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DISTRIBUTED SYSTEMS FOR SIMULATION ANALYSIS OF MOTOR DRIVE SYSTEMS USING ADAPTIVE ALGORITHMS

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Abstract. High processing needs and latency make it difficult to simulate motor drive systems in distributed environments, which affect accuracy and real-time performance. Optimizing motor control and cutting energy use require effective modeling. Conventional simulation techniques have trouble scaling up and down, frequently demanding large amounts of resources and being unable to adjust to changing load circumstances, which leads to sluggish or imprecise simulations. This method improves scalability and lowers latency by dynamically adjusting computing loads in a distributed system through the use of adaptive algorithms. It improves the accuracy and efficiency of simulation by utilizing real-time adaption and parallel processing. The purpose of this work was to suggest distributed systems for motor drive system simulation analysis utilizing adaptive algorithms. Initially, the dataset was gathered from a test bench-mounted momentum permanent magnet synchronous motor (PMSM) in a three-phase system motor vehicle. The exponentially weighted moving standard deviation (EWMS) utilized in standardized data process representations for training. We proposed the Adaptive Controller with dynamic fuzzy system ensemble (AC-DMFSE) for distributed systems for simulation analysis of motor drive systems. To optimize motor performance in dynamic situations, adaptive techniques are used, such as fuzzy logic-based optimization and model predictive control. Our test findings show that the suggested distributed technique reduced simulation times and MSE while enhancing the accuracy of system performance evaluation. The foundation for scalable and effective motor drive system simulations is laid by this work, which also offers insightful information for improving the systems' performance in practical applications.

Key words: Simulation Analysis, Motor Drive Systems, permanent magnet synchronous motor (PMSM), exponentially weighted moving standard deviation (EWMS), Adaptive Controller with dynamic fuzzy system ensemble (AC-DMFSE)

1. Introduction. To create a distributed system that uses adaptive algorithms to simulate and analyze motor drive systems. In this regard, motor drive systems are essential parts of many industrial applications, such as automation systems, manufacturing machinery, and electric cars. Conventional simulation techniques for examining complex systems frequently result in inefficiencies since they need large amounts of computing power and centralized handling. Many processing nodes operate in parallel by utilizing a distributed system technique, greatly cutting down on the amount of time needed for simulations. The system incorporates adaptive algorithms to enhance simulation speed and accuracy by dynamically modifying system parameters in response to demands and conditions in real time [4].

Traction motors for new energy vehicles (NEVs) need be modified for challenging operating conditions in contrast to industry motors. They alternate between motoring and generating on a regular basis. The automobile industry demands a lot from its vehicles: frequent starting and stopping, rapid acceleration and deceleration, high torque at low speeds and high power during high-speed climbing, high power density, large, highly efficient operating area, low vibration and noise, high reliability, and a high performance-to-price ratio. The essential components for transforming the electromechanical energy in NEVs are traction motors and motor power electronic controllers [2].

Either an end-to-end controller or a structured controller can serve as the foundation for the AC system. The end-to-end controller is a single core controller that processes input from sensors to provide the required torque [1]. Conversely, the organizational framework is based on an upper and a lower controller. In the AC command hierarchy, every controller has a major function. While the higher control functions as a decision layer, the lower controller is a control layer. The car would maintain a speed that the driver had initially pre-set;

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this is known as a speed control mode, provided there were no leading vehicles ahead of it and the road was clear [14].

Key advantages of this system include increased precision, scalability, and shorter simulation times all of which are critical for enhancing motor drive designs, boosting energy efficiency, and cutting development costs in many industries [20]. Real-world implementation, however, is not without its difficulties. These include managing the complexity of integrating adaptive algorithms into various hardware and software ecosystems, minimizing network latency, and guaranteeing synchronization across dispersed nodes. In order to fully utilize distributed systems in motor drive simulations, several issues need to be resolved. As a result, we suggested using distributed systems and adaptive algorithms to simulate and analyze motor drive systems.

