Intelligent Improvement of Kalman Filter based on Artificial Intelligence for Sensorless Speed Estimation and Control of DC Motors

Mohamed El-sayed M. Essa
Associate Professor
Electrical Power and Machines Dept,
Institute of Aviation Engineering and Technology
Egyptian Aviation Academy
Ministry of Civil Aviation
Imbaba Airport, Giza,
Egypt

Mahmoud M. Khalil
Teaching Assistant
Mathematics and Engineering Physics Dept,
Institute of Aviation Engineering and Technology
Egyptian Aviation Academy
Ministry of Civil Aviation
Imbaba Airport, Giza,
Egypt

Mohamed A. El-Beltagy
Professor
Mathematics and Engineering Physics Dept,
Faculty of Engineering
Cairo University
Giza 12613,
Egypt

The state estimation is considered as an essential and complex task for accurate and efficient plant control and monitoring in industrial applications. The measuring system including sensors is a significant investments for any control systems to monitor both non-measurable and measurable variables of state for dynamic systems. As a result, the limitation of cost can be reduced by using sensorless strategies that estimate variables of state. The aim of this paper is to implement an intelligent improved Kalman Filter (KF) based on different machine learning algorithms for sensorless speed estimation of DC motor. The intelligent methods are Artificial Neural Network (ANN), Adaptive Neuro Fuzzy Inference System (ANFIS), Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). These algorithms are used to improve and tune the KF. To improve accuracy of estimation, the parameters of KF were optimized using PSO and GA. The research explores three kinds of architectures of ANN were implemented and compared with ANFIS to estimate the motor speed, employing collected data that involved voltage, current, and outputs speed of traditional KF. The models were tested and evaluated using multiple error criteria metrics. Results indicated that ANN-based Baysian Regulation Algorithm (BR) significantly outperformed other models, achieving minimum values of error metrics. The proposed intelligent sensorless speed estimation based on ANN-based BR strategy proves potential as adaptive solution, accurate, and cost-effective methodology for speed control of DC motor. The study findings offer valuable and distinct insights for investigation cost-effective and efficient sensorless cost-effective and efficient sensorless control schemes.

Keywords: *DC Motor, Kalman Filter, Speed Estimation, ANFIS, ANN, PSO, GA.*

1. INTRODUCTION

The approach of KF has been proposed as a viable way to deal with different issues in various industrial applications. The KF is defined as a recursive mathematical algorithm that optimally estimates system states. It is also a mathematical technique that optimally estimates system states by combining multiple measurement sources, gradually improving accuracy. This method enables accurate DC motor speed estimate while mitigating the effect of noise ripple [1]. Besides, investigation of sensorless DC motors control of speed via a KF, which incorporates the motor's mathematical model, as presented in [2]. In [2], the system inputs include noisy measurements of armature current, angular velocity, and voltage, the estimated motor speed is the output of the system. The KF estimates speed, mitigating noise interference. This estimated speed is then compared to a reference value as discussed in [2].

Received: February 2025, Accepted: June 2025
Correspondence to: Dr. Mohamed El-sayed M. Essa
Institute of Aviation Engineering and Technology,
Egyptian Aviation Academy, Giza, Egypt,
E-mail: mohamed.essa@iaet.edu.eg
doi: 10.5937/fme2504525E

The study in [3], demonstrates the modeling, inspection, and impact of the KF in a noisy environment while comparing the performance of filtered controllers for a DC motor. The KF was implemented to enhance controller performance in noisy environments. The controller was designed and simulated with MATLAB, with results analyzed based on the simulated environment [3]. The research in [4], discusses recent academic developments in state estimation, focusing on integrated models that combine KFs and neural networks. This incorporation signifies an important growth in the field of technology of state estimation and demonstrating some of the research progresses, emphasizing their benefits and functions. The study starts by observing the properties and concept of KFs, comprising their different improved versions. It then delivers a short-lived introduction to numerous widely utilized ANN technique [4]. Furthermore, estimation of state plays very important role in industrial situations, helping as a basis for effective plant control and monitoring [5]. In fact, recent control systems often need expensive measurement equipment and sensors to precisely assess both unmeasurable and measurable state variables in processes of dynamic industrial. This requirement for expensive hardware poses a significant obstacle in applying comprehensive strategies of state estimation across numerous industrial applications [5].

Alternatively, in [6], it discusses an innovative method for sensorless speed control of discretely excited DC motors using technology of ANN. The suggested method relies solely on measurements of current sensor, removing the need for conventional sensors of speed and their related physical and mec–hanical limitations. By leveraging the adaptive abilities of ANN, the system forecasts the speed of motor based on two main inputs: current of motor readings from the recreated waveform of terminal voltage and the circuit of driving resulting from the pulses of PWM for the DC chopper. This strategy of sensorless control offers an efficient and powerful alternative to traditional speed measurement methods in applications of DC motor [6]. In addition, a technique of sensorless speed control ac–complished of adjusting a DC motor separately excited through ANN methodology without utilizing sensors of speed has been suggested in [7]. An algorithm of sensorless based on ANN is applied for estimating of shaft speed for DC motor in systems with closed-loop control as depicted in [8]. In this method, the ANN is utilized to give optimal adjustment, so as to increase the accuracy of the actual speed model. Three different architectures were gave and used evaluated using a set of three performance metrics. Based on the assessment results, the LM back-propagation algorithm is consi–dered as the best performance for optimal learning for this model. It was then equated with the KF in the identical conditions [8].

The research in [9], discusses the usage of an ANN for controlling the speed of DC drive without commissioning a sensor of speed. In [9], the control of sensorless system integrates an ANN based feed for–ward for speed simulation and estimation using toolbox of MATLAB-Simulink package. In [10], ANN cont–roller is demonstrated for responsive and precise regu–lation of speed. The model is structured through toolbox of ANN in MATLAB package. Furthermore, an alter–native ANN's controller was applied as a distinct replacement for the conventional PID regulators in controlling the angular DC motor position operating a robot arm. The ANN was trained utilizing supervised learning, and its performance was tested via simulations in MATLAB. The results depicted thatthe ANN strategy is a distinct selection for applications of reference con–trol in industrial usage, presenting superior performance or comparable to the PID methodology [11]. A comparative research in [12] is discussed for ANFIS and ANN as approaches for speed control of DC motor based on Matlab package. The main objective of research in [12] is to compare and evaluate the performance of two methods for control of DC motor, to obtain the greatest efficient technique to attain efficient and accurate control. Authors in [13], discusses a comprehensive study of DC motor speed control using an ANN methodology. The primary aim is to improve an adaptable and efficient system for attaining accurate regulation of speed. Through using of MATLAB, a controller of ANN has been investigated, that can precisely adjustand estimate the speed of motor to cover the chosen specifications. The research in [13], shows the practical implementation, theoretical framework, and processes with fine-tuning of the controller of ANN. The study in [13], donates to the increasing field of intelligent systems for control and gives visions into the real technology of ANN application in control engineering of motor. In [14], suggests an ANN model for adaptable the speed of a separately excited DC motor. In addition, ANN model can regulate both non-linear and linear systems via training network.

A novel hybrid method for speed control of DC motors is discussed in [15]. The used methodology merges ANN and KF methods. The core of this scheme is to use ANN to dynamically regulate the sca–ling factors of both the outputs and inputs of the control strategy. This mechanism drives to improve the res–ponse and accuracy of the motor speed, which may deliver enhanced performance in comparing to tradi–tional methods of control as presented in details in [15]. The study in [16] demonstrates the KF usage for estimation of DC motor speed. Kirchhoff's law is used to build a theoretical model based on electrical modules, while modeling of dynamic parts are utilized for the mechanical aspects. Estimation of parameters are achieved via simulations in MATLAB/Simulink package. The methodology in [16], used to develop speed control that may lead to upgraded performance in different applications [16]. A comparative analysis of different techniques for adjustable the speed of DC motors as presented in [17]. The paper in [18] focus on DC motor that are recognized for their high effec–tiveness in systems for electric traction. They are wi–dely utilized for applications with high-power, such as ship propulsion and aircraft [18]. Additionally, the authors in [19], demonstrated a novel employed of ANNs for speed control and estimation of separately excited DC motor. The kalman filter is proposed for different applications such as smart knee joint prosthesis in [20], estimation of roll angles of a motorcycle in [21], and drone SLAM in [22] which demonstrates the wide range of using of KF. The techniques suggested in this research are not only of academic interest but also have strong practical relevance. They can be used in different real-world fields and domains such as smart Knee joint prosthesis, roll angles of a motorcycle, drone, air con–ditioning system, renewable energy, battery manage–ment, vehicle localization, indoor positioning and navigation, fault diagnosis, and industrial automation where nonlinear, complex, and uncertain environments need intelligent tools of decision-making.

The motivation for this paper stems from the gro–wing demand for cost-effective, maintenance-free motor drive systems, and compact, particularly in robotics, industrial automation, electric vehicles, and other prac–tical embedded systems. Conventional speed sensors, while precise and accurate, present several limitations, including susceptibility to environmental damage, increased cost, and constraints of space. As a result, methods of sensorless estimation are highly distinct and desirable, but they constitute technical challenges rela–ted to uncertainty of model, parameter variations, and external disturbances.

It is emphasize that although traditional KFs are wi–dely utilized for tasks of estimation, their performance can destroy in the presence of un-modeled dynamics or nonlinearities. To address and cover this issue, this research present an AI-based mechanism to adaptively optimize parameters of KF in real-time. This integration permits the KFs to reject noise, better track dynamics of motor, and enhance overall performance of control. As a result, the proposed strategies consequently contributes both practically and theoretically to the field of DC motor applications. From a perspective of theoretical, it suggests a hybrid estimation approaches combining data-driven (AI) methods and the strengths of model-based KF. Besides, from a practical perspective, it improves the performance of DC motor drives in configurations of sensorless, creating them cost-efficient and more reliable. The conclusion of this paper could be summarized as points in the following.

1. Proposed different ANN techniques based on Levenberg-Marquardit Algorithm (LM), Baysian Regulation Algorithm (BR), Scaled Congugate Gradient Algorithm (SCG).
2. Proven significant reductions of error in speed estimation of DC motor using KF- based ANN-LM, KF- based ANN-BR, KF- based ANN-SCG, KF-based ANFIS, KF-based GA and KF-based PSO.
3. Comprehensive Error Evaluation based Mean Square Error (MSE), Root Mean Square Error (RMSE), Integral Square Error (ISE), Integral Time Absolute Error (ITAE) and Average Absolute Error (AAE) to compare suggested estimation models for speed estimation.
4. Showed that the ANN-based BR strategy achieved MSE of 0.2526, RMSE of 0.5026, ISE of 0.11367, ITAE of 0.0347, and AAE of 0.3422, outper–forming others techniques.
5. Demonstrated the effectiveness of PSO and GA in enhancing performance of KF, reducing errors criteria compared to traditional KF.
6. Provided recommendations for choosing models based on requirements of accuracy and system dynamics.
7. Validated obtained models using real data, underlining applicability of practical.

The rest of the article is organized as follows: Section 2 discusses the problem formulation, section 3 describes the methodology, section 4 shows the simu–lation results, and section 5 summarizes conclusions and recommends potential avenues for future research.

2. PROBLEM FORMULATION

DC motor systems often used for position and velocity control for different industrial applications [23, 24, 25]. The independently excited DC motor is chosen since the study of linear speed control for a DC motor is the main issue of this work. The velocity of the DC motor is controlled via the armature voltage control technique. With this technique, the armature voltage regulates the motor speed while the field current fixes the flux, which results in a constant flux. Figure 1 displays the DC motor's control equivalent circuit based on armature voltage control technique.

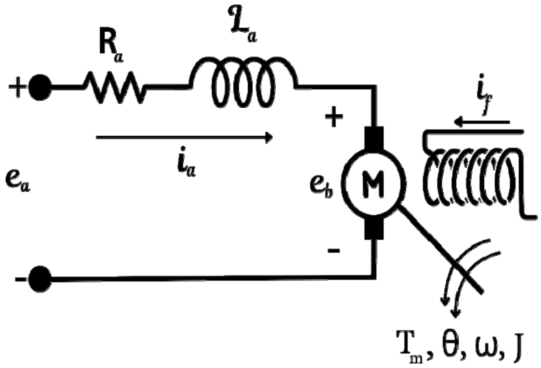

Figure 1. Equivalent Circuit of DC Motor using the Armature Voltage Control.

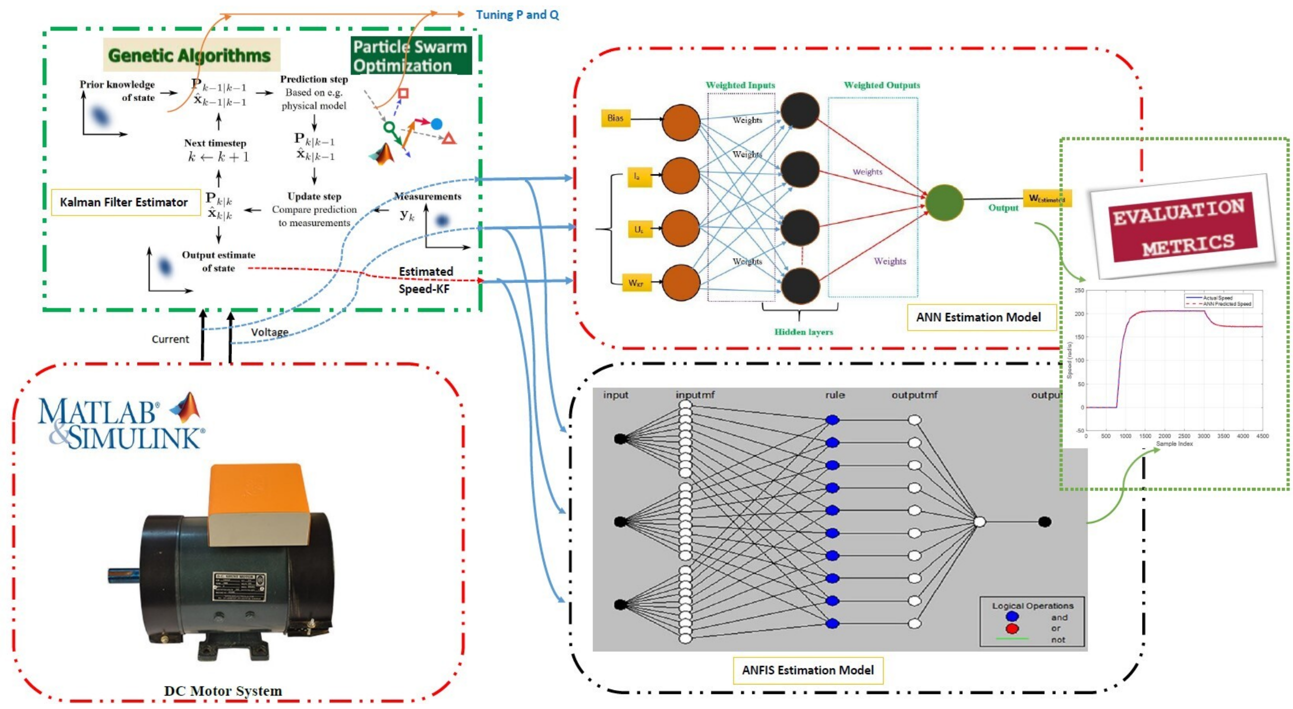

Figure 2. Proposed Structure of Speed Estimation for DC Motor

The armature resistance is denoted by R_a, the ar–mature inductance by L_a, the armature current by i_a, and the field current by i_f . e_a stands for the input voltage, and e_b for the back electromotive force (EMF). T_m indicates the motor torque, while ω shows the rotor's angular velocity. With K_b stands for the EMF constant and K_t as the torque constant, J is the motor and bearing's rotational inertia. Given that the speed ω is linearly proportional to the back EMF e_b [25]:

$$e_b(t) = K_b \cdot \frac{d\theta}{dt} = K_b \cdot \omega(t) \tag{1}$$

Using Kirchhoff's Voltage Law (KVL), we can express the armature voltage as:

$$e_a(t) = R_a \cdot i_a(t) + L_a \cdot \frac{di_a(t)}{dt} + e_b(t) \tag{2}$$

Newton's law states that the torque of the motor is given by:

$$T_m(t) = J \cdot \frac{d^2\theta(t)}{dt^2} + K_t \cdot i_a(t) \tag{3}$$

Taking the Laplace transform of (1) to (3), we ob–tain:

$$E_a(s) = (R_a + L_a \cdot s) \cdot l_a(s) + E_b(s) \tag{4}$$

$$E_b(s) = K_b \cdot \omega(s) \tag{5}$$

$$T_m(s) = J \cdot s \cdot \omega(s) = K_t \cdot I_a(s) \tag{6}$$

Figure 2 demonstrates the proposed structure of speed estimation system based on suggested intelligent techniques and optimization methods

