*35th International Electric Vehicle Symposium and Exhibition (EVS35)*
*Oslo, Norway, June 11-15, 2022*

# Preliminary Design of Permanent Magnet Motor using Machine Learning Algorithm and Analytical Method

Aravind Chandrashekhar[1], Bolagond Vrashabha[2] Aniruddha Atre[3]

*[1]Mercedes-Benz Research and Development India, Embassy Crest, Plot No 9 & 10, EPIP Zone, Phase 1, Whitefield Road, 560 066, Bangalore Karnataka – India*

*aravind.a_l@mercedes-benz.com[1], vrashabha.bolagond@mercedes-benz.com[2],*

*aniruddha.nitin_atre@mercedes-benz.com[3]*

This paper presents a procedure for determining the initial design parameters using analytical calculation method for a PMSM (Permanent magnet synchronous motors), followed by developing a machine learning algorithm with the available benchmarking data to determine the motor design parameters. A comparison study with the results obtained from Analytical calculation and machine learning algorithm carried out in determining the initial sizing parameters, also the severity of impact is accessed qualitatively and results are presented.

*Keywords: e-Motor, PMSM, Artificial Neural Network, Motor Design, Machine Learning*

## 1 Abstract

The global attention towards Electric Vehicles is growing tremendously, mainly because of environmental issues in recent years. There has been a significant increase in the development of hybrid and pure electric vehicles as they are considered as an effective solution for reducing the carbon footprint. There is a lot of research happening, especially in the design of high performance e-motors for Electric Powertrain applications.

In this paper, we have presented an ANN algorithm design approach, which will help in saving the time needed for theoretical design, and with an optimum design solution, can reduce the time and iterations of FEA required while designing an e-motor.

In this paper, the focus is on the PMSM due to its higher efficiency and more advantageous torque characteristics compared to other types of motors.

## 2 Introduction

In current scenario, performance improvements such as reducing the overall time and enhancing the efficiency of the electric motor are one of the most important challenges. There are many studies conducted and documented on the sizing of the electric motor to reduce the losses and increase the torque density of the machine.

In general, an electric machine designer translate a set of design specifications to design choices and ensuring that the final product meets the requirements. To support the design decision, analysis and modelling of the machine is required and that depends on the level of details that is targeted based on that approach depend, either analytical equations or detailed 2D or 3D finite element analysis tools can be used.

Data analytics approach involving the analysis of data to draw a conclusion is gaining traction is various domains. Though a data analytic approach involves big data to predict the result closest to the actual, a trial is carried out in this paper with the available data and discussed in detail on the step by step process on determining the major electric motor design parameters using the Machine-learning (ML) algorithm (ANN algorithm) using python software.

The result obtained, can then be used with any FEA tool to improve the accuracy and efficiency of the final design. Using this data - based approach reduces the time for any FEA iterative design process, and enhances the accuracy of the design in a shorter time span.

# 3 Sizing of Permanent Magnet Synchronous Motor

The design of electric machine largely an iterative process implying that parts of the design have to be repeated in order to obtain the desired solution. In most of the cases, the limitation in terms of size is determined from the available packaging volume for any BEV or PHEV, the electric machine designer has to provide a solution that meets the speed, torque and power requirement and target for high Torque to volume ratio as a primary objective.

In the Theoretical Design approach, we first determine the stator and rotor geometry based on key assumptions. Then we calculate the required electrical loading (E) and magnetic loading (M) followed by calculating the Back EMF. The calculations are concluded with the Torque per rotor volume (TRV).

## 3.1 Determining the stator and rotor geometry

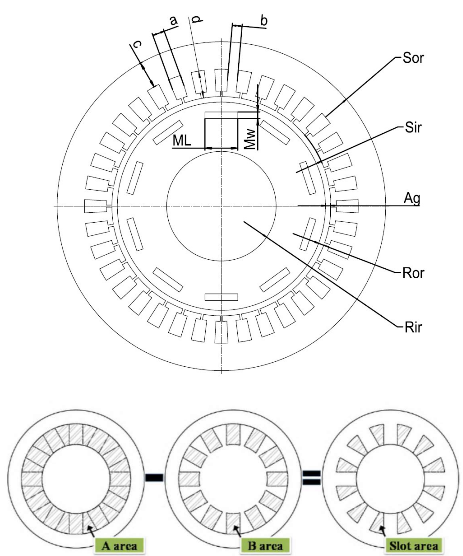



Figure 1. PMSM Geometry

$$d = S_{or} - c - S_{ir} \quad (1)$$

$$S_{ir} = R_{or} + G_{air} \quad (2)$$

$$SN_{teeth} = SN_{slot} \quad (3)$$

$$SA_{tooth} = d \ x \ b \quad (4)$$

$$SA_{slot} = A - B \quad (5)$$

Table1: Nomenclature for Motor Geometry. (Refer Fig. 1)

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| $S_{or}$ | Stator outer radius | a | Slot width | $M_w$ | Magnet width | $SA_{slot}$ | Stator slot area |
| $S_{ir}$ | Stator inner radius | b | Lamination width | $M_l$ | Magnet length | $SN_{teeth}$ | Stator no of teeth |
| $R_{or}$ | Rotor outer radius | c | Yoke width | $G_{air}$ | Air gap | $SN_{slot}$ | Stator no of slot |
| $R_{ir}$ | Rotor inner radius | d | Slot height | $A_m$ | Magnet area | $SA_{yoke}$ | Stator yoke area |
| $L_{stk}$ | Stack length | $N_p$ | No of pole | $RA_{steel}$ | Rotor steel area | $SA_{steel}$ | Stator steel area |

$$SA_{slot} = \frac{\pi(S_{ir}+d)^2 - \pi S_{ir}{}^2 - SN_{teeth} x S\ \ _{tooth}}{SN_{slot}} \quad (6)$$

$$SA_{steel} = B + SA_{yoke} \quad (7)$$

The overall magnet area - $A_m = M_w \ x \ M_l \ x \ N_p$ (8)