The design and deployment of sophisticated motor drive systems in modern vehicles as well as in industrial applications demands innovative simulation methods that are accurate and efficient. Distributed environments offer an interesting opportunity for overcoming the challenges of simulating large systems, but current approaches do not perform well in integrating optimization techniques with dynamically changing scenarios. This research is driven by the necessity to create a framework that is adaptive and scalable while integrating advanced tools such as fuzzy logic, model predictive control and real time adaptation. By altering the amount of computing workload and decreasing the amount of latency, the proposed Adaptive Controller with Dynamic Fuzzy System Ensemble (AC-DMFSE) aims at transforming the way motor drive system simulations are performed. As such, this study aims at attaining the desired theoretical level and implementing sophisticated methods for the improvement of the motor control, energy consumption and performance of distributed systems.

1.1. Research contributions. The study contribution concerned networked systems for adaptive algorithm-based simulation analysis of motor drive systems.

1. The dataset was originally collected from a three-phase system motor vehicle with a momentum permanent magnet synchronous motor (PMSM) installed on a test bench.
2. The training representations for standardized data processes use the exponentially weighted moving standard deviation (EWMS).
3. We presented the Adaptive Controller with Dynamic Fuzzy System Ensemble (AC-DMFSE) for distributed systems purpose of simulating motor drive systems,. Adaptive methods, like fuzzy logic-based optimization and model predictive control, are used to maximize motor performance in dynamic conditions.

1.2. Organization of the research, . The remainder of the document is structured as follows: In Section II, pertinent material is reviewed. We discuss the concept, the methodology, and the importance of the intended effort in Section III. The procedures and results of the experiment are described in Section IV. Section V summarizes the analysis and offers some recommendations for further study.

2. Related works. A summary of the most current particular investigations is provided below, along with the accompanying solutions. The research [5] improved the intelligence, adaptability, and resilience of smart production-logistics systems, a self-adaptive collaborative control (SCC) mode is suggested. Cyber-physical systems (CPSs) and the industrial Internet of things (IIoT) are utilized to gather and interpret real-time status data for the purpose of optimization and decision making. This work [16] offered an adaptive Fractional Order PID (FOPID) controller that uses the Artificial Bee Colony (ABC) method to enhance the performance of a Brushless DC (BLDC) motor. This work [15] examined a class of nonlinear systems that have sensor failures and an uncertainty problem. The architecture of the suggested control strategy is predicated on the backstepping process. In order to demonstrate the viability of the suggested system, a simulation of a single-link robot arm example is performed. The study [13] covered the history of electric vehicle (EV) motors, different types of EV motors, mathematical modeling of EV motor drives, and EV motor design process. The hardware outcomes have also been contrasted using various BLDC hub and SRM control strategies. This work [12] demonstrated its superiority over all existing signature identification techniques by outperforming them all. Afterwards, the indices created with the suggested technique were fed into a fuzzy decision box. The ultimate outcomes, which combined suggested methods with fuzzy decisions, were discovered to be 100% correct and effective. The research [10] suggested a unique control scheme for a commuter pull-in hybrid vehicle's adaptive real-time energy management. As long as the deterministic driving condition is met, the simulation results demonstrate that the suggested technique can achieve an optimal energy distribution on a nearly global optimal level, or near the dynamic programming (DP) level. In order to improve cloud computing data access storage techniques, HDFS was established in the study [17]. Next, the effect algorithm is used to optimize both the data block size and the Internet of Things' topology. At last, the file storage design has been optimized. It is demonstrated through simulated experiments that the optimized cloud storage approach provides clear performance benefits in terms of memory utilization and file read and write speeds. This work [3] introduced the frequency control for the engine generators that manage an islanded MMG's frequency. By taking operating point fluctuations and load uncertainty into account, the suggested method minimizes the rejection of uncertain disturbances and lessens the effects of nonminimum phase dynamics brought on by engine delay. A virtual adaptive inertia control (VAIC) approach is presented in this research [18]. The dual extended Kalman filter is used to estimate the states of energy storage battery packs (ESBPs) in real time. Throughout the microgrid's whole operation, it can reduce voltage fluctuations, enhance system stability, and accomplish decentralized and coordinated control. This work [11] described a DTC of the Double Fed Induction Motor (DFIM) powered by two voltage inverters. Based on a Genetic Algorithm (GA), which has been proposed for optimizing the PID controller's parameters through a weighted combination of objective functions, the DFIM's regulation speed is regulated using a PID controller. The research [6] suggested a optimizing the energy distribution of hybrid energy storage systems (HESS) and its enhanced semi-active architecture in order to further minimize energy loss and degradation of battery capacity. The simulation's findings demonstrate that, under various driving scenarios, battery capacity degradation and energy loss are reduced when compared to the conventional MMC and semi-active topologies. This work [9] presented a controller tuning algorithm called the multi-role exploration strategy distributed deep deterministic policy gradient (MESD-DDPG). It expands on the deep deterministic policy gradient (DDPG) by using a multi-role exploration strategy among other tricks. The simulation results show that the MESD-DDPG adaptive PI controller performs exceptionally well and is highly adaptive.

