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Enhanced PMDC Motor Modeling Using a Neural Network Multi-Model Approach

This paper presents a novel modeling methodology for Permanent Magnet DC (PMDC) motors using a multi-model framework based on Neural Network (NN) Multi-Layer Perceptron (MLP) architecture. Departing from conventional single-model paradigms, the proposed approach emp–loys an ensemble of specialized MLP networks, whose optimal confi–guration is guided by adaptive performance evaluation. Comprehensive experimental and simulation results reveal that this multi-model framework achieves substantial enhancements in modeling precision, increased resilience to operational disturbances, and superior overall performance when contrasted with single-network implementations. Laboratory bench tests verify the method's efficacy across varied operational scenarios, including transient states. Owing to its adaptable and scalable nature, this methodology emerges as a valuable asset for sophisticated control strategies and real-time diagnostic applications in PMDC motor systems.

Keywords: *Modeling, Neural Network, MLP, Permanent Magnet DC motors, Multi Model.*

1. INTRODUCTION

Modern industry faces growing systemic complexity, posing significant challenges in modeling and control for automation engineers [1]. The effective operation of these systems requires not only advanced control strategies but also mathematical models capable of faithfully representing their dynamic behavior [2].

Permanent Magnet DC (PMDC) motors are key components of these systems, distinguished by their energy efficiency, high torque density, and rapid res–ponse [3]. Their simple construction and maintenance-free operation make them suitable for various appli–cations [4]. The 220 W motor modeled in this study is representative of the precision actuators used in deman–ding fields such as collaborative robotics, industrial automation, and medical devices, where model accuracy is crucial for performance and reliability.

However, accurate modeling of these motors re–mains a major technical challenge due to complex influ–encing factors such as load fluctuations, friction, mag–netic saturation, and environmental disturbances [5, 6]. These factors can lead to performance degradation if not properly accounted for. Therefore, developing a reliable model is essential for performance optimization, control strategy refinement, and the implementation of effective diagnostic systems [7].

To address this challenge, Artificial Neural Net–works (ANNs) offer a promising approach for modeling PMDC motors [8, 9]. Recognized as a revolutionary advancement in information processing [10, 11], ANNs can learn autonomously and make decisions, serving as powerful tools in fields like modeling and diagnosis [12, 13]. They are distinguished by their learning capacity and their ability to process data in a parallel and distributed manner [14, 15].

The literature presents various neural network approaches for tackling such complexities. The work in [16] introduces a method for nonlinear dynamic system identification using a Recurrent Multilayer Perceptron (RMLP) and a dynamic gradient descent algorithm, re–porting an order-of-magnitude improvement in conver–gence speed. Similarly, [17] employs a Multilayer Per–ceptron (MLP) as a universal approximator for non-linear problems in atmospheric sciences, bypassing the need for prior assumptions about data distribution.

Multi-model strategies have also been extensively explored. The study in [18] proposes a neural multi-mo–del method that decomposes a system's operating space into local zones, each represented by a distinct MLP, with outputs combined via Gaussian weighting func–tions. Expanding on this, [19] presents a multimodel approach using a Recurrent Trainable Neural Network (RTNN) with stability constraints, integrated within a fuzzy-neural structure. Reference [20] offers a syste–matic three-step method to determine the base models for a multimodel representation, using Kohonen net–works for clustering and recursive least squares for esti–mation. This concept is applied in [21] for fault diag–nosis in induction motors using a multi-model neuro-fuzzy approach and the LOLIMOT algorithm. Further, [22] investigates heterogeneous multiple models and concludes that a combined learning algorithm is most effective for systems with strongly overlapped validity functions.

However, recent single-network approaches still suffer from limited accuracy across the full operating range, especially during transient states. They often fail

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to capture local nonlinearities such as friction variations or magnetic saturation. This gap motivates our multi-model strategy, where several specialized neural networks collectively cover different dynamic regimes.

Recent research continues to leverage these con–cepts. The work in [23] defines a novel multimodal adaptive control strategy for Permanent Magnet Synch–ronous Motors (PMSMs) using embedded neural net–works for real-time adaptability. In reference [24], a multi-neural network architecture for modeling asyn–chronous machines is proposed, where the number of networks is adaptively determined based on learning error, demonstrating improved accuracy over a single-network model.

This research focuses on using neural networks as a modeling approach to develop a multi-model for a PMDC motor, aiming to achieve a more accurate and robust representation. The objective of the proposed approach is to establish an intelligent model capable of adapting to the system's different operational ranges.

This article is structured as follows: Section 2 pre–sents the mathematical model of PMDC motors; Section 3 details neural network modeling and the construction of the neural multi-model; Section 4 evaluates the per–formance of the proposed system via simulation; Sec–tion 5 presents the experimental validation conducted at the laboratory of the Higher School of Electrical and Energy Engineering of Oran (ESGEE); finally, Section 6 synthesizes the main conclusions of the study.

