International Journal of Scientific Research and Engineering Development-– Volume 6 Issue 1, Jan-Feb 2023

Available at www.ijsred.com

RESEARCH ARTICLE OPEN ACCESS

Prediction of Excitation Current in a Synchronous Motor Using Machine Learning

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***Abstract*:**An electro-mechanical converter called a synchronous machine consists of a stator and a rotor. A synchronous machine's stator, which is formed of phase-shifted armature windings in which voltage is produced, is its fixed component, and its rotor, which is built of permanent magnets or electromagnets, is its revolving component. To maintain the smooth and high-quality functioning of the synchronous machine itself, the excitation current is a crucial parameter that must be constantly monitored for potential value changes.. The goal of this study is to use artificial intelligence methods to predict the excitation current utilising the following input parameters: Iy: load current; PF: power factor; e: power factor error; and df: change of excitation current of synchronous machine. Random forest was the method employed in this study, and it produced the best results, with R2 2 = 0.9963, MSE = 0.0001, and MAPE = 0.0057, respectively.

Keywords: Forecast, Bills, Consumption, Lasso, Monthly.

I. INTRODUCTION

Electromechanical devices known as electrical machines are able to change one form of energy into another [1]. EMs may be divided into single-phase and three-phase machines depending on the kind of input [2], with synchronous (SM) and asynchronous machines being the two most used kinds of three-phase electric machines (AM). A stator, the static component of an electrical machine (EM), is made of phase-shifted coiled poles, and a rotor, the rotary component, is formed based on the duties the machine is supposed to do.. While SMs are typically used to produce electricity in fossil fuel power plants [10,11,12] or in renewable energy plants, such as hydroelectric power [13,14] and wind power [15,16], AMs are most frequently used as motor-driven machines [3,4,5] in the automotive industry [6,7], construction [8,], elevators [9], etc. Alternating current (AC) must be used for energy transmission from the source to the ultimate user [17]. Direct current (DC) is preferable than AC for the reasons listed below [17,18]:

• AC transmission facility costs (switches, transformers, etc.) are far lower than similar DC transmission. • AC voltage for transmission and distribution is simple to modify and maintain.

•Why Using AC rather than DC rather than converting is preferable since the power plant provides AC electricity.

•Because the sinusoidal current tends to zero at a given point, disconnecting an AC system in the event of significant network problems is simpler.

An SM has two characteristic parts, the armature on the stator and the excitation on the rotor where the armature winding (most often three-phase) is symmetrically distributed in slots around the circumference of the machine and indicates the part of the machine in which the changes of the magnetic flux induce a voltage [19

Using AI more precisely, fuzzy logic in combination with ANN represents an advanced method that is applied for AM control logic. AM is a nonlinear machine, where the influence of temperature, age, and additional vibration elements related to electromagnetism affect the operation of the machine.

After training the resulting RF with 394 samples and testing with 200 test data, the estimation accuracies are found to be approximately similar to those reported in [9, 11, 12] despite having less number of hidden layers and neurons. It is stressed in [14] that artificial intelligence (AI)-based models produce good estimation results, but they cause problems in a real-time implementation such as increased computation burden, delay time resulting from a complex calculation process and the difficulty faced in realization of such complex models in real-time. To amend these problems, multiple linear and nonlinear regression models are developed in [14] in order to create the most representative mathematical equation for estimating the SM excitation current If with regard to the considered input parameters $<IL$,pf, e, $\Delta If>$, where the relationship among the SM parameters are regarded as mostly complex and nonlinear task [15-17]. To optimize the regression coefficients in the proposed models, genetic algorithm (GA), artificial bee colony (ABC) and gravitational search algorithm (GSA) are applied individually. It is shown that the proposed two models are simpler and more effective than other published studies [9, 11, 12], where GSA-tuned quadratic regression model is the pioneer for the estimation of excitation current which is followed by the models based on ABC and GA, respectively. In the study, it is also presented which verify that presented models have improved the response time compared to those using RF.

II. LITERATURE REVIEW

Mutoh R et. Al [4] This study suggests that both continuous and discrete features are treated equally well. There are methods of constructing trees according to data with omitted values of features. High scalability of the method. Disadvantages of the Random Forest method [39-48]: The algorithm tends to relearn on some tasks, especially with a lot of noise in the data set; Learning large numbers of deep trees can be costly (but can be parallel) and use a lot of memory.

Syahputra, R et.al [5] stated that Over the years, the importance of monitoring component temperatures as a critical indicator of the performance of electric motors and controlling the consumption of electrical energy necessitated the deep and extensive study of these electrical machines. Several techniques have been applied to measure and control temperature, including direct sensorbased measurements which yield satisfactory results for the stator part and is easily implemented on the stator.

III. OBJECTIVES

Identify a reliable test bench dataset of a Excitation current SM, perform pre-processing and exploratory data analysis to understand the data and extract preliminary insights.

- Apply random forest regressor and decision trees regressor algorithms to estimate the excitation current in the synchronous motor. .

Compare and evaluate the results from the data set to check the MAPE values

IV. METHODOLOGY

In the Materials and Methods section, the SM used for data collection is presented. The dataset is described as well as the input and output variables. The input data and statistical analysis before the actual use of ML algorithms are presented. Additionally, the potential challenges are indicated, and the importance of AI implementation is highlighted.

A. Potential Challenges When Modelling a Synchronous Motor

In modern EM modelling, the contribution of Štumberger et al. , Kron [is important, in which the general theoretical background for EM modelling is outlined. The generality of Kron's tensor-based approach diminishes when using matrices. By using matrices, EMs are mostly treated as magnetic (deterministic) linear systems, while nonlinear properties are ignored. However, to create positive ratios between measured and calculated results, nonlinear theory must be included in the model of the SM.

A complete thermal analysis would require full CFD/FEM coupling. As for the modelling of the SM, the turn insulation in the field winding in the case of the silent pole synchronous machine (generator) is thin, so it is often neglected in calculations. However, surface insulation is of similar dimensions, almost equal to the surface of the conductor, so it would affect the result of the heat calculation. On the other hand, the calculation of the temperature field of a synchronous machine with silent pole rotor insulation in terms of the insulating layer is often neglected; even with little insulation there is a temperature drop, which can affect the modelling of the EM itself .

This subsection highlights the limitations of calculations when modelling or estimating EM. This highlights the importance of using AI algorithms for the optimization or estimation of synchronous machine parameters. AI algorithms are based on the data contained in the dataset, and the more data the dataset (algorithm) has, the greater the robustness and readiness, as well as the accuracy of the obtained model. In this work, the parameters of the used synchronous motor and the statistical analysis and distribution of data for input into the AI model are described.

B. General Information about SM

As presented in the introduction of this paper, all AC machines consist of a stator and a rotor. The main difference between AM and SM is the speed of rotation of the rotor, which in the case of SM, as the name indicates, rotates synchronously. This means that there is no delay in the rotating magnetic field of the rotor relative to the stator. In terms of the design of the rotor, SM has two versions. The first one is the salient pole [**48**] shown in **Figure 3.1**, and the other one is the non-salient pole (round/cylindrical) rotor [**49**] shown in **Figure 3. 2**.

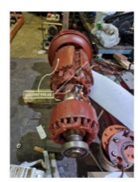


Figure 1 Salient-pole type rotor SM.

Figure 2 Round rotor type SM

Figure 3.2 shows the section of the rotor and stator (armature) inside the SM. The figure shows the position of the rotor field winding for both configurations and the position of the polarization for both designs.

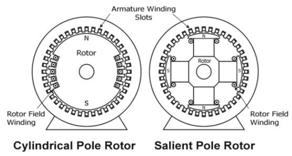


Figure 3 Representation of the salient pole and cylindrical pole rotor type SM

The overall configuration is shown in **Figure 3.4**, which shows each component of the SM operation. In **Figure 3.4**, every part of SM is visible. To create a rotating magnetic field with a phase shift of 120 degrees, a three-phase voltage is required, with each phase marked as a, b, c and a', b', c'. The dotted dashed lines indicate the position of the phased coils, while the hatched part indicates the location of the conductors located in the armature SM.

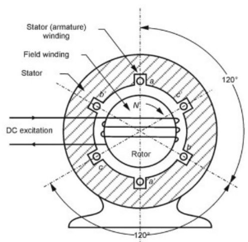


Figure 4 The basic operation of SM

The working principle of SM is based on the establishment of a magnetic field that rotates at a synchronous speed, as follows:

n=120·fp.=120·.(1)

As shown in Equation (**1**), the speed of the rotating magnetic field of the stator depends on two factors f which are the frequency of the rotating magnetic field and p the number of poles. If the speed of the rotor (magnetic field caused by the DC component) [**50**], and the speed of the rotating magnetic field of the rotor are equal, under the condition that there is no load torque, both magnetic fields will tend to align against each other. When the load is applied, the rotor lags a little, i.e., "slips" by a certain degree, but at the same time adheres to the revolutions of the rotating magnetic field . The achievement of the highest torque is due to the relationship between the magnetic field of the rotor and the stator, which attempt to maintain a value of 90 degrees, as can be seen from **Figure 5**.

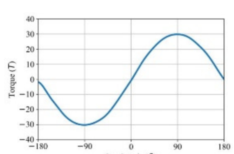


Figure 5 The effect of load angle on produced torque

Figure 3.5 shows the production of torque (T) under the effect of load angle (δ); it is visible that when SM has an angle of 90 degrees, the maximum T is produced .

T=Tmax·sin(δ). ·sin(). (2)

In addition to displaying the maximum torque at a rotor angle of 90 degrees [2], it is possible to calculate the current torque using Equation (**2**), where:

- T is the calculated torque.
- Tmax is the maximum torque for SM.
- sin(δ)sin () is the sinus function of load angle.

C. Operation Conditions and Dataset Collection

So far, the general view of SM has been described, but it is also important to describe the working conditions of the synchronous motor in which the measuring of the parameters is performed. The working conditions of the SM (synchronous motor regime of work) that were measured are shown and described in **Table 1** [**2**].

Table 1 Operating properties of experimental synchronous motor used in this research.

Condition			
Star connected motor (Y) voltage [V]	Star connected motor (Y) current [A]	Triangle connected motor (Δ)	Star connected motor (Y) current [A]
400	5.8	231	10
Power factor (cos ∅)			
0.8			
Apparent power (kVA)			
4			
Revolutions per minute (rpm)			
1000			

An auxiliary motor is used to drive the synchronous motor in the test rig. In the star connection (YY), the motor has a voltage of 400 V with a 5.8 A current. In the delta connection (ΔΔ), the values are different, and the voltage amount is 231 V with a current of 10 A. The values for the power factor (cos ∅), apparent power, and revolutions per minute (rpm) are the same, at 0.8, 4 kVA, and 1000, respectively [**2**].

The data collection procedure for the synchronous motor is shown in **Figure 1.6** of this investigation, and it was conducted in the following four steps: firstly, the motor was used as an auxiliary motor in a laboratory environment, while a series rheostat was used to obtain information about the DC supply variable in the field circuit (If). Secondly, using the AC voltage, the stator windings of the synchronous motor are powered to achieve a synchronous speed. In the third step, DC voltage is applied to the field winding of the synchronous motor, and the motor enters synchronism. In the last step, synchronous speed is realized, and the field current is modified to the minimum value (using a serial rheostat connected in series to the field circuit.) After performing all the steps, the motor takes the minimum current value from the power supply and obtains the maximum efficiency with a stable power factor [**52**].

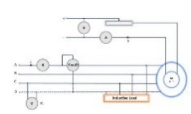
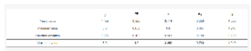


Figure 6 The scheme of work for the experiment with an SM.

The previously described data are sufficient for the description of the dataset collection process and the dataset creation; however, it is also recommended to additionally analyze the dataset with the aim of obtaining better insight into the state of the variables and their interrelationships. In **Table 2**, there are four specific values that were analyzed for each individual variable, namely the mean value, minimum value, standard deviation, and maximum value.

Table .2 Dataset analysis used in research.



