Technical University of Applied Sciences
Würzburg-Schweinfurt (THWS)

Faculty of Computer Science and Business Information Systems

Master Thesis

Electric Motor Modelling via Graph Neural Networks

Submitted to the Technical University of Applied Sciences Würzburg-Schweinfurt in the Faculty of Computer Science and Business Information Systems to complete a course of studies in Master of Artificial Intelligence

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Abstract

The thesis explores an approach to to predict key parameter indicators(KPIs) of topology invariant Electric Motors by transforming its geometric, physical and simulation parameters into a graph representation.
The KPIs to be predicted are plots on Efficiency grid(3D) and Torque curve(2D).
We aim to first parameterize the EM design such that it is feasible to convert into a graph representation.
Next, we would create a Graph with relevant attributes and design a Graph Neural Network(GNN) with the graph as input and the plots in the format of vectors as target values.
Additionally we may also need to customize the loss function in a way that would smoothen out the plot curves of the prediction values.
Then, we would evaluate the predictions with the test target values by experimenting with various hyperparameter tuning methods and as a baseline with an Multi Layer Perceptron(MLP) model of the parameters in tabular form.
Finally we will enable the KPI's plot visualisation in a manner presentable to the client Valeo(Automaker Company).

Abstrakt

The aim of the Master Thesis is to train a neural network to learn the parameters of Electric Motors and thus be able to predict its Key Performance Indicators(KPIs). The KPIs are 2D and 3D plots on Torque(Mgrenz) curve(Mgrenz) and Efficiency grid(ETA). Other KPIs can be calculated from these two KPIs. For instance the Vibration Costs are inversely proportional to the Efficieny values predicted.

Acknowledgement

I would like to thank my supervisor Prof. Dr. Magda Gregorova for her guidance and support throughout the course of this thesis and Valeo for providing the data. Special thanks to Mr Daniel and Leo for sharing valuable insights of the data from a electromechanincal standpoint

Contents

Introduction

In the design of electric motors vast amounts of data are generated to determine which design of an electric motor(EM) fits best to KPIs.
KPIs of an Electric Motor are essential to judge the performance of the motor before it is manufactured.
Traditionally these KPIs are inferred from a description of an EM design via a finite element method (FEM) approximating the solutions of the Maxwell's equations. This process, though well established in the EM design, is very time consuming and does not allow for high-throughput engine design optimization.
The actual engine data of Valeo is used here as the dataset comprising of multiple variant designs of the Double-V topology.
The 3 motor topologies manufactured by Valeo are as below:

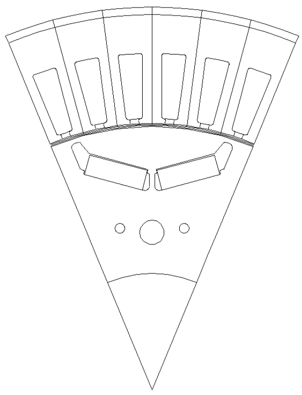

Figure 1: V1 Magnet

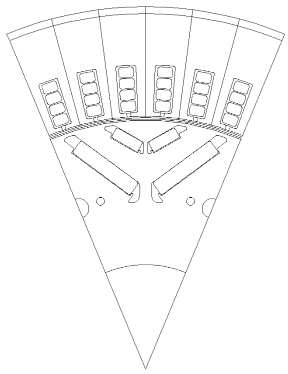

Figure 2: V2 Magnet

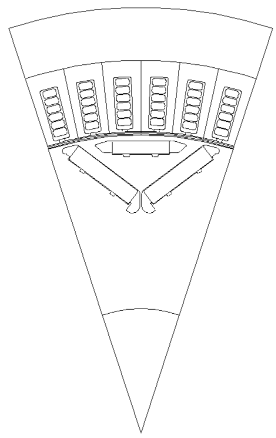

Figure 3: Nabla Magnet

This master thesis explores a way to do surrogate modelling of the current process as is higlighted in Figure 4 by making use of GNN/MLP for the modelling of electrical engine designs described parameterically.

