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CONTENTS

Research Articles:

- 1 Neural Networks-Based 12-Sector Direct Torque Control of Asynchronous Machine Drives: Experimental Results**
Abdessmad Milles, Habib Benbouhenni, Adil Yahdou, Nicu Bizon
- 32 Benchmarking Deep Learning Architectures for 24-Hour Energy Forecasting in Smart Buildings Using Real-World IoT Data**
Jura Arkhangelski, Rakibul Hasan, Mahamadou Abdou Tankari, Gilles Lefebvre
- 41 Neural Networks in Control Systems for Multi-Drive Facilities of Metallurgical Enterprises**
Stanimir Valtchev, Tatyana Sinyukova, Alexey Sinyukov
- 55 Frequency Stability Control in Low-Inertia Microgrids Using Optimized Virtual Damping Stabilizers**
Sabo Aliyu, I. Dabo Abdulmalik, Dauda Dahiru, K. Abubakar Tureta, Kenneth Okedu, N. Izri Abdulwahab
- 74 ML Models for Predicting Remaining Useful Life-Time of EV's Batteries for Stakeholders**
Ali Sina Saifi, Serik Aibol, Ibragim Kuandykov, Berik Zayniddinov, Ruslan Omirgaliyev, Nurkhat Zhakiyev

Review Articles:

No review articles are included in this issue.

Neural Networks-Based 12-Sector Direct Torque Control of Asynchronous Machine Drives: Experimental Results

Abdessmad Milles *, Habib Benbouhenni **, Adil Yahdou ***, Nicu Bizon****

* University of Bordj Bou-Arerdj, Algeria.

** Department of Electrical Engineering, Faculty of Technology, Hassiba Benbouali University of Chlef, Chlef, Algeria.

*** University of Chlef, Chlef, Algeria.

**** The National University of Science and Technology Politehnica Bucharest, Pitești University Centre, 110040 Pitesti, Romania.

(abdessmad.milles@univ-bba.dz, habib0264@gmail.com, a.yahdou@univ-chlef.dz, nicu.bizon1402@upb.ro)

† Corresponding Author: Habib Benbouhenni, Department of Electrical Engineering, Faculty of Technology, Hassiba Benbouali University of Chlef, Chlef, Algeria, habib0264@gmail.com.

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Abstract- Achieving optimal performance from industrial asynchronous motors requires precise control of both torque and magnetic flux. The conventional six-sector direct torque control (6-DTC) method is widely used for this purpose, but it suffers from several drawbacks, including significant torque and flux ripple and excessive switching activity in the power converter, which leads to energy losses. This research addresses these issues by introducing an enhanced control method that integrates neural networks (NNs) with a refined twelve-sector direct torque control (12-DTC) scheme. Unlike traditional approaches that depend on hysteresis comparators and fixed lookup tables, the proposed NN-based controller intelligently determines voltage vectors in real time, enabling smoother and more adaptive motor operation. Simulation studies verified the method's effectiveness, showing substantial reductions in torque ripple, improved control tracking, and lower total harmonic distortion (THD). Experimental validation on a dSPACE DS1104 hardware platform confirmed these improvements in practice. The 12-sector NN-DTC achieved THD reductions of 30.87%, 42.22%, and 49.73% across different test conditions, along with 47% faster dynamic speed response. Overall, the proposed neural network-based 12-sector DTC represents a significant advancement over the traditional 6-DTC. It delivers smoother performance, more rapid response, higher efficiency, and robust real-world applicability—offering a more precise and energy-efficient solution for controlling industrial asynchronous machines.

Keywords: Neural networks, asynchronous machine, direct torque control, 12-sector DTC, torque ripple, THD reduction.

1. Introduction

Advancements in highly efficient technologies have expanded the range of applications for electrical machines (EMs) within industrial settings, including the asynchronous machine (AM). Numerous researchers in the literature have

proposed various approaches for controlling these types of EMs, such as the conventional direct torque control (DTC) and field-oriented control (FOC) [1, 2].

The DTC approach involves directly selecting the inverter's switching states through a predefined switching

table (ST), offering advantages like a simple structure and rapid response when compared to the FOC strategy. However, the basic DTC technique relies on hysteresis comparators (HCs) that operate with variable switching frequencies (SFs), leading to significant torque and flux ripples that can negatively impact the performance of the AM [3-5].

To address the limitations of the conventional DTC technique, many researchers have suggested enhancements that maintain a constant SF and minimize torque and flux ripples. One of the designed solutions is the application of space vector modulation (SVM) to the DTC strategy, which effectively manages the SF and minimizes flux, torque, and current fluctuations.

The SVM-DTC approach replaces HCs with proportional-integral (PI) regulators to produce the reference voltage components [6]. Although this algorithm significantly improves performance, it requires precise information about the system's parameters [7].

In [8], sliding mode controllers (SMCs) were introduced as a substitute for linear PI regulators to achieve a more robust and nonlinear control. This approach offers strong dynamic performance and high resilience to external disturbances. However, a major disadvantage of this technique is the phenomenon known as "chattering," which restricts the motor's operational range. Table 1 presents various studies that address the drawbacks of applying the DTC technique to the rotor speed control of an AM.

In the literature, various studies have utilized AMs in renewable energy (RE) systems. Reference [16] describes the design of a wind turbine (WT) emulator using a squirrel-cage AM and a separately excited direct current machine to emulate WT behavior in a laboratory environment. The system incorporates user-friendly software for selecting wind data and WT models, alongside hardware for real-time control and monitoring. Key components include a PI-controlled AM, a non-isolated step-up converter supporting maximum power point tracking (MPPT), and a load simulator for evaluating efficiency under variable conditions. The emulator facilitates the testing of small-scale wind systems while providing comprehensive electrical and mechanical data monitoring. However, the study focuses primarily on design and simulation, with limited exploration of advanced control strategies or thorough experimental validation under diverse environmental conditions, which may restrict its broader applicability.

In the work of Ghizlane et al. [17], a photovoltaic-powered water pumping system was designed, utilizing a three-phase AM controlled through a sinusoidal PWM (SPWM) technique. The system incorporates a DC-DC boost converter managed by a perturb-and-observe MPPT algorithm to optimize energy extraction from the photovoltaic array. A PI controller adjusts the SPWM frequency to regulate the motor speed according to the calculated reference speed, ensuring operation at maximum efficiency. MATLAB/Simulink simulations were performed to test the system under varying climatic conditions, demonstrating the

PI regulator's effectiveness in maintaining motor speed and extracting maximum power. The study emphasizes the importance of integrating RE sources for sustainable water pumping solutions. However, the approach experiences torque oscillations during climatic variations, indicating a need for more advanced control strategies or improved tuning of the PI regulator to ensure smoother operation.

In [18], a single-phase induction motor is proposed to be powered by a solar system, using a DTC strategy to control the operation of this machine. Additionally, a matrix-type power converter is used to change the motor speed and manage the inverter output voltage. Using this converter allows for significant improvements in current and torque quality compared to a conventional inverter. This proposed strategy has been implemented in the MATLAB environment, and the results demonstrate the effectiveness of the designed approach in improving the quality of current and torque compared to the traditional approach. The drawback of the proposed approach lies in the use of a matrix converter, which is characterized by complexity, high costs, and difficulty in implementation.

In the work by Masood et al. [19], a variable frequency drive (VFD) was proposed to address frequency fluctuations in micro-hydro power plants caused by variations in water flow and consumer load. The system integrates an electronic governor using a variable-speed AM to consume excess generated power, enabling its use for irrigation or water storage. The VFD converts the variable-frequency AC output of the micro-hydro system into a stable 50 Hz AC signal through AC-DC-AC conversion. Additionally, the design includes a DC bus that supports integration with other renewable energy sources, such as solar or fuel cells, enhancing system scalability. The study validates the VFD and electronic governor under various load and water flow conditions, demonstrating improved frequency stabilization. However, the proposed system's economic feasibility in large-scale applications remains unclear, particularly concerning the costs of integrating additional renewable energy sources and maintaining the motor as a secondary load.

In [20], a hybrid combination of the SPWM technique and PI regulator is proposed to enhance the performance of a single-phase AM (1-phase AM) powered by solar energy. The research emphasizes the importance of improving electricity quality in smart grids, particularly through harmonic analysis. The authors implemented a matrix converter alongside a multistage power conversion system, which includes a boost converter and a PV module, to optimize speed and voltage. The THD of the input voltage was analyzed, revealing a significant improvement with the proposed model, achieving a THD of 3.5 % compared to traditional methods.

Additionally, the perturb and observed MPPT technique was utilized to maximize energy extraction from the photovoltaic system. However, a notable con of this approach is the complexity involved in the hardware implementation and the potential challenges in real-time adjustments during varying operational conditions.

Table 1. Some works addressing the limitations of the conventional DTC strategy

Techniques	Type of validation	Pros	Cons
Twelve sectors DTC technique using backstepping speed control [9].	Simulation and experimental.	- Reduced torque and flux ripples for improved stability. - Enhanced speed tracking with robust backstepping control (BC). - Reduced total harmonic distortion (THD) in stator currents. - Effective stator resistance estimation using P-model reference adaptive control (MRAC). - Validated improvements through simulations and experiments.	- Increased computational complexity with the twelve-sector DTC approach. - Dependence on precise parameter identification. - Hardware realization requires high-performance processing. - Limited analysis of scalability for larger systems.
Ant colony optimization (ACO) algorithm-DTC technique [10].	Experimental.	- Integration of ACO algorithm to enhance PI controller performance in DTC systems. - Improved flux and torque fluctuation reduction compared to DTC technique. - Enhanced system robustness against nonlinearity and parameter variations. - Experimentally validated gains in speed tracking and system stability. - Reduction in THD of stator and rotor currents.	- High computational demand for ACO algorithm. - Dependence on precise parameter tuning for optimal PI controller performance. - Limited exploration of scalability for industrial applications. - Increased complexity for real-time implementation on low-resource hardware.
Fractional-order SMC (FOSMC) technique [11].	Simulation.	- The FOSMC technique outperforms traditional PI and SMC controllers in AM control, offering superior robustness, reduced overshoot, faster response, minimized chattering, and adaptive design for dynamic conditions.	- While FOSMC technique improves control performance, it introduces design complexity, requires adaptive tuning, and depends on accurate system modeling, with challenges like residual chattering and performance sensitivity under extreme conditions.
Duty ratio control technique [12].	Simulation and experimental.	- The paper presents a simplified duty ratio control technique that minimizes torque and current ripples, enhancing performance in DTC drives. - It retains the simplicity of traditional ST-based DTC algorithms, making it easier to implement. - The proposed method utilizes parallel low-speed control loops, reducing computational burden and eliminating the need for delay compensation. - By modulating the duty ratio based on torque error, the technique effectively improves the overall efficiency of AM drives in electric vehicles.	- The paper does not address potential limitations in the modified duty ratio control algorithm, such as its dependency on accurate torque error measurement. - The complexity of the control algorithm may still pose challenges in real-time applications, despite efforts to simplify it. - The reliance on lookup tables for duty ratio modulation could introduce additional computational overhead in certain scenarios. - The proposed method may not fully eliminate torque and current ripples, especially under varying load conditions.
Novel reference flux selection technique [13].	Simulation.	- Introduces a novel reference flux selection algorithm to reduce torque fluctuation in AMs for electric vehicles. - Demonstrates improved performance over conventional DTC methods. - Achieves significant reductions in torque ripple and current THD. - Validated through simulations using a 50-hp AM, ensuring practical applicability. - Contributes to energy efficiency, reducing battery energy consumption by 37.3% compared to classical DTC technique.	- Limited to simulation results, lacking real-world experimental validation. - Focuses primarily on torque ripple, potentially overlooking other performance metrics. - May require complex implementation in practical applications. - Assumes ideal conditions that may not reflect all operational scenarios. - The proposed method's scalability to larger systems is not addressed.

Table 1. cont.

Fuzzy second-order SMC (FSOSMC) optimized by genetic algorithm (GA) [14].	Simulation.	- The FSOSMC technique enhances control performance, reduces torque ripples, improves robustness against disturbances, minimizes chattering, and optimizes parameters using GA techniques for dual star AMs.	- The paper does not address potential complexities in implementing FSOSMC technique, reliance on GA techniques may introduce computational overhead, and variable SF issues remain unresolved.
Multi-level inverter [15].	Simulation.	- The paper analyzes losses in dual-inverter-fed open-end winding AM drives, introducing an improved loss model, comparing pulse width modulation (PWM) schemes, and highlighting significant efficiency gains with DPWM technique for safer, reliable operation.	- The paper's limitations include lacking experimental validation, focusing solely on dual inverter systems, model complexity, limited environmental impact discussion, and narrow exploration of PWM techniques, restricting broader applicability and practicality.

In the field of control, the DTC strategy is one of the most prominent linear strategies used to control electrical machines [21]. This strategy has several advantages that make it a promising solution for controlling electrical machines, especially AM. This strategy relies on estimating both torque and flux [22]. The strategy aims to make torque vary directly with current, making the machine similar in principle to a direct current machine [23]. Therefore, this strategy is of great importance in the field of control, as evidenced by the number of works that have addressed it. This strategy has several drawbacks that limit its spread, the most prominent of which are low robustness and high torque and flux ripples [24]. Furthermore, the high THD of the current is another major drawback of this strategy.

Several solutions have been proposed to overcome the problems of the DTC strategy, the most prominent of which is replacing both ST and HC with other more, efficient strategies. In [25], a new strategy is proposed for the DTC technique of an induction motor. This designed strategy relies on the use of a dual PI controller to control the flux and torque, where the outputs of these controllers are reference voltage values. The modified SVM strategy is used to compensate for the use of ST in controlling the machine's inverter. This designer is designed for simplicity, fast dynamics, and excellent performance. The MATLAB Neo environment was used, along with the Liberals, and the results showed that the designer achieved an excellent THD value of 28.57 % compared to the traditional DTC approach.

A fuzzy super-twisting SMC technique is the proposed solution in [26] to overcome the problems and drawbacks of the DTC strategy of the induction generator. This designed controller is characterized by high robustness and excellent performance, as it uses two controllers to control the flux and torque. In addition to using this designed controller, the modified SVM strategy is used to generate the pulses necessary to operate the machine's inverter. This strategy was compared to the DTC-based PI controller approach. Compared to the DTC-PI strategy, the proposed approach is more complex and expensive. The MATLAB environment was used to implement this proposed approach under various operating conditions, and the results showed that the proposed

approach significantly reduced torque/flux ripples compared to the DTC-PI strategy. Furthermore, the proposed approach reduced the THD of the current by approximately 61.54% and 46.55% in all tests compared to the DTC-PI approach. Despite this remarkable performance, there is a drawback to this proposed approach. It features a significant number of gains, making it difficult to fine-tune the dynamic response to torque and flux. Furthermore, the use of fuzzy logic (FL) makes it difficult to easily fine-tune the control, given the lack of a mathematical rule that specifies the number of rules required to achieve optimal performance. As is well known, the FL method relies heavily on experience, requiring experimentation and iteration to achieve optimal results.

An adaptive network-based fuzzy inference system is combined with the second-order super-twisting sliding mode (STSM) algorithm [27] to obtain a robust controller that overcomes the DTC problem. In this designed approach, a modified SVM strategy is used along with the proposed controller to develop the DTC strategy. The proposed DTC strategy is characterized by high robustness, high efficiency, ease of implementation, and fast dynamic response. This proposed DTC strategy uses the same torque and flux estimation equations as the traditional approach. The proposed strategy was implemented in MATLAB using several different tests, comparing its performance and effectiveness with the DTC-PI approach. The results showed that the designed approach reduced the THD of current by 61.54 % and 57.33 % percent compared to the DTC-PI approach. Furthermore, the designed approach yielded better results compared to DTC-PI in terms of reference tracking and reduced torque/flux ripples. This approach has drawbacks, the most notable of which are its complexity and the presence of a significant number of gains. This designed approach is affected by changes in machine parameters in robustness testing, manifested in increased torque/flux ripples and higher THD of current, necessitating the search for a more effective and high-performance strategy.

In [28], an FL method-based DTC technique is proposed for synchronous motor control. The FL method is used to compensate for the controller's PI of speed, and 25 FL rules are used to embody the FL controller. In this designed

strategy, ST is used to control an inverter. This designed strategy is compared with a conventional approach, implemented using MATLAB/SIMULINK. The effectiveness of the designed approach is verified under different speeds and load disturbances. The obtained results demonstrate the effectiveness of the proposed control in reducing torque and current ripples at different speeds while improving the dynamic response to speed and flux.

In [29], a new DTC strategy is proposed for controlling an induction machine. This strategy is a neural network (NN)-based discrete predictive direct torque and flux control (NNPDFTFC). This strategy uses the SVM technique to drive the machine inverter, which makes it different from the conventional approach that uses both ST and HC. The performance and effectiveness of the proposed approach are compared with a DTC strategy based on PI controllers. In this work, the gain values of the proposed approach were calculated using the particle swarm optimization algorithm. Minimized disturbances, simple control, and real-time implementation are key features of the designed approach, which also enhances the transient performance of the motor drive by reducing settling time and peak overshoot. The performance of the designed approach was analyzed using MATLAB. The obtained results show that the proposed approach significantly improves the flux and torque ripples compared to the conventional PI controller-based approach. Furthermore, this designed approach was experimentally implemented using a low-cost digital signal processor (DSP) controller, where a 3.7 kW induction motor was used. Experimentally, the designed approach yielded highly satisfactory results under uncertain system parameters and external load disturbances. Furthermore, it yielded enhanced dynamic performance as well as static performance with reduced ripples in signal flux, torque, and current compared to the conventional PI controller-based approach.

Another strategy proposed in [30] for controlling an induction motor is the DTC based on a decision tree (T-DTC), which uses actively trained artificial NNs (ANNs) to enhance accuracy and robustness. The goal of the T-DTC strategy proposal is to significantly reduce flux and torque ripples, ensuring efficient control of induction motors. Conventional stator flux and electromagnetic torque hysteresis controllers have been replaced with two advanced controllers known as M5 Prime model trees. Additionally, the conventional switching table has been replaced with a new decision tree using the classification algorithm 4.5. The effectiveness of the proposed T-DTC strategy was demonstrated using MATLAB/Simulink, comparing the performance with the conventional approach. Several different tests were used. The validity and efficiency of this approach were also validated in real-time using the HIL platform based on the OPAL-RT OP 5600 and the Virtex 6 FPGA ML605. The results show that the proposed approach offers a significant improvement over existing techniques in the literature, making it a promising solution. One of the most prominent solutions proposed to overcome the problems of the DTC strategy is the use of NNs as a suitable solution due to their accuracy and ease of use [31]. In [32], an NN technique was used to improve the properties of the DTC strategy of a permanent magnet

synchronous motor (PMSM). This strategy is different from the traditional strategy, as its use allows for reducing torque ripples. Moreover, the use of this strategy allows for a lower value of the THD of the current compared to the traditional approach.

Another work in [33] addressed the application of the ANN strategy to overcome the problems of the DTC technique of induction motor. In this work, ANN techniques were used to compensate for both HC and ST of the DTC technique. The designed strategy is characterized by fast dynamic response, high robustness, and ease of implementation. The results obtained showed the high performance of the designed approach compared to the conventional approach in terms of torque/current ripples and THD value of current. In [34], the adaptive NN approach was proposed to overcome the DTC strategy problems of linear induction motor drives. This strategy was implemented in the MATLAB environment using various tests. The results demonstrated the effectiveness and efficiency of the adaptive NN approach in improving the operational performance of DTC. In [35], the neural DTC technique of the induction motor was experimentally implemented using an FPGA. After giving the mathematical model of the induction motor and the equations expressing the DTC approach, the designed approach was experimentally implemented using an FPGA. The results of the tests conducted prove the effectiveness of the designed approach in improving the performance and efficiency of the machine when using the neural DTC approach compared to the traditional technique.

In [36], deep reinforcement learning is used to improve the DTC strategy properties of PMSM with parameter robustness. The use of deep reinforcement learning improves the operational performance of the DTC approach and increases its robustness. The MATLAB environment is used to verify the effectiveness of the designed approach. Various tests are performed, and the results are compared with the traditional strategy. Simulation results show that the use of DTC reduces flux/torque ripples and significantly reduces the THD of current compared to the traditional DTC technique. FL technique was combined with NN techniques in [37] to create a robust controller that overcomes the drawbacks of the DTC strategy. The author used a three-level inverter to power the machine. Furthermore, to improve the performance of the DTC strategy, 24 sectors were used instead of the usual six. In this designed strategy, an NN-FL controller was used to control both flux and torque. ST was also used to generate the pulses required to drive a three-level inverter. MATLAB was used to implement the designed approach and compare its performance with the conventional approach under various operating conditions. Simulation results demonstrated the superior performance of the designed approach, reducing the THD of current by 77.50%, 48.34%, 75%, and 81.43% compared to the conventional approach. Furthermore, torque ripples were reduced by 30%, 39.24%, 31.94%, and 59.31% compared to the conventional approach. Despite this performance, the designer's approach has drawbacks, the most significant of which lies in its use of ST and torque/flux estimation, which significantly impacts machine parameter changes.

This experimental work proposes to study the effectiveness of using an NN controller to overcome the drawbacks of the 12-sector DTC (12-DTC) algorithm applied to AM while comparing the results with the 6-sector DTC (6-DTC) technique. Therefore, the main contribution of the paper lies in the application of NN techniques to overcome the problems of the 12-sector DTC algorithm. This strategy is a modification and development of the 6-DTC technique. In this designed algorithm, NNs are used to compensate for both HC and ST. The 12 sectors neural DTC strategy is a different strategy, as it differs from related businesses such as [29] and [30] in terms of principle, simplicity, and ease of implementation. First, this algorithm is tested using MATLAB, and the results are compared with the traditional approach. Various tests were used to prove the effectiveness and efficiency of applying NNs. All tests demonstrated the strength of the algorithm in reducing torque ripples and reducing the THD of the current. Secondly, the simulated results were confirmed using real tools, where the dSPACE 1104 was used to control the operation of the 3.5 kW AM drive. Therefore, implementing the proposed algorithm using real equipment is considered the second main contribution of this paper. The obtained experimental results confirm the simulation results, making the proposed approach applicable in various industrial fields such as electric vehicles and electric power generation. Experimentally, the proposed 12-sector neural DTC (12-NDTC) algorithm, compared to the traditional approach, has high competence and great efficacy, as the torque and flux ripples are reduced. Also, this proposed algorithm improved the speed response time value and the THD value of the current compared to the 6-DTC technique. In addition to these experimental results obtained, the designed algorithm is simple, easy to realize, and inexpensive. Accordingly, the objectives achieved from this paper can be extracted in the form of the following points:

- Experimentally verify the effectiveness of applying NNs in overcoming DTC technique defects.
- Significantly improve dynamic speed response.
- Significantly underestimates the THD of the current compared to the 6-DTC technique.
- Reduce stator flux fluctuations.
- Reducing the value of exceeding the speed limit compared to the traditional approach.
- Reduce torque and current fluctuations.
- Increasing the robustness and efficacy of the AM control system compared to using the 6-DTC technique.

The sections of the article are as follows: The second section deals with the AM model. In the third section, the 12 sectors DTC approach algorithm is discussed in detail, mentioning the pros and cons. 12 sectors neural DTC algorithm are listed in Section IV. In Section V, a simulation of the designed algorithm using MATLAB is discussed. In the sixth section, the suggested algorithm was realized using experimental work (dSPACE 1104), where real tools were used to implement it. In Section VII, all conclusions of the work are listed.

2. AM Model

In this section, the mathematical model (MM) of AM used in this work is discussed. To give the model, the Concordia transform is used. This conversion is based on simplifying the machine model, where mathematical equations are given for each part of the machine. This model has been detailed in several scientific works [38, 39]. Equation (1) represents the AM voltages in the axis ($\alpha\beta$).

$$\begin{cases} V_{\alpha s} = R_s I_{\alpha s} + \frac{d}{dt} \Phi_{\alpha s} \\ V_{\beta s} = R_s I_{\beta s} + \frac{d}{dt} \Phi_{\beta s} \\ V_{\beta r} = R_r I_{\beta r} + \frac{d}{dt} \Phi_{\beta r} - w \Phi_{\alpha r} \\ V_{\alpha r} = R_r I_{\alpha r} + \frac{d}{dt} \Phi_{\alpha r} + w \Phi_{\beta r} \end{cases} \quad (1)$$

The rotor currents in the axis ($\alpha\beta$) can be written by Equation (2). This equation was obtained based on Equation (1).

$$\begin{cases} I_{\alpha r} = \frac{\Phi_{\alpha s} - L_s I_{\alpha s}}{M_{sr}} \\ I_{\beta r} = \frac{\Phi_{\beta s} - L_s I_{\beta s}}{M_{sr}} \end{cases} \quad (2)$$

From Equation (1), the expression for the flux in the $\alpha\beta$ axis can be extracted according to Equation (3) [40].

$$\begin{cases} \Phi_{\alpha r} = \frac{L_r}{M_{sr}} (\Phi_{\alpha s} - \sigma L_s I_{\alpha s}) \\ \Phi_{\beta r} = \frac{L_r}{M_{sr}} (\Phi_{\beta s} - \sigma L_s I_{\beta s}) \end{cases} \quad (3)$$

Derivation of Equation (3) allows writing Equation (4). This equation is used to create an AM model in MATLAB.

$$\begin{cases} \frac{d\Phi_{\alpha r}}{dt} = \frac{L_r}{M_{sr}} \left(\frac{d\Phi_{\alpha s}}{dt} - \sigma L_s \frac{dI_{\alpha s}}{dt} \right) \\ \frac{d\Phi_{\beta r}}{dt} = \frac{L_r}{M_{sr}} \left(\frac{d\Phi_{\beta s}}{dt} - \sigma L_s \frac{dI_{\beta s}}{dt} \right) \end{cases} \quad (4)$$

The torque of the AM is calculated according to the Equation (5). To change the torque, it is enough to change the current or flux.

$$T_e = \frac{p M_{sr}}{L_r} (\Phi_{\alpha r} I_{\beta s} - \Phi_{\beta r} I_{\alpha s}) \quad (5)$$

Equation (6) shows the relationship between speed and torque. Through this relationship, the operation of the AM and the rotational speed can be controlled.

$$J \frac{d\Omega_r}{dt} = T_e - T_r - f_r \Omega_r \quad (6)$$

In the next section, a 12-sector DTC approach is proposed for AM control instead of using the traditional algorithm. In this section, the operating principle will be given, mentioning the cons and pros.

3. 12 Sectors DTC Algorithm

The 12-DTC algorithm is considered one of the most prominent solutions designed to defeat the problems of the conventional DTC algorithm [41]. Its use allows for a significant increase in competence and robustness. This approach is a modification and development of the conventional DTC algorithm. In the 12-DTC algorithm, a four-level HC is used to control torque, and a 2-level HC is used to control flux. Also, in the 12-DTC algorithm an ST is used to control the inverter of the AM [42]. Therefore, the 12-DTC algorithm is described by its simplicity, ease of implementation, satisfactory performance, low costs, and fast dynamic response [43].

The 12-DTC algorithm is listed in Figure 1, which has the same structure as the traditional algorithm. In this algorithm, estimation of both torque and flux is used, which is a necessary process to calculate the torque and flux error. Also, the PI controller is used to calculate the torque reference value. The input to this regulator is the speed error and its output is the torque reference value. This controller was relied upon for its simplicity, ease of operation, fast dynamic response, and ease of adjustment.

In the 12-DTC algorithm, both voltage and current are measured to estimate torque and flux. In this algorithm, no sensors are used to capture speed, which makes it easy to maintain, inexpensive, and highly accurate.

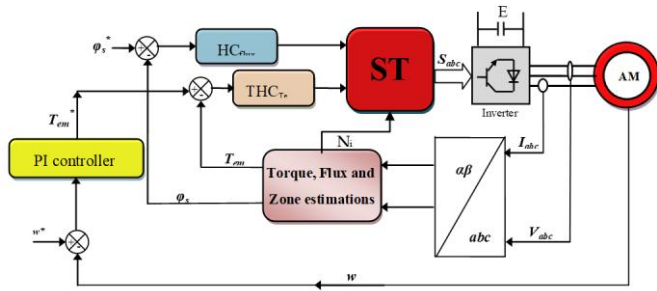


Fig. 1. 12-DTC algorithm of AM.

Table 2. The ST of 12-DTC algorithm

N _i		1	2	3	4	5	6	7	8	9	10	11	12
HC	HC												
flux	torque												
0	2	3	4	4	5	5	6	6	1	1	2	2	3
	1	4	4	5	5	6	6	1	1	2	2	3	3
	-1	7	5	0	6	7	1	0	2	7	3	0	4
	-2	5	6	6	1	1	2	2	3	3	4	4	5
1	2	2	3	3	4	4	5	5	6	6	1	1	2
	1	2	2	3	3	4	4	5	5	6	6	1	1
	-1	1	1	2	2	3	3	4	4	5	5	6	6
	-2	6	1	1	2	2	3	3	4	4	5	5	6

To produce the pulses necessary to run the inverter, Table 2 is used, which contains 12 sectors [42]. This table is larger than the ST of the traditional algorithm, which gives it greater efficiency. Changes in flux, sector, and torque make it possible to select voltage vectors to follow torque and flux reference values. ST is the basic element in the DTC algorithm, and the selection of efforts plays an important role in the efficiency and performance of this algorithm.

Figure 2 represents the HC used to control torque. This regulator has the following outputs: 2, -2, 1, and -1 [43]. Outputs with negative values are used to be able to reverse the rotation direction of the AM. Figure 3 represents the HC proposed in this algorithm for flux control. Therefore, this HC has two states: 0 and 1 [41]. The strategy depends on measuring voltage and current, and to calculate these values in axis (αβ), Equation (7) is used for this purpose.

$$\begin{bmatrix} V_{\alpha s} \\ V_{\beta s} \end{bmatrix} = \frac{2}{3} \begin{bmatrix} 1 & -1/2 & -1/2 \\ 0 & \sqrt{3}/2 & -\sqrt{3}/2 \end{bmatrix} \begin{bmatrix} V_{sa} \\ V_{sb} \\ V_{sc} \end{bmatrix} \quad (7)$$

The DTC algorithm is characterized by three errors: flux error, torque error, and speed error (ϵ_{Φ_s} , ϵ_{T_e} , and ϵ_{Ω}). In addition to the angle θ_s that determines the location of the vector Φ_s based on the components Φ_{sa} and Φ_{sb} . Equation (8) shows the errors used in the DTC algorithm [44].

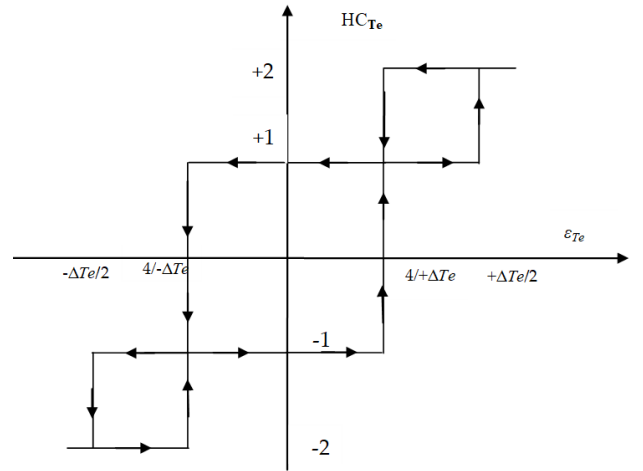


Fig. 2. Torque HC regulator.

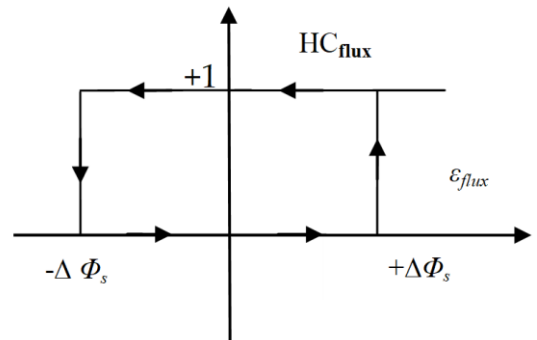


Fig. 3. Flux HC regulator.

$$\begin{cases} \mathcal{E}\Phi_s = \Phi_s^* - \Phi_s \\ \mathcal{E}T_e = T_e^* - T_e \\ \mathcal{E}\Omega = \Omega^* - \Omega \end{cases} \quad (8)$$

Equation (9) can be used to calculate the AM flux of voltage.

$$\begin{cases} V_s = \frac{d\Phi_s}{dt} + R_s i_s \\ V_r = \frac{d\Phi_r}{dt} + R_r i_r \end{cases} \quad (9)$$

$$\text{with: } V_s = V_{s\alpha} + jV_{s\beta}, i_s = i_{s\alpha} + ji_{s\beta}, i_r = i_{r\alpha} + ji_{r\beta}, \Phi_s = \Phi_{s\alpha} + j\Phi_{s\beta}, \Phi_r = \Phi_{r\alpha} + j\Phi_{r\beta}$$

From Equation (9), the flux expression can be extracted according to Equation (10).

$$\frac{d\Phi_s}{dt} = -R_s i_s + V_s \quad (10)$$

Equation (10) becomes as follows [45]:

$$\Phi_s = \int_0^t (-R_s i_s + V_s) dt \quad (11)$$

$$\Phi_s = V_s T_e + \Phi_{s0} - \int_0^t R_s i_s dt \quad (12)$$

Where, Φ_{s0} is the flux value in $t = 0$ s.

The flux can be calculated from the inverter operating pulses according to Equation (13). This flux is related to the DC voltage value [46].

$$\Phi_s(t) = \frac{2(S_1 + aS_2 + a^2S_3)}{3} V_{dc} + \Phi_{s0} - \int_0^t R_s i_s dt \quad (13)$$

Equation (14) shows the expression stator flux modulus used in this work. The angle of the flux is neglected to determine the sectors, and to calculate it, Equation (15) is used. Equation (16) expresses the stator current of the AM.

$$|\Phi_s| = \sqrt{(\Phi_{s\beta}^2 + \Phi_{s\alpha}^2)} \quad (14)$$

$$\alpha_s = \arctg \frac{\Phi_{s\beta}}{\Phi_{s\alpha}} \quad (15)$$

$$i_s = ji_{\beta} + i_{\alpha} \quad (16)$$

The current expressions in the $\alpha\beta$ axis are included in Equation (17) [46].

$$\begin{cases} i_{\alpha} = \sqrt{\frac{2}{3}} i_{s\alpha} \\ i_{s\beta} = \frac{1}{\sqrt{2}} (-i_{s\alpha} + i_{s\beta}) \end{cases} \quad (17)$$

To estimate the torque, the flux must be estimated first, and Equation (18) is used for this purpose. Estimating torque is related to measuring current, as the more accurate the current value is, the better the results.

$$T_e = 1.5 \times p(-\Phi_{s\beta} \cdot I_{s\alpha} + \Phi_{s\alpha} \cdot I_{s\beta}) \quad (18)$$

Despite the many advantages of this algorithm, such as rapid dynamic response, it gives unsatisfactory results in the event of a malfunction in the system, such as a change in machine parameters. Using this algorithm does not significantly reduce torque and current ripples. Also, this approach provides a higher THD value for the current which is not desirable. In the next section, a simple and effective solution is designed to overcome the problems and disadvantages of the 12 sectors DTC of the AM, mentioning the disadvantages and advantages of the proposed solution.

4. 12 Sector NN-DTC Algorithm

The 12-sector NN-DTC algorithm is the solution designed in this work to defeat the problems of the 12-sector DTC algorithm of AM. This algorithm relies on the use of NNs to enhance performance and robustness. NNs were adopted as a suitable solution due to the results obtained in the works [47-49].

This algorithm was relied upon for its ease of use, high robustness, and no need for an MM of the machine, which gives it greater efficiency if the AM parameters change, and a fast dynamic response. Therefore, the algorithm proposed in this section is a modification of the traditional algorithm, where ST and HC were dispensed with and replaced with a NN regulator, as shown in Figure 4. A neural regulator is used with three inputs: torque lines, sectors, and flux lines. Also, this regulator has three outputs which are pulses to operate the machine's inverter (Sa, Sb, and Sc).

The 12-NDTC algorithm is based on estimating torque, flux, and sectors. To estimate these values, both voltage and current are measured. Therefore, it is necessary to use measuring devices with high accuracy to minimize the error between the reference value and the measured value. In this approach, the estimation equations are the same as those mentioned in Section 3 of this paper. In this work, the training data source for the proposed NN-based DTC algorithm was taken from the traditional 12 sectors DTC approach, where the algorithm was trained and tested using data from the traditional 12 sectors DTC approach.

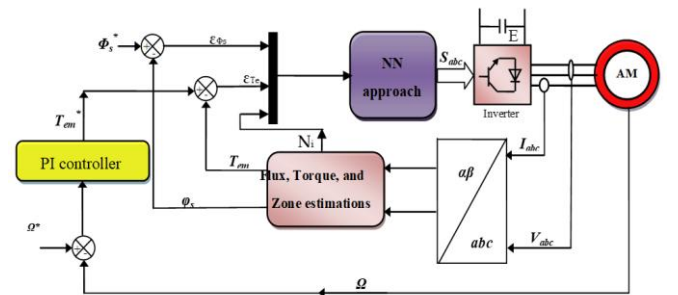


Fig. 4. 12 sectors NN-DTC algorithm of AM.

The 12-NDTC algorithm is based on the use of a PI-type regulator to control and change the speed, and it is the same controller used in the traditional 12-DTC algorithm listed in the third section. The gain values of this regulator were calculated using the method of simulation and experimentation, where values were taken that gave satisfactory results in terms of the value of THD of current and torque ripples.

Figure 5 represents the neural regulator used to control the operation of the AM inverter. The Levenberg–Marquardt (LM) algorithm was relied upon to obtain this neural regulator. The LM algorithm is known as the damped least squares approach, as it is used to solve nonlinear least squares problems. Using this algorithm allows for high performance and great efficiency. A neural algorithm of the type Gradient Descent with Momentum & Adaptive Learning Rate Backpropagation was used to embody the neural controller. This type is characterized by distinctive and effective performance. Also, it can be applied without having to know the MM of the AM. Table 3 represents the characteristics of the neural regulator used to improve the efficacy and competence of the 12-DTC algorithm of AM.

Figure 6 represents training for the neural controller. It is noted from Figure 6 that at 1000 epoch we obtain the best value for training performance, which is estimated at 0.027372. Figure 7 represents the internal structure of a neural regulator used to overcome the disadvantages of the 12-DTC strategy.

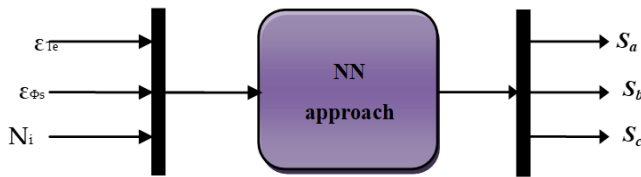


Fig. 5. Neural controller.

Table 3. Characteristics of the NN technique used.

Parameters	Value
Number of hidden layers	2
Number of neurons in first hidden layer	25
Learning rate	0.05
Display step (error display interval)	60 iterations
Number of input layers	1
Number of iterations (epochs)	1000
Number of output layers	1
Number of neurons in the input layer	3
Momentum coefficient (mc)	0.8
Number of neurons in the output layer	12
Error (goal)	0.005
Activation functions	Linear (output)

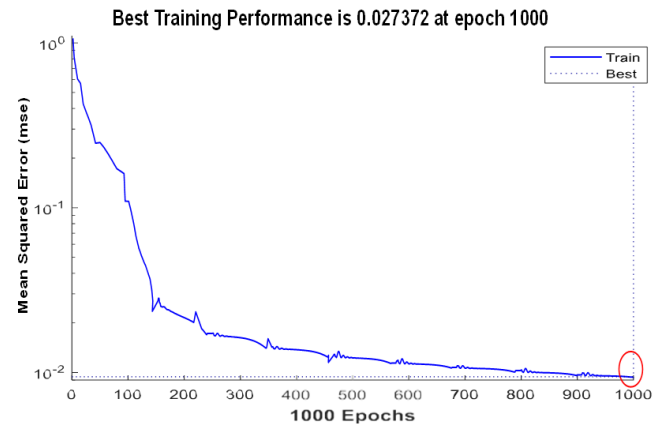
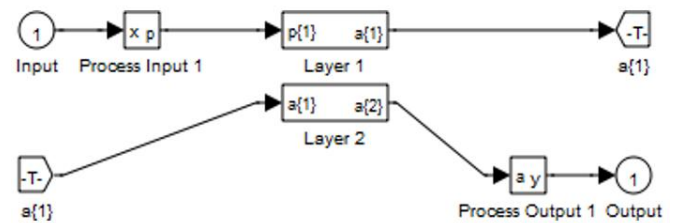
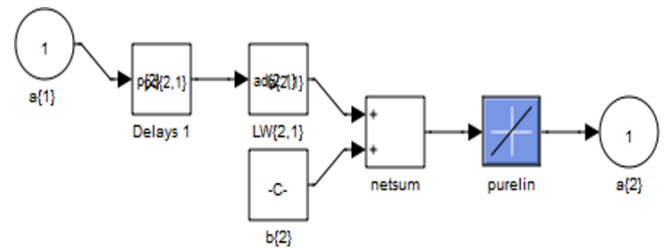


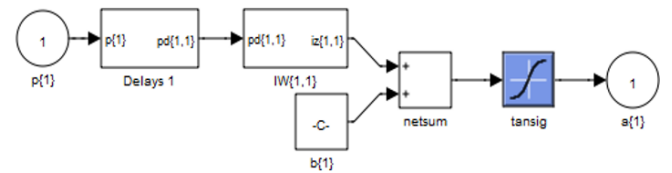
Fig. 6. Training.



(a)



(b)



(c)

Fig. 7. Internal structure of a neural controller: (a) NN, (b) layer 1, (c) layer 2.

In Table 4, a comparison is made between the proposed 12-NDTC algorithm and the traditional DTC algorithm. The similarities and differences between the two algorithms are mentioned in this table. This table gives a clear picture of the proposed algorithm in terms of structure and its effectiveness, as the results of the fourth section were used to fill out this table.

The use of the 12-NDTC algorithm allows for a reduction in torque fluctuations and the THD of current compared to the 6-DTC, as confirmed in the next section. In the next section, a simulation of the designed algorithm is performed using several different tests.

Table 4. Similarities and differences between two algorithms.

Features	Traditional DTC algorithm	12 sectors DTC technique	Designed 12 sectors NN-DTC algorithm
ST	Yes	Yes	No
THD	High	Medium	Low
PI regulator of speed	Yes	Yes	Yes
Flux estimation	Yes	Yes	Yes
Torque estimation	Yes	Yes	Yes
Response dynamic	Fast	Fast	Very fast
NN controller	No	No	Yes
Robustness	Low	Medium	High
Number of sectors	6	12	12
Concordia transform	Yes	Yes	Yes
Flux/torque ripples	High	Medium	Low
Affected if machine parameters change	Great impact	Great impact	Little impact.

Although the replacement of hysteresis comparators and switching tables with NN method or intelligent networks has been explored previously, the present work introduces a distinct conceptual and technical framework within the 12-sector DTC paradigm. Specifically, the proposed method employs a unified neural decision structure that jointly determines the optimal voltage vector by considering both torque and flux sector information, rather than treating them as independent processes. Furthermore, NNs are considered a strategy that does not require knowledge of the mathematical model of the system under study, which ensures robustness in the face of parameter changes and load disturbances. This is fundamentally different from current 12-sector DTC approaches, including the method mentioned in [9], which rely on fixed control parameters and do not take advantage of online adaptation or integrated optimization for torque and flux control. Using this strategy requires a thorough understanding of the mathematical modeling of the system under consideration, making the proposed approach susceptible to changes in machine parameters. Furthermore, the proposed framework was validated through immediate implementation, demonstrating improved torque ripple suppression and dynamic response while reducing computational costs. These features together represent the most significant innovations in the proposed approach, surpassing previous improvements in the 12-sector DTC.

In Table 5, the approach designed in this paper is compared with the approach listed in Reference [9]. From this table, it is observed that the work done in this paper is completely different from the strategy designed in the work done in Reference [9] in terms of principle, type of controller used, performance, effectiveness, simplicity, etc.

Table 5. Comparison of the designed approach with the work done in reference [9].

Features	Proposed work in [9]	Suggested technique
Conceptual novelty	Enhancement within existing DTC structure	Reformulation of DTC decision process as an intelligent optimization problem using adaptive neural inference
Learning /Adaptation	Fixed control parameters; no adaptive learning	Adaptive neural network with self-adjusting weights that responds to changes in parameters/load
Core control strategy	12-sector DTC with Backstepping speed controller and P-MRAS stator resistance identification	12-sector DTC using unified neural decision structure replacing hysteresis comparators and tables
Torque and flux estimations	Yes	Yes
Integration of torque & flux control	Treated independently in the switching decision process	Joint optimization of torque and flux within a single neural decision framework
Robustness	High	High
Torque ripple reduction	Moderate improvement compared to classical DTC	Significant reduction due to adaptive neural control and finer voltage vector selection
Real-time implementation	Simulation and limited experimental validation	Fully validated in real-time embedded system implementation
Dynamic response	Improved using Backstepping control	Faster transient response through continuous, data-driven decision mapping
Complexity	High	Moderate

Table 5 therefore, illustrates the difference between the designer's work in this paper and the work completed in reference [9], summarizing the most important technical and conceptual differences. As demonstrated, the proposed controller offers a unified neural architecture capable of making real-time adaptive decisions, whereas current studies (such as [9]) rely on fixed control laws or offline-trained models. This integration of learning capabilities within a twelve-segment DTC framework is the key novel feature of this work.

5. Results

This section implements the algorithm proposed in this work using MATLAB. The results obtained are compared with the traditional 6-sector approach using a 3.5 kW AM. A comparison is made between the two strategies in terms of tracking references, reducing torque and flux fluctuations, and the value of the THD of the current. The AM parameters used in the simulation are as follows: $f = 0.00325$ Nm/rad/s, $J = 0.043$ kg·m², $L_m = 0.267$ H, $L_s = 0.336$ H, $L_r = 0.2036$ H, $R_r = 1.88$ Ω, $R_s = 4.28$ Ω, $\Phi_s = 0.83$ Wb, $p = 2$, $n_r = 1480$ rpm, $P_n = 3.5$ kW, $T_{en} = 20$ N·m, $I_n = 11.1/6.5$ A, $V_n = 230/400$ V, and $f_s = 50$ Hz.

5.1. Test 1: No-load Start-up and Steady-state Operation

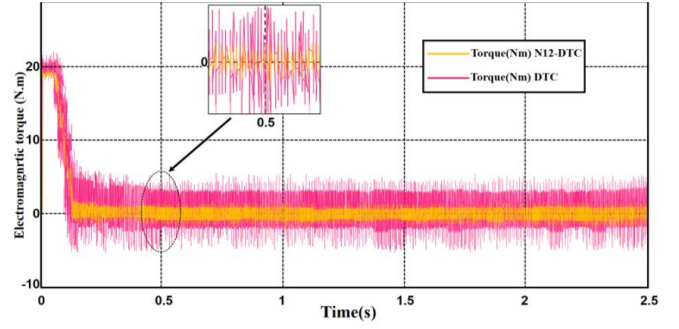
In the first test, the motor is operated at a constant speed of 1000 rpm without applying any load. The results of this test are represented in Figure 8. Figure 8a illustrates the torque for the two algorithms. This torque reaches a value of 20 N·m in the case of startup and then gradually decreases until it reaches a value of 0 N·m when the speed is equal to the value of 1000 rpm. It is also noted that the 6-DTC algorithm significantly reduced torque ripples compared to the 6-DTC algorithm.

Figure 8b represents the speed of the two algorithms. This speed initially changes gradually until it reaches the reference value estimated at 1000, after which it remains constant. It is noted that the designed algorithm provided a faster response time than the DTC technique, which indicates the effectiveness and efficiency of this algorithm.

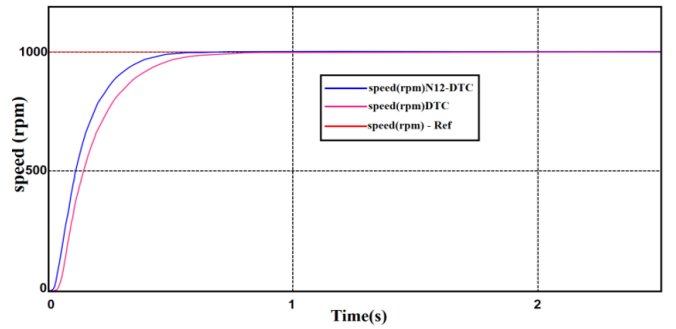
Figure 8c represents the current for the algorithms used in this work. This current has a sinusoidal shape for the two algorithms with ripples. The proposed algorithm gave the high quality of the current compared to the DTC algorithm, which shows its high performance and the extent of its ability to enhance the quality of the current.

Figure 8d represents the trajectory of the stator flux components Φ_{isd} and Φ_{isq} for the two algorithms. This is a circular trajectory for both controls with ripples. The proposed algorithm gave a better trajectory than the DTC technique in terms of ripples.

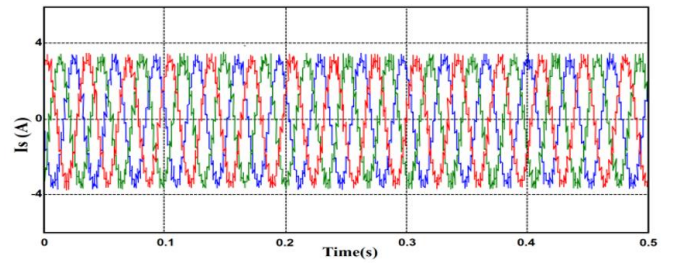
Figure 8e represents the position of the flux vector Φ_s for the two controls. It is noted that the two algorithms have the same value as the position of the flux vector Φ_s . This position takes the shape of saw teeth. Figure 8f represents the THD value if the two algorithms are used.



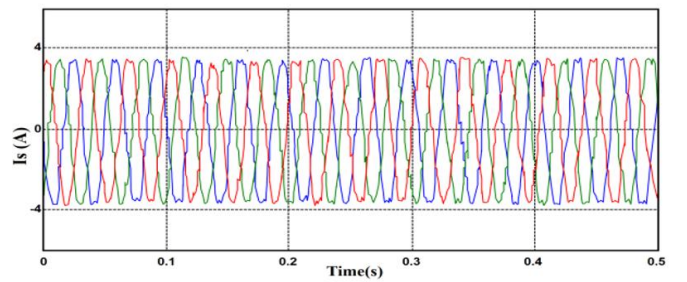
(a) Torque



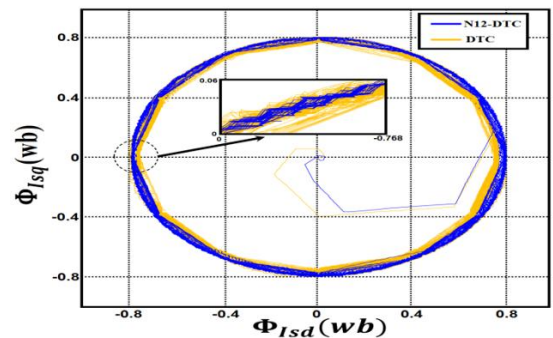
(b) Speed



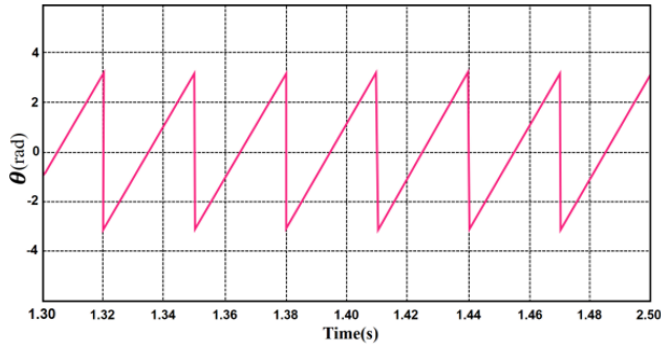
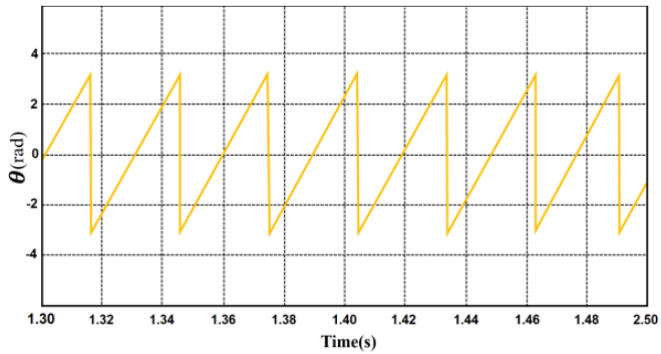
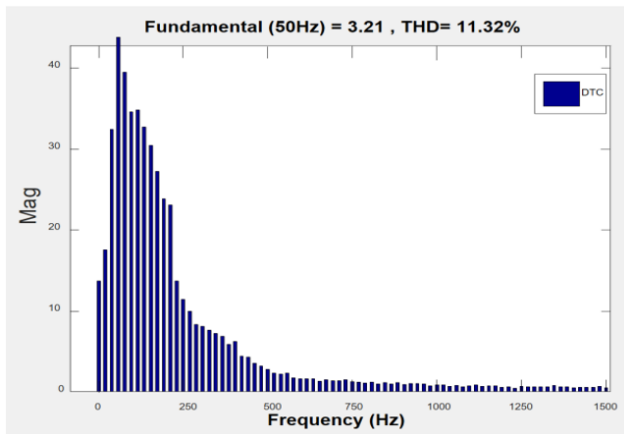
(c.1) Current: DTC



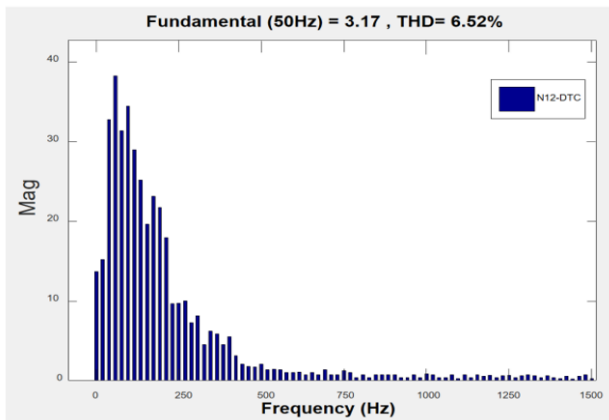
(c.2) Current: 12 sectors neural DTC



(d) Trajectory of the stator flux components Φ_{isd} and Φ_{isq}


(e.1) Position of the flux vector Φ_s : DTC

(e.2) Position of the flux vector Φ_s : 12 sectors neural DTC


(f.1) THD of current: DTC



(f.2) THD of current: 12 sectors neural DTC

Fig. 8. Results of the first test.

According to the two figures in Figure 8f, the THD value was 11.32 % and 6.52 % for DTC and 12-NDTC, respectively. Therefore, the proposed algorithm significantly minimized the THD value, as this minimization was estimated at 42.40 % compared to the DTC technique. On the other hand, it is noted that the amplitude value of the fundamental signal (50 Hz) for the two controls was estimated at 3.21 A and 3.17 A for the traditional approach and the 12-sector neural DTC strategy, respectively. These values indicate that the conventional 6 sectors DTC approach has an advantage in amplitude value compared to the 12-sector neural DTC approach. Therefore, the amplitude value of the approach designed in this test can be considered negative, as this disadvantage can be attributed to the characteristics of the neural approach used. This disadvantage can be overcome in the future by adding other strategies integrated with the neural controller.

Table 6 presents the numerical results of the first test of the two approaches. This table presents the values and reduction ratios for torque/flux ripples and velocity/flux response time. This table shows that the designed approach yielded significantly better numerical results than the conventional 6 sectors DTC technique. From Table 6, the designed approach reduced the torque, flux, and current ripples by 55 %, 55 %, and 74.81 %, respectively, compared to the conventional 6 sectors' DTC strategy. On the other hand, the designed 12 sectors' neural DTC technique yielded significantly better times for both velocity and flux than the conventional 6 sectors' DTC strategy, with ratios of 43.91 % and 39 %, respectively. These ratios demonstrate the effectiveness of the designed 12 sectors' neural DTC approach in improving the properties of the studied system.

Table 6. Numerical results of the first test.

Performance metric	Traditional technique	Proposed technique	Ratios (%)
Torque ripples (Nm)	4.50	2.0	55
Speed response time (ms)	230	129	43.91
Flux ripples (Wb)	0.045	0.020	55
Flux response time (ms)	140	85	39
Current ripples (A)	0.393	0.099	74.81

5.2. Test 2: Speed Variation Under No-load Conditions

In this test, the 12-NDTC technique is studied in the case of changing the speed from 1000 rpm to 1500 rpm while no load is applied. The results of this test are listed in Figure 9.

Figure 9a represents the speed change as a function of time for the two algorithms. The speed follows the reference for the two algorithms, with the proposed algorithm having an

advantage in terms of response time compared to the 6 sectors DTC algorithm.

Figure 9b represents the torque change for the two algorithms. This torque is affected by a change in speed at the moment $t = 1$ s, where an increase in the value of the torque is observed until it reaches a value of 20 N·m, then it gradually decreases to a value of 0 N·m with the presence of ripples. The torque ripples are much lower when using the proposed algorithm compared to the DTC technique.

Figure 9c represents the current for the two algorithms. This current is affected by the change in the speed of the machine, as its value increases at $t = 1$ s. The current remains sinusoidal for both algorithms. Also, the designed algorithm gave high quality for this current compared to the DTC.

Figure 9d represents the trajectory of the stator flux components Φ_{isd} and Φ_{isq} for the two controls. This flux trajectory remains circular, with the proposed algorithm having an advantage in terms of ripples compared to the DTC technique, and the results of the previous test are the same.

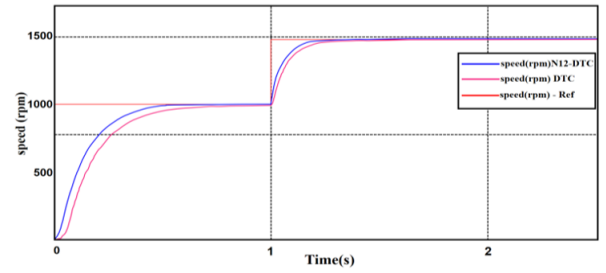
These results highlight the superiority of the 12-NDTC technique and its competence in reducing flux ripples, current, and torque. In this test, it is noted that the position of the flux vector Φ_s remains the same shape as in the previous test for the two controls (Figure 9e).

The THD of current value for the two algorithms is represented in Figure 9f. This value was 7.46 % and 14.25 % for the designed algorithm and DTC technique, respectively. So, the proposed algorithm provided a better value for THD compared to the DTC technique. The proposed algorithm reduced the THD value by an estimated 47.65 %.

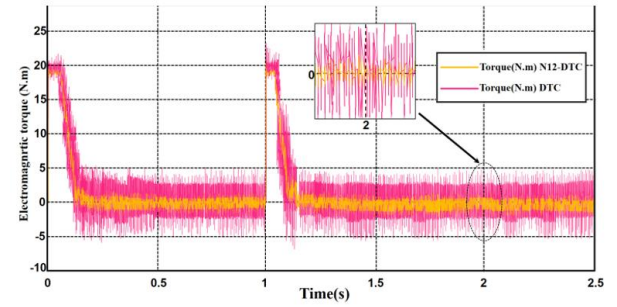
It is also noted that the amplitude values of the fundamental signal (50 Hz) were estimated to be 2.95 A and 3.23 A for both the conventional approach and the 12-sector neural DTC technique, respectively. These values demonstrate that the amplitude value is better in the case of using the designed approach compared to the conventional 6 sectors DTC approach, where the amplitude value was improved by a percentage of 8.67 %. This percentage indicates that the quality of the current is very high if the designed algorithm is used, which is a good thing.

Table 7 presents the numerical results of the second test of the two controllers. This table clearly demonstrates the superiority of the designed approach over the conventional 6 sectors DTC approach in terms of reducing torque/current ripples and improving the response time to velocity and flux. From this table, the designed 12 sectors neural DTC technique reduces the torque, flux, and current ripples by 54 %, 54 %, and 68.43 %, respectively, compared to the conventional approach.

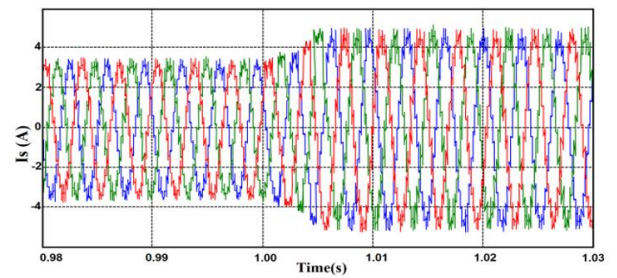
On the other hand, the designed approach reduced the response time to speed and flux by 44 % and 39.46 % compared to the traditional 6 sectors DTC technique. These figures demonstrate the effectiveness of the designed 12 sectors neural DTC technique in this test and its high ability to improve the properties of the studied system, making it a promising solution.



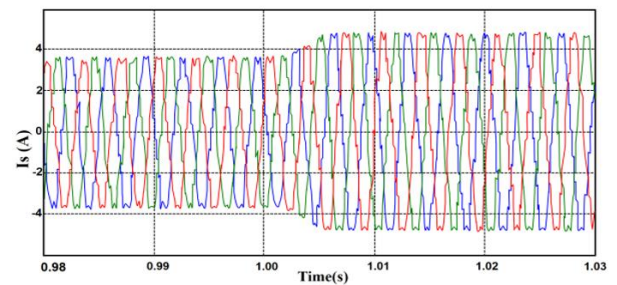
(a) Speed



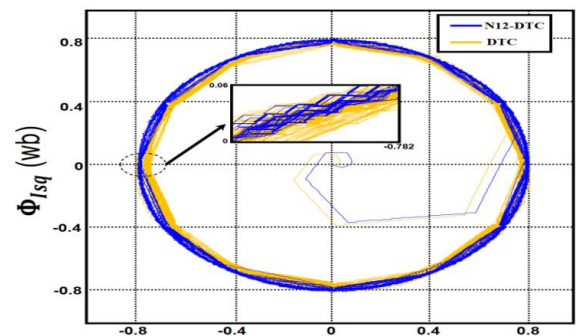
(b) Torque

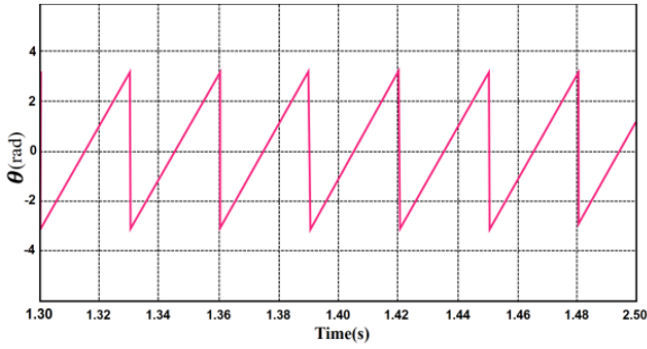
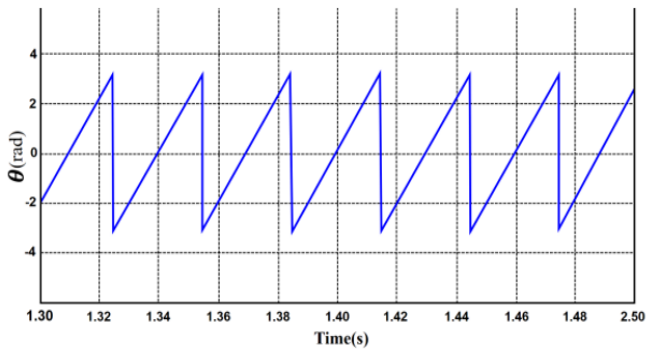
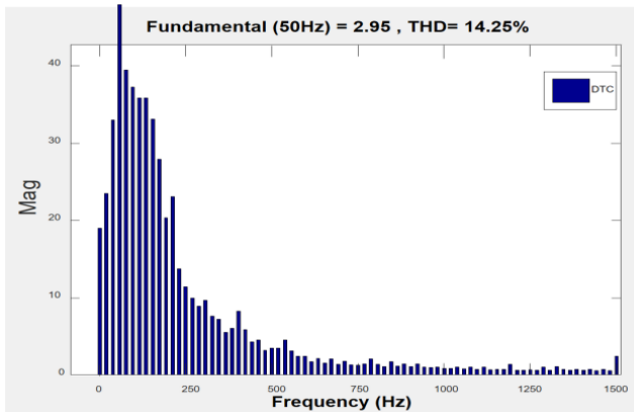


(c.1) Current: DTC

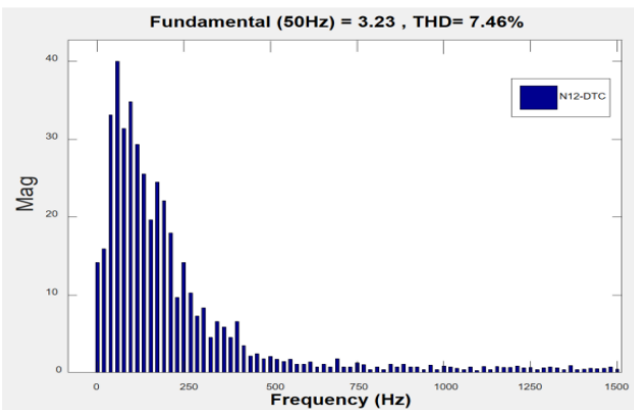


(c.2) Current: 12 sectors neural DTC


(d) Trajectory of the stator flux components Φ_{isd} and Φ_{isq}


(e.1) Position of the flux vector Φ_s : DTC

(e.2) Position of the flux vector Φ_s : 12 sectors neural DTC


(f.1) THD of current: DTC



(f.2) THD of current: 12 sectors neural DTC

Fig. 9. Results of the second test.

Table 7. Numerical results of the second test.

Performance metric	Traditional technique	Proposed technique	Ratios (%)
Torque ripples (Nm)	5.00	2.3	54
Speed response time (ms)	330	185	44
Flux ripples (Wb)	0.050	0.023	54
Flux response time (ms)	147	89	39.46
Current ripples (A)	1.036	0.327	68.43

5.3. Test 3: Test with Resistive Torque (Load Condition)

This test is different from previous tests. In this test, the speed is fixed at 1000 rpm, and the load (10 N·m) is applied in the time range from 1 to 2 s. The results of this test are listed in Figure 10.

Figure 10a represents the torque change as a function of time. This torque follows the reference well while having a quick dynamic response. It is noted that there are fluctuations at the level of this torque, and these fluctuations are less when using the proposed algorithm compared to the 6 sectors DTC technique.

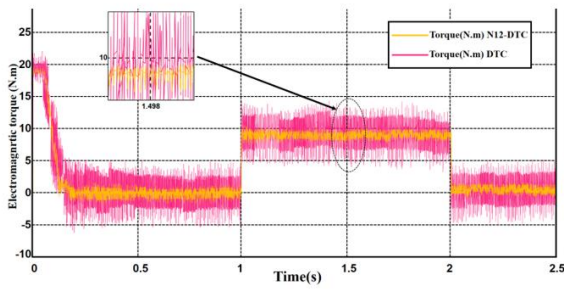
Figure 10b represents the speed change for the two algorithms as a function of time. First, the speed changes gradually until it reaches the reference value, with the proposed algorithm having an advantage in terms of response time compared to the DTC technique. After that, the speed remains constant and follows the reference value well, with an exceedance of the limit value at the time points of 1 s and 2 s as a result of the torque change.

Figure 10c represents the current for the two algorithms. This current is affected at the moment of 1s, where its value is observed to increase, and this is a result of applying a load at this moment. This current remains sinusoidal for both algorithms, with the proposed algorithm having an advantage in terms of current quality compared to 6 sectors DTC technique. In this test, the trajectory of the stator flux components Φ_{isd} and Φ_{isq} remains circular (Figure 10d), with the proposed algorithm having an advantage in terms of undulations compared to the 6 sectors DTC technique, which produces the same results as the previous two tests. These results highlight the advantage of the designed algorithm and its high efficiency.

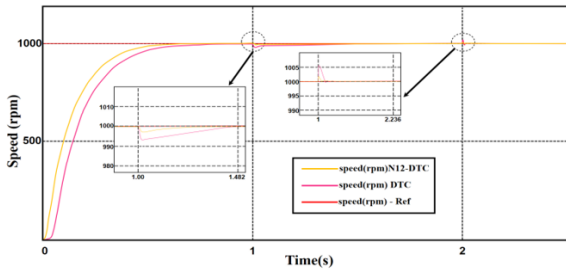
Figure 10e represents the position of the flux vector Φ_s in this test for the two controls. This position remains the same as in the previous tests, as it is not affected by changes in speed, load torque, or machine parameters.

Figure 10f represents the THD of the current for the two algorithms in the third test. This value was 16.76 % and 10.13

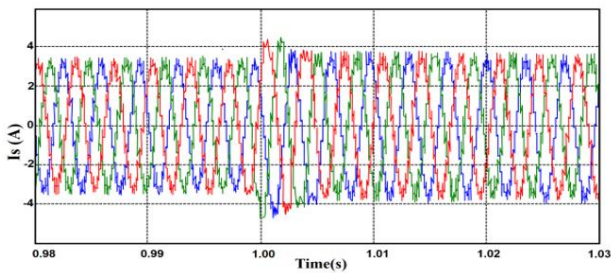
% for the DTC technique and the proposed approach, respectively. The proposed algorithm significantly minimized the THD value compared to the 6 sectors DTC technique, which highlights that the current quality is high if the proposed algorithm is used. This reduction in THD value was estimated at 39.56 %. On the other hand, it is noted that the amplitude value of the fundamental signal (50 Hz) was equal to 3.32 A for the traditional 6 sectors DTC approach and 3.28 A for the proposed approach. Therefore, the amplitude value is higher in the case of using the conventional DTC approach compared to the designed approach. Therefore, this amplitude value can be considered a disadvantage of the designed approach in this test. This disadvantage can be attributed to the number of neurons and the number of internal layers, which can be overcome in the future by using other strategies, such as the NARX algorithm.



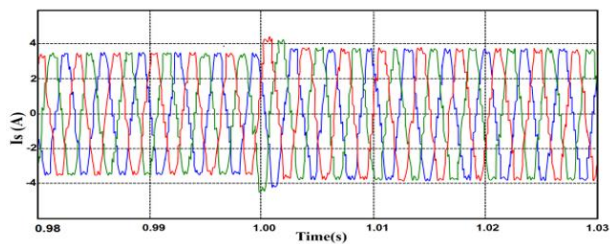
(a) Torque



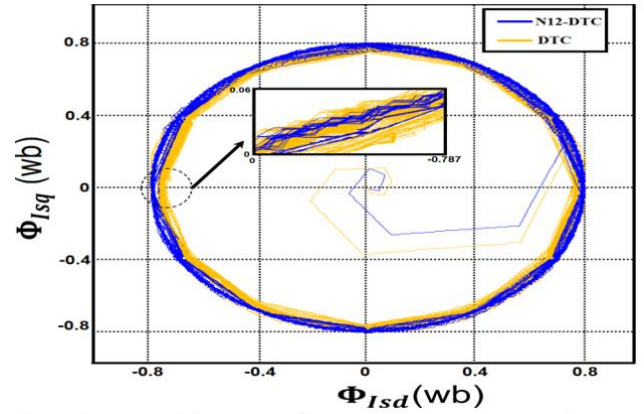
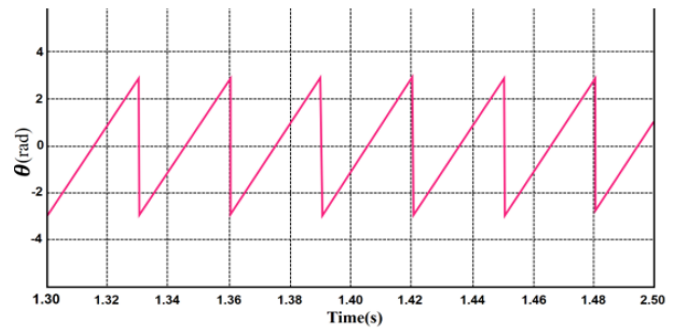
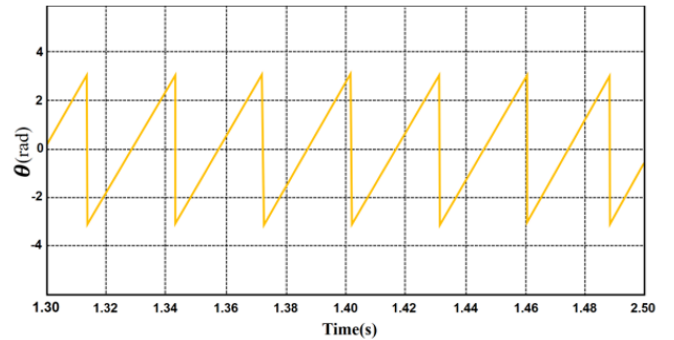
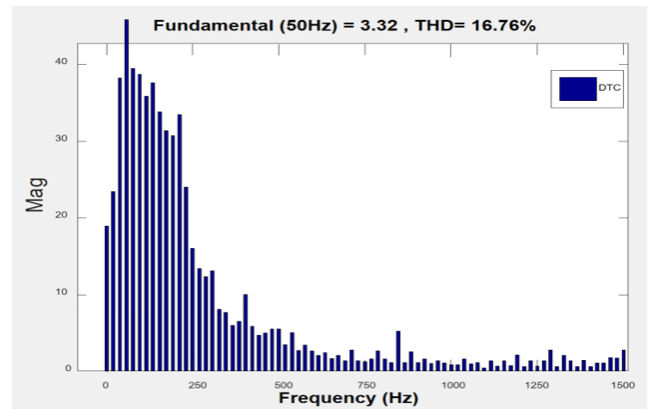
(b) Speed



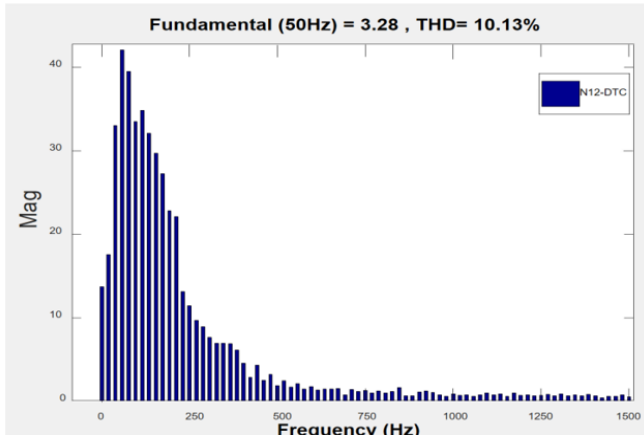
(c.1) Current: DTC



(c.2) Current: 12 sectors neural DTC


(d) Trajectory of the stator flux components Φ_{isd} and Φ_{isq}

(e.1) Position of the flux vector Φ_s : DTC

(e.2) Position of the flux vector Φ_s : 12 sectors neural DTC


(f.1) THD of current: DTC



(f.2) THD of current: 12 sectors neural DTC

Fig. 10. Results of the third test.

Table 8 presents the numerical results of the third test of the two techniques. This table gives the values and reduction ratios for the torque, flux, and current ripples. It also gives the reduction ratios and response time values for the flux and velocity. From this table, it is observed that the proposed 12 sectors' neural DTC strategy gave better values than the conventional approach. Table 8 shows that the designed 12 sectors neural DTC approach reduced the torque, current, and flux ripples by 54.39 %, 66.12 %, and 62.32 %, respectively, compared to the conventional approach. Furthermore, the designed 12 sectors neural DTC technique reduced the response time to flux and speed by 40.96 % and 49.52 %, respectively, compared to the conventional 6 sectors DTC approach. These results demonstrate the effectiveness of the designed approach in this test and its high performance in improving the current/torque quality and dynamic speed/flux response. These results make the designed 12 sectors' neural DTC approach attractive for other industrial applications.

Table 8. Numerical results of the third test.

Performance metric	Traditional technique	Proposed technique	Ratios (%)
Torque ripples (Nm)	5.70	2.6	54.39
Speed response time (ms)	420	212	49.52
Flux ripples (Wb)	0.069	0.026	62.32
Flux response time (ms)	166	98	40.96
Current ripples (A)	1.684	0.469	66.12

5.4. Test 4: Robustness Test

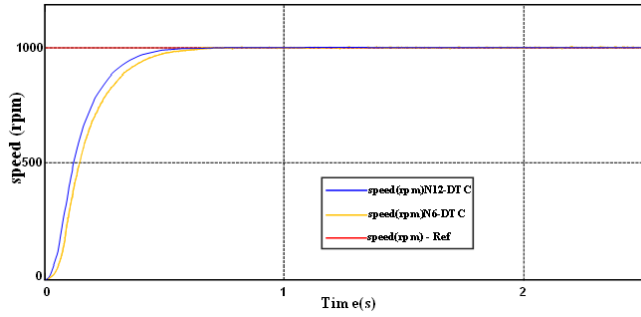
This test is completely different from the previous tests. This test examines the effectiveness and efficiency of the designed approach under the condition of changing machine parameters. In this test, the machine parameters are modified so that the resistance values are multiplied by 2 and the inductance values are multiplied by 0.5. Furthermore, the

speed is held at 1000 rpm with no load applied.

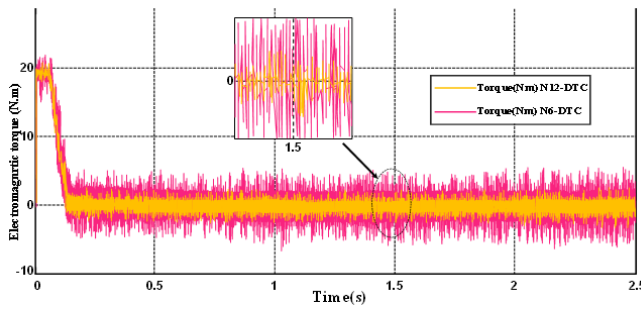
The purpose of this test is to study the impact of the designed approach on machine parameter changes compared to the conventional 6 sectors' DTC approach. The graphical results of this test are shown in Figure 11. Figure 11a represents the speed changes for two controls. Despite the machine parameter changes, the speeds for both controls closely follow the reference value, with the designed approach having an advantage in response time over the conventional 6 sectors' DTC technique. Figure 11b represents the torque variation for the two controls as machine parameters change. This figure shows that the torque is affected by machine parameter changes, as this change is evident in the height of the ripples. However, the designed approach produced significantly lower ripples than the conventional approach, demonstrating the effectiveness of the designed approach and its insensitivity to machine parameter changes compared to the conventional approach.

Figure 11c represents the change in current as the machine parameters change. This figure demonstrates that the current is affected by the change in machine parameters for the two controls, as evidenced by the presence of ripples. Despite the change in machine parameters, this current remains sinusoidal. Figure 11c demonstrates that the current quality is higher when using the proposed approach compared to the traditional 6 sectors DTC technique, proving that the designed approach is less affected by machine parameter changes. Figure 11d represents the trajectory of the stator flux components F_{ISD} and F_{ISC} using both controls. Despite the parameter changes, the trajectory of the stator flux components remains circular, similar to the observations in the previous tests. However, ripples are observed, and these ripples are significantly lower in the designed technique compared to the traditional 6 sectors DTC technique. Figure 11e represents the change in the position of the flux vector for the two controls as the machine parameters change. From this figure, it is noted that despite the change in the machine parameters, the change in the position of the flux vector for the two controls remains the same as in the previous tests, proving that the position of the flux vector for the two controls is not affected by changes in the AM parameters.

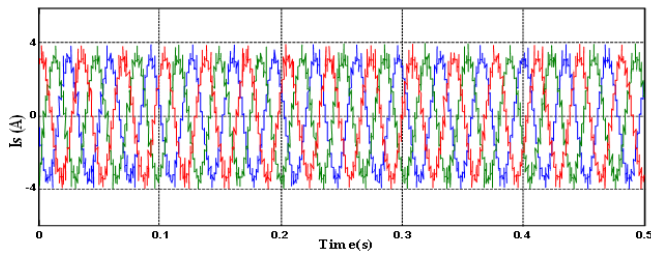
Figure 11f represents the THD of current for two controls under the condition of changing machine parameters. From this figure, it is noted that the THD value was estimated at 14.06 % for the traditional 6 sectors DTC strategy and 7.98 % for the proposed approach. These values highlight the superiority of the proposed approach over the traditional approach, as the THD value was reduced by approximately 43.24% compared to the traditional 6 sectors DTC approach. On the other hand, Figure 11f shows that the amplitude value of the fundamental signal (50 Hz) was estimated to be 3.28 A and 3.29 A for both the conventional and proposed approaches, respectively. Therefore, the proposed 12 sectors neural DTC strategy gave a better amplitude value compared to the conventional approach, which highlights the effectiveness and efficiency of this designed approach in improving the current quality despite the change in the machine parameters compared to the conventional approach.



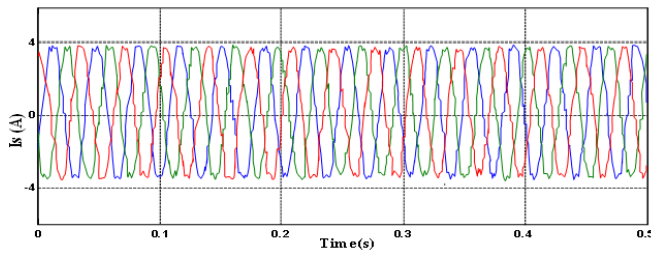
(a) Speed



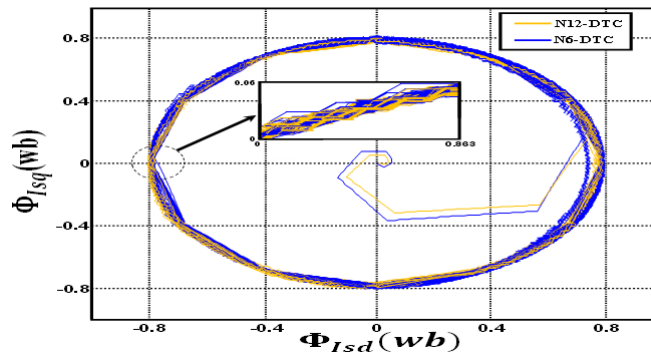
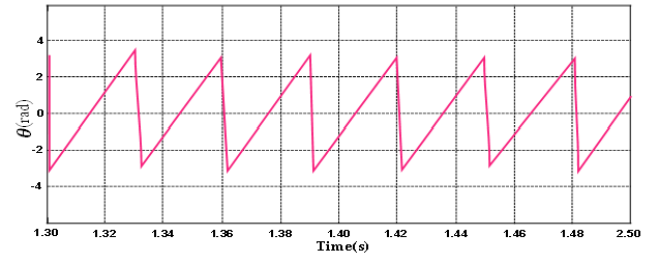
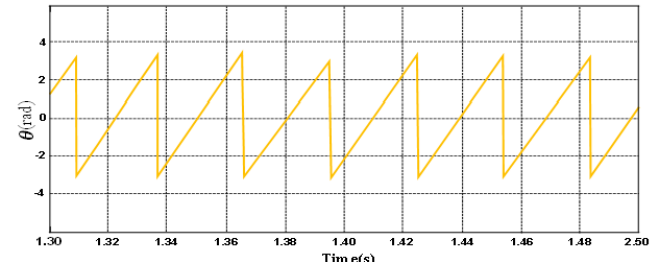
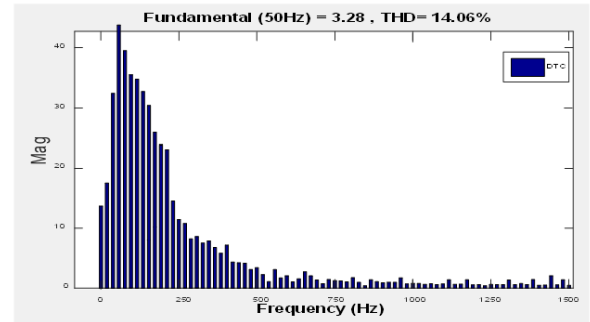
(b) Torque



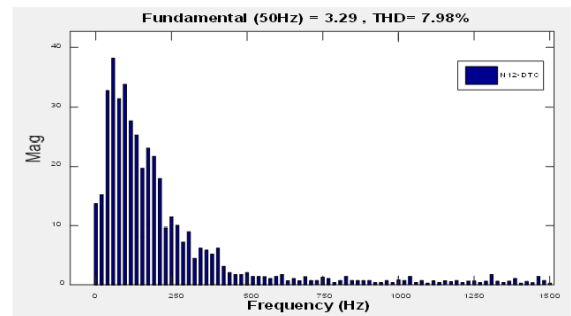
(c.1) Current: DTC



(c.2) Current: 12 sectors neural DTC


(d) Trajectory of the stator flux components Φ_{isd} and Φ_{isq}

(e.1) Position of the flux vector Φ_s : DTC

(e.2) Position of the flux vector Φ_s : 12 sectors neural DTC


(f.1) THD of current: DTC



(f.2) THD of current: 12 sectors neural DTC

Fig. 11. Results of the fourth test.

Table 9 presents the numerical results of the fourth test of the two controllers. Table 9 shows that the proposed 12 sectors neural DTC approach yielded very satisfactory results compared to the conventional 6 sectors DTC approach in terms of current, torque, and flux ripples. Table 9 also demonstrates the effectiveness of the proposed 12 sectors neural DTC approach in improving the response time to velocity and flux compared to the conventional 6 sectors DTC technique. The proposed 12 sectors neural DTC technique reduced the torque, flux, and current ripple values by 54.15%, 59.32 %, and 48.32 %, respectively, compared to the

conventional 6 sectors DTC strategy. Furthermore, the proposed approach reduced the response time to velocity and flow by 30.45 % and 42.31 %, respectively, compared to the conventional 6 sectors DTC approach. These ratios demonstrate the effectiveness, efficiency, and high performance of the proposed 12 sectors neural DTC technique compared to the conventional 6 sectors DTC approach, making it a promising solution for future control applications.

Table 10 represents a study of the extent to which the values of current THD and amplitude of the fundamental signal (50 Hz) were affected between tests using both controls. Table 10 shows that the THD value changed across tests for both controls. Therefore, it can be said that the THD value is affected by both load and speed changes. Using the 6 sectors DTC approach, the THD value changed by 20.56 % between Test 2 and Test 1 and by 32.46 % between Test 1 and Test 3. In the case of the proposed 12 sectors neural DTC approach, the THD value changed by 12.60 % between Test 1 and Test 3 and by 35.64 % between Test 3 and Test 1. These ratios indicate that the proposed 12-sector NN-DTC approach had a lower impact on the THD value between Test 2 and Test 1 compared to the traditional approach. However, between Test 3 and Test 1, the proposed 12-sector neural DTC had a greater impact compared to the 6 sectors DTC. On the other hand, the amplitude value of the fundamental signal (50 Hz) was significantly affected in the two control tests. Table 10 shows that the value of the amplitude changed between the first and second tests by a percentage of -7.85 % and +1.86 % for the traditional and proposed approaches, respectively. Therefore, the value of the amplitude decreased when the 6 sectors DTC was used, but its value increased when the proposed 12-sector neural DTC approach was used. Furthermore, in the third test, the amplitude value increased significantly compared to the first test for both controls. This increase was estimated at 3.31 % and 3.35 % for the 6-DTC and proposed approaches, respectively. Therefore, the 12-sector NN-DTC provided a greater amplitude effect between the third test and test 1, demonstrating the effectiveness and efficiency of the proposed designed 12-sector NN-DTC in improving the fundamental signal (50 Hz) amplitude value compared to the 6-DTC. Table 10 also shows that the THD of current increased in the fourth test compared to the first test for both controls. This increase can be attributed to the change in the machine parameters in the fourth test. The difference in THD between the fourth and first tests was estimated to be +2.74 % and +1.46 % for the classical and designed approaches, respectively. Therefore, the proposed approach produced a lower THD difference than the conventional approach, demonstrating its effectiveness despite the change in AM parameters. Also, the value of the fundamental signal (50 Hz) amplitude increased significantly in the fourth test compared to the first test, which shows that the value of this amplitude was affected by changing the machine parameters for the two controls. The difference in amplitude between the fourth and first tests was estimated at +0.07 A and +0.12 A for the conventional and proposed approaches, respectively. Therefore, the proposed 12 sectors neural DTC approach yielded a larger difference compared to the conventional approach, highlighting the effectiveness of the proposed 12 sectors neural DTC in improving the amplitude value despite the change in the machine parameters.

Table 9. Numerical results of the fourth test.

Performance metric	Traditional technique	Proposed technique	Ratios (%)
Torque ripples (Nm)	5.89	2.7	54.15
Speed response time (ms)	289	201	30.45
Flux ripples (Wb)	0.059	0.024	59.32
Flux response time (ms)	156	90	42.31
Current ripples (A)	0.896	0.463	48.32

Table 10. Study the extent to which the values of the fundamental signal (50 Hz) amplitude and current THD are affected in the case of using the two controls.

Current THD and amplitude of fundamental signal (50 Hz)		Traditional DTC technique	12 sectors neural DTC
Amplitude of fundamental signal (50 Hz)	Test 1	3.21	3.17
	Test 2	2.95	3.23
	Test 3	3.32	3.28
	Test 4	3.28	3.29
	Test 2 – Test 1	-0.26	+0.06
	Test 3 – Test 1	+0.11	+0.11
	Test 4 – Test 1	+0.07	+0.12
	(Test 2 – Test 1)/ Test 2	-7.85%	+1.86%
	(Test 3 – Test 1)/ Test 3	3.31%	+3.35%
	(Test 4 – Test 1)/ Test 4	+2.13%	+3.65%
Current THD (%)	Test 1	11.32	6.52
	Test 2	14.25	7.46
	Test 3	16.76	10.13
	Test 4	14.06	7.98
	Test 2 – Test 1	+2.93	+0.94
	Test 3 – Test 1	+5.44	+3.61
	Test 4 – Test 1	+2.74	+1.46
	(Test 2 – Test 1)/ Test 2	+20.56%	+12.60%
	(Test 3 – Test 1)/ Test 3	+32.46%	+35.64%
	(Test 4 – Test 1)/ Test 4	+19.49%	+18.30%

6. Empirical Results

In this part, the experimental implementation of the designed algorithm is discussed, comparing the results obtained with the 6-DTC technique. The experimental work of the designed algorithm was designed using the experimental setup shown in Figure 12. This experimental work differs from several previously completed experimental works such as [19, 29].

In experimental work, the computational burden is a major factor and is taken into consideration in the case of industrial applications. Requests for lower arithmetic regulators with better competence, and performance are always high. Therefore, the 12-NDTC technique is most suitable for industrial applications. In this experimental work, real tools were used to implement it, as a permanent magnet synchronous motor with a power of 3.5 kW and a load of 5.5 kW was used. In this experimental work, a two-level inverter was used to feed the machine. The experimentally completed inverter consists of an array of IGBT-type transistors.

The experimental work consists of two main sections, as shown in Figure 12. These two sections are the control part, which expresses the elements related to control, such as the proposed algorithm, and the second section is the power section, which consists of several elements, such as the AM machine.

In this experimental work, we relied on a control panel dSPACE 1104 for generating PWM control signals with TTL 0/5 V logic. Use a control panel dSPACE is based on the use of MATLAB, where the 12-NDTC technique is realized in MATLAB and is linked between MATLAB and the dSPACE control panel.

Using MATLAB/Simulink real-time applications are easy to program in Simulink using specific blocks of the real-time interface (RTI) toolbox, which allows the inputs and outputs of the dSPACE DS1104 board to be configured. ControlDesk is the second program used in this experimental work, which is used to load the program code onto the board (written graphically in Simulink, compiled, and converted to C code). It also enables real-time monitoring of measured or calculated data using graphical or digital displays. The Texas Instrument DSP (Digital signal processor) type TMS320F240 is used to handle additional processing tasks.

In this experimental work, information exchange between components and experimental work parts is managed via an external connector board (CP1104/dSPACE), connected to the board through a shielded cable. This board facilitates the reception of analog signals through BNC connectors. Also, it adapts the signal to PWM control signals and possible error signals from the Semikron converter. The use of this board allows the integration of different measuring sensors into the experimental setup.

The signal conditioning interface converts between 0/5 V TTL logic and 0/15 V CMOS logic. This conversion is critical as the DS1104 control board operates with 0/5 V TTL signals, while the inverter requires 0/15 V CMOS signals.

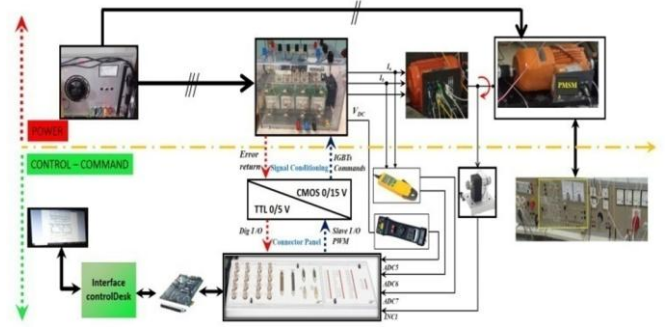


Fig. 12. Schematic diagram of the experimental platform.

To measure current, closed-loop Hall effect current sensors LEM LA55TP are used, and to measure voltage, closed-loop Hall effect voltage sensors LEM LV100-500 are used. Also, an incremental encoder is used to measure the motor speed. In this experimental work, a protection filter with a cut-off frequency of about 500 Hz (well above the fundamental frequency of 50 Hz) was used between each sensor and the analog-to-digital converter.

Figure 13 represents the experimental work performed for the proposed algorithm. This figure gives a clear picture of the various parts used and composing the experimental work.

Three different tests are proposed to experimentally verify the efficacy and efficiency of the 12-NDTC technique. Also, the competence of the 12-NDTC technique is compared with the 6-sector DTC algorithm. Experimentally, the same machine parameters used in the simulation section are used.

6.1. Test 1: No-Load Startup and Steady-State Operation

In this test, a torque scale was used: 5 V and a gain of 0.1, and for flux a gain of 1 and a gain of 2 V was used. The reference speed is fixed at 1000 rpm. The results of this test are represented in Figure 14. Figure 14a represents the experimentally obtained torque and speed for the two controls. The torque follows the reference well and is the same thing for speed. It is noted that the designed algorithm gave fewer undulations than the 6 sectors DTC technique and a faster dynamic response to speed compared to the 6 sectors DTC technique.

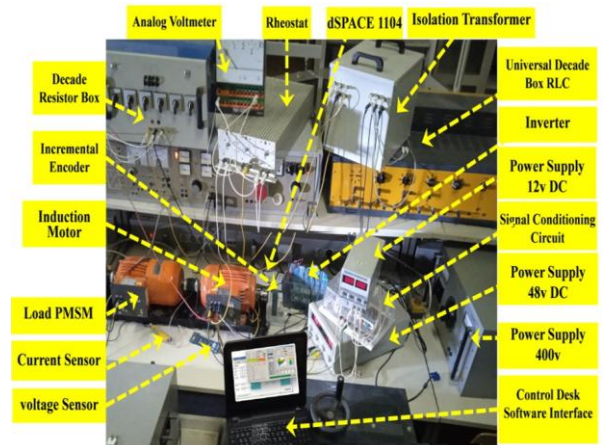


Fig. 13. Experimental prototype setup.

Figure 14b represents zoom-in rotor speed. This figure shows that using the proposed algorithm increases the dynamic speed performance compared to using the 6 sectors DTC technique. Also, it is noted that the speed response time was 212 ms and 400 ms for both the 12-NDTC strategy and the DTC technique. Therefore, the 12-NDTC technique significantly reduced the response time compared to the 6 sectors DTC technique. This reduction was estimated at 47 % compared to the 6 sectors DTC technique, as this percentage highlights the strength and competence of the designed algorithm and its ability to improve dynamic response.

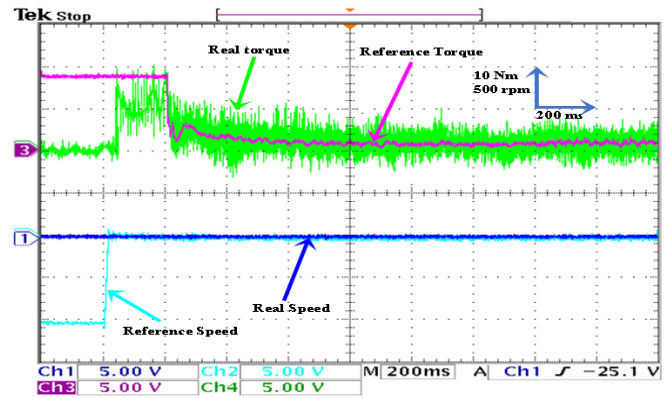
Figure 14c shows a zoom representation of the stator currents (1 div = 5 A) for the two algorithms. These currents are absorbed by the motor, and it is noted that these currents have a sinusoidal shape with ripples. These fluctuations are low when using the 12-NDTC strategy compared to DTC technique.

Figure 14d represents the change of both the stator flux and its components as a function of time for the three control methods. It is noted that the flux takes a constant value and follows the reference well (1 div = 0.2 Wb). The flux fluctuations are low when using the designed algorithm compared to the 6 sectors DTC technique (see Figure 13e). Also, the flux components take a sinusoidal shape with distortions. These distortions are less in the proposed algorithm compared to the 6 sectors DTC technique.

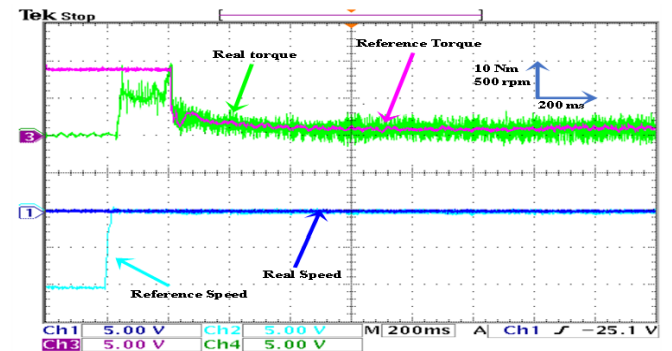
Figure 14e represents zoom in both position and flux. The results listed in this figure are the same as the results listed in the simulation, where the position of stator flux takes the form of saw teeth.

