Interdisciplinary Description of Complex Systems 22(3), 329-340, 2024

IMPROVING SYNCHRONOUS MOTOR MODELLING WITH ARTIFICIAL INTELLIGENCE

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DOI: 10.7906/indecs.22.3.8
Regular article

Received: 22 May 2024.
Accepted: 16 June 2024.

ABSTRACT

Synchronous motors are essential in various industrial and commercial applications because of their efficiency and constant speed operation. Accurate modelling of these motors is crucial for optimizing performance, control, and maintenance. Traditional modelling methods, such as the d-q reference frame method, often fall short in terms of complexity and accuracy, especially under dynamic conditions. This study aims to enhance synchronous motor modelling using machine learning algorithms, specifically focussing on predicting the excitation current, a critical parameter for motor performance.

In this research, a dataset comprising synchronous motor operational parameters was analysed using various machine learning techniques. The primary methods evaluated include regression and M5 algorithms. The evaluation criteria were the time required to build and test the models and the accuracy of their predictions. Our findings indicate that both the regression and M5 algorithms significantly outperform traditional methods, providing more precise and efficient models for synchronous motor behaviour under diverse operating conditions.

KEY WORDS

synchronous motors, parameters, machine learning, prediction, excitation current

CLASSIFICATION

ACM: I.2.6, I.5.1

JEL: C45, C63

PACS: 07.05.Mh

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INTRODUCTION

Synchronous motors are widely used in industrial and commercial applications because of their high efficiency, reliability, and constant-speed operation. These motors work by maintaining a constant rotation speed regardless of the load on the motor. This makes them ideal for use in applications where rotation speed is critical, such as pumps, fans, and compressors.

Accurate modelling of the behaviour of synchronous motors is crucial for efficient operation and control. The models can be used to predict the performance of the motor under different operating conditions and to develop control strategies that optimize the performance of the motor. The models can also be utilized for fault detection and troubleshooting, which helps lower maintenance costs and minimize downtime.

Traditional modelling methods, such as the dq reference frame method, have been used to model the behaviour of synchronous motors. However, these methods are limited by their complexity and accuracy. For example, the synchronous reference frame control, which is also known as the dq control, assumes that the motor is operating in steady state, which may not be the case in practice. In addition, the method is based on a set of nonlinear differential equations that are difficult to solve.

Traditional modelling methods for synchronous motors have some limitations, such as: (i) they often require a significant amount of prior knowledge about the system and can be difficult to implement in practice; (ii) they are based on the assumption that the motor is operating in steady state, which may not be the case in practice; (iii) they are based on a set of nonlinear differential equations that are difficult to solve; (iv) they may not be able to accurately model the behaviour of the motor under different operating conditions; (v) they may not be able to handle the complexity and variability of real-world systems.

Considering these limitations, new methods are needed to improve the accuracy and efficiency of synchronous motor modelling. Machine learning algorithms have the potential to overcome these limitations and provide more accurate and efficient models than traditional methods.

LITERATURE REVIEW

Mathematical equations are frequently used in conventional modelling techniques for synchronous motors to represent the motor’s physical properties. However, these models may have several disadvantages, such as:

- limited accuracy – predictions from traditional models could be inaccurate because the complex dynamics of a synchronous motor is not completely represented by the mathematical equations used in these models.
- having trouble getting model parameters – the physical characteristics of the motor should typically be measured precisely, which can be expensive or difficult to do.
- lack of adaptability – traditional models are less useful in real-world applications because they cannot adjust to changes in the motor’s operating circumstances or physical characteristics.

On the other hand, synchronous motors can be more accurately and adaptably modelled using machine learning methods like neural networks, decision trees, and random forests. Without relying on a priori mathematical equations, these algorithms are able to learn from data and generate predictions. Furthermore, machine learning models can easily represent complicated systems and manage nonlinear interactions.

Synchronous motors have been modelled in several ways using machine learning algorithms. One method is to model the link between the input variables (such as voltage and current) and the output variables of the motor using supervised learning methods, such as neural networks and support vector machines (e.g. torque and speed). These models can be used to forecast the motor's behaviour under various operating situations after being trained on a dataset of measurements taken from the motor.

By utilizing techniques like linear regression, decision trees, support vector machines, and ensembles of trees, the authors in [1] assesses the effectiveness of various machine learning algorithms to develop a torque control method to counteract the effects of changes in temperature parameters of various parts in the synchronous motor.