The overall rotor steel area assuming that the impact of flux barriers negligible and no further holes in the rotor $R_{sa} = \pi R_{or}{}^2 - \pi R_{ir}{}^2 - A_m$ (9)

Considering the densities of the material used such as electrical steel (7650 kg/m3), copper (8960 kg/m3) and NdFeB magnet (7400 kg/m3), the rotor inertia as below

Rotor inertia $I_r = \frac{\pi x \rho_{steel} x L_{stk}}{2} x \ (R_{or}{}^4 - R_{ir}{}^4)$ (10)

## 3.2 Electrical loading (E) and Magnetic loading (M)

The electrical loading E in general defined as -

$$E = \frac{Total\ amphere{-}conducto}{Airgap\ circumference} = \frac{2\ x\ m\ x\ T_{ph} x\ I}{\pi\ x\ 2{*}R_{or}} \quad (10)$$

$m$- No of phases, $T_{ph}$ - no of turns in series per phase, $I$ – RMS value of the phase current

This by assuming the air gap is small and as a result outer rotor diameter and the inner rotor diameter are equal.

The electrical loading is limited by factors such as the stator slot depth, the achievable packing factor of copper in the stator slots (or else known as slot fill factor), and the allowable copper current density based on the maximum allowable temperature raise. Typical values for the electrical loading are in the region f 15-45(kA/m), for continuous operation.

The electrical loading is related to current density (J) in the conductors and are shown as

$$J = \frac{A\ x\ P_{slot}}{SS_{ff}\ \ x\ S_{slot}} \quad (11)$$

Typical values for the maximum $F_{slot}$ are in the range od 0.4-0.5 and may vary with the chosen winding distribution. Additionally as the voltage rating of the machine increase, lower values for $F_{slot}$ should be encountered as, more space required for the insulation. These values might seems small to what one would expect, but indicate the big part that insulation and air occupy in a slot. Higher values can be achieved with the rectangular slots and use of rectangular copper bars, which on the other hand have the drawback of high copper losses at high frequencies, caused by the skin effect

The magnetic loading is the average flux density over the rotor surface due to the permanent magnets. It can be associated with the average flux per pole through with the assumption of sinusoidal flux density distribution.

$$\varphi = B\ x\ \frac{\pi x D x L_{stk}}{2p} \quad (12)$$

$\varphi$ –Average flux per pole with the assumption of a sinusoidal flux density distribution

$p$ – Number of pole pairs

The magnetic loading is usually limited by saturation of the stator teeth of the machine and hence by the saturation flux density of the stator iron. The ratio of stator teeth width to the tooth pitch defines the maximum allowed value for the magnetic loading assuming sine-distributed flux.

$$B = \frac{2\sigma}{\pi} x \ B_{t,peak} \tag{12}$$

$\sigma$ - Ratio of stator teeth width to the tooth pitch

Typical values of magnetic loading are in region of 0.4 – 0.7T, while in special occasions where the high torque density is required; it may reach the value of greater than or equal to 1T. High values of magnetic loading are required to achieve high torque and power performance.

## 3.3 Generated EMF (back-EMF) per phase ($B_{emf}$)

The generated EMF (or else known as back – EMF) per phase € is associated with B and its RMS value is given as

$$E = \sqrt{2x\pi x k_{w1} x T_{ph} x\varphi x f_e} = \frac{\sqrt{2x\pi x k_{w1} x T_{ph} x \varphi x p x \quad m}}{\sqrt{2}} = \frac{\pi^2}{\sqrt{2}} x \frac{k_{w1} x T_{ph} x M x D x \quad _{stk} x f_e}{p} = \frac{\pi x k_{w1} x T_{ph} x M x D x L_{stk} x \omega_m}{2\sqrt{2}} \tag{13}$$

$f_e$ - Fundamental electrical frequency

$\omega_m$ - Mechanical rotational speed in rad/sec $({}^{2x\pi x f_e}/_{p})$

$k_{w1}$ - Fundamental harmonic winding factor typical in the region of 0.85 to 0.95

Below equation denotes the flux density at the air gap as created from the permanent magnet

$$B = \frac{B_r}{\frac{S_g}{S_m} + \frac{\mu_r x l_g}{l_m}} \tag{14}$$

$B_r$ - Intrinsic flux density, $S_g$- Air gap area per pole considering ${}^{\pi x D x L_{stk}}/_{N_p}$

$S_m$ - Magnet surface facing the air gap considering$L_{stk} x \omega_m$, $\mu_r$ - Magnet relative coil permeability

## 3.4 Torque per rotor volume calculation

The torque per unit rotor volume (TRV) describes the amount of torque available from the given rotor volume. As such, it is the common measure for comparing the motors and for initial motor sizing for a given application. Under the assumptions that the power factor is unity and all the available power at the air gap is converter into mechanical power, the generated torque on the shaft of the electrical machine can be estimated as

$$P_g = m x B_{emf} x I \quad \text{(Watt)} \tag{15}$$

Assuming that the power factor is unity and all the available power at the air gap $P_g$ is converter into mechanical power and the generated torque on the shaft of the electric machine $T_e$ can be estimated using. The assumption is because of desire to minimize the volt-ampere rating of the inverter.

$$T_e = \frac{mEI}{\omega_m} = \frac{\pi x m x k_{w1} x T_{ph} x 2 x R_{or}}{2\sqrt{2}} \ x M x I = \frac{\pi^2 x k_{w1} x (2 * R_{or})^2 x L_{stk}}{4\sqrt{2}} \ x M x E \tag{16}$$

$$TRV = \frac{T_e}{V_r} = \frac{\pi x k_{w1}}{\sqrt{2}} x M x E \qquad \text{(Considering} \quad V_r = \frac{\pi x D^2 x L_{stk}}{4}) \tag{17}$$