Figure 14f represents the evolution of the flux components for the two algorithms. It is noted that the shape of the evolution of the flux components takes a circular shape, which is the same as the simulation results. Also, the proposed algorithm provided better development than traditional 6 sectors DTC technique in terms of ripples.

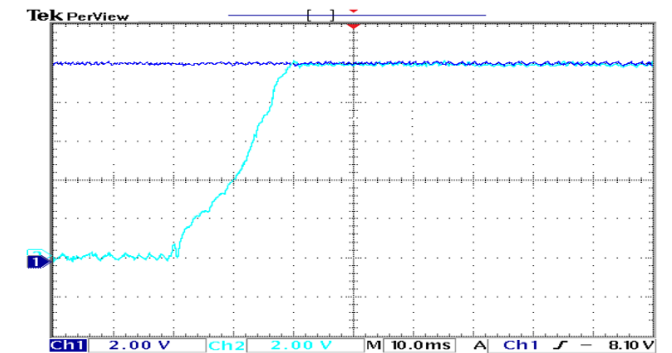
Figure 14g represents the THD of the current obtained from the experimental work of the two algorithms. This value was 12.83 % and 8.87 % for the 6 sectors DTC technique and the 12-NDTC strategy, respectively. Therefore, the designed algorithm minimized the value of THD experimentally compared to the 6 sectors DTC technique. This reduction was estimated at 30.87 %. This percentage proves that the algorithm has an effective performance in reducing current ripples and improving its quality compared to the 6 sectors DTC technique. Experimentally, it was observed that the amplitude of the fundamental signal (50 Hz) was 3.29 A for the conventional 6 sectors DTC technique and 3.22 A for the designed 12 sectors neural DTC approach. These results are almost the same as the simulation results in the first test. Therefore, the conventional 6 sectors DTC technique gave a better amplitude value than the designed 12 sectors neural DTC approach. Therefore, this amplitude can be considered a drawback of the designed approach in this test. This drawback can be overcome in the future by using a fractional-order control strategy or by changing the number of internal layers of the neural controller.



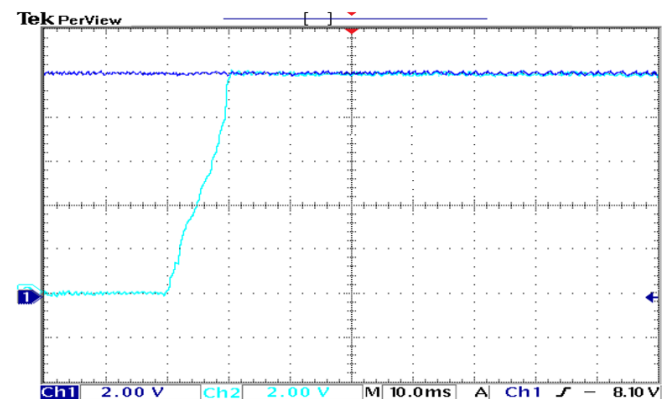
(a.1) Torque and speed (first empirical test): DTC



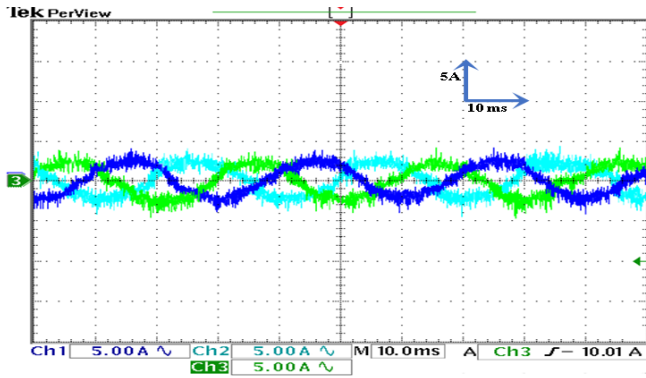
(a.2) Torque and speed (first empirical test): 12 sectors neural DTC



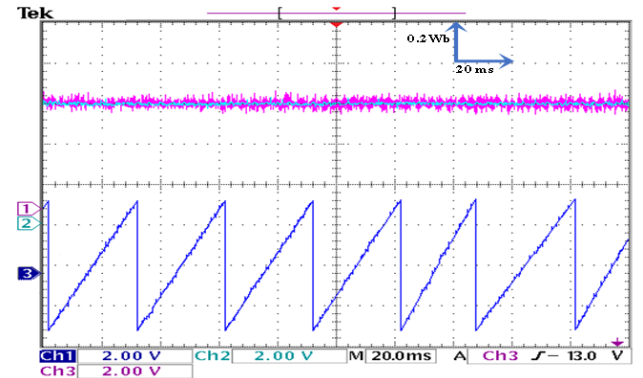
(b.1) Zoom on the rotor speed (first empirical test): DTC



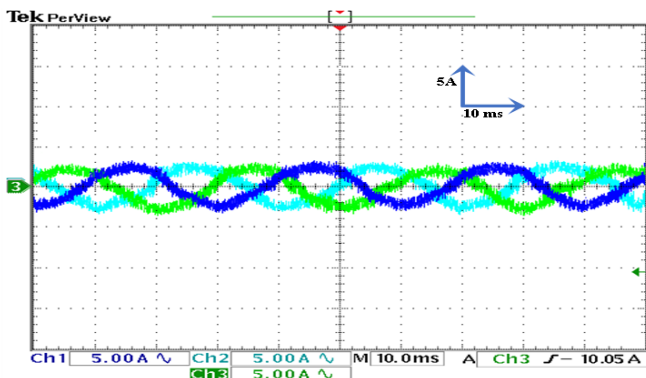
(b.2) Zoom on the rotor speed (first empirical test): 12 sectors neural DTC



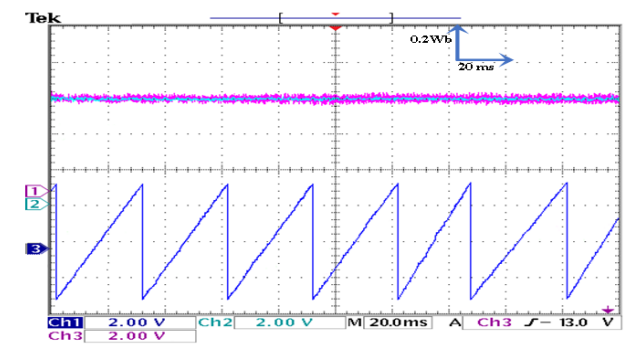
(c.1) Zoom in the currents (first empirical test): DTC



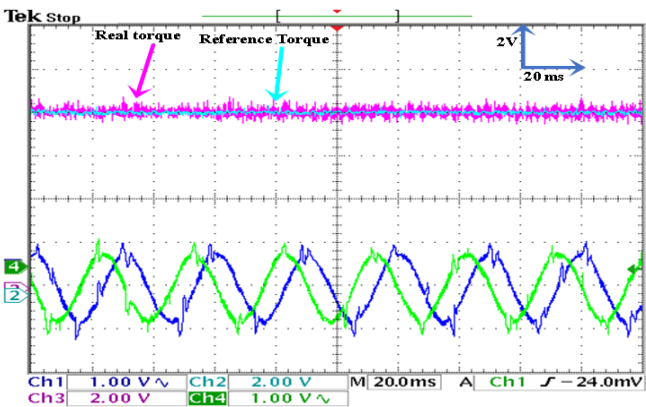
(e.1) Zoom in the stator flux and position (first empirical test): DTC



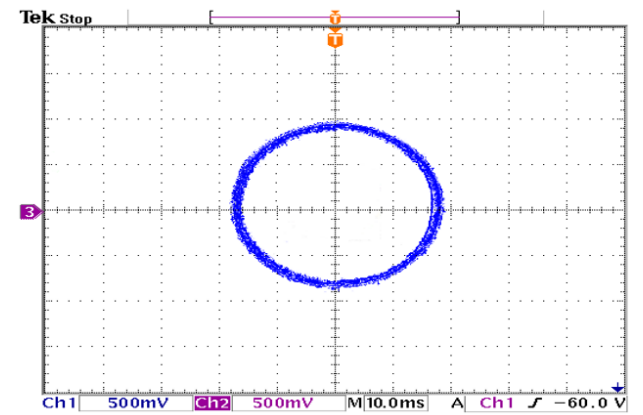
(c.2) Zoom in the currents (first empirical test): 12 sectors neural DTC



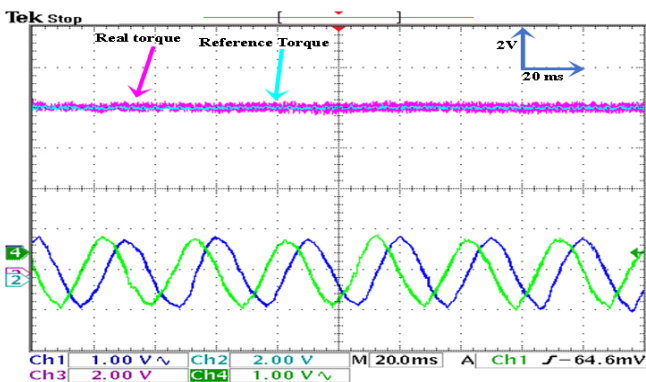
(e.2) Zoom in the stator flux and position (first empirical test): 12 sectors neural DTC



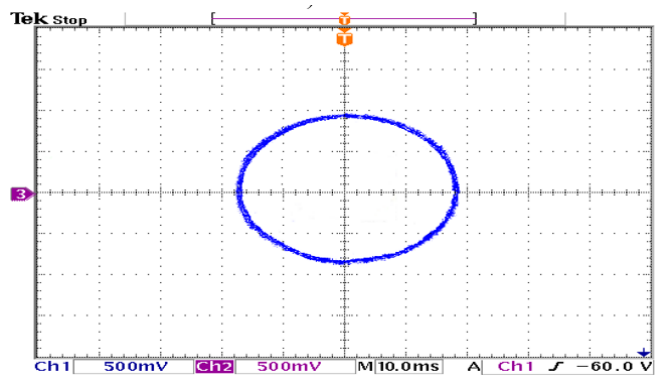
(d.1) Stator flux (first empirical test): DTC



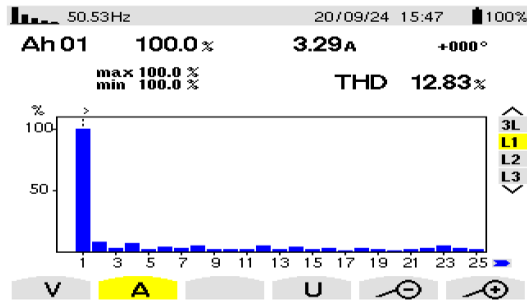
(f.1) Trajectory of the stator flux (first empirical test): DTC



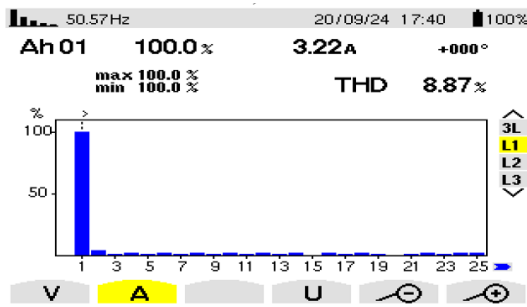
(d.2) Stator flux (first empirical test): 12 sectors neural DTC



(f.2) Trajectory of the stator flux (first empirical test): 12 sectors neural DTC



(g.1) THD of current (first empirical test): DTC



(g.2) THD of current (first empirical test): 12 sectors neural DTC

Fig. 14. Results of the first empirical test.

6.2. Test 2: Speed Variation

In this subsection, the 12-NDTC technique is tested in the case of changing rotational speed. The reference speed is changed from 1000 rpm to 1480 rpm under no-load conditions. The results of this test are represented in Figure 15. For this test, a 500 mV scale with a gain of 0.01 was used for torque measurements, a 500 mV scale with a gain of 0.0001 for speed measurements, and a 200 mV scale with a gain of 0.1 for flux measurements.

Figure 15a represents the torque and motor speed of the two algorithms. The speed follows the reference well with some distortion. These distortions are non-existent in the proposed approach compared to the 6 sectors DTC technique. It is noted in this test that the designed algorithm provided a better dynamic response to rotational speed than the 6 sectors DTC technique. Also, the proposed algorithm minimized exceeding the limit value of rotation speed compared to the 6 sectors DTC technique.

When changing the rotation speed from 1000 rpm to 1480 rpm, it is noted that the torque value increased. Therefore, an increase in rotational speed corresponds to an increase in the torque value, after which the torque returns to its previous value as a result of the use of the PI regulator. From Figure 15a, it is noted that the designed algorithm reduced the value of torque ripples compared to the 6 sectors DTC technique.

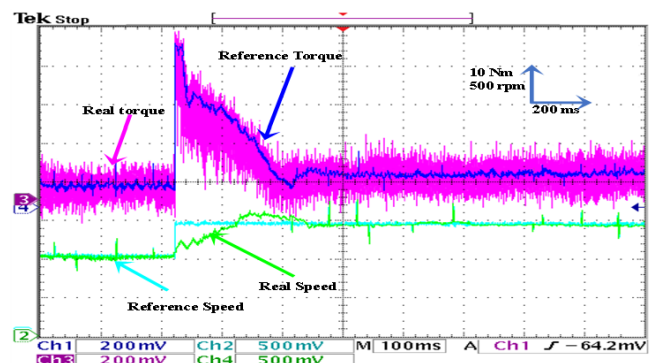
Figure 15b represents the change in current for the two algorithms in Test 2. This current takes a sinusoidal shape, with an increase in the value of the current observed at the moment of the speed change, which is normal. Also, the

proposed algorithm provided a high quality of current compared to the 6 sectors DTC technique.

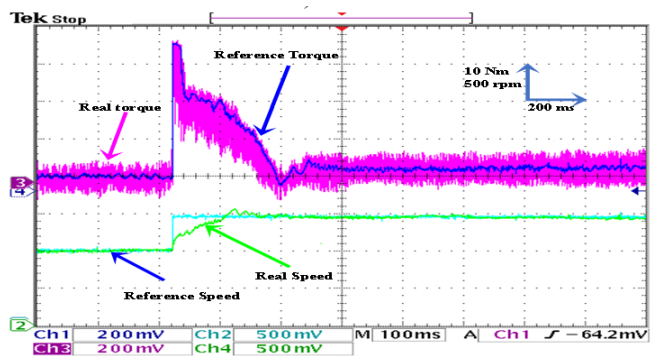
Figure 15c represents the flux (1 div = 0.2 Wb) and its components (1 div = 1 Wb) at the value of 1480 rpm. From this figure, it is noted that the flux is affected by changing the value of the rotation speed, as it is observed that the limit value is exceeded. This overshoot was less severe when using the proposed algorithm compared to the 6 sectors DTC technique. Moreover, the designed algorithm minimized the value of flux ripples in this test compared to the 6 sectors DTC technique. The flux components are sinusoidal for the two controls, with the proposed algorithm having an advantage in terms of quality compared to the DTC technique.

Figure 15d represents the evolution of the flux components of the two algorithms. This development is the same as in the previous test and in the simulation. It is noted that the designed algorithm provided better development than the 6 sectors DTC technique in terms of quality.

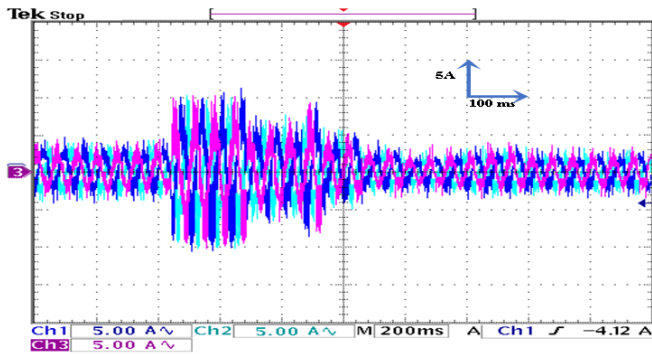
The value of THD of the current is listed in Figure 15e. This value is estimated to be 19.09 % and 11.03 % for both the DTC technique and the proposed algorithm. Therefore, the designed algorithm minimized the THD value in this test compared to the 6 sectors DTC technique. This minimization was estimated at 42.22 %. On the other hand, Figure 15e shows that the amplitude of the fundamental (50 Hz) current signal was 3.29 A for both controls. Therefore, the amplitude values were the same for both controls. These results highlight the effectiveness of the designed approach in improving the characteristics of the current and the control system as a whole.



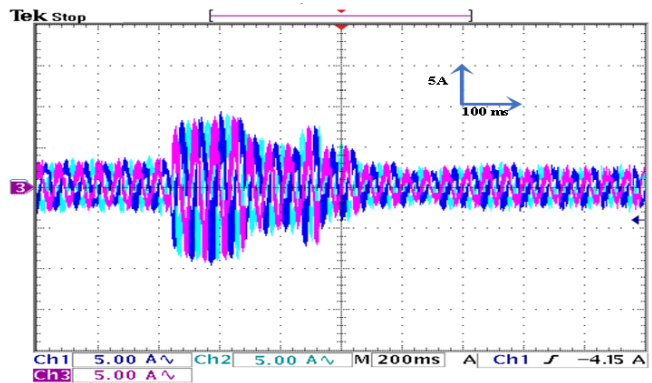
(a.1) Rotor speed and torque (experimental test 2): DTC



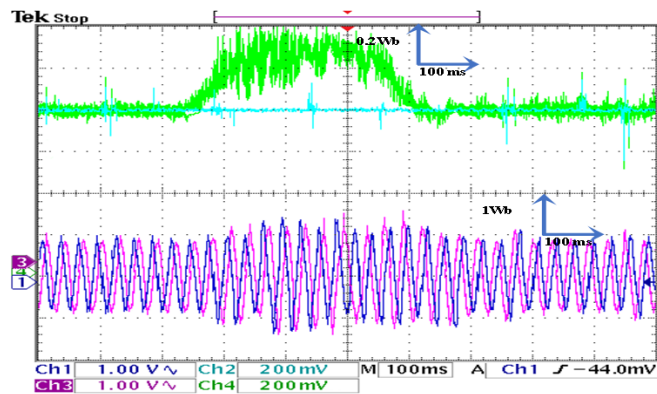
(a.2) Rotor speed and torque (experimental test 2): 12 sectors neural DTC



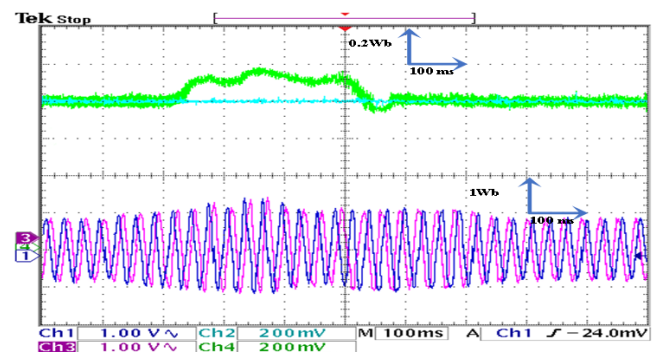
(b.1) Stator currents (experimental test 2): DTC



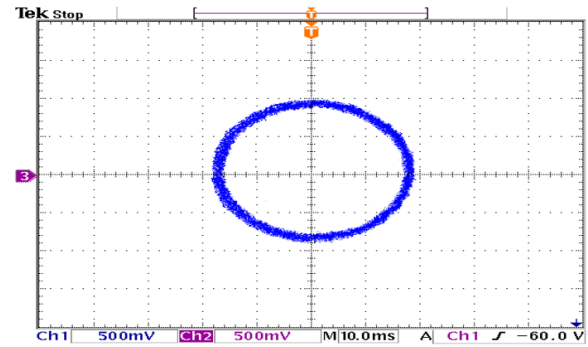
(b.2) Stator currents (experimental test 2): 12 sectors neural DTC



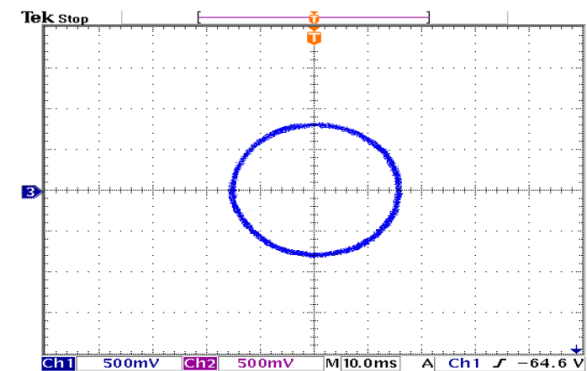
(c.1) Stator flux and its components for 1480 rpm (experimental test 2): DTC



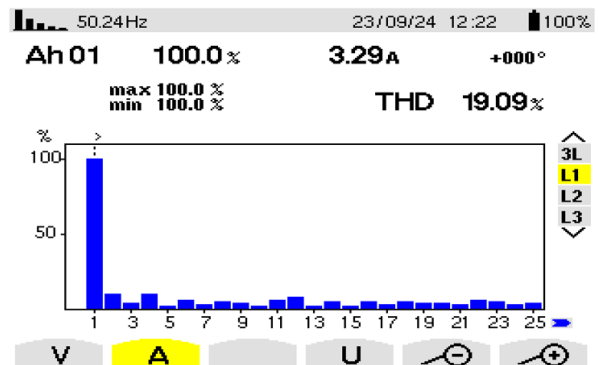
(c.2) Stator flux and its components for 1480 rpm (experimental test 2): 12 sectors neural DTC



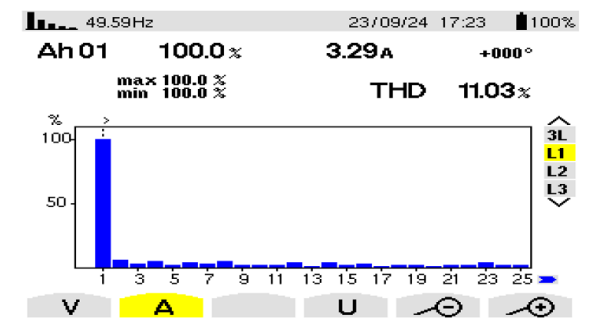
(d.1) Evolution of flux components (experimental test 2): DTC



(d.2) Evolution of flux components (experimental test 2): 12 sectors neural DTC



(e.1) THD of current (experimental test 2): DTC



(e.2) THD of current (experimental test 2): 12 sectors neural DTC

Fig. 15. Results of the second empirical test.

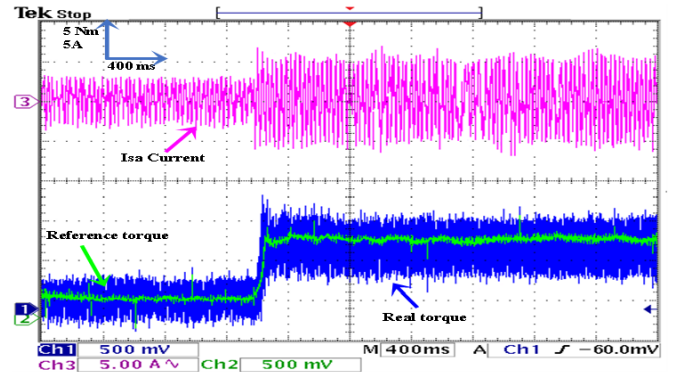
6.3. Test 3: Load Test

This test differs from the previous two experimental tests. In this test, the speed is fixed at 1000 and a load is applied. The sampling time is set to $T_e = 10^{-4}$ s using Euler's method. The reference static flux is 0.8 Wb. In this test, a 500 mV scale with a gain of 0.01 was used for torque measurements, and a 500 mV scale with a gain of 0.0001 was used for speed measurements. The results of the third pilot test are shown in Figure 16.

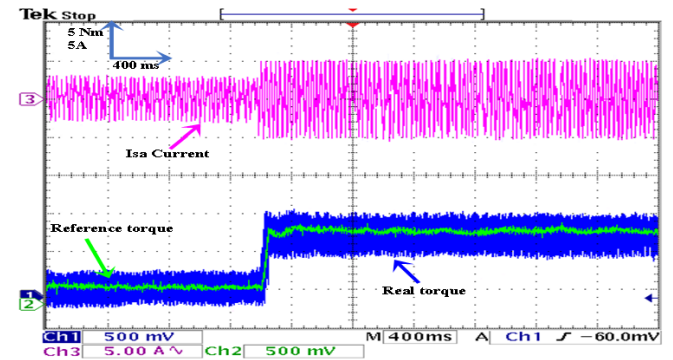
Figure 16a shows the torque (1 div = 5 N.m) and the current I_{sa} (1 div = 5 A) of the AM at the moment when the load is applied. It can be observed from this figure that the AM torque closely follows the reference torque for the three proposed algorithms. Additionally, the electrical current increases at the moment the load is applied, with this increase corresponding to the applied load (the value of the applied resistant torque). Furthermore, there are torque and current ripples, as shown in Figure 16b, which are more pronounced in the case of the 6 sectors DTC technique compared to the proposed algorithm. These applied results are consistent with those presented in the simulation section, indicating the validity of the previously presented results and the superiority of the 12-NDTC technique.

The AM speed and torque are illustrated in Figure 16c. From this figure, it is observed that the speed (1 div = 500 rpm) closely follows the reference for the proposed algorithm. The DTC technique and proposed algorithm experience overshoot, and their response times can be compared to the proposed algorithm when the load is applied. These results convincingly confirm the simulation results and demonstrate that the 12-NDTC technique is superior to both the 6 sectors DTC technique, particularly in terms of reducing torque fluctuations. The evolution of the flux components of the AM in this test is shown in Figure 16d for the two controls. The evolution of the flux components in this test remains the same as in the previous two tests with a circular shape. The proposed algorithm gave a much better shape for the evolution of flux components than the 6 sectors DTC technique.

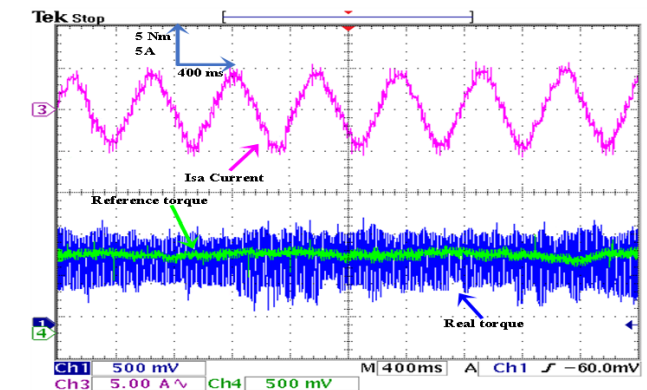
In this test, the THD of the current value is listed in Figure 16e for the two algorithms. According to Figure 16e, the THD value experimentally was 23.93 % and 12.03 % for both the 6 sectors DTC technique and the designed algorithm, respectively. Therefore, the designed algorithm minimized the value of THD experimentally by an estimated percentage of 49.73 % compared to the 6 sectors DTC technique. Figure 16e shows that the fundamental (50 Hz) current amplitude was 3.19 A for the conventional 6 sectors DTC technique and 3.29 A for the designed approach. These values indicate that the amplitude is larger in the designed approach. The experimental amplitude value for the designed approach is almost the same as the amplitude obtained using simulation in the third test. These experimental results highlight the efficacy and strength of the 12-NDTC technique in improving the control system features and current quality compared to the 6 sectors DTC technique. Therefore, the proposed algorithm can be relied upon in the future in industrial applications such as propulsion and traction.



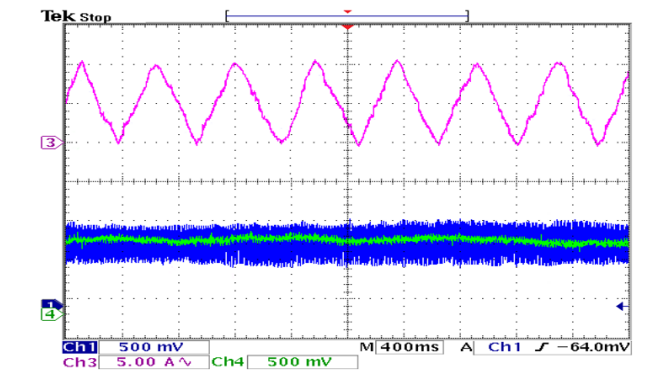
(a.1) Torque and stator current I_{sa} (experimental test 3): DTC



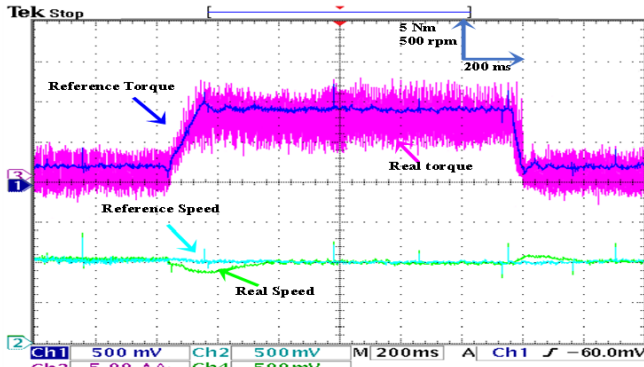
(a.2) Torque and stator current I_{sa} (experimental test 3): 12 sectors neural DTC



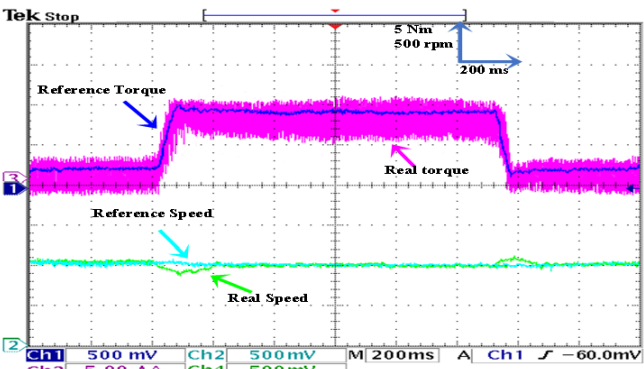
(b.1) Zoom in the torque and current (experimental test 3): DTC



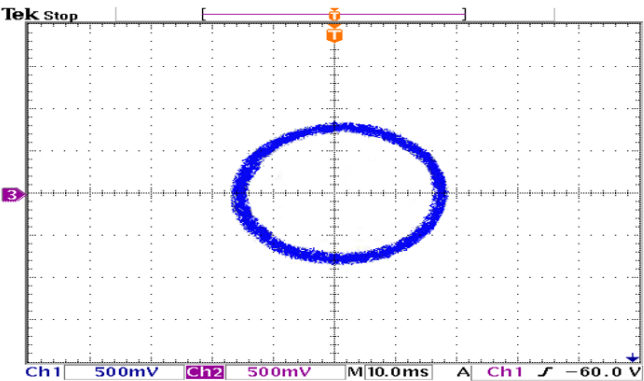
(b.2) Zoom in the torque and current (experimental test 3): 12 sectors neural DTC



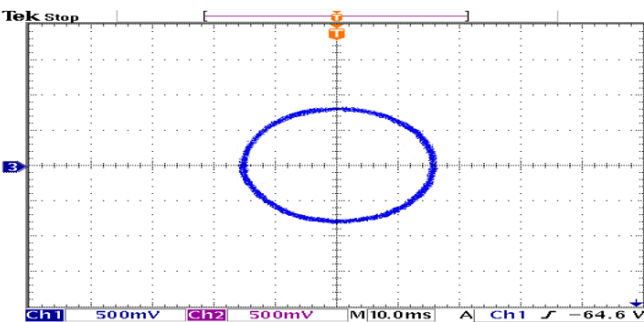
(c.1) Rotor speed and electromagnetic torque (experimental test 3): DTC



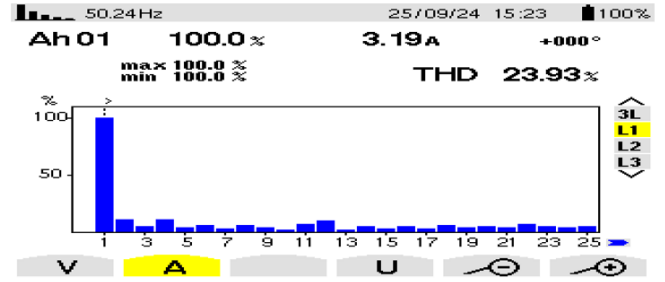
(c.2) Rotor speed and electromagnetic torque (experimental test 3): 12 sectors neural DTC



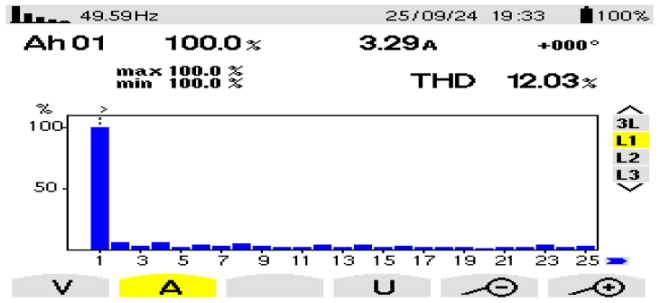
(d.1) Evolution of flux components (experimental test 3): DTC



(d.2) Evolution of flux components (experimental test 3): 12 sectors neural DTC



(e.1) THD of current (experimental test 3): DTC



(e.2) THD of current (experimental test 3): 12 sectors neural DTC

Fig. 16. Results of the third empirical test.

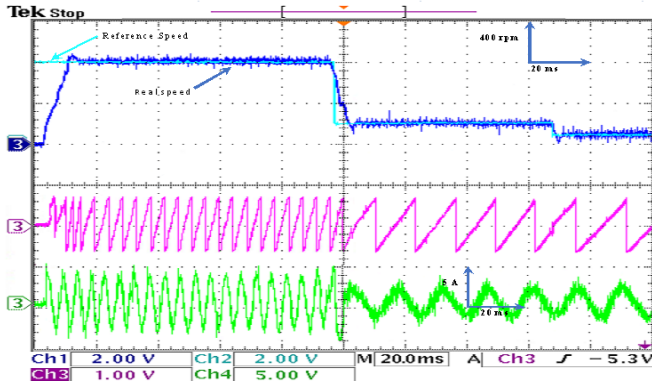
6.4. Fourth Experimental Test: Low Speed Operation

This experimental test differs from previous experimental tests. In this test, the effectiveness of the designed 12 sectors neural DTC approach is studied at low speeds. The speed varies from 800 rpm to 250 rpm and then to 125 rpm, with the results shown in Figure 17.

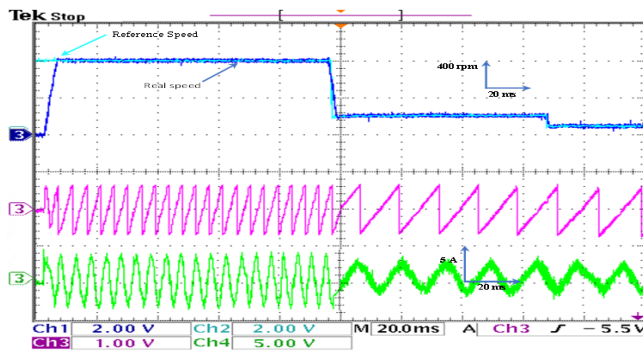
According to Figures 17a and 17b, the speed of the two techniques follows the reference value well, with the designer approach having an advantage over the traditional 6 sectors DTC approach regarding response time (blue curve). Also, a threshold value is observed when using the traditional 6 sectors DTC approach, but the designed approach does not exceed the threshold value for speed, demonstrating the great capability and effectiveness of this approach.

The position of the flux vector for the two techniques is represented by the purple curve. It is noticeable that the shape of the position of the flux vector is a sawtooth signal as in the previous tests. From Figures 17a and 17b, it is observed that the period of the position of the flux vector signal varies with the change in rotational speed, where the period is lowest for a speed value equal to 800 rpm, and the lower the speed, the higher the period value. On the other hand, it is observed that the quality of the position of the flux vector signal is better in the case of using the proposed 12 sectors neural DTC strategy compared to the conventional 6 sectors DTC technique.

The current for the two controls is represented by the green curve. This current for the two controls remains sinusoidal with ripples. These ripples are lower in the designed 12 sectors neural DTC approach compared to the conventional 6 sectors approach.



(a) DTC

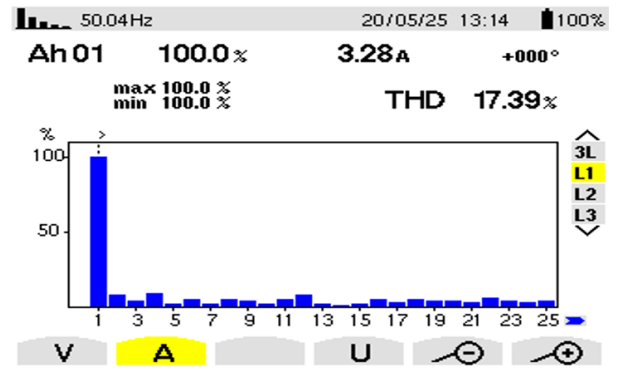


(b) 12 sectors neural DTC

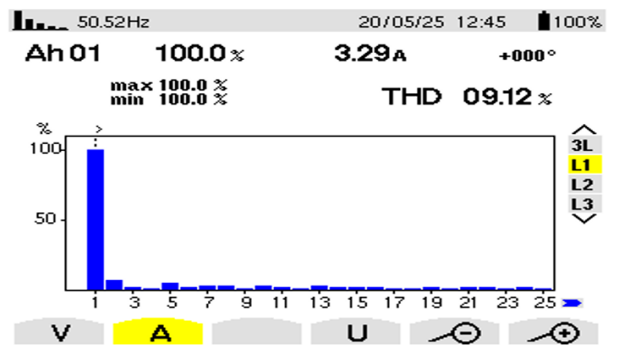
Fig. 17. Results of the fourth empirical test.

Furthermore, it is noted that a change in speed value directly affects the period of the current signal for the two controls. At low speeds, the period value increases significantly for the two techniques. On the other hand, it is noted that current ripples increase significantly at low speeds for the two controls. Therefore, it can be said that low speed affects current quality. Therefore, low-speed operation can be considered one of the most significant drawbacks of the traditional and proposed approaches.

Figure 18 represents the THD of current for the two controls in the fourth test. This value was 17.39 % for the conventional approach and 9.12 % for the proposed 12 sectors neural DTC approach. Therefore, the proposed approach yielded a THD value significantly lower than that obtained by the conventional method. The proposed approach reduced the THD value at low speed by a percentage of 47.56 %. This percentage demonstrates the effectiveness of the designed 12 sectors neural DTC approach and its ability to reduce THD despite the lower rotational speed compared to the conventional approach. On the other hand, Figure 18 shows that the fundamental signal (50 Hz) amplitude was 3.28 A for the conventional 6 sectors DTC approach and 3.29 A for the proposed 12 sectors neural DTC approach. These values demonstrate the effectiveness of the designed approach in improving the amplitude value compared to the conventional approach. These obtained results highlight the effectiveness, efficiency, and high operational performance of the designed 12 sectors neural DTC approach, making it a reliable solution for other industrial applications such as electric vehicles and renewable energy.



(a) DTC



(b) 12 sectors neural DTC

Fig. 18. Current THD (fourth empirical test).

Table 11 compares the proposed strategy with related works in terms of the THD value of current data. This comparison highlights the effectiveness of the proposed 12 sectors neural DTC approach in providing a significantly better value than several related scientific works. Based on this table, the designed approach reduced the THD value by 26.24 %, 17.47 %, and 46.95% compared to the fuzzy predictive control strategy [52], fuzzy DTC approach [54], and seven-level neural DTC with fuzzy speed controller [56], respectively.

The designed strategy reduced the THD value by 5.92%, 24.19 %, 85.61%, and 27.47 % compared to the neural DTC technique [30], Conventional SMC-based DTC-SVM scheme [58], 12 sectors DTC based on super-twisting controllers [59], and neuro-fuzzy DTC technique [55], respectively.

These ratios highlight the effectiveness of the designed approach in reducing the THD of current compared to several strategies found in the literature, such as the 12-sector DTC based on super-twisting controllers and the conventional SMC-based DTC-SVM scheme. This comparison demonstrates that the designed approach has a significant potential to improve current quality, making it a promising and reliable solution for electric vehicles and renewable energy (wind energy).

On the other hand, the work designed in this paper is compared with the work completed in [60, 61], as this comparison aims to highlight the importance of the work completed compared to several works found in the literature.

Table 11. Comparison with other related works in terms of current THD value.

References and techniques			THD (%)
[30]	Neural DTC technique		6.93
	Tree DTC technique		6.60
	Traditional DTC strategy		11.78
[50]	Optimized stator flux reference by TOA method		7.20
[51]	Neural network method		22.48
[52]	Fuzzy predictive control		8.84
[53]	Low speed	Traditional DTC technique	9.30
		Fuzzy DTC technique	7.90
	High speed	Traditional DTC technique	9.10
		Fuzzy DTC technique	7.50
[54]	Traditional DTC technique		9.30
	Fuzzy DTC technique		7.90
	Optimized DTC strategy		7.30
[55]	Neuro-fuzzy DTC technique		8.99
[56]	Seven-level DTC technique		26.92
	Seven-level neural DTC with fuzzy speed controller		12.29
[57]	Standard DTC		7.27
	DTC technique with ramp modulator		7.10
[58]	DTC-SVM with single PI controller		13.85
	Conventional SMC-based DTC-SVM scheme		8.60
[59]	Basic DTC technique		76.92
	12 sectors DTC based on super-twisting controllers		45.30
Proposed technique			6.52

In the study by J. Park, et al. ("Direct Torque Control in PMSM Using a 12-Segment Approach and Pulse Width Modulation Based on the Supplied Voltage Function," 2018) [60], a 12-segment DTC scheme coupled with pulse width modulation is implemented for the PMSM, using constant switching logic and voltage vector selection rules. In contrast, our work focuses on an inductive (asynchronous) machine instead of a PMSM, replacing the fixed comparator/switchable structure with a neural network decision unit, enabling adaptive mapping of flow/torque error signals and sector information for voltage vector selection. While J. Park et al.'s approach aims to improve vector modification and switching behavior within a 12-segment framework, it retains the classical rationale; our approach develops this by adopting machine learning-based reasoning for the switching decision and demonstrates full experimental implementation rather than just simulation.

The second reference study, conducted by A. Pal, et al. [61], applies torque comparison (DTC) to a 12-segment induction motor in the simulation by increasing the levels of the comparator (a five-level torque comparator) and thus

improving the accuracy of the hysteresis switching. While it improves upon classical hysteresis comparison tables and comparisons, it remains within the traditional hysteresis + search table model and is limited to simulation. Our proposed work deviates from this by eliminating hysteresis comparisons and completely replacing the switching table with a neural network for voltage vector selection, and by providing real-time experimental verification on hardware.

Taken together, while reference works drive incremental improvements to the 12-sector DTC architecture (via enhanced comparison levels or PWM modulation) within the framework of the traditional logic table, our designed work transforms the model into an adaptive neural-based selection mechanism, extends the application to induction machines, and demonstrates practical device performance gains (e.g., lower torque ripple, faster transient response) that go beyond the simulation-only context of previous studies.

7. Conclusions

This work discusses the application of neural algorithms to address the issues associated with traditional direct torque control techniques. The algorithm was initially implemented in MATLAB with various tests, and its results were compared to those of the traditional 6 sectors DTC approach. Subsequently, an experimental implementation of the proposed algorithm was conducted using real equipment based on dSPACE 1104. Three different tests were proposed to evaluate the efficiency and effectiveness of the 12-sector neural DTC strategy in comparison to the traditional 6-sector DTC technique. The experimental results confirmed the simulation outcomes, demonstrating the competence and capabilities of the 12 sectors of the neural DTC technique in enhancing the proposed control system. The findings indicate that the suggested algorithm effectively overcomes the challenges posed by the traditional 6 sectors' DTC method. Key results from the experimental work can be summarized as follows:

- An improved dynamic speed response by 47% compared to the traditional 6 sectors DTC technique.
- A significant reduction in the incidence of exceeding the speed limit.
- Decreased fluctuations in current, torque, and flux compared to the traditional 6 sectors DTC method.
- A 30.87%, 42.22%, and 49.73% reduction in the THD of current, relative to the traditional 6 sectors DTC technique.

These experimental results highlight the effectiveness of utilizing a neural algorithm to overcome the limitations of the traditional DTC approach. This algorithm has potential applications in various sectors, including factories producing electric motors, where it can serve as an effective tool for controlling electrical machines. In the industrial sector, the proposed algorithm could enhance the power quality and current stability of large generators used in offshore wind turbines and hydro pumps. Unlike strategies that rely on mathematical modeling of the studied system—which can

increase vulnerability to changing system parameters—the designed algorithm is characterized by its simplicity and does not rely on mathematical modeling of the system being studied. This simplicity underscores the importance of the proposed algorithm for future applications in other fields.

In the future, additional experimental work will be conducted on the DTC technique for the AM drive algorithm, employing nonlinear strategies such as the SMC approach or BC technique, with results compared to those obtained from the algorithm proposed in this work.

Nomenclature

DTC	Direct torque control
NN	Neural network
SMC	Sliding mode controller
PI	Proportional-integral controller
EM	Electrical machine
HC	Hysteresis comparator
MM	Mathematical model
MRAC	Model reference adaptive control
WT	Wind turbine
SPWM	Sinusoidal pulse width modulation
VFD	Variable frequency drive
AM	Asynchronous machine
THD	Total harmonic distortion
GA	Genetic algorithm
RE	Renewable energy
FOC	Field-oriented control
ST	Switching table
SVM	Space vector modulation
BC	Backstepping control
ACO	Ant colony optimization
FSOSMC	Fuzzy second-order sliding mode controller
MPPT	Maximum power point tracking
SF	Switching frequency

Author Contributions

Conceptualization: H.B., A.Y., and A.M.; Methodology: H.B., A.Y., A.M., and N.B.; Software: H.B. and A.M.; Validation: H.B. and A.M.; Formal analysis: A.Y., A.M., H.B., and N.B.; Investigation: A.M., H.B., and N.B.; Resources: A.M. and H.B.; Data curation: A.Y., A.M., and H.B.; Writing—original draft preparation: A.Y., A.M., and H.B.; Writing—review and editing: A.M., H.B., and N.B.; Visualization: A.M., A.Y., H.B., and N.B.; Supervision: A.Y., A.M., H.B., and N.B.; Project administration: A.M. and H.B.; Funding acquisition: A.M. and H.B. All authors have read and agreed to the published version of the manuscript.

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Conflict of Interest

The authors declare no conflict of interest.