3. METHODOLOGY

The proposed methodology includes KF, ANN, and ANFIS. Besides, the most popular optimization techniques such as GA and PSO are also proposed to fine-tune of parameters of KF. In this study, we have selected PSO and GA as the main heuristic algorithms for tasks of optimization. These techniques were chosen due to their capability to effectively explore complex and large search spaces, which are distinguishing of the problem at hand. GA is recognized for its robustness and efficient in discover global optima by mimicking processes of natural evolutionary, while PSO offers an efficient and fast search mechanism, mainly appropriate for problems of continuous optimization. Both techniques have been widely utilized in similar research areas, proving their success in achieving distinct and high-quality solutions. While other heuristic techniques and algorithms, such as Ant Colony Optimization (ACO) and Simulated Annealing (SA) were considered, PSO and GA were chosen because of their properties of better performance and faster convergence in our specific study domain. SA, for example, tends to need longer times of computational to find an optimal solution, and ACO struggles with large spaces of dimension, creating them less appropriate for this work. The used strategies are discussed in details as follows.

3.1 Kalman Filter

The KF approach is widely used in dynamic systems to reduce estimation mistakes, such as RMSE [26]. It is a popular choice for a variety of applications due to its precision and adaptability. The KF's efficiency with uncertain models enables strong projections of future occurrences as well as exact evaluation of current and historical data [27]. Several versions of KF have been produced to solve various issues, comprising the extended KF, standard KF [28, 29], ensemble KF, and unscented KF [30,31]. The standard type of KF is applied to make a distance estimation as it offers suitable criteria for decreasing noise and assuring stability in different systems such as DC motors [32], [33]. Prediction and updating are the two important phases for the KF method. The current status of the system is estimated throughout the step of prediction utilizing historical data. In addition, the stage of update improves this process of estimation through integrating extra measurements, resulting in gradually precise estimates over time. The iterative technique develops the precision of the filter with each cycle [1]. The mathematical model of the standard KF has been decreased for convenience of usage. The governing mathematical equations identify the relation–ships between the estimated variables, gain factor, and covariance matrices. By means of these mathematical equations, the KF offers a strong basis for both prediction and estimation, resulting in considerable enhancements in efficiency and performance across a varied range of applications. The mathematical representation of prediction is demonstrated in the following equations:

$$x_{t|t-1} = x_{t-1|t-1} \tag{7}$$

$$P_{t|t-1} = p_{t-1|t-1} + Q_t \tag{8}$$

Process of update created based on following, 9 to 11

$$x_{t|t} = x_{t|t-1} + PSI_M \cdot \left(y_t + X_{t|t-1}\right) \tag{9}$$

$$PSI_M = P_{t|t-1}\left(P_{t|t-1} + R\right)^{-1} \tag{10}$$

$$P_{t|t} = (1 - PSI_M) \cdot P_{t|t-1} \tag{11}$$

In this circumstance, the value of input being calcu–lated is signified by the variable x, throughout the process of estimation, the matrix of covariance is symbolized by P_t. The matrix Q_t relates to the cova–riance process of noise, accounting for uncertainties in the model. The gain Kalman factor, signified as PSI_M, is critical in regulating the estimation based on new measurements. Furthermore, the covariance matrix of measurement noise is symbolized by R, which cal–culates the uncertainty in the observed data. The notation $t|t$ point to the value of the adaptable at this time step, t-1|t-1 denotes to its value at the prior time step, and $t|t$ - 1signifies the forecasted value prior to integrating the most latest measurement.

3.2 Artificial Neural Network

ANNs are very effective in approximating complex, non-linear systems because they can identify and depict non-linear correlations in their inputs. Because of this capability, ANNs can be applied in scenarios where more conventional control strategies, such the propor–tional-integral (PI) controller, might not work well, particularly when there are fluctuations in loads, distur–bances, and system uncertainties. In difficult situations, PI controller performance can be greatly improved by integrating ANNs [34]. Interconnected neurons repre–sent input, output, and hidden layers in ANNs. Several factors influence the performance of the network, inc–luding the activation function, learning rate, neural count in the hidden layers, as well as the training pro–cess [35]. Key performance indicators for ANNs inc–lude: MSE is used to measures the accuracy of the model by evaluating. The discrepancy between expec–ted and real results, Number of Epochs refers to the number of complete training cycles through the data–set, Training Time that represents the time taken to train the network, Validation Checks is used to monitor performance and prevent overfitting during training and Gradient helping to determine how weights should be adjusted during backpropagation for improved accuracy. The deep learning and ANN are proposed for prediction and control tasks as in [36] and [37].

Since ANNs map information of input over a non–linear space, the hidden layers and number of neurons significantly impacts the ability of model to capture relationships and complex patterns in the data. Incre–asing the layers and neurons generally improves the capacity of the model to learn complicated nonlinear mappings, but it also increases and raises the overfitting risk and increases cost of computation. To guarantee effective nonlinear transformation and present nonli–nearity into the model, the Rectified Linear Unit (ReLU) is used as activation function in the hidden layers, due to it is computationally effective and helps mitigate the problem of vanishing gradient, resulting to faster and distinct convergence during process of training. Besides, different numbers of numbers of neu–rons and hidden layer are taken into consideration. The ANNs had 10, 20 and 40 hidden layers with 15 neurons in each.

3.1.1 Bayesian regularization algorithm

The method of BR entails altering the frequently used primary function, like MSE or E_d, to enhance The capacity of the model to generalize [38]. The typical primary function is expressed as:

$$F = E_d = \frac{1}{N}\sum_{i=1}^{N} e_i^2 \tag{12}$$

Where e_i is the error for each point of data, and the sum of the points of data is N. This objective function is extended to improve generalization by adding a regularization term, E_ω that represents the network weights' sum of squares. The modified objective function is given by:

$$F = \beta \cdot E_d + \alpha \cdot E_\omega \tag{13}$$

Where α and β are regularization parameters optimized within the Bayesian framework [39-41].

3.1.2 Levenberg-Marquardt algorithm

The algorithm of LM is a widespread optimization technique for training ANNs, mainly effective for redu–cing functions of error in problems of least-squares. It carries together the merits of both Gradient Descent and Gauss-Newton approaches to attain faster convergence and enhanced performance in training ANN [42-45], it is often stared as a robust marginal for optimization tasks in non-linear least squares for applications of machine learning. The significant idea overdue the algorithm of LM is to update iteratively the weights and biases of the ANN to reduce the function of MSE.

3.1.3 Scaled Conjugate Gradient algorithm

The algorithm of SCG is a conjugate gradient algo–rithms variant that enhances the process of compu–tational through avoiding the requirement for a search of line at each iteration. Conventional methods of conjugate gradient depend on searches of line, which can be computationally costly, whereas SCG is intended to bypass it, decreasing consumption of time while keeping performance. Most significant merit of SCG is that it uses a step size depending on a function of error estimation that is quadratic. As a result, it is parti–cularly tough and less sensitive to user-quantified settings [35].

3.3 Adaptive Neuro-Fuzzy Inference System

The ANFIS is a hybrid system that combines the advantages of fuzzy logic systems and neural networks to model complex systems with improved learning and generalization capabilities. ANFIS combines the interpretability of fuzzy inference systems with the learning capacity of neural networks, making it a powerful tool for various applications, including system modeling and control [46]. ANFIS is structured in a five-layer architecture, where each layer serves a specific function in processing the input data and generating the output. The fuzzification layer is a layer that uses functions of fuzzy membership to the data of input. Each node implies set of fuzzy, and the output is the degree of membership for the input in this set of fuzzy. This layer transforms crisp inputs into values of fuzzy [47, 48]. The ANFIS training includes fine-tuning the parameters of both the consequents of rule and membership functions to decrease the inconsistency between actual and expected results. This is accomplished via optimization methods such as algorithm of LM or Gradient Descent [46]. ANFIS is mostly valuable in uses where a clear sympathetic of the system is desirable, as it offers models and interpretable rules that are easy to modify and understand. Its capability to regulate to varying data and its mixture of neural network and fuzzy logic learning create it a adaptable tool for system control and modeling [46].