Thus, the torque is directly proportional to square of diameter and length of the stack. With the help of similar, various empirical relations including the different loss calculations, the sizing of the electric machine is calculated

# 4 Preliminary Motor Design using Artificial Neural Networks

## 4.1 Dataset for Motor Design Parameters

To build a Machine Learning model, the primary requirement is clean data from reputed sources. We have collected most of the data from A2Mac1 Automotive Benchmarking website, and created a dataset by considering the key parameters for an E-Motor design. We obtained data for the following Traction Motor parameters for an Permanent Magnet Synchronous Motor with rotor having Double V Shape slots–

Table 2. Parameters considered while data collection for PMSM

| Motor Parameters | Stator Parameters | Rotor Parameters |
|---|---|---|
| Motor Type – PMSM | Stator Outer Diameter (SD1) (mm) | Rotor Outer Diameter (RD1) (mm) |
| Peak Power (kW) | Stator Inner Diameter (SD2) (mm) | Rotor Shaft Diameter (RD2) (mm) |
| Maximum Torque (N-m) | Stack Height (mm) | No. of Rotor Poles |
| Continuous Power (kW) | No. of Stator Slots | No. of Rotor Slots |
| Continuous Torque (Nm) | Depth of Stator Slot (DSS) (mm) | Magnet Width (mm) |
| Battery Voltage (Volts) | Width of Stator Slot Opening (WSSO) (mm) | Magnet Thickness (mm) |
| Stator Winding – Hairpin Winding or Round Copper Wire Winding | Width of Stator Slot Bottom (WSSB) (mm) | Magnet Angle (deg) |
| | Core Back Width (CBW) (mm) | Magnet Position from shaft centre (mm) |
| | Air Gap Length (mm) | |

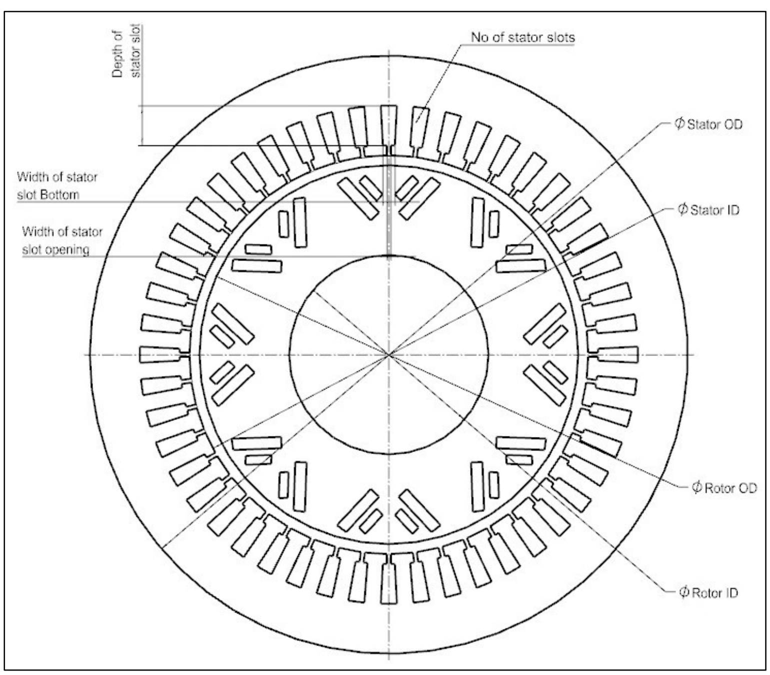
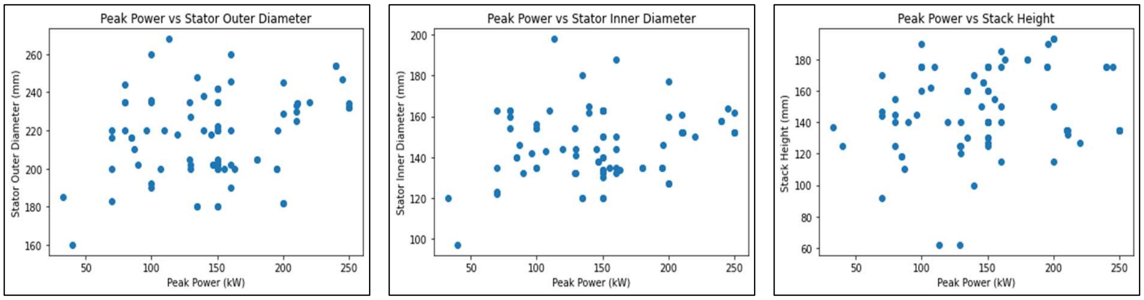



Figure 2. Nomenclature of Stator and Rotor Parameters considered for ANN Model




(a) (b) (c)

Figure 3. a) Peak Power vs Stator OD, b) Peak Power vs Stator ID, c) Peak Power vs Stack Height

For creating the ANN Model, we have used open source software – Jupyter Notebook, and written the code in Python.

Data Pre-Processing was carried out before creating the model, like converting all numeric data into uniform data type, Data Cleaning to fill in missing data, Normalization to scale the data for more accurate comparison, Feature Selection for extracting relevant and important variables for analysis. After pre-processing, the clean data set was divided into training, validation and testing data to be fed as input to the ANN Model

As per the proposed approach, we created two different ANN Models for prediction of Stator and Rotor design parameters.

## 4.2 Neural Network Schematic

The first ANN Model focuses on predicting the main dimensions of the motor. The below schematic depicts the parameters considered for the first ANN Model.

