Prediction and Optimization of Key Performance Indicators in the Production of Stator Core Using a GA-NN Approach

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Abstract. With the rapidly changing demands of the manufacturing market, intelligent techniques are being used to solve engineering problems due to their ability to handle non-linear complex problems. For example, in the conventional production of stator cores, it is relied upon experienced engineers to make an initial plan on the number of compensation sheets to be added to achieve uniform pressure distribution throughout the laminations. Additionally, these engineers must use their experience to revise the initial plans based upon the measurements made during the production of stator core. However, this method yields inconsistent results as humans are incapable of storing and analysing large amounts of data. In this article, first, a Neural Network (NN), trained using a hybrid Levenberg-Marquardt (LM) – Genetic Algorithm (GA), is developed to assist the engineers with the decision-making process. Next, the trained NN is used as a fitness function in an optimization algorithm to find the optimal values of the initial compensation sheet plan with the aim of minimizing the required revisions during the production of the stator core.

1. Introduction

Even though, over the years, the bounds of what manufacturing industries can accomplish has increased significantly, with the rapid development of global industry, manufacturing industries are facing many challenges, such as the higher complexity and flexibility of problem as well as increasing human labor cost. These problems create bottleneck to the traditional manufacturing system due to the engineer’s limitations on handling uncertainties, complexity and memorizing large amount of data [1]. The recent advancement in computing has enabled researchers to develop many artificial intelligence techniques that have enabled the transfer of the years of experience stored in the minds of the human operators to computers, thereby transferring the decision-making burden form man to machine. Furthermore, optimization techniques have enabled engineers to find optimal process parameters that can help them achieve the desired outputs.

The intelligent techniques have showed great results when used for creