FRONT-LOADING THE DESIGN PROCESS FOR ELECTROMAGNETIC DEVICES

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Abstract

The design of electromagnetic devices often involves a basic sizing system, to provide a fast suggestion of the structure needed, followed by a multi-physics analysis of the performance. This is a computationally expensive task and can take significant engineering time. If an issue is found with the device performance, it can often mean a significant redesign. Machine learning can be used to enhance the sizing process to provide an initial design along with an estimate of the multi-physics performance accelerating the design process and reducing the probability of a significant redesign.

1 Introduction

Designing an electromagnetic device, such as an electrical machine, is an inverse problem. The designer is given a set of performance requirements often referred to as "key performance indicators" (KPIs) together with, possibly, some constraints in terms of the overall dimensions, the power supply, etc., and the objective is to create a structure which will satisfy the KPIs subject to the constraints. The classical approach to solving an inverse problem is to wrap a forward problem analysis, i.e. given a device specification compute its KPIs, in a feedback loop where adjustments are made to the input parameter vector based on the mismatch (error) between the predicted KIPs and the required performance. Design thus becomes an optimization problem. However, before this process can start, an initial design "guess" is needed and the closer this guess is to the final solution, the faster the optimization process will converge. The creation of the starting point can be determined in two ways: either the designer specifies a starting point based on experience and a few simple rules, or a system, based on a simple electromagnetic model, e.g. a magnetic circuit, is used to "size" the device. Often, these approaches do not provide good starting points and the iterations to a final design can take significant time or the process may not even be successful. In some situations, a design may "fail" because the multi-physics performance, e.g. the thermal behaviour, may result in an unacceptable outcome.

The advances in machine learning over the past few years offer the possibility of directly dealing with the inverse problem and including the multi-physics effects as well as the electromagnetics performance. Such a system could provide significantly more information to the designer, in effect, "front-loading" the design process enabling more effective design decisions and minimizing the probability of issues being discovered late in the process.

2 Machine Learning and Inverse Problems

The recent developments in machine learning based on neural networks have resulted in a range of possible architectures for either classifying data or generating the response of a system to a given input vector. This is a situation where the problem is uniquely defined and there is a single valid output response vector. However, in the design situation, the typical requirements result in an underspecified system in which a relatively small input vector of KPIs leads to the generation of a large output vector of device parameters. This is a classic situation in which there are multiple possible solutions in the design space.

While it is possible to generate a forwards response surface model using a neural network model and couple this with a classical optimizer, this does not address the needs of a "front-loading" system where the goal is to avoid optimization.. Such a design is shown in Figure 1.

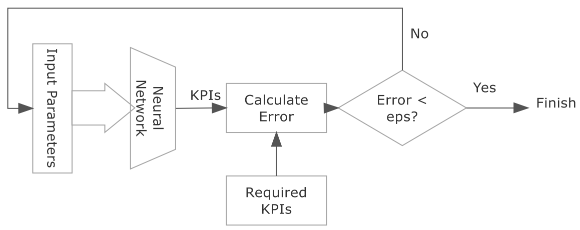

Figure 1 Neural network in an optimization loop

A second approach might be to consider an auto-encoder system. In such an approach, two neural networks are designed and trained such that the first network reduces the input vector to a lower dimensional latent space – in this case, the space of KPIs required – and the second network does the reverse – it generates an output vector based on the latent vector, to match the input vector, i.e. it solves the inverse problem. Figure 2 illustrates this architecture. Once trained, only the second half of the network is needed, and the design requirements are presented as the latent vector. While this approach can work, for any particular set of KPIs it will generate a single output solution within the space defined by the training set.

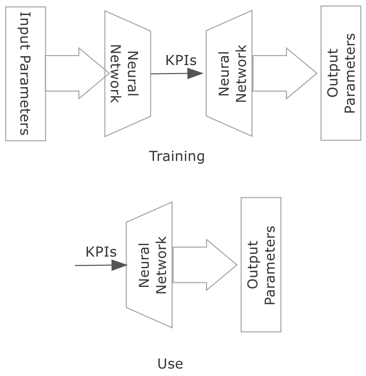

Figure 2. Autoencoder structure

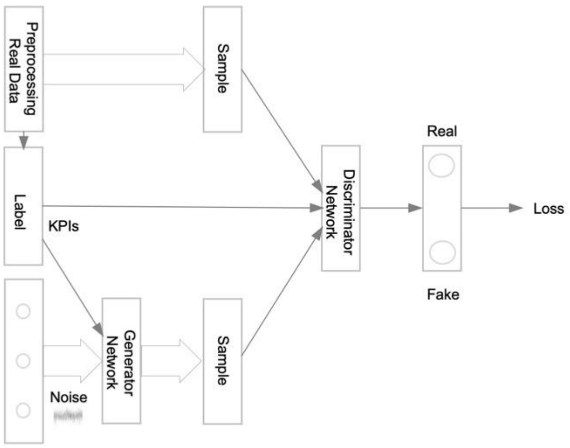

Figure 3. Conditional Generative Adversarial Network/

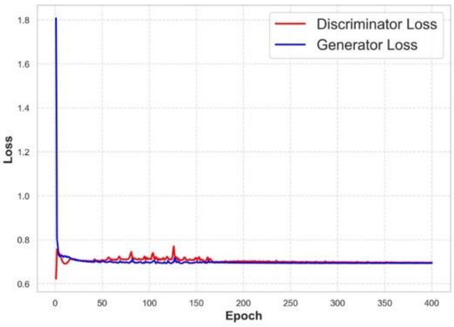

Figure 4. Training performance of the network

A third approach also uses two networks but in this case, they operate together. The architecture is outlined in Figure 3 and is often referred to as a "Generative Adversarial Network" (GAN). In this case, one network proposes a possible solution to a problem, the other criticizes the solution. The criticism is in the form of a loss, or error, which is fed back to the original. The generator network starts by creating random structures but, over time, it learns what makes a valid solution. In this case, the designer can ask for several solutions which should satisfy the KPIs.

In addition to feeding a noise signal to the Generator, the network shown in Figure 3 includes information such as the KPIs. These constrain the output of the generator. This architecture is referred to as a "Conditional GAN".

3 Training the Networks

As a first test, the GAN was trained with 3573-examples of an axial flux machine, with each having a 6 parameter input vector representing the physical dimensions. The samples were chosen using an Enhanced Latin Hypercube Sampling scheme. Figure 4 shows the training performance.

4 Results

Once trained, the GAN can accept a specification for a machine in terms of the KPIs and will generate a set of designs which it estimates will meet the specifications. These are then tested in a simulation to verify that they actually meet the specifications. Figure 5 shows the match for a target torque of 100Nm.

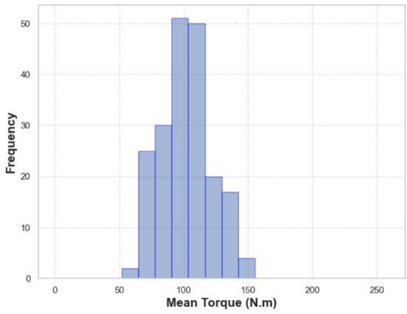

Figure 5. Histogram of torque output for 200 machines

5 Conclusions

The paper has described a machine learning based generative system as an effective sizing tool for an electrical machine. The system can be expanded to include multi-physics and thus provide a front-loading approach to the design process.

References

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