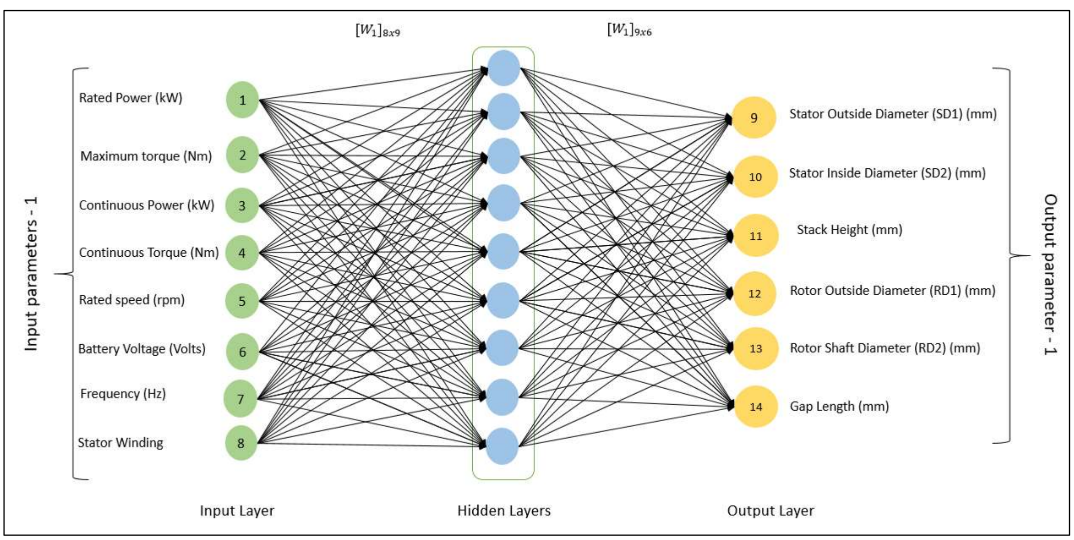



Figure 4. Schematic for ANN Model 1

The second ANN Model uses the output of the first ANN Model as an input, and predicts the below mentioned stator and rotor lamination design parameters as output.

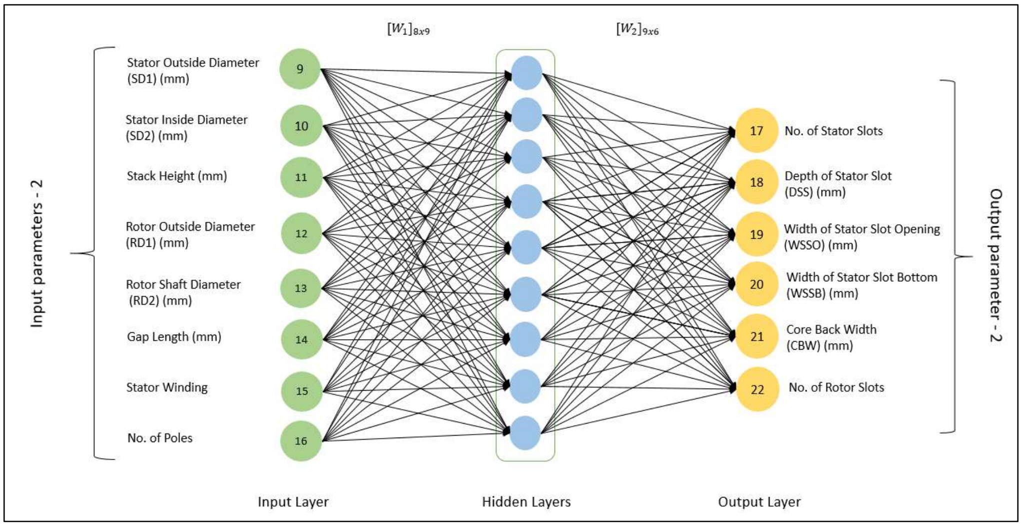



Figure 5. Schematic for ANN Model 2

## 4.3 Hyper parameters

Table 3 summarises the hyper-parameters used to create the ANN Models 1 and 2, which determine the Neural Network structure and how the network is trained.

Table 3. Hyper-parameters for ANN Model 1 and ANN Model 2

| Hyper parameters | ANN Model 1 | ANN Model 2 |
|---|---|---|
| Input Layer Neurons | 8 | 7 |
| Output Layer Neurons | 6 | 6 |
| Hidden Layers | 3 | 3 |
| Hidden Layers Neurons | 10 | 10 |
| Hidden Layer Activation Function | Rectified Linear Activation Unit (RELU) | Rectified Linear Activation Unit (RELU) |
| Output Layer Activation Function | Linear Function | Linear Function |
| Loss Function | Mean Squared Error | Mean Squared Error |
| Optimizer | Adaptive Moment Estimation (ADAM) | Adaptive Moment Estimation (ADAM) |
| Batch Size | 10 | 10 |
| Epochs | 10 | 10 |

## 4.4 Python Code for ANN Model

We have chosen python language for building the ANN Model, to utilize the ease with which neural networks can be created with the use of TensorFlow. Figure 5 and Figure 6 shows the python code for the ANN Model 1 and 2.

In Machine Learning context, accuracy is the ratio of the number of correctly predicted samples to the total number of samples. The training accuracy and validation accuracy for both the models is increasing, however overall value can be improved with more data. We can have a more mature ANN model with greater confidence and prediction accuracy after creating a larger data set.