References

- [1] I. Takahashi, T. Noguchi, “A new quick-response and high-efficiency control strategy of an induction motor,” *IEEE Transactions on Industry Applications*, vol. 5, pp. 820–827, 1986.
- [2] A. Ammar, B. Talbi, T. Ameid, Y. Azzoug, A. Kerrache, “Predictive direct torque control with reduced ripples for induction motor drive based on T-S fuzzy speed controller,” *Asian Journal of Control*, vol. 21, No. 4, pp. 2155–2166, 2019.
- [3] N. El Ouanjli, A. Derouich, A. El Ghzizal, S. Motahhir, A. Chebabhi, Y. El Mourabit, M. Taoussi, “Modern improvement techniques of direct torque control for induction motor drives—a review,” *Protection and Control of Modern Power Systems*, vol. 4, No. 1, pp. 1–12, 2019.
- [4] T. Sutikno, N. R. N. Idris, A. Jidin, “A review of direct torque control of induction motors for sustainable reliability and energy efficient drives,” *Renewable and Sustainable Energy Reviews*, vol. 32, pp. 548–558, 2014.
- [5] S. El Daoudi, L. Lazrak, N. El Ouanjli, M. A. Lafkih, “Sensorless fuzzy direct torque control of induction motor with sliding mode speed controller,” *Computers and Electrical Engineering*, vol. 96, pp. 107490, 2021.
- [6] A. Ammar, A. Bourek, A. Benakcha, “Nonlinear SVM-DTC for induction motor drive using input-output feedback linearization and high order sliding mode control,” *ISA Transactions*, vol. 67, pp. 428–442, 2017.
- [7] S. Jadhav, K. Jaladi, “Advanced VSC and intelligent control algorithms applied to SVM-DTC for induction motor drive: A comparative study,” 2016 12th World Congress on Intelligent Control and Automation (WCICA), IEEE, pp. 2694–2698, 2016.
- [8] S. El Daoudi, L. Lazrak, B. El Ouanjli, M. Ait Lafkih, “Applying sliding mode technique for the nonlinear DTC-SPWM control strategy of sensorless squirrel cage asynchronous motor,” *International Journal of Dynamics and Control*, vol. 9, No. 4, pp. 1633–1644, 2021.
- [9] E. Najib, M. Said, A. Ameena Saad, E. Soukaina, D. Aziz, E. Mohammed, “Improved twelve sectors DTC strategy of induction motor drive using Backstepping speed controller and P-MRAS stator resistance identification-design and validation,” *Alexandria Engineering Journal*, vol. 80, pp. 358–371, 2023, Doi: 10.1016/j.aej.2023.08.077.
- [10] M. Said, D. Aziz, I. Atif, E. Najib, “ANT-colony optimization-direct torque control for a doubly fed induction motor: An experimental validation,” *Energy Reports*, vol. 8, pp. 81–98, 2022, Doi: 10.1016/j.egy.2021.11.239.
- [11] M. Dursun, “Enhancement fractional-order sliding mode controller design for induction motor vector control,” *Iranian Journal of Science and Technology, Transactions*

- of Electrical Engineering, vol. 47, pp. 1059–1080, 2023, Doi: 10.1007/s40998-023-00637-2.
- [12] S. Sharma, B. Singh, A. Datar, “Duty ratio control technique with torque ripple minimization for induction motor-based electric vehicle applications,” *Journal of Power Electronics*, vol. 23, pp. 617–624, 2023, Doi: 10.1007/s43236-023-00595-2.
- [13] A. K. Sahoo, R. K. Jena, “Reduction of torque ripple in induction motor-driven electric vehicle using optimized stator flux,” *International Journal of Information Technology*, vol. 15, pp. 1333–1346, 2023, Doi: 10.1007/s41870-023-01172-3.
- [14] G. Boukhalfa, S. Belkacem, A. Chikhi, “Fuzzy-second order sliding mode control optimized by genetic algorithm applied in direct torque control of dual star induction motor,” *Journal of Central South University*, vol. 29, pp. 3974–3985, 2022, Doi: 10.1007/s11771-022-5028-3.
- [15] S. Siliveru, N. R. Reddy, “Comparative switching and conduction loss analysis of a SVPWM and DPWM based DTC of open end winding induction motor drive,” *International Journal of Renewable Energy Research*, vol. 12, No. 4, pp. 1954–1965, 2022, Doi: 10.20508/ijrer.v12i4.13466.g8618.
- [16] G. Goksel, A. K. Ahmet, “Design and implementation of a wind turbine emulator using an induction motor and direct current machine,” *International Journal of Renewable Energy Research*, vol. 10, No. 3, pp. 1426–1438, 2020, Doi: 10.20508/ijrer.v10i3.10723.g8018.
- [17] C. Ghizlane, M. Zakaria, A. Abdelouahed, M. Mustapha, “Speed control of induction motor driving a pump supplied by a photovoltaic array,” *International Journal of Renewable Energy Research*, vol. 10, No. 1, pp. 237–242, 2020, Doi: 10.20508/ijrer.v10i1.10320.g7859.
- [18] S.F.A. Bukhari, H. Kahveci, M. E. Şahin, “Single Phase Induction Motor Driver for Water Pumping Powered by Photovoltaic System,” *Electronics* vol. 14, No. 16, pp. 1189, 2025. Doi: 10.3390/electronics14061189.
- [19] M. F. Masood, I. A. Muhammad, S. K. Muhammad, M. Tasawar, A. R. Muhammad, H. Ur Rehman, Z. Tausif, “A novel solution to eliminate frequency intermittency by adding spinning reserve to the micro-hydro turbine generator using real-time control of induction motor through AC-DC-AC power converters,” *International Journal of Smart Grid*, vol. 4, No. 4, pp. 149–156, 2020, Doi: 10.20508/ijsmartgrid.v4i4.120.g106.
- [20] P. P. Vinodkumar, T. Prashant, Z. Pankaj, “Hardware Implementation and Closed Loop Simulation of SPWM and PI based Hybrid Control for Matrix Converter fed Single Phase Induction Motor Powered by PV system,” *International Journal of Renewable Energy Research-IJRER* vol. 13, no. 4, pp. 1481–1496, 2023. <https://doi.org/10.20508/ijrer.v13i4.14001.g8822>.
- [21] P. Aurobinda, K. P. Mukesh, P. S. Satya, “Solar direct torque controlled induction motor drive for industrial applications,” *International Journal of Renewable Energy Research*, vol. 3, No. 4, pp. 794–802, 2013, Doi: 10.20508/ijrer.v3i4.848.g6207.
- [22] H. Benbouhenni, Z. Boudjema, “Two-level DTC based on ANN controller of DFIG using 7-level hysteresis command to reduce flux ripple comparing with traditional command,” *2018 International Conference on Applied Smart Systems (ICASS)*, Medea, Algeria, pp. 1–8, 2018, Doi: 10.1109/ICASS.2018.8652013.
- [23] H. Benbouhenni, Z. Boudjema, “Speed regulateur and hysteresis based on artificial intelligence techniques of three-level DTC for induction motor,” *Acta Electrotechnica et Informatica*, vol. 17, No. 4, pp. 48–54, 2017.
- [24] A. Milles, H. Benbouhenni, N. Bensedira, “Experimental verification of the six sectors neural DTC approach of squirrel cage induction motors,” *Scientific Reports*, vol. 15, pp. 10787, 2025, Doi: 10.1038/s41598-025-95333-y.
- [25] B. Habib, “Rotor flux and electromagnetic torque regulation of DFIG using dual PI controllers,” *International Journal of Smart Grid*, vol. 7, No. 4, pp. 227–234, 2023, Doi: 10.20508/ijsmartgrid.v7i4.308.g311.
- [26] B. Habib, “Stator current and rotor flux ripples reduction of DTC DFIG drive using FSTSMC algorithm,” *International Journal of Smart Grid*, vol. 3, No. 4, pp. 226–234, 2019, Doi: 10.20508/ijsmartgrid.v3i4.82.g72.
- [27] B. Habib, “Utilization of an ANFIS-STSM algorithm to minimize total harmonic distortion,” *International Journal of Smart Grid*, vol. 4, No. 2, pp. 56–67, 2020, Doi: 10.20508/ijsmartgrid.v4i2.98.g82.
- [28] K. K. Danduprolu, R. D. G. Tulasi, “Fuzzy logic controller based performance of SPMSM fed with improved direct torque control,” *International Journal of Renewable Energy Research*, vol. 9, No. 3, pp. 1346–1354, 2019, Doi: 10.20508/ijrer.v9i3.9625.g7714.
- [29] A. Sahu, B. M. Kanungo, N. M. Rabi, “Development and experimental realization of an adaptive neural-based discrete model predictive direct torque and flux controller for induction motor drive,” *Applied Soft Computing*, vol. 108, pp. 107418, 2021, Doi: 10.1016/j.asoc.2021.107418.
- [30] A. Oualid, R. Abderrahim, K. Abdelbasset, B. Rabah, T. Hicham, A.-R. Haitham, “Advanced direct torque control based on neural tree controllers for induction motor drives,” *ISA Transactions*, vol. 148, pp. 92–104, 2024, Doi: 10.1016/j.isatra.2024.03.017.
- [31] G. Soufien, M. Abdellatif, F. M. Mohamed, “Artificial neural network-based DTC of an induction machine with experimental implementation on FPGA,” *Engineering Applications of Artificial Intelligence*, vol. 121, pp. 105972, 2023, Doi: 10.1016/j.engappai.2023.105972.
- [32] X. Liu, C. Zhang, K. Li, “Neural network-based direct torque control of PMSM with reduced torque ripple,”

- IEEE Transactions on Industrial Electronics, vol. 66, No. 11, pp. 8638–8647, 2019.
- [33] Y. Zhang, J. Zhu, W. Xu, “Direct torque control of induction motors using an artificial neural network,” IEEE Transactions on Power Electronics, vol. 26, No. 2, pp. 580–588, 2011.
- [34] J. Hu, W. Xu, L. Huang, “Adaptive neural network-based direct thrust control for linear induction motor drives,” IEEE Transactions on Industrial Electronics, vol. 65, No. 12, pp. 9926–9935, 2018.
- [35] M. A. Khan, M. A. Rahman, “FPGA-based neural network controller for direct torque control of IM,” IEEE Transactions on Industrial Informatics, vol. 13, No. 3, pp. 1172–1181, 2017.
- [36] F. Wang, S. Li, X. Mei, “Deep reinforcement learning-based direct torque control for PMSM with parameter robustness,” IEEE Transactions on Power Electronics, vol. 35, No. 7, pp. 7341–7352, 2020.
- [37] M. Abderrahmane, B. A. Djilani, B. Habib, B. Youcef, N. Benharir, Z. M. S. Elbarbary, “Enhanced direct torque control based on intelligent approach for doubly-fed induction machine fed by three-level inverter,” Heliyon, vol. 10, No. 21, pp. e39738, 2024, Doi: 10.1016/j.heliyon.2024.e39738.
- [38] A. El Idrissi, A. Derouich, S. Mahfoud, N. El Ouanjli, H. Chojaa, A. Chantoufi, “Bearing faults diagnosis by current envelope analysis under direct torque control based on neural networks and fuzzy logic—A comparative study,” Electronics, vol. 13, pp. 3195, 2024, Doi: 10.3390/electronics13163195.
- [39] M. A. Khan, B. Asad, T. Vaimann, A. Kallaste, “An advanced diagnostic approach for broken rotor bar detection and classification in DTC controlled induction motors by leveraging dynamic SHAP interaction feature selection (DSHAP-IFS) GBDT methodology,” Machines, vol. 12, pp. 495, 2024, Doi: 10.3390/machines12070495.
- [40] L. P. Chisedzi, M. Muteba, “Detection of broken rotor bars in cage induction motors using machine learning methods,” Sensors, vol. 23, pp. 9079, 2023, Doi: 10.3390/s23229079.
- [41] H. Benbouhenni, N. Bizon, I. Colak, M. Iliescu, P. Thounthong, “A new direct torque control of an efficient and cost-effective traction system using two squirrel cage induction motors fed by a single inverter,” Electric Power Components and Systems, In Press, pp. 1–21, 2024, Doi: 10.1080/15325008.2024.2325541.
- [42] N. H. Viet, N. Paraschiv, “An investigation on twelve sectors direct torque control for induction motors fed by matrix converter,” 2020 12th International Conference on Electronics, Computers and Artificial Intelligence (ECAI), Bucharest, Romania, pp. 1–5, 2020, Doi: 10.1109/ECAI50035.2020.9223148.
- [43] S. Younes, T. Salah, L. B. Sofia, B. Mohit, B. Youcef, R. S. Arvind, F. E. Mohamed, K. Salah, “Effectiveness analysis of twelve sectors of DTC based on a newly modified switching table implemented on a wind turbine DFIG system under variable wind velocity,” Ain Shams Engineering Journal, vol. 14, No. 11, pp. 102221, 2023.
- [44] M. Jafari, K. Abbaszadeh, M. A. Mohammadian, “A 12-sector space vector switching table for parallel-connecting to dual induction motors fed by matrix converter based on direct torque control,” SN Applied Sciences, vol. 3, pp. 849, 2021, Doi: 10.1007/s42452-021-04763-6.
- [45] H. Albalawi, S. A. Zaid, M. E. El-Shimy, A. M. Kassem, “Ant colony optimized controller for fast direct torque control of induction motor,” Sustainability, vol. 15, pp. 3740, 2023, Doi: 10.3390/su15043740.
- [46] S. Krim, S. Gdaim, A. Mtibaa, M. F. Mimouni, “Modeling and hardware implementation on the FPGA of a variable structure control associated with a DTC-SVM of an induction motor,” Electric Power Components and Systems, vol. 45, No. 16, pp. 1806–1821, 2017, Doi: 10.1080/15325008.2017.1351010.
- [47] B. Habib, Z. Dalal, “Neural modified super-twisting filed-oriented approach of asynchronous machine drives,” Artificial Intelligence Research and Applications, vol. 1, No. 1, pp. 1–18, 2025, Doi: 10.20508/ijaira/n32q3x57.
- [48] B. Habib, “Application of five-level NPC inverter in DPC-ANN of doubly fed induction generator for wind power generation systems,” International Journal of Smart Grid, vol. 3, No. 3, pp. 128–137, 2019, Doi: 10.20508/ijsmartgrid.v3i3.66.g59.
- [49] M. Keddar, L. D. Mamadou, D. Mohamed, B. Karim, M. Abdelhami, “Interconnection performance analysis of single phase neural network based NPC and CHB multilevel inverters for grid-connected PV systems,” International Journal of Renewable Energy Research, vol. 9, No. 3, pp. 1451–1461, 2019, Doi: 10.20508/ijrer.v9i3.9593.g7730.
- [50] X. Sun, J. Wu, G. Lei, Y. Guo, J. Zhu, “Torque ripple reduction of SRM drive using improved direct torque control with sliding mode controller and observer,” IEEE Transactions on Industrial Electronics, vol. 68, pp. 9334–9345, 2021, Doi: 10.1109/TIE.2020.3020026.
- [51] K. Bouhoune, K. Yazid, M. S. Boucherit, B. N. Mobarakeh, “Simple and efficient direct torque control of induction motor based on artificial neural networks,” Proceedings of the IEEE International Conference on Electrical Systems for Aircraft, Railway, Ship Propulsion and Road Vehicles & International Transportation Electrification Conference, pp. 1–6, 2018, Doi: 10.1109/ESARS-ITEC.2018.8607747.
- [52] A. Berzoy, J. Rengifo, O. Mohammed, “Fuzzy predictive DTC of induction machines with reduced torque ripple and high-performance operation,” IEEE Transactions on

- Power Electronics, vol. 33, pp. 2580–2587, 2018, Doi: 10.1109/TPEL.2017.2690405.
- [53] K. S. Anjan, K. J. Ranjan, “Improved DTC strategy with fuzzy logic controller for induction motor driven electric vehicle,” *AIMS Electronics and Electrical Engineering*, vol. 6, No. 3, pp. 296–316, 2022, Doi: 10.334/electreng.2022018.
- [54] K. S. Anjan, K. J. Ranjan, “Teamwork optimization based DTC for enhanced performance of IM based electric vehicle,” *Turkish Journal of Electrical Engineering & Computer Sciences*, vol. 31, No. 2, pp. 360–380, 2023, Doi: 10.55730/1300-0632.3989.
- [55] A. Oualid, R. Abderrahim, T. Hicham, Z. Djamel, S. Abdelhakim, “An improved direct torque control with an advanced broken-bar fault diagnosis for induction motor drives,” *International Transactions on Electrical Energy Systems*, vol. 2023, pp. 1–18, 2023, Doi: 10.1155/2023/8816896.
- [56] B. Habib, “Seven-level direct torque control of induction motor based on artificial neural networks with regulation speed using fuzzy PI controller,” *Iranian Journal of Electrical and Electronic Engineering*, vol. 14, No. 1, pp. 85–94, 2018.
- [57] E. E. El-Kholy, S. Mahmoud, R. Kennel, A. El-Refaei, F. Elkady, “Torque ripple minimization for induction motor drives with direct torque control,” *Electric Power Components and Systems*, vol. 33, No. 8, pp. 845–859, 2005, Doi: 10.1080/15325000590909804.
- [58] S. K. Gudey, M. Malla, K. Jasthi, S. R. Gampa, “Direct torque control of an induction motor using fractional-order sliding mode control technique for quick response and reduced torque ripple,” *World Electric Vehicle Journal*, vol. 14, pp. 137, 2023, Doi: 10.3390/wevj14060137.
- [59] Z. Yassine, M. Mohamed, T. Souad, F. Chaymae, E. Sara, “Induction motor performance improvement using super twisting SMC and twelve sector DTC,” *International Journal of Robotics and Control Systems*, vol. 4, No. 1, pp. 50–68, 2024, Doi: 10.31763/ijrcs.v4i1.1090.
- [60] J. Park, J.-W. Kim, D.-H. Lee, “Direct torque control of PMSM using 12-sector and PWM approach based on the supplied voltage function,” 2018 10th International Conference on Information Technology and Electrical Engineering (ICITEE), Bali, Indonesia, pp. 476–481, 2018, Doi: 10.1109/ICITEE.2018.8534831.
- [61] A. Pal, G. D. Srivastava, R. D. Kulkarni, “Simulation of sensorless speed control of induction motor using direct torque control technique employing five level torque comparator and twelve sector method,” 2019 International Conference on Nascent Technologies in Engineering (ICNTE), Navi Mumbai, India, pp. 1–6, 2019, Doi: 10.1109/ICNTE44896.2019.8945936.

Benchmarking Deep Learning Architectures for 24-Hour Energy Forecasting in Smart Buildings Using Real-World IoT Data

Jura Arkhangelski *, Rakibul Hasan *, Mahamadou Abdou Tankari *, Gilles Lefebvre *

* Center for Studies and Research in Heat, Environment and Systems, Paris-Est Creteil University (UPEC), Creteil, France.

(jura.arkhangelski@u-pec.fr, rakibul.hasan@u-pec.fr, mahamadou.abdou-tankari@u-pec.fr, lefebvre@u-pec.fr)

†Corresponding Author: Jura Arkhangelski, Center for Studies and Research in Heat, Environment and Systems, Paris-Est Creteil University (UPEC), Creteil, France, jura.arkhangelski@u-pec.fr.

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Abstract- Accurate 24-hour energy forecasting in smart buildings remains a challenging real-world problem due to the highly non-linear, dynamic, and heterogeneous nature of IoT sensor data. This study extensively expands upon previous research that demonstrated the effectiveness of Bi-LSTM as a univariate predictor. To address existing gaps, we make two primary contributions: (1) developing a multivariate forecasting framework that incorporates eight diverse IoT sensor streams, including HVAC (heat pump) energy consumption and indoor environmental comfort metrics, and (2) benchmarking advanced attention-based architectures, such as the Temporal Fusion Transformer (TFT), optimized for interpretable, high-performance multidimensional time-series forecasting. Using real-world datasets from a multifunctional smart building in France (Pôle Culturel), experiments were conducted over approximately four months (October 23, 2024, to February 27, 2025) at 10-minute intervals. The preprocessing pipeline includes timestamp harmonization, Akima interpolation for non-linear data gaps, outlier correction, and feature scaling. Using MAE, RMSE, MAPE, and R^2 as evaluation metrics, the experiments compare a multivariate Bi-LSTM against standard models such as LSTM, GRU, and the TFT. The results indicate that the multivariate Bi-LSTM ($R^2 = 0.9656$) significantly reduces errors compared to univariate approaches, accurately capturing daily trends and peak loads. Furthermore, while the TFT effectively models complex multivariate dependencies ($R^2 = 0.8130$), it demonstrates that attention-based models require specific architectural tuning for medium-scale IoT datasets, providing practical guidance for sustainable, data-driven energy management.

Keywords: - Smart buildings, IoT, deep learning, energy forecasting, LSTM.

1. Introduction

The building sector's significant environmental footprint, accounting for nearly 40% of global energy-related CO₂ emissions, has positioned it as a critical front in decarbonization efforts. Setting climate sustainability goals and reducing environmental impact requires a paradigm shift

towards energy-efficient buildings and the adoption of decentralized energy generation methods [1]. IoT sensors are now being used to provide high-speed, high-dimension data streams in smart buildings, which are crucial for real-time monitoring, demand-side optimization, and predictive control system deployment. By evaluating the economic benefits of smart-community microgrids and optimizing building energy management [2, 3]. It is possible to facilitate efficient energy

procurement, grid interaction, and compliance with increasingly strict regulatory frameworks, such as the Décret Tertiaire.

Estimating energy usage in practical scenarios is challenging because consumption patterns are highly non-linear and influenced by various factors, including occupant behavior, fluctuating environmental conditions, and the state of different subsystems like HVAC and lighting. Although various statistical models, such as ARIMA and SVR, have been implemented to analyze data in real time, they frequently lack the necessary features to capture long-range temporal dependencies and intricate nonlinearity.

As a result, deep learning has become increasingly popular, with Recurrent Neural Networks (RNNs) used to model large amounts of sequential data. Among these, Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) are considered robust baselines that offer strong temporal memory. The utilization of Bi-LSTM, an advancement that captures sequences in both forward and backward directions, has demonstrated additional potential for enhancing forecasting accuracy.

The research methodology adopted in this study is centered on the systematic integration of IoT data with advanced predictive analytics. This approach is visualized in Figure 1, which presents the conceptual framework of AI-driven energy forecasting using IoT sensor data. The framework outlines the end-to-end process of leveraging high-resolution sensor streams from smart building infrastructure to inform a predictive model. By capturing these real-world dynamics, the model facilitates accurate forecasting, which is essential for optimizing energy use and enhancing the sustainability of modern infrastructure.

The limitations of the original research are addressed in this journal article through two significant contributions. First, the study moves beyond univariate analysis to adopt a multivariate forecasting framework, integrating the full range of IoT sensor data from the Pôle Culturel, such as heat pump status and indoor comfort metrics. This tests the hypothesis that contextual data can significantly enhance forecast accuracy. Second, the study addresses the limitations of basic Transformers by implementing and benchmarking advanced, time-series attention-based architectures, such as the Temporal Fusion Transformer (TFT).

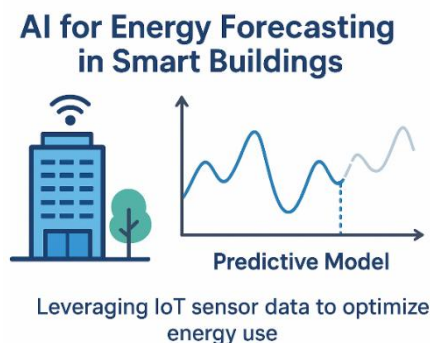


Fig. 1. Conceptual framework of AI-driven energy forecasting using IoT sensor data.

Using a dataset collected over approximately four months (October 23, 2024, to February 27, 2025) from a real-world smart building, this study employs an efficient preprocessing pipeline with Akima interpolation to handle non-linear data gaps. By comparing the performance of the Bi-LSTM with more advanced attention-based models, this work provides a practical evaluation for the deployment of next-generation energy management systems.

The remainder of this paper is organized as follows: Section 2 discusses related work in multivariate energy forecasting. Section 3 details the dataset and preprocessing methodology. Section 4 outlines the experimental setup and model architectures. Section 5 presents and discusses the comparative results. Finally, Section 6 provides concluding remarks and future research directions.

2. Related Work

Developing and merging traditional statistical methods with advanced deep learning architectures has brought about significant changes in building energy forecasting [4, 5]. This section outlines the primary methodologies, their inherent drawbacks, and the research gaps this study addresses.

2.1. Traditional and Statistical Forecasting Methods

Early research is primarily focused on using statistical and econometric models for energy forecasting. The Auto Regressive Integrated Moving Average (ARIMA) family, including its seasonal variant (SARIMA), served as a typical baseline [6, 7]. While these models are suitable for stable, linear time-series, they exhibit significant limitations when dealing with the high volatility and complex temporal dependencies found in real-world building energy data [8, 9]. To address the lack of linearity, shallow machine learning models like Support Vector Regression (SVR) and Random Forest (RF) were introduced [10]. However, recent research has demonstrated that the accuracy of such models is highly sensitive to the preprocessing pipeline, particularly when handling non-linear gaps and abrupt consumption ramps in IoT data [11].

2.2. Recurrent Neural Networks as a Deep Learning Baseline

Traditional methods were often insufficient for sequential data analysis, leading to the adoption of Recurrent Neural Networks (RNNs) [7, 12]. While RNNs can theoretically represent temporal dependencies, simple architectures often suffer from the vanishing gradient problem. This issue was resolved with the development of the Long Short-Term Memory (LSTM) network [13] and the Gated Recurrent Unit (GRU) [6], which use gating mechanisms to selectively retain information over long periods. Recent research has also explored the integration of these models within broader urban smart grid frameworks [14]. The Bidirectional LSTM (Bi-LSTM) further improved these approaches by processing sequences in both forward and backward directions [15]. Recent case studies emphasize that maintaining proper evaluation protocols is essential for reliability [16].

2.3. The Rise and Challenges of Transformers in Time Series

The self-attention mechanism of the Transformer allows for the visualization of global dependencies in parallel [17]. However, applying standard "vanilla" Transformers to time-series data has often yielded mixed results. Standard Transformers may struggle to generalize on smaller datasets because they lack the sequential inductive biases inherent in RNNs [16]. To address this, specialized models like the Temporal Fusion Transformer (TFT) were developed to enable high-performance, interpretable, multivariate forecasting. The TFT is specifically designed to handle uncertainty and the noise found in imperfect IoT datasets, providing more robust performance in real-world applications [18]. As highlighted by Nouri and Jalilrad [19] addressing these uncertainties is critical for the deployment of AI-driven energy management systems [18] in infrastructure with potentially heterogeneous data quality.

2.4. Research Gaps and Our Contribution

Two significant research gaps are addressed in this study. First, there is a lack of direct, practical benchmarking between the strongest RNN baselines (e.g., multivariate Bi-LSTM [17]) and the latest generation of time-series specific Transformers (such as TFT [18]) on the same real-world IoT datasets. Second, the precise performance impact of moving from a simple univariate forecast to a context-rich multivariate framework is not sufficiently documented. This journal paper fills these gaps by: (1) integrating a full multivariate dataset from the Pôle Culturel using Akima interpolation [13], and (2) implementing the TFT to scientifically evaluate if it can outperform the optimized Bi-LSTM baseline [17]. The strengths and weaknesses of these forecasting methods are summarized in Table 1.

Table 1. Comparison of forecasting methods.

Method	Strengths	Weaknesses
ARIMA	Simple, interpretable	Poor nonlinear modelling
SVR / RF	Good for nonlinear data	Cannot model sequential dependencies
LSTM	Captures long-term memory	Requires large datasets, slow training
Bi-LSTM	Considers past and future context	Increased complexity
GRU	Faster training, fewer parameters	Slightly less accurate than LSTM
Transformer	Captures global dependencies	Requires large training data

3. Dataset & Preprocessing Methodology

This section details the real-world IoT dataset used as the empirical basis for this study and the rigorous preprocessing pipeline developed to prepare it for multivariate, deep-learning-based forecasting.

3.1. Real-World IoT Sensor Dataset

The empirical data for this research originates from an operational, multifunctional smart building located in France, formally identified as the Pôle Culturel. The facility is equipped with a comprehensive IoT sensor network that monitors both energy consumption and environmental conditions. Our analysis is based on a high-resolution dataset collected over approximately four months (October 23, 2024, to February 27, 2025). As shown in Figure 2, a one-week sample of the target variable (total energy consumption) illustrates complex daily and weekly periodic patterns.

The IoT network captures sensor readings at a consistent 10-minute frequency, resulting in 144 data points per feature per day. A primary focus of this study is the transition to a multivariate forecasting framework using eight distinct IoT streams, as detailed in Table 2. The primary forecasting target, Compteur General POC, represents the total aggregated energy usage of the Pôle Culturel. All power-related features are measured in Watts (W), while environmental comfort metrics are recorded in degrees Celsius (°C) to ensure technical precision.

3.2. Data Preprocessing Pipeline

Raw IoT sensor data is inherently noisy, asynchronous, and incomplete. To ensure data integrity and prepare the multivariate dataset for deep learning models, we developed a systematic preprocessing pipeline. The sensitivity of forecasting results to these steps is a critical factor, as improper handling of missing values or outliers can distort the underlying consumption statistics [12].

- **Timestamp Harmonization and Resampling:** All eight data streams were synchronized to a uniform master datetime index to correct for sensor drift or timestamp misalignment. The data was resampled to a consistent 10-minute frequency using mean aggregation.

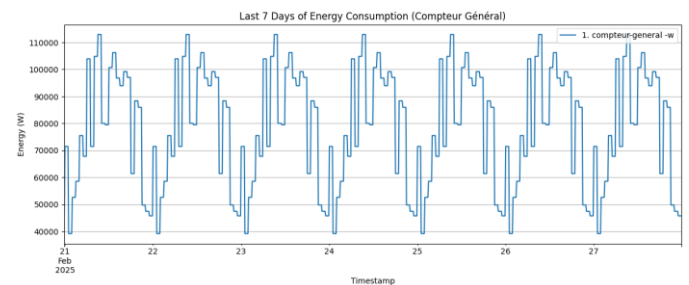


Fig 2. A one-week sample of the target variable (total energy consumption), illustrating complex daily and weekly periodic patterns.

Table 2. Standardized multivariate IoT sensor features and units

Sensor Name	Formal Definition	Purpose	Units
PAC Terrasse	Terrace Heat Pump	HVAC energy consumption	Watts (W)
PAC General	Main Heat Pump	HVAC energy consumption	Watts (W)
Compteur General POC	Pôle Culturel Main Meter	Total building energy usage (Target)	Watts (W)
Arrive Generale AGM	Media Library Panel	Incoming power (Media library)	Watts (W)
Arrive Generale AGS	Scene Control Panel	Incoming power (Stage control)	Watts (W)
Comfort 1	Concert Hall Sensor	Indoor temperature (Salle de Spectacle)	Celsius (°C)
Comfort 2	Administrative Area	Indoor temperature (Office/Admin)	Celsius (°C)
Comfort 5	Multipurpose Room	Indoor temperature (Salle Polyvalente)	Celsius (°C)

- **Handling Missing Data (Sensitivity Analysis):** Addressing data gaps from sensor or network failures was a critical step. We employed Akima Interpolation, a non-linear method specifically chosen to preserve the sharp "peaks and ramps" characteristic of building energy consumption.

Unlike linear interpolation, which can smooth out critical peak demand signals, Akima interpolation maintains the local curvature of the data [12]. The sensitivity of deep learning models to preprocessing is high; therefore, we ensured that our interpolation strategy did not alter the statistical distribution of the energy spikes. This approach minimizes the risk of artificially lowering the RMSE, which is highly sensitive to peak prediction errors.

Similar preprocessing strategies using Akima interpolation have demonstrated effectiveness in high-frequency IoT tasks such as non-intrusive load monitoring [20].

- **Data Cleaning and Smoothing:** The dataset was filtered to remove physical impossibilities, such as negative energy values. A light-touch rolling mean filter (window size = 3) was applied to reduce high-

frequency noise from the Pôle Culturel sensors while strictly preserving the integrity of the 10-minute intervals.

- **Feature Scaling and Transformation:** To optimize neural network convergence, a log-transformation ($\log(1+x)$) was applied to stabilize variance. Subsequently, all eight features were scaled independently to a (0, 1) range using Min-Max normalization, ensuring that high-magnitude power readings do not overshadow indoor temperature metrics.

4. Experimental Setup and Evaluation Metrics

4.1. Experimental Design and Training

The primary objective of this study is to move beyond the univariate baseline established in previous research [17] and evaluate the impact of multivariate inputs and advanced architectures. The forecasting task is formulated as a multivariate, sequence-to-sequence problem: given the past 7 days (1008 time steps) of all 8 sensor features (X), the models must predict the next 24 hours (144 time steps) of the target variable.

All models utilize a 1-hidden-layer architecture with an initial learning rate of 0.001, optimized using the Adam algorithm. A 10% validation subset was utilized to implement an early stopping callback with a patience of 10 epochs, ensuring the restoration of the best weights.

Two main experiments are conducted:

- **Multivariate Baseline Comparison:** The baseline LSTM and Bi-LSTM models are re-trained using the full multivariate dataset to establish the best-performing recurrent model.
- **SOTA Benchmark:** The winning recurrent model (Multivariate Bi-LSTM) is then benchmarked against the Temporal Fusion Transformer (TFT) to determine if this advanced architecture provides a superior solution.

All models were implemented using the Python 3.11+ ecosystem, primarily with the TensorFlow and Keras libraries, on a Google Colab instance equipped with an NVIDIA Tesla T4 GPU (16GB VRAM). To prevent data leakage a critical risk in sequence-to-sequence forecasting with overlapping windows a strictly chronological split was employed. The first 80% of the dataset (October 23, 2024, to January 31, 2025) was utilized for training, while the final 20% (February 1, 2025, to February 27, 2025) was reserved exclusively for out-of-sample testing. Within the training phase, a 10% validation subset was separated to facilitate early stopping and hyperparameter tuning. The key implementation details, hardware specifications, and architectural hyperparameters are summarized in Table 3.

Each model was trained until validation loss plateaued, with early stopping applied to prevent overfitting and improve generalization.

Table 3. Key training configurations and hyperparameters.

Parameter	Configuration and Architectural Details
Data Range	October 23, 2024 – February 27, 2025 (Approximately four months)
Data Split	80% Train, 20% Test (Strictly Chronological)
Windowing Strategy	7-day sliding window (1008 time steps) with 1-step overlap
Hidden Layers	1 Hidden Layer (Common across all baseline architectures)
Hidden Units	64 units (LSTM, Bi-LSTM, TFT); 32 units (GRU)
Initial Learning Rate	0.001 (Adam Optimizer)
Batch Size	32 (LSTM), 64 (Bi-LSTM, GRU, TFT)
Dropout Rate	0.2 (LSTM, Bi-LSTM, TFT), 0.3 (GRU)
Early Stopping	Enabled (Patience = 10 epochs with best weights restoration)
Loss Function	Mean Squared Error (MSE)
Hardware	Google Colab (NVIDIA Tesla T4 GPU, 16GB VRAM)

4.2. Evaluation Metrics

To objectively evaluate and compare the 24-hour forecasting performance of the different architectures, four standard regression metrics are utilized. These metrics measure the error magnitude, relative percentage error, and the proportion of variance captured by the models, following standardized reporting protocols for energy demand prediction [16].

Mean Absolute Error (MAE): Measures the average absolute magnitude of the errors, providing a linear score of the average error in Watts (W): "Eq. (1)"

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (1)$$

Root Mean Squared Error (RMSE): Calculates the square root of the average of the squared errors, emphasizing large error spikes: "Eq. (2)"

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (2)$$

Mean Absolute Percentage Error (MAPE): Evaluates the average prediction error in relative percentage terms: "Eq. (3)"

$$MAPE = \frac{100\%}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (3)$$

R-squared (R^2) Score: Represents the coefficient of determination, measuring the proportion of variance predictable from the input features: "Eq. (4)"

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (4)$$

In these equations, n represents the total number of time steps in the 24-hour horizon, y_i denotes the ground truth building energy values, $\hat{y}_i$ represents the model's predicted values, and $\bar{y}$ is the mean of the observed values.

5. Experimental Results and Discussion

This section establishes a baseline by presenting the original univariate study results from previous work [17], followed by a comparison with new multivariate experiments to demonstrate the performance improvements achieved in this journal extension.

5.1. Baseline Performance: Univariate Model Comparison

The initial research phase involved benchmarking four deep learning models LSTM, Bi-LSTM, GRU, and a standard Transformer on a univariate task using only the "Compteur General POC" data [17]. Models utilized 7 days of historical data to predict the next 24-hour horizon.

5.1.1. Qualitative analysis of baseline models' visual inspection of the forecast plots reveals the distinct behaviors of each architectur

- **Long Short-Term Memory (LSTM):** Utilizes memory cells and gating mechanisms to maintain long-term dependencies. The model comprised 64 units per layer with a 0.2 dropout rate. The results are illustrated in Figure 3 and Figure 4.

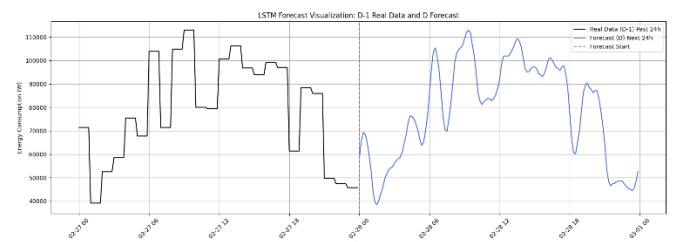


Fig 3. LSTM: real past 24h data (black line) with 24h data forecast (blue line).

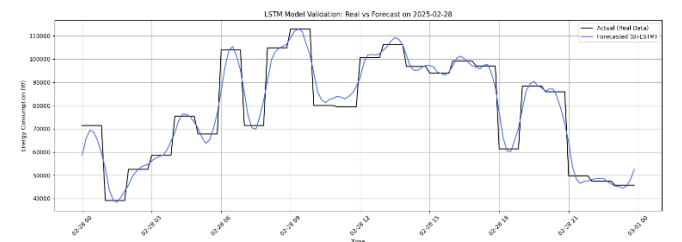


Fig 4. Real IoT building energy data (black line) and LSTM data forecast (blue line).

- **Bidirectional LSTM (Bi-LSTM):** Processes data in both forward and backward directions to capture dual-perspective temporal dependencies. Forecasting outcomes are shown in Figure 5 and Figure 6.
- **Gated Recurrent Unit (GRU):** A lightweight alternative that merges forget and input gates into a single update gate. Results are visualized in Figure 7 and Figure 8.
- **Transformer Model:** Employs a self-attention mechanism to model global dependencies simultaneously. Despite its theoretical advantages, it exhibited poor generalization in this specific energy context, as seen in Figure 9 and Figure 10.

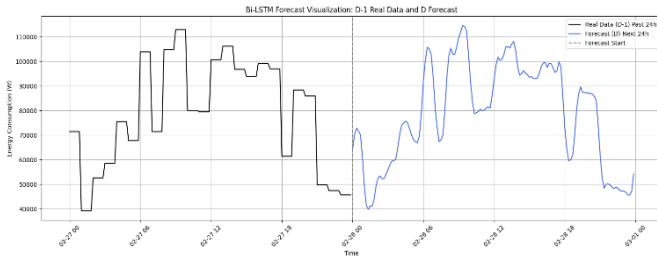


Fig 5. Bi-LSTM: real past 24h data (black line) with 24h data forecast (blue line).

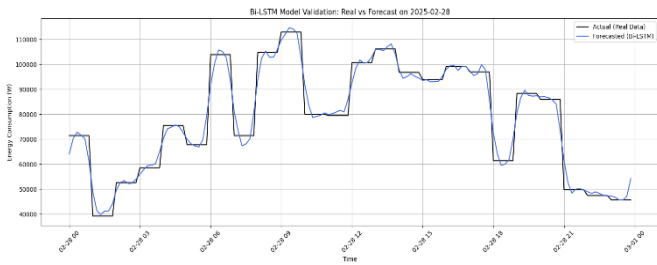


Fig 6. Real IoT building energy data (black line) and Bi-LSTM data forecast (blue line).

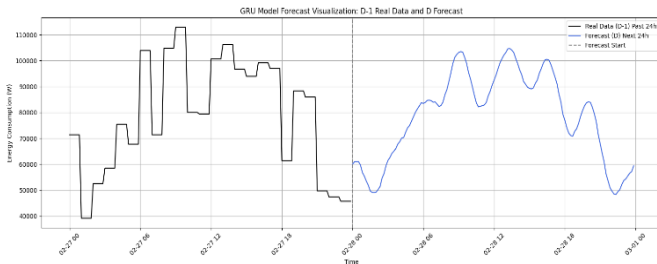


Fig 7. GRU: real past 24h data (black line) with 24h data forecast (blue line).

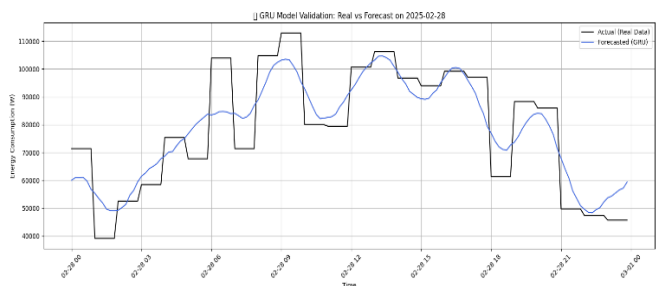


Fig 8. Real IoT building energy data (black line) and GRU data forecast (blue line).

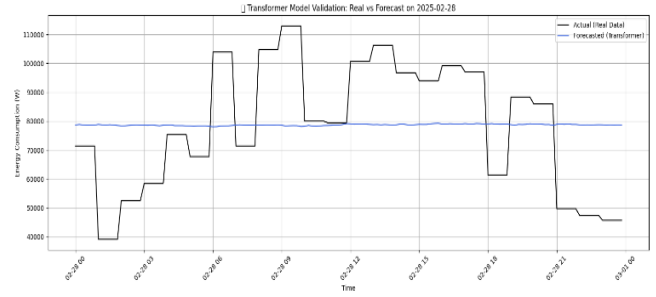


Fig 9. Transformer: real past 24h data (black line) with 24h data forecast (blue line).

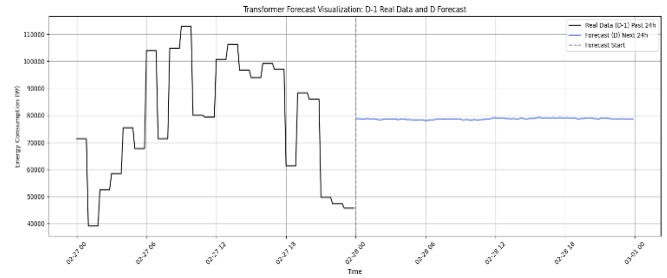


Fig 10. Real IoT building energy data (black line) and Transformer data forecast (blue line).

5.2. Quantitative and Training Analysis

Quantitative metrics in Table 4 confirm visual observations [16]. The Bi-LSTM model was the top performer, achieving the lowest MAE (2763.90W), lowest RMSE (4281.31W), and the highest R^2 score (0.9610).

The Transformer model had the lowest performance across all metrics, with an R^2 close to 0. These methods are compared via MAE, RMSE, and R^2 , as illustrated in Figure 11.

Table 4. Baseline Forecasting Performance

Model	MAE (W)	MAPE (%)	RMSE (W)	R^2 Score
LSTM	3452.71	4.82	5049.88	0.9457
Bi-LSTM	2763.90	3.87	4281.31	0.9610
GRU	7324.35	10.37	8931.50	0.8303
Transformer	18793.32	28.09	21682.57	-0.0001

5.2.1. Training and validation loss analysis

Convergence behavior, illustrated in Figure 12, shows that Bi-LSTM consistently achieved the highest accuracy, while GRU provided faster training at the cost of moderate precision. The standard Transformer's performance was unsatisfactory, yielding the highest error rates.

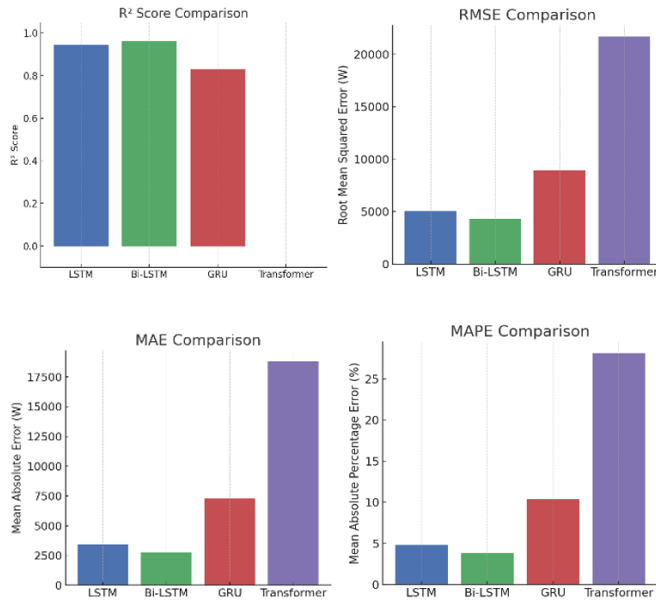


Fig 11. Performance metrics comparison of forecasting models.

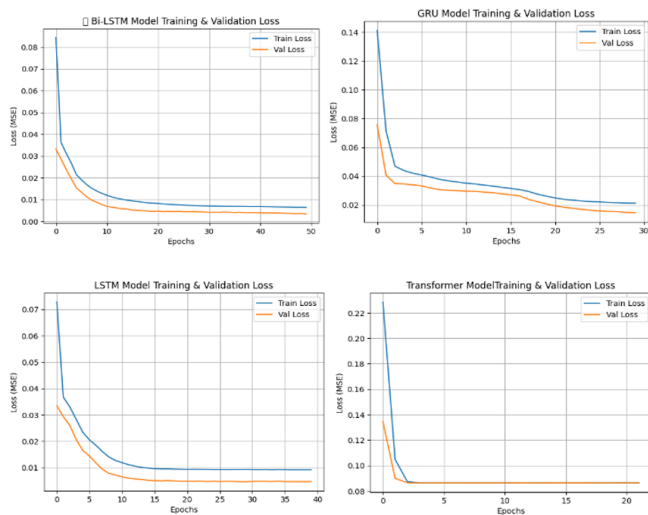


Fig 12. Training and validation loss curves for all models.

5.2.2. Discussion of results

The superior performance of the Bi-LSTM can be attributed to its ability to capture temporal dependencies from both past and future states, which is critical for modeling the daily cyclic patterns of building energy consumption. Conversely, the standard Transformer failed because it lacks the sequential inductive biases inherent in RNNs. Without a larger dataset or specialized time-series modifications, the self-attention mechanism struggled to prioritize recent local temporal features over global noise.

5.3. Multivariate Forecasting and Advanced Benchmarking

This section presents the core contribution of this journal extension: the implementation of a multivariate framework and the benchmarking of the specialized Temporal Fusion Transformer (TFT) against the optimized Multivariate Bi-LSTM.

5.3.1. Impact of multivariate contextual data

The transition from a univariate approach to a multivariate framework allowed the models to leverage correlations between the total energy consumption (Compteur General POC) and eight contextual IoT features, including heat pump activity and indoor temperature metrics. This integration provided the models with the necessary environmental signals to handle the non-linear energy "ramps" and consumption peaks that univariate models often struggle to capture. As shown in Table 5, the transition to multivariate inputs resulted in a significant reduction in forecasting error across all metrics compared to the baseline results in Section 5.1.

5.3.2. Quantitative benchmarking: Bi-LSTM vs. TFT

The quantitative performance for the multivariate experiments is summarized in Table 5. The Multivariate Bi-LSTM achieved the highest overall accuracy, maintaining superior stability for 24-hour horizons. While the TFT showed a significant improvement over the "vanilla" Transformer (R^2 approx 0), it did not surpass the recurrent baseline in this specific real-world setup.

Table 5. Multivariate forecasting performance comparison

Model	MAE (W)	MAPE (%)	RMSE (W)	R^2 Score
Multivariate Bi-LSTM	2214.35	3.12	3685.90	0.9656
Temporal Fusion Transformer (TFT)	5421.18	7.45	6932.40	0.8130

5.3.3. Discussion of model performance

The results provide critical insights into the behavior of advanced architectures on medium-sized IoT datasets:

- **Inductive Bias of Bi-LSTM:** The Bi-LSTM's superior R^2 of 0.9656 confirms that bidirectional recurrent architectures possess a strong inductive bias for sequential energy data, allowing them to capture cyclic daily patterns with high precision.
- **TFT and Data Volume:** The TFT achieved an R^2 of 0.8130, proving it is far more capable of handling time-series data than standard Transformers. However, its complexity including Gated Residual Networks (GRNs) and multi-head attention likely requires a larger training volume or longer historical horizons to fully outperform optimized recurrent models for this specific building dataset [19].
- **Preprocessing Stability:** The high accuracy of the multivariate models demonstrates that the Akima interpolation pipeline successfully preserved the non-

linear "ramps" in the sensor data, which is essential for precise peak demand forecasting and regulatory compliance [21].

6. Conclusion

This research provided a comprehensive comparative evaluation of deep learning architectures, including LSTM, Bi-LSTM, GRU, and the Temporal Fusion Transformer (TFT), specifically tailored for 24-hour building energy forecasting using high-resolution IoT sensor data. A major contribution of this work is the transition from a univariate baseline to a context-rich multivariate framework, validating the importance of environmental covariates in enhancing predictive accuracy.

The findings demonstrate that the Multivariate Bi-LSTM model offers the highest accuracy ($R^2 = 0.9656$), effectively capturing the complex, non-linear temporal dependencies inherent in the energy consumption patterns of the Pôle Culturel. While the TFT model demonstrated significant improvement over the standard "vanilla" Transformer by achieving an R^2 of 0.8130, it did not surpass the recurrent baseline, suggesting that attention-based models may require larger data volumes to fully realize their theoretical advantages in this specific context.

These results have significant practical implications for the development of Intelligent Energy Management Systems (IEMS) and regulatory compliance with frameworks such as the Décret Tertiaire. By integrating the proposed multivariate framework, facility managers can achieve more precise demand-side management and optimize energy distribution. Future extensions of this work will explore the integration of these models into a real-time Digital Twin to enhance the resilience of forecasting across diverse climatic conditions and multi-zonal thermal environments.

Author Contributions

J.A., M.A.-T., and G.L. conceptualized the study and supervised the work; J.A. and R.H. developed the methodology; R.H. performed software development, data curation, validation, formal analysis, investigation, visualization, and prepared the original draft; M.A.-T. and J.A. reviewed and edited the manuscript; M.A.-T. administered the project; G.L. provided funding and resources. All authors approved the final version of the manuscript.

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Conflict of Interest

The authors declare no conflict of interest.