2. MATHEMATICAL MODELLING OF THE DC MOTORS

Mathematical model of the permanent magnet *DC* motor can be found very often in the literature. Here, it will be referred to briefly [25].

The supply voltage $u(t)$ is equal to the sum of the counter-electromotive force (back EMF) and the voltage drops across the armature resistance and inductance [26]:

$$u(t) = Ri(t) + L\frac{di(t)}{dt} + e(t) \qquad (1)$$

where: $i(t)$ is the armature current, R is the armature resistance, L is the armature inductance, and $e(t)$ is the back EMF given by :

$$e(t) = K_e \omega(t) \qquad (2)$$

with the angular velocity of the rotor and the back EMF constant.

The equation of motion is :

$$J\frac{d\omega(t)}{dt} = T_m(t) - T_f(t) - T_l(t) \qquad (3)$$

where: $J$is the total moment of inertia (rotor and load), $T_m(t)$ is the motor torque, $T_f(t)$ is the friction torque, and $T_l(t)$ is the load torque.

The motor torque is given by :

$$T_m(t) = K_t i(t) \qquad (4)$$

where K_t is the torque constant.

The friction torque can be modeled as the sum of several components:

$$T_f(t) = T_c sign(\omega(t)) + B\omega(t) + T_s \delta(\omega(t)) \qquad (5)$$

where: T_c is the Coulomb friction torque (constant, opposed to motion), B is the viscous friction coefficient, T_s is the static friction torque (which occurs when the velocity is zero), and $\delta(\omega(t))$ is a function that equals 1 if and 0 otherwise.

However, a more common and simpler modeling approach is to use viscous friction and Coulomb friction:

$$T_f(t) = B\omega(t) + T_c sign(\omega(t)) \qquad (6)$$

Magnetic saturation can be accounted for by varying the constants K_e and K_t as a function of the current. A simple approach is to model the saturation as a non–linear function of the current.

The load torque can vary with time and position. It can be modeled as a given function or as a disturbance. Thus, the complete model becomes:

$$L\frac{di(t)}{dt} = u(t) - Ri(t) - K_e(i)\omega(t) \qquad (7)$$

$$J\frac{d\omega(t)}{dt} = K_t(i)i(t) - B\omega(t) - T_c sign(\omega(t)) - T_l(t) \qquad (8)$$

Magnetic saturation makes the system nonlinear be–cause and depend on the current.

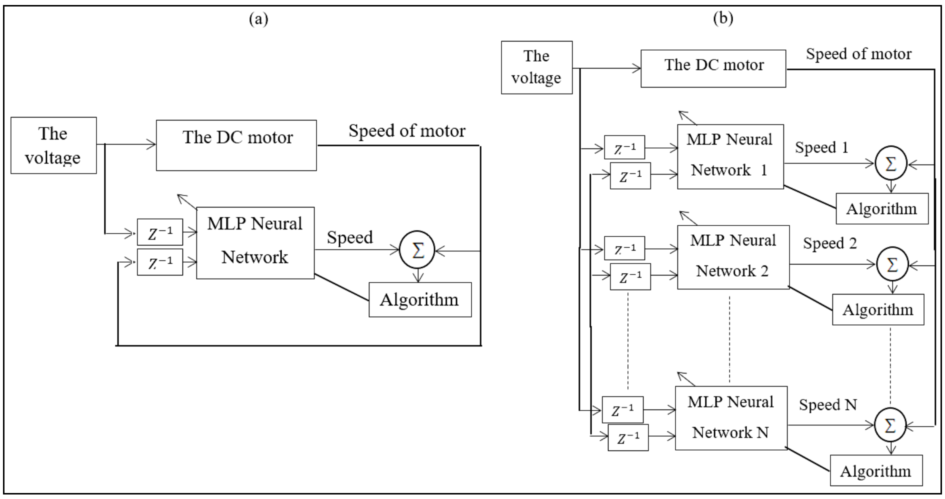

Figure 1. (a) The architecture series-parallel for the identification, (b) The architecture for the identification of multi model

3. NEURAL NETWORK MODELING

Neural networks are widely employed across numerous industrial fields. Indeed, there are various types of neural networks, each characterized by its unique learning capability and capacity to explain decisions [27, 28].

Consequently, modeling accuracy is fundamentally determined by the chosen neural architecture [29, 30].

Figure 1 (a) presents the series-parallel modeling approach, where the neural network is fed with his–torical machine data, encompassing both input and output variables.

