

Averaging Grad Cam Images to Study Large Topology Variations with Potentially Smaller Datasets in Electrical Machine Optimization

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Utilizing Neural Networks to identify the regions for topology optimization (computed by numerical analysis) associated with certain performance parameters using the Grad Cam method is on the bleeding edge of research these days. This method seems to work very well when the topology to be optimized is generally well defined and the small changes do not give rise to a large variation of the topology. When that happens the identification of the optimization target regions becomes difficult as the activation map of the neural network by Grad Cam becomes highly different in each design and difficult to interpret. In this paper we propose a method to handle the large topology variation and provide straightforward interpretation of the Grad Cam heat maps which would otherwise be difficult to manage for a large set of very different geometries. The principal idea of the proposed method is the averaging of the activation heat maps for all designs not only for a single picture as it is typical for Grad Cam. Another approach is also proposed based on providing an animation of the Grad Cam heat plots which will be explained in more details in the full paper.

Index Terms—Electrical Machines, Grad-Cam, Neural Networks, Numerical Analysis

I. INTRODUCTION

GRAD CAM is a well researched method for picture recognition with AI using Neural Networks (NN) [1]. It has been gaining popularity in electrical machine optimization also utilizing numerical methods and the corresponding picture of the design, such as the 2D cross section of stator and rotor. [2] Grad-Cam can be seen as an alternative solution for causal analysis and design rule discovery for electrical machines which is also a hot research topic. [3]-[5] Grad-Cam seems to work very well to identify the sensitive regions of the machine where the optimization shall be focused. The examples shown in Compumag 2023 showcased problems where the geometry variation is contained and the resulting heat map from Grad Cam can be interpreted from a single picture. This however limits the applicability of the method to small topology variations. We recommend a new method to interpret Grad Cam for large topology variations in electrical machine design combined with numerical computation methods.

II. LARGE TOPOLOGY VARIATION EXAMPLES

While Grad Cam has been demonstrated to be a powerful tool providing better results than traditional Genetic Optimization, its application has been limited to relatively small variation topologies where the interpretation of the Grad Cam heat map is meaningful for a single image also. There are however optimization cases where the variation of the topology in the electrical machine geometry can be very large.

One such example is the optimization and sensitivity analysis of material grades and material types for a large variation of designs. In such case a designer could run the optimization for subsets of the topologies with the existing Grad Cam approach, but the method we suggest here allows searching for a “generic truth” applicable across all existing topology variations.

Another case where large topology variations make it difficult to interpret Grad Cam results from a single picture is when the pole numbers, slot numbers, flux guide numbers are

allowed to change. In such case the topology changes so much that the interpretation of a single Grad Cam picture simply does not make sense or results in a restricted perspective of the ground truth learned by the neural network.

We must state here clearly that the approach to average the Grad Cam images suggested in this paper only makes sense if the Neural Network has actually learned to distinguish between the classes we intended to teach it. This is easy to see by monitoring the “loss” / error of the neural network during the teaching process.

There are two cases when the proposed method can be very powerful:

1. If the Neural Network does learn to distinguish with a notable success rate between the classes using the large topology variation dataset computed by numerical analysis the method proposed below can show the relevant areas for optimization in a single image to be interpreted by design engineers and domain experts.
2. When the Neural Network teaching did not fully succeed according to the error rate, but started to “grasp” a “ground truth”. In the full paper we will show example cases where the training data set did not result in “successful teaching” in the traditional sense, but the averaged Grad Cam images already provide new insight into the problem arena.

In this paper we show in detail an example case where a set of induction machines have been evaluated with varying pole number, slot number and slot shapes to identify the regions of the motor which effect the ratio of total losses vs the iron loss. The size of the dataset was also limited and the neural network teaching concluded with a relatively high loss ratio. Even in this not ideal situation the average of the Grad Cam images was able to convey a message of the Neural Network regarding the selected classification criteria.