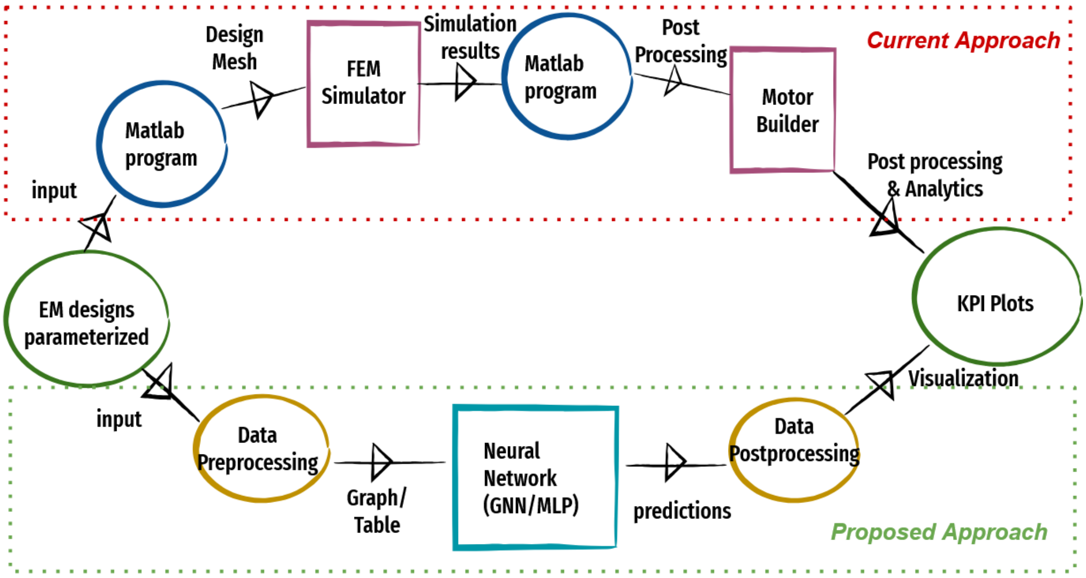

Figure 4: EM Design Flowchart

Background

There has been extensive research in modeling the Electric Motor with Convolution Neural Networks(CNN) based on the images of the motor cross-section. However our approach is progressive in the sense that once the KPIs are predicted we would like to be able to generate the inputs and generating images is not ideal for our usecase. Instead by generating the parameters of the motor we can be rest assured of more precise results. Hence the need to focus on the inputs as they are with their parametric description. Literature also covers works on modelling this work as tabular data using MLPs. Although this is fairly good forseeing the impact of generating the inverse process yet MLPs cannot necessarily learn all the intricacies within motor components. Hence the need to better represent the data typically in the form of graphs and model Graph Neural Networks to achieve the desired results. There has been close to no work of GNNs in this domain. Although we see progress of GNNs in molecular chemistry, social networks usecases from which we draw inspiration from.

Dataset

Valeo an automotive company has supplied the dataset consisting of close to 1500 Double V Electric Motor parameters. There are close to 196 parameters which comprises of the geometric, physical and simulation properties of the motor.

The geometry of a whole Double V motor is as below

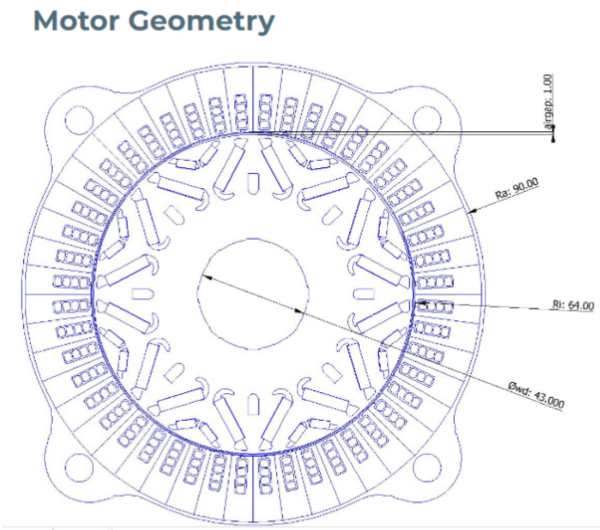

Figure 5: EM Geometry

Below is the geometry of 1/8 cross-section of the same motor.

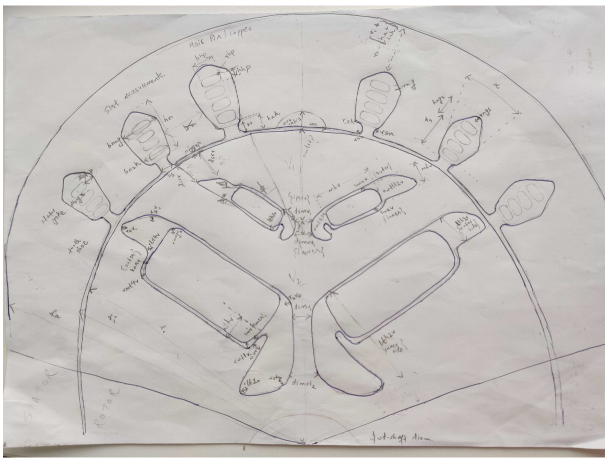

Figure 6: 1/8 Motor Crossection

For modelling the GNN, we represent the data in the form of a heterogeneous graph with different node and edge types.