The proposed approach involves using several interconnected neural network models, linked in parallel, to create a global model. The number of neural models was determined based on an analysis of the learning results from a single neural network after initial modeling. This single model reproduces the PMDC output but exhibits learning errors, which are localized at specific ranges of the network's output. Accordingly, the machine data was partitioned into intervals based on the analysis of these error values. These intervals were then used to construct a neural multi-model, as illustrated in figure 1 (b).

4. SIMULATION AND RESULT

Figures 2 and 3 show the voltage used and the machine speed, respectively.

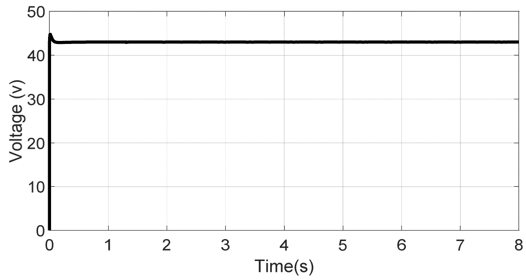

Figure 2. The supply voltage of dc motors.

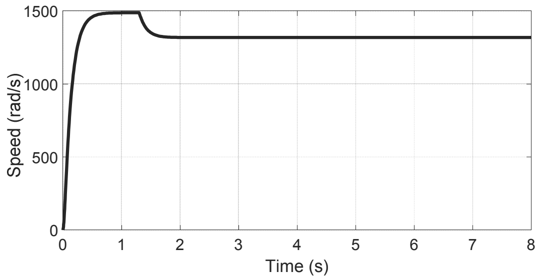

Figure 3. The speed of dc motors.

Figure 4 shows the neural network used, which comprises a hidden layer of 6 neurons, each neuron in this layer use a hyperbolic tangent activation function (equation 9), an input layer of 2 neurons and an output layer of a single neuron, this layer uses a linear activation function as:

$$Tansig(n) = \frac{2}{\left(1+e^{-2n}\right)-1} \tag{9}$$

$$Purelin(n) = 1 \tag{10}$$

The neural network is trained using the Levenberg – Marquardt algorithm as the core optimization method. The model's performance is assessed by computing the mean squared error (MSE), defined as follows:

$$MSE = \frac{\sum_{j=1}^{N}\left(z_j - \sigma_j\right)^2}{N} \tag{11}$$

The same type of neural network was used to generate the neural model and multi model.

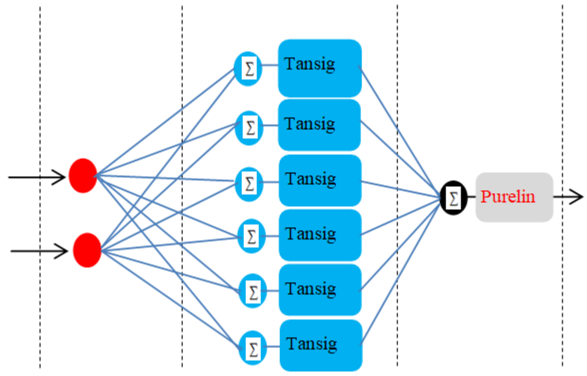

Figure 4. The MLP machine speed model

When comparing the machine output and the neural network model output, the training error is detected, as shown in figure 5.

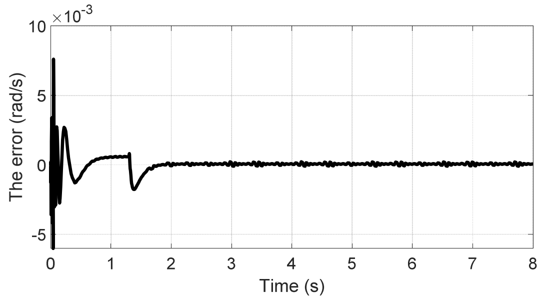

Figure 5. The training error of speed

The error curve displays a uniform spread of error values, visible on this curve, over the time intervals [0s 0,22s] and [0,22s 8s].

To solve this precision problem, we propose the multi-model neural network technique, based on de–composing the machine data (voltages and speed) according to the spread of error values. In this study, the data was split into two distinct segments:

The first segment covered the time interval [0s 0,22s], and the second segment included the interval [0,22s 8s]. Two neural network models were generated, each corresponding to one of these time intervals. The error of this multi-model is shown in figure 6.

The data was then divided into three segments cor–responding to the time intervals [0s 0,22s], [0,22s 2s], and [2s 8s]. Three separate neural models were deve–loped to handle these segments. The corresponding errors of the multi-model are shown in figure 7.

The neural model error (fig. 5) has a minimum value almost equal to -6.02·10^{-3} *rad/s* and a maximum value almost equal to 7.6·10^{-3} *rad/s*.