Robotic arms with permanent magnet synchronized motors (PMSM) are frequently employed in light load applications as industrial, medical, and home service. Because they are likely to be used close to people, these robotic applications need to be able to understand their working conditions for safety concerns. Rotor torque, which is often measured by a torque transducer, is one of the key variables to be looked at while analysing the circumstances. However, the use of such a device comes at an additional cost and requires a large mechanical setup and data collection electronics. The study by [2] provides a machine learning-based solution to predict the rotor torque. In this work, a variety of statistically based machine learning techniques have been used, including regression using neural networks, linear regression, and stepwise regression. The outcomes demonstrated the potential for successfully implementing the suggested senseless torque estimation for robot applications.

The broad adoption of PMSM as the preferred motor for electric vehicles and a variety of other applications requires strict temperature monitoring to prevent increased temperatures. Temperatures below a certain threshold can cause serious operational problems with PMSM, which can increase maintenance expenses. In [3] authors compare the performance of three different machine learning algorithms (support vector regression, random forest regression and polynomial regression) in the estimation of parameters in a permanent magnet synchronous motor.

For some time, monitoring the magnet temperature in PMSMs for automotive applications has been a complicated issue because signal injection or sensor-based approaches are still not practical in a practical setting. The major motor damage from overheating is a serious worry for the machine's control scheme and design. Lack of accurate temperature predictions results in reduced device usage and greater material costs. The accuracy of the estimation of multiple machine learning models for the purpose of forecasting latent high-dynamic magnet temperature profiles is empirically examined in [4, 5].

THE SYNCHRONOUS MOTOR

Typically, an electric motor is a device that transforms electrical energy into mechanical energy. An alternating current (AC) motor is an electric motor that, as a basic construction element, contains a stator with a coil supplied with alternating current to convert the electric current into mechanical power. AC motors are divided into asynchronous and synchronous motors. In both types, there are alternating currents in the stator conductors that create a rotating magnetic field [6].

The magnetic stator circuit, as well as the stator windings of asynchronous and synchronous machines, are identical in everything. In both cases, the three-phase AC system of the stator creates a rotating field whose speed is determined by the circular frequency of the supply. Synchronous and asynchronous machines differ in the construction of the rotor. The rotor winding of asynchronous machine is usually a cage consisting of aluminium rods placed in the grooves of the rotor. The synchronous motor (SM) has an excitation winding, whose direct current creates rotor flux. Instead of excitation winding, the rotor of synchronous machine may have permanent magnets built into the magnetic circuit of the rotor [7].

The rotor of synchronous motor is an electromagnet or a permanent magnet. The position of the rotor flux is therefore uniquely determined by the position of the rotor. The rotor rotates synchronously with the rotating magnetic field and creates a moment proportional to the vector product of the stator and rotor fluxes. Synchronous rotation of the rotor and the field is the reason for the name synchronous machine [7].

A synchronous motor contains an inductor, like the inductor of a direct-current (DC) motor, where the inductor winding is supplied with a DC current. The inductor of this motor is like the inductor (stator) of a three-phase asynchronous motor and is powered by a system of three-phase symmetrical voltages of constant frequency. Its rotation speed is equal to the synchronous speed, which corresponds to the frequency of the power supply and is independent of the load moment. The main problem of this type of machine is commissioning, because its starting moment, with the usual construction, is small. In order to increase that moment, a cage is usually placed on the side of the inductor along with the excitation winding. This cage enables asynchronous mode of operation when the motor starts up to synchronous speed. Another way to overcome the initial problem of a synchronous motor is to connect it to a DC motor, which in this case has the task of bringing the synchronous motor to synchronous speed [7].

A synchronous motor has a constant rotation speed that does not depend on the mechanical moment, but only on the frequency of the power supply and the number of pole pairs. Due to this feature, the area of application of the synchronous motor is oriented to those drives where no change in speed is required. Particularly interesting is the case where the engine is idle (without electromechanical conversion), when reactive energy is produced (power compensator). Such drives are often used because of their significant advantage over other motors, contained in the fact that they can produce reactive energy and thereby im-prove the power factor (cos φ) of the entire plant. With a permanent load, when a constant rotation speed is required, the task of choosing an electric motor is quite simple. In this case, it is best to opt for a synchronous motor. This motor, for these driving conditions, proves to be economical [8].