2.1. Research Gap. The motor drive system dynamic modeling in a distributed environment is extremely challenging mainly due to the high computational requirements, time lag, and lack of scalability. Traditional simulation methods are primarily impeded by harsh static resource provisioning and adjustment to the workload, thus being inefficient and inaccurate in real-time performance. These conventional approaches have also reported the use of energy optimization without considering the dynamic nature of the conditions under which the control systems are implemented. Furthermore, very few studies have reported the fusion of adaptable algorithms such as fuzzy logic based optimization and model predictive control into distributed systems for the case of motor simulation. This gap calls for appropriate mechanisms which are urgently needed to deal with the timing characteristics, precision, and the conformativeness while applying the proposed models in real-life scenarios.

2.2. Problem statement. The difficulty of precisely modeling and analyzing motor drive systems in real-time across distributed environments is the root cause of the issue in Distributed Systems for Simulation Analysis of Motor Drive Systems using Adaptive Algorithms. As motor drive systems become increasingly complex, traditional simulation techniques find it difficult to meet the needs of large computational loads, real-time performance, and adaptability. Adaptive algorithms provide an answer by optimizing performance through dynamic parameter adjustments. To ensure simulation accuracy and efficiency, however, integrating these methods into a distributed system for real-time simulation poses a number of issues, including synchronization, communication latency management, and distributing the computing load among nodes. The problem is even more difficult in real-time settings where system design, control validation, and optimization depend on precise and timely simulation findings. Additionally, conventional methods are constrained by their incapacity to scale effectively, adjust to varying system characteristics, or handle the massive volumes of data produced during the simulations, leading to a slower analysis and inferior overall performance.

3. Proposed system model. The lower computer measurement implements random position control in the distributed motor control system with random position control. The random number algorithm generates the sequence, and then control debugging occurs. The distributed motor measurement and control system's adaptive analysis extraction principles should be compatible with random position control technology, high precision control, precise signal collection, stability and reliability, and model training and generalization capacity. For verification and analysis, the research chooses the random position control and the random number

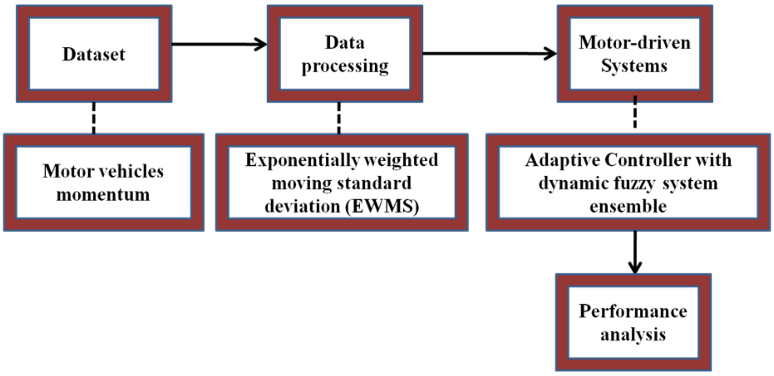

Fig. 3.1: Overall Proposed System

sequence performance. Fig 3.1 depicts the overall proposed architecture.

In the case when Fuzzy Logic is used for control purposes, it fakes human Qualitative Judgment in order to modify motor control parameters. It is a rule based method wherein input variables which include, motor speed, load torque, temperature etc. are controlled through fuzzy membership functions.

Input Variables: Motor speed interruptions caused by deviations, and variations in load torque.

Fuzzy Rules: If the speed deviation is high and the load torque is low, increase the motor current.

These rules allow motor parameters such as current, voltage, etc. to be constantly adjusted in order to improve energy consumption efficiencies whilst ensuring operational stability. Fuzzy Logic achieves this by having the motor performance monitored automatically so as to adjust the motor performance and reduce energy wastage according to changes in load behavior.