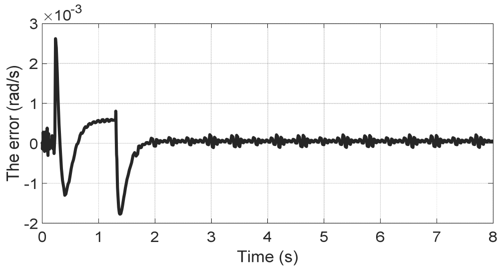

Figure 6. The training error of the multi model (2 models)

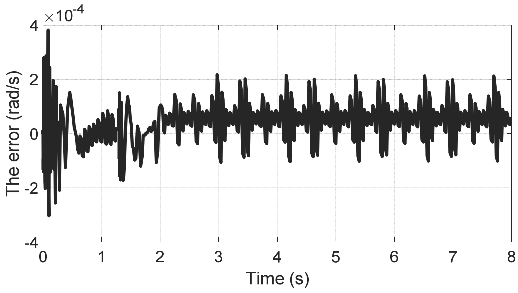

Figure 7. The training error of the multi model (3 models).

On the other hand, (fig. 6). the neural multi model error has a minimum value almost equal to $-1.76\cdot10^{-3}$ *rad/s* and a maximum value almost equal to $2.62\cdot10^{-3}$ *rad/s*.

It can be observed that the error values of the neural multi-model are consistently lower than those of the single neural model.

This indicates that the model composed of two neural networks achieves higher accuracy than the model based on a single network.

Furthermore, the model incorporating three neural networks demonstrates improved performance compared to the two-network version.

Specifically, both the minimum and maximum error values are reduced in the three neural networks model (fig. 7) (minimum ≈ $-3.03\cdot10^{-4}$ *rad/s*, maximum ≈ $3.81\cdot10^{-4}$ *rad/s*.

These results suggest that increasing the number of specialized networks within the multi-model framework enhances the overall modeling accuracy.

The mean square error (MSE) of the neural model is $6.7918\cdot10^{-5}$, while that of the neural multi model with two model is $3.9505\cdot10^{-7}$. This significant suggests that the neural multi model has significantly higher accuracy than the neural model. The MSE of the neural multi model with three models is $1.9758\cdot10^{-7}$.

This significantly suggests that the neural multi model with three model has significantly higher accuracy.

Figure 8 shows the electromagnetic torque of dc motors.

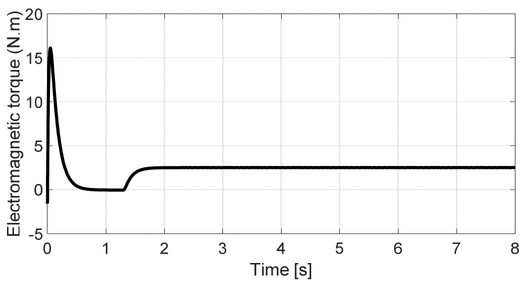

Figure 8. The electromagnetic torque of dc motors.

Figure 9 shows the neural network used for the electromagnetic torque, and the error of this model is shown in figure 10.

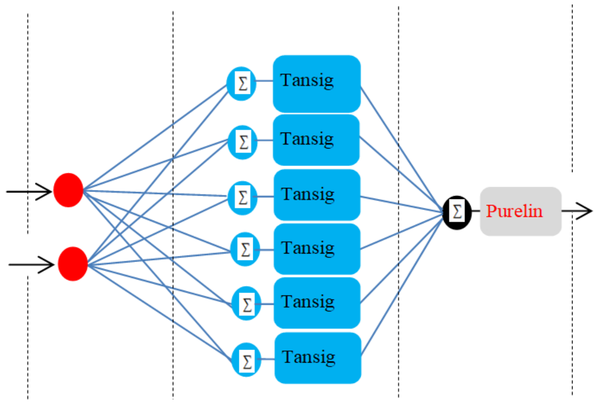

Figure 9. The MLP machine electromagnetic torque model

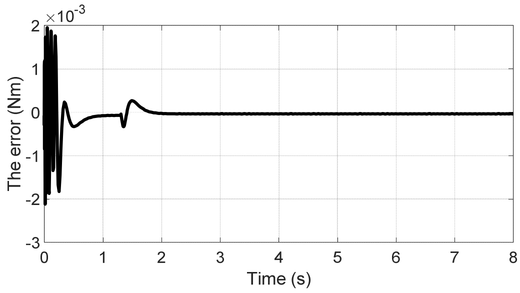

Figure 10. The training error of electromagnetic torque

The error curve displays a uniform distribution of error values, visible over the time intervals [0s 0,33s] and [0,33s 8s].

To address this precision issue, we propose a multi-model neural network approach, which involves decomposing the machine data (voltages and electromagnetic torque) based on the spread of error values.