Unlike an asynchronous motor (runs only at a lagging power factor), a synchronous motor has the significant characteristic, such as ability to operate at any power factor leading, lagging or unity over a broad range, which can be easily tuned with the aid of altering its excitation current. There are three main operating states [9]:

1) **Over excitation.** The characteristic of this condition is that the field excitation (E_f) is such that $E_f > V$. The armature (stator) current leads the supply voltage (V) and the SM supplies lagging reactive power to the system. SM behaves like a condenser and improves the power factor of the system (reactive power compensator). So, motor power factor is leading.
2) **Normal excitation.** If $E_f = V$, then the SM is said to be normally excited. In this scenario, the reactive power (Q) of the motor is null, indicating that the motor is not consuming or supplying reactive power. Consequently, the motor operates at a power factor of one. At unity power factor ($\cos \varphi \approx 1$) for a specific load, the resultant voltage (Er), and consequently, the armature current are minimized.
3) **Under excitation.** In the case of under-excitation, SM is described as having a field excitation where $E_f < V$. In this scenario, the armature current lags behind the supply voltage (V) and draws lagging reactive power ($\cos \varphi < 1$), leading to a lagging power factor for the motor.

PARAMETRIC MODELLING OF SYNCHRONOUS MOTOR

Modelling of SM by parameters under various operational situations is a challenging problem. Most correlations between parameters are complex. Different methods have been proposed for modelling and/or predicting the excitation current: artificial intelligence (AI) based nonlinear techniques, such as PID controller [10], pulse width modulation [11, 12], fuzzy logic [13, 14], Kalman filter-based methods [15, 16], artificial neural networks and adaptive artificial neural networks [17, 18, 19], particle swarm optimization [20], k-nearest neighbour (k-NN) estimator and genetic algorithms [21, 22].

AI-based solutions have proven to be efficient, however in real environment implementations, these models encountered serious problems. The results of the simulations and experimental applications had significant differences. Compared to real-time contexts, the response time in simulation environments was quicker. The functionality of the microprocessor or digital signal processor and the motor drivers' switching frequency also played a role in this. These factors limit the response times of real-time applications [23]. AI-based models also have a negative impact on the response times of real-time applications and simulation environments.

Five parameters used in this paper to describe the operational behaviour and model the SM are: (i) load current, (ii) power factor, (iii) power factor error, (iv) variation in excitation current, and (v) excitation current. Among the parameters specified, the excitation current is designated as the target (output), while the remaining parameters are considered inputs. To investigate the impact of input parameters on the variable output, the following steps [24] was conducted:

1) The test SM is driven by an auxiliary (pony) motor (inductive load). Besides, a serial rheostat is also utilized to manually create a variable DC supply in the field circuit.
2) An AC voltage is utilized to the stator windings till the rotor speed is close to the synchronous speed.
3) A DC voltage is connected to the winding and thus begins the synchronous operation of the motor.
4) After the synchronous speed, the field current is adjusted to a minimum by changing the value of the rheostat.

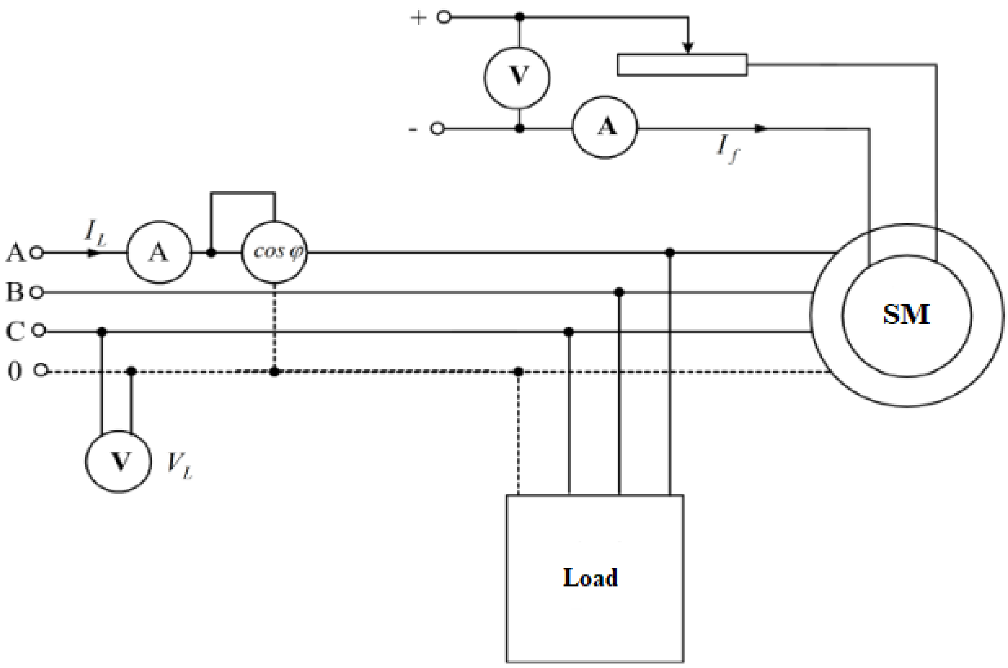

Figure 1. Parameter measurement scheme [24].