4. RESULTS AND DISCUSSIONS

In this research, we analyzed the speed estimation of a DC motor system utilizing a conventional KF, KF -based

ANN, KF-based ANFIS, GA-based KF, and PSO-based KF. The traditional KF, as a baseline technique, had fixed coefficients and was employed with a simple linear classical model. In addition, for the models of ANN, three various kinds were considered: LM, BR, and SCG. The three kinds of ANN had 10, 20 and 40 hidden layers with 15 neurons in each. The model of ANFIS, uniting the strengths of fuzzy logic and neural networks, was applied to capture dynamics of non-linear in the system of DC motor more effectively. The configuration of ANFIS involved of a lot of fuzzy rules with a Gaussian membership function for each variable of input. The model of ANFIS was trained with 1000 epochs and utilized a method of hybrid learning integrating least squares and gradient descent. Moreover, the optimization of the performance of KF was approved by applying two popular techniques of optimization: GA and PSO. These approaches were used to tune the parameters of filter for improved speed estimation in the system of DC motor. For GA technique, the parameters involved a size of population about 50, a rate of crossover about 0.8**,** a rate of mutation about 0.05, and a maximum value of generations set to 200. Different scenarios and error metrics were taken into account to compare and evaluate the effectiveness of these approaches. On the other hand, PSO used a size of swarm about 30 particles, a weight of inertia about 0.7, a coefficient of cognitive of 1.5**,** and a coefficient of social of 1.5**.** The strategies used in this study for speed estimation of DC motor divided into three scenarios. Scenario 1 discusses the traditional KF with fixed parameters, scenario 2 presents the improved mo–dels of estimation such as ANN and ANFIS. Besides, scenario 3 demonstrates the used of popular optimization algorithms like GA and PSO to tune the parameters of KF.

Scenario 1: speed estimation based on traditional KF

The conventional KF used as a standard estimation of the speed in the system of DC motor, achieving an MSE of 0.6513, RMSE of 0.807, ISE of 1.9539, ITAE of 2.9015, and AAE of 0.6448. While effective in giving acceptable accuracy and filtering out to some extent for high noise underneath steady environments, the KF struggled to preserve precision throughout dynamic variations in the speed of DC motor system (see Figure 3).

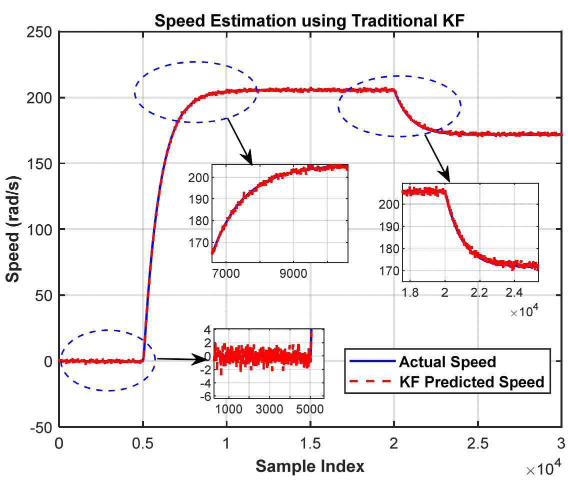

Figure 3. Speed Estimation of DC Motor based traditional KF.

The limitations were recognized to its dependence on fixed parameters and linear assumptions, which reduced it less behavior and effective in covering dynamics of non-linear intrinsic in the speed estimation of DC motor. Figure 3 presents the comparison between the actual DC motor speed and the predicted speed based on traditional algorithm of KF.

Scenario 2: speed estimation based on GA-based KF, and PSO-based KF

To further enhance the performance of KF, PSO and GA were employed to fine-tune its parameters. The GA was selected for its capability to discover the space of parameter efficiently, resulting to balanced enhancements through all metrics of error (see Figure 4), an MSE of 0.454, RMSE of 0.6738, ISE of 1.3622, ITAE of 2.5509, and AAE of 0.5772. While PSO presented faster convergence, it infrequently struggled with local minima, yielding to some extent higher errors in comparing to GA, with MSE of 0.455, RMSE of 0.6747, ISE of 1.3659, ITAE of 2.552, and AAE of 0.5672. GA con–firmed an effective exploration of the space of parameter, giving this values of errors given that balanced enric–hments across all metrics of error. PSO algorithm, with its rapid convergence, reached this results (see Figure 5), Though PSO exhibited encoura–ging results, it occasionally suited trapped in local minima, creating GA a more accurate and stable opti–mization technique. In Fig. 4, this graph proves the effectiveness of joining GA with KFs for accurate estimation of real-time speed, showcasing the ability of the system to adjust faster to sudden deviations in speed while preserving very precise predictions.

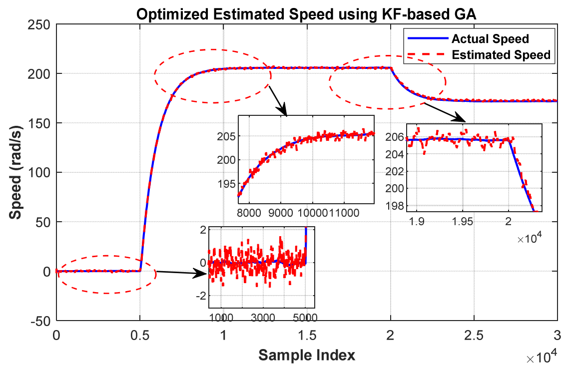

Figure 4. GA-based KF for Estimated Speed and Actual Speed.

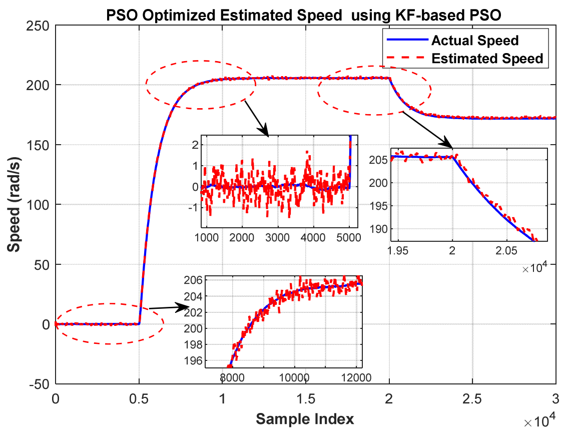

Figure 5. PSO-based KF for Estimated Speed and Actual Speed.

Moreover, in Figure 5, this graph shows the success of combining PSO with KFs for precise real-time speed estimation. The PSO-optimized estimated speed closely tracks the actual speed through sudden changes, showcasing the system's quick adaptation and high accuracy in speed prediction tasks.

Scenario 3: speed estimation based on KF-based ANN, and KF-based ANFIS

Models of ANN were established as an alternative to improve the process of estimation. Inputs comprised current (i_a), voltage (us) and speed of traditional KF (W_{KF}) while proposed estimated motor speed functioned as the output variable (W) (see Figure 6). The model of ANN used a 21000 sample for training phase, 4500 sample for testing phase, and 4500 sample for validation phase. Figure 7 shows the decaying of MSE during training ANN model with best value of MSE about 0.19719 at 1000 epoch. Besides, the training state including gradient of 0.1515 and M_U of 0.01 at 1000 epoch is depicted in Figure 7. Moreover, error histogram with 20 bins for ANN model is given in Figure 8. Figure 6 illustrates a multilayer feed-forward network that is suggested for speed estimation in this paper. However, Figure 7 displays the ANN's training performance, while Figure 8 clarifies its training state, and Figure 9 displays the error histogram.

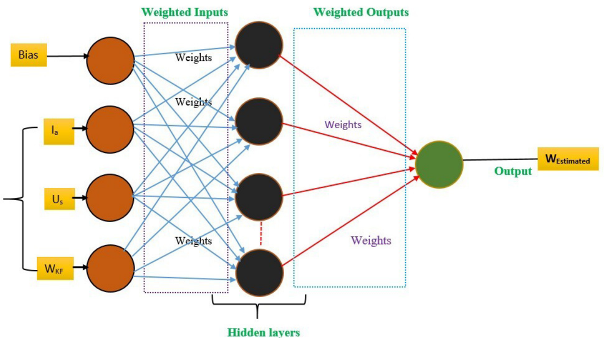

Figure 6. Schematic diagram for proposed ANN

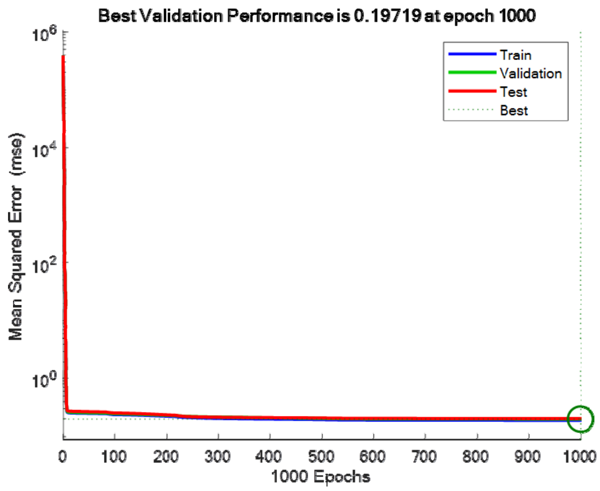

Figure 7. Training performance of ANN

Three kinds of ANNs LM, BR, and SCG were trained utilizing the captured data from the system based on different numbers of hidden layers including 10, 15 and 40. The ANN results for 10 hidden layers are provided in Table 1. This table shows the results of training an ANN model with ten hidden neurons using three distinct training algorithms: LM, BR, and SCG. The LM algorithm performed the best, with an MSE of 0.2504 and an R^2-value of 1.0000 for the training network.

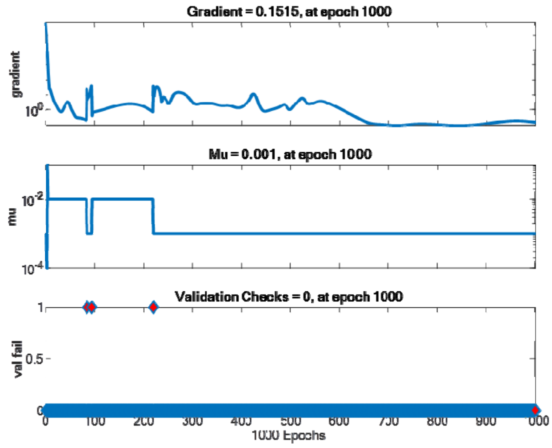

Figure 8. Training State of ANN

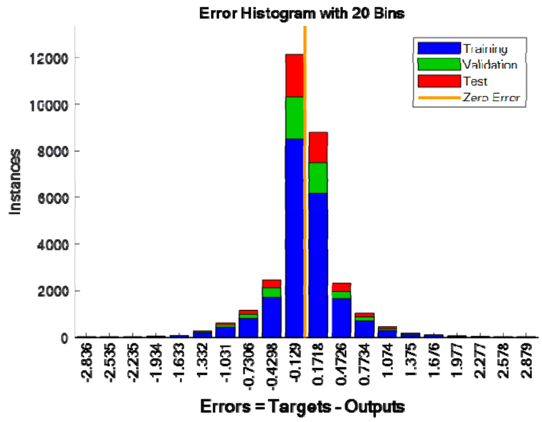

Figure 9. Error Histogram of ANN

BR was also effective, with an MSE of 0.2699 and an R^2-value of 1.0000 for the training network. In contrast, the SCG method had the highest MSE forthe training network, at 7.7113. Moreover, Table 2 shows the results of the ANN model with 20 hidden layers. Overall, performance increased as comparedto the 10-hidden neuron model. The LM algorithm continued to perform well, with an MSE of 0.2135 and an R^2-value of 1.0000 for the training network. BR and SCG both worked nicely. In Table 3, the results for the ANN model with 40 hidden layers are displayed. The LM approach achieved an MSE of 0.1878 and an R^2-value of 1.0000 for the training network, considerably improving the model's performance overthe last one. Although SCG and BR also showed good performance, the LM approach seems to be the most effective training procedure among the three models. In summary, the LM algorithm-trained ANN model with 40 hidden neurons appears to be the most successful setup based on the results (see Tables 1,2 and 3). The LM strategy outperforms others, and the model's enhanced complexity with 40 hidden neurons makes it the best option for the task at hand.

Among the three kinds of ANN, LM exhibited the best performance with MSE of 0.2398, RMSE of

0.4897, ISE of 0.1079, ITAE of 0.267, and AAE of 0.4131, followed by BR with, MSE of 0.2526, RMSE of 0.5026, ISE of 0.11367, ITAE of 0.0347, and AAE of 0.3422 (see Table 4). In addition, SCG achieved a results of MSE of 0.4233, RMSE of 0.6506, ISE of 0.19048, ITAE of 0.0493, and AAE of 0.487. While the ANNs presented significant enhancement over the classical KF, their performance was to some extent inconsistent when exposed to sudden speed variants, demonstrating sensitivity to fast variations in the studied system. The ANN-based LM, signifying its strong point in dealing with complex, relationships of non-linear in the system of DC motor (see Figure 10). The models of BR and SCG achieved sensibly well but were considerably less accurate, with achieving several of errors metrics. These results presented that while ANNs, specifically LM, offer a significant enhancement over the conventional KF, they still demonstrate some sensitivity to fast speed deviations. In Figure 10, this graph demonstrates the performance of an ANN for speed estimation. The ANN-predicted speed closely follows the actual speed through various changes, demonstrating the network's ability to accurately estimate speed in real-time, even during sudden transitions (see Table 4).

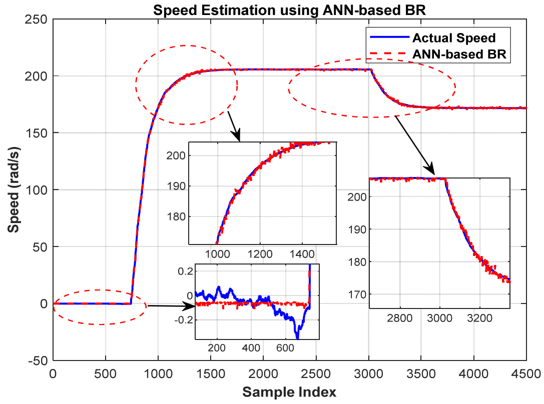

Figure 10. Estimated Speed based on ANN model with comparison to Actual Speed

The structure of ANFIS is the same of ANN model in inputs, output and number of samples. As a results, inputs included current (i_a), voltage (us) and speed of traditional KF (ω_{KF}), while proposed estimated motor speed functioned as the output variable (ω). The ANFIS model utilized a 21000 sample for training, 4500 sample for testing, and 4500 sample for checking. Figure 11 shows the training error for speed estimation using ANFIS, while Figure 12 displays the dataset checking, and Figure 13 demonstrate the testing results.

Table 1. Results of ANN for 10 Hidden Layers

Performance Metrics Training Algorithm	Results			Test Network		
	Samples	MSE	R^2	Samples	MSE	R^2
ANN-based LM	21001	0.2504	1.0000	4500	0.2574	1.0000
ANN-based BR	21001	0.2699	1.0000	4500	0.2630	1.0000
ANN-based SCG	21001	7.7113	0.9993	4500	5.0775	0.9995

Table 2. Results of ANN for 20 Hidden Layers

Performance Metrics Training Algorithm	Results			Test Network		
	Samples	MSE	R^2	Samples	MSE	R^2
ANN-based LM	21001	0.2135	1.0000	4500	0.2102	1.0000
ANN-based BR	21001	0.2854	1.0000	4500	0.2843	1.0000
ANN-based SCG	21001	0.4376	1.0000	4500	0.4297	1.0000

Table 3. Results of ANN for 40 Hidden Layers

Performance Metrics Training Algorithm	Results			Test Network		
	Samples	MSE	R^2	Samples	MSE	R^2
ANN-based LM	21001	0.1878	1.0000	4500	0.2013	1.0000
ANN-based BR	21001	0.1981	1.0000	4500	0.2050	1.0000
ANN-based SCG	21001	2.1572	0.9998	4500	1.9277	0.9998