Fuzzy control in addition helps oneself to application development by forecasting the future state of the system including a reasonable state error. It can also be defined as PFC where P is predictive and F is Fuzzy control. It is one of the methods of control operation and predictions that use the physical model of the motor system to establish the probable trajectories in the time frame that has been set earlier. Some of the steps undertaken while working with MPC include:

1. State Estimation: The current state of the system is defined as the last recorded state utilization information such as the motor voltage and current.
2. Optimization: The main function of the MPC observational algorithm is to establish the probable movements of the motor in the near future. It achieves this as it has a pre-defined cost function most of the time for the speed deviation minimization or the power usage minimization.
3. Implementation: The control action must first be selected from the sequence and this action repeats itself as new information is collected about the system. The proposed architecture also utilizes fuzzy logic and Adaptive Controller with Dynamic Model Predictive Fifth Element which integrates model predictive capability in structure control with fuzzy adaptable rule base decision logic integration. Fuzzy helps out in reaction orientation to current active participation, whereas MPC assures maintaining and controlling the robustness in a more strategic sense over a long period.

3.1. Dataset. The dataset comprises 140 hours of multivariate indicators taken at a frequency of 2 Hz from an a 3-phase system motor vehicles momentum permanent magnet synchronous motor (PMSM) (52 kW) that is installed on a test bench[8]. The motor speed of the PMSM is controlled by torque, and it is fed by a two-level IGBT inverter (Semikron: 3xSKiiP 1242GB120-4DW). In addition, a test bench is equipped with a dSPACE DS1006MC rapid-control-prototyping system. dSPACE analog-digital converters, which have been synchronized with the control task, recorded all measurements.

3.2. Data processing. Standardized data representations must be used for training purposes. Each feature is then scaled further to show unit variance in the training set by subtracting the mean from every observer. All input signals x have their exponentially weighted moving average (EWMA) and exponentially weighted standard deviation (EWMS) conformed to the original input space. Thus, as extra regressors, for each signal z_s at time step s, the following two values are given.

$$\mu_s = \frac{\sum_{k=0}^{s} y_k z_{s-k}}{\sum_{k=0}^{s} y_k} \tag{3.1}$$

$$\sigma_s = \frac{\sum_{k=0}^{s} y_k (z_s - \mu_s)}{\sum_{k=0}^{s} y_k} \tag{3.2}$$

Here $y_k = (1-\alpha)_k$ and s is an arbitrary span and $\alpha = 2/s+1$. Strong linear regressors are indicated by different smoothed versions of all time series and their standard deviation that result from multiple, differently spanned EWMAs and EWMSs. To limit memory requirements, only four alternative values for the span in the EWMA and EWMS computation are simultaneously examined. In light of this, the total number of input quantities, which is constant across all tests, indicates 108 characteristics.

Combined with the linear regression the EWMA shifts the focus from the noise in the short term fluctuations in the data. It helps trends or patterns to be more identifiable. This is handy in dealing with inputs with lots of noise, such as in sensor readings or in motor control datasets. With EWMA, more importance is placed on more current observations, allowing for more changes to be introduced to the entire dataset which is ideal for monitoring ever-changing conditions. EWMS takes into account variability in the data on a moving basis, with the most emphasis given to the most current and recent ones, thereby assisting in the interpretation of the changes in data dispersion or volatility most up to the moment. This model stated that the cubic weighting function can effectively suppress the influence of outliers and past observations' noise while still allowing for standard estimates of variability since skewed distributions are known.

Shift of variance in processes and systems is easy to be captured by EWMS however such change can indicate the existence of problem or instability in the system which may lead to failure. This is vital in many industrial settings especially in motor drive systems.

3.3. Adaptive Controller with dynamic fuzzy system ensemble for motor-driven Systems. The motor's performance is tested during the entire process of design, development, and manufacture. The window motor in use has a start-stop location and start-stop interval that follow a normal distribution law rather than being uniformly distributed with equal probability. This must adhere to the specifications for the motor test, accurately depict the motor's operating circumstances, and simulate passenger handling behaviors during the test. In order to increase test efficiency and achieve adaptability, the research incorporates random position control into the motor control system. A distributed motor control system with one primary control center managing three motors for testing is the need for the system test.