The mean value represents the mean value in each variable, the minimum represents the lowest measured value, while the maximum represents the highest measured value. It is especially important to analyze the standard deviation of the data. This is performed to consider the possibility of implementing the pre-processing methods for the input variables of the dataset, which were Iy, PF, e, and df for the estimation of the target variable If. **Table 2** shows that the deviation of the data is not too high, while the mean value of the data is mostly above the ideal mean value (concerning the minimum and maximum value of the individual variable). This leads to the conclusion that it is not necessary to perform data pre-processing. Further on, the training of the AI model is performed using the original dataset values for each variable.

Furthermore, in addition to defining operating conditions and statistical analysis of data, it is necessary to consider the distribution of data in each variable, so starting from Iy shown in **Figure 7**, the distribution of data for each variable was analyzed.

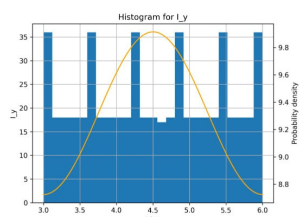


Figure 7 Data distribution/histogram for Load current in the dataset, the histogram consists of an analyzed parameter as the number of inputs with the given value.

Figure 7 shows a histogram plot of the data distribution for the Iy parameter. The blue bars represent input bins while the orange curve represents the best-fitted distribution for the given data. In statistics and probability theory, this form of data distribution belongs to Von Mises lines, also known as a circular normal distribution, and is a continuous probability distribution of the circle. It is a close approximation of the wrapped normal distribution, which is the circular analogy of the normal distribution. The circular analogy can be seen by the repeating peaks of individual values (interval maximum values of individual bar plots). The Von Mises probability density function can be presented as follows:

f(x|μ,κ)=eκcos(x−μ)2πI0(κ),(3)

where is:

- x, angle of the density function.
- μ is a representation of measure location (the given cluster distribution around μ);
- κ is a representation of the measure concentration.
- I0(κ)0() is the modified Bessel function with order zero.

Figure 8 shows the data distribution related to PF and e. Based on the entered data, the best possible distribution function corresponds to the Three-Parameter Kappa distribution. In statistics, K-distribution or Kappa 3 distribution is a family of continuous probability distributions that consists of three parameters and is constructed by combining two gamma distributions. The probability density function is presented as follows:

f(x,a)=a(a+xa)−(a+1)/a, ,(4)

for $x > 0$ and $a > 0$ and a and x are the shape parameters of the function.

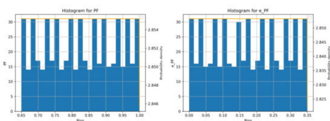


Figure. 8 Data distribution/histogram for power factor PF and power factor error e in the dataset, the histogram consists of an analyzed parameter as the number of inputs with the given value.

In the case of an If and df of the SM, the distribution of data is slightly different than in the previous cases. By observing **Figure 9**, it is evident that the distribution of the data resembles a standard Gaussian distribution; however, due to the shift of the data for a certain parameter, the best-fitted distribution is Johnson's SB distribution. From **Figure 9**, it is evident that the highest ratio of data is at smaller values. The probability density function can be represented mathematically as follows:

f(x,a,b)=bx(1−x)ϕ(a+blogx1−x), (5)

where:

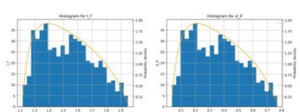


Figure 9 Data distribution/histogram for excitation current If and changing of excitation current df of synchronous machine; the histogram consists of an analyzed parameter as the number of inputs with the given value

- x, a, and b are real scalars.
- $b > 0$ and $x \in [0, 1]$ is the probability density function of the normal distribution.
- ϕ is the cumulative distribution function of the normal distribution.

At the given distribution of data, shown in the histograms in **Figure 7**, **Figure 8** and **Figure 9**, the first logic attempt is to train the ML model without data pre-processing. The given dataset has favourable conditions for training ML algorithms, and in this paper, the prediction of If is performed with the non-pre-processed dataset

V. SYSTEM ARCHITECTURE

. Linear models, ensembles, and even more complex Hyperparameter optimization was performed using randomly selected hyperparameters and by training the model using the grid-search (GS) and was validated using 5 k-fold cross-validations. During this research, the Python programming language and scikit learn library (known as sklearn) version 1.0.2 were used. The aforementioned Python library holds all of the used machine learning algorithms (the exception was the extreme gradient boosting regressor), whereby an initial investigation was conducted using default hyperparameters for individual algorithms. After the initial investigation, the hyperparameter optimization was conducted using random values that are presented in each table for every algorithm used, where the used algorithms are as follows:

A. Random forest regressor (RFR).

The algorithm will be described in a separate subsection where the hyperparameter values used for training the model will be shown. During the investigation, the following two search methods were applied: the initial search with default hyperparameters, and then the randomized hyperparameter search. After the initial search, all the algorithms were optimized using GS and cross-validation.

1. . Extra Trees Regressor

ETR belongs to the group of ML ensemble methods that combines predictions from multiple decision trees. It belongs to a random forest algorithm although it is based on a simpler approach where each member is a decision tree. In this case, the mentioned algorithm often results in a similar or better result than the base algorithm, which is the random forest algorithm. ETR trees differ from the usual decision trees in terms of the principle of building the tree itself. The search for the best division for separating the hub samples into two rough ones is drawn for a random division of the selected features, i.e., max_features, and the best division among them is selected . The varied hyperparameters of the algorithm are visible in **Table 3** and are varied based on previous research according to [2]

Table 3 An overview of the varied hyperparameters used for the ETR

Parameter Name	Minimum Value	Maximum Value
n_estimators	1000	10,000
criterion	squared error, friedman_mse	
max_depth	None	
min_samples_split	2	10
max_features	auto, sqrt, log2	
random state	0	93

The criterion is a quality measurement of split data. For this kind of decision tree algorithm, supported criterion inputs are squared error for the mean squared error (MSE) and fried man mse for the improved Friedman mean squared error. The main difference between these two criteria are that the Friedman MSE calculates the impurity of the current node which leads to a reduction in the leaf impurity. The number of trees that ETR produces is regulated with n_estimators. Max_depth indicates the maximum depth of the tree. It was set to none where the main reason was to remove all of the leaf impurities from the tree. Max_features is the number of considered features when looking for the optimal split. Input values can be sqrt, log2, integer, or float number. Random state controls the randomness of the instance of bootstrapping samples while building trees and the feature sampling for consideration when looking for optimal node split, and draws the splits for maximum features. The lowest value of the sample number for splitting the internal node is defined with minimum samples split. If the given value is an integer, then minimum samples leaf is considered as the minimum number; in the case of the float value, the minimum samples split is considered as a fraction.

2. Elastic net Regressor

EN belongs to the group of linear models of the scikit library where the regression process uses the penalties from both lasso and ridge techniques. This technique provides a learning spares model, where several weights are not 0 as is the case in lasso, while still maintaining the regularization characteristic from the ridge. The combined technique from lasso and ridge regression methods helps to overcome the deficiency and improve the statistical regulation model . During the investigation of this AI algorithm, the parameters shown in **Table 4** were varied according to

Table 4 An overview of the varied hyperparameters used for the EN

Parameter Name	Minimum Value	Maximum Value
alpha	0.1	10
l1_ratio	0.1	10
max_iter	1000	10,000
selection	random, cyclic	

Alpha constantly multiplies the penalty terms if its value is set to 0.0; then, the mathematical meaning of this parameter is equivalent to a linear ordinary least square regression. The elasticnet l_1_ratio is the mixing parameter between 0.0 and 1.0. The maximum number of iterations is maximum iteration set to 10,000. The selection parameter is the coefficient updated for every iteration by choosing the right coefficient of selection, and the results often converge faster.

3. K-nearest Neighbour Regressor

The k-NN algorithm is one of the decision tree supervised ML algorithms based on determining the local minimum of the target function that is used to learn the unknown function with precision and accuracy. The decision system essentially calculates the distance between data points in space. It relies on observable data similarity and near-distance metrics for accurate prediction generation When modelling k-NN based on research in the parameters shown in **Table 5** were varied.

Table 5 An overview of the varied hyperparameters used for the k-NN

Parameter Name	Minimum Value	Maximum Value
n_neighbours	1	1000
weights	uniform, distance	
leaf_size	1	1000
algorithm	auto, ball_tree, kd_tree, brute	
p	2	50

N neighbours is the number of neighbours data in the decision tree. There are three ways in which the weights of the prediction function are distributed, which are uniform, inverse, and callable. The computation of the closest neighbours is achieved with an algorithm. The eaf -size can be used in BallTree or KDTree. It can be used to determine the memory of a given leaf of the tree as well as speed up the construction of the building process.