In this study, the data was divided into two distinct segments:

- The first segment covered the interval [0s 0,33s],
- The second segment included [0,33s 8s].

Two neural network models were trained, each corresponding to one of these intervals. The error of this multi-model approach is illustrated in figure 11.

Next, the data was split into three segments corresponding to the intervals [0s 0,33s], [0,33s 1,8s], and [1,8s 8s]. Three separate neural network models were developed for these segments. The corresponding errors of the multi-model system are shown in figure 12.

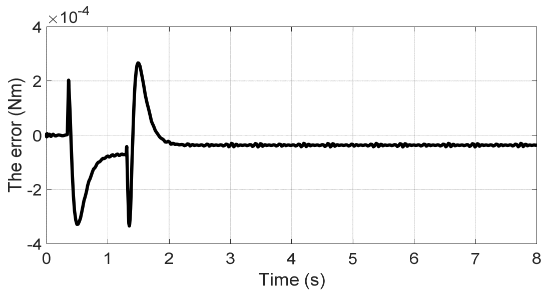

Figure 11. The training error of the neural multi model (2 models)

Figures 11 and 12 demonstrate that the two-model neural multi-model achieves lower minimum and maxi–

mum error values than the single neural model. More– over, the three-model neural multi-model further reduces these error values compared to the two-model version.

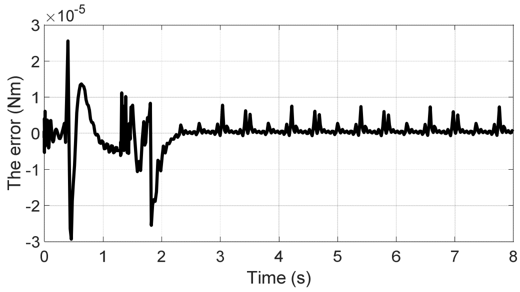

Figure 12. The training error of the neural multi model (3 models)

Table 1. Shows the values of the models.

Model type	The value of training model	Model of Single MLP	Multi model of two MLP	Multi model of three MLP
The Speed model	The minimum value of error (rad/s)	$-6,02\cdot10^{-3}$	$-1,76\cdot10^{-3}$	$-3,03\cdot10^{-4}$
	The maximum value of error (rad/s)	$7,6\cdot10^{-3}$	$2,62\cdot10^{-3}$	$3,81\cdot10^{-4}$
	The MSE	$6,79\cdot10^{-5}$	$3,95\cdot10^{-7}$	$1,97\cdot10^{-7}$
The torque model	The minimum value of error (Nm)	$-2,11\cdot10^{-3}$	$-3,34\cdot10^{-4}$	$-2,93\cdot10^{-5}$
	The maximum value of error (Nm)	$1,94\cdot10^{-3}$	$2,67\cdot10^{-4}$	$2,55\cdot10^{-6}$
	The MSE	$1,58\cdot10^{-7}$	$1,034\cdot10^{-9}$	$8,76\cdot10^{-10}$

Quantitatively, the single neural model has an MSE of $1,58\cdot10^{-8}$, whereas the two-model multi-model yields an MSE of $1.034\cdot10^{-9}$. Notably, the three-model multi-model achieves an even lower MSE of $8.76\cdot10^{-9}$. This substantial improvement confirms that the three-model approach delivers significantly higher accuracy.

5. EXPERIMENTAL RESULTS

Experimental tests were conducted using a LabVolt test bench equipped with a data acquisition interface (Model 9063-01), an IGBT chopper/inverter (Model 8837-B6), a four-quadrant power supply (Model 8960-36), and a permanent magnet DC motor (Model 8213-11, 220 W, 3600 rpm, 48 V, 5.5 A). The system, controlled by the IGBT inverter, was instrumented to measure electrical quantities (voltage, current, speed, torque) in real time via analog and digital I/O. Acquired data was processed and visualized on a computer, confirming strong agreement between simulated and experimental results.

The experimental tests were conducted in the laboratory of the Higher School of Electrical Engineering and Energetics of Oran (ESGEE), as shown in the photograph of figure 13.

