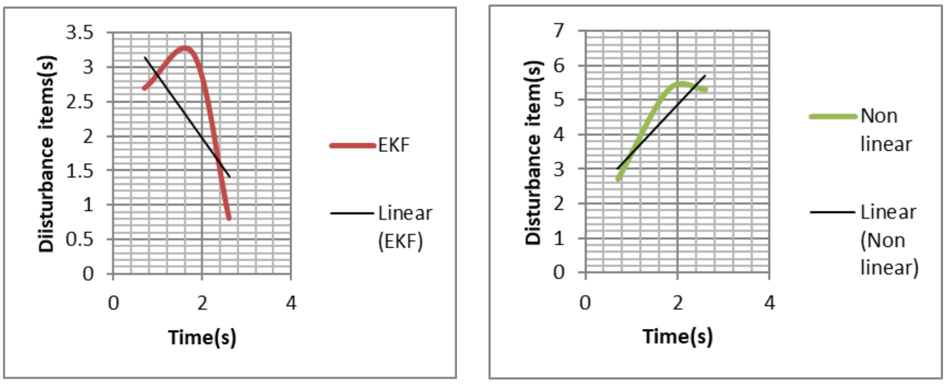
Figure 3.5. Structure of the neural network

In figure 3.5 all inputs, outputs, and network weights must first be organized as input vectors before a neural network can be trained [15].

4. IMPLEMENTATION AND EXPERIMENTAL RESULTS

The selected situation is presented first. Following that, the NN-ability EKF's to reconstruct disturbances is tested. The effectiveness of the NN models using test data was determined by the section, advanced stage state combinations are used as inputs, and their implementations to state estimation under various circumstances are discussed [14].

Assessment of the neural network models:



Figures 4.1 and 4.2. The disturbance acceleration term's estimation

Robustness Test:

This approach evaluated the parameter estimation reaction to various load conditions, just as the device was evaluated using various loading conditions in the simulation.

The following is a list of the tests:

Test 1: Frequency change with a 20 Hz step from 30 Hz to 60 Hz.

Test 2: differing the load Variation in current from 0.72 A to 2.25 A with a 0.75 A phase at a constant 30 Hz frequency.

In assay methods at numerous frequencies (30 Hz, 40 Hz, 50 Hz, and 50 Hz) and in the presence of 6%, 10%, 14%, and 18% transformer inter-turn fault in phase A, the EKF demonstrated a continual response with a load current of 0.82 A in a good position in Table 1.

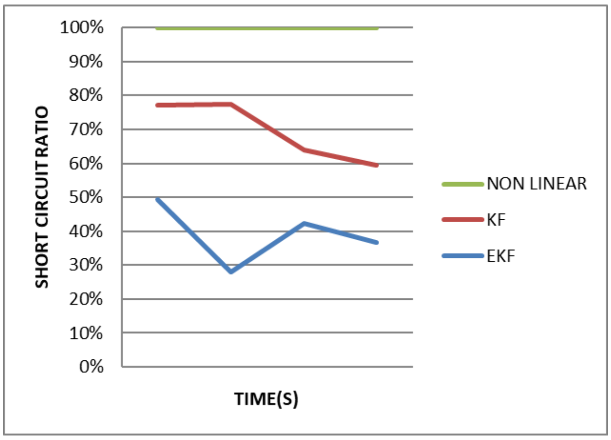


Figure 4.3. Estimation of 12-16% short circuit turns ratio in phase A

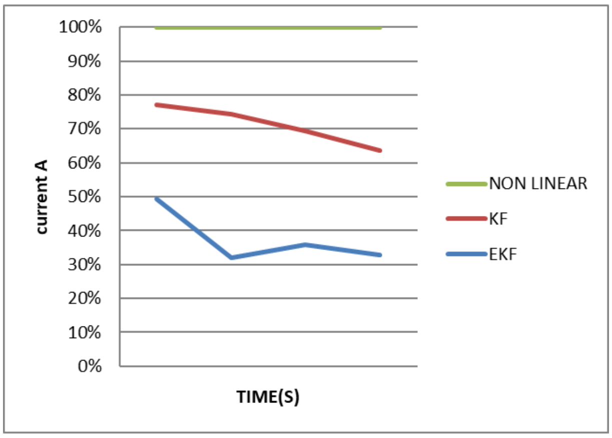


Figure 4.4. Phase A current with n/n = 16…%.

This highlighted the technique's robustness in the face of frequency variation. Additionally, the outcomes supported those of the simulation for the same machine under the same operation and maintenance and fault circumstances.

