Artificial Neural Network-based Control of a Switched Reluctance Motor for a High-precision Positioning System

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Abstract: — This paper presents a approach to control a switched reluctance motor (SRM) in the context of a high-precision positioning system using artificial neural networks (ANNs). The SRM is known for its robustness and simplicity, making it suitable for various applications, including positioning systems where precision is paramount. Traditional control methods often struggle to achieve the desired level of accuracy due to the non-linear and dynamic nature of the SRM. In this study, we propose an advanced control strategy leveraging the adaptive learning capabilities of ANNs. The neural network is trained to capture the intricate relationships between the motor's inputs and outputs, allowing for precise control in real-time. By measuring the electromagnetic torque and phase currents, the neural network is able to estimate the rotor position, facilitating the elimination of the rotor position sensor. The training data set of the neural network consists of magnetization data for the SRM with the electromagnetic torque and current as inputs and the corresponding position as outputs in this set. With a sufficiently large training data set, the artificial neural networks (ANN) can be correlated for appropriate network architecture.

Key-words: — Switched Reluctance Motor (SRM), Rotor Position, artificial neural networks, and electromagnetic torque.

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1. Introduction

Switched reluctance motors (SRM) are a type of stepper motor that are receiving increased attention for high-precision positioning applications. SRMs have several advantages over other motors:
• Simple and robust structure with no windings or permanent magnets on the rotor. This makes them reliable and suitable for harsh environments.
• Low cost due to the simple construction and absence of rare earth materials.
• Good torque-to-weight ratio and torque density, enabling high-precision motion control.
However, SRMs also possess some challenges for effective control:
• Highly nonlinear torque-speed and torque-current characteristics. The torque produced depends on the relative positions of the stator and rotor poles.
• Parameter variations due to temperature changes, aging effects, and load disturbances. This affects the motor's performance over time.
Conventional control methods for SRM include closed-loop PID control and open-loop voltage control. These methods struggle to adapt to the motor's nonlinearities and variations.
Artificial neural networks (ANN) can potentially solve this problem as they can learn the complex input-output relationships of the SRM through training. An ANN controller can be developed based on experimental motor data to produce optimal control signals for the inverter driving the SRM.
Previous research has demonstrated the benefits of ANN control for SRMs, including:
• Improved steady-state and dynamic performance
• Higher precision for speed and position control
• Better adaptation to motor nonlinearities and parameter variations, [1, 2].

In order to get more accurate characteristics than those given by analytical modelling, numerical analysis methods are a potentially effective means and often produce results that are very close to reality. In particular, in the field of electromagnetic structures, the use of finite elements methods allows a precise characterization of electromagnetic devices using materials with non-linear characteristics and complex geometry. These finite elements methods are the basis for powerful electromagnetic calculation software known as computer-aided design. Recent work has often combined these methods with non-conventional modelling techniques. Among these modelling techniques, artificial neural networks are particularly noteworthy, as they have shown their power in modelling non-linear systems, [3, 4]. In addition, the works published in the recent literature propose various contributions, mainly focused on improving the performance of SRM's used in propulsion mode and not in positioning mode. Obviously, the strong distortion of the angular characteristics is a handicap for the use of this actuator for positioning purposes. This handicap is all the more pronounced the more demanding the positioning requirements are in terms of accuracy. It is in this perspective that our research work, developed in this paper, is situated. It consists mainly in proposing control approaches for the use of this actuator in positioning.

The main contributions are:

1. An ANN-based position estimator that learns the nonlinear relationship between stator current and rotor position of the SRM. This ANN (ANN1) is trained offline using FEA data and estimates the rotor position based on the supplied current.
2. An ANN-based controller that generates the optimal stator current required driving the rotor to a desired position. This ANN (ANN2) is trained online during motor operation to minimize position error.
3. An integrated control approach that combines ANN1 and ANN2 to achieve high-precision positioning of the SRM. ANN1 estimates the current position based on the stator current, while ANN2 generates the next current command based on the position error.

This paper is divided into two distinct parts. In the first section, a finite element study is carried out to characterize the SRM in order to determine its electromagnetic properties. This electromagnetic study is based on the CAD environment "Magnet 2D". The second part is dedicated to the development of a control approach, using both the database generated by the finite element method (FEM) and a cascade of estimators based on artificial neural networks, in order to correct the asymmetry of the machine through the control and to achieve precise positioning of the actuator, operating at constant load or fluctuating by stages.