III. THE GRAD CAM AVERAGING METHOD

The following steps of the Grad Cam method are applied in this study on a set of induction motor designs which varied in pole number, slot number and slot shapes. The proposed approach was able to high light the sensitive areas even

1. Mass creation of electrical machine cross section images from the 2D Finite element geometries. Symmetry sector plots have been avoided for each geometry and images have been created as a “full geometry” to be able to average the Grad Cam images in a meaningful manner.
2. Classification of the images according to the design requirement. In this case we classified the designs according to total loss vs iron loss ratio.
 - a. Several classification methods tested.
3. Teaching the neural network the classified set of images by a code based on PyTorch.
4. Generating the Grad Cam activation image for all design figures in each classification folder.
5. Averaging all Grad Cam images for all classifications.

IV. RESULTS

The result of summarizing all Grad Cam images for each geometry in all classification folders is shown in Fig. 1. The neural network teaching concluded with a large error due to the small dataset and possibly due to the large variation in pole numbers, slot numbers and slot shapes affecting the topology.

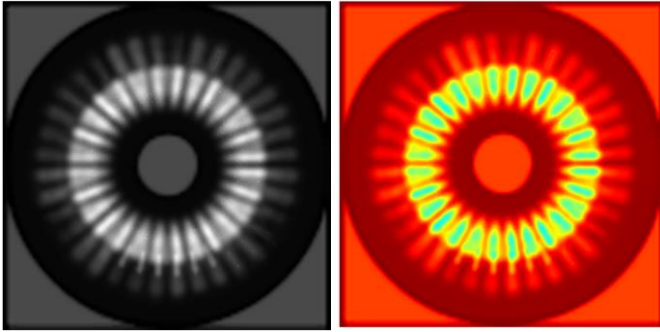


Fig. 1. Averaged picture of Grad Cam images (grayscale and color) for all studied designs in all classification folders for the classification criteria: Total losses / iron losses. Higher values are represented by black / dark red colors appearing in the inner rotor yoke and outer stator yoke regions.

The classification criteria was:

$$Classifier = \frac{Total\ loss}{Iron\ loss} \quad (1)$$

The machines have been classified to 8 classes accordingly and the Neural Network has been taught with the top and bottom eight of the classes.

As mentioned above in step 2 several classification methods have been tested. These have been evaluated in light of how efficiently the neural network could be taught each classification. Some examples of the classifications tried

included classifying according to loss ratio ranges in 8 classes and classifying according to loss ratio ranges in 8 classes but only using top and bottom classes when teaching the NN which further reduced the sample size.

The results show that for the given classification the stator and rotor iron yoke regions further away from the air gap have had the highest activations along all designs, which is the logical conclusion.

V. DISCUSSION OF THE RESULTS & CONCLUSION

Using an electrical machine design dataset which has large variation in the topology, such as pole number, slot number and slot shape, and relatively low number of designs, has not been the ideal input for traditional Grad Cam analysis because of the difficulty in interpreting the results from a single Grad-Cam image and the likelihood for low success of teaching.

The proposed averaged Grad-Cam image of all participating designs in such study allows for a robust tool to summarize the “ground truth” learned by the neural network and to be seen by the design engineers and domain experts in an interpretable manner.

The results show that for studying electrical machine cross sections with this approach, using the images for full cross sections helps to guide the averaging method. This approach would not work if the different symmetry sectors of design sets would be used but works fine for full geometries.

The results highlighted the outer stator yoke and inner rotor yoke as the highest activation areas associated with the ratio of total losses vs. iron loss according to the neural network teaching. This is a logical conclusion as higher yoke areas reduce the flux density and consequently the iron losses. The Grad-Cam image hints that the rotor bar region had lower effect on the loss ratio in this dataset, meaning that an optimization of that region can be done “independently”. This is similar to the optimization approach recommended in [4] for targeted and selective optimization regions where one optimization can be run independently from the other because of the insight we gained by Grad-Cam.

Thanks to the proposed method we could gain this insight and conclusion for a high topology variation by averaging the Grad-Cam images.

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