After realizing these steps, the motor draws minimum current from the network, the efficiency is maximum, and the power factor is at unity. To determine this value, the field current is adjusted by the rheostat. In such a way, the load and voltage remain constant. These measurements are repeated several times with different loads. The input and output parameters are measured and recorded by the test equipment [14, 22], thus forming a data set (in CSV format, with 557 instances).

The main goal of this article was to identify the appropriate algorithms in the domain of machine learning that require the least time to build and evaluate the model and that result in the most accurate predictions of the excitation current of SM. In this sense, an appropriate dataset [25] was used for the analysis and the Weka (Waikato Environment for Knowledge Analysis) software package to model and test the parameters of SM. Weka is appropriate for this use since it has a variety of visualization tools and algorithms for data analysis and predictive modelling that are simple to apply with the dataset in question.

MODELLING EXCITATION CURRENT OF SYNCHRONOUS MOTOR BY ML ALGORITHMS

The development of control functions requires a deep understanding of the traditional models of systems and processes, which are frequently based on physical and mathematical tools. To compensate for changes in work, a trained machine learning model built on an effective algorithm can automatically adapt the parameters of motor power drivers. In general, the most typical types of issues with machine learning implementations are the following:

Classification: the process that seeks to forecast discrete values (for example, efficiency {maximum, not maximum}, {true, false}, motor speed {synchronous, not synchronous}).

Regression: the process whose aim is to forecast continuous values.

Forecasting: creating forecasts based on historical and current data (used to analyse trends).

The two basic groups of machine learning algorithms are typically supervised and unsupervised algorithms. Based on a set of examples, supervised learning algorithms generate predictions. In the case of supervised learning, there is a desired output variable and an input variable made up of labelled training data. Unsupervised learning uses entirely unlabelled data, which is fed to the model. It is crucial to identify the fundamental patterns within the data, such as clustering structures, low-dimensional manifolds, or sparse trees and graphs.

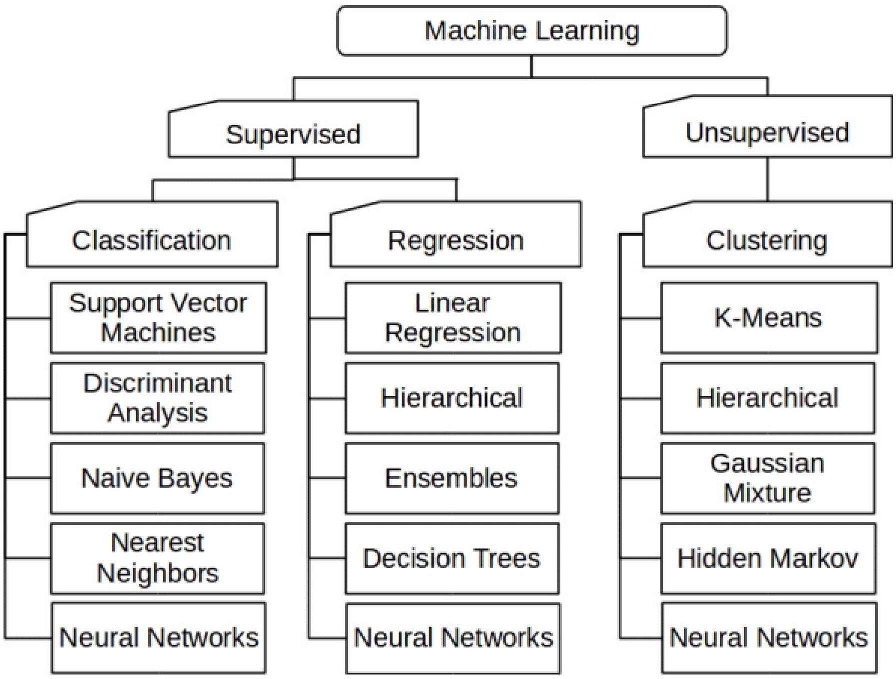

Figure 2. Classification of the most common machine learning algorithms [26].