2. Electromagnetic characteristics of the SRM

The SRM performance analysis, both electric and magnetic, depends on its geometric construction and materials used. It is almost impossible to determine exact mathematical equations that take into account all these influential parameters. In this way , it is able to give useful results to calculate the electric machine performance. Figure 1 presents all the dimensions of the SRM. Some significant mechanical parameters of the three topologies are shown in Table 1.

Table. 1. Mechanical and electrical parameters of the SRM 8/6 considered

Parameters	Symbol	Value
Rotor pole angle	βr	24.5°
Stator pole angle	βs	22.5°
Stator external diameter	Ds	160mm
Rotor diameter	Dr	91.1mm
Air gap length	g	0.3mm
Stator pole height	Hr	13mm
Rotor pole height	Hs	22mm
Stator yoke	Ys	12.45mm
Rotor yoke	Yr	15mm
Shaft diameter	D0	34.5mm

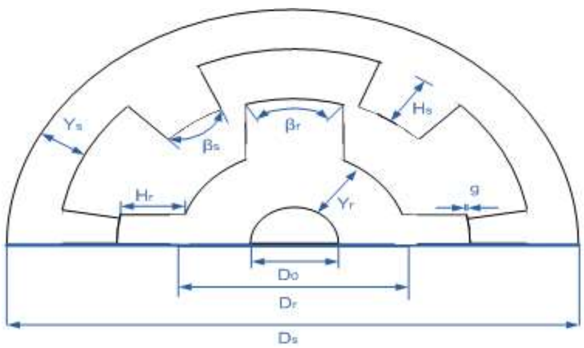


Fig. 1- Switched reluctance machine dimensions

The SRM 8/6 exhibits a symmetric and homogeneous structure and geometry, enabling us to analyze and obtain the properties of other phases based on the analysis of a single phase. To understand the characteristics of the SRM, we can model the system from aligned and unaligned positions.

Figure 2 shows the magnetic spectrum of the SRM at the aligned position where the rotor and stator poles are perfectly aligned. Figure 2(a) depicts the flux linkage which is maximum in this position indicating high inductance. Figure 2(b) shows the high density of Mesh distribution in the overlapped region of rotor and stator poles. Figure 2(c) illustrates the magnetic field distribution which is strongly concentrated in the pole overlap region. Figure 3(d) displays the induction vector which is uniformly distributed in this region of maximum inductance aiding development of torque.

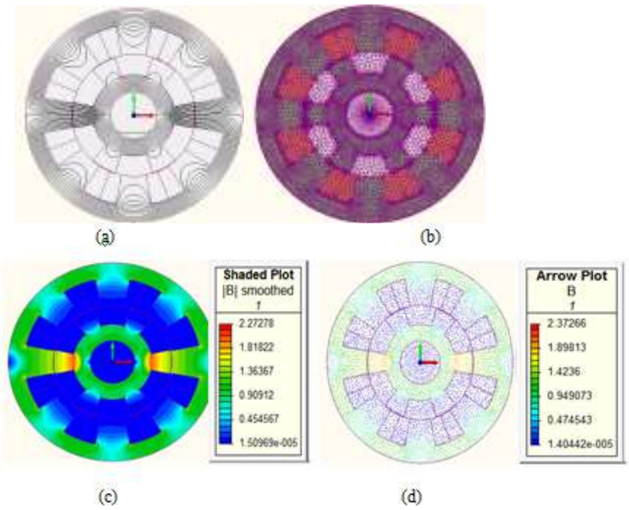


Fig.2- Magnetic spectrum of SRM at aligned position
(a)- Flux linkage **(b)-** Mesh distribution
(c)- Magnetic field distribution **(d)-** Induction vector