Table 4 Comparison of performance metrics for various speed estimation algorithms

Algorithm	Type of Error				
	MSE	RMSE	ISE	ITAE	AAE
Traditional KF	0.6513	0.807	1.9539	2.9015	0.6448
KF- based GA	0.454	0.6738	1.3622	2.5509	0.5772
KF- based PSO	0.4552	0.6747	1.3659	2.5525	0.5672
ANN-based LM	0.2398	0.4897	0.1079	0.267	0.4131
ANN-based BR	0.2526	0.5026	0.11367	0.0347	0.3422
ANN-based SCG	0.4233	0.6506	0.19048	0.0493	0.487
ANFIS- based KF	0.20824	0.45633	0.6474	0.7373	0.356

The model of ANFIS, in contrast, evidenced to be a robust methodology for speed estimation. By integrating the strengths of fuzzy logic and neural networks, ANFIS covered the non-linear relations more efficiently than the models of ANN. Its capability to adapt to conditions of dynamic caused in superior performance, attaining an MSE of 0.20824, RMSE of 0.45633, ISE of 0.6474, ITAE of 0.7373, and AAE of 0.356 (see Table 4) . This benefit was mainly evident throughout abrupt variations in speed, where ANFIS reliably outperformed both the conventional KF, optimized KF based on GA and PSO and models of ANN in terms of performance metrics, filtering, accuracy and robustness (see Figure 14). In Figure 14, this plot compares the performance of a standard KF and an Integrated KF-ANFIS approach for speed estimation. The ANFIS-based KF closely track the actual speed more than traditional type, demonstrating its effectiveness in real-time speed estimation, parti–cularly during rapid changes. Figure 15 demonstrates the compa–rison between suggested techniques in this study. Figure 16 presents comparison chart for performance metrics of errors. In addition, Table 4 summarizes the obtained comparative simulation results of all approaches, disp–laying ANN-based BR as the most efficient and reliable estimation model for scenarios including fast and frequent changes in speed, while ANFIS depicted a reasonable alternative for smoother environments.

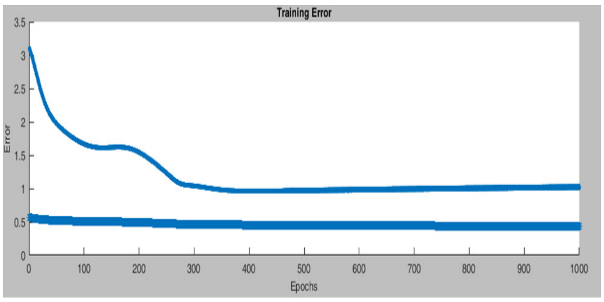

Figure 11. ANFIS Training for Speed Estimation of DC Motor

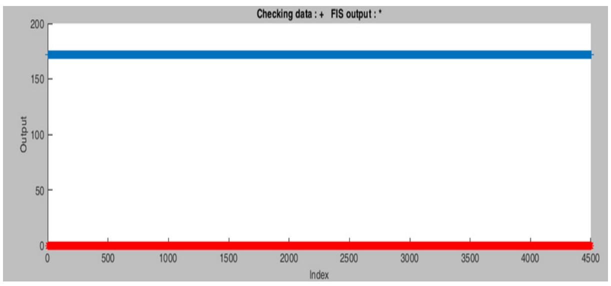

Figure 12. ANFIS Checking Dataset for Speed control of DC Motor

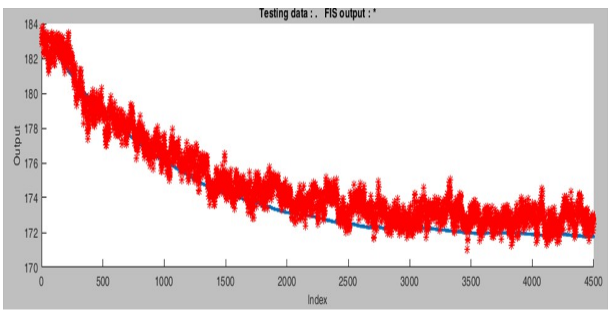

Figure 13. ANFIS Testing for Speed Control of DC Motor

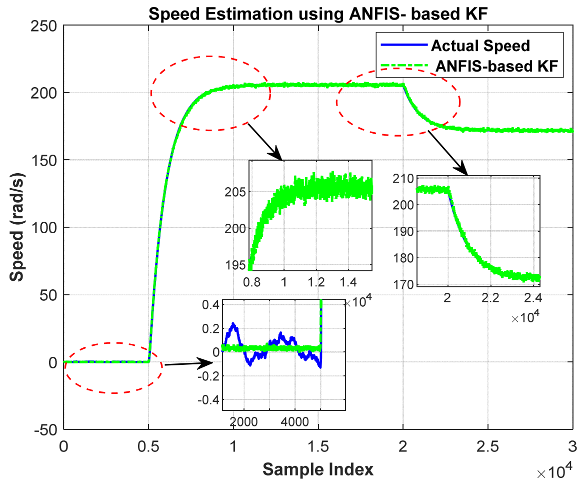

Figure 14. Speed Estimation using ANFIS-based KF

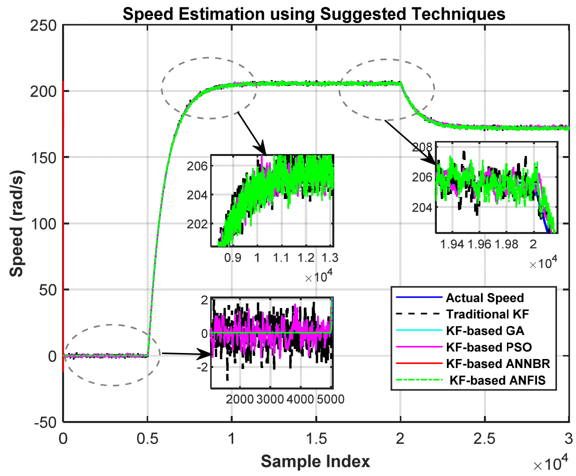

Figure 15. Speed Estimation using Suggested Techniques

5. CONCLUSION

This paper highlights the efficient and effectiveness of intelligent algorithms in enhancing accuracy of estimation task of speed for DC motor. A comparative study involving traditional KF, GA-optimized KF, PSO-optimized KF, , and hybrid approaches that incorporate nominal KF with ANN and ANFIS exposes significant and distinct disparities of performance, highlighting the importance of choosing suitable algorithms based on needs of application. ANN models, particularly BR, pointedly enhanced accuracy of estimation and outperformed others suggested models, achieving MSE of 0.2526, RMSE of 0.5026, ISE of 0.11367, ITAE of 0.0347, and AAE of 0.3422 demonstrating robustness in dynamic scenarios. The paper obviously presents how effective and efficient these strategies are in precisely the speed estimation of studied motor, which was implemented encouraging by a Matlab\Simulink package that recreates the DC motor dynamics based on identified mathematical equations. Furthermore, the paper highlights the simplicity and robustness of each methodology of speed estimation, indicating how integrating ML and optimization techniques may enhance accuracy of estimation. In order to improve accuracy of estimation, this strategy may be hybridized and optimized in the future with recent techniques.