4. Linear Regressor

LR is better known as the ordinary least squares method. The method consists of establishing a correlation between the dependent variable and the independent variable, where the best approximation fits a straight linear line The variation of parameters is presented in **Table 6**.

Table 6 An overview of the varied hyperparameters used for the LR.

Parameter Name	Minimum Value	Maximum Value
fit_intercept	True, False	
normalize	True, False	
positive	True, False	

Fit intercept calculates the intercept for the given model. Normalize is used for normalization of the input parameter, and positive is used if the True forces modulation coefficients are positive.

5. . Random Forest Regressor

The RFR algorithm belongs to the class of machine learning algorithms that, in combination with random decision trees, trains a model on sub-datasets . The use of multiple trees contributes to the stability of the algorithm and reduces the variance of the result itself. Each tree created by this algorithm uses a different sample of input data; furthermore, different features are taken into account at each node where, after training each tree, the mean value of the unique result is calculated . The varied hyperparameters are shown in **Table 7** and are based on

Table 7 An overview of the varied hyperparameters used for the RFR.

Parameter Name	Minimum Value	Maximum Value
n_estimators	100	5000
criterion	squared_error, absolute_error, Poisson	
max_features	sqrt, log2	

It is originated from the basic RFR, the parameters that were varied in this investigation will not be described in detail. When investigating this algorithm, the guiding principle was that differences between the two algorithms exist in terms of ETR . In this case, RFR uses bootstrap replicas, i.e., it uses subsamples of the input data and replaces it, whereas ETR uses the original complete samples. In addition, RFR uses an optimal node split point, while ETR takes a random one.

6. Ridge Regressor

RR belongs to the linear model method of the scikit-learn python library. The specialization of RR lies in the fact that it analyzes multiple regressions that are multicollinear. Because of the complex science behind this ML algorithm, it is not the most used algorithm; however, because of its regularization methods, it is sometimes the best fit. RR is a linear least squares method with an additional regularization parameter. The selection of the varied parameters presented in **Table 8** was carried out according to previous articles on related issues.

Table 8 An overview of the varied hyperparameters used for the RR.

Parameter Name	Minimum Value	Maximum Value
alpha	1.0	100.0
max_iter	1000	50,000
tol	1×10^{-5}	1×10^{-1}
fit_intercept	True, False	
solver	svd, cholesky, lsqr, sparse_cg, sag, saga	

The parameters alpha and maximum iterations are explained in the previous subsections, to indicates the precision of the solution, while the novelty is the solver where the solver is the principle of model optimization.

7. Stochastic Gradient Descent Regressor

The SGD regressor belongs to the group of linear models of the scikit-learn python library. It is a generic optimized algorithm that can find a high-quality and optimal solution for a wide range of situations. The idea for altering the parameters is an iterative process of selecting hyperparameters to reduce the cost function. The proportions of the step are one of the most crucial parameters determined by varying the learning rate, which in the case of setting too small a value can lead to slow convergence and the opposite of that can exceed the optimal value . In line with to , the hyperparameters in **Table 9** are as follows.

Table 9 An overview of the varied hyperparameters used for the SGD.

Parameter Name	Minimum Value	Maximum Value
alpha	0.0001	10.0
max_iter	1000	10,000
validation_fraction	0.15	
power_t	0.1	0.5
learning_rate	invscaling, optimal, constant	
shuffle	True, False	
l1_ratio	0.0001	0.5

The validation set is a proportion of training data used for early stopping defined with validation_fraction. The power_t parameter is an exponent for the invscalinglearning_rate module which defines the result of the value of the learning rate parameter. The role of the shuffle parameter is to shuffle data points for each training epoch. The elasticnet mixing parameter is varied with the l1_ratio, and its value is in the range from 0 to 1.