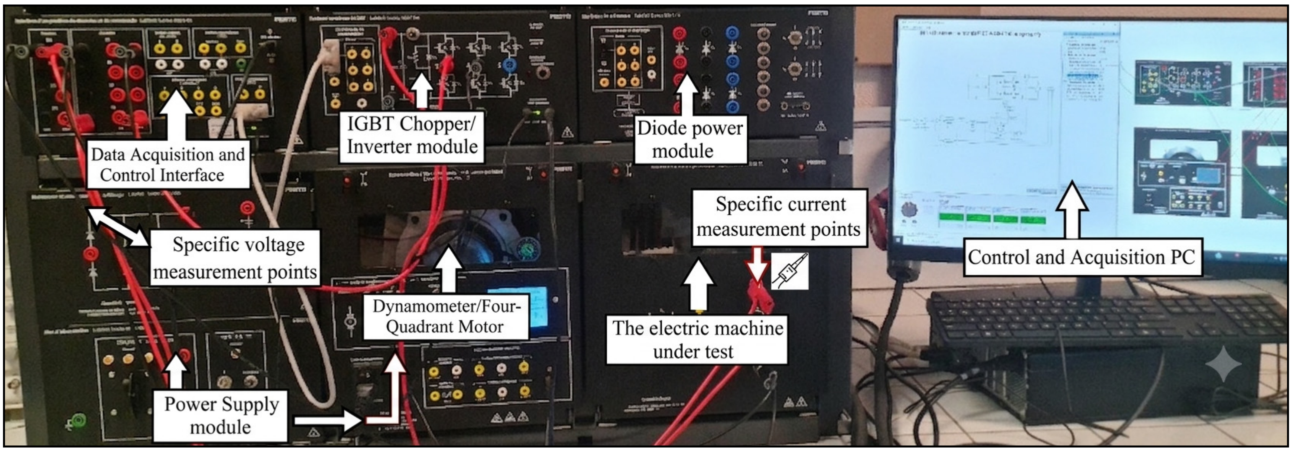

Figure 13. The experimental test-rig

Figure 14 and 15 show the voltage used and the machine speed, respectively.

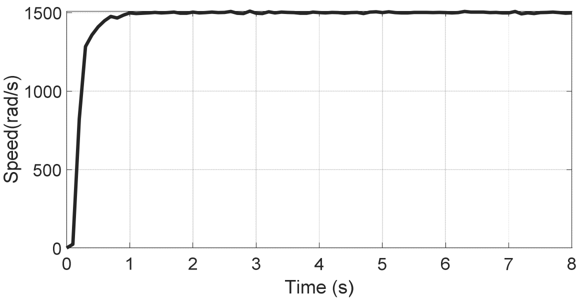

Figure 14. The speed of dc motors.

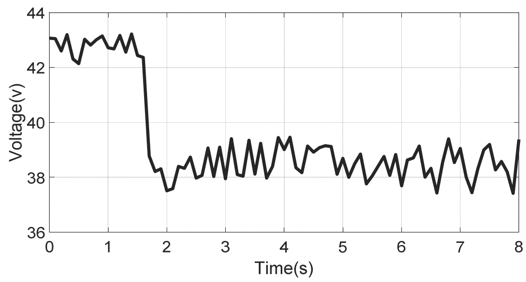

Figure 15. The supply voltage of dc motors.

Figure 16 highlights a learning discrepancy between the actual and predicted outputs, characterized by a uniform distribution of residuals across two distinct phases: the transient period [0s 3s] and the steady-state regime [3s 8s].

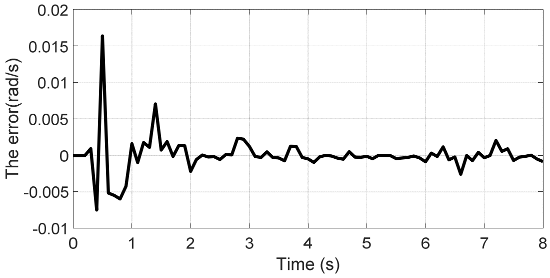

Figure 16. The training error of speed

Learning error analysis revealed a uniform distri–bution of residuals between actual and predicted out–puts, divided into two distinct phases: transient [0s 3s] and steady-state [3s 8s]. To improve accuracy, a neural network-based multi-model approach was implemented. Data was segmented into time intervals reflecting error distribution (fig. 19).

The two-network model was structured around two distinct intervals: Interval 1 [0s 3s] corresponding to the transient regime and Interval 2 [3s 8s] covering the steady-state operation. This approach significantly reduced the minimum and maximum errors to $-7.5 \cdot 10^{-3}$ *rad/s* and 0.016 *rad/s* respectively, achieving a mean square error (MSE) of $3.9505 \cdot 10^{-7}$, demonstrating notable improvement compared to the single-network model which had an MSE of $6.7918 \cdot 10^{-5}$ (fig. 17).

To further optimize performance, a three-network model was implemented with finer temporal segmen–tation: [0s 3s] for the initial transient phase, [3s 6s] for the transition to established operation, and [6s 8s] for advanced steady-state behavior.

Further error reduction was achieved (min: $-1.06 \cdot 10^{-3}$ *rad/s*, max: $1.35 \cdot 10^{-3}$ *rad/s*) with an MSE of $1.9758 \cdot 10^{-7}$, validating the efficacy of adding networks (fig. 18).