References

- [1] M. B. Camara and J. Arkhangelski, Renewable energies for decentralized energy generation: DC microgrids power management methods. Eliva Press, 2023.
- [2] J. Arkhangelski, M. Abdou-Tankari, and G. Lefebvre, "Data forecasting for optimized urban microgrid energy management," in Proc. IEEE Int. Conf. Environment and Electrical Engineering, Genova, Italy, pp. 1–6, Jun. 11–14, 2019, doi: 10.1109/EEEIC.2019.8783853.
- [3] J. Arkhangelski, M. Abdou-Tankari, and G. Lefebvre, "Day-ahead optimal power flow for efficient energy management of urban microgrid," IEEE Trans. Ind. Appl., vol. 57, no. 2, pp. 1285–1293, Mar. 2021, doi: 10.1109/TIA.2020.3049117.
- [4] J. Arkhangelski, "Autoconsommation et optimisation de la gestion énergétique des bâtiments," ResearchGate, Dec. 2021, doi: 10.13140/RG.2.2.20384.92160.
- [5] J. Arkhangelski, P. Siano, M. Abdou-Tankari, and G. Lefebvre, "Evaluating the economic benefits of a smart-community microgrid with centralized electrical storage and photovoltaic systems," Energies, vol. 13, no. 7, pp. 1–18, Apr. 2020, doi: 10.3390/en13071764.
- [6] J. Arkhangelski, M. Abdou-Tankari, G. Lefebvre, P. Roncero-Sanchez, and E. J. Molina-Martinez, "Grid synchronization and injection control of HRES power generation," in Proc. 7th Int. Conf. Renewable Energy Research and Applications, Paris, France, pp. 1276–1281, Oct. 14–17, 2018, doi: 10.1109/ICRERA.2018.8567003.
- [7] J. Arkhangelski, M. Abdou-Tankari, and G. Lefebvre, "Ancillary services for distribution grid: demand response of building thermal inertia case," in Proc. Int. Conf. Computational Intelligence for Smart Power System and Sustainable Energy, pp. 1–5, Jul. 29–31, 2020, doi: 10.1109/CISPSSE49931.2020.9212239.
- [8] K. E. ArunKumar, D. V. Kalaga, C. M. S. Kumar, M. Kawaji, and T. M. Brenza, "Comparative analysis of gated recurrent units (GRU), long short-term memory (LSTM), autoregressive integrated moving average (ARIMA), and seasonal autoregressive integrated

- moving average (SARIMA) for forecasting COVID-19 trends,” *Alexandria Eng. J.*, vol. 61, no. 10, pp. 7585–7603, Oct. 2022, doi: 10.1016/j.aej.2022.01.011.
- [9] M. A. Yahya, T. Prasetyo, and M. Fikri, “Recurrent neural network model for short-term electric load forecasting,” *J. Edukasi Elektro*, vol. 9, no. 2, pp. 114–129, Nov. 2025, doi: 10.21831/jee.v9i2.86643.
- [10] B. Bargam, A. Boudhar, C. Kinnard, H. Bouamri, K. Nifa, and A. Chehbouni, “Evaluation of the support vector regression (SVR) and the random forest (RF) models accuracy for streamflow prediction under a data-scarce basin in Morocco,” *Discovery Appl. Sci.*, vol. 6, no. 6, p. 306, Jun. 2024, doi: 10.1007/s42452-024-05994-z.
- [11] J. Arkhangelski, M. Abdou-Tankari, and G. Lefebvre, “Day-ahead optimal power flow for smart-community microgrid with centralized electrical storage and wind turbine,” in *Proc. 11th Int. Conf. Smart Grid (icSmartGrid)*, Paris, France, pp. 1–5, Jun. 4–7, 2023, doi: 10.1109/icSmartGrid58556.2023.10170978.
- [12] H. Satan, G. Altın, and M. E. Taner, “Evaluation of preprocessing pipeline sensitivity in energy forecasting,” *Energy Informatics*, vol. 8, no. 1, pp. 45–52, Jan. 2025.
- [13] J. Arkhangelski, M. Abdou-Tankari, G. Lefebvre, and M. Karkri, “Combined Akima interpolation and deep learning LSTM method based building energy efficiency prediction,” in *Proc. Int. Conf. Intelligent Systems and Computer Vision (ISCV)*, pp. 1–5, May 15–17, 2024, doi: 10.1109/ISCV60512.2024.10620126.
- [14] J. Arkhangelski, M. Abdou-Tankari, and G. Lefebvre, “Energy transition in France: urban communities smart grids integration case,” in *Proc. Int. Conf. Evolving Cities*, 2022, doi: 10.55066/procicec.2.
- [15] K. Feng and Z. Fan, “A novel bidirectional LSTM network based on scale factor for atrial fibrillation signals classification,” *Biomed. Signal Process. Control*, vol. 76, p. 103663, 2022, doi: 10.1016/j.bspc.2022.103663.
- [16] K. Kayisli, N. Zhakiyev, and I. Colak, “Deep recurrent forecasting case study with proper evaluation protocols and reporting for energy demand prediction,” *J. Astana IT Univ.*, vol. 5, no. 1, pp. 12–24, 2024.
- [17] J. Arkhangelski, M. Abdou-Tankari, R. Hasan, and G. Lefebvre, “Comparative evaluation of deep learning-based AI models for 24-hour energy forecasting in smart buildings using IoT sensor data,” in *Proc. 13th Int. Conf. Smart Grid (icSmartGrid)*, Glasgow, United Kingdom, pp. 1–6, May 22–24, 2025, doi: 10.1109/icSmartGrid66138.2025.11071776.
- [18] T.-Y. Dai, D. Niyogi, and Z. Nagy, “CityTFT: a temporal fusion transformer-based surrogate model for urban building energy modeling,” *Appl. Energy*, vol. 389, p. 125712, 2025, doi: 10.1016/j.apenergy.2025.125712.
- [19] A. Nouri and S. Jalilrad, “Handling uncertainty and robustness in energy-related AI applications and imperfect data in IoT forecasting,” *Artificial Intelligence Research and Applications*, vol. 1, no. 1, pp. 88–95, 2025.
- [20] J. Arkhangelski, M. Abdou-Tankari, and G. Lefebvre, “Effective non-intrusive load monitoring through IoT building data using Akima interpolation and deep learning LSTM method,” in *Proc. 12th Int. Conf. Renewable Energy Research and Applications (ICRERA)*, pp. 34–39, Aug. 29–Sep. 1, 2023, doi: 10.1109/ICRERA59003.2023.10269367.
- [21] J. Arkhangelski, M. Abdou-Tankari, and G. Lefebvre, “Efficient abnormal building consumption detection by deep learning LSTM IoT data classification,” in *Proc. 11th Int. Conf. Renewable Energy Research and Applications (ICRERA)*, pp. 125–129, Sep. 18–21, 2022, doi: 10.1109/ICRERA55966.2022.9922844.

Neural Networks in Control Systems for Multi-Drive Facilities of Metallurgical Enterprises

Stanimir Valtchev ^{*†}, Tatyana Sinyukova ^{**†}, Alexey Sinyukov ^{**}

* FCT-UNINOVA-CTS, University NOVA of Lisbon, Portugal.

** Institute of Computer Science, Department of Automated Electric Drives and Robotic, Lipetsk State Technical University, Russian Federation.

(ssv@fct.unl.pt, stw0411@mail.ru, zeitsn@yandex.ru)

† Corresponding Authors: Stanimir Valtchev and Tatyana Sinyukova, ssv@fct.unl.pt and stw0411@mail.ru.

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Abstract- Metallurgical plants use mechanisms with multiple motors, and their control systems must account for the specifics of the process and the impact of external and internal disturbances. Standard controllers don't always achieve the desired results, especially when systems contain various uncertainties, such as signal, parametric, and structural ones. Therefore, it has been proposed to integrate neural network-based control systems to account for and minimize nonlinearities and disturbances present in the systems. The study developed an algorithm for creating a nonlinear control system that takes into account processes occurring in the mechanical part of the object, as well as random disturbances. An algorithm for creating neural controllers for multi-drive systems was developed. Compared to a standard neural controller, its use allowed for a reduction in the number of neurons in the inner layer and the number of internal layers, reducing the training set by approximately 28 percent. The proposed universal structure of neural controllers and observers enables the creation of stable control systems for multi-drive mechanisms, while maintaining the operational capability of the devices and ensuring high-quality process control even when unmeasured parameters or distorted signals are involved in their formation.

Keywords: Neuroregulators, multi-drive systems, neuroobservers, nonlinear control system.

1. Introduction

Metallurgical plants utilize production machinery that incorporates multiple motors. Cranes and rolling mills are among the most common types of such machinery.

In complex structures of devices containing multi-motor mechanisms, elastic deformations, play, gaps, friction, and dynamic impacts occur in the mechanical part. There is a high probability of exposure of the control system to disturbances, which can arise both externally and within the mechanisms [1, 2]. Currently, there is no clear algorithm that takes into account the characteristics of transient processes in nonlinear systems.

In devices containing multiple drives, the interconnection between them occurs through mechanical structures and the object being moved (load)/processed (metal). To achieve effective control, closed-loop feedback loops must be introduced into the control system [3, 4]. Ensuring both specified and required indicators in dynamics at industrial facilities is achieved by reconfiguring the parameters of the mechanism, as a response to changes in the parameters of the control signal, by means of a regulator [5, 6].

Overhead cranes operate by moving loads on flexible suspensions, the swaying of which has a negative impact on the entire structure. In continuous rolling mills, the material being processed moves through several units (stands)

simultaneously during the rolling process, which can result in elastic deformations in the stand components [7, 8].

The objects in question have complex electromechanical systems that are affected by both internal and external interference; the load on these mechanisms is often variable, which leads to the conclusion that due to the uncertainties present in the mechanisms in question, it is advisable to introduce neural network technologies into their structure, in particular, observers and regulators based on them [9, 10].

When constructing control systems, it is necessary to take into account that in addition to load and disturbance effects, their structure contains elements such as electric motors, during the operation of which parametric disturbances are formed as a consequence of constantly changing electromagnetic moments [11, 12].

Often, when formulating requirements for electric drives, both for crane mechanisms and rolling mills, the primary focus is on regulating or maintaining the speed of the mechanism at the required values, maintaining the accuracy of the operations performed (accuracy of load positioning, accuracy of metal rolling to ensure a given strip thickness), real-time monitoring of changing process parameters, and compensation for the influence of disturbing effects [13, 14].

Regardless of the type of motor used (DC or AC), their internal systems are nonlinear, since during operation the state (parameters) of electrical machines changes as a response to existing and random internal and external influences [15].

In practice, without complicating the system, the main motor parameters that can be monitored (measured) include voltage, current, and speed. The process of determining the necessary but unknown parameters usually occurs indirectly, using various types of observers [16].

Large industrial mechanisms are multi-mass systems with a significant number of degrees of freedom. Elastic vibrations are observed in the subsystems of these objects due to the flexibility of the mechanical elements. However, during research, without significantly distorting the results, multi-mass systems are simplified to two- or three-mass systems, which allows for the development of more suitable models for research [17].

Recently, electronic converters have become widespread in industrial machinery. These can be with or without rectifier control, with autonomous current or voltage inverters, as well as frequency converters with direct galvanic coupling to the grid or with a DC link in the form of a "rectifier-filter" circuit. The use of frequency converters often results in disturbances that affect not only the converter's dynamic characteristics but also its operational stability, resulting in interference, errors, and so on. The use of neural networks helps avoid these problems [18].

Neural networks are becoming widespread in many areas due to their high demand and are being actively developed and improved. This has resulted in the emergence of neural networks that use supervised and unsupervised learning, with fixed and dynamic weight settings, with discrete and analog input information, single-layer and multi-layer, with and

without feedback, synchronous and asynchronous, and many others [19].

An analysis of work in the field of electric drive control systems showed that recurrent neural networks containing dynamic multilayer perceptrons in their structure are most often used in these systems; a feature of these networks is the presence of feedback [20].

The most optimal structures for multi-drive electric drives, according to the research conducted, are:

- Elman neural network, which is a neural network with feedback and the ability to learn due to the presence of hidden neurons that record their previous states.
- The NARX neural network, which is a multi-layer network, is capable of storing information about previous system indicators, as well as predicting the state of output signals in the future, this network is also trainable.

The process of developing control systems for multi-drive objects using neural networks is directly related to determining the required number of neural layers in the neural network and the number of neurons in each layer. It is necessary to determine these parameters due to the fact that the resulting system, resulting from an incorrect selection of layers and neurons, may become excessively complex, may require retraining, and may introduce an output parameter error due to the lack of a training stage in the original neural network. Various methods exist to prevent these errors. For example, work [21] proposes algorithms for estimating the error that arises during neural network training.

Also, an important factor in the synthesis of neural networks is the correct choice of parameters of the initial weighting coefficients [22-24]. The most acceptable approaches are those based on:

- on the random selection of weighting coefficients, in this case, when using high-dimensional data, an increase in computing resources is observed;
- depending on the activation function, the method is simple to implement and does not require large computing resources.

Developments in neural networks and fuzzy logic have enabled efficient control of multi-motor mechanisms by compensating for disturbances arising both within the controlled object and outside the object but affecting its operation. Optimization of control systems is observed in both static and dynamic modes, due to reduced error detection time and timely adjustment of the control signal.

During the study of multi-drive control systems, it was discovered that classical control methods are used, with developments primarily focused on solving specific problems. The research objectives in this paper included developing control systems for multi-drive mechanisms using classical methods and neural network theory, considering the nonlinearities inherent in the mechanical components of industrial mechanisms, disturbances, and the interrelationships between output variables.

This study developed an industrial mechanism control algorithm that accounts for disturbances arising during the operation of the plant, the nonlinearity of the control system, and so on. Algorithms for generating universal observers and controllers based on neural networks were developed, which require less time to respond to control inputs. In the practical implementation of unified models of the mechanical components of multi-drive systems with elastic links, the use of transfer matrices that link output data in analytical form is relevant.

When synthesizing control systems for multi-drive mechanisms using neural networks, the problem arises related to the correct selection of the number of neural layers and neurons in each layer. Overestimating these parameters complicates the implementation of neural controllers and neural observers. Increasing the complexity of the neural network structure may necessitate retraining the neural network. Adjusting the number of input signals arriving at the input of a neural controller or neural observer without training the network with the new signal increases the likelihood of increasing the error in the output parameter.

Equally important when synthesizing neural network-based blocks is the correct selection of weighting coefficients. The most appropriate approach is a method based on sequencing the control parameters according to their importance, depending on the degree of their impact on the output parameter.

2. Sequence of Neuroregulator Development

2.1. Development of an Algorithm for Generating a Nonlinear Control System

Before introducing neural controllers into the control system of a multi-drive object, an algorithm for synthesizing a nonlinear system was proposed. This algorithm is based on accepted functional properties, making it possible to obtain non-measurable parameters and parameters that are generated with distortion. The developed algorithm improves the dynamic performance of the object.

Algorithm Synthesis:

- Generating initial parameters: operating modes of interconnected mechanisms, initial data for electric drives, etc.
- Description of the interconnected part of the mechanical system, taking into account the geometry and parameters of the gears, sensor location, and the elastic properties of the object being moved/processed. At this stage, the design (initial) data for the mechanical part of the control system is adjusted to regulate the mechanism's moment of inertia, stiffness, and damping coefficient. Models of the electrical part of the electric drives are also developed.
- Applying decomposition: If the final mathematical model being developed becomes too complex, horizontal and/or vertical decomposition must be applied to the system.

- Forming a quality criterion or criteria that take into account the synthesis objectives.
- Synthesizing a nonlinear control system taking into account quality criteria, constraints, and disturbances.
- Forming a basic version of the control system.
- Developing interconnected electromagnetic and mechanical subsystems. Refinement of the mechanical subsystem to improve the dynamic characteristics of the drives.
- Developing an interconnected multi-drive system.
- Checking the resulting system for compliance with the technical specifications: if the system complies, the algorithm execution is considered complete; if not, the initial data must be adjusted and a step-by-step development of the nonlinear system with the adjusted parameters must be performed.

2.2. Development of an Algorithm for Generating a Nonlinear Control System

When synthesizing the neuroregulator, nonlinearities present in control systems and in the electric drives themselves were taken into account; a deterministic method was used as the basis for choosing the architecture.

It is proposed to select the initial parameters of the neuroregulator for interconnected multi-drive systems in several stages:

- Synthesis of a multi-drive model based on the reference model, taking into account the control signals ($u(t)$), the transfer functions of the controller ($W_{reg}(p)$), the transfer functions of the linear multi-drive model ($W_{mo}(p)$), the changing output signal ($V(t)$), and the matrix reflecting the disturbances present in the system ($d(t)$). The reference model has the following form: $F(u(t), W_{reg}(p), W_{mo}(p), d(t), V(t))$.
- Checking the stability of a multi-drive system based on the analysis of transient processes obtained in a nonlinear control system. If the transient processes are stable, then we proceed to the next step; if not, then we return to the first stage and adjust the controller parameters.
- Acceptance of assumptions (at the initial stage of developing a neuroregulator, we assume that the impact of external and internal disturbances on the object is not significant).
- We accept that the value of the output signal can vary within a certain range from the minimum to the maximum value.

It is proposed to develop a neuroregulator according to the following algorithm:

- Bringing the controller transfer function ($W_{reg}(p)$) to a discrete form ($W_{reg}(z)$), where the sampling step (Δt) depends on the transient time (t_{tr}), which ranges from

10 to 20 of the small time constant of the link in the drive control system, therefore the step is determined as $\Delta t = t_{tt} / (10 \div 12)$.

The proposed sampling step is sufficient to ensure a stable synthesis of the controller architecture. Also at this stage, it is necessary to compare the dynamic characteristics formed in the linear system and obtained using the controller described in this section. If the difference is not 10% [25], then when moving to the next stage, if the specified values are observed to be exceeded, then it is necessary to make adjustments to the observation time.

- Introduction of a discrete controller into the structure of a multi-motor electric drive.
- Synthesis of a neuroregulator ($W^* \text{reg}(z)(NN)$) using the linear function *purelin*. Also at this stage, it is necessary to enter the number of the current layer and the neuron in the layer; it is necessary to take into account that the gain coefficients are numerically equal to the values of the weight coefficients of the neural network.
- Transformation of the neural controller architecture ($NN \rightarrow NN^*$) – depends on the neural network layers and the number of neurons in each layer. It is proposed to add the same number of neurons to the first layer as to the second layer.

Next, instead of the *purelin* activation function, we use the hyperbolic tangent *tanh(n)*, which allows us to approximate the linear function at the origin. At this stage, the weighting coefficients are adjusted. If the activation of each layer reduces the number of layers in the neural network, the number of layers must be increased by one.

- To ensure stable operation of the entire system, it is necessary to determine the changing parameters of the output value ($V(t)$). It is proposed to use a random number generator operating according to the law of uniform distribution over the entire range of the activation function, but we should also consider that, as noted above, the output signal value can vary within a certain range from the minimum to the maximum value.

If the dynamic characteristics of the object are stable at this stage, the controller synthesis process is considered complete, and we proceed to its training. If stability is not achieved, gradually increase the controller coefficients using the hyperbolic tangent function, first by a factor of two, then by the same amount, increasing the $V(t)$ gain. Check the transient stability of the control system. If it is achieved, the controller is synthesized and can be trained. If not, sequentially prove the transient stability.

- It is necessary to generate a training data set taking into account the object's control tasks, ensuring system control within a given control signal range: $\text{data} = \{u_m e_m\}_{m=0}^s$, where m is the current training

sample parameter, s is the finite number of training sample elements, u_m is the current input parameter, and e_m is the current output error parameter in the control system. Experience shows that high-quality training of a neural controller occurs using training, validation, and test sets. The data volume depends on the complexity of the object.

- It is necessary to generate a training data set taking into account the object's control objectives, so as to ensure system control within a given control signal range: Experience shows that high-quality training of a neural controller occurs using training, validation, and test samples. The data volume depends on the complexity of the object.

The structural diagram of the developed algorithm is shown in Fig. 1.

Different approaches are used in training the neuroregulator:

- The backpropagation algorithm using gradient descent minimizes the error function by adjusting network weights in the direction opposite to the gradient of the function. The error gradient of each network weight is calculated from the output layer to the input layer, with the weight adjusted so that the error tends to a minimum. Training occurs online, and this method utilizes sigmoid activation functions, including the hyperbolic tangent.
- The algorithm for backpropagation of errors using the gradient descent method with perturbation is based on the principle described above. The disadvantages include the duration of data processing, and when using this method, finding the global minimum is not guaranteed.
- The Levenberg-Marquardt backpropagation algorithm [26] is a damped least squares method that provides a balance between convergence speed and stability. The disadvantages include complex calculations that require an increase in the time required to train the algorithm.
- The backpropagation algorithm of Bayesian regularization—network weight adjustments are based on the difference between predicted and actual data, considering a priori information about the distribution of weight coefficients. Disadvantages include inefficiency in the presence of local minima forming on the surface of the error function.
- The imitation learning method – learning occurs based on the dynamics of the original controller using feedback data. Upon completion of training, the neural controller functions identically to the original controller. This method is most often used for initial training.

For training, the backpropagation algorithm using the gradient descent method was selected.

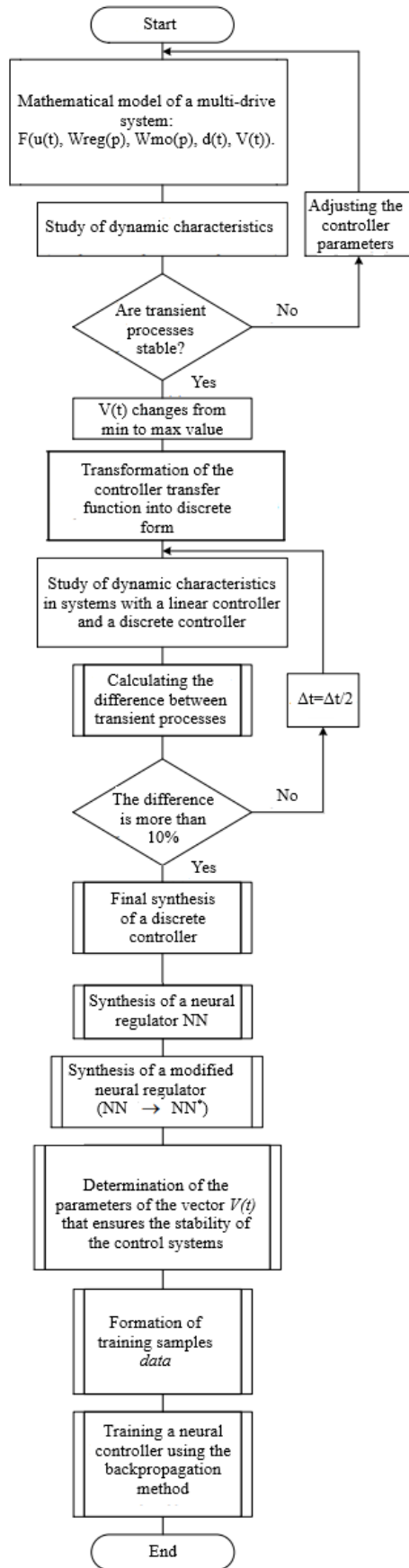


Fig. 1. Structural diagram of the developed algorithm.

2.3. Development of Discrete Predictive Control for A Multi-Engine System

Interconnected multi-mass mechanical systems, which represent multi-drive production mechanisms, are characterized by a large number of inputs and outputs. The mathematical description of these objects includes the physical processes that form during the object's operation as separate subsystems.

The process of controlling output signals involves regulating mechanical variables and, through them, electromagnetic parameters. This leads to the formation of types of assessments of control quality indicators for parameters at each level.

Each subsystem with multiple inputs and outputs can be represented as:

$$\begin{cases} \dot{x} = F(a, b, c, t) = A(x, t)a + B(x, t)b + C(x, t)c \\ - \text{this non-little function is continuously differentiable;} \\ y = z(x) = D(x, t). \end{cases} \quad (1)$$

All presented vectors of state variables a , control b , disturbance c , measured variables y , are time-varying values that are influenced by both external and internal factors. By t we mean time, which is a discrete quantity. $A(x, t)$ is the state matrix, $B(x, t)$ is the control matrix, $C(x, t)$ is the disturbance matrix, $D(x, t)$ is the scaling matrix

When developing systems of this kind, it is proposed to use the predictive control method, the main advantages of which are:

- Possibility of controlling electromechanical mechanisms of different types (linear and non-linear).
- Possibility of application in multidimensional and multichannel control systems, even in the presence of delay.
- Correction of the control signal when various types of disturbing influences occur.
- Possibility of controlling a multi-drive mechanism using data on the technological process of the object recorded in the memory of the control controller.

The assumptions made at the stage of developing the control methodology are the system under study has feedback, the quantities involved in the control process are measurable, the differential equations describing the system are continuous and real, the equilibrium point of the nonlinear function F is formed at $x=0$ ($a_{equ}=0$, $b_{equ}=0$).

Discrete control algorithm using predictive models (sampling time $t=nT_s$):

- Carrying out the linearization of a nonlinear object to a pseudolinear model, for this, the differential equation (1), considering all types of disturbing effects and the equilibrium point, is written in the form:

$$\begin{cases} \dot{x}(y) = A_p(x)a(t) + B_p(x)b(t) + (F(a, b, c, t) - \\ -A_p(x)a(t) + B_p(x)b(t)); \\ y(t) = D_p(x)a(t), \end{cases} \quad (2)$$

where $A_p(x) = \frac{\partial F}{\partial a^T} \Big|_{\substack{a=a_{equ} \\ b=b_{equ}}}$ – matrix of state variables;

$$B_p(x) = \frac{\partial F}{\partial b^T} \Big|_{\substack{a=a_{equ} \\ b=b_{equ}}} \text{ – control variable matrix;}$$

$$D_p(x) = \frac{\partial z}{\partial a^T} \Big|_{\substack{a=a_{equ} \\ b=b_{equ}}} \text{ – matrix of observation variables.}$$

Using Euler's method, we will reduce it to a discrete form (n is the iteration number, $n=0,1,2 \dots k-1$).

$$\begin{cases} x(n+1) = A(n)a(n) + B(n)b(n) + (F(a, b, c, t) - \\ -A(n)a(n) + B(n)b(n)); \\ y(n) = D(n)x(n). \end{cases} \quad (3)$$

where $A(n)=I+TsA_p(x)$ is a discrete matrix of state variables, $B(n)=TsB_p(x)$ is a discrete matrix of control variables, $D(n)=TsD_p(x)$ is a discrete matrix of disturbance variables.

- Development of a predictive model, at this stage it is necessary to determine the state variables for the entire prediction horizon (N_p):

$$\begin{aligned} \hat{x}(n+1|n) &= A(n|n)\hat{a}(n) + B(n|n)b(n|n) + B_d(n|n)\hat{d}(n); \\ &\vdots \\ \hat{x}(n+N_p|n) &= A(n+N_p-1|n)\hat{a}(n+N_p-1|n) + \\ &+ B(n+N_p-1|n)b(n+N_p-1|n) + B_d(n+N_p-1|n)\hat{d}(n). \end{aligned} \quad (4)$$

Control action:

$$\begin{aligned} b(n|n) &= b(n-1) + \Delta b(n|n); \\ b(n+1|n) &= b(n-1) + \Delta b(n|n) + \Delta b(n+1|n); \\ &\vdots \\ b(n+N_c-1|n) &= b(n-1) + \Delta b(n|n) + \dots + \Delta b(n+N_c-1|n). \end{aligned}$$

- Optimization of the model by the quality functional (u) using the nonlinear programming method allows to reduce the prediction error.

Optimization of the quality functional occurs taking into account the vector of desired output parameters ($y_{zad}(n)$) of the control object at iteration n , the weight matrices of the state ($Q(n)$) and control ($R(n)>0$) of the control system of the multi-drive object.

$$J(n) = [y_{zad}(n) - y(n)]^T Q(n) [y_{zad}(n) - y(n)] + \Delta u(n)^T R(n) \Delta u(n). \quad (5)$$

- Calculation of predicted output signals:

$$\begin{bmatrix} \hat{y}(n+1|n) \\ \hat{y}(n+2|n) \\ \vdots \\ \hat{y}(n+N_p|n) \end{bmatrix} = \begin{bmatrix} C(n+1|n) & 0 & \dots & 0 \\ 0 & C(n+2|n) & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & C(n+N_p|n) \end{bmatrix} \times \begin{bmatrix} \hat{x}(n+1|n) \\ \hat{x}(n+2|n) \\ \vdots \\ \hat{x}(n+N_p|n) \end{bmatrix} \quad (6)$$

- Determination of the optimal control action (N_c – control horizon).

The process described is iterative; during the study, the model parameters are updated over the entire forecast range; the data obtained during the previous forecast iteration are the basis for subsequent iterations. Let's consider the development of a discrete predictive speed controller for a rolling mill (Fig. 2).

The discrete control method involves obtaining current parameters from the controlled object. The combination of a Kalman filter and training data obtained using an artificial neural network allows for work with systems in which an incomplete database of controlled signals is available.

During the prediction stage, the state variable is updated and the relationship between the estimated state variable and the actual measured value is calculated. The optimization algorithm, an iterative process, enables optimal values for the parameters of the multi-drive system.

The stages of development of a predictive controller are shown in Fig. 3.

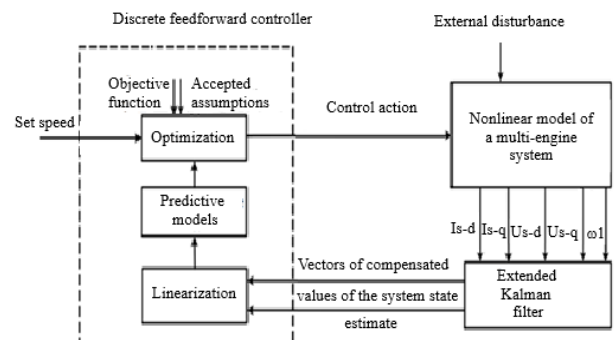


Fig. 2. Speed controller.

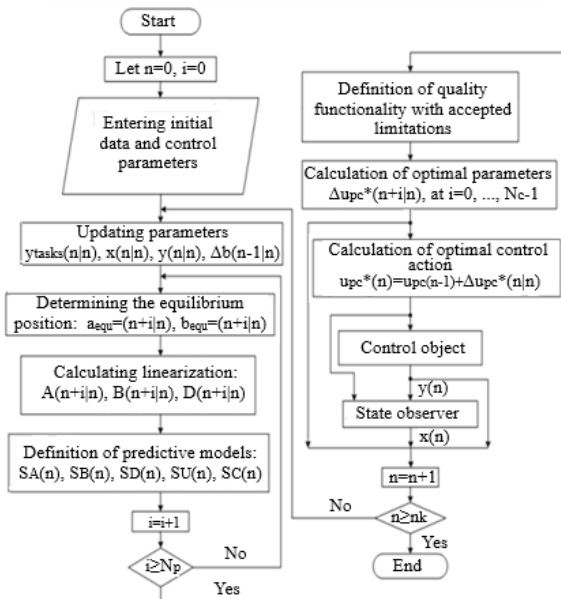


Fig. 3. Stages in regulator development.

In operating machinery, it is often necessary to obtain information about an object in real time. This requires all the data necessary for optimal operation, but this data is not always available. In this case, the use of observers becomes relevant. Fig. 4 shows a state observer proposed for use in a multi-mass rolling mill stand control system. Angular velocity sensors are included in the system to record the angular velocities of the first (equivalent mass on the rolling mill motor shaft) and fourth masses (the upper roll of the rolling stand), while the third mass is the lower roll of the rolling stand).

The control signal is sent to the input of the first mass speed control unit. The system evaluates the speed control error of the fourth mass. The observer development process is shown in Fig. 5. Fig. 6 shows transient processes that clearly demonstrate the influence of changing controller parameters during operation, which directly depend on the parameters of the controlled object (dynamic characteristics), for different values of the prediction horizon N_p and control N_c . The presented graphs indicate that the proposed observer operates effectively, providing the required dynamic characteristics for $N_p = 20$ and $N_c = 10$ and 15. The training sample declined by approximately 28 percent.

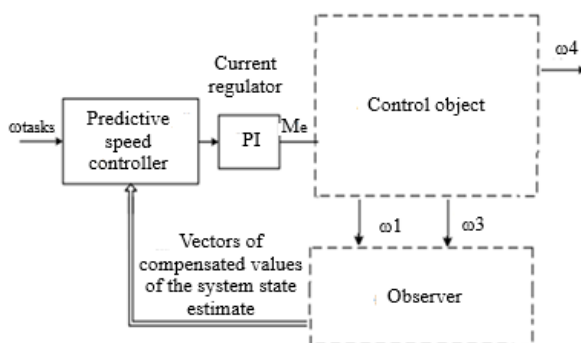


Fig. 4. State observer.

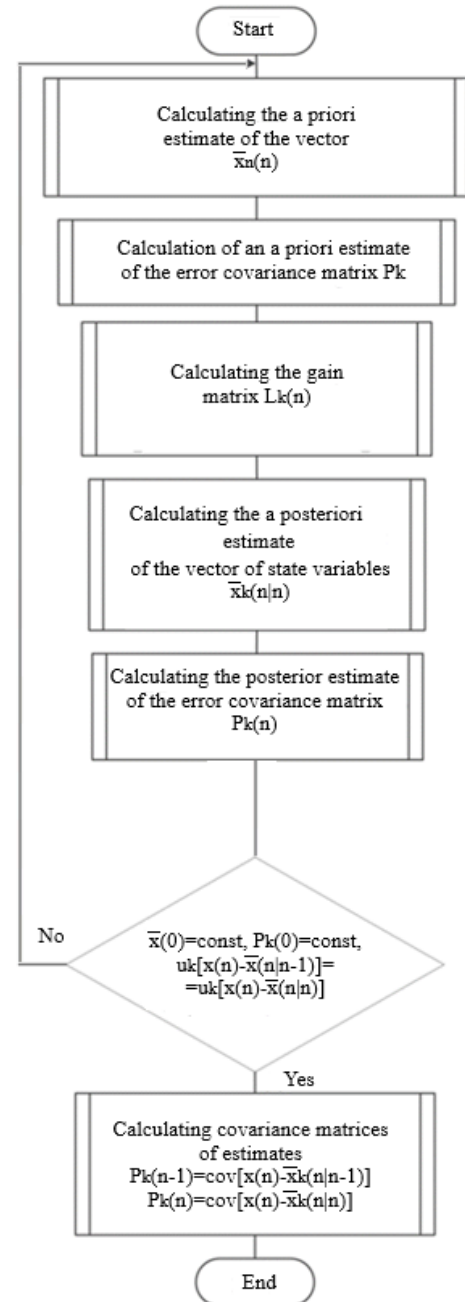


Fig. 5. Stages of observer development.

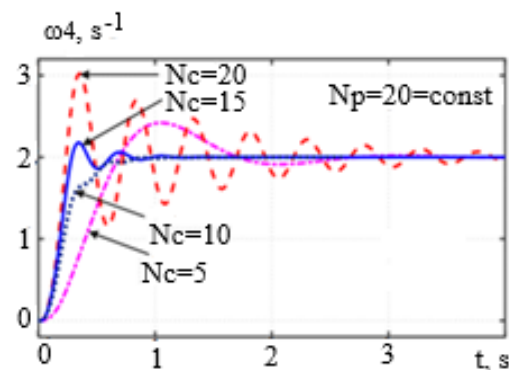


Fig. 6. Formation of transient processes.

2.4. Identification of Parameters Using a Neural Network

Due to the presence of various types of uncertainties in multi-drive mechanisms and their control systems, there is a need to apply identification methods; the use of the NARX neural network architecture is proposed (Fig. 7).

NARX is a multilayer perceptron consisting of two layers with direct data exchange between them. The hidden layer of the neural network under consideration contains k neurons, and the output layer contains one neuron. The network has one input, which contains a delay memory block consisting of d_u elements, and one output of d_o elements, which is connected to the input via a delay memory block. These two memory blocks feed the input layer of the perceptron. Fig. 6 shows the network state for the n th iteration.

In the study, a neural network with one hidden layer $z_u=z_y=2$ was used, the architecture of this neural network is shown in Fig. 8.

For the objects under consideration, the priority is to obtain an identification model $\hat{F}(u)$ with parameters accessible for determination, with a given accuracy $F(u)$ for all control signals $u(n)$, where $n=1, 2, \dots, k$, while the outputs of the models are designated as y , and e is taken to be the root mean square error (Fig. 9).

The functioning of the neural network occurs according to the diagram shown in Fig. 10.

At the activation stage, when performing identification, it is proposed to use the hyperbolic tangent and logistic function. For training, it is proposed to use the algorithm of inverse recognition in time with Bayesian regularization. When minimizing the quality function, it is proposed to use the gradient descent method; at this stage, the weighting coefficients are adjusted.

Fig. 11 shows a system with one input and one output, where $\hat{y}(n+1)$ is an estimate of the output parameter of the multi-drive control system $y(n+1)$. The optimal response is $y(n+1)$; if an error occurs, the synaptic weights of the neural network are adjusted.

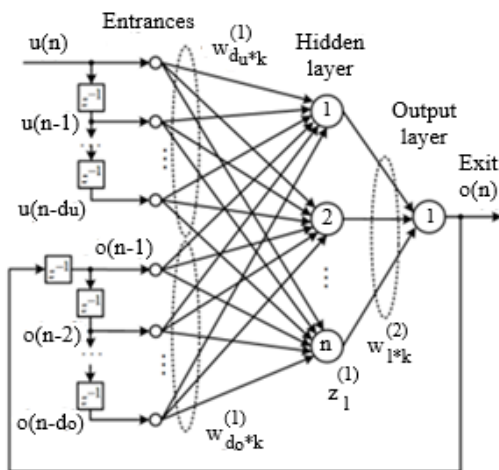


Fig. 7. How NARX works.

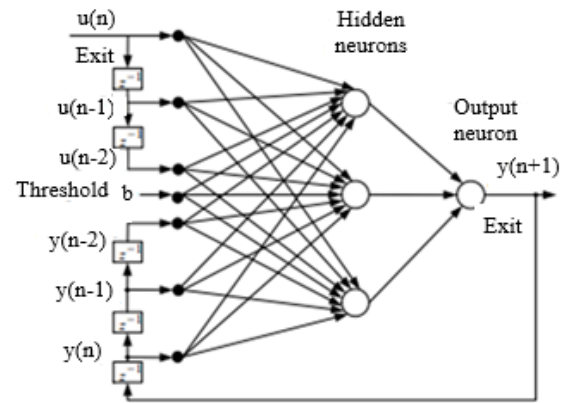


Fig. 8. NARX structure with one hidden layer.

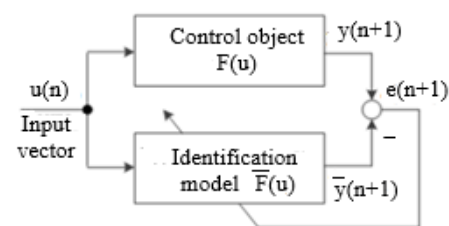


Fig. 9. Explanation of the process of parameter setting using the NARX-based identification technique.

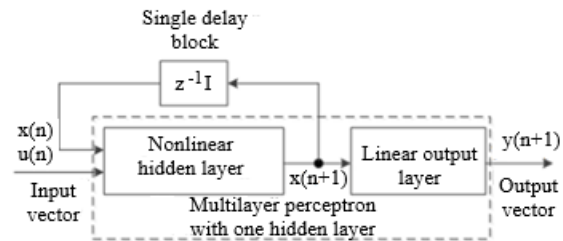


Fig. 10. NARX operation.

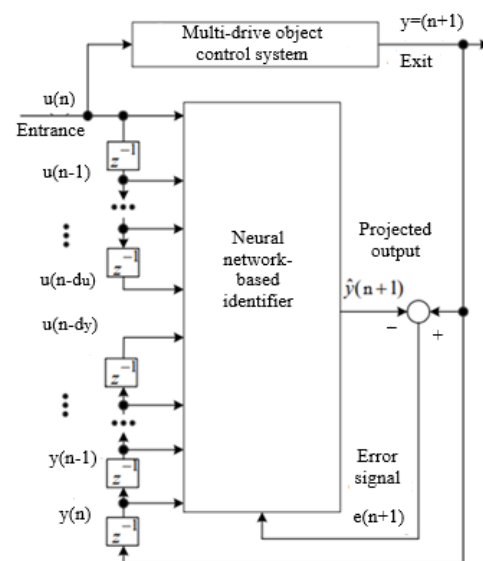


Fig. 11. Introducing NARX to the facility management system.

3. Introduction of a Neuroregulator Operating According to the Developed Algorithm into the Control System of Multi-Drive Mechanisms

As mentioned above, a rolling mill is a multi-drive system, the operation of which requires control of variables such as rolling speed in the stands, rolling force, strip tension, etc.

The process of strip rolling may be accompanied by a change in pressure between the pressure rolls, which leads to the appearance of elastic deformations in the components of the stand and, as a consequence, causes a change in the thickness of the rolled metal as a result of inaccuracies that may arise in any of the processes of forming a metal strip.

Often, the deviation of the thickness of the rolled metal strip from the required parameters is formed in the finishing group of stands, and is influenced by:

- Characteristics of the rolled strip.
- Characteristics of the cages.

The control system under study (Fig. 12) considers data from sensors measuring the speed, thickness of the rolled metal between stands, and the thickness of the metal at the mill exit. In the structural diagram shown, h_{i-1} is the strip thickness at the entrance h_i is the thickness of the rolled metal after i

pressure rolls, σ_{i-1} is the rear tension, σ_i is the front tension, and v is the rolling speed of the metal.

Fig. 13 shows the structural diagram of the control of adjacent stands of a rolling mill.

Using a classic speed and thickness controller in the control system, the characteristics shown in Figs. 14-15 were obtained. The graphs show that the deviation from the set value occurs in the form of oscillations, with a minimum value of approximately 0.026 mm and a maximum of 0.032 mm, both in the direction of increasing and decreasing the set value of the metal strip thickness. Strip tension is established at approximately 0.4 seconds, and the process is oscillatory in nature.

At the next stage of the research, instead of the classical controller, a standard NN Predictive Controller was used, the structural diagram of the system using which is shown in Fig. 16.

Further research was carried out using a regulator in the control system developed according to the algorithm proposed above (Fig. 17).

The results of modeling with a standard neuroregulator are shown in Fig. 18-19, with a neuroregulator developed according to the proposed algorithm, in Fig. 20-21.

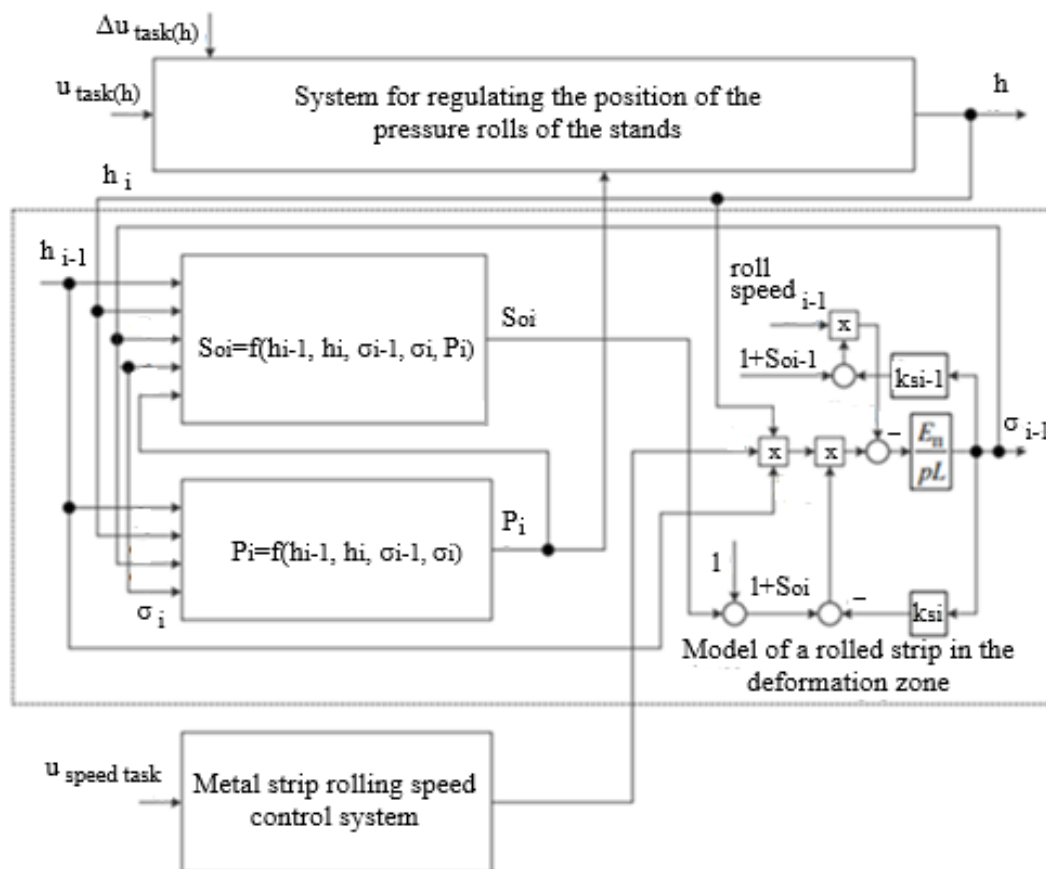


Fig. 12. Finishing stand roll control system.

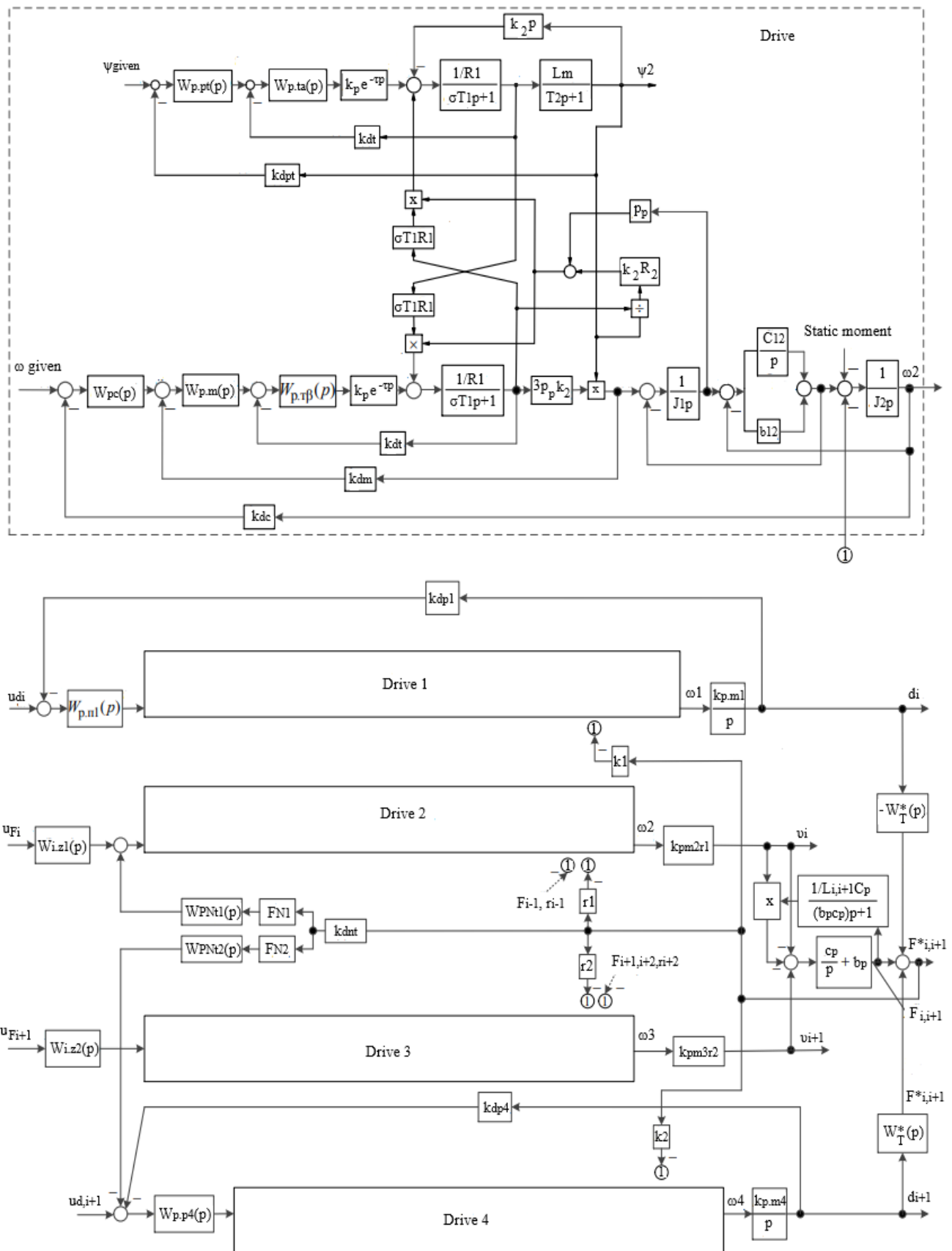


Fig. 13. Adjacent cage control system.

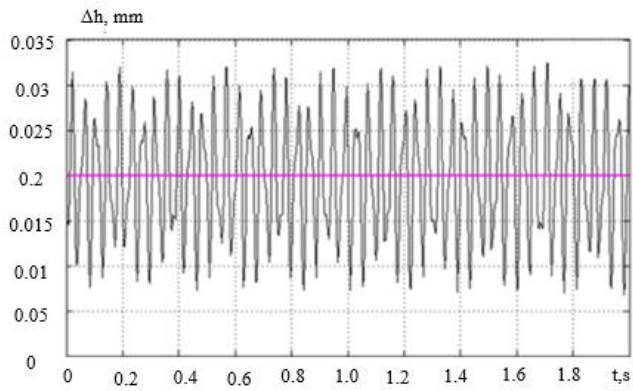


Fig. 14. Graph of deviation of metal strip thickness from a given value in a system with a classic regulator.