Table 1. Phase a EKF valuation reaction at constant load current and various frequencies

EVENT	OCCURRENCE	EXACT	REPLICATION	APPLIED
		%	%	%
1.	30	4%	2.16	1.95
2.	30	6%	4.4	4.62
3.	30	8%	8.4	7.52
4.	30	10%	11.3	9.77
5.	30	12%	13.22	13.1
6.	30	2%	16.9	17.5
7.	40	4%	2.16	2.97
8.	40	6%	4.4	4.8
9.	40	8%	8.4	8.85
10.	40	10%	11.3	10.81
11.	40	12%	12.24	12.8
12.	40	14%	15.8	17.1
13.	60	16%	2.3	2.97
14.	60	2%	4.4	4.7
15.	60	4%	8.6	8.53
16.	60	6%	10.3	10.9
17.	60	8%	12.4	13.3
18.	60	10%	2.3	2.2
19.	60	12%	4.3	5.1
20.	60	6%	11.2	8.94

Additionally, the prediction response was examined under different current conditions (1.6 A and 2.35 A) and at a continual frequency of 40 Hz. The EKF method once more demonstrated an accurate estimate of load current variation at a given frequency in Table 2. For safety purposes, it was unable to imitate more than 14% of low voltage inter turns faults because the current in the faulty state exceeded 6 A; 6 A becoming the ultimate load latest iteration for this device [16].

Table 2. Response to EKF estimation with various loading currents in phase A at a given frequency

EVENT	OCCURRENCE	EXACT	REPLICATION	APPLIED
		(%)	(%)	(%)
1.	0.82	4%	2.16	1.98
2.	0.82	6%	4.4	3.9
3.	0.82	8%	8.4	7.86
4.	0.82	10%	11.3	10.81
5.	0.82	12%	13.22	12.8
6.	0.82	4%	16.9	17.1
7.	1.6	6%	2.16	3
8.	1.6	8%	5.3	4.9

9.	1.6	10%	8.4	8.3
10	1.6	12%	11.3	10.9
11.	1.6	14%	13.22	12.2
12.	2.35	2%	2.3	2.97
13.	2.35	4%	4.4	4.85
14.	2.35	6%	9.5	8.9
15.	2.35	8%	11.2	10.5
16.	2.35	10%	13.3	13

Figure 4.4 displays the optimized extended Kalman filter identification results show that the suggested procedure has a greater identifier precision and a lower recognition normal deviance compared to the conventional EKF outcome shown in Figure 4.3.

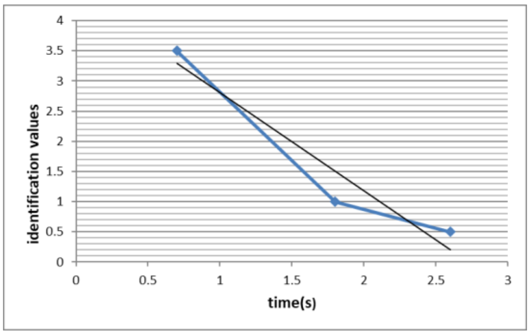


Figure 4.5. Results of an enhanced extended Kalman filter for identification

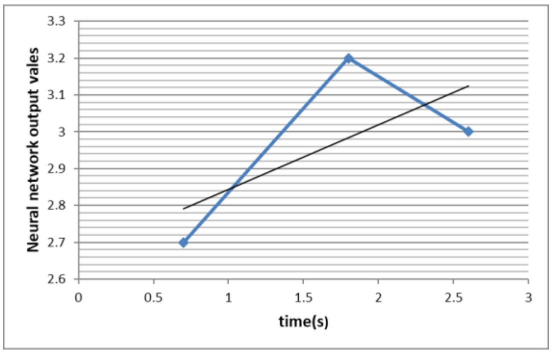


Figure 4.6. Values of neural network output

In above Figure 4.5 shows that the output only exhibits minor variations of 0.001 seconds or less. The network has good generalization capabilities and does a good job of identifying the two errors and figure 4.7 proposed diagram of extended kalman filter based neural networks.

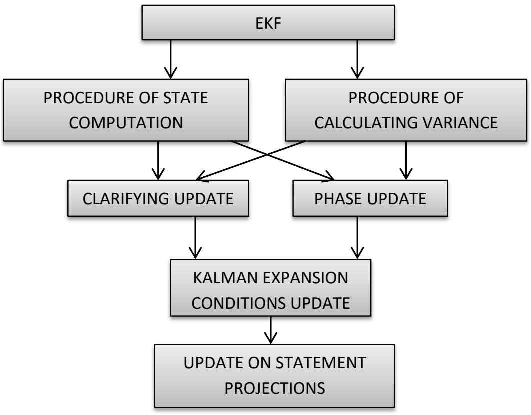


Figure 4.7. Proposed diagram of EKF-based neural networks

CONCLUSION

This paper shows how to train a neural network using Kalman filter variations. Kalman filters estimate a neural network's weights by treating the weights as a dynamic and upgradable system. The Extended Kalman Filter (EKF) is a method that many authors have used to train Neural Networks (NN) over the years. As a result, numerous authors have shown that the Kalman Filter variant is superior to the EKF in terms of convergence, speed, and accuracy. Due to its linear reprocessing methods, training with this algorithm tends to become more precise than training with EKF. The results of this study confirm the effectiveness and precision of the Kalman filter variants described by other authors, with their superior performance in nonlinear systems when compared to traditional approaches.

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