This increased granularity provided additional preci–sion in modeling the system's different operational phases.

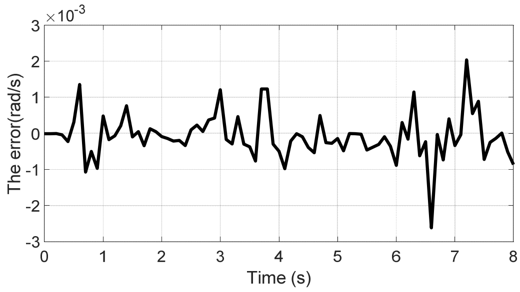

Figure 17. The training error of the multi model (2 models)

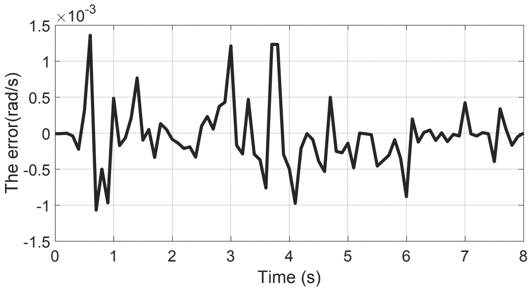

Figure 18. The training error of the multi model (3 models).

Figure 19 shows the electromagnetic torque of DC motors.

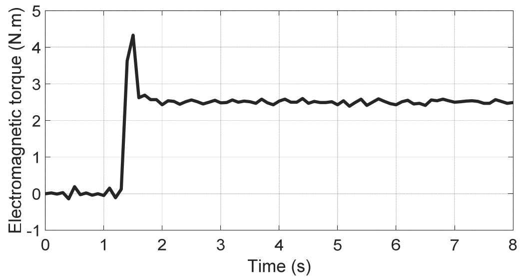

Figure 19. The electromagnetic torque of dc motors.

The error of this model is shown in figure 20.

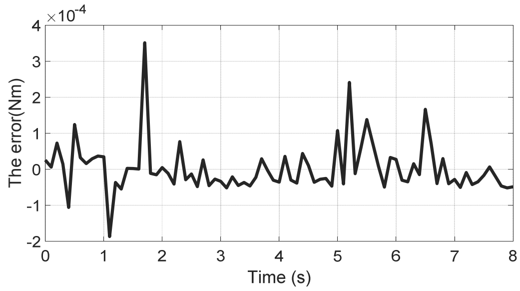

Figure 20. The training error of electromagnetic torque

A similar analysis was applied to electromagnetic tor–que, with adjusted segments ([0s 2s], [2s 5s] and [5s 8s]).

The three-network model achieved an MSE of $6.1695 \cdot 10\text{-}^{10}$ (fig. 22), compared to $2.4065 \cdot 10^{-9}$ for two networks (fig. 21) and $4.8899 \cdot 10^{-9}$ for a single network, confirming the robustness of the multi-model approach .

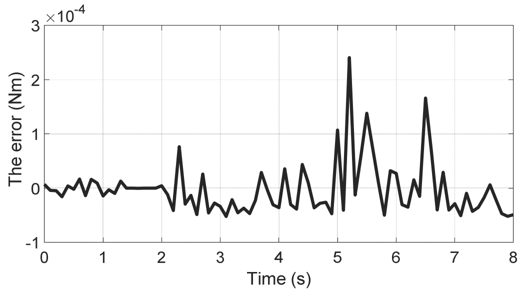

Figure 21. The training error of the neural multi model (2 models)

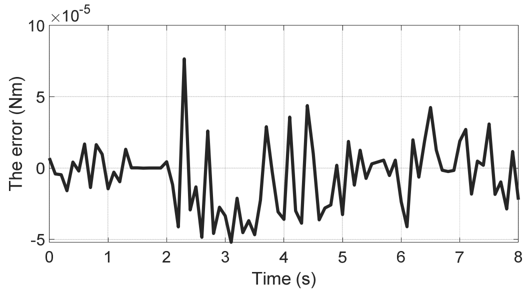

Figure 22. The training error of the neural multi model (3 models)

Table 2 summarizes the comparative performance of the models, highlighting:

- Progressive reduction in errors (min/max) and MSE as the number of networks increases.
- System adaptability to dynamic variations, critical for real-time industrial applications.

This methodology, experimentally validated, provides a precise and flexible alternative to traditional models, with potential for optimization in more complex systems.

Table 2. Shows the values of the models.