In addition to the previously mentioned two groups, there are also algorithms for semi-supervised learning and reinforcement learning. The practical issue with supervised learning is that it can be expensive and time-consuming to label data. Unlabelled samples with a modest amount of labelled data are used to increase learning accuracy when labels are scarce. Semi-supervised refers to the fact that the machine in this instance is not fully supervised.

Most solutions employ reinforcement learning for sequential decision-making. Contrary to supervised and unsupervised learning, this type of learning does not require any prior data. Instead, the learning agent interacts with the environment and discovers the best course of action depending on the environment's response.

The classification process consists of following steps:

- loading and filtering the dataset – prior to training a model, input and output variables are rescaled using techniques like normalization and standardization. The practice of arranging data in accordance with several normal forms to decrease redundancy and enhance data integrity is known as normalization (unsupervised attribute filters),
- training and test sets from the original data,
- classifier evaluation.

After running the classification test on the SM data set, Weka software generates the appropriate summary (given in Figure 3). The aggregate result of all performed tests is shown in the following tables. During testing, the test data option was used to form the model, while the parameter being tested is set to the excitation current (I_f). The training set option was employed, with the training and testing data split set to 66% (the default value).

```
Attributes (explanation): load current (Iy), power factor (pf), power factor error (e), variation in
excitation current (d1f), and excitation current (If).
     === Run information ===
     Scheme:       weka.classifiers.trees.RandomForest -P 100 -I 100 -num-slots 1 -K 0 -M 1.0 -V 0.001
-S 1
     Relation:     Synchronous machine1-weka.filters.unsupervised.attribute.Normalize-S1.0-T0.0
     Instances:    557
     Attributes:   5
                   Iy
                   PF
                   e
                   dIf
                   If
     Test mode:    evaluate on training data
     === Classifier model (full training set) ===
     RandomForest
     Bagging with 100 iterations and base learner
     weka.classifiers.trees.RandomTree -K 0 -M 1.0 -V 0.001 -S 1 -do-not-check-capabilities
     Time taken to build the model: 0.3 seconds
     === Predictions on training set ===
         inst#     actual  predicted      error
             1      1.563      1.564      0.001
             2      1.552      1.552     -0
             3      1.54       1.542      0.002
     === Evaluation on training set ===
     Time taken to test the model on training data: 0.73 seconds
     === Summary ===
     Correlation coefficient                0.9999
     Mean absolute error                    0.0014
     Root mean squared error                0.0018
     Relative absolute error               0.8984 %
     Root relative squared error           1.0239 %

        Total Number of Instances            557
```

Figure 3. Summary of classification test results generated by Weka software.

The classification results are shown in Table 1 (the best algorithms are marked). The accuracy of the prediction is expressed through the relative absolute error, the difference between the actual and predicted values.

Table 1. Characteristics of categorized learning algorithms examined on the SM dataset.

Classifiers – learning algorithms	**Time to build model, s**	**Time to test model, s**	**Prediction error, %**
Functions			
Gaussian processes	0.5	0.38	10.1867
Linear regression	0.01	0.19	0
Multilayer perceptron (NN)	0.31	0.19	1.1558
Simple linear regression	0	0.19	0
SVR (Support Vector Machine for regression)	0.05	0.25	0.1622
Lazy classifiers			
k-nearest neighbours (k-NN)	0	0.23	9.6684
k-star (k*)	0	0.44	9.6684
Locally weighted learning (LWL)	0	0.75	47.6729
Metalearning algorithms			
Additive regression	0.01	0.19	21.1939
Bagging	0.06	0.23	1.6368
Cross-validation parameter selection	0	0.19	100
Multi-scheme selection using error on training data	0	0.2	100
Random committee	0.1	0.27	2.3601
Randomizable filtered classifier	0	0.22	13.4059
Random subspace	0.04	0.2	9.453
Regression by discretization	0.03	0.56	12.6173
Stacking	0	0.2	100
Vote	0	0.2	100
Weighted instances handler wrapper	0	0.19	100
Miscellaneous classifiers			
Input mapped classifier	0	0.32	100
Rules			
Decision table	0.05	0.27	12.6173
M5	0.23	0.27	0
ZeroR	0	0.25	100
Time Series			
Holt-Winters triple exponential smoothing	0	0.22	125.9974
Trees			
Decision stump	0	0.22	55.3224
M5 reduced (pruned) model	0.05	0.23	0
Random forest	0.14	0.28	1.6352
Random tree	0.01	0.22	3.7205
REPTree	0.01	0.22	3.4971