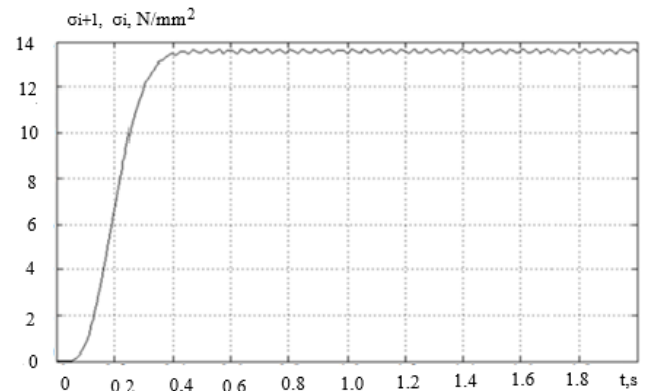


Fig. 15. Formation of strip tension in a system with a classic regulator.

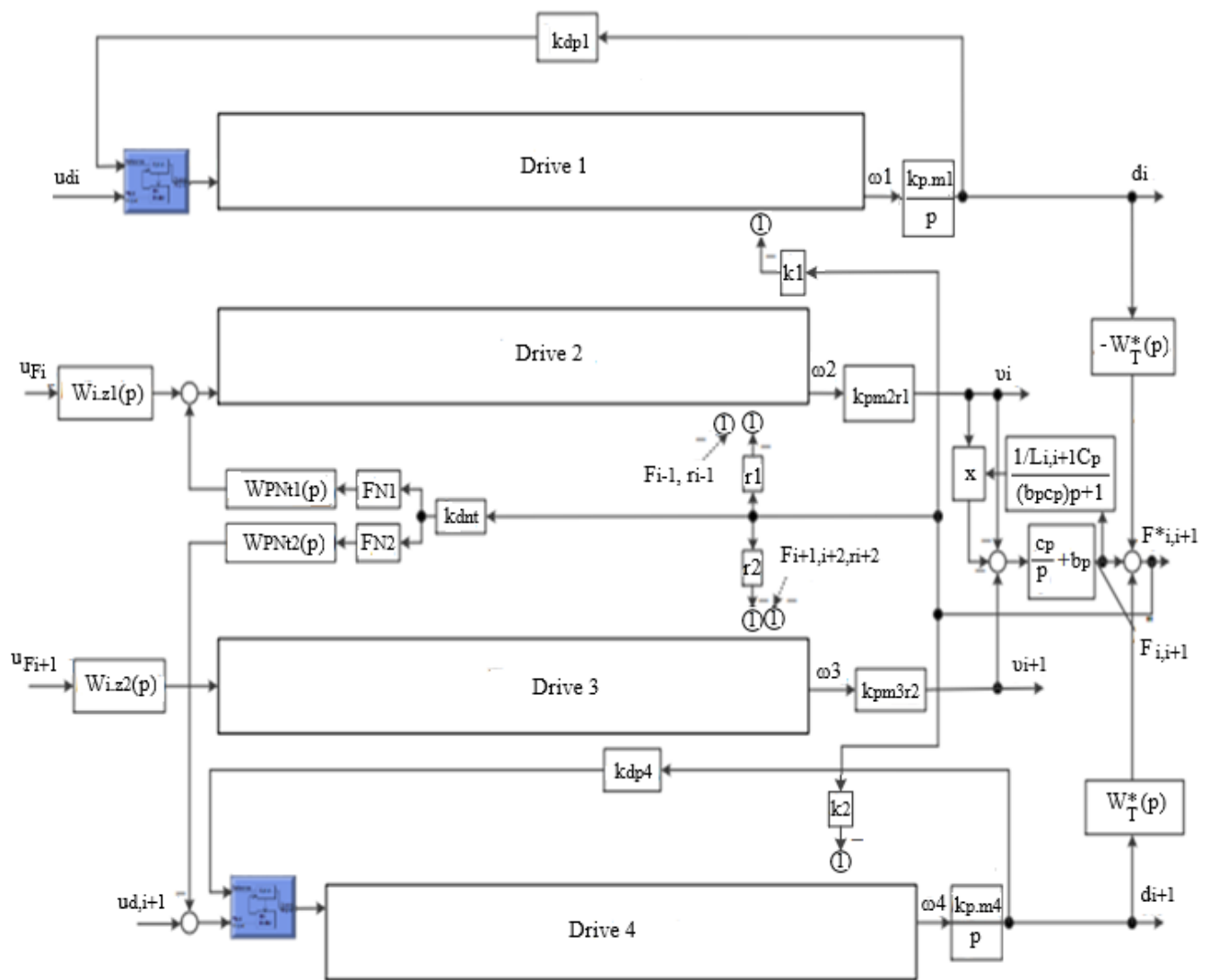


Fig. 16. System with NN predictive controller.

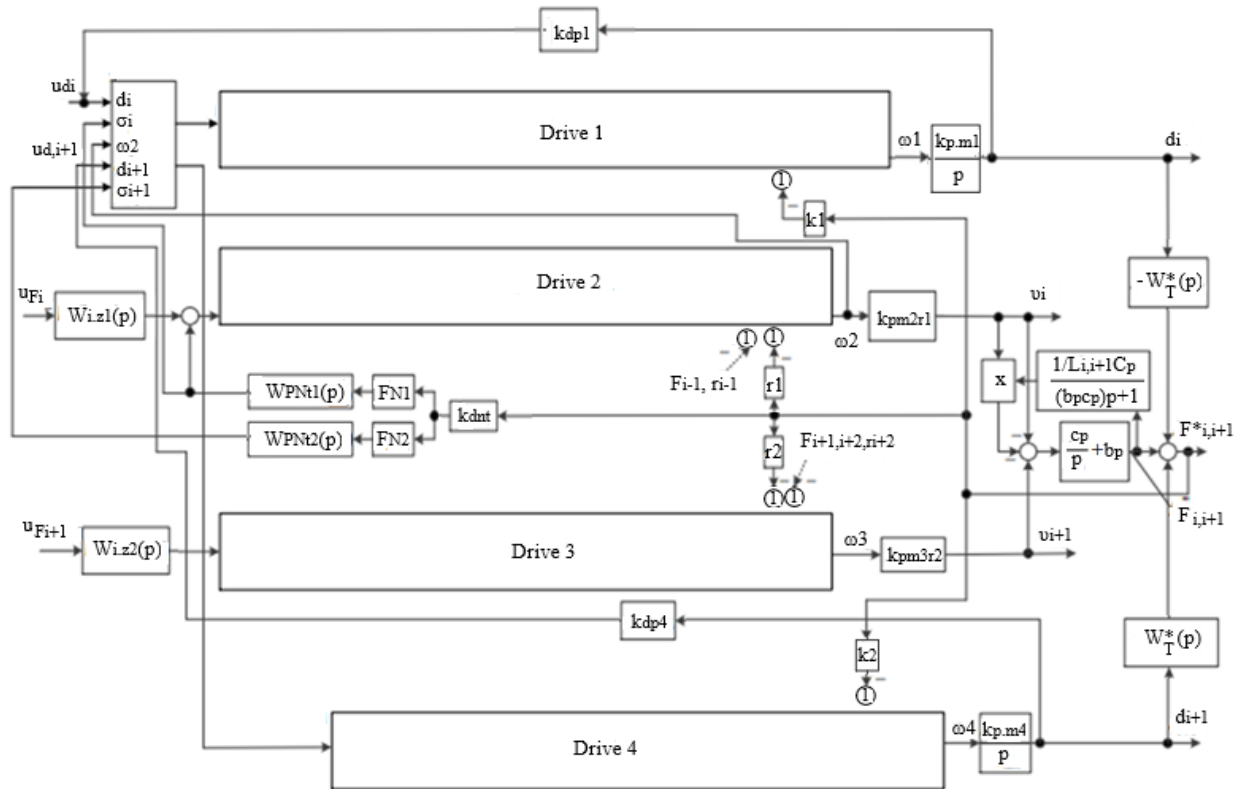


Fig. 17. System with developed algorithm.

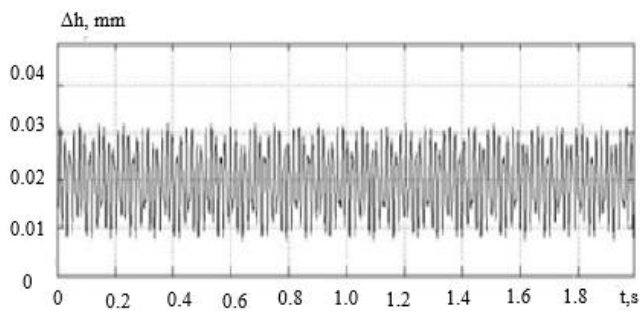


Fig. 18. Graph of deviation of metal strip thickness from a given value in a system with NN predictive controller.

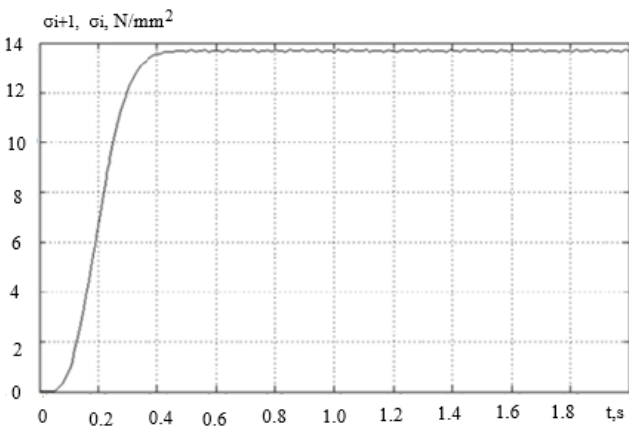


Fig. 19. Formation of strip tension in a system with NN predictive controller.

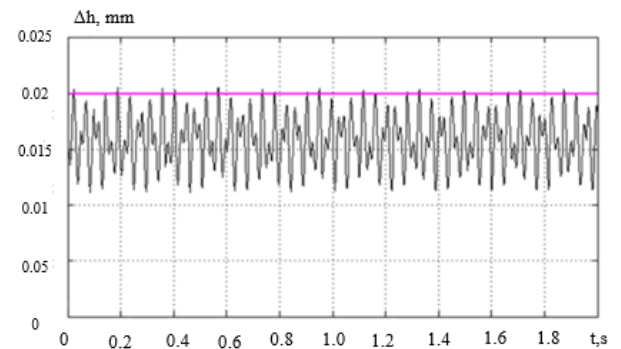


Fig. 20. Graph of the deviation of the thickness of a metal strip from a given value in a system with a neuroregulator operating according to the developed algorithm.

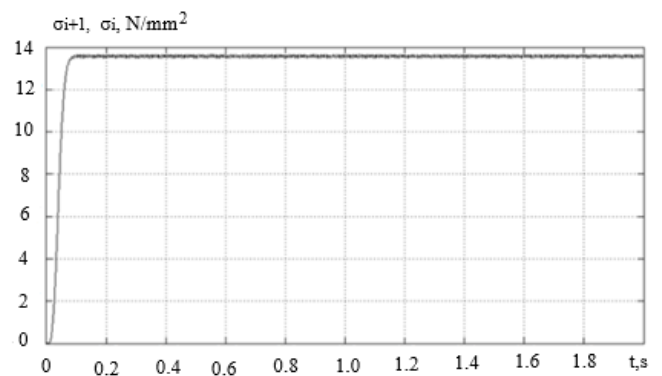


Fig. 21. Formation of band tension in a system with a neuroregulator operating according to the developed algorithm.

When using the NN Predictive Controller speed and thickness control system, the obtained characteristics indicate that deviations from the set value occur as oscillations, with a minimum value of approximately 0.005 mm and a maximum of up to 0.012 mm, both in the direction of increasing and decreasing the set value of the metal strip thickness. Strip tension is established at approximately 0.4 seconds, with a noticeable reduction in oscillations.

When using a speed and thickness neural controller in the control system, operating according to the developed algorithm and the presented characteristics, it can be concluded that deviations from the set value are generated as oscillations. The minimum oscillation value is approximately 0.001 mm for increasing rolled metal thickness, and the maximum is up to 0.02 mm for decreasing the set value of the metal strip thickness. Strip tension is generated at approximately 0.08 seconds.

4. Conclusion

Neural networks are currently widely used, but there is no universal neural network structure suitable for use in multi-drive mechanism control systems. The proposed method for identifying multi-drive mechanism control system parameters using neural networks enables the reconstruction of multi-drive system data in the presence of uncertainties (signal, parametric, or structural) and the identification of control system parameters. The proposed algorithm for synthesizing a neural controller and neural observer reduces the number of neurons in the inner layer, the number of inner layers, and the training sample. This is all made possible by using a mathematical description of the processes and taking into account various types of influences affecting the control system, which are considered during controller synthesis. The proposed neural network-based controllers and observers require less training time, which improves the speed of mechanism operation when responding to control inputs.

The developed neural controller was used to regulate the rolling process in adjacent stands, improving the accuracy of rolled metal thickness control by more than 10 percent. The proposed model considers the processes occurring in metal during rolling. The results obtained, allow to conclude that the proposed algorithm is effective.

Further testing of the proposed method, which improves the dynamic performance of the object, is planned for use on multi-drive crane systems

Author Contributions

S.V. conceptualized and supervised the study; T.S. performed the data analysis; A.S. drafted the manuscript; all authors reviewed and approved the last version.

Acknowledgements

Conflict of Interest

The authors declare no conflict of interest.

References

- [1] M. Zhang, X. Ma, X. Rong, X. Tian, and Y. Li, "Adaptive tracking control for double-pendulum overhead cranes subject to tracking error limitation, parametric uncertainties and external disturbances," *Mechanical Systems and Signal Processing*, vol. 76–77, pp. 15–32, Aug. 2016, doi:10.1016/j.ymssp.2016.02.013.
- [2] S. P. Sayali, W. Vijayraj, P. D. Shendge, and S. B. Phadke, "Sliding mode and inertial delay based direct yaw moment control for AGVs," in *Proc. 6th Int. Conf. Convergence in Technology (I2CT)*, Maharashtra, India, Apr. 2–4, 2021, doi:10.1109/I2CT51068.2021.9418161.
- [3] L. A. Chumakova, D. A. Argunov, A. V. Matveev, and P. A. Maksimov, "Dynamic loads in the drive of a reduction mill stand," *Steel*, no. 10, pp. 56–57, 2018.
- [4] F. Zhang, Y. Zhang, J. Hou, and B. Wang, "Thickness control strategies of plate rolling mill," *International Journal of Innovative Computing, Information and Control*, vol. 11, no. 4, pp. 1227–1237, 2015.
- [5] J. Sun, S.-Z. Chen, H.-H. Han, X.-H. Chen, Q.-J. Chen, and Z. Hua, "Identification and optimization for hydraulic roll gap control in strip rolling mill," *Journal of Central South University*, vol. 22, no. 6, pp. 2183–2191, 2015, doi:10.1007/s11771-015-2742-0.
- [6] V. R. Gasiyarov, A. A. Radionov, A. S. Karandaev, V. Khrumshin, and B. Loginov, "Improving the algorithm of automated gage control during shaped feed rolling on a plate mill," in *Proc. IEEE 11th Int. Conf. Mechanical and Intelligent Manufacturing Technologies (ICMIMT)*, Cape Town, South Africa, Jan. 20–22, 2020, doi:10.1109/ICMIMT49010.2020.9041207.
- [7] S. Valtchev, A. V. Sinyukov, V. N. Meshcheryakov, and T. V. Sinyukova, "Development of a fuzzy controller for damping oscillations of a flexible suspended load in electromechanical systems of crane mechanisms," *Electricity*, no. 4, pp. 13–27, 2025, doi:10.24160/0013-5380-2025-4-13-27.
- [8] A. V. Sinyukov, E. Y. Abdullazyanov, T. V. Sinyukova, N. N. Zaruckiy, and E. I. Gracheva, "Using a fuzzy logic-based apparatus for damping vibrations of a flexible load," *Power Engineering: Research, Equipment, Technology*, vol. 26, no. 3, pp. 33–49, 2024, doi:10.30724/1998-9903-2024-26-3-33-49.
- [9] S. V. Langraf, A. I. Sapozhnikov, and A. S. Glazyrin, "Dynamics of an electric drive with a fuzzy controller," *Bulletin of Tomsk Polytechnic University*, vol. 316, no. 4, pp. 168–173, 2010.
- [10] Y. Niu, H. Li, and F. Liu, "A loss-aware continuous Hopfield neural network (CDN)-based mapping

- algorithm in optical network-on-chip,” in Proc. 20th Int. Conf. Optical Communications and Networks (ICON), 2022.
- [11] W. M. Haddad, V. Chellaboina, J. L. Fausz, and A. Leonessa, “Optimal nonlinear robust control for nonlinear uncertain systems,” *International Journal of Control*, vol. 73, no. 4, pp. 329–342, 2000.
- [12] S. H. Asgari, M. Jannati, T. Sutikno, and N. R. N. Idris, “Vector control of three-phase induction motor with two stator phases open-circuit,” *International Journal of Power Electronics and Drive Systems*, vol. 6, no. 2, pp. 282–292, 2015, doi:10.11591/ijpeds.v6.i2.
- [13] P. J. Shaija and E. D. Asha, “An intelligent speed controller design for indirect vector-controlled induction motor drive system,” *Procedia Technology*, vol. 25, pp. 801–807, 2016, doi:10.1016/j.protcy.2016.08.177.
- [14] L. A. Amézquita-Brooks, C. E. Ugalde-Loo, E. Licéaga-Castro, and J. Licéaga-Castro, “In-depth cross-coupling analysis in high-performance induction motor control,” *Journal of the Franklin Institute*, vol. 355, pp. 2142–2178, 2018, doi:10.1016/j.jfranklin.2018.01.002.
- [15] B. Kada, M. Hebali, I. F. Bouguenna, B. Ibari, and M. Bennaoum, “High-performance inverse artificial neural network controller for asynchronous motor control,” *The Journal of Engineering and Exact Sciences*, vol. 10, no. 9, p. 20857, 2024, doi:10.18540/jcecvl10iss9pp20857.
- [16] H. Sudheer, S. F. Kodad, and B. Sarvesh, “Improvements in direct torque control of induction motor for wide-range of speed operation using fuzzy logic,” *Journal of Electrical Systems and Information Technology*, vol. 5, pp. 813–828, 2018.
- [17] Y. Yao and B. Zhang, “Influence of the elastic modulus of a conveyor belt on the power allocation of multi-drive conveyors,” *PLoS ONE*, vol. 15, no. 7, e0235768, 2020.
- [18] D. A. Dementev, E. D. Maximova, I. A. Sysoletin, and S. V. Mezin, “Research of the influence of feedback signals in the neuroregulator on the quality of regulation,” *Journal of Physics: Conference Series*, vol. 1889, no. 2, p. 022053, 2021, doi:10.1088/1742-6596/1889/2/022053.
- [19] R. D. Diwan, “Induction motor testing using MATLAB/Simulink,” *International Research Journal of Engineering and Technology*, vol. 8, no. 6, pp. 1810–1815, 2021.
- [20] D. Rai, S. Sharma, and V. Bhuria, “Fuzzy speed controller design of three phase induction motor,” *International Journal of Emerging Technology and Advanced Engineering*, vol. 2, pp. 145–149, May 2012.
- [21] S. Haykin, *Neural Networks: A Complete Course*. Moscow: Williams, 2016.
- [22] A. J. da Silva, W. R. de Oliveira, and T. B. Ludermit, “Weightless neural network parameters and architecture selection in a quantum computer,” *Neurocomputing*, vol. 183, pp. 13–22, 2016.
- [23] A. M. Bruckstein, D. L. Donoho, and M. Elad, “From sparse solutions of systems of equations to sparse modeling of signals and images,” *SIAM Review*, vol. 51, no. 1, pp. 34–81, 2009.
- [24] M. Hyder, M. Shahid, M. Kashem, and M. Islam, “Initial weight determination of a MLP for faster convergence,” *Journal of Electronics and Computer Science*, pp. 1–6, 2009.
- [25] V. A. Besekersky and E. P. Popov, *Theory of Automatic Control Systems*. St. Petersburg: Profession, 2003.
- [26] Y. Bengio, P. Simard, and P. Frasconi, “Learning long-term dependencies with gradient descent is difficult,” *IEEE Transactions on Neural Networks*, vol. 5, no. 2, pp. 157–166, 1994.

Frequency Stability Control in Low-Inertia Microgrids Using Optimized Virtual Damping Stabilizers

Sabo Aliyu *, I. Dabo Abdulmalik *, Dauda Dahiru *, Kabiru Abubakar Tureta *
Kenneth Okedu **, Noor Izri Abdulwahab ***

* Department of Electrical Engineering, Faculty of Engineering and Engineering Technology, Nigerian Defense Academy, Kaduna, Nigeria.

** School of Information Technology and Engineering, Melbourne Institute of Technology, 3000, Victoria, Australia.

*** Department of Electrical and Electronic Engineering, Faculty of Engineering, University Putra Malaysia.

(saboaliyu98@gmail.com, abdulmalikdaboi@gmail.com, dawooddahiru@gmail.com, kabiruabubakartureta@gmail.com, kokedu@academic.mit.edu.au, izzri@upm.edu.my)

† Corresponding Authors: Kenneth Okedu and Dauda Dahiru, kokedu@academic.mit.edu.au and dawooddahiru@gmail.com.

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Abstract- Inverter-based Generators generally lack natural inertia required for ascertaining the frequency stability of Electrical Microgrid Power Systems. A robust virtual inertia emulation technique is required in ensuring that frequency stability of low-inertia systems is greatly improved. This paper presents a hybrid control strategy that combines Fractional Derivative Inertia Control (FDIC) and a Virtual Damping Stabilizer (VDS) modelled as lead-lag compensator, and then as FOPID, implemented via a Battery Energy Storage System (BESS) to address these challenges. The FDIC is a BESS-based virtual inertia controller that leverages fractional calculus to emulate inertia and damping, while the VDS generates the appropriate compensating power that helps dampen out oscillations. A comprehensive MATLAB/Simulink model of an islanded microgrid comprising a diesel generator, photovoltaic (PV), and wind generation is developed to evaluate the proposed approach. Control parameters are optimized using the Beluga Whale Optimization Algorithm (BWO), ensuring robust performance under various disturbances and its performance is evaluated by comparison with Particle Swarm Optimization (PSO) based VDS design. Simulation results demonstrate that the FDIC+VDS scheme significantly improves frequency deviation compared to traditional virtual inertia. The findings highlight the efficacy of advanced BESS-based control strategies in enhancing the resilience and stability of low-inertia, renewable-rich microgrids.

Keywords: Microgrid, frequency control, virtual damping stabiliser, FOPID, FDIC.

1. Introduction

The transition towards sustainable and low-carbon energy systems has driven a rapid proliferation of renewable energy

sources (RES) such as photovoltaic (PV) and wind energy in power systems. Islanded microgrids, often deployed in remote or off-grid areas, have become a practical platform for integrating these intermittent energy sources due to their

ability to operate independently of the main grid. However, the high penetration of inverter-based RES introduces significant technical challenges, primarily due to the lack of inherent inertia [1, 2, 3] and damping typically provided by synchronous generators. This deficiency leads to frequency instability, degraded power quality, and a general decline in system resilience under disturbances. Microgrid control is essential, because it helps keep the system stable. . Microgrid control strategies are mainly of two types, Primary/Secondary control and peer-to-peer control [4]. The prime control perspectives in the MG based on Primary/Secondary control are: voltage, current, frequency, proper power-sharing active, and reactive [5, 6, 7]. Droop control is a common control strategy in peer-to-peer control which uses real power output from a generator to calculate the operating frequency and offset the effect of fast changing loads [8]. Droop control involves controlling voltage droop or frequency droop. When multiple micro-sources engage in providing power balance, they will follow either the voltage droop or the frequency droop method [9]. This control level aims to maintain output voltage regulation and active power [10, 11, 12, 13]. In conventional grid-tied systems, rotational inertia and power system stabilizers (PSS) inherently mitigate frequency deviations and oscillations following load or generation disturbances [14]. However, in islanded microgrids dominated by power-electronics-based generation, these stabilizing mechanisms are either absent or significantly reduced [15]. Consequently, the dynamic performance of such systems becomes highly sensitive, especially during events such as load changes, RES intermittency, and faults [16, 17, 18]. The limited availability of primary frequency control and insufficient damping necessitate the design of advanced control strategies capable of emulating the stabilizing effects of conventional generators.

Virtual inertia control is a control technique that was first developed using the derivative control technique to mimic the inertia offered by the rotating mass of synchronous generators (SG) but neglected the damping properties. Authors in [19] introduced fractional derivative virtual inertia integrated into the virtual inertia control loop to address microgrid (MG) stability issues. Though it was an improvement on the derivative technique, but it also neglected the damping properties. Subsequent studies like that of [20, 2] have proved that the virtual inertia control incorporated with the virtual damping has a better frequency response than the virtual inertia control based on derivative inertia control (DIC) technique regarding damping frequency oscillation and shortening the settling time.

Over the years, researchers have proposed various control methods to reduce frequency deviations and enhance system stability. The authors in [21] propose a self-tuning PI-controller that utilizes a combination of Artificial Neural Networks (ANN) and Genetic Algorithms (GA), which enables online training and adjustment of the PI-controller coefficients. The proposed method showed improved performance in terms of frequency stability, with reduced fluctuations in the microgrid's frequency response compared to traditional methods. While the proposed method enhanced the stability and performance of the microgrid, the integration

of ANN and GA introduces computational complexity that may not be manageable with standard processing units. The authors acknowledge that high-resolution processors are necessary to handle the extensive calculations involved, which can increase the overall cost and complexity of the control system. In another study, [22] proposed a Decentralized utilization of distributed energy storage resources for simultaneous frequency regulation in a microgrid. Wind and PV generation systems were combined for the enhancement of inertia and frequency support. The result showed that using PV only, wind only, or simultaneously using both enhanced the frequency deviation by 44.4 %, 29.5 % and 53.3 % respectively. In addition, the required energy from PV and wind using both simultaneously, is reduced by 29.5 % and 13.7 % and ROCOF is enhanced by 61.9 %. While the proposed method proved effective, the effectiveness of the proposed control scheme is inherently tied to the availability of sunlight and wind. Variability in these renewable resources can lead to inconsistent performance, particularly during periods of low generation, which may not be adequately addressed in the proposed strategy. Furthermore, [23] proposed a coordinated control parameter setting of DFIG wind farms with virtual inertia control by utilizing virtual inertia from wind farms to enhance the frequency stability of power systems. The propose method adjusts the active power output based on system frequency feedback which is significant as it mimics the behavior of synchronous generators, providing necessary inertia support in systems with low natural inertia. While the authors present a comprehensive approach, it could benefit from a more detailed comparison with existing methods to provide a clearer context for the advantages of the proposed approach. In [24], the authors presented a frequency control method that utilizes electric spring (ES) technology to provide virtual inertia and primary frequency response through smart loads (SL). The ES technology allows voltage-dependent loads to operate as smart loads, which can modulate their power consumption within a specified voltage range ($\pm 5\%$ of nominal voltage). The control design allowed the system to provide up to 2.5 seconds of virtual inertia under specific conditions. The system frequency nadir improved from 48.95 Hz to 49.3 Hz when the smart load was active. While the frequency nadir improved, the practical implementation challenges, such as the integration of electric spring (ES) technology into existing infrastructure and the economic feasibility of widespread adoption, are not thoroughly addressed. In [25] a Variable Synthetic Inertia Controller for Wind Turbine Generators was presented as an innovative frequency control method through the design and implementation of a Variable Hidden Inertia Emulator (VHIE) for Wind Turbine Generators (WTGs) equipped with Permanent Magnet Synchronous Generators (PMSGs). The initial tests were conducted on a simplified configuration, followed by more realistic simulation. The simulations demonstrated that the VHIE controller effectively reduced the Rate of Change of Frequency (RoCoF) by approximately 40%. The frequency nadir, which is the lowest point of frequency during a transient, showed a 35% improvement. Although the VHIE aims to provide effective frequency support, its performance during rapid frequency transients may still be limited. The synthetic inertia

coefficient's dependence on rotor speed means that during critical moments of frequency deviation, the controller's effectiveness could diminish, potentially leading to inadequate support when it is most needed.

Furthermore, [26] proposed an innovative frequency control method known as Adaptive Optimal Model Predictive Control (AOMPC). The AOMPC method was compared with various existing controllers, including optimal proportional-integral (OPI), optimal fractional order PID (OFOPID), optimal fuzzy PID (OFPID), and adaptive MPC (AMPC). The results indicated that AOMPC provided the best performance in terms of frequency regulation during multiple load disturbances and changes in weather patterns. Although the AOMPC proved to be better than the compared controllers, the implementation of AOMPC may involve complex computations and require advanced algorithms, such as the CPSO algorithm for parameter tuning. This complexity could pose challenges in real-time applications, especially in systems with limited computational resources.

In [27], the authors presented a virtual inertia control-based vehicle-to-grid (V2G) concept for the secondary load frequency control of AC islanded microgrids (MGs). The proposed control approach outperforms conventional MPC (CMPC) and model-free Sliding Mode Control (MFSMC) in terms of frequency regulation. The stored energy in electric vehicles was effectively utilized to enhance both steady-state and transient performance, showcasing the benefits of integrating V2G technology into frequency control strategies. The study assumes that electric vehicles can be effectively controlled as mobile energy storage devices. However, this assumption may not hold true in all cases, as user behavior, charging patterns, and vehicle availability can vary significantly. These factors could impact the reliability of the V2G system and its ability to provide the necessary virtual inertia.

In another study, [28] proposed a frequency control method that combines virtual inertia and damping, optimized through genetic algorithms. The proposed VI control system not only enhances the dynamic response and frequency regulation of the microgrid but also demonstrates robustness against various operational challenges. The study relies heavily on Genetic Algorithm (GA) for optimizing the parameters of the VI control system. While GA is known for its fast convergence, the study does not explore alternative optimization methods or provide a comparative analysis of their effectiveness.

In [29], the authors proposed a frequency control method which is an adaptive virtual inertia control method. The adaptive virtual inertia control led to a marked improvement in frequency response, minimizing frequency deviations and enhancing overall system stability. The proposed method-maintained effectiveness even with communication delays of up to 100ms, ensuring continued performance in large networks. While the proposed control method shows promise, the control strategy relies heavily on distributed communication among VSG units. This dependency can introduce vulnerabilities if communication is disrupted.

The authors in [30] proposed a virtual inertia emulator (VIE) based Model predictive control MPC as a frequency control method. The MPC approach can reduce the minimum Energy Storage System (ESS) capacity required for frequency regulation by 55% compared to a P controller and by 2% compared to a PI controller. The energy throughput of the ESS using MPC was found to be reduced by 86% compared to a P controller and by 36% compared to a PI controller. The study emphasizes that MPC effectively minimizes frequency deviation during disturbances, showcasing its superior performance over traditional control methods. While the authors claim that the MPC can operate in real-time due to its one-step prediction horizon, the computational demands of MPC can still be significant, especially in larger and more complex systems.

In [31], the authors proposed a virtual inertia control based on proportional-integral (PI) controller optimally designed by the Manta Ray Foraging Optimization (MRFO) as a frequency control method. The study investigates the microgrid's performance under step load changes, specifically highlighting a 50% reduction in overall inertia. Although the MRFO-based PI controller demonstrated improved system performance in frequency disturbance alleviation and reference frequency tracking, the results indicate significant frequency fluctuations and deviations during these disturbances, suggesting that there is a clear need for more advanced control mechanisms that can provide better damping and stability. Virtual damping stabilizers, for instance, could offer a more robust solution by improving system response to disturbances and sudden load change.

This study proposes an enhanced frequency control scheme combining Fractional Derivative Inertia Control (FDIC) and a Virtual Damping Stabilizer (VDS) integrated through a Battery Energy Storage System (BESS). The FDIC extends traditional virtual inertia concepts by incorporating fractional calculus to provide a more flexible and accurate dynamic response, which better mimics the non-local and history-dependent nature of real physical inertia. This approach allows for tunable control dynamics that adapt to varying system conditions, resulting in improved frequency nadir, settling time, and overshoot performance.

Simultaneously, the VDS complements the inertia emulation by providing synthetic damping through active power modulation. The BESS acts as the physical actuator, delivering rapid response capabilities essential for dynamic support in inverter-based systems. Together, the FDIC and VDS form a coordinated control framework aimed at stabilizing frequency oscillations and improving system damping without the need for mechanical inertia.

This work contributes the following key innovations:

- Development of a hybrid FDIC-VDS scheme that combines the benefits of fractional order dynamics with fast-acting synthetic damping control.
- Modelling of VDS in two different configurations: VDS modelled as a lead-lag compensator, then as FOPID for performance evaluation.

- Integration of BESS for dynamic support, acting as both inertia emulator and damping stabilizer within a unified control architecture.
- Optimization and tuning of control parameters using Beluga Whale optimizer (BWO), a nature-inspired algorithm to enhance system performance across a range of operating conditions.

The system is modelled and simulated in MATLAB/Simulink, where the dynamic interactions between the diesel generator, renewable energy sources, and BESS-based control mechanisms are comprehensively evaluated. The performance of the proposed control strategy is benchmarked against conventional virtual inertia and droop control methods, demonstrating superior frequency stability, reduced oscillations, and enhanced robustness to disturbances. The proposed control strategy is also modelled in two different architectures: as a lead-lag compensator and as FOPID, with the FOPID configuration showing better overall performance.

1.1. Problem Statement

The increasing integration of renewable energy sources (RESs) into microgrids has led to a significant reduction in system inertia, resulting in instability issues during frequency disturbances. Inverter-based generators lack natural inertia, which exacerbates frequency fluctuations and can lead to severe operational challenges in maintaining system stability. Another advantage offered by synchronous generator-based systems is the incorporation of Power system stabilizers (PSS) which is absent in inverter-based systems. The low capacity of BESS restricts their ability to respond effectively to frequency disturbances. Addressing this limitation with larger energy storage will significantly increase the initial investment cost.

2. System Modelling

The proposed study models an islanded microgrid with high renewable energy penetration, integrating a diesel

generator (DG), photovoltaic (PV) arrays, a wind turbine generator (WTG), and a Battery Energy Storage System (BESS) controlled via a hybrid Fractional Derivative Inertia Control (FDIC) and Virtual Damping Stabilizer (VDS) schemes. All disturbances were introduced as step inputs applied at $t = 15$ s, representing sudden changes in load demand or renewable generation. These are represented by the disturbance vector $u = [\Delta P_{LOAD}, \Delta P_{WIND}, \Delta P_{SUN}]^T$, applied to the microgrid state-space model to assess system resilience. This simplification isolates the transient response of the microgrid frequency control mechanism without stochastic weather dynamics. The magnitude of the step was normalized to $\pm 20\%$ for load and $\pm 10\%$ for renewable generation. The model is developed in MATLAB/Simulink, capturing the dynamic behaviors of the microgrid under various operating conditions.

2.1. Microgrid Architecture

The frequency dynamics of an islanded microgrid are critically influenced by the balance between generation and demand [32], especially in systems with high renewable energy penetration and limited rotational inertia. The schematic presented in Figure 1 shows the detailed frequency control architecture adopted for this study. The presented model offers a comprehensive dynamic frequency response framework that captures the contribution of both conventional and inverter-based resources (solar PV and wind) in regulating frequency deviation (Δf) following active power imbalances (ΔP).

Frequency stability during contingency events in the traditional power system is attributed to the PSS in SGs, damping winding, and inherited rotating mass inertia. The relationship between power imbalance, damping, frequency deviation, and system inertia is explained by the well-known swing equation in Equation 1.

$$\Delta P_m(s) + \Delta P_{Load}(s) = 2 H_s \Delta F(s) + D \Delta F(s) \quad (1)$$

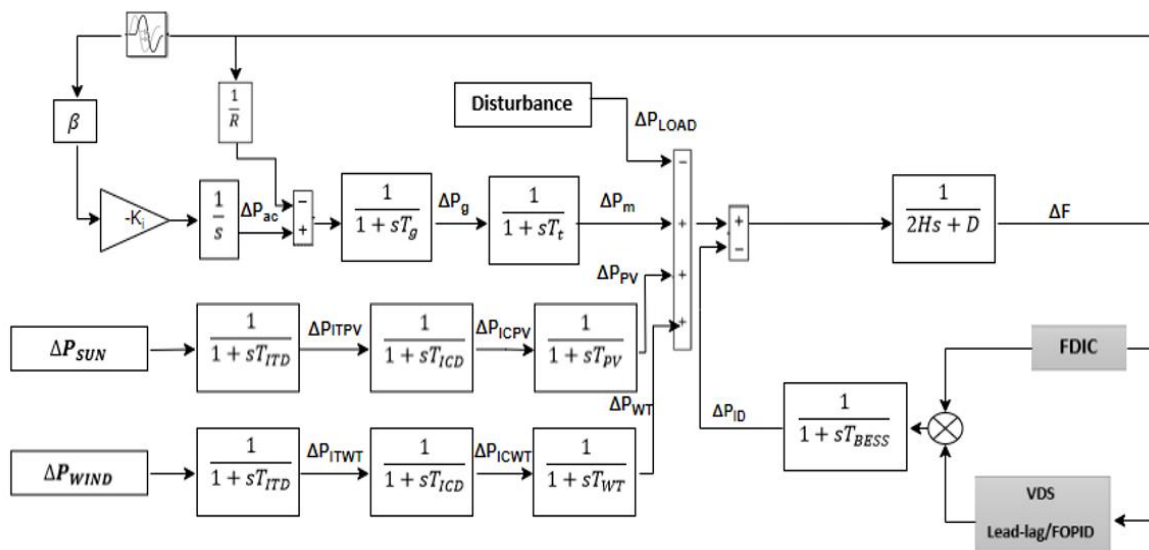


Fig. 1. Dynamic frequency response model of islanded microgrid.

Here, H represents the equivalent per-unit inertia constant of the microgrid, while D denotes the damping coefficient that captures the load-frequency sensitivity. The net power imbalance, defined as the deviation between total generation (including BESS compensation) and load demand, directly drives the frequency deviation Δf . The swing equation block thereby serves as the dynamic integrator translating power perturbations into frequency excursions. Therefore, the frequency deviation can be expressed from the model as:

$$\Delta f = \frac{(\Delta P_m + \Delta P_{PV} + \Delta P_{WT} - \Delta P_{ID} - \Delta P_{Load})}{2Hs + D} \quad (2)$$

The simulated islanded microgrid includes:

- A conventional diesel generator (DG), as the primary inertial component in the system, is modeled with detailed governor and turbine dynamics.
- Both photovoltaic (PV) and wind generation modeled using first-order transfer functions that reflect the dynamics of inverter-based control and active power injection.
- A BESS in augmenting the frequency stability of the microgrid by emulating both virtual inertia and virtual damping through injection/absorption of active power.
- A control loop implementing FDIC and VDS to emulate inertia and damping.

2.2. Diesel Generator Dynamics

The diesel generator is modeled using a second-order swing equation that captures the mechanical-electrical dynamics, including governor and turbine time constants. Its contribution to frequency regulation is also parameterized through droop control [33].

$$\Delta f = \frac{1}{2H} (\Delta P_m - \Delta P_g - D\Delta f) \quad (3)$$

where;

Δf : The rate of change of frequency deviation (ROCOF)-how quickly the frequency is changing over time due to imbalances in power.

H : The inertia constant of the machine (in seconds), representing stored rotational kinetic energy. A higher H implies more resistance to frequency change.

ΔP_m : The change in mechanical input power from the prime mover.

ΔP_g : The change in governor action.

Δf : The deviation in system frequency from the nominal value.

D : The damping coefficient, which models how the system naturally opposes frequency deviation (due to load-frequency sensitivity or artificial damping mechanisms).

The modeling of governor and turbine:

$$\Delta P_m = \frac{1}{1+sT_t} \Delta P_g \quad (4)$$

$$\Delta P_g = \frac{1}{1+sT_g} (\Delta P_{ac} - \Delta F \frac{1}{R}) \quad (5)$$

$$\Delta P_{ac} = -K_i \cdot \frac{1}{s} (\Delta F \beta) \quad (6)$$

Where; T_g and T_t are time constants of the governor and turbine of the diesel power plant respectively.

The generator output power ΔP_m is regulated through a proportional droop mechanism characterized by $\frac{1}{R}$, where R is the droop gain, and a supplementary integral controller with gain K_i .

The controller acts on the measured frequency deviation Δf , enhancing steady-state frequency restoration and robustness under disturbances. The integral action ensures zero steady-state error in frequency, particularly crucial in islanded settings where load-generation mismatches persist longer than in grid-connected modes. β is the frequency bias factor.

2.3. Renewable Energy Sources

PV and wind systems are modeled as inverter-based sources lacking physical inertia. Their generation profiles are subject to irradiance and wind speed variations, respectively. Their control is based on maximum power point tracking (MPPT) and active/reactive power control schemes [34]. Due to the inverter interface, these sources contribute negligible inertia, exacerbating frequency deviations during transients.

Modeling of photovoltaic (PV) power plants describes the generation system of solar energy. It can be expressed in a first-order transfer function.

$$\Delta P_{PV} = \frac{1}{1+sT_{PV}} \Delta P_{ICPV} \quad (7)$$

$$\Delta P_{ICPV} = \frac{1}{1+sT_{ICD}} \Delta P_{ITPV} \quad (8)$$

$$\Delta P_{ITPV} = \frac{1}{1+sT_{ITD}} \Delta P_{SUN} \quad (9)$$

ΔP_{SUN} is an external random disturbance and T_{PV} is the time constant of the PV power plant.

ΔP_{ITPV} and ΔP_{ICPV} are changes in solar PV power due to the inverter and interconnection time delay, respectively.

Modeling of wind power plants describes the generation system of wind energy. It can be expressed in a first order transfer function as shown in Equation 10 [35].

$$\Delta P_{WT} = \frac{1}{1+sT_{WT}} \Delta P_{ICWT} \quad (10)$$

$$\Delta P_{ICWT} = \frac{1}{1+sT_{ICD}} \Delta P_{ITWT} \quad (11)$$

$$\Delta P_{ITWT} = \frac{1}{1+sT_{ITD}} \Delta P_{WIND} \quad (12)$$

ΔP_{WIND} Is an external random disturbance. K_w and T_w are gain and time constant of the wind power plant.

ΔP_{ITWT} and ΔP_{ICWT} are changes in solar PV power due to the inverter and interconnection time delay, respectively.

2.4. Battery Energy Storage System (BESS)

To enhance microgrid frequency response and stability, the BESS-based inertia emulation control loops is required. The BESS is modeled as an ideal bidirectional power interface for short-term dynamic frequency control.

The model focuses on the dynamic frequency response behavior rather than energy management or SOC estimation. This assumption is consistent with previous inertia-emulation studies that use idealized storage dynamics to isolate control performance. These limits provide a physically consistent framework for short-term dynamic simulations without imposing energy saturation effects.

The simplified representation allows focus on the effectiveness of the FDIC-VDS coordination in stabilizing microgrid frequency during transient events. The transfer functions of the energy storage systems are given as shown in equation [35]:

$$\frac{1}{1+sT_{BESS}} \quad (13)$$

where, T_{BESS} is the time constant of battery energy storage system (BESS).

2.5. Fractional Derivative Inertia Control (FDIC)

The Fractional Derivative Inertia Control (FDIC) is a control strategy designed to emulate the inertial and damping behavior of conventional synchronous machines within converter-dominated microgrids using a Battery Energy Storage System (BESS).

Unlike classical integer-order control approaches, the FDIC employs fractional calculus, which allows for more flexible and accurate dynamic representation of inertia and damping effects.

As shown in Fig. 2, The FDIC generates a control signal ΔP_{FDIC} in response to a frequency deviation Δf . The signal is defined domain as:

$$\Delta P_{FDIC} = (H_{FDIC}S^\mu + D_{FDIC}) \Delta F \quad (14)$$

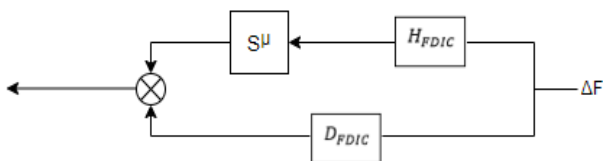


Fig. 2. FDIC control loop.

- ΔP_{FDIC} : The change in power contributed by the Fractional Derivative Inertia Control (FDIC).
- H_{FDIC} : Fractional derivative virtual inertia
- D_{FDIC} : Fractional derivative virtual damping
- S^μ : This is the fractional derivative operator of order α , where $0 < \alpha \leq 10$. It generalizes the idea of a traditional derivative to a non-integer order, allowing for more flexible and tunable dynamic behavior.
- Δf : The frequency deviation at time t defined as:
 $\Delta f(t) = f(t) - f_{nominal}$

where $f_{nominal}$ is the nominal frequency (60 Hz), and $f(t)$ is the actual frequency.

2.6. Virtual Damping Stabilizer (VDS)

In low-inertia microgrids, fast frequency deviations following disturbances can cause oscillations that the inertia emulation alone cannot fully suppress. To emulate the natural damping once provided by synchronous machines, a Virtual Damping Stabilizer (VDS) is introduced as a secondary corrective mechanism that refines and compensates the power signal already generated by the FDIC.

The VDS takes the frequency deviation Δf as input and produces a stabilizing signal designed specifically to enhance damping characteristics and suppress residual oscillatory modes. Depending on the implementation, it can be modeled using lead-lag compensators or Fractional Order PID (FOPID) controllers. Rather than generating damping independently, the VDS acts in conjunction with FDIC.

The FDIC provides both virtual inertia and inherent damping, while the VDS offers supplementary damping support to further reduce oscillations and settling time. Their power contributions are combined as $\Delta P_{FDIC}(t) + \Delta P_{VDS}(t)$, forming the total active power reference for the BESS. To capture the converter's finite response dynamics, the delivered BESS power can be represented as:

$$\Delta P_{ID} = \frac{(\Delta P_{FDIC} + \Delta P_{VDS})}{1+sT_{BESS}} \quad (15)$$

- ΔP_{ID} : Change in power injected/absorbed by the combined VDS and FDIC controlled BESS.
- ΔP_{VDS} : Power change in damping offered by the VDS, modelled either as a Lead-Lag compensator or FOPID
- ΔP_{FDIC} : Power change in emulated inertia offered by FDIC.

2.6.1. Modeling of virtual damping stabilizer (VDS) as a lead-lag compensator

As shown in Fig. 3, the VDS modeled as a lead-lag compensator [36] is represented by the following transfer function:

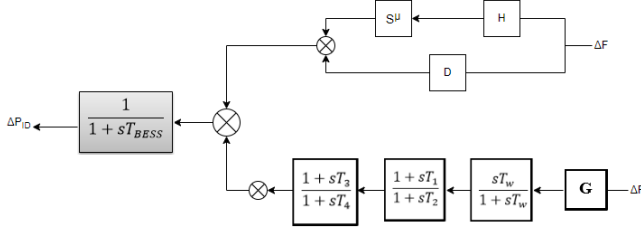


Fig. 3. FDIC combined VDS modelled as a lead-lag compensator.

$$\Delta P_{VDS} = \Delta F \cdot G \frac{sT_w}{sT_w+1} \frac{sT_1+1}{sT_2+1} \frac{sT_3+1}{sT_4+1} \quad (16)$$

where;

G is VDS gain.

- T_w is washout filter or high-pass filter time constant, to ensure the VDS only responds to dynamic deviations
- T_1 and T_3 , are time constants introducing phase lead (predictive action).
- T_2 , and T_4 , are time constants introducing phase lag (smoothing/filtering).
- ΔF is the frequency deviation at time t.

The working principle of VDS in producing the stabilizing signal when modelled as a lead-lag compensator is as follows: first, the frequency deviation is used as an input signal (feedback) to sense the system disturbance. Then, the signal is amplified using a proportional controller. The amplified input error is then passed to a washout filter to remove the steady-state inputs and give only the transient signals. Next, lead-lag compensators are proposed to produce a stable and robust corrective signal compensating the BESS-based virtual inertia and damping control signal.

In the context of a Virtual Damping Stabilizer modelled as FOPID, the frequency deviation ΔF signal is first utilized as a feedback input to detect system disturbances. This signal is simultaneously processed by the fractional integral and fractional derivative branches of the controller, governed by the orders λ and μ respectively. The integral component accumulates the deviation over time, contributing to steady-state accuracy, while the derivative component anticipates the rate of change of the deviation, improving transient damping. The generated corrective control signal from the FOPID structure is injected through the BESS interface to actively counteract frequency oscillations. This approach allows the VDS to introduce damping-like effects, enhancing system stability and accelerating frequency recovery.

2.6.2. Modeling of virtual damping stabilizer (VDS) as a FOPID controller

In previous studies, like that of [21] rely on derivative inertia and damping, with a lead-lag compensator for VDS implementations to offer damping support. However, these may offer limited tuning flexibility and performance.