8. . Support Vector Regressor

SVR is an ML regression algorithm that is compatible with both linear and polynomial regression. This algorithm works on the principle support vector machine (SVM), but in the case of SVR, it differs in the way that SVM is a classifier for the prediction of discrete categorical values, while SVR is a regressor used for continuous order predicting variables [**75**,**76**]. In this investigation, several hyperparameters are varied, as shown in **Table 10**.

Table 10 An overview of the varied hyperparameters used for the SVR

Parameter Name	Minimum Value	Maximum Value
kernel	linear, poly, rbf, sigmoid	
degree	1	10,000
gamma	scale, auto	
coef0	0.0	10.0
tol	1×10^{-5}	1×10^{-10}
C	0.5	20.0
epsilon	0.05	20.0
max_iter	100	10,000

According to previous research, [**39**], the varied hyperparameters are as follows. The kernel hyperparameter specifies a data-mapping function. The degree is the degree of the polynomial kernel function, and gamma is the kernel coefficient but only in the case of rbf, poly, and sigmoid functions. Coef0 is an independent term in kernel function and can only be significant in the poly or sigmoid kernel function, C is a regularization parameter where the amplitude of regularization is inversely proportional and must be strictly positive. The last hyperparameter is epsilon, which defines the margin of tolerance.

9. Multi-Layer Perceptron Regressor

An MLP is a feed-forward ANN that generates a set of defined outputs from an input value. Specifically, it is characterized by a node that is connected to several layers as a direct link between input, hidden, and output layers where a backpropagation logic is used for training the neural network itself. Its design allows it to predict any continuous function and it can solve nonlinearly separable problems. In this investigation, several hyperparameters are modified according to research shown in .

Table 3.11 shows the varied hyperparameters used in this investigation. In addition to the previously described hyperparameters, such as olver, alpha, power_t, max_iter, and tol, new parameters unique to the MLP ML algorithm have been changed. Activation stands for the activation function which decides whether a neuron contained in MLP should be activated or left in stasis. Using simple mathematical operations, it determines the importance of the selected neuron in the ANN network for the prediction process. Hidden_layer is a number of hidden layers inside the MLP ANN, and the solver is the algorithm specified for weight optimization along all of the nodes contained in MLP.

Table 11 An overview of the varied hyperparameters used for the MLP

Parameter Name	Minimum Value	Maximum Value
hidden_layer_sizes (2,3 and 4 hidden layers)	5	600
activation	tahn, relu, identity, logistic	
solver	adam, lbfgs	
alpha	0.02	0.5
power_t	0.5	2.0
max_iter	1000	10,000
tol	1×10^{-5}	1×10^{-1}
max_iter	1000	10,000

VI. SIMULATION AND RESULTS

A. Create The Model

In [11]:

```
X=df.drop(['I_f','d_if'],axis=1).values
y=df['I_f'].values
```

In [12]:

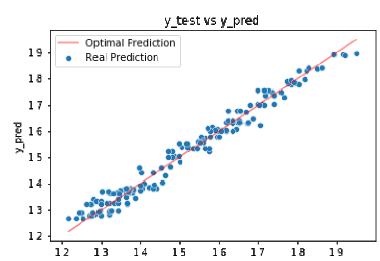
```
fromsklearn.model_selectionimporttrain_test_split,GridSearchCV
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.3,random_state=1)
```

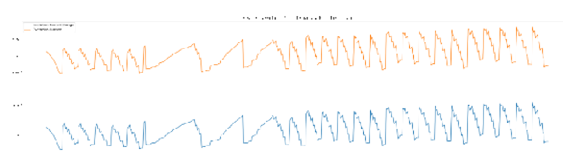
In [13]:

```
fromsklearn.ensembleimportRandomForestRegressor
fromsklearn.metricsimportmean_squared_erroras MSE
model=RandomForestRegressor(n_estimators=100,max_depth=5)
model.fit(X_train,y_train)
y_pred=model.predict(X_test)
print('RSE=',MSE(y_test,y_pred)**(0.5))
RSE= 0.0294139859557978
```

In [14]:

```
df=pd.DataFrame({'y_test':y_test,'y_pred':y_pred})
sns.scatterplot(x='y_test',y='y_pred',data=df,label='Real Prediction')
sns.lineplot(x='y_test',y='y_test',data=df,color='red',alpha=0.5,label='Optimal Prediction')
plt.title('y_test vs y_pred')
plt.legend()
plt.show()
```