As is known, regression is a machine learning technique that uses continuous numerical values to predict the result. Regression analysis is frequently applied in many fields to determine the relationship between a single dependent variable (the target variable) and several independent variables. Considering the results presented in Table 1, the regression algorithms (linear regression and support vector regression) showed excellent applicability to the parametric data on the synchronous motors. Abbreviated time to form a model with these algorithms is a significant advantage in terms of updating the decision models i.e., speed of adaptation to new operational situations.

The known advantages of M5 model trees are that they generate more accurate predictions than regression trees, are easy to use and train, are robust when dealing with missing data, can manage large number of attributes and high dimensions. Both M5 algorithms confirmed the specified characteristics with their results from the Table 1.

In addition to the previous testing, the authors were interested in how the percentage split (training set/testing set) of data affects the results. In this sense, the algorithms that showed the best results in the previous analysis were evaluated and the following situation was obtained, Table 2.

Table 2. Examination of the influence of percentage split on prediction accuracy.

Classifiers – learning algorithms	**Time to build model, s**	**Time to test model, s**	**Prediction error, %**
Linear Regression			
40 %	0.13	0.45	0
50 %	0.02	0.38	0
60 %	0.02	0.23	0
70 %	0.02	0.19	0
80 %	0	0.14	0
SVR			
40 %	0.06	0.42	0.2708
50 %	0.03	0.33	0.1495
60 %	0.04	0.27	0.1524
70 %	0.03	0.22	0.1672
80 %	0.04	0.16	0.2177
M5			
40 %	0.09	0.38	0
50 %	0.06	0.33	0
60 %	0.05	0.23	0
70 %	0.03	0.2	0
80 %	0.03	0.13	0
M5 pruned			
40 %	0.02	0.36	0
50 %	0.01	0.28	0
60 %	0.03	0.23	0
70 %	0.02	0.19	0
80 %	0.02	0.11	0

Based on the obtained results, it can be concluded that the percentage split does not significantly affect the accuracy of the prediction.

Clustering can be understood as dividing of data points into a group (or cluster) of similar objects. Objects within each cluster are alike but differ from those in other clusters. In order to examine the clustering capabilities of the used SM data, several clusters enabled by Weka were analysed. The tests yielded the following results shown in Table 3 and the best results are marked.

These results show that the category of hierarchical clustering (Cobweb and hierarchical clusterer) is the most suitable approach to enhance classification accuracy of the SM data set.

Table 3. Clustering test results.

Clusterer	Accuracy, %	Time to build model (full training data), s
Canopy	53	0
Cobweb	100	0.06
Expectation-maximization (EM)	10	39.18
Farthest first	71	0.01
Filtered clusterer	53	0
Hierarchical clusterer	85	0.34
Density based (DBSCAN)	54	0
Simple k-means	53	0

CONCLUSION

This article proposes the use of machine learning algorithms for modelling synchronous motors. Synchronous motors are widely used in industrial and commercial applications, and accurate modelling of their behaviour is crucial for efficient operation and control. However, traditional modelling methods, such as the synchronous reference frame method, have limitations in terms of complexity and accuracy.

The goal of this paper was to, using a suitable data set, examine the possibility of applying machine learning algorithms to model a synchronous motor and predict its excitation current.

The following criteria were used to evaluate the suitability of the algorithms: the time to build and evaluate the model, as well as the accuracy of the prediction. Based on the test results, the most suitable algorithms for synchronous motor simulation were determined. It has been shown that regression and M5 algorithms have the best suitability for describing the behaviour of synchronous motors. It was demonstrated that varying the percentage split between training and test data does not notably impact the prediction accuracy of the employed algorithms. We also investigated the possibility of clustering synchronous motor data and found the best clustering algorithms for this use.

The application of machine learning algorithms for modelling synchronous motors shows significant promise. These models can accurately predict excitation currents, thereby optimizing motor performance and operational efficiency. Future research could focus on refining these models further and evaluating them in industrial settings to validate their effectiveness and reliability. The insights gained from this study provide a solid foundation for developing advanced control strategies for synchronous motors using machine learning techniques.

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