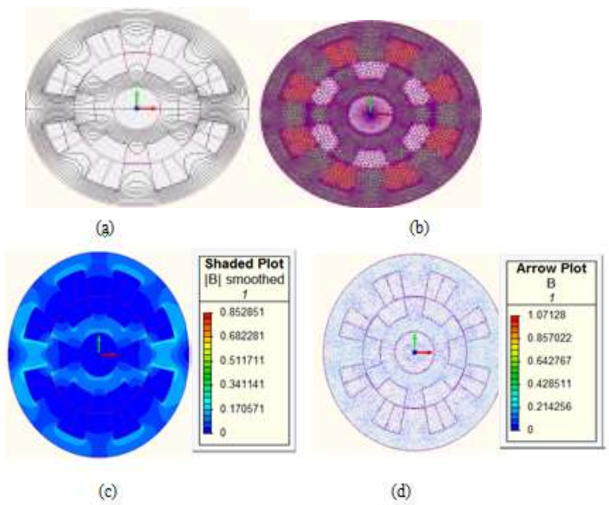
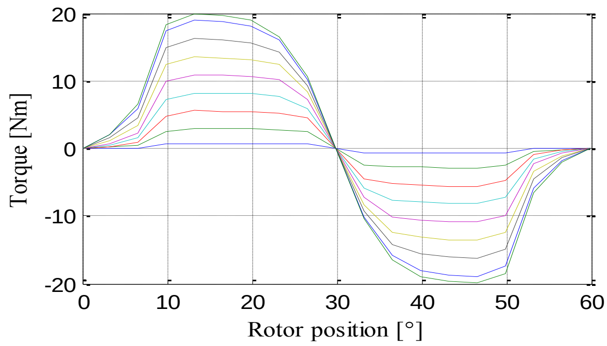


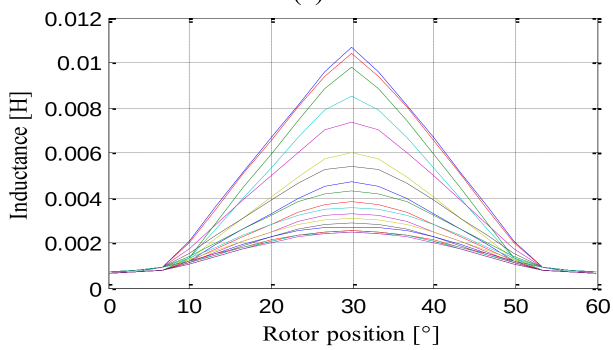
Fig.3- Magnetic spectrum of SRM at unaligned position
(a)- Flux linkage **(b)-** Mesh distribution
(c)- Magnetic field distribution **(d)-** Induction vector

Figure 3 shows the magnetic spectrum of SRM at the unaligned position where rotational misalignment exists between rotor and stator poles. Figure 3(a) presents the flux linkage which is now minimum in this position of low inductance. Figure 3(b) reveals sparse distribution of flux lines between the poles. Figure 3(c) depicts the magnetic field spreading wider instead of being focused in the overlap region. Figure 3(d) shows the induction vector spreading unevenly outside the region of highest inductance not contributing to torque. These spectral representations provide a visual insight into variation of magnetic quantities affecting operation from aligned to unaligned position, helping better understand SRM electromagnetic behavior.

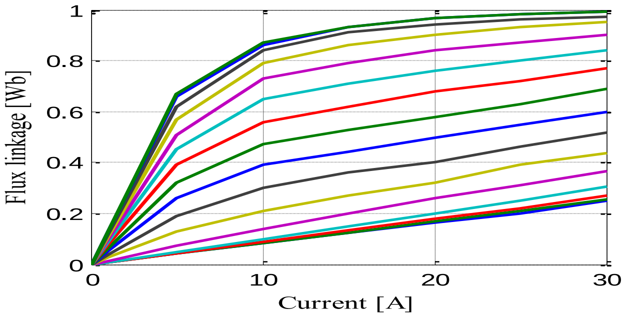
Understanding the SRM requires a detailed analysis of the torques, flux linkage and inductances for different rotor positions and different values of stator excitation currents based on FEA. Therefore, an FEA simulation tool was used to solve the magnetic circuit to determine the magnetic fields and electromagnetic quantities of each machine. This simulation tool allows us to obtain a data set that fully characterizes the magnetic and electromagnetic states of the SRMs. Examples of this data are shown in Figure 4.



(a)



(b)



(c)

Fig.4- Electromagnetic performances of SRM (a)- Torque profile (b)- Inductance profile (c)- Flux linkage profile

The evolution of the magnetic flux depends essentially on the level of saturation of the magnetic circuit. In fact, for a constant position, such as that of alignment, it is observed that the more the excitation current increases, the more the flux variation is limited, figure 4c. The value of the inductance can be determined by using the calculation results of the magnetic flux as a function of the rotor position at constant excitation levels. The results shown in Figure 4b show that the inductance of a stator phase varies inversely with the excitation current in the vicinity of the alignment position (30°), while in the vicinity of the opposition position (0°) the influence of the current on this inductance is very limited. For a fixed position, it can be seen that the influence on the inductance decreases as the saturation level increases. The real angular characteristics determined by the finite element method are distorted and far from being sinusoidal, which shows the inadequacy of the analytical method based on the simplifying assumptions adopted. Thus, in Figure 4a we can see the presence of some oscillations at the levels of these characteristics.