**ANN Model 1**

```
In [31]:
input_size = 8
output_size = 6
hidden_layer_size = 10

model = tf.keras.Sequential([
                            tf.keras.layers.Dense(input_size, input_shape=(8,)),
                            tf.keras.layers.Dense(hidden_layer_size, activation='relu'),
                            tf.keras.layers.Dense(hidden_layer_size, activation='relu'),
                            tf.keras.layers.Dense(hidden_layer_size, activation='relu'),
                            tf.keras.layers.Dense(output_size, activation='linear')
                            ])

model.compile(optimizer='adam', loss='mean_squared_error', metrics=['accuracy'])

batch_size = 10
max_epochs = 10
early_stopping=tf.keras.callbacks.EarlyStopping(patience=1)

model.fit(x_train_tensor,
         y_train_tensor,
         batch_size = batch_size,
         epochs = max_epochs,
         validation_data = (x_validation_tensor,y_validation_tensor),
         verbose = 2)

Epoch 1/10
6/6 - 2s - loss: 1.3039 - accuracy: 0.0769 - val_loss: 1.2033 - val_accuracy: 0.2308 - 2s/epoch - 274ms/step
Epoch 2/10
6/6 - 0s - loss: 1.2317 - accuracy: 0.0577 - val_loss: 1.1968 - val_accuracy: 0.2308 - 83ms/epoch - 14ms/step
Epoch 3/10
6/6 - 0s - loss: 1.1890 - accuracy: 0.0962 - val_loss: 1.1918 - val_accuracy: 0.3077 - 90ms/epoch - 15ms/step
Epoch 4/10
6/6 - 0s - loss: 1.1541 - accuracy: 0.0962 - val_loss: 1.1880 - val_accuracy: 0.3077 - 93ms/epoch - 16ms/step
Epoch 5/10
6/6 - 0s - loss: 1.1354 - accuracy: 0.1154 - val_loss: 1.1856 - val_accuracy: 0.2308 - 83ms/epoch - 14ms/step
Epoch 6/10
6/6 - 0s - loss: 1.1183 - accuracy: 0.1154 - val_loss: 1.1829 - val_accuracy: 0.2308 - 82ms/epoch - 14ms/step
Epoch 7/10
6/6 - 0s - loss: 1.1053 - accuracy: 0.1538 - val_loss: 1.1812 - val_accuracy: 0.3077 - 88ms/epoch - 15ms/step
Epoch 8/10
6/6 - 0s - loss: 1.0961 - accuracy: 0.1731 - val_loss: 1.1793 - val_accuracy: 0.3846 - 82ms/epoch - 14ms/step
Epoch 9/10
6/6 - 0s - loss: 1.0875 - accuracy: 0.1923 - val_loss: 1.1779 - val_accuracy: 0.3846 - 96ms/epoch - 16ms/step
Epoch 10/10
6/6 - 0s - loss: 1.0812 - accuracy: 0.2308 - val_loss: 1.1756 - val_accuracy: 0.2308 - 87ms/epoch - 14ms/step

Out[31]: <keras.callbacks.History at 0x18c1ebf1dc0>
```

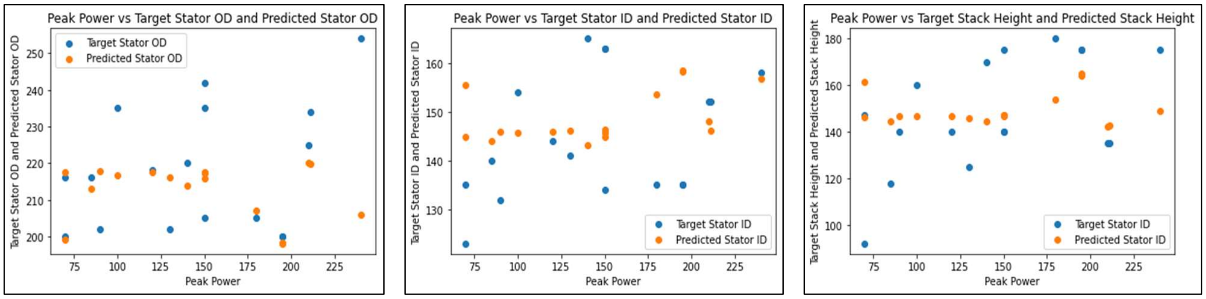
Figure 6. Code for ANN Model 1

**ANN Model 2**

```
In [18]:
input_size = 9
output_size = 6
hidden_layer_size = 10

model = tf.keras.Sequential([
                            tf.keras.layers.Dense(input_size, input_shape=(9,)),
                            tf.keras.layers.Dense(hidden_layer_size, activation='relu'),
                            tf.keras.layers.Dense(hidden_layer_size, activation='relu'),
                            tf.keras.layers.Dense(hidden_layer_size, activation='relu'),
                            tf.keras.layers.Dense(output_size, activation='linear')
                            ])

model.compile(optimizer='adam', loss='mean_squared_error', metrics=['accuracy'])

batch_size = 10
max_epochs = 10
early_stopping=tf.keras.callbacks.EarlyStopping(patience=1)

model.fit(x_train,
         y_train,
         batch_size = batch_size,
         epochs = max_epochs,
         validation_data = (x_validation,y_validation),
         verbose = 2)

Epoch 1/10
6/6 - 1s - loss: 1.0253 - accuracy: 0.0962 - val_loss: 1.0510 - val_accuracy: 0.2308 - 1s/epoch - 188ms/step
Epoch 2/10
6/6 - 0s - loss: 1.0136 - accuracy: 0.1346 - val_loss: 1.0429 - val_accuracy: 0.3077 - 63ms/epoch - 11ms/step
Epoch 3/10
6/6 - 0s - loss: 1.0071 - accuracy: 0.1154 - val_loss: 1.0369 - val_accuracy: 0.3077 - 54ms/epoch - 9ms/step
Epoch 4/10
6/6 - 0s - loss: 1.0015 - accuracy: 0.1346 - val_loss: 1.0295 - val_accuracy: 0.3077 - 55ms/epoch - 9ms/step
Epoch 5/10
6/6 - 0s - loss: 0.9955 - accuracy: 0.1346 - val_loss: 1.0224 - val_accuracy: 0.1538 - 62ms/epoch - 10ms/step
Epoch 6/10
6/6 - 0s - loss: 0.9901 - accuracy: 0.1346 - val_loss: 1.0154 - val_accuracy: 0.1538 - 58ms/epoch - 10ms/step
Epoch 7/10
6/6 - 0s - loss: 0.9850 - accuracy: 0.0962 - val_loss: 1.0091 - val_accuracy: 0.1538 - 57ms/epoch - 9ms/step
Epoch 8/10
6/6 - 0s - loss: 0.9808 - accuracy: 0.0962 - val_loss: 1.0029 - val_accuracy: 0.1538 - 58ms/epoch - 10ms/step
Epoch 9/10
6/6 - 0s - loss: 0.9774 - accuracy: 0.0769 - val_loss: 0.9957 - val_accuracy: 0.1538 - 66ms/epoch - 11ms/step
Epoch 10/10
6/6 - 0s - loss: 0.9733 - accuracy: 0.0962 - val_loss: 0.9892 - val_accuracy: 0.1538 - 56ms/epoch - 9ms/step
```