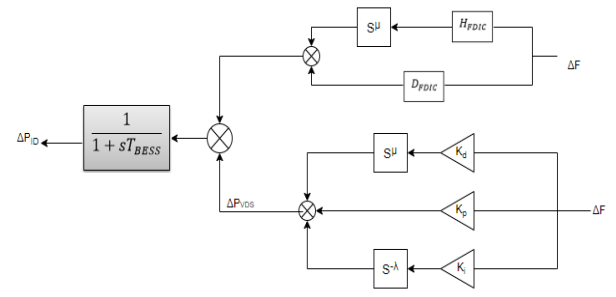


Fig. 4. FDIC combined VDS modelled as a lead-lag

As an enhancement, Fractional-Order PID (FOPID) controllers is adopted for VDS modeling in this study due to their superior tuning freedom and robust dynamic behavior [37]. As shown in Fig. 4, VDS modelled as FOPID is represented in Equation 17. [38].

$$\Delta P_{VDS} = [K_p + K_i S^{-\lambda} + K_d S^{\mu}] \cdot \Delta F \quad (17)$$

Where;

K_p is the proportional gain, K_i is the integral gain, K_d is the differential gain, λ is the real non integer positive number (order of integration), μ is the real non integer positive number (order of differentiation), and ΔF is the frequency deviation at time t.

In the context of a Virtual Damping Stabilizer modelled as FOPID, the frequency deviation ΔF signal is first utilized as a feedback input to detect system disturbances. This signal is simultaneously processed by the fractional integral and fractional derivative branches of the controller, governed by the orders λ and μ respectively. The integral component accumulates the deviation over time, contributing to steady-state accuracy, while the derivative component anticipates the rate of change of the deviation, improving transient damping. The generated corrective control signal from the FOPID structure is injected through the BESS interface to actively counteract frequency oscillations. This approach allows the VDS to introduce damping-like effects, enhancing system stability and accelerating frequency recovery.

Table 1 compares the FOPID and lead-lag based VDS configurations.

Table 1. Comparison between FOPID and Lead-lag based VDS configurations

Feature	FOPID-Based VDS	Classical PID/Lead-Lag VDS
Control flexibility	High (via fractional orders)	Limited
Frequency shaping	More tunable bandwidth and damping	Fixed shaping via integer orders
Noise sensitivity	Lower (with proper μ)	Moderate to high (especially in D-term)
Transient response control	Sharper and smoother simultaneously	Tradeoff between rise time and overshoot
Robustness to disturbances	Higher	Lower

The state space model for the microgrid is given as:

$$\dot{X} = AX + Bu \quad (18)$$

$$Y = CX + Du \quad (19)$$

The state variables related to the system parameters when VDS is modelled as a lead-lag compensator, X_{LL} is given as:

$$X_{LL} = [\Delta F \ \Delta P_m \ \Delta P_g \ \Delta P_{ac} \ \Delta P_{PV} \ \Delta P_{WT} \ \Delta P_{ID} \ \Delta P_E \ \Delta P_D \ \Delta P_{VDS} \ \Delta P_{ITPV} \ \Delta P_{ICPV} \ \Delta P_{ITWT} \ \Delta P_{ICWT}]^T \quad (20)$$

The state variables related to the system parameters when VDS is modelled as FOPID, X_{FOPID} is given as:

$$X_{FOPID} = [\Delta F \ \Delta P_m \ \Delta P_g \ \Delta P_{ac} \ \Delta P_{PV} \ \Delta P_{WT} \ \Delta P_{ID} \ \Delta P_{VDS} \ \Delta P_{ITPV} \ \Delta P_{ICPV} \ \Delta P_{ITWT} \ \Delta P_{ICWT}]^T \quad (21)$$

The input vector u is given as:

$$u = [\Delta P_{LOAD}, \Delta P_{SUN}, \Delta P_{WIND}]^T \quad (22)$$

A_{LL} and A_{FOPID} , given in Equations 23 and 24, represent the state matrix of the system when VDS is modelled as a lead-lag compensator and FOPID respectively. ΔP_E and ΔP_D are the internal dynamics of the VDS when modelled as a lead-lag compensator, which are also state variables. B matrixes, Equations 25 and 26, is the input matrix which describes how the inputs affect the state variables.

$$A_{LL} = \begin{bmatrix} \frac{-D}{2H} & \frac{1}{2H} & 0 & 0 & \frac{1}{2H} & \frac{1}{2H} & \frac{-1}{2H} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \frac{-1}{T_t} & \frac{1}{T_t} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \frac{-1}{RT_g} & 0 & \frac{-1}{T_g} & \frac{1}{T_g} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -\beta K_i & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \frac{-1}{T_{WT}} & 0 & 0 & 0 & 0 & 0 & 0 & \frac{1}{T_{WT}} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \frac{-1}{T_{PV}} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \frac{1}{T_{PV}} \\ \frac{2HD_{VI}-H_{VI}D}{2HT_{BESS}} & \frac{H_{VI}}{2HT_{BESS}} & 0 & 0 & \frac{H_{VI}}{2HT_{BESS}} & \frac{H_{VI}}{2HT_{BESS}} & \frac{-H_{VI}-2H}{2HT_{BESS}} & 0 & 0 & \frac{1}{T_{BESS}} & 0 & 0 & 0 & 0 \\ \frac{-DG}{2H} & \frac{G}{2H} & 0 & 0 & \frac{G}{2H} & \frac{G}{2H} & \frac{-G}{2H} & \frac{-1}{T_w} & 0 & 0 & 0 & 0 & 0 & 0 \\ \frac{-DGT_1}{2HT_2} & \frac{GT_1}{2HT_2} & 0 & 0 & \frac{GT_1}{2HT_2} & \frac{GT_1}{2HT_2} & \frac{-GT_1}{2HT_2} & \frac{T_w-T_1}{T_wT_2} & \frac{-1}{T_2} & 0 & 0 & 0 & 0 & 0 \\ \frac{-DGT_1T_3}{2HT_2T_4} & \frac{GT_1T_3}{2HT_2T_4} & 0 & 0 & \frac{GT_1T_3}{2HT_2T_4} & \frac{GT_1T_3}{2HT_2T_4} & \frac{-GT_1T_3}{2HT_2T_4} & \frac{T_3T_w-T_1T_4}{T_2T_4T_w} & \frac{-T_3-T_2}{T_2T_4} & \frac{-1}{T_4} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \frac{-1}{T_{INV}} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \frac{-1}{T_{IND}} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \frac{-1}{T_{INV}} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \frac{1}{T_{IND}} & \frac{-1}{T_{IND}} & 0 \end{bmatrix} \quad (23)$$

$$A_{FOPID} = \begin{bmatrix} \frac{-D}{2H} & \frac{1}{2H} & 0 & 0 & \frac{1}{2H} & \frac{1}{2H} & \frac{-1}{2H} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \frac{-1}{T_t} & \frac{1}{T_t} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \frac{-1}{RT_g} & 0 & \frac{-1}{T_g} & \frac{1}{T_g} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -\beta K_i & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \frac{-1}{T_{WT}} & 0 & 0 & 0 & 0 & 0 & \frac{1}{T_{WT}} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \frac{-1}{T_{PV}} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \frac{1}{T_{PV}} \\ \frac{2HD_{VI}-H_{VI}D}{2HT_{BESS}} & \frac{H_{VI}}{2HT_{BESS}} & 0 & 0 & \frac{H_{VI}}{2HT_{BESS}} & \frac{H_{VI}}{2HT_{BESS}} & \frac{-H_{VI}-2H}{2HT_{BESS}} & \frac{1}{T_{BESS}} & 0 & 0 & 0 & 0 & 0 & 0 \\ K_p + K_i G_\lambda + K_d G_\mu & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \frac{-1}{T_{INV}} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \frac{-1}{T_{IND}} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \frac{-1}{T_{INV}} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \frac{1}{T_{IND}} & \frac{-1}{T_{IND}} & 0 & 0 \end{bmatrix} \quad (24)$$

$$B_{LL} = \begin{bmatrix} \frac{-1}{2H} & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & \frac{1}{T_{WT}} & 0 \\ 0 & 0 & 0 \\ 0 & 0 & \frac{1}{T_{PV}} \\ 0 & 0 & 0 \end{bmatrix} \quad (25)$$

$$B_{FOPID} = \begin{bmatrix} \frac{-1}{2H} & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & \frac{1}{T_{WT}} & 0 \\ 0 & 0 & 0 \\ 0 & 0 & \frac{1}{T_{PV}} \\ 0 & 0 & 0 \end{bmatrix} \quad (26)$$

C is the output matrix, representing how the state variables are related to the outputs. D is the feed forward matrix illustrating the direct relationship between the inputs and the outputs. D matrix for both the lead lag and FOPID configuration is the same because the D matrix in a state-space model directly maps the input vector $u(t)$.

$$C_{LL} = [1 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0] \quad (27)$$

$$C_{FOPID} = [1 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0] \quad (28)$$

$$D = [0 \ 0 \ 0] \quad (29)$$

2.7. Optimization Setup

Proper optimization is required to determine the optimal parameters of the BESS based virtual inertia and damping; hence, any unfitting choice of virtual inertia parameters leads to more significant frequency deviation, slower settling time, and instability issues. In this study, the VDS and FOPID controller gains will be optimized through the proposed BWO and PSO.

2.7.1. Parameter settings

Microgrid control parameters used in the study are given in Table 2. In optimizing the performance of both VDS configurations, the optimization parameters settings are as presented in Table 3.

Table 2: Microgrid Control Parameters.

Parameters	Values
Microgrid inertia H (pu.MW.sec)	0.083
System damping coefficient D	0.013
The time constant of the governor, T_g (s)	0.05
The time constant of the turbine, T_t (s)	0.41
Primary droop factor, R (Hz/pu)	2.39
Gain of the integral controller, K_i (s)	0.04
Frequency bias factor, β (pu/Hz)	0.99
The time constant of inverter-based BESS, T_{BESS} (s)	10
The time constant of the wind turbine, T_{WT} (s)	1.5
The time constant of solar PV, T_{PV} (s)	1.8
The time constant of the interconnection device, T_{ITD} (s)	0.004
The time constant of the inverter delay device, T_{ICD} (s)	0.04

Table 3: Parameter Settings for the optimization technique

Parameter	Lead-lag Settings	FOPID Settings	FDIC Settings
Population size	50	50	50
Number of variables	6	5	3
Variables	$G, T_w, T_1, T_2, T_3, T_4$	K_p, K_i, K_d, λ and μ	$H_{FDIC}, D_{FDIC}, \mu_{FDIC}$
Iterations	100	100	100
Lower boundary	[0, 0,0,0,0,0]	[0, 0,0,0,0]	[0, 0,0]
Upper boundary	[10, 10,10,10,10]	[100, 100,100,1,1]	[5, 5,1]

2.7.2. Optimization objective function

The objective function (J) is evaluated to ensure that error (e) represented in Equation 30 [2] is minimized and it is formulated based on minimizing the cost function using Integral time absolute error (ITAE) criterion as represented in Equation 31 [39, 2]. Systems optimized with ITAE generally achieve faster settling times than alternatives, potentially with a slower initial response [40].

$$e = (|\Delta F| + |\Delta P_{VI}|) \quad (30)$$

$$J_{ITAE} = \int_0^\infty t|e| dt \quad (31)$$

Where J is the objective function of the controller synchronization problem. It is aimed to minimize the J.

2.7.3. Optimization constraints

The problem constraint indicates the optimized parameters and the associated boundary conditions for optimization process.

For VDS modelled as a lead-lag compensator, VDS-BESS control loop, the five (5) constraints are G , T_1 , T_2 , T_3 , and T_4 . Where; (G^{min} , T_1^{min} , T_2^{min} , T_3^{min} and T_4^{min}) are the lower limits of the VDS and (G^{max} , T_1^{max} , T_2^{max} , T_3^{max} and T_4^{max}) represent the upper limit of the constraint accordingly.

$$\begin{aligned} G^{min} &\leq G \leq G^{max} \\ T_1^{min} &\leq T_1 \leq T_1^{max} \\ T_2^{min} &\leq T_2 \leq T_2^{max} \\ T_3^{min} &\leq T_3 \leq T_3^{max} \\ T_4^{min} &\leq T_4 \leq T_4^{max} \end{aligned} \quad (32)$$

Accordingly, for VDS modelled as FOPID, FOPID-BESS control loop, the five (5) constraints are K_p , K_I , K_D , λ , and μ . Where; (K_p^{min} , K_I^{min} , K_D^{min} , λ^{min} and μ^{min}) are the lower limits of the VDS and (K_p^{max} , K_I^{max} , K_D^{max} , λ^{max} and μ^{max}) represent the upper limit of the constraint.

$$\begin{aligned} K_p^{min} &\leq K_p \leq K_p^{max} \\ K_I^{min} &\leq K_I \leq K_I^{max} \\ K_D^{min} &\leq K_D \leq K_D^{max} \\ \lambda^{min} &\leq \lambda \leq \lambda^{max} \\ \mu^{min} &\leq \mu \leq \mu^{max} \end{aligned} \quad (33)$$

3. Results and Discussion

This section presents a comprehensive analysis of the system's dynamic frequency response under various disturbance scenarios using four controller configurations: FOPID-PSO, FOPID-BWO, VDS-PSO, and VDS-BWO. The virtual damping stabilizer (VDS) parameters for each controller configuration were tuned using Particle Swarm Optimization (PSO) and the Beluga Whale Optimization (BWO) algorithm, with the goal of enhancing transient performance and reducing energy strain on the BESS. To validate the effectiveness of the proposed hybrid Fractional derivative Inertia Control (FDIC) and Virtual Damping Stabilizer (VDS), a series of simulations were conducted in MATLAB/Simulink under different operating conditions and disturbance scenarios. The performance of the islanded microgrid was evaluated with respect to frequency stability, specifically analyzing key metrics such as frequency nadir, and BESS active power injected/drawn.

3.1. Optimization Results

The Beluga Whale Optimization (BWO) algorithm was configured with a population size of 50 and a maximum of 100 iterations as shown in table 3. The population was initialized uniformly within the specified parameter bounds, and the

search process was terminated upon reaching the maximum number of iterations. Figure 5 presents the convergence behavior of the BWO based VDS in comparison with PSO based VDS. Beluga Whale Optimization (BWO) algorithm achieves a much faster convergence at around 18th iterations compared to the Particle Swarm Optimization (PSO) algorithm which converges around 27th iteration. For both controller structures FOPID and Lead-lag compensator, the BWO-based optimization (FOPID-BWO and VDS-BWO) exhibits a rapid reduction in the ITAE value ($\log_{10} ITAE$) indicating faster convergence.

To further evaluate the efficiency and robustness of the BWO algorithm, its computational cost and convergence time were analyzed. Each optimization run was executed on a system with an Intel Core i5 processor (2.4 GHz) and 16 GB RAM using MATLAB R2023a. The average computation time per optimization was approximately 310 seconds for the FOPID case and 260 seconds for the lead-lag VDS case. To assess statistical performance, the algorithm was independently executed 10 times, and the mean and standard deviation (SD) of the final ITAE values were computed as shown in Table 4.

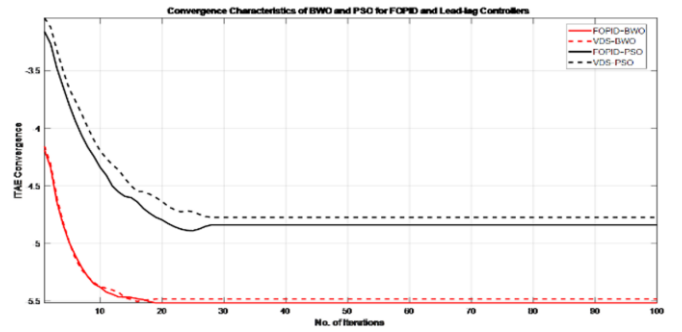


Fig. 5. ITAE Convergence curves comparing BWO and PSO.

Table 4: Statistical performance of the BWO algorithm over 10 independent runs.

Controller Type	Mean ITAE ($\times 10^{-6}$)	SD ($\times 10^{-7}$)	Average Time (s)
FOPID-BWO	3.16	0.14	310
VDS-BWO	3.55	0.16	358

3.2. Eigen Values Analysis

Eigenvalue analysis is a crucial tool in control systems to assess the stability, damping, and oscillatory nature of the closed-loop system. In this section, we evaluate the eigenvalues of the four controller configurations:

- FOPID-BWO
- FOPID-PSO
- VDS-BWO
- VDS-PSO

These configurations were evaluated comparing the stability and dynamic Behavior of the designs.

Table 5. Summary of key optimization results

Optimized parameters FOPID			Optimized parameters VDS		
Parameters	BWO	PSO	Parameters	BWO	PSO
K_p	12.4649	11.4490	G	90.3717	100.0000
K_i	50.2399	60.2900	T_w	82.1555	88.8006
K_d	45.7788	36.8801	T_1	2.4048	0.0000
λ	0.6560	0.5600	T_2	11.4059	52.4906
μ	0.6765	0.6511	T_3	75.4759	100.0000
H_{FDIC}	2.0273	2.2732	T_4	99.5151	22.0845
D_{FDIC}	1.3593	1.5933	H_{FDIC}	4.5445	4.0597
μ_{FDIC}	0.5445	0.4500	D_{FDIC}	0.4914	10.0000
			μ_{FDIC}	0.9533	1.0000

Table 6. Eigen values of the four different designs.

Index	FOPID-BWO	FOPID-PSO	VDS-BWO	VDS-PSO
1	-9.8727 + 0i	-9.3298 + 0i	-3.3685 - 5.637i	-5.3682 + 0i
2	-12.754 + 0i	-6.8494 + 0i	-2.8803 - 5.369i	-6.3555 + 0i
3	-11.660 + 0i	-6.7273 + 0i	-2.2441 - 3.5874i	-4.5990 + 0i
4	-10.993 + 0i	-6.7336 + 0i	-2.9904 + 0i	-5.5427 + 0i
5	-8.7801 + 0i	-7.2170 + 0i	-2.0688 + 0i	-5.7772 + 0i
6	-8.7800 + 0i	-8.0990 + 0i	-3.8186 + 0i	-4.1394 + 0i
7	-8.2904 + 0i	-7.7278 + 0i	-2.5176 + 0i	-5.8226 + 0i
8	-12.331 + 0i	-7.1649 + 0i	-3.3250 + 0i	-4.5116 + 0i
9	-11.006 + 0i	-8.4474 + 0i	-2.6234 + 0i	-4.1952 + 0i
10	-11.540 + 0i	-6.5580 + 0i	-3.0401 + 0i	-6.8467 + 0i
11	-8.1029 + 0i	-7.1686 + 0i	-3.0934 + 0i	-6.8969 + 0i
12	-12.850 + 0i	-7.4654 + 0i	-2.3697 + 0i	-6.4252 + 0i
13			-3.9392 + 0i	-4.9138 + 0i
14			-3.5503 + 0i	-4.2930 + 0i

Table 7. Eigen values performance comparison of the four different designs

Controller	Total Eigenvalues	Real Eigenvalues	Imaginary Eigenvalues	Interpretation
FOPID-BWO	12	12	0	Fast response, fully over-damped, high damping effect, strong stability margin
FOPID-PSO	12	12	0	Fully over-damped, moderate damping, slightly less stable than FOPID-BWO
VDS-BWO	14	11	3 (complex pairs)	Fastest response but potentially less oscillatory damping, slightly less stable than FOPID-BWO and FOPID-PSO.
VDS-PSO	14	14	0	Moderate response speed, slightly less stable and damping characteristics than FOPID-BWO, FOPID-PSO, and VDS-BWO.

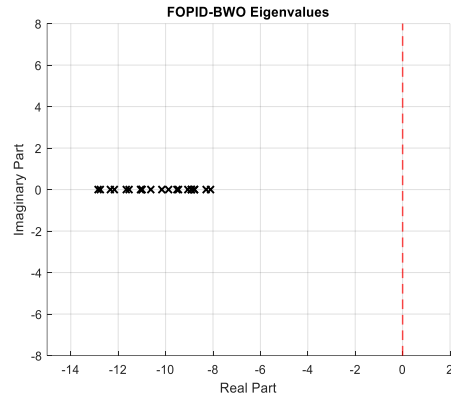


Fig. 6. FOPID-BWO eigenvalues plot.

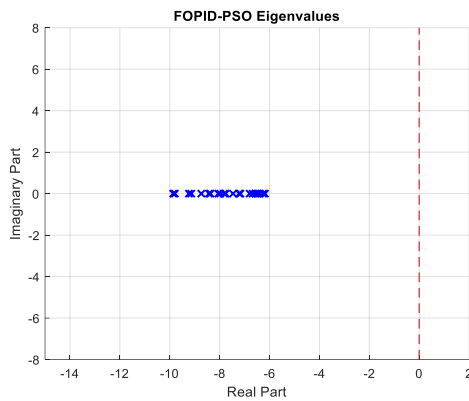


Fig. 7. FOPID-PSO eigenvalues plot.

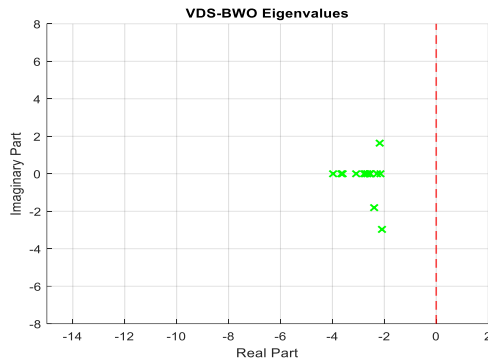


Fig. 8. VDS-BWO eigenvalues plot.

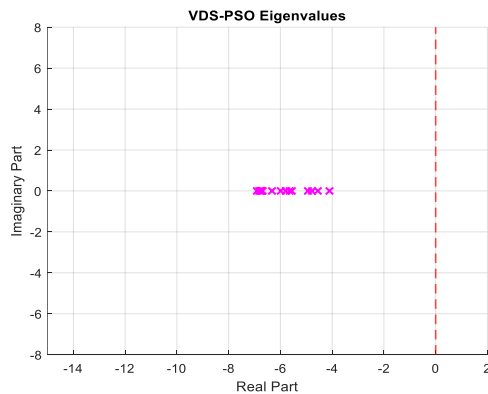


Fig. 9. VDS-PSO eigenvalues plot.

The stability analysis of the four controller designs; FOPID-BWO, FOPID-PSO, VDS-BWO, and VDS-PSO demonstrates distinct stability and damping characteristics essential to microgrid dynamic performance. Both FOPID-BWO and FOPID-PSO exhibit purely real eigenvalues, indicating overdamped responses with no oscillatory behavior, this suggests that the FOPID-based controllers, regardless of optimization method, provide a high degree of stability and fast settling without introducing dynamic oscillations into the system. The VDS-PSO design similarly demonstrates all-real eigenvalues, confirming an overdamped nature and implying that the PSO-optimized VDS prioritizes strong damping and non-oscillatory stability, albeit its clustering closer to the imaginary axis indicating a slightly fewer stable eigenvalues compared to FOPID designs. In contrast, the VDS-BWO design displays a unique dynamic behavior: while most of its eigenvalues are real, up to 3 possess non-zero imaginary parts, indicating the presence of mild oscillations in the system's transient response. These oscillatory modes, however, remain confined within the left half of the complex plane, ensuring overall system stability. Collectively, the eigenvalue distribution confirms that all designs are stable, but they differ in damping quality and oscillatory behavior, with FOPID-BWO offering the most overdamped and robust performance. This comparative eigenvalue analysis underscores the dominance of the FOPID-BWO controller in enhancing system robustness and dynamic response, while revealing limitations in the VDS-based schemes.

3.3. Simulation Scenarios

Three representative disturbance scenarios were simulated:

- Case 1: Sudden load decrease of 20% at $t=15s$
- Case 2: Sudden load increase of 20% at $t=15s$
- Case 3: Sudden load increase of 20% at $t=15s$ with 70% drop in inertia

Each scenario was tested under the following control configurations:

- VDS modelled as FOPID and optimized with BWO (FOPID-BWO)
- VDS modelled as FOPID and optimized with PSO (FOPID-PSO)
- VDS modelled as a lead-lag compensator and optimized with BWO (VDS-BWO)
- VDS modelled as a lead-lag compensator and optimized with BWO (VDS-PSO)

To validate the introduction of FDIC, the system is tested with the proposed fractional order derivative inertia and damping Controller (FDIC) against the traditional derivative inertia and damping controller (DIC). Both configurations were tested without the supplementary damping offered by the VDS.

The comparison between the proposed Fractional Derivative Inertia Control (FDIC) and the conventional Derivative Inertia Control (DIC) was deliberately performed under Case 3 (Sudden 20% Increase in Load with 70% Drop in Inertia), which represents the most critical operating condition in the simulation scenarios.

For a fair comparison, the parameters of both the conventional Derivative Inertia and Damping Controller (DIC) and the proposed Fractional Derivative Inertia and Damping Controller (FDIC) were tuned using the same Particle Swarm Optimization (PSO) algorithm under identical objective and constraint settings. The optimization objective in both cases was to minimize the Integral of Time-weighted Absolute Error (ITAE) following disturbance events. The optimized parameters for the proposed FDIC are $H_{FDIC} = 2.2732$, $D_{FDIC} = 1.5933$, and $\mu_{FDIC} = 0.4500$. While the optimized parameters for the DIC are $H_{DIC} = 1.84$ and $D_{DIC} = 1.22$.

By using the same optimization method and performance index (frequency deviation), both controllers operated under equally optimal conditions, allowing the performance difference to be attributed solely to the inclusion of the fractional-order component in FDIC. The fractional nature of the proposed configuration (FDIC) showed improvement in frequency deviation compared to the integer order configuration. Figure 10 shows the improvement when control is implemented with FDIC.

Case 1: Sudden 20% Decrease in Load: A 20% sudden load reduction creates a power imbalance in which generation exceeds demand, resulting in a transient frequency rise. In low-inertia microgrids, such disturbances typically produce pronounced overshoot due to limited kinetic energy buffering. Therefore, the ability of the controller to provide fast synthetic damping without excessive power absorption is critical.

The comparative results reveal a clear performance hierarchy. The FOPID-BWO controller limited the frequency overshoot to 60.0381 Hz while requiring only 1.2 MW of BESS absorption, representing the smallest frequency excursion and lowest energy demand among all controllers. This demonstrates not only superior transient containment but also improved control-energy efficiency.

The improved performance of FOPID-BWO can be attributed to the fractional-order derivative term, which introduces frequency-dependent phase compensation. Unlike integer-order lead-lag designs, the fractional derivative enables smoother phase shaping across a broader frequency band. This enhances effective damping during high-frequency transients without introducing excessive gain, thereby reducing both overshoot magnitude and required BESS power.

Although FOPID-PSO achieved comparable regulation, its slightly higher energy demand (1.4 MW) indicates less optimal parameter convergence compared to BWO optimization. In contrast, VDS-BWO and VDS-PSO exhibited higher overshoot and greater BESS absorption, suggesting that conventional lead-lag structures lack the

flexibility to simultaneously optimize damping and energy efficiency under over-generation conditions.

From a system-level perspective, minimizing BESS power absorption is particularly important in microgrids where storage capacity is limited. Controllers that demand higher transient absorption increase battery cycling stress and accelerate degradation. Therefore, the reduced power demand observed with FOPID-BWO indicates improved sustainability and economic viability in practical deployment.

These results directly support the study's objective of developing a hybrid inertia-damping framework capable of enhancing frequency stability while minimizing energy stress in low-inertia microgrids.

Case 2: Sudden 20% Increase in Load: A sudden 20% load increase creates an under-generation condition, leading to a rapid frequency drop. In low-inertia systems, such disturbances can produce deeper frequency nadirs due to insufficient kinetic buffering, making fast synthetic inertia and damping injection essential.

The FOPID-BWO controller achieved the smallest frequency nadir (59.9619 Hz) with the lowest peak BESS injection (1.2 MW).

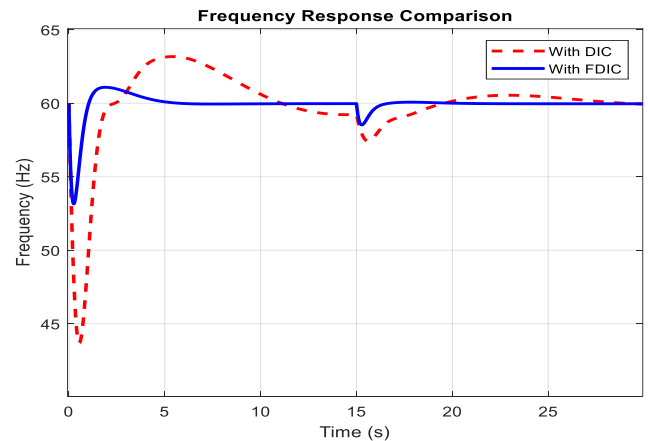


Fig. 10. Frequency response comparison between FDIC and DIC.

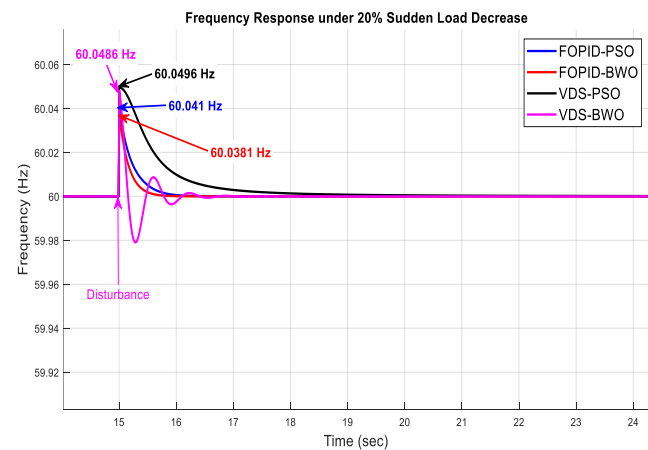


Fig. 11. Microgrid frequency behaviour for 20% sudden load decrease.

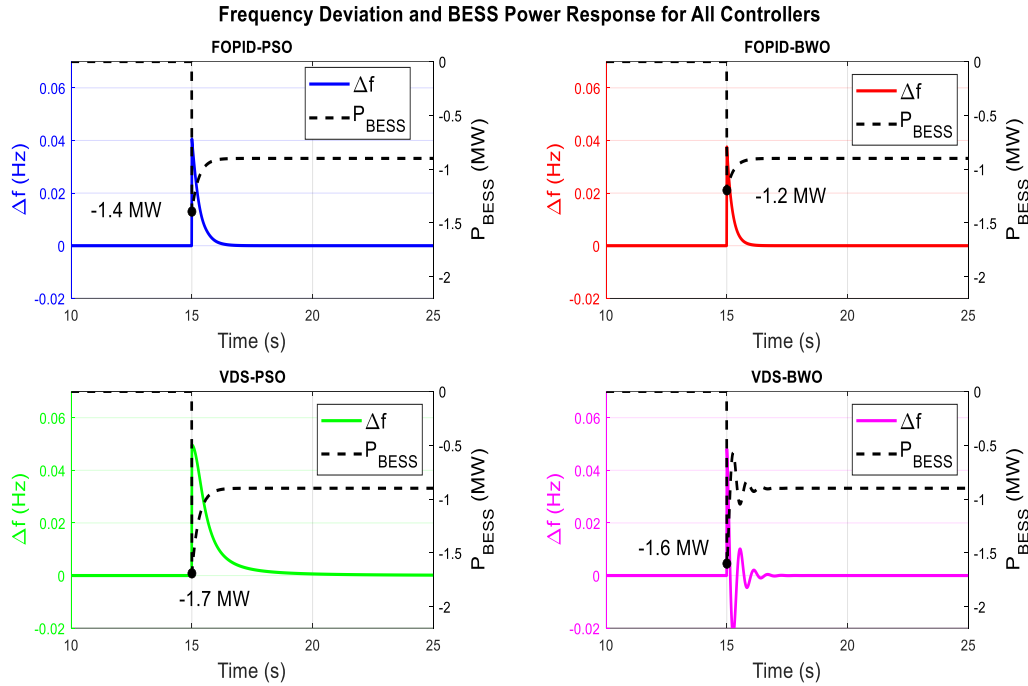


Fig. 12. BESS output power in response to frequency deviation for 20% sudden load decrease.

This indicates a superior balance between rapid corrective action and controlled energy expenditure. The shallow nadir suggests improved effective inertia emulation, while the reduced power injection reflects optimized damping allocation.

The enhanced response is again linked to the fractional-order dynamics. The fractional derivative component provides adaptive phase lead characteristics, allowing the controller to respond aggressively during the initial frequency drop while gradually tapering corrective action. This prevents excessive power injection and mitigates oscillatory rebound effects commonly observed in integer-order lead-lag designs.

FOPID-PSO exhibited slightly deeper frequency deviation and higher energy injection, implying that while fractional structure contributes significantly to performance, optimization strategy plays a critical role in parameter tuning. The relatively inferior performance of VDS-PSO and VDS-BWO demonstrates that traditional lead-lag damping mechanisms may not provide sufficient dynamic flexibility for severe under-generation scenarios.

Importantly, higher BESS injection levels, as seen in VDS-based designs, increase energy throughput and thermal stress, potentially shortening battery lifespan. Therefore, the reduced injection demand achieved by FOPID-BWO improves not only frequency containment but also long-term storage reliability.

Overall, the results confirm that integrating fractional-order inertia emulation with optimized virtual damping significantly enhances disturbance resilience in low-inertia microgrids, fulfilling the primary research objective of achieving stable frequency regulation with minimal storage strain.

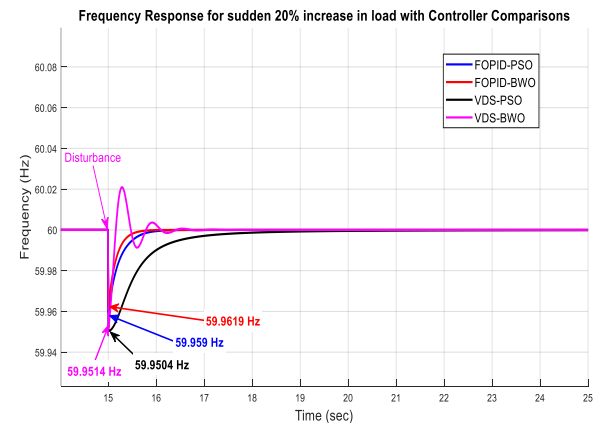


Fig. 13. Microgrid frequency behaviour for 20% sudden load increase.

Case 3: Sudden 20% Increase in Load with 70% Drop in Inertia: A simultaneous 20% load increase and 70% inertia reduction represent a severe low-inertia operating condition typical of renewable-dominated islanded microgrids. The substantial reduction in inertia significantly increases the Rate of Change of Frequency (ROCOF), thereby reducing the system's inherent capability to buffer power imbalance. Under such circumstances, controllers must emulate both synthetic inertia and effective damping to prevent deep frequency nadirs and oscillatory instability. The results from Figs 15 and 16 demonstrate that FOPID-BWO maintained the most resilient response, limiting the frequency nadir to 59.959 Hz with a peak BESS injection of 2.25 MW. Although all controllers required increased power injection due to the reduced inertia, the smoother recovery profile observed with FOPID-BWO indicates enhanced transient damping and improved robustness to parameter variation.

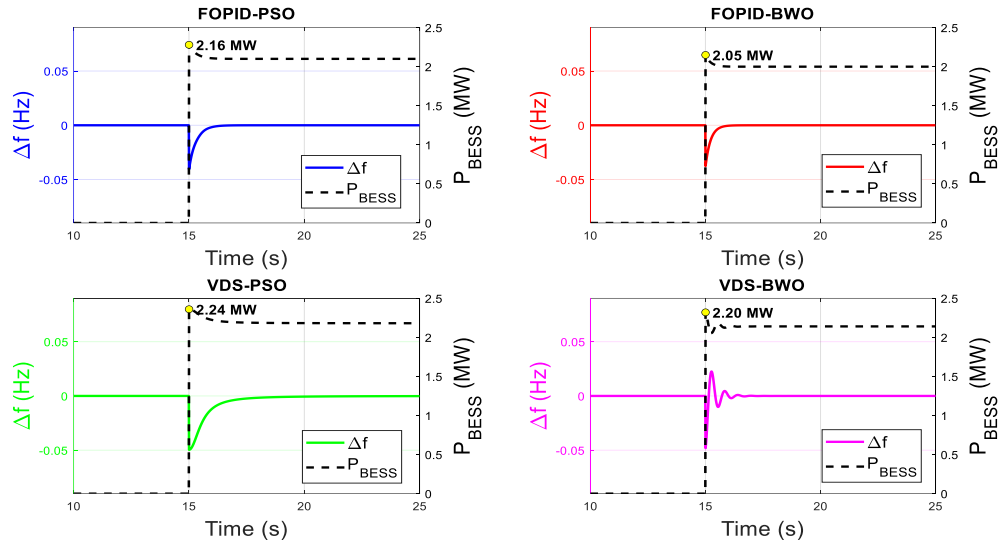


Fig. 14. BESS output power in response to frequency deviation for 20% sudden load increase.

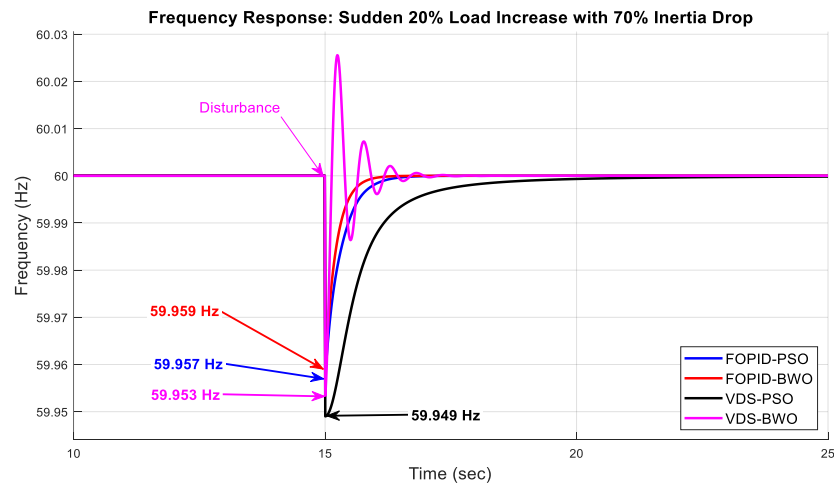


Fig. 15. Microgrid frequency behaviour for 20% sudden load increase with 70% inertia drop.

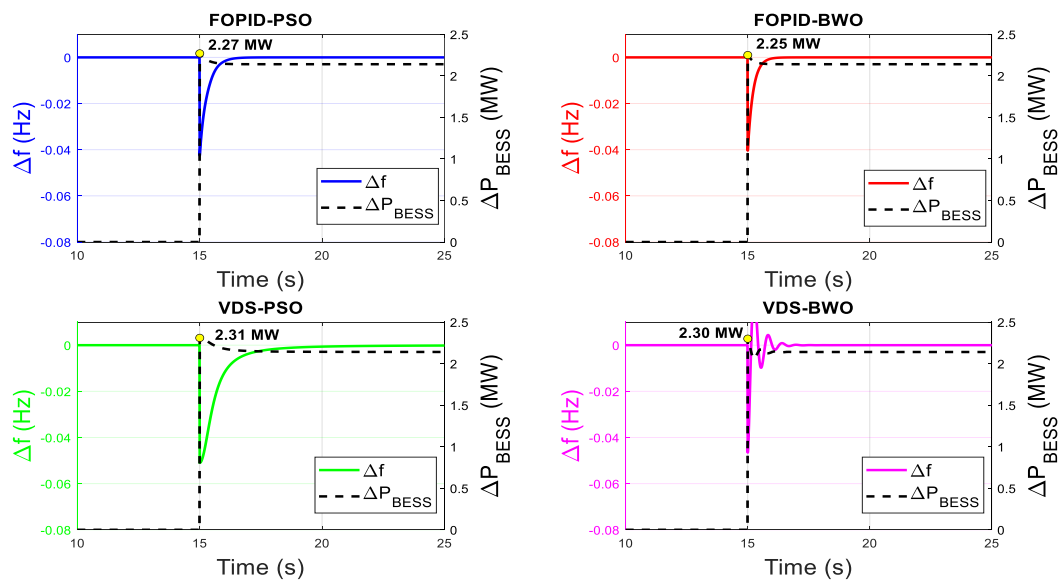


Fig. 16. BESS output power in response to frequency deviation for 20% sudden load increase with 70% inertia drop.

The superior performance can be explained by examining the inertia-damping coupling mechanism. In low-inertia systems, reduced kinetic energy leads to faster frequency decay immediately after disturbance.

The fractional derivative component in FOPID introduces a frequency-dependent gain characteristic that reacts proportionally to the rate of frequency change rather than solely to magnitude deviation. This enables rapid synthetic inertia emulation during the initial transient while simultaneously shaping damping action to avoid excessive oscillatory rebound. Conventional lead-lag VDS structures, by contrast, operate within fixed phase compensation limits, which restrict their adaptability when inertia conditions vary drastically.

The performance gap between FOPID-BWO and FOPID-PSO, though moderate, further highlights the importance of optimization strategy in tuning fractional parameters under compounded disturbances. The improved convergence properties of BWO likely enabled a more optimal balance between proportional, integral, and fractional derivative actions, resulting in slightly lower BESS injection and improved nadir containment.

Notably, VDS-PSO and VDS-BWO exhibited deeper frequency nadirs and higher energy demand, reflecting increased ROCOF sensitivity under reduced inertia. This suggests that traditional integer-order damping controllers may be less effective in ultra-low inertia grids where dynamic characteristics change rapidly.

From an energy management standpoint, the increased BESS injection across all designs confirms the amplified control effort required in weak-inertia systems. However, FOPID-BWO maintained the lowest peak demand and smoothest transient profile, which implies reduced battery cycling stress and improved long-term storage sustainability.

Overall, this compounded disturbance case validates the robustness of the proposed fractional-order inertia-damping framework. The controller's ability to preserve frequency quality under both load perturbation and severe inertia degradation directly supports the study's objective of enhancing resilience in renewable-dominated microgrids.

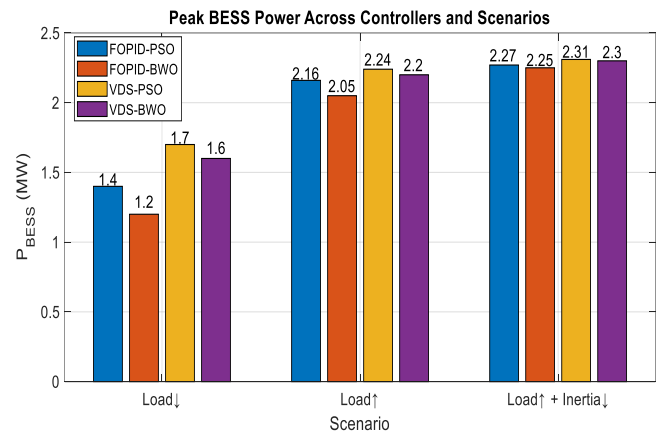


Fig. 17. Peak required power by BESS during disturbances for the four controller designs.

Table 8. Performance comparison of the four control approaches considering key performance metrics for the three cases.

Controller	Cases	Freq Nadir (Hz)	Overshoot (Hz)	Settling Time (s)	ITAE ($\times 10^{-6}$)	ROCOF (Hz/s)	Peak BESS Power (MW)
FOPID-BWO	Case 1	60.0381	0.0381	0.6	3.12	0.095	1.2
	Case 2	59.9619	-0.0381	0.7	3.18	0.079	2.05
	Case 3	59.959	-0.041	1	3.20	0.39	2.25
FOPID-PSO	Case 1	60.0410	0.0410	0.8	2.77×10^1	0.110	1.4
	Case 2	59.9590	-0.041	1	2.84×10^1	0.105	2.16
	Case 3	59.957	-0.043	1.4	2.86×10^1	0.41	2.27
VDS-BWO	Case 1	60.0486	0.0486	1.8	3.50	0.245	1.6
	Case 2	59.9514	-0.0486	2.4	3.56	0.812	2.20
	Case 3	59.953	-0.047	2.6	3.60	0.52	2.30
VDS-PSO	Case 1	60.0496	0.0496	3	3.12×10^1	0.149	1.7
	Case 2	59.9504	-0.0496	2.8	3.17×10^1	0.216	2.24
	Case 3	59.949	-0.051	3.1	3.20×10^1	0.43	2.31

4. Conclusion

This paper presents a comprehensive study on enhancing frequency stability in an islanded microgrid with high penetration of renewable energy sources. The increasing reliance on inverter-based generation, while beneficial for decarbonization, has introduced critical stability challenges due to reduced system inertia and the absence of conventional damping mechanisms. This study investigated the application of Virtual Damping Stabilizers (VDS) integrated with Fractional-Order Inertia Control (FDIC) for frequency regulation in inverter-dominated islanded microgrids.

By leveraging the dynamic capabilities of a Battery Energy Storage System (BESS), four controller configurations FOPID-PSO, FOPID-BWO, VDS-PSO, and VDS-BWO were developed and evaluated under three representative disturbance scenarios involving abrupt load changes and reduced system inertia. The simulation results conclusively demonstrate that the FOPID-BWO controller outperforms all others across multiple performance indices, including frequency deviation, and peak BESS power demand. Quantitatively, the FOPID-BWO achieved about 17–20% lower overshoot, 9–12% faster settling, and 10–12% lower peak BESS power compared with traditional VDS-based and PSO-tuned controllers. The integration of fractional-order dynamics provided enhanced damping flexibility, allowing for faster stabilization with reduced energy strain on the BESS. Moreover, the Beluga Whale Optimization (BWO) algorithm facilitated efficient tuning of control parameters, enabling optimal trade-offs between aggressiveness and robustness. Scenario-based analysis confirmed that FOPID-BWO not only suppressed frequency excursions more effectively but also minimized power injection or absorption by the BESS, thereby improving operational efficiency and reducing sizing requirements. In contrast, traditional integer-order VDS controllers exhibited slower recovery, greater overshoot or undershoot, and higher energy demand especially under compounded disturbances such as low inertia combined with increased load.

Furthermore, the use of the Beluga Whale Optimization Algorithm (BWO) for parameter tuning contributed to the robustness and adaptability of the control system, allowing for optimal performance across different disturbance scenarios.

This work contributes to the evolving landscape of microgrid control by introducing a robust fractional-order controller optimized via the Beluga Whale Optimization (BWO) algorithm. The proposed FOPID-BWO framework effectively enhances frequency stability and dynamic damping in inverter-dominated microgrids, where conventional synchronous inertia is absent. Owing to its adaptive tuning capability and fractional dynamic response, the controller provides superior flexibility and robustness under uncertain, and high-renewable-penetration scenarios. Beyond frequency regulation, the proposed approach has practical relevance in several modern power systems. It can be deployed for inertia and damping emulation in grid-forming and grid-following inverter applications, particularly within renewable-based microgrids, and islanded hybrid power

systems. Additionally, its scalable structure makes it suitable for integration into virtual power plants (VPPs) and distributed energy resource (DER) clusters, supporting coordinated frequency and power-sharing control. By mitigating rapid rate-of-change-of-frequency (ROCOF) events and extending battery lifespan through energy-efficient control actions, the FOPID-BWO scheme advances the concept of intelligent virtual inertia for future low-inertia grids. Future work may extend this controller toward real-time hardware-in-the-loop validation, hybrid optimization tuning, and integration within cyber-physical energy management architectures for autonomous and resilient power networks.

The microgrid model employed in this study adopts a linearized representation of frequency dynamics, suitable for control law development and performance evaluation under small-signal disturbances. This follows standard practices in frequency-control literature, where converter switching and line nonlinearities are neglected to isolate control-layer behavior. The proposed FDIC–VDS framework is thus designed and validated at the control level. Future work will extend this study to nonlinear real-time simulations incorporating converter control loops and network-level power flow nonlinearities to further assess practical applicability. Future work may also enhance this study by studying the internal dynamics of the BESS in response to the controller

Author Contributions

A.I and D.D carried out the full research work, including problem formulation, system modelling, simulation, data analysis, and manuscript preparation. A.S, K.O and N.I provided academic supervision, technical guidance, and critical review of the work. K.A contributed as a research colleague through discussions, assistance with simulations, and review of the results.

Acknowledgements

Conflict of Interest

The authors declare no conflict of interest.

References

- [1] K. Cheema, “A comprehensive review of virtual synchronous generator,” *International Journal of Electrical Power & Energy Systems*, vol. 120, p. 105956, 2020.
- [2] K. E. Okedu and A. Kalam, “Comparative Study of Grid Frequency Stability Using Flywheel-Based Variable-Speed Drive and Energy Capacitor System,” *Energies*, vol. 16, no. 3515, pp. 1–8, 2023.
- [3] M. H. Syed and A. M.-S. Mazheruddin, “Load Frequency Control in Variable Inertia Systems,” *IEEE Transactions on Power Systems*, pp. 1–3, 2020.