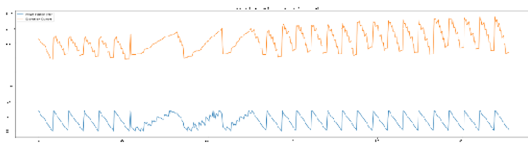


In [19]:

```
df.iloc[:,[2,4]].plot(use_index=True, figsize=(32,8), title='Samples vs Power Factor Error & Excitation Current')
```

Out[19]:

<matplotlib. axes. _subplots.AxesSubplot at 0x7ff263125c50>

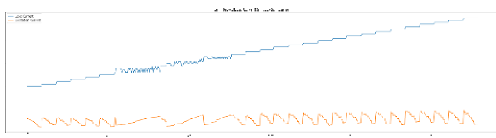


In [20]:

df.iloc[:,[0,4]].plot(use_index=**True**, figsize=(32,8), title='Samples vs Load Current & Excitation Current')

Out[20]:

<matplotlib. axes. _subplots.AxesSubplot at 0x7ff2627db850>

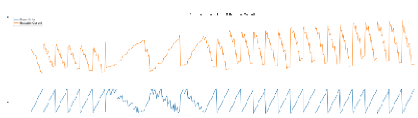


In [21]:

df.iloc[:,[1,4]].plot(use_index=**True**, figsize=(32,8), title='Samples vs Power Factor & Excitation Current')

Out [21]:

<matplotlib. axes._subplots.AxesSubplot at 0x7ff26270f990>



Epoch	**w1**	***w2***	***w3***	***w4***	***w5***	**function**
5	0.000246	0.595301	0.611129	0.989786	0.584195	0.000266
10	0.069097	0.135676	0.815564	0.575546	0.824279	0.007626
15	0.010779	0.637809	0.637809	0.946734	0.533464	0.010840
20	0.117146	0.286163	0.999948	0.304766	0.557133	0.005586

VII. CONCLUSION

A. Conclusion

Various AI methods were employed in this study to estimate the SM excitation current. Three distinct tactics were used during the inquiry to find a solution. To get good results for further thought, the initial strategy included linear, ensemble, tree-based, and neural network methods. The hyperparameters used for training the specified algorithms were simultaneously set to default values. The results show that more algorithms were taken into consideration, which indicates the possibility of making the best choice for estimating the excitation current. However, it was unclear whether the developed model resulted in overfitting, specifically whether this was true for the samples in the train/test ratio that were impacted.The data was then subjected to 5 k-fold cross-validation using randomized hyperparameters. The advantages of this approach over other control methods described in the literature include Because it just considers the synchronous motor's highlighted weight characteristics, and because it allows for the potential of establishing a correlation between those values and the excitation current, the findings are simpler and more accurate. Finally, compared to prior research for classes of smaller motors, it offers a fresh method for excitation current estimate utilizing a different kind of algorithm.

.The following are the responses to the speculative questions in the Introduction based on the research that was done:

• A synchronous motor's excitation current may be accurately and precisely estimated using an AI system. The most effective algorithm, according to the presented research, was RF.

• The parameters of the AI model were improved using GS and cross-validation, which validated the values and provided appropriate assessment metrics for the excitation current estimation.

• RF has the highest R22 value, the shortest MSE and MAPE values, and is the simplest method that can produce optimal results.

B. Future scope

Finally, it is important to note the following aspects in light of future research goals. It is first necessary to add more recent points to the existing dataset, such as those for millisecond or microsecond ratios, i.e., changes in these ratios. The impact of heat on SM should be taken into account as a further step because it is widely known that every electrical equipment, device, etc., that is affected by heat suffers changes in the specified parameters. For instance, the resistance of electrical conductors on the stator or rotor of a synchronous motor under low temperatures varies (depending on the version)..

A specified model would be implemented to control logic as the goal of further study in order to assess the outcomes in a genuine experiment. After putting all the aforementioned ideas into practice, a dataset will be generated, and the best AI model that roughly approximates the excitation current will be discovered once more. This will lead to a more accurate and practical conclusion for the investigation described in this article

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