Figure 7. Code for ANN Model 2

# 5 Results




(a) (b) (c)

Figure 8. a) Peak Power vs Target and Predicted Stator OD, b) Peak Power vs Target and Predicted Stator ID, c) Peak Power vs Target and Predicted Stack Height

Out[38]:

| | Stator OD target | Stator ID target | Stack Height target | Rotor OD target | Rotor Shaft Dia target | Gap Length target | Stator OD pred | Stator ID pred | Stack Height pred | Rotor OD pred | Rotor Shaft Dia pred | Gap Length pred |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 202.00 | 132.00 | 140.00 | 130.00 | 45.00 | 1.00 | 217.95 | 145.84 | 146.80 | 143.60 | 54.90 | 1.15 |
| 1 | 235.00 | 154.00 | 160.00 | 152.00 | 65.00 | 1.00 | 216.66 | 145.79 | 146.64 | 144.10 | 55.29 | 1.15 |
| 2 | 216.00 | 140.00 | 118.00 | 138.00 | 50.00 | 1.00 | 212.90 | 144.11 | 144.60 | 145.31 | 56.43 | 1.17 |
| 3 | 220.00 | 165.00 | 170.00 | 161.00 | 63.00 | 2.00 | 213.79 | 143.23 | 144.31 | 145.49 | 56.50 | 1.18 |
| 4 | 235.00 | 163.00 | 140.00 | 160.00 | 58.00 | 1.50 | 217.55 | 146.46 | 147.28 | 143.68 | 55.28 | 1.15 |
| 5 | 234.00 | 152.00 | 135.00 | 150.00 | 47.00 | 1.00 | 219.72 | 146.14 | 142.61 | 143.92 | 54.72 | 1.18 |
| 6 | 254.00 | 158.00 | 175.00 | 156.00 | 63.00 | 1.00 | 205.98 | 156.82 | 149.01 | 141.62 | 57.07 | 1.21 |
| 7 | 218.00 | 144.00 | 140.00 | 142.00 | 47.00 | 1.00 | 217.60 | 145.91 | 146.64 | 143.70 | 55.05 | 1.15 |
| 8 | 200.00 | 135.00 | 175.00 | 133.00 | 56.00 | 1.00 | 198.21 | 158.34 | 164.21 | 145.58 | 58.16 | 1.05 |
| 9 | 225.00 | 152.00 | 135.00 | 150.00 | 47.00 | 1.00 | 220.13 | 148.06 | 142.07 | 142.83 | 54.51 | 1.17 |
| 10 | 216.00 | 123.00 | 147.00 | 121.00 | 45.00 | 1.00 | 217.54 | 144.89 | 146.28 | 143.98 | 55.05 | 1.15 |
| 11 | 205.00 | 134.00 | 175.00 | 132.00 | 60.00 | 1.00 | 215.97 | 144.80 | 146.54 | 145.31 | 55.43 | 1.15 |
| 12 | 205.00 | 135.00 | 180.00 | 133.00 | 50.00 | 1.00 | 206.97 | 153.64 | 153.93 | 143.14 | 55.66 | 1.11 |
| 13 | 202.00 | 141.00 | 125.00 | 139.00 | 63.00 | 1.00 | 216.08 | 146.13 | 145.95 | 143.80 | 55.32 | 1.15 |
| 14 | 200.00 | 135.00 | 92.00 | 132.00 | 55.00 | 1.50 | 199.24 | 155.53 | 161.34 | 145.74 | 57.55 | 1.04 |
| 15 | 200.00 | 135.00 | 175.00 | 133.00 | 56.00 | 1.00 | 198.04 | 158.48 | 164.84 | 145.73 | 58.29 | 1.04 |
| 16 | 242.00 | 163.00 | 140.00 | 160.00 | 57.00 | 1.50 | 217.27 | 145.81 | 147.29 | 143.94 | 54.98 | 1.14 |