Model type	The value of training model	Model of Single MLP	Multi model of two MLP	Multi model of three MLP
The Speed model	The minimum value of error (rad/s)	$-7,50\cdot10^{-3}$	$-2,61\cdot10^{-3}$	$-1,06\cdot10^{-3}$
	The maximum value of error (rad/s)	$0,016$	$2,03\cdot10^{-3}$	$1,35\cdot10^{-3}$
	The MSE	$6.79\cdot10^{-5}$	$3.95\cdot10^{-7}$	$1.97\cdot10^{-7}$
The torque model	The minimum value of error (Nm)	$-1,86\cdot10^{-4}$	$-5,2\cdot10^{-5}$	$-5,20\cdot10^{-5}$
	The maximum value of error (Nm)	$3,51\cdot10^{-4}$	$2,40\cdot10^{-4}$	$7,64\cdot10^{-5}$
	The MSE	$4.88\cdot10^{-9}$	$2.40\cdot10^{-9}$	$6.16\cdot10^{-10}$

6. CONCLUSION

This paper introduces an innovative modeling approach for Permanent Magnet DC (PMDC) motors using a multi-model neural network architecture.

The results demonstrate that this method signifi–cantly outperforms single-network models in terms of accuracy and robustness, both in simulation and experimental validation. The key advantages of this multi-model approach include substantial error reduction (minimum, maximum, and MSE) through specialized networks for different operational ranges, enhanced adaptability to dynamic variations (critical for real-time industrial applications), and increased flexibility for seamless integration into advanced diagnostic and control systems.

Experimental validation conducted on a LabVolt test bench confirmed strong agreement between simulation results and practical measurements, reinforcing the met–hod's reliability. Future research directions may include extending this approach to other electrical machine types or optimizing neural network architectures for further performance improvements. In conclusion, this research advances intelligent modeling techniques for electric actuators, providing a precise, adaptable solu–tion for demanding industrial applications.

The multi-model neural network approach estab–lishes a new paradigm for accurate motor modeling, with potential applications, including embedded fault diagnosis, predictive maintenance in servo drives, high-precision positioning in collaborative robots, and torque control in medical robotic systems. Its modular design allows easy adaptation to other actuator types.

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NOMENCLATURE

$u(t)$	Supply voltage (V)
$i(t)$	Armature current (A)
R	Armature resistance (Ω)
L	Armature inductance (H)
$e(t)$	Back electromotive force (V)
$\omega(t)$	Angular velocity (rad/s)
K_e	Back-EMF constant (V/(rad/s))
J	Moment of inertia (kg·m²)
T_m	Motor torque (Nm)
T_f	Friction torque (Nm)
T_l	Load torque (Nm)
K_t	Torque constant (Nm/A)
B	Viscous friction coefficient (Nm/(rad/s))
T_c	Coulomb friction torque (Nm)

ACRONYMS AND ABBREVIATIONS

ANN	Artificial Neural Network
EMF	Electromotive Force
IGBT	Insulated-Gate Bipolar Transistor
MLP	Multi-Layer Perceptron
MSE	Mean Squared Error
NN	Neural Network

PMDC Permanent Magnet Direct Current

RMLP Recurrent Multi-Layer Perceptron

RTNN Recurrent Trainable Neural Network

APPENDIX

Motor Parameters	Symbol	Value	Unit
Armature resistance	R_a	$1,4$	Ω
Armature inductance	L_a	$2,8$	mH
Rotor inertia	J	$0,0012$	$kg \cdot M^2$
Back-EMF constant	K_e	$0,015$	$V/(rad/s)$
Viscous friction coefficient	B	$0,001$	$Nm/(rad/s)$
Torque constant	K_t	$0,015$	Nm/A

УНАПРЕЂЕНО МОДЕЛИРАЊЕ PMDC МО–ТОРА КОРИШЋЕЊЕМ ВИШЕМОДЕЛСКОГ ПРИСТУПА НЕУРОНСКЕ МРЕЖЕ

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Овај рад представља нову методологију моделирања за DC моторе са перманентним магнетима (PMDC) коришћењем вишемоделског оквира заснованог на архитектури вишеслојног перцептрона (MLP) неу–ронске мреже (NN). Одступајући од конвенцио–налних парадигми једног модела, предложени прис–туп користи ансамбл специјализованих MLP мрежа, чија је оптимална конфигурација вођена адаптивном евалуацијом перформанси.
Свеобухватни експери–ментални и симулацијски резултати показују да овај вишемоделски оквир постиже значајна побољшања у прецизности моделирања, повећаној отпорности на оперативне поремећаје и супериорним укупним перформансама у поређењу са имплементацијама једне мреже. Лабораторијски тестови потврђују ефикасност методе у различитим оперативним сценаријима, укључујући прелазне стања. Захваљу–јући својој прилагодљивој и скалабилној природи, ова методологија се појављује као вредна предност за софистициране стратегије управљања и дијагнос–тичке примене у реалном времену у PMDC моторним системима.