There are n-order subsystems in the multivariable PMSM servo system breakdown. For each stage in the design process, the corresponding state variables' control law and parameter adaptive law are solved to enable the step's state variables to reach the necessary asymptotic properties. Ensure that the goal angle z_c is tracked by the motor angle $\dot{z}_1$.

Step 1: In accordance with (3.3) first, insert two errors.

$$\begin{cases} \dot{z}_1 = z_2 \\ \dot{z}_2 = b_1 z_{31} + b_1 z_2 + e + c \\ \dot{z}_{31} = b_2 z_{31} + b_2 z_2 z_{32} + b_3 z_2 + b_3 v_p \\ \dot{z}_{32} = b_2 z_{32} + b_2 z_2 z_{31} + b_3 v_c \end{cases} \tag{3.3}$$

$$w_1 = z_1 - z_c \tag{3.4}$$

$$w_2 = z_2 - \alpha_1 \tag{3.5}$$

Step 2: Next, as per (3.3), introduce the third fault. Since there is no field weakening control with this control approach $\alpha_{21}(\text{the d} - \text{axis current}) = 0$.

$$w_{31} = z_{31} - \alpha_{21} \tag{3.6}$$

Step 3: The third and fourth differential equations in equation (3.3) are addressed at this point. The final phase involves simultaneously solving two control laws because this system has multiple inputs. After determining in Step 2 that α_{21} is a function of z_{31}, z_{32} and $\alpha_{31} = 0$, errors (3.7) and (3.8) from the previous step are built based on this information to determine the system's final input.

$$w_{31} = z_{31} - \alpha_{31} \tag{3.7}$$

$$w_{32} = z_{32} \tag{3.8}$$

The real PMSM servo steering system's unknown properties are taken into consideration in the control technique design. If certain factors can be precisely determined beforehand using sophisticated measurement techniques, create the FSE combination model for forecasting. Using each fuzzy logic classifier, this method sorts the dataset and generates a probability outcome. They are mixed probability outputs to produce an ensemble output. The formula for the FSE combination prediction model is provided by equation (3.9):

$$\hat{z}_s = \sum_{k=s}^{m} x_k \hat{z}_s^k \tag{3.9}$$

In equation (3.13), $\hat{z}_s^k$ denotes the predicted value of the kth predictive model for the given year t, x_k stands for the kth model's weight coefficient, $\hat{z}_s$ for the combined model for the same year s, and m is the number of cities. Equation (3.10) shows how the weights are calculated using the DMFSE approach, which uses mean square error:

$$x_k = \overline{\Big[\Big[\sum_{s=1}^{t} \gamma^{t-s+1} (z_s - \hat{z}_s^s)^2\Big] * \Big\{\sum_{k=1}^{m} \Big| \sum_{s=1}^{t} \gamma^{t-s+1} (z_s - \hat{z}_s^s)^2 \Big]^{-1} \Big\}} \tag{3.10}$$

The discount factor is denoted by γ, while the data length utilized for weight calculation is represented by t. The FSE model can be obtained as illustrated in equation (3.11) by replacing equation (3.11) into Eq. (3.10).

$$\hat{z}_s = \sum_{k=s}^{m} x_k \hat{z}_s^k = \sum_{k=s}^{m} \overline{\Big[\Big[\sum_{s=1}^{t} \gamma^{t-s+1} (z_s - \hat{z}_s^s)^2\Big] * \Big\{\sum_{k=1}^{m} \Big| \sum_{s=1}^{t} \gamma^{t-s+1} (z_s - \hat{z}_s^s)^2 \Big]^{-1} \Big\}} \tag{3.11}$$

We implement the FSE mixed-model predictive model that has been tuned with the controller method.