3. Neural approach to SRM position control

Knowing the angular characteristics of the SRM allows it to be used for positioning. The results obtained show that the angular characteristics describing the evolution of the torque as a function of the rotor position of the variable reluctance machine are clearly affected by distortions. Therefore, the use of this type of actuator in positioning applications cannot be envisaged without the development of powerful control approaches that allow the appropriate adjustment of the stator excitations, taking into account both the load to be positioned and the level of distortion affecting the characteristics [5-6-7]. In order to develop this control strategy, and after having carried out a detailed characterization of the machine using CAD, we resorted to non-conventional control techniques, known as intelligent, to develop a cascade of control blocks based on artificial neural networks.

Several works prove that multilayer perceptrons are the most widely used neural networks today, [5-6-7] they are able to realize nonlinear associations between input and output. The architecture of this type of neural network is shown in Figure 5. Each neuron has an activation function, which can be sigmoid, bipolar sigmoid, log-sigmoid, etc. The weights on the connections can be determined by the back-propagation algorithm during the training process and then used to calculate the outputs.

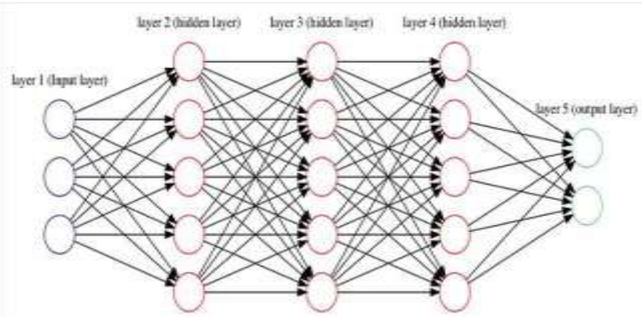


Fig.5- Architectural graph of a multilayer network

Error back-propagation in a multilayer network is supervised learning. The input is presented for which the output is determined. The set of synaptic weights determines the operation of the neural network. The neurons outputs of the output layer are compared with the model values which are the desired outputs and the error of each is calculated as clearly shown in Figure.6. The most commonly used function that we have adopted in this work is the squared error function. This function is defined for each example (n) a number of behavioural examples (N) as inputs to the network, associated with the same number (N) of desired outputs as follows:

$$E(n) = \frac{1}{2}\sum_{k=1}^{K}\left[d_k(n) - y_k(n)\right]^2 \quad (1)$$

For all examples we consider the mean square error as follows:

$$E_{moy} = \frac{1}{N}\sum_{n=1}^{N} E(n) \quad (2)$$

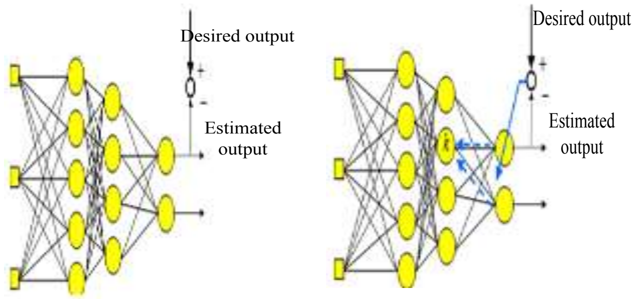


Fig.6- Multi-layer network learning with error determination and back- propagation

The realization of the learning phase is strongly related to the relevant choice and number of examples that must be made available to the network. These examples must be sufficiently representative of the evolution of these angular characteristics for the reconstruction to succeed in completing this important phase [8-9-10-11].

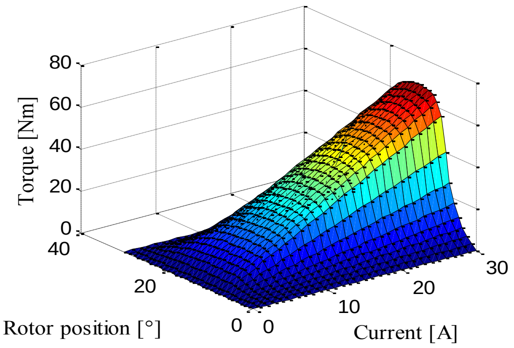


Fig.7- training database of artificial neural network (ANN)

For this purpose, we used a numerical interpolation technique available in the Matlab environment, which led us to develop a computer program based on cubic interpolation. The response surface shown in Figure.7 is a graphical representation of the database describing the evolution of the torque as a function of the rotor position for the whole operating range of the machine.