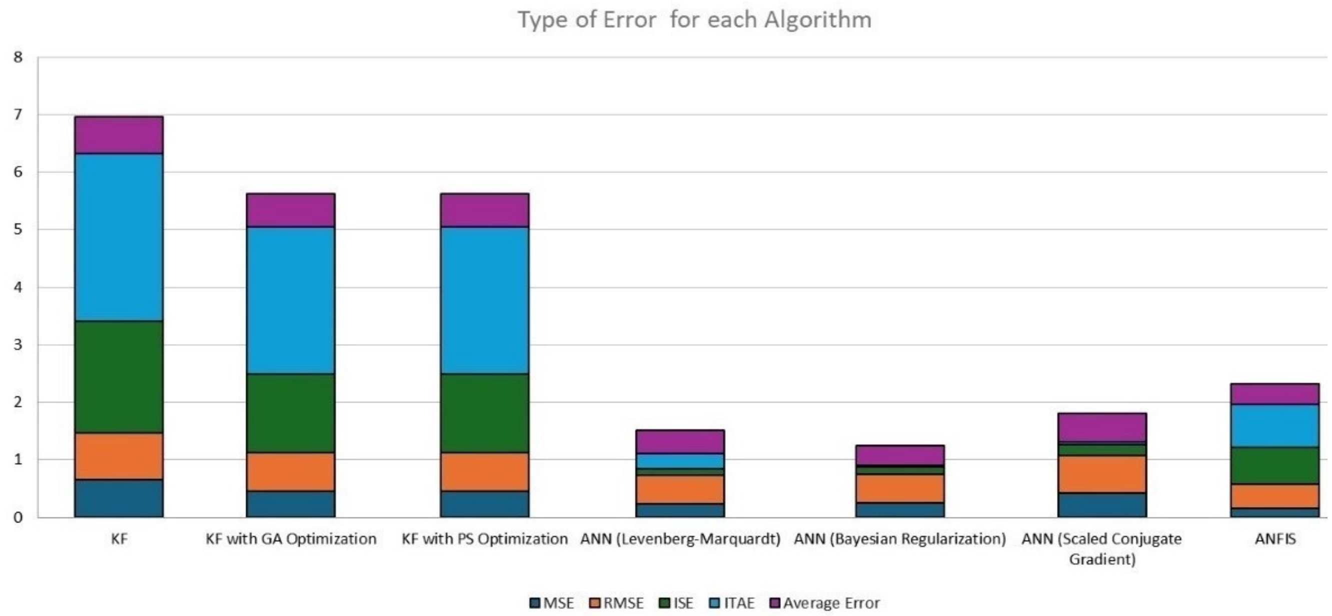

Figure 16. Comparison Chart for Performance Metrics of Errors

APPENDIX:

Motor Parameters	
Parameters	Values
Voltage (U_n)	280 V
Nominal angular speed (w_n)	172 rad/s
Power ($P_{n)}$)	1.5 kw
Torque ($T_{n)}$)	8.85 N.m
Current ($I_{n)}$)	7.2 A
Resistance ($R_{a)}$)	6.41 Ω
Inductance (L_a)	23 mH
Moment of inertia (J)	0.026 Kg.m^2
Sampling time ($T_{s)}$)	10^{-4} s
Time delay (T_{delay})	2 T_s

REFERENCES

[1] Setiawan, M. H., Ma'arif, A. Rekik, C. Abougarair A. J., Mekonnen, A., "Enhancing speed estimation in dc motors using the kalman filter method: A comprehensive analysis," *Jurnal Ilmiah Teknik Elektro Komputer dan Informatika*, vol. 10, no. 1, pp. 30–38, 2024.

[2] Praesomboon, S., Athaphaisal, S., Yimman, S., Boontawan, R., Dejhan, K., "Sensorless speed control of dc servo motor using kalman filter," in *2009 7th International Conference on Information, Communications and Signal Processing (ICICS)*. IEEE, 2009, pp. 1–5.

[3] Abut, T., "Modeling and optimal control of a dc motor," *Int. J. Eng. Trends Technol*, vol. 32, no. 3, pp. 146–150, 2016.

[4] S. Feng et al. "A review: State estimation based on hybrid models of kalman filter and neural network," *Systems Science & Control Engi–neering*, vol. 11, no. 1, p. 2173682, 2023.

[5] Tripathi, R. P., Singh, A. K., Gangwar, P., "Frac–tional order adaptive kalman filter for sensorless speed control of dc motor," *International Journal of Electronics*, vol. 110, no. 2, pp. 373–390, 2023.

[6] Allu, A. A. Antar, R. K., "Design and modeling of speed sensorless control of dc motor drive system," *Al-Rafidain Engineering Journal, Unive–rsity of Mosul, College of Engineering*, vol. 22, no. 5, pp. 89–100, 2014.

[7] Dakhil, A. M., Jasim, B. H., "Speed sensorless control based artificial neural network for direct current motor," *University of Thi-Qar Journal for Engineering Sciences*, vol. 5, no. 1, pp. 73–84, 2014.

[8] Aydogmus, Z., Aydogmus, O., "A comparison of artificial neural network and extended kalman fil–ter based sensorless speed estimation," *Measurement*, vol. 63, pp. 152–158, 2015.

[9] Brandstetter, P., "Sensorless control of dc drive using artificial neural network," *Acta Polytechnica Hungarica*, vol. 11, no. 10, pp. 5–20, 2014.

[10] Zaidan, M. R., "Impact of artificial neural network for dc motor speed control over the conventional controller," *Journal of Engineering and Applied Sciences*, vol. 13, no. 21, pp. 9156–9163, 2018.

[11] Aamir, M., "On replacing pid controller with ann controller for dc motor position control," *arXiv preprint arXiv:1312.0148*, 2013.

[12] Maidanov, A. Atanov, S. K., Canbolat, H., Aljawarneh, S. A., "Advanced control strategies for dc motor speed regulation: A comparative study of artificial neural networks and anfis." in *DTESI (workshops, short papers)*, 2023.

[13] Sharma, M., "A review on dc motor speed control using artificial neural network," *International Journal of Engineering, Science and Mathematics*, vol. 7, no. 8, pp. 27–33, 2018.

[14] Kumar, S. B., Ali, M. H., Sinha, A., "Design and simulation of speed control of dc motor by artificial neural network technique," *International Journal of Scientific and Research Publications*, vol. 4, no. 7, pp. 1–4, 2014.

[15] Amiri, M. S., Ibrahim, M. F., Ramli, R., “Optimal parameter estimation for a dc motor using genetic algorithm,” *Int. J. Power Electron. Drive Syst*, vol. 11, no. 2, pp. 1047–1054, 2020.

[16] Mohamed, M. E. A., Guo, Y., “Separately excited dc motor speed tracking control using adaptive neuro-fuzzy inference system based on genetic algorithm particle swarm optimization and fuzzy auto-tuning pid,” in *IOP Conference Series: Earth and Environmental Science*, vol. 300, no. 4. IOP Publishing, 2019, p. 042114.

[17] Mahmood, Z. S., Nasret, A. N., Mahmood, O. T., “Separately excited dc motor speed using ann neural network,” in *AIP Conference Proceedings*, vol. 2404, no. 1. AIP Publishing, 2021.

[18] Dzung, P. Q., Phuong, L. M., “Ann-control system dc motor,” *IEEE Transactions*, pp. 82–90, 2002.

[19] Kamel, S. H., Hamzah, M. N., Abdulateef, S. A., Atiyah, Q. A. (2023). A Novel Design of Smart Knee Joint Prosthesis for Above-Knee Amputees. *FME Transactions*, *51*(2).

[20] Romualdi, L., Mancinelli, N., De Felice, A., Sorrentino, S. (2020). A new application of the Extended Kalman Filter to the estimation of roll angles of a motorcycle with Inertial Measurement Unit. *FME TRANSACTIONS*, *48*(2), 255-265.

[21] Šoštarić, D., Mester, G. (2019). Drone SLAM using TDOA-RSS signal with applied EKF on PF data. *FME Transactions*, *47*(4), 914-924.

[22] Montiel, O., Sepulveda, R., Melin, P., Castillo, O., Porta, M. A., Meza, I. M., “Performance of a simple tuned fuzzy controller and a pid controller on a dc motor,” in *2007 IEEE Symposium on Foundations of Computational Intelligence*. IEEE, 2007, pp. 531–537.

[23] Kamaruddin, N., Janin, Z., Yusuf, Z., Taib, M., “Pid controller tuning for glycerin bleaching pro–cess using well-known tuning formulas-a simula–tion study,” in *2009 35th Annual Conference of IEEE Industrial Electronics*. IEEE, 2009, pp. 1682–1686.

[24] Kanojiya, R. G., Meshram, P., “Optimal tuning of pi controller for speed control of dc motor drive using particle swarm optimization,” in *2012 international conference on advances in po–wer conversion and energy technologies (APCET)*. IEEE, 2012, pp. 1–6.

[25] Feng, D. et al., “Kalman-filter-based integration of imu and uwb for high-accuracy indoor positioning and navigation,” *IEEE Internet of Things Journal*, vol. 7, no. 4, pp. 3133–3146, 2020.

[26] Maghfiroh, H., Nizam, M., Anwar, M., Ma’Arif, A., “Improved lqr control using pso optimization and kalman filter estimator,” *IEEE Access*, vol. 10, pp. 18 330–18 337, 2022.