The goal of this study is to convert the discount factor γ used in weight calculations into a matrix so γ^{t-s+1} that the difference between expected and actual values at various time periods can be eliminated. Equations (3.12) and (3.13) represent the weight equation and the improved predictive model, respectively.

$$x_k = \frac{1}{\Big[\Big[\sum_{s=1}^{t} \gamma^{t-s+1} (z_s - \hat{z}_s^s)^2\Big] * \Big\{\sum_{k=1}^{m} \Big| \sum_{s=1}^{t} \gamma^{t-s+1} (z_s - \hat{z}_s^s)^2 \Big]^{-1} \Big\}} \tag{3.12}$$

$$\hat{z}_s = \sum_{k=s}^{m} x_k \hat{z}_s^k = \sum_{k=s}^{m} \frac{\mathbb{C}_s^k}{\Big[\Big[\sum_{s=1}^{t} \gamma^{t-s+1} (z_s - \hat{z}_s^s)^2\Big] * \Big\{\sum_{k=1}^{m} \Big| \sum_{s=1}^{t} \gamma^{t-s+1} (z_s - \hat{z}_s^s)^2 \Big]^{-1} \Big\}} \tag{3.13}$$

Table 4.1: Evaluation of Current and Proposed Methods' Performance

Methods	**Performance Metric of Proposed and Existing Methods**		
	MSE (%)	**Simulation Time (Sec)**	**Motor Frequency (%)**
IPSO-GA[19]	56	90	82
LFDNM[7]	45	77	90
AC-DFSE [Proposed]	37	65	97

Find the best matrix of discount factors. The selection of $\mathbb{C}$ should not be done randomly, since it could result in poor prediction performance. Hence, the optimization problem of the objective function is used to determine the discount factor matrix γ^{t-s+1}. Using a variety of forecast time points and models, the controller seeks out the best discount factors. Get the best potential predictions by plugging in the best possible discount factors into the model.

The effectiveness and dependability of the entire control system can be raised with this tactic. These findings show that the measuring and control system performs exceptionally well in terms of voltage stability. In the meantime, it is possible to retain the least amount of voltage variations under various working situations, guaranteeing the motor's excellent stability and dependability. As a result, the data collection system can record the electrical current and voltage level at the motor's two ends in real time. The accuracy test requirements are satisfied because the relative error is within 0.8.

The AC-DMFSE model is incorporated in a multi-variable Permanent Magnet Synchronous Motor (PMSM) servo system which is subdivided into several subsystems. Each subsystem is controlled with adaptive laws to accomplish the required performance by managing state variables. laws are responsible for attempting to alter parameters of the motor, including Zc (the goal angle). They work by controlling torque, speed, and voltage amongst many other variables in real time.

4. Experimental analysis. The numerical evaluation of AC-DFSE for distributed systems for simulation analysis of motor drive systems is presented in this part. This research proves that the offered strategy works wonders. In this study, we evaluate our suggested approach in comparison to current methods, including improved particle swarm optimization–genetic algorithm (IPSO-GA) [19], and Lévy flight distribution Nelder–Mead (LFDNM) algorithm [7]. The following indicators are essential for assessing how well distributed systems for simulation analysis of motor drive systems. This study examined a number of parameters, including motor frequency, MSE and stimulation time. Table 4.1 compares the performance of the existing approaches with the recommendations.

4.1. Motor Frequency. The term "motor frequency" describes the number of cycles per hour at which the electrical system of the motor runs. It is equivalent to the supply frequency of the electrical current that powers alternating current (AC) motors. Usually, the electrical supply's frequency and the motor's speed are proportionate.

Fig. 4.1 shows how effective the motor frequency is. With an efficacy of at least 97%, the recommended AC-DFSE is far less effective than cutting-edge methods like 82% IPSO-GA and 90% LFDNM. Since motor frequency directly impacts the motor's speed and performance, it is a crucial component in motor drive system simulations. The dynamic behavior of the motor may change if its frequency is changed, which could jeopardize the accuracy of the simulation analysis.

4.2. MSE (Mean Squared Error). A statistical metric called mean squared error is used to express how much the actual and anticipated values differ from one another. The average of the squared differences between these two sets of values is determined.