3.1. Design and development of the position estimation network (ANN1)

In order to estimate the stopping position of the considered SRM when the coupled load and the stator excitation are known, we preceded to the creation of a multilayer neural network (ANN1) using predefined functions in the MATLAB environment. The inputs of this network are the torque exerted by the load and the excitation current, while its output is the angular position of the rotor. This network consists of a single hidden layer of 13 neurons and an output layer of a single neuron. The activation function chosen for the hidden layer neurons is that of the hyperbolic tangent of the sigmoid, while for the output layer neuron the activation is provided by the linear function. Through repeated learning and the use of the previously developed database, we have ensured that this network is capable of estimating the stop position over the entire working range of the machine, regardless of the level of stator excitation and the magnitude of the torque imposed by the coupled load [12-13-14-15-16].

In order to verify the effectiveness of the estimation provided by the developed neural network across the entire operating range of the considered SRM, we proceeded by conducting a learning test. This test involved reconstructing several other examples that were not included in the database presented to the network during the training phase and comparing the calculated results by the network with the expected results. They display, for an excitation current vector ranging from 20A to 36A with a step of 0.5A, the evolution of the electromagnetic torque based on the target positions and the positions estimated by ANN1, Figure 8. . For all these examples, the error did not exceed 0.8%.

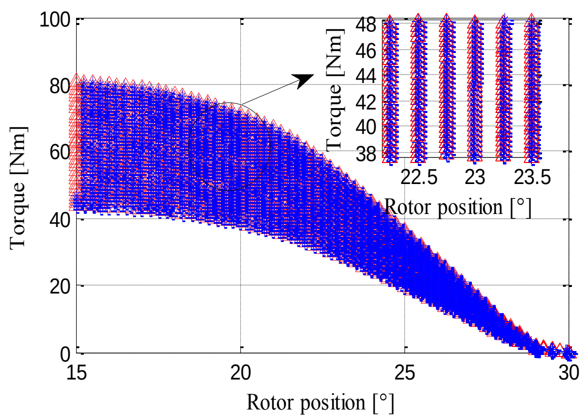


Fig.8-effectiveness of ANN1 for unlearned responses

3.2. Design and development of the current estimation network (ANN2)

In order to give the rotor a well defined stop position, for an SRM with a given angular characteristic, it is necessary to modulate the stator excitation according to the resistance force imposed by the coupled load. This is the basic idea behind the design of the second multilayer neural network, ANN2, whose objective is to determine the amplitude of the excitation current required to reach the target position. Therefore, the inputs or attributes for this network can only be the load torque and the target position, while the output or class is none other than the excitation current. The ANN2 is composed of a single hidden layer structured around 14 neurons and an output layer composed of a single neuron. We have chosen the hyperbolic tangent function of the sigmoid for the activation of all the neurons of this hidden layer, while the activation of the neuron of the output layer is provided by the linear function.

Similarly to the previously designed ANN1 position estimation network and in order to show that the network has learned the characteristics presented in the learning base and that the performance obtained is satisfactory, we have presented in the same Figure 9, for different stable positions, the evolution of the torque as a function of the target currents and the currents calculated by the ANN2 network. In fact, for several positions considered by successions of steps of 0.75° and delimited by the terminals 15° and 30°, the evolution of the torque is plotted by triangular patterns as a function of the target intensities and by star patterns as a function of the intensities estimated by the ANN2. These characteristics are determined with a gradual current variation of 1A. The results obtained show a satisfactory agreement with the error between the values of the target intensities and the intensities calculated by the designed RMC2 network not exceeding 0.16%.

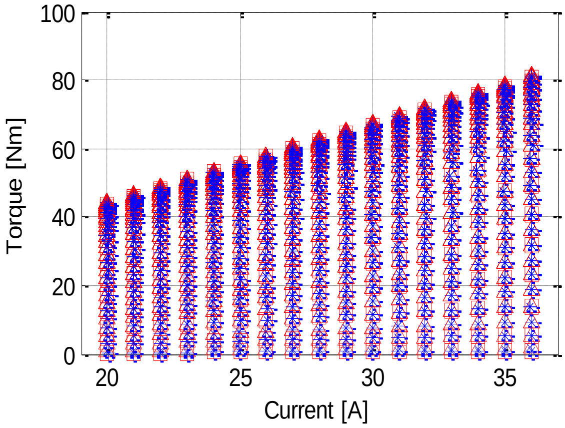


Fig.9- Comparison of target currents and calculated currents by ANN2.