Node types

1. **General**

   - General parameters:
   $$r = \{r_i\} \quad \forall i \in \{a, r, o\}$$
   where:
     - r_a: *Outer Radius of the Stator*
     - r_r: *Outer Radius of the Rotor*
     - r_o: *Center of the EM*

2. **Stator**

   - Slot windings:
   $$sw = \{s_i w_j\} \quad \forall i \in \{1, \ldots, QSim\}, \quad \forall j \in \{1, \ldots, N\}$$
   - Slots:
   $$s = \{s_i\} \quad \forall i \in \{1, \ldots, QSim\}$$
   where
     - *Qsim : Count of slots in the Stator*
     - *N : Count of copper windings per slot*

3. **Rotor**

   - Magnet Flux Barriers:
   $$v = \{v_{ij}\} \quad \forall i \in \{1, \ldots, T\}, \quad \forall j \in \{1, \ldots, V\}$$
   - Magnets:
   $$vm = \{v_i m_j\} \quad \forall i \in \{1, \ldots, T\}, \quad \forall j \in \{1, \ldots, V\}$$
   where
     - *T : Topology type of the EM*
     - *V : Type of Magnet*

   As Valeo only manufactures Double V magnets we consider it to be 2

Edge types

1. **Angle**
   Relevant Paths

   $$vm{-}{-}vm = \{v_{i_1} m_{j_1} - v_{i_2} m_{j_2}\} \forall i_1, i_2 \in \{1, \ldots, T\}, \quad \forall j_1, j_2 \in \{1, \ldots, V\} \mid i_1 = i_2, \quad j_1 \neq j_2$$

   angle=vm-vm

2. **Distance**
   Relevant Paths

$$vi--vi = \{v_{ij_1} - v_{ij_2}\}, \forall i \in \{1,\ldots,T\}, \forall j_1, j_2 \in \{1,\ldots,V\} \mid j_1 \neq j_2$$

$$vi--vj = \{v_{i_1 j} - v_{i_2 j}\}, \forall i_1, i_2 \in \{1,\ldots,T\}, \forall j \in \{1,\ldots,V\} \mid i_1 \neq i_2$$

$$v--vm = \{v_{ij} - v_i m_j\} \forall i \in \{1,\ldots,T\}, \quad \forall j \in \{1,\ldots,V\}$$

$$v--rr = \{v_{ij} - r_r\}, \forall i,j \in \{1,\ldots,T\}$$

$$o--r = \{(o - r_r), (o - r_a)\}$$

$$rr--s = \{r_r - s_i\}, \forall i \in \{1,\ldots,QSim\}$$

$$s--sw = \{s_i - s_i w_j\}, \forall i \in \{1,\ldots,QSim\}, \forall j \in \{1,\ldots,N\}$$

$$s--ra = \{s_i - r_a\}, \forall i \in \{1,\ldots,QSim\}$$

$$sw--sw = \{s_i w_{j_1} - s_i w_{j_2}\}, \forall i \in \{1,\ldots,QSim\}, \forall j \in \{1,\ldots,N\} \mid (j_1 == j_2 - 1)$$

   distance = vi–vi + vi–vj + v–vm + v–rr + o–r + rr–s + s–sw + s–ra + sw–sw

Node Features

1. **v** = {lmsov, lth1v, lth2v, r1v, r11v, r2v, r3v, r4v, rmt1v, rmt4v, rlt1v, rlt4v, hav}
2. **vm** = {mbv, mhv, rmagv}
3. **r** = {r}
4. **s** = {b_nng, b_nzk, b_s, h_n, h_s, r_sn, r_zk, r_ng, h_zk}
5. **sw** = {bhp, hhp, rhp}

Path Features

1. **vm–vm** = {deg_phi}
2. **vi–vi** = {dsm, dsmu}
3. **vi–vj** = {amtrvj-amtrvi}
4. **v–vm** = {lmav, lmiv, lmov, lmuv}
5. **v–r** = {amtrv, dsrv}
6. **o–r** = {r}
7. **rr–s** = {airgap}
8. **s–sw** = {dhphp}
9. **sw–sw** = {dhpng}
10. **s–ra** = {r_a-(r_i + h_n + h_zk)}

The heterogeneous graph that was constructed earlier is as below:

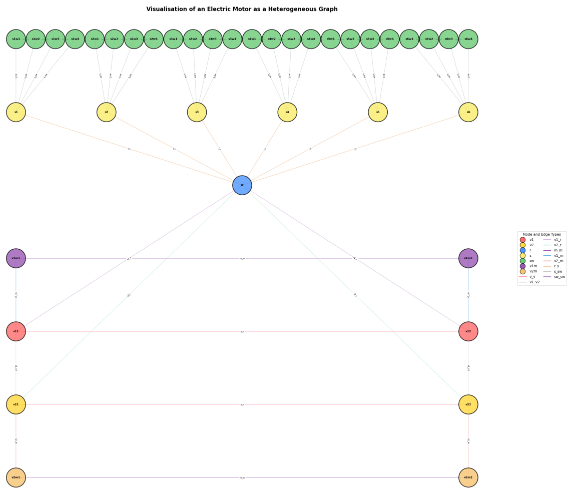

Figure 7: HetGraph

Modelling

We find the heterogeneous graph to be most apt for our use case with its different node and edge types. As it preserves both the structural and semantics of our data. Heterogeneous graph Neural Networks generally work by having separate non linear functions convolve over each edge type during message computation and over each node type when aggregating the learned information.

Experiments and Results

Conclusion

List of Figures

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Appendix

Bibliography

Declaration on oath

I hereby certify that I have written my master thesis independently and have not yet submitted it for examination purposes elsewhere. All sources and aids used are listed, literal and meaningful quotations have been marked as such.

Lilly Abraham K64889, 11.12.2024

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