Figure 9. Output of ANN Model 1 based on testing data

Out[27]:

| | No. of Stator Slots target | Depth of Stator Slot target | WSSO target | WSSB target | Core Back Width target | No. of Rotor Slots target | No. of Stator Slots pred | Depth of Stator Slot pred | WSSO pred | WSSB pred | Core Back Width pred | No. of Rotor Slots pred |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 48 | 25.0 | 2.5 | 6.0 | 22.5 | 16 | 48 | 22.571062 | 2.216803 | 5.234860 | 24.089870 | 24 |
| 1 | 60 | 27.0 | 2.5 | 7.3 | 27.0 | 16 | 48 | 22.380831 | 2.235023 | 5.289814 | 24.099308 | 24 |
| 2 | 72 | 24.0 | 1.0 | 3.1 | 26.0 | 16 | 48 | 22.926216 | 2.154611 | 4.819057 | 24.229361 | 24 |
| 3 | 48 | 22.0 | 2.5 | 5.2 | 16.5 | 24 | 48 | 22.662691 | 2.137862 | 4.816354 | 24.419706 | 24 |
| 4 | 48 | 37.0 | 3.0 | 8.2 | 17.5 | 32 | 48 | 22.289301 | 2.249445 | 5.324045 | 24.080383 | 32 |
| 5 | 54 | 27.0 | 2.7 | 6.0 | 27.5 | 32 | 48 | 22.442272 | 2.248318 | 5.298482 | 24.016689 | 32 |
| 6 | 48 | 30.0 | 3.0 | 7.2 | 33.0 | 32 | 48 | 22.289526 | 2.244270 | 5.316882 | 24.101751 | 32 |
| 7 | 48 | 20.0 | 2.0 | 4.5 | 27.0 | 24 | 48 | 22.499264 | 2.238860 | 5.276509 | 24.030455 | 24 |
| 8 | 48 | 18.0 | 2.0 | 4.2 | 23.5 | 24 | 48 | 22.462112 | 2.224880 | 5.263085 | 24.105059 | 24 |
| 9 | 54 | 26.0 | 2.5 | 6.2 | 23.5 | 32 | 48 | 22.448689 | 2.248559 | 5.297807 | 24.012821 | 32 |
| 10 | 48 | 22.0 | 1.5 | 4.6 | 35.5 | 16 | 54 | 22.533131 | 2.190613 | 5.204741 | 24.215475 | 24 |
| 11 | 48 | 26.0 | 2.0 | 5.7 | 22.5 | 24 | 48 | 22.417028 | 2.222006 | 5.266203 | 24.137131 | 24 |
| 12 | 48 | 20.0 | 2.0 | 4.5 | 25.0 | 24 | 48 | 22.504778 | 2.216781 | 5.245234 | 24.119587 | 24 |
| 13 | 72 | 18.0 | 1.0 | 1.9 | 21.5 | 24 | 48 | 22.862106 | 2.141027 | 4.756421 | 24.297523 | 24 |
| 14 | 48 | 22.0 | 2.0 | 5.1 | 21.5 | 16 | 48 | 22.900074 | 2.155841 | 4.842900 | 24.233299 | 24 |
| 15 | 48 | 18.0 | 2.0 | 4.2 | 23.5 | 24 | 48 | 22.462112 | 2.224880 | 5.263085 | 24.105059 | 24 |
| 16 | 48 | 35.0 | 3.0 | 7.9 | 22.0 | 24 | 48 | 22.350100 | 2.247948 | 5.312441 | 24.059420 | 32 |

Figure 10. Output of ANN Model 2 based on testing data

Table 4.a) Result Table for ANN Model 1

| Sr. No. | Stator OD Target (mm) | Stator OD Predicted (mm) | Accuracy (%) | Stator ID Target (mm) | Stator ID Predicted (mm) | Accuracy (%) | Stack Height Target (mm) | Stack Height Predicted (mm) | Accuracy (%) |
|---|---|---|---|---|---|---|---|---|---|
| 1. | 235 | 217 | 92.2 | 154 | 146 | 94.7 | 160 | 147 | 91.6 |
| 2. | 235 | 218 | 92.6 | 163 | 146 | 90 | 140 | 147 | 94.8 |
| 3. | 234 | 220 | 93.9 | 152 | 146 | 96.1 | 135 | 143 | 94.4 |
| 4. | 218 | 218 | 100 | 144 | 146 | 98.7 | 140 | 147 | 95.3 |
| 5. | 200 | 198 | 99.1 | 135 | 158 | 83 | 175 | 164 | 93.8 |
| 6. | 225 | 220 | 97.8 | 152 | 148 | 97.4 | 135 | 142 | 94.8 |
| 7. | 205 | 216 | 94.6 | 134 | 145 | 91.9 | 175 | 147 | 83.7 |
| 8. | 205 | 207 | 99 | 135 | 154 | 86.2 | 180 | 154 | 85.5 |
| 9. | 200 | 198 | 99 | 135 | 158 | 82.6 | 175 | 165 | 94.2 |
| 10. | 242 | 217 | 89.8 | 163 | 146 | 89.5 | 140 | 147 | 94.8 |

Table 4.b) Result Table for ANN Model 1

| Sr. No. | Rotor OD Target (mm) | Rotor OD Predicted (mm) | Accuracy (%) | Rotor ID Target (mm) | Rotor ID Predicted (mm) | Accuracy (%) | Gap Length Target (mm) | Gap Length Predicted (mm) | Accuracy (%) |
|---|---|---|---|---|---|---|---|---|---|
| 1. | 152 | 144 | 94.8 | 45 | 55 | 78.0 | 1 | 1.15 | 84.9 |
| 2. | 160 | 144 | 89.8 | 47 | 55 | 84.0 | 1.5 | 1.15 | 76.4 |
| 3. | 150 | 144 | 95.9 | 65 | 55 | 85.1 | 1 | 1.18 | 82.4 |
| 4. | 142 | 144 | 98.8 | 63 | 55 | 87.8 | 1 | 1.15 | 84.9 |
| 5. | 133 | 146 | 90.5 | 50 | 56 | 88.7 | 1 | 1.05 | 95.2 |
| 6. | 150 | 143 | 95.2 | 63 | 57 | 89.7 | 1 | 1.17 | 83.4 |
| 7. | 132 | 145 | 89.9 | 60 | 55 | 92.4 | 1 | 1.15 | 84.5 |
| 8. | 133 | 143 | 92.4 | 58 | 55 | 95.3 | 1 | 1.1 | 88.7 |
| 9. | 139 | 144 | 96.5 | 55 | 58 | 95.4 | 1 | 1.15 | 84.8 |
| 10. | 133 | 146 | 90.4 | 56 | 58 | 96.2 | 1 | 1.04 | 95.5 |