The results presented in Figure 9, show that the developed ANN2 is able to accurately estimate the appropriate level of stator excitations, allowing to give the rotor the target position, taking into account the coupled load.

3.3. Simulation Validation of the Proposed Control Approach

In this section, we propose to perform numerical simulation tests to verify the effectiveness of the proposed control approach. For this purpose, we have used the first network ANN1 to simulate the behavior of the switched reluctance machine through its angular characteristics and we have inserted the network ANN2 to calibrate the stator excitations as a function of both the set position and the magnitude of the coupled load, Figure 10.

The tests carried out consist of applying a well-defined resistive torque to the machine each time and successively varying the position setpoint. The ANN2 neural network then estimates the amount of stator current that must be applied to the machine so that its rotor stops at the target position. To verify this target position by simulation, we have represented the machine by the neural network ANN1, which describes the electromagnetic behavior of the machine through its angular characteristics.

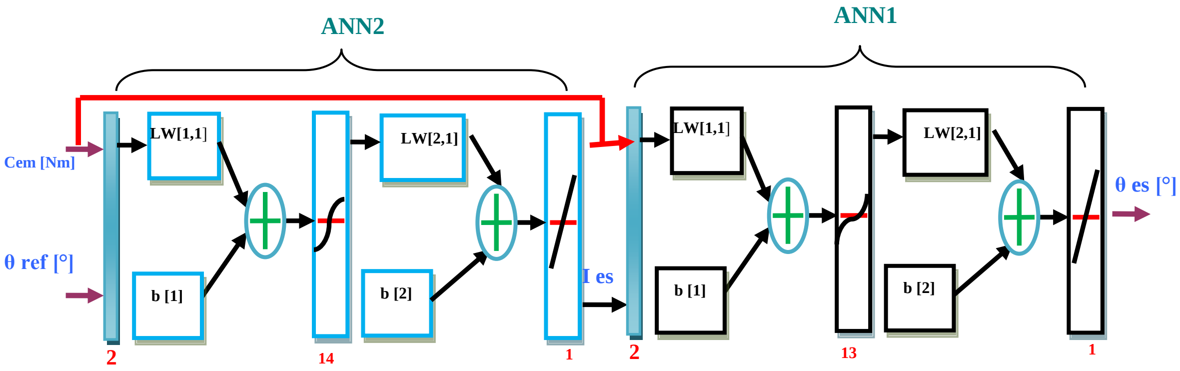


Fig.10- General overview of the proposed control approach

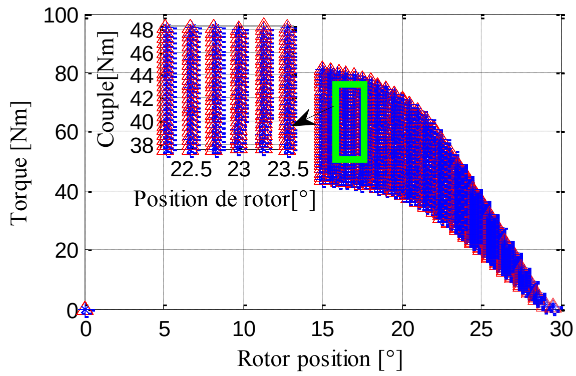


Fig.11-Comparison between the reference and the achieved positions

The result presented in Figure 11 highlight the effectiveness of the proposed control approach for using SRMs as positioning actuators and show that control can provide effective solutions to significantly mitigate natural machine imperfections.

4. Conclusion

The choice of SRM is based on its many advantages, such as excellent performance in extreme environments, simple rotor structure, robustness, no coils, no permanent magnets, no brushes, high overload capability, low manufacturing, repair and maintenance costs, and operation in a wide power range. The problem discussed is how to overcome the constraint of torque ripple for its best use as an electric vehicle drive motor in underground mines to replace highly polluting diesel vehicles.

In this paper, we have proposed a control approach for the operation of the SRM as a positioning actuator. This approach is based on artificial intelligence control techniques and in particular on artificial neural networks. The results obtained show the potential power of the proposed control approach for the exploitation of variable reluctance machines in the positioning domain.

Overall, the presented research demonstrates the potential of artificial neural networks in enhancing the control of switched reluctance motors for high-precision applications, opening new avenues for advancements in positioning system technology.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

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Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.