[27] Yan, W., Zhang, B., Zhao, G., Tang, S., Niu, G., Wang, X., “A battery management system with a lebesgue-sampling-based extended kalman filter,” *IEEE Transactions on Industrial Electronics*, vol. 66, no. 4, pp. 3227–3236, 2019.

[28] Liu, J., Guo, G., “Vehicle localization during gps outages with extended kalman filter and deep learning,” *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–10, 2021.

[29] Carquex, C., Rosenberg, C., Bhattacharya, K., “State estimation in power distribution systems based on ensemble kalman filtering,” *IEEE Tran–sactions on Power Systems*, vol. 33, no. 6, pp. 6600–6610, 2018.

[30] Fan, R., Liu, Y., Huang, R., Diao, R., Wang, S., “Precise fault location on transmission lines using ensemble kalman filter,” *IEEE Transactions on Power Delivery*, vol. 33, no. 6, pp. 3252–3255, 2018.

[31] Ye, L., Woodford, N., Roy, S., and Sundaram, S., “On the complexity and approximability of optimal sensor selection and attack for kalman filtering,” *IEEE Transactions on Automatic Control*, vol. 66, no. 5, pp. 2146–2161, 2021.

[32] Lian, B. et al., “Robustness analysis of distributed kal–man filter for estimation in sensor networks,” *IEEE Transactions on Cybernetics*, vol. 52, no. 11, pp. 12 479–12 490, 2022.

[33] Lai, Y.-S., Chen, J.-H., “A new approach to direct torque control of induction motor drives for constant inverter switching frequency and torque ripple reduction,” *IEEE Transactions on Energy Conversion*, vol. 16, no. 3, pp. 220–227, 2001.

[34] Babani, L., Jadhav, S., Chaudhari, B., “Scaled conjugate gradient based adaptive ann control for svm-dtc induction motor drive,” in *Artificial Intel–ligence Applications and Innovations: 12th IFIP WG 12.5 International Conference and Workshops, AIAI 2016, Thessaloniki, Greece, September 16-18, 2016, Proceedings 12*. Springer, 2016, pp. 384–395.

[35] Gavali, P. M., Yadav, S. D. (2024). Predicting Automotive Air Conditioning System Performance through Deep Learning. *FME Transactions*, *52*(3).

[36] Perišić, N., Jovanović, R. (2023). Control of direct current motor by using artificial neural networks in Internal model control scheme. *FME Transac–tions*, *51*(1), 109-116.

[37] Doan, C. D., Liong, S.-y., “Generalization for multilayer neural network bayesian regularization or early stopping,” in *Proceedings of Asia Pacific association of hydrology and water resources 2nd conference*, 2004, pp. 5–8.

[38] MacKay, D., “A practical bayesian framework for backpropagation networks,” *Neural Computation - NECO*, vol. 4, 05 1992.

[39] MacKay, D. J., “Bayesian interpolation,” Neural computation, vol. 4, no. 3, pp. 415–447, 1992.

[40] Foresee, F., Hagan, M., “Gauss-newton approxi–mation to bayesian learning,” vol. 3, 07 1997, pp. 1930 – 1935 vol.3.

[41] Levenberg, K., “A method for the solution of cer–tain non-linear problems in least squares,” Quar–terly of applied mathematics, 1944.

[42] Hagan, M. T., Demuth, H. B., Beale, M. H., Neural Network Design. PWS Publishing Co., 1996.

[43] Bishop, C. M., Neural Networks for Pattern Recog–nition. Oxford University Press, 1995.

[44] Beale, M. H., Hagan, M. T., Demuth, H. B., Neural Network Toolbox User's Guide, MathWorks, Inc., 1992.

[45] Jang, J.-S., "Anfis: adaptive-network-based fuzzy inference system," IEEE transactions on systems, man, and cybernetics, vol. 23, no. 3, pp. 665–685, 1993.

[46] Takagi, T., Sugeno, M., "Fuzzy identification of systems and its applications to modeling and control," IEEE transactions on systems, man, and cybernetics, no. 1, pp. 116–132, 1985.

[47] Lin, C.-T., Lee, C. S. G., "Neural-network-based fuzzy logic control and decision system," IEEE Transactions on computers, vol. 40, no. 12, pp. 1320–1336, 19

NOMENCLATURE

U_n	Voltage
w_n	Nominal angular speed
P_n	Power
T_n	Torque
I_n	Current
R_a	Resistance
L_a	Inductance
J	Moment of inertia
T_s	Sampling time
T_{delay}	Time delay
PSI_M	Gain Kalman Factor
$e_a(t)$	Input Voltage
$e_b(t)$	Back electromotive force (EMF).
$\theta(t)$	Rotor position angle
K_b	EMF constant
K_t	Torque constant
P_t	Matrix of covariance
Q_t	Covariance Process of Noise
R	Covariance Matrix of Measurement Noise
x	Value of input being calculated
$t\|t$	Notation point to the value of the adaptable at this time step
$t-1\|t$-1	Value at the prior time step
$t\|t-1$	Forecasted value prior to integrating the most latest measurement
F	Objective Function
e_i	The error for each point of data
N	Sum of the points of data.
E_d	Typical primary function of BR
E_ω	Network Weights
α and β	Regularization parameters optimized

Acronyms and abbreviations

AAE	Average Absolute Error
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
ACO	Ant Colony Optimization
BR	Bayesian Regularization
DC	Direct Current
EMF	Electromotive Force
GA	Genetic Algorithm
ITAE	Integral of Time-weighted Absolute Error
ISE	Integral of Squared Error
KVL	Kirchhoff's Voltage Law
KF	Kalman Filter
KFNNS	KF and Neural Network Succession
LM	Levenberg-Marquardt
MSE	Mean Squared Error
MMSE	Minimum Mean Square Error
RMSE	Root Mean Square Error
PWM	Pulse Width Modulation
PSO	Particle Swarm Optimization
PID	Proportional-Integral-Derivative
SEDCM	Separately Excited DC Motor
SCG	Scaled Conjugate Gradient
SA	Simulated Annealing

ИНТЕЛИГЕНТНО ПОБОЉШАЊЕ КАЛМАНОВОГ ФИЛТЕРА ЗАСНОВАНО НА ВЕШТАЧКОЈ ИНТЕЛИГЕНЦИЈИ ЗА ПРОЦЕНУ БРЗИНЕ И УПРАВЉАЊЕ ЈЕДНОСМЕРНИМ МОТОРИМА

М.Е.М. Еса, М.М. Халил, М.А. Ел-Белтаги

Процена стања се сматра суштинским и сложеним задатком за прецизно и ефикасно управљање и праћење постројења у индустријским применама. Мерни систем који укључује сензоре представља значајну инвестицију за било који систем управљања за праћење и немерљивих и мерљивих променљивих стања динамичких система. Као резултат тога, ограничење трошкова може се смањити коришћењем безсензорских стратегија које процењују променљиве стања. Циљ овог рада је имплементација интелигентног побољшаног Калмановог филтера (KF) заснованог на различитим алгоритмима машинског учења за процену брзине једносмерног мотора без сензора. Интелигентне методе су вештачка неуронска мрежа (ANN), адаптивни неуро-фази инференцијски систем (ANFIS), генетски алгоритам (GA) и оптимизација роја честица (PSO). Ови алгоритми се користе за побољшање и подешавање KF. Да би се побољшала тачност процене, параметри KF су оптимизовани коришћењем PSO и GA. Истраживање истражује три врсте архитектура вештачких неуронских мрежа (ВНМ) које су имплементиране и упоређене са ANFIS-ом ради процене брзине мотора, користећи прикупљене податке који укључују напон, струју и излазну брзину традиционалног KF-a. Модели су тестирани и евалуирани коришћењем вишеструких метрика критеријума грешке. Резултати су показали да је Бајсов регулациони алгоритам (БР) заснован на ВНМ значајно надмашио друге моделе, постижући минималне вредности метрика грешке. Предложена интелигентна процена брзине без сензора заснована на БР стратегији заснованој на ВНМ доказује потенцијал као адаптивно решење, тачна и исплатива методологија за контролу брзине једносмерног мотора. Резултати студије нуде вредне и различите увиде за истраживање исплативих и ефикасних шема управљања без сензора.