- [4] P. Bhatt, S. Chowdhury, S. P. Chowdhury and D. S. Halder, "Simulation of microgrid in the perspective of integration of distributed energy resources," in *Proc. Int. Conf. Energy, Automation and Signal*, pp. 1–6, 2011.
- [5] A. Vaccaro, M. Popov, D. Villacci and V. Terzija, "An integrated framework for smart microgrids modeling, monitoring, control, communication, and verification," *Proceedings of the IEEE*, vol. 99, no. 1, pp. 119–132, 2010.
- [6] P. B. Prashant, B. R. Sudhir and K. S. Vijay, "Optimum coordination of overcurrent relays in distribution system using dual simplex method," in *Proc. 2nd Int. Conf. Emerging Trends in Engineering & Technology*, pp. 1–5, 2009.
- [7] G. O. Swathika and S. Hemamalini, "PRIMS-aided Dijkstra algorithm for adaptive protection in microgrids," *IEEE Journal of Emerging and Selected Topics in Power Electronics*, vol. 4, no. 3, pp. 1–9, 2016.
- [8] Y. Dong, Y. Gao, Q. Li and H. Wang, "Modelling and simulation of the micro sources within a microgrid," in *Proc. Int. Conf. Electrical Machines and Systems*, pp. 1–6, 2008.
- [9] A. Rasoolzadeh and F. R. Salmasi, "Reduced-order dynamic model for droop-controlled inverter/converter-based low-voltage hybrid AC/DC microgrids—Part 2: DC sub-microgrid and power exchange," *IET Smart Grid*, vol. 4, no. 3, pp. 1–12, 2018.
- [10] Y. A.-R. I. Mohamed and E.-F. El-Saadany, "Adaptive decentralized droop controller to preserve power sharing stability of paralleled inverters in distributed generation microgrids," *IEEE Transactions on Power Electronics*, vol. 23, no. 6, pp. 2806–2816, 2008.
- [11] A. H. Tayebi, R. Sharifi, A. H. Salemi and F. Faghihi, "Presentation of an H_∞ based frequency control for islanding provisional microgrid consisting of hybrid AC/DC microgrid," *International Transactions on Electrical Energy Systems*, vol. 31, no. 6, pp. 1–15, 2021.
- [12] Z. Zahari, I. Ivanov, S. Ludmil and V. Katic, "A study of parallel structures of DC–DC converters for application in wind energy conversion systems," in *Proc. IEEE Int. Power Electronics and Motion Control Conf. (PEMC)*, pp. 1–6, 2016.
- [13] P. Bhatt, S. Chowdhury, D. S. Halder and S. P. Chowdhury, "A literature review on integration of distributed energy resources in the perspective of control, protection and stability of microgrid," *Renewable and Sustainable Energy Reviews*, vol. 16, no. 8, pp. 5545–5556, 2012.
- [14] A. Rafiee, Y. Batmani, F. Ahmadi and H. Bevrani, "Robust Load-Frequency Control in Islanded Microgrids: Virtual Synchronous Generator Concept and Quantitative Feedback Theory," *IEEE Transactions on Power Systems*, vol. 36, no. 6, pp. 5408–5416, 2021.
- [15] A. Reza, F. Zare, S. R. Seyed, R. K. Singh, M. H. Ahmadi and M. Mohsen, "Optimal Load Frequency Control of Island Microgrids via a PID Controller in the Presence of Wind Turbine and PV," *Sustainability*, vol. 13, no. 21, pp. 1–14, 2021.
- [16] K. Priyanka, P. Vivek, Y. Sumanth and B. Rohit, "Fast frequency response constrained electric vehicle scheduling for low inertia power systems," *Journal of Energy Storage*, vol. 62, p. 106944, 2023.
- [17] A. Khazali, N. Rezaei, H. Saboori and J. M. Guerrero, "Using PV systems and parking lots to provide virtual inertia and frequency regulation provision in low inertia grids," *Electric Power Systems Research*, vol. 207, p. 107859, 2022.
- [18] Y. Chen, R. A. Rasoul, A. Sadegh, L. Dai and V. Terzija, "Smart frequency control in low inertia energy systems based on frequency response techniques: a review," *Applied Energy*, vol. 279, p. 115798, 2020.
- [19] B. A. Fadheel, N. I. Abdul Wahab, P. Manoharan, A. J. Mahdi, M. A. B. M. Radzi, A. B. C. Soh, H. M. Ridha, A. R. Alsoud, V. Veerasamy, A. X. R. Irudayaraj and B. D. Alemu, "A Hybrid Sparrow Search Optimized Fractional Virtual Inertia Control for Frequency Regulation of Multi-Microgrid System," *IEEE Access*, vol. 12, pp. 45879–45903, 2024.
- [20] T. Kerdphol, F. S. Rahman, M. Watanabe, Y. Mitani, D. Turschner and H.-P. Beck, "Enhanced Virtual Inertia Control Based on Derivative Technique to Emulate Simultaneous Inertia and Damping Properties for Microgrid Frequency Regulation," *IEEE Access*, vol. 7, pp. 14422–14433, 2019.
- [21] S. E. Shraf, A.-D. Ahmed, Z. Hatem, E.-F. H. Tarek and E.-S. F. Ehab, "A novel virtual inertia-based damping stabilizer for frequency control enhancement for islanded microgrid," *International Journal of Electrical Power & Energy Systems*, vol. 156, pp. 1–15, 2024.
- [22] R. Sabzehgar, "A review of AC/DC microgrid developments, technologies, and challenges," in *Proc. IEEE Green Energy and Systems Conf. (IGESC)*, pp. 1–6, 2015.
- [23] A. Sindhu and A. Dube, "Comparative analysis of passive islanding detection methods for grid connected distributed generators," in *Proc. IEEE India Conf. (INDICON)*, pp. 1–6, 2015.
- [24] C. Tong, J. Guo, B. Chaudhuri and R. H. Lasseter, "Virtual Inertia from Smart Loads," *IEEE Transactions on Smart Grid*, vol. 11, no. 2, pp. 1–10, 2020.
- [25] A. Bonfiglio, M. Invernizzi, A. Labella and R. Procopio, "Design and Implementation of a Variable Synthetic Inertia Controller for Wind Turbine Generators," *IEEE Transactions on Power Systems*, vol. 33, no. 4, pp. 1–10, 2018.
- [26] A. Abazari, M. M. Soleymani, M. Babaei, M. Ghafouri, H. Monsef and M. T. H. Beheshti, "High penetrated renewable energy sources-based AOMPC for microgrid frequency regulation during weather changes, time-varying parameters and generation unit collapse," *IET Generation, Transmission & Distribution*, vol. 14, no. 18, pp. 1–19, 2020.
- [27] M.-H. Khooban, "An Optimal Non-Integer Model Predictive Virtual Inertia Control in Inverter-Based Modern AC Power Grids Based on V2G Technology," *IEEE Transactions on Energy Conversion*, vol. 35, no. 3, pp. 1–10, 2020.
- [28] M. Rajasi and C. Kalyan, "Virtual inertia emulation and RoCoF control of a microgrid with high renewable

- power penetration,” *Electric Power Systems Research*, vol. 196, p. 107262, 2021.
- [29] S. Feng, Y. Sun, Z. Li, X. Hu, H. Hua and S. Mei, “Power oscillation suppression in multi-VSG grid with adaptive virtual inertia,” *International Journal of Electrical Power & Energy Systems*, vol. 138, p. 107824, 2022.
- [30] N. Silva, J. Guerrero, B. Kroposki and M. Shahidehpour, “Virtual Inertia Emulator-Based Model Predictive Control for Grid Frequency Regulation Considering High Penetration of Inverter-Based Energy Storage System,” *IEEE Transactions on Sustainable Energy*, vol. 11, no. 4, pp. 1–10, 2020.
- [31] A. Saleh, W. A. Omran, H. M. Hasanien, M. Tostado-Véliz and A. Alkuhayli, “Manta Ray Foraging Optimization for the Virtual Inertia Control of Islanded Microgrids Including Renewable Energy Sources,” *Sustainability*, vol. 14, no. 2, pp. 1–15, 2022.
- [32] S. Irshad, X. Ai, M. J. U. Rehman, A. A. Mohamed, H. Ur Rehman, S. Salman, R. A. A. Syed and A. Muhammad, “Aggregation of EVs for Primary Frequency Control of an Industrial Microgrid by Implementing Grid Regulation and Charger Controller,” *IEEE Access*, vol. 8, pp. 1–13, 2020.
- [33] N. Narayan and S. Omkar, “Investigation and damping of electromechanical oscillations for grid integrated microgrid by a novel coordinated governor-fractional power system stabilizer,” *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, vol. 41, no. 18, pp. 2335–2363, 2025.
- [34] M. Agoundedemba, C. K. Kim, H.-G. Kim, R. Nyenge and N. Musila, “Modelling and optimization of microgrid with combined genetic algorithm and model predictive control of PV/Wind/FC/battery energy systems,” *Energy Reports*, vol. 13, pp. 238–255, 2025.
- [35] K. Dharmesh, S. P. Vijay and M. A. Mallick, “Frequency Control of Interlinked Microgrid System Using Fractional Order Controller,” *Electrica*, vol. 24, no. 1, pp. 1–12, 2024.
- [36] N. M. Ibrahim, A. A. El-Fergany and B. A. Hemade, “Enhancing power system stability by coordinating a wind turbine voltage regulator and lead-lag power system stabilizer using GOOSE optimization,” *Scientific Reports*, vol. 15, p. 15242, 2025.
- [37] E. Yokuş, Y. E. Yunus, E. A. Umut and K. Aslıhan, “A Review of the State-of-the-Art in Fractional-Order PID Controllers,” *Fractional Calculus: From Theory to Applications*, pp. 1–20, 2024.
- [38] A. Sabo, B. Yunus, E. Sani, M. Nwachukwu, D. Auta, A. Danladi, M. Mordi, N. Aliyu, Y. David and P. Oluwadamilare, “PID Controller Tuning Performance Evaluation for an Isolated Power System,” in *Proc. IEEE Int. Conf. Power Systems Technology*, pp. 1–6, 2022.
- [39] M. F. Roslan, A.-S. Q. Ali, M. A. Hannan, P. J. Ker and A. W. Zuhdi, “Particle swarm optimization algorithm-based PI inverter controller for a grid-connected PV system,” *PLoS ONE*, vol. 15, no. 12, p. e0243581, 2020.
- [40] A. Fathy and A. G. Alharbi, “Recent Approach Based Movable Damped Wave Algorithm for Designing Fractional-Order PID Load Frequency Control Installed in Multi-Interconnected Plants with Renewable Energy,” *IEEE Access*, vol. 9, pp. 71072–71089, 2021.

ML Models for Predicting Remaining Useful Life-Time of EV's Batteries for Stakeholders

Ali Sina Saifi *, Serik Aibol **, Ibragim Kuandykov *, Berik Zayniddinov*
Ruslan Omirgaliyev*, Nurkhat Zhakiyev***

* School of Computer Science, Astana IT University, Kazakhstan.

** School of AI and Data Science, Astana IT University, Kazakhstan.

*** Davis Center, Harvard University, MA, USA.

(232133@astanait.edu.kz, serikaibol048@gmail.com, 230276@astanait.edu.kz, 230799@astanait.edu.kz, ruslan.omirgaliyev@astanait.edu.kz, nzhakiyev@fas.harvard.edu)

‡ Corresponding Author: Serik Aibol, School of AI and Data Science, Astana IT Univ., Kazakhstan, serikaibol048@gmail.com.

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Abstract- Proper forecasting of remaining useful life (RUL) of lithium-ion batteries is critical for safety, operational stability, and cost-effectiveness in modern electric vehicles. Because battery degradation arises from complex electrochemical and thermal processes, data-driven approaches have become a practical alternative to physics-based modeling. This study develops and critically compares supervised machine learning models, including Random Forest, Gradient Boosting, Linear Regression, Ridge Regression, K-Nearest Neighbors, Deep Neural Networks (DNN), and Convolutional Neural Networks (CNN), for cycle-level RUL estimation using a publicly available lithium-ion battery dataset. The dataset comprises engineered voltage-time features, capacity, and charge-discharge indicators, which are preprocessed using Min-Max normalization to support stable training and fair model comparison. Among the evaluated methods, the Random Forest regressor achieved the best overall performance, reaching an R^2 of 0.9998 with lower MAE and RMSE than both traditional regressors and deep learning architectures. The results indicate that ensemble tree-based models are especially effective at capturing nonlinear degradation behavior when trained on engineered tabular features rather than raw time-series signals. While the DNN and CNN achieved high R^2 values, their error metrics were comparatively larger, suggesting that deep architectures may benefit from higher-resolution time-series inputs or alternative sequence modeling formulations. Finally, the top-performing model was integrated into an end-to-end prediction system using FastAPI, SQLite, and a responsive web dashboard to demonstrate real-world applicability. The deployment allows estimating RUL in real time and at lowlatency and provides stakeholders with an accessible tool for battery health monitoring. Overall, the study shows that ensemble learning techniques can deliver strong performance for battery condition monitoring and provides a deployable architecture to practical RUL prediction in electric-vehicle battery management systems.

Keywords: Remaining useful life, lithium-ion batteries, machine learning, ensemble learning, battery condition monitoring.

1. Introduction

The recent growth of electric cars (EVs) has made precise

prediction of the Remaining Useful Life (RUL) of lithium-ion batteries a major issue of concern in terms of safety, cost, and system durability. The latest research demonstrates that

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machine learning techniques may identify degradation trends at an earlier stage and forecast cycle life with an increasing degree of accuracy, especially with massive battery data as the model training data [1], [2]. Nonlinear aging behaviors can be captured with high-performance by data-driven models, such as CNN-LSTM hybrids and ensemble deep learning architectures [3-6]. Classical machine learning methods are also useful, as they can be interpreted and have computational advantages to stakeholders who require the ability to understand the decision made [7-8].

The issue of battery degradation undergoes complex chemical, thermal, and operational variations, so the problem of RUL prediction can be seen as a difficult problem within the broader context of intelligent energy systems. It has been established in research that the use of signal decomposition, feature engineering, and deep neural structures is essential in order to improve the strength of prediction in different cycling conditions [9]. Moreover, machine learning has been instrumental in other related areas including optimizing protocols of fast charging, which has a direct effect on the health and performance of the battery in the long run [7]. According to industry reports, better RUL forecasting helps to plan the EV supply chain and estimate costs, which is further proof of the strategic importance of it on the national and industrial level [10, 11].

Even with these developments, the field cannot yet offer a reliable universal technique because of the heterogeneous data, the use of different chemistries, and the use of different testing procedures as was observed in a number of surveys and comparative studies [9, 12]. This is the gap that inspires this work. The primary purpose of the given paper is to assess machine learning models that predict the RUL of EV lithium-ion batteries and define whether the hybrid deep learning models could be more efficient than the traditional ones in numerous cycling conditions. The research is informed by the premise that a combination of time-series feature extraction and hybrid neural networks will provide more generalizable and consistent prediction. To test this hypothesis, the following methods have been applied: dataset pre-processing, feature extraction, model training and comparative evaluation.

2. Methods and Materials

2.1. Research Design

This work is based on an experimental method of data-driven quantitative study of predicting the Remaining Useful Life (RUL) of lithium-ion batteries with supervised machine learning models. It is aimed at modeling nonlinear degradation trends that take place during charge-discharge cycles and provides an estimation of the number of cycles left before the end-of-life. The rationale behind this methodology is that cycle-level voltage, time, and capacity values have been shown to make good predictors of battery RUL when used together with data-driven regression techniques [13, 11].

The study also combines conventional ensemble-based regressors with deep neural models and tests their effectiveness on a structured dataset and then chooses the most effective model to be used in an operational RUL prediction system.

2.2. Dataset and Variables

The experiments are based on a publicly available lithium-ion battery data that was acquired at Kaggle and has 15,064 records with nine engineered features that characterize operational conditions and deterioration patterns. The target variable is Remaining Useful Life, which will be the amount of cycles that the battery has completed before it can reach the end-of-life limit. The independent variables are discharge time, capacity in ampere-hours, the duration that the voltage drops between 3.6 V and 3.4 V, the maximum voltage on discharge, the minimum voltage in charging, the time that is maintained at 4.15 V constant-voltage charging, and the total charging time. These variables are in line with the previous literature that stresses that time-voltage degradation indicators are useful predictive variables in the modeling of RUL [1, 8].

Figure 1 and Table 1 present a sample of the first ten rows of the dataset to illustrate the structure and values of the input features. Dataset URL: <https://www.kaggle.com/code/exceededdose/best-rul-prediction-model/input>.

	A	B	C	D	E	F	G	H	I
	Cycle_Index	Discharge Time (s)	Decrement 3.6-3.4V (s)	Max. Voltage Dischar. (V)	Min. Voltage Charg. (V)	Time at 4.15V (s)	Time constant current (s)	Charging time (s)	RUL
1									
2	1	2595.3	1151.4885	3.67	3.211	5460.001	6755.01	10777.82	1112
3	2	7408.64	1172.5125	4.246	3.22	5508.992	6762.02	10500.35	1111
4	3	7393.76	1112.992	4.249	3.224	5508.993	6762.02	10420.38	1110
5	4	7385.5	1080.32067	4.25	3.225	5502.016	6762.02	10322.81	1109
6	6	65022.75	29813.487	4.29	3.398	5480.992	53213.54	56699.65	1107
7	7	3301.18	1194.23508	3.674	3.504	5023.633636	5977.38	5977.38	1106
8	8	5955.3	1220.13533	4.013	3.501	5017.495	5967.55	5967.55	1105
9	9	5951.2	1220.13533	4.014	3.501	5017.496	5962.21	5962.21	1104
10	10	5945.44	1216.92091	4.014	3.501	5009.993667	5954.91	5954.91	1103

Fig. 1. Sample of raw battery cycling data showing key parameters measured during charge-discharge cycles.

Table 1. Description of dataset variables and their types for predicting the remaining useful life (rul) of lithium-ion batteries.

Variable	Type	Measurement / Description
RUL	Dependent Variable	Remaining Useful Life – number of charge-discharge cycles left until battery failure (continuous numeric target).
Discharge Time (s)	Independent Variable	Time taken to fully discharge the battery (seconds). Strong indicator of degradation.
Capacity	Independent Variable	Measured battery capacity in ampere-hours (Ah) at the current cycle. Top predictive feature.
Decrement 3.6-3.4V (s)	Independent Variable	Time difference for voltage to drop from 3.6 V to 3.4 V during discharge. Captures internal resistance increase.
Max. Voltage Dischar. (V)	Independent Variable	Highest voltage reached during discharge phase.
Min. Voltage Charg. (V)	Independent Variable	Lowest voltage during charging phase.
Time at 4.15V (s)	Independent Variable	Duration battery is held at 4.15 V (constant-voltage charging stage).
Charging time (s)	Independent Variable	Total time required to fully charge the battery.
Predicted RUL	Dependent Variable (Model Output)	Continuous value (cycles) predicted by the Random Forest Regressor (primary model).

2.3. Data Pre-processing and Normalization

The entire process of preprocessing had been applied in Python, NumPy, and pandas. As seen in Fig. 2, the data set was cleaned by eliminating inconsistent or missing measurements as well as non-predictive identifiers to eliminate data leakage.

The training-testing divide was in 80/20 proportion and was the same in all model set-ups. Since the predictors are working with non-homogenous numeric scales, all the features were made equalized via Min-Max scaling to the range [0,1] as a way of guaranteeing consistent convergence when using both standard regressors and neural networks. Scaling transformation of a feature value x is given by:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

Scikit-learn MinMaxScaler was used to do the normalization and the same scaling parameters were used during deployment which are used to guarantee consistency between training and inference.


Fig. 2. Overview of the data processing pipeline workflow for lithium-ion battery remaining useful life (RUL) prediction.

2.4. Model Architectures and Training

The development of the models was carried out in Python with the help of scikit-learn on traditional regressors and TensorFlow/Keras on the deep learning models. These traditional ones were Random Forest Regressor, Gradient Boosting Regressor, Linear Regression, Ridge Regression, and K-Nearest Neighbors. Random Forest and Gradient Boosting were the ensemble methods of choice because they perform well on nonlinear tabular data and have been shown to perform well in RUL forecasting problems in the literature [8, 11]. Each model has hyperparameters, such as tree depth, number of estimators, learning rate, and number of neighbors, which were optimized by trial and error through validation performance.

The deep learning models were fully connected Deep Neural Network (DNN) and one-dimensional Convolutional Neural Network (1D-CNN). The DNN structure incorporated a number of dense layers with ReLU activations and dropout layers to regularize the network, whereas the CNN structure incorporated stacked convolutional and max-pooling layers to find the local patterns of features before the regression output. Both networks were trained with Adam optimizer and mean squared error was used as loss function and early stopping was used to reduce overfitting. These architectures are based on deep learning solutions that have recently been considered to predict battery RUL [6, 9, 12, 14]. Table 2 summarizes the tools and libraries used throughout the data processing, model development, evaluation, and system implementation stages. Figures 3 and 4 illustrate the detailed layer configurations of the DNN and CNN architectures implemented in this research.

Table 2. Machine learning workflow and libraries used in the RUL prediction system.

Steps	Libraries / Tools
Data Loading & Preprocessing	pandas, NumPy, scikit-learn (MinMaxScaler)
Exploratory Data Analysis (EDA)	Matplotlib, Seaborn
Feature Engineering & Selection	pandas, NumPy
Model Development	scikit-learn (Random Forest, Gradient Boosting, Linear Regression, Ridge Regression, KNN), TensorFlow/Keras (DNN, CNN)
Evaluation & Visualization	scikit-learn (MAE, RMSE, R ² , Accuracy, Precision, Recall, F1), Matplotlib, Seaborn
Backend Integration	FastAPI, Python
Database Management	SQLite
Frontend Visualization	HTML, CSS, JavaScript

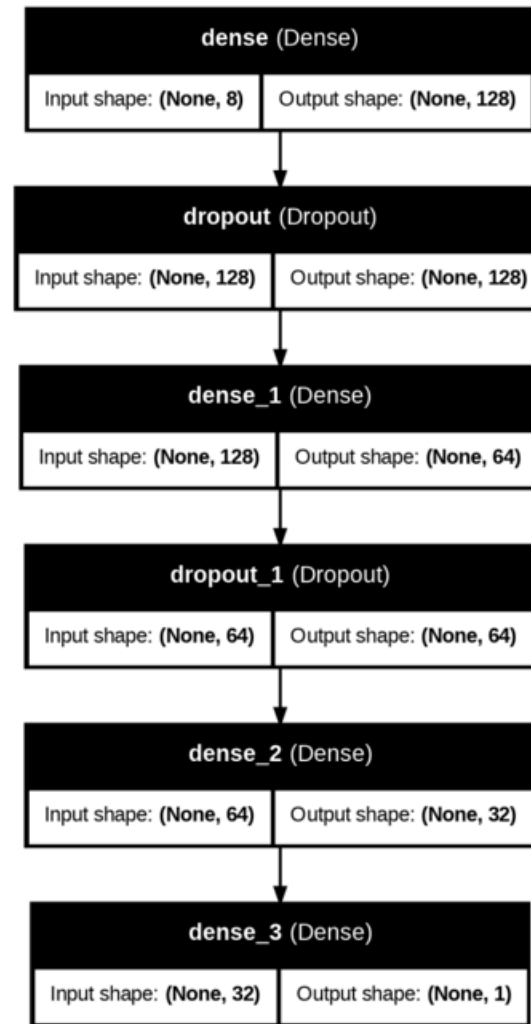


Fig. 3. Architecture of the deep neural network for lithium-ion battery remaining useful life (RUL) prediction.

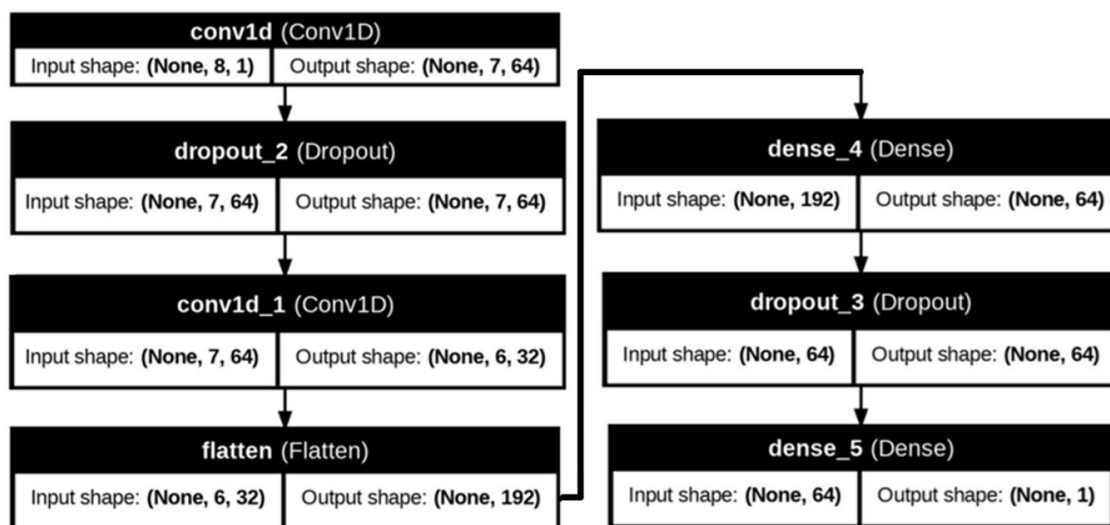


Fig. 4. Architecture of the convolutional neural network for temporal pattern recognition experimental setup and implementation.

Google Colab Link: https://colab.research.google.com/drive/1S_b1GSz2S7gLvHR7fsIE8TTG8YNqFMco?usp=sharing

2.5. Evaluation Metrics

Mean Absolute error (MAE), Root mean squared error (RMSE), and coefficient of determination (R2) were used as the measures of model performance. MAE also gives the mean absolute difference between predicted and real RUL values whereas RMSE punishes greater deviations and is also outlier sensitive. R2 is the degree to which the model predicts the actual RUL with values moving towards the 1 marking a good predictive power. These measures are typical of battery degradation and RUL prognosis research and can be directly compared with the current benchmark [15, 16].

2.6. System Implementation

The most efficient model was implemented with the full-stack architecture that included FastAPI backend, SQLite database, and a web-based frontend. The backend provides

RESTful endpoints, which receive battery feature values and use the identical pre-processing pipeline as in training and provide RUL predictions produced by the trained Random Forest model. The database component maintains the prediction history and sets of features posted by the user so that longitudinal monitoring and analysis could be performed.

The front part was created on the basis of HTML, CSS, and JavaScript. It offers a user interface, in which to enter new input values, visualize predicted RUL and examine stored results. Originally, the interface design was prototyped on Figma, and the final implementation is based on this design to a great extent. To guarantee reproducibility and accessibility of the codebase and model training notebook, they were created and tested in Google Colab.

Link to Figma: <https://www.figma.com/design/1fOOsmkBJVoM8gf29UbW9Q/RUL?node-id=0-1&m=dev&t=ajlSTLsuxsDkthe1-1>

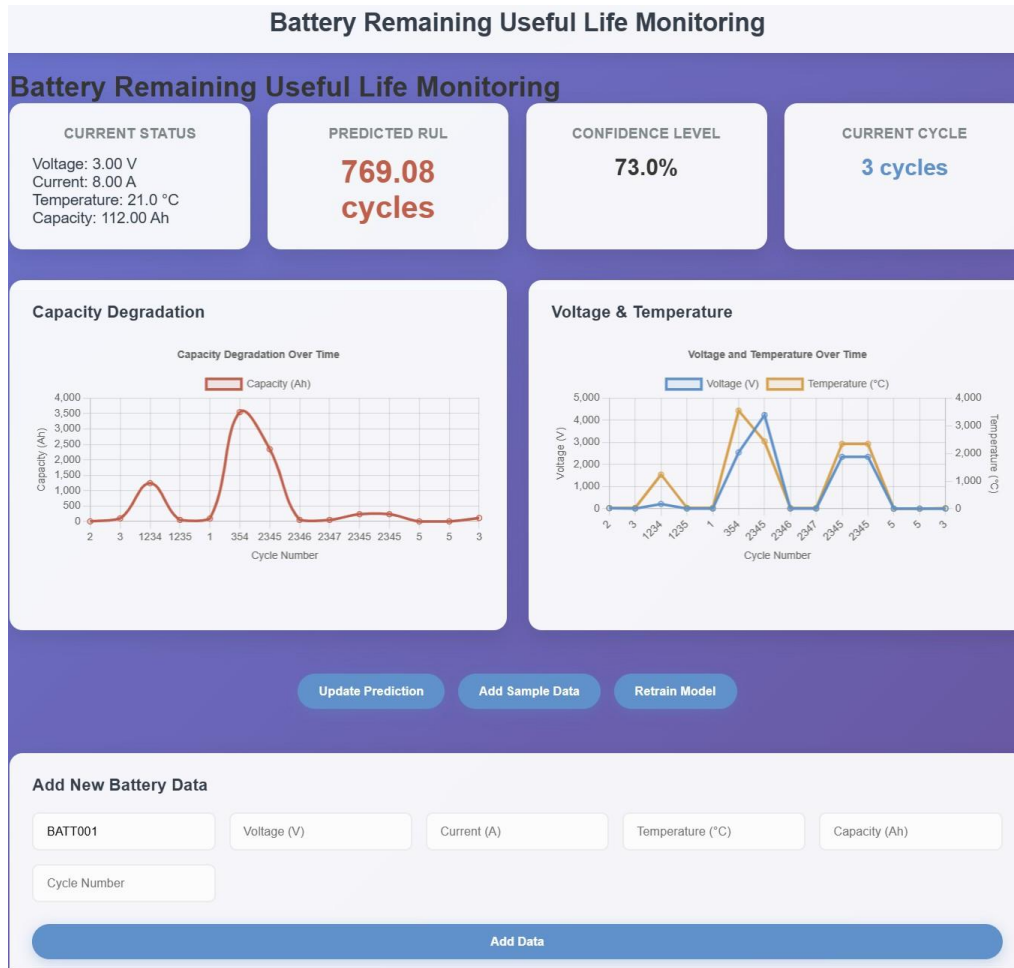


Fig. 5. Web dashboard interface for battery RUL prediction.

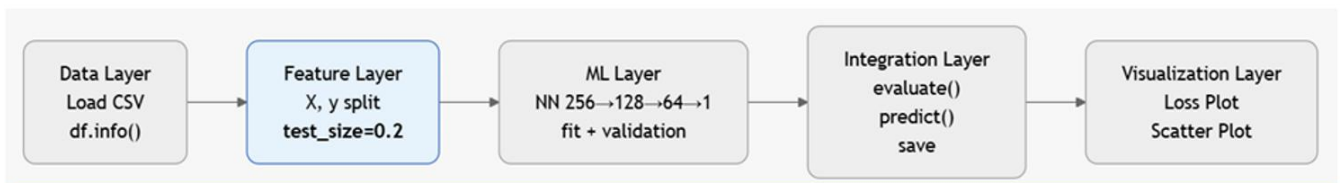


Fig. 6. System architecture diagram.

3. Results

3.1. Overall Model Performance

The models were tested on the held-out test set with MAE, RMSE and R2 (Table 3). Predictive performance of ensemble based regressors was the best with the Random Forest Regressor performing better than other models with the lowest MAE, RMSE, and R2 value of approximately 0.9998. Gradient Boosting presented with equally competitive results but with slightly higher values of error. Linear Regression, Ridge Regression and K-Nearest Neighbors were also

competitive with their results but they failed to match the accuracy of the ensemble models.

Deep learning models, such as the DNN and CNN, had high R2 values but a higher error measure compared to the ensemble models, indicating that a tabular battery degradation data is more likely to be modeled by a tree-based approach than a deep architecture that often takes advantage of raw temporal signal inputs [4, 17, 18].

Figure 7 presents the R² scores and RMSE values for all evaluated models, providing a comparative view of predictive accuracy and error magnitude.

Table 3. Model evaluation and metrics, with random forest performing best (R² = 0.9998, MAE = 2.26).

Model	MAE	RMSE	R ²	Accuracy	Precision	Recall	F1-Score	Training Time (s)
Random Forest	2.261	3.953	0.9998	0.9960	0.9960	0.9960	0.9960	8.01
Gradient Boosting	3.588	5.720	0.9997	0.9963	0.9963	0.9963	0.9963	5.79
Linear Regression	4.644	7.385	0.9995	0.9927	0.9927	0.9927	0.9927	0.03
Ridge Regression	4.641	7.416	0.9995	0.9927	0.9927	0.9927	0.9927	0.01
K-Nearest Neighbors	2.580	5.726	0.9997	0.9940	0.9940	0.9940	0.9940	0.08
Deep Neural Network	6.461	9.012	0.9992	0.9920	0.9920	0.9920	0.9920	87.65
Convolutional Neural Network	7.000	10.376	0.9990	0.9920	0.9920	0.9920	0.9920	106.16

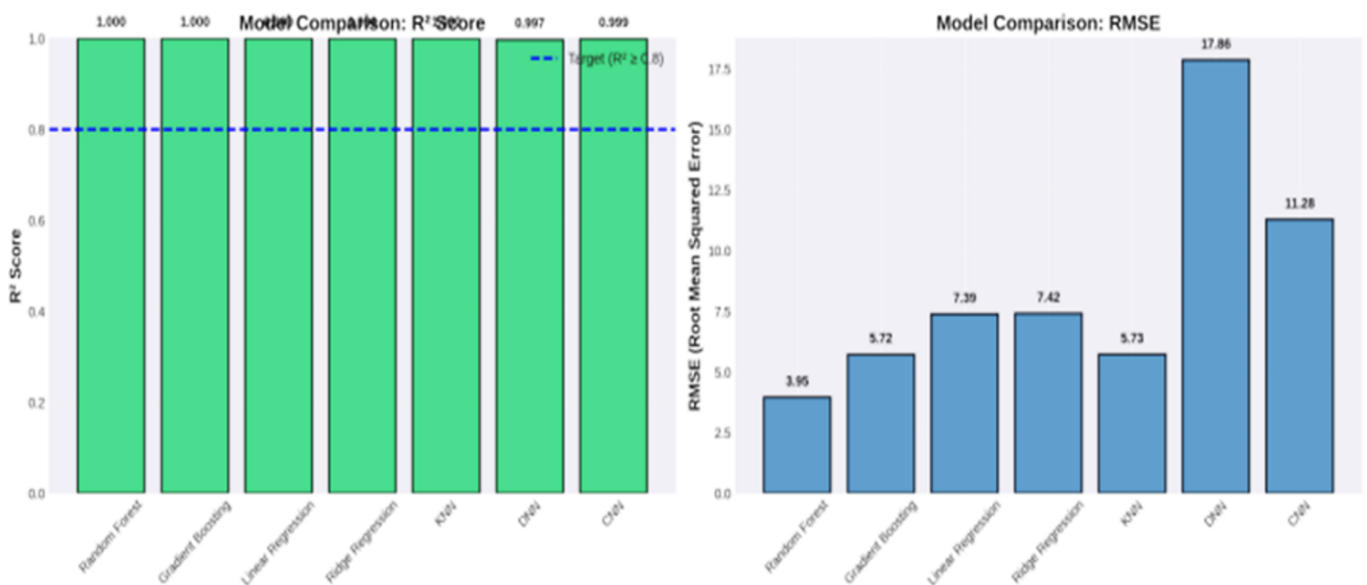


Fig. 7. Comparison of R² scores and RMSE values across different machine learning models.

3.2. Detailed Analysis of the Best Model

The best model was used because the Random Forest Regressor performed better compared to all the measurements. Its projections are very consistent with real RUL values in the entire cycle range and a slight variation is observed at the battery aging stages. The high degree of performance suggests that the nonlinear relationship between discharge time and capacity loss as well as that between voltage behavior and other degradation patterns have been well-represented by the Random Forest, which is in line with other recent publications in the field of ensemble-based RUL predictor literature [1,19]. The comparison of a scatter plot of the predicted and actual RUL values also shows the accuracy of the model with all the points being clustered closely around the optimum diagonal reference line.

Figure 8 shows the relationship between the actual and predicted RUL values produced by the Random Forest model, demonstrating a near-perfect fit along the diagonal reference line.

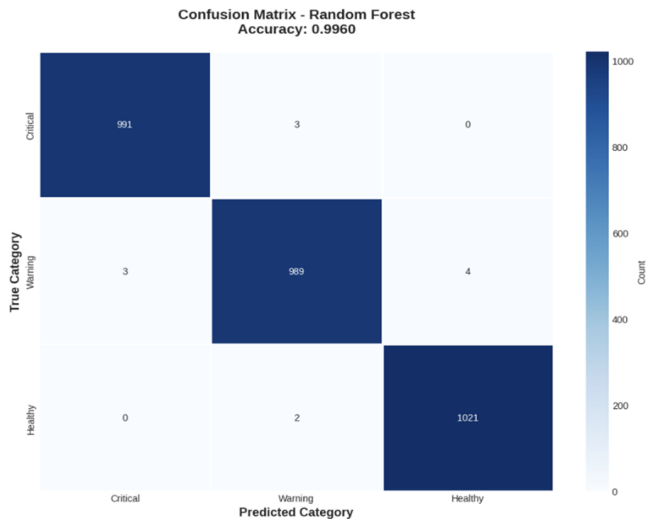


Fig. 8. Predicted vs. actual RUL distribution for random forest model.

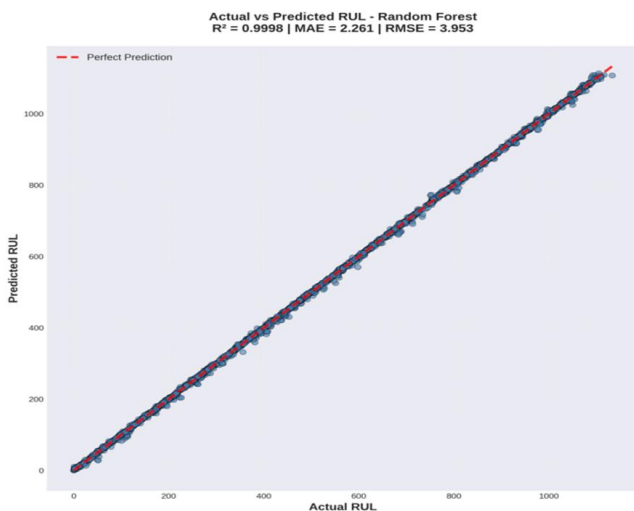


Fig. 9. Actual versus predicted RUL values for the best-performing model.

3.3. Comparison of Ensemble and Deep Learning Models

Although the DNN and CNN both showed good generalization capability, they had values of MAE and RMSE that were larger in comparison to the values of the Random Forest and the Gradient Boosting models. Deep networks are generally sensitive to high-resolution sequential data, e.g. voltage-time curves or current profiles at milliseconds resolution. This paper assumed the aggregation of input features as numerical indicators rather than the raw temporal signals, which preferred the use of ensemble. These findings can be correlated with comparative studies that demonstrate that in many cases, traditional machine learning models perform better than deep learning architecture on medium-sized tabular data, which are used to predict battery RUL [10, 12].

3.4. System-Level Performance

Real-time RUL estimation in interactive applications is feasible thanks to the implemented backend system's low latency, which consistently produced prediction responses in less than a second. User-submitted inputs are successfully processed by the web dashboard, which also logs the results in the database for later analysis and returns the predicted RUL values. These results are consistent with earlier research investigating the application of machine learning models in near-real-time battery management systems [7, 13, 15]. They also show great promise for real-world implementation in battery health monitoring applications

4. Discussion

This paper aimed to make a precise and practical machine learning predictive system to determine the remaining useful life of lithium-ion batteries. The findings are very clear that the ensemble learning models, especially the Random Forest regressor, are highly appropriate in this task, as they beat the traditional linear models as well as more complicated deep learning models on the given dataset. This result agrees with our original hypothesis that tree-based models would be able to describe the complex, nonlinear relationships that are available in the data on battery degradation that are defined by engineered features based on charge-discharge cycles.

The high quality of performance demonstrated by the fact that the R^2 value of the Random Forest is almost perfect (0.9998), and the error values (MAE = 2.26) are low may be ascribed to the nature of its abilities. Its ensemble nature prevents overfitting through averaging a group of decision trees and also naturally accommodates nonlinear interaction among features, e.g., discharge time, capacity fade, voltage characteristics, without the use of large-scale feature scaling [1,2]. The results of our study are in line with an increasing literature that indicates the effectiveness of tree-related approaches to tabular data in prognostics and health management [8]. As an example, the excellent predictive power supports the findings of other researchers such as mentioned by authors of [11], who observed that ensemble techniques were very effective in prediction of RUL.

On the other hand, the relatively increased errors of the Deep Neural Network (DNN) and Convolutional Neural Network (CNN) models, even though they showed great R2 scores, should be interpreted. This does not always imply that deep learning is inappropriate to RUL prediction, but the strengths of the latter are not used to their full potential with the existing feature set. Deep learning architectures are usually very effective in high-resolution, raw sequential inputs, including full voltage and current curves at high frequencies [12,14]. The features we used in our study (e.g., decrement time, charging time) are pre-engineered features, which combine time-related information into scalar values. Such a representation of data seems better and more succinctly modeled by tree-based algorithms as recent comparative studies indicate [12]. The decision between ensemble and deep learning models, thus, should be informed by the fineness of available data.

The fact of successful implementation of a full-stack prediction system highlights the usefulness of our research in practice. The fast performance of the FastAPI backend shows that it is possible to integrate such ML models into a real-time or near-real-time battery management system (BMS) to preemptively manage system conditions and ensure health, which is a direction taken by researchers [13].

This research has a number of limitations despite the promising results. To begin with, this model was trained and tested on one publicly available dataset. Its applicability to other types of batteries, including chemistries, manufacturers, and operating regimes (e.g., different temperature and load profiles) is yet to be confirmed. Secondly, the input features were pre-engineered. Although practical, the method can miss small-scale patterns of degradation that can be revealed through deep learning models that are run on raw, high-frequency cycling data. Future research must aim at testing the model on a larger and more varied dataset which covers more types of batteries and failure modes. Moreover, it could be possible that deeper fusion of the feature learning abilities of CNNs or LSTMs on raw data and the strength of ensemble techniques can provide even more accuracy and strength. Lastly, it may be possible to combine these data-driven predictions and physics-based battery degradation models to create a more complex, and interpretable, prognostic system.

5. Conclusion

The paper has managed to create an integrated machine learning methodology to forecast the remaining useful life (RUL) of battery packs in electric vehicles that use lithium-ion as its active material. The main finding proves the undoubted superiority of the ensemble technique and the Random Forest model turns out to be the most stable and accurate predictor. The fundamental ability to represent the complex, nonlinear degradation behavior due to engineered cycle-based characteristics gave it a superior predictive behavior ($R^2 = 0.9998$), which validates its applicability to real applied predictive maintenance tasks, a conclusion that is also in line with other more recent comparative studies in the discipline.

In addition to the analysis of the comparative model, another important input of this work is the translation of the trained model into a workable deployment-ready system. A complete example of operationalizing predictive analytics may be seen in the integration of a Fast API backend, an SQLite database, and an interactive web dashboard. This system is an end-to-end system that provides the stakeholders with a practical solution to real-time battery health monitoring showing that machine learning can be integrated into battery management systems (BMS) to make proactive decisions.

To conclude, the paper highlights the potential of data-driven solutions and, specifically, ensemble methods to improve the safety, reliability, and cost-efficiency of electric vehicle energy systems. The contribution of the present work to the sustainability and reliability of electric mobility is by offering a helpful and understandable model of the provision of electric mobility in battery management by providing a highly accurate and practical solution of RUL prediction.

Author Contributions

A.S.S. conceptualized the study, developed the methodology, performed data curation and formal analysis, and prepared the original draft; S.A. developed the methodology, implemented the software, conducted validation and investigation, and reviewed and edited the manuscript; I.K. performed data curation, developed the software, conducted experimental validation, and prepared visualizations; B.Z. conducted formal analysis and validation, reviewed and edited the manuscript; R.O. supervised the study, administered the project, and reviewed and edited the manuscript; and N.Z. supervised the study, acquired funding, and reviewed and edited the manuscript. All authors approved the final manuscript.

Acknowledgements

Conflict of Interest

The authors declare no conflict of interest.

References

- [1] K. A. Severson, P. M. Attia, N. Jin, N. Perkins, B. Jiang, Z. Yang, M. H. Chen, M. Aykol, P. K. Herring, D. Fraggidakis, M. Z. Bazant, S. J. Harris, W. C. Chueh and R. D. Braatz, "Data-driven prediction of battery cycle life before capacity degradation," *Nature Energy*, vol. 4, no. 5, pp. 383–391, 2019.
- [2] Q. Xu, X. Zhang, Y. Zhang, Z. Yang and Y. Liu, "A hybrid ensemble deep learning approach for early prediction of battery remaining useful life," *IEEE/CAA Journal of Automatica Sinica*, vol. 10, no. 1, pp. 177–187, Jan. 2023.
- [3] L. Ren, J. Dong, X. Wang, Z. Meng and L. Zhao, "A data-driven auto-CNN-LSTM prediction model for lithium-ion battery remaining useful life," *IEEE*

- Transactions on Industrial Informatics, vol. 17, no. 5, pp. 3478–3487, 2021.
- [4] A. Géron, *Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow*, 3rd ed. Sebastopol, CA, USA: O'Reilly Media, 2022.
- [5] M. Iftikhar, S. Kim, J. Lee and H. Kim, “A deep learning approach to optimize remaining useful life prediction for Li-ion batteries,” *Scientific Reports*, vol. 14, art. no. 25838, 2024.
- [6] Y. Fan, X. Li, H. Zhang and J. Wang, “A hybrid approach for lithium-ion battery remaining useful life prediction using signal decomposition and machine learning,” *Scientific Reports*, vol. 15, art. no. 8161, 2025.
- [7] P. Attia, N. Jin, N. Perkins, Z. Yang, M. H. Chen, M. Aykol, P. K. Herring, D. Fraggedakis, M. Z. Bazant, S. J. Harris, W. C. Chueh and R. D. Braatz, “Closed-loop optimization of fast-charging protocols for batteries with machine learning,” *Nature*, vol. 578, pp. 397–402, 2020.
- [8] M. Ansari, T. Kim and R. Cruz, “Remaining useful life prediction for lithium-ion battery: A comprehensive survey,” *Energy Reports*, vol. 8, pp. 11304–11325, 2022.
- [9] A. Rastegarpanah, M. Asif and R. Stolkin, “Hybrid neural networks for enhanced predictions of remaining useful life in lithium-ion batteries,” *Batteries*, vol. 10, no. 3, 2024.
- [10] C. Shen, P. Slowik and A. Beach, “Investigating the U.S. battery supply chain and its impact on electric vehicle costs through 2032,” *International Council on Clean Transportation*, Washington, DC, USA, Rep., Feb. 2024.
- [11] V. Safavi, A. Mohammadi Vaniar, N. Bazmohammadi and J. C. Vasquez, “Battery remaining useful life prediction using machine learning models: A comparative study,” *Information*, vol. 15, no. 3, art. no. 124, 2024.
- [12] M. O. Tarar, I. H. Naqvi, Z. Khalid and M. Pecht, “Accurate prediction of remaining useful life for lithium-ion battery using deep neural networks with memory features,” *Frontiers in Energy Research*, vol. 11, art. no. 1059701, 2023.
- [13] E. Kim, J. Lee and K. G. Shin, “Real-time prediction of battery power requirements for electric vehicles,” in *Proc. 4th ACM/IEEE Int. Conf. Cyber-Physical Systems (ICCPs)*, Philadelphia, PA, USA, Apr. 2013, pp. 11–20.
- [14] D. Chen, X. Zheng, C. Chen and W. Zhao, “Remaining useful life prediction of the lithium-ion battery based on CNN-LSTM fusion model and grey relational analysis,” *Electronic Research Archive*, vol. 31, no. 2, pp. 633–655, 2023.
- [15] N. K. Zhakiyev, K. Kayisli, A. Kushekkaliyev, N. Sagadatova and A. Biloshchytskyi, “Forecasting of GHG emissions from energy and industrial sectors of Kazakhstan and assessment of mitigation scenarios with high share of renewables,” *International Journal of Renewable Energy Research*, vol. 15, no. 2, pp. 300–309, 2025.
- [16] F. Demirbas, K. Kayisli and N. Zhakiyev, “Comparative analysis of the control algorithms for the capacitor charging power supplies,” in *Proc. 13th Int. Conf. Renewable Energy Research and Applications (ICRERA)*, 2024, pp. 952–958.
- [17] A. Zhanbolatov, S. Zhakiyeva, N. Zhakiyev and K. Kayisli, “Blockchain-based decentralized peer-to-peer negawatt trading in demand-side flexibility driven transactive energy system,” *International Journal of Renewable Energy Research*, vol. 12, no. 3, pp. 1475–1483, 2022.
- [18] B. Azibek, N. Zhakiyev, A. Ibarimova and Y. Akhmetbekov, “Increasing total hosting capacity using energy storages during renewable energy expansion,” in *Proc. 11th Int. Conf. Renewable Energy Research and Applications (ICRERA)*, 2022, pp. 414–417.
- [19] G. R. Sylvestrin, J. N. Maciel, M. L. M. Amorim, J. P. Carmo, J. A. Afonso, S. F. Lopes and O. H. Ando Junior, “State of the art in electric batteries’ state-of-health estimation with machine learning: A review,” *Energies*, vol. 18, no. 3, p. 746, 2025.