$$MSE = \frac{1}{q}\sum_{l=1}^{q} |a_m - \hat{a}_m| \tag{4.1}$$

Here,

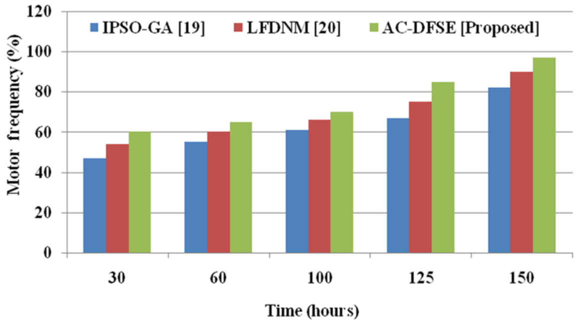

Fig. 4.1: Motor Frequency

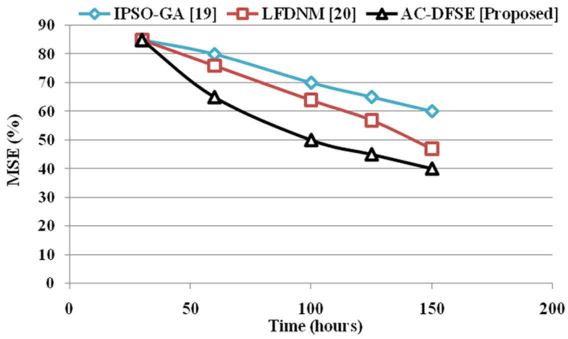

Fig. 4.2: MSE Analysis

a_m is the observed value,
$\hat{a}_m$is the predicted value,
$\overline{a}_m$ is the mean of the observed values,

The effectiveness of the current and recommended strategies is shown in Fig. 4.2. At least 40% efficacy is produced by the suggested AC-DFSE, a far cry from state-of-the-art methods like 60% IPSO-GA and 47% LFDNM. MSE is frequently used in motor drive simulations to assess an adaptive algorithm's effectiveness by gauging how effectively the algorithm can forecast the behavior of the system over time. The predictions are shown by lower mean square error (MSE), which is important for optimizing the algorithm's parameters.

4.3. Simulation Time. The term "simulation time" describes the amount of time that a motor or system is exposed to a specific input or excitation, like torque, voltage, or current. It is the period of time that the motor's reaction to this input is monitored and examined in the context of simulation. The motor's dynamic response analysis is impacted by the duration of stimulus. Engineers can predict transient behaviors and modify the control algorithm by observing how quickly the motor responds to changes in input by adjusting the stimulation time.

Figure 4.3 illustrates the effectiveness of the existing and recommended solutions. Compared to state-of-the-art methods like 81% IPSO-GA and 67% LFDNM, the suggested alternatives can achieve up to 55% maximum efficiency. IPSO-GA and LFDNM tests show that the suggested method outperforms the existing one in terms of Simulation time for the motor drive system.

5. Conclusion. This work proposed AC-DMFSE for distributed systems of simulating motor drive systems. The dataset was originally collected from a three-phase system motor vehicle with a momentum PMSM installed on a test bench. The training representations for standardized data processes use the EWMS. Adaptive

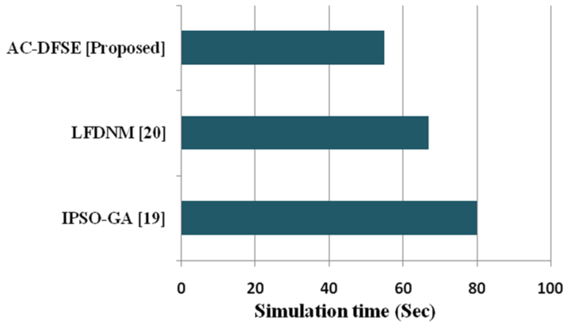

Fig. 4.3: Simulation Time

methods, like fuzzy logic-based optimization and model predictive control, are used to maximize motor performance in dynamic conditions. Simulations and experimental validation show that the robot performs better than existing methods in improving accuracy, simulation time and MSE. According to the simulation results, the suggested AC-DMFSE performed better than the others in terms of motor frequency (97%), simulation time (55sec), and MSE (40%). Challenges such as network latency, synchronization problems between distributed nodes, and the difficulty of implementing adaptive algorithms across heterogeneous hardware platforms are encountered by the distributed system for simulation study of motor drive systems. Furthermore, communication network performance may limit scalability, and sophisticated data handling methods may be needed to manage big information in real time. Future developments might concentrate on enhancing scalability through cloud computing, integrating machine learning for more adaptive algorithms, and optimizing network infrastructure for reduced latency. In future, models that would merge this technique with neural networks or other deep models would enhance their capacity to perform on tasks that have a non-linear trend and interdependencies.

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