Table 1.a) Result Table for ANN Model 2

| Sr. No. | Stator Slots Target | Stator Slots Predicted | Width of Stator Slot Opening Target (mm) | Width of Stator Slot Opening Predicted (mm) | Accuracy % | Width of Stator Slot Bottom Target (mm) | Width of Stator Slot Bottom Predicted (mm) | Accuracy % |
|---|---|---|---|---|---|---|---|---|
| 1. | 48 | 48 | 2.5 | 2.22 | 88.7 | 6 | 5.23 | 87.2 |
| 2. | 54 | 48 | 2.7 | 2.25 | 83.3 | 6 | 5.3 | 88.3 |
| 3. | 48 | 48 | 3 | 2.24 | 75 | 7.2 | 5.32 | 74 |
| 4. | 48 | 48 | 2 | 2.24 | 88.1 | 4.5 | 5.28 | 83 |
| 5. | 48 | 48 | 2 | 2.22 | 88.8 | 4.2 | 5.26 | 75 |
| 6. | 54 | 48 | 2.5 | 2.25 | 89.9 | 6.2 | 5.3 | 85.4 |
| 7. | 48 | 54 | 2 | 2.22 | 88.9 | 5.7 | 5.27 | 92.4 |
| 8. | 48 | 48 | 2 | 2.22 | 89.2 | 4.5 | 5.25 | 83.4 |
| 9. | 48 | 48 | 2 | 2.16 | 92.2 | 5.1 | 4.84 | 95 |
| 10. | 48 | 48 | 2 | 2.22 | 88.8 | 4.2 | 5.26 | 75 |

Table 5.b) Result Table for ANN Model 2

| Sr. No. | Depth of Stator Slot Target (mm) | Depth of Stator Slot Predicted (mm) | Accuracy % | Core Back Width Target (mm) | Core Back Width Predicted (mm) | Accuracy % | Rotor Slots Target | Rotor Slots Predicted |
|---|---|---|---|---|---|---|---|---|
| 1. | 25 | 22.57 | 90.3 | 22.5 | 24 | 93 | 16 | 24 |
| 2. | 27 | 22.5 | 83.1 | 27.5 | 24 | 87.3 | 32 | 32 |
| 3. | 30 | 23 | 74.3 | 33 | 24 | 73 | 32 | 32 |
| 4. | 20 | 22.5 | 87.5 | 27 | 24 | 89 | 24 | 24 |
| 5. | 18 | 22 | 75.2 | 23.5 | 24 | 97.4 | 24 | 24 |
| 6. | 26 | 22.45 | 86.3 | 23.5 | 24.3 | 97.8 | 32 | 32 |
| 7. | 26 | 22.4 | 86.2 | 22.5 | 24 | 92.7 | 24 | 24 |
| 8. | 20 | 22.5 | 87.5 | 25 | 24 | 96.5 | 24 | 24 |
| 9. | 22 | 22.9 | 95.9 | 21.5 | 24 | 87.3 | 16 | 24 |
| 10. | 18 | 22 | 75.2 | 23.5 | 24 | 97.4 | 24 | 24 |

## 6 Conclusion

In this paper, an Artificial Neural Network (ANN) – based prediction algorithm for the preliminary motor design of a PMSM is proposed. Initially we have discussed the theoretical design of a PMSM and the importance of Torque per rotor volume. Further, we have discussed in detail the two set of ANN model approach to predict the motor dimensional parameters. The prediction algorithm has been developed using python, and it has provided satisfactory results, which are in close agreement with those obtained from the benchmark data. The accuracy of the predicted values with respect to the target values varies from 70% to 99%.

The ANN based Machine-learning approach for optimum design of electric motor design parameters, presented in this paper, will help to avoid the intensive use of numeric techniques such as finite element method. With the more product line-up on electric vehicle globally and with the availability of more data, the model can be matured and the model will gain more confidence and have a prediction accuracy of 99% can be achieved.

This ANN-based design approach may also be expanded to include many other electrical and thermal design parameters as well and can be expanded other engineering fields.

## References


[1] [1] Dr. Duane Hanselman. *Brushless Permanent magnet motor design*, ISBN 1-881855-15-5

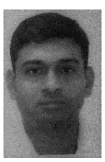
[2] K. T. CHAU. *Electric vehicle machines and drives*, ISBN 978-1-118-75252-4.

[3] V.B. Honsinger*, Sizing equation for electric machinery* IEEE Trans. On Energy conversion

[4] Christian Alteheld, Raimund Gottkehaskamo. *Automated preliminary design of induction machines aided by artificial neural networks*. 2019 International conference on Electric drives & power electronics (EDPE)

[5] Kamel Idir & Liuchen Chang, Heping Dai. *A Neural network – based optimisation approach for induction motor design*. IEEE Trans.


## Authors



Aravind Chandrashekhar A L has completed Bachelor of engineering in Mechanical engineering and Masters in Computer aided design and manufacturing, having expertise in electric powertrain domain as electro mechanical engineer and currently working in designing of electric traction motor components.

Bolagond Vrashabha completed Bachelor of engineering in Automobile engineering, having expertise on traction electric vehicle motor design, testing and currently working in the hybrid and electric powertrain systems.

Aniruddha Atre is pursuing Bachelor of Technology in Mechanical Engineering from Vishwakarma Institute of Technology, Pune. He is currently doing an internship at MBRDI in the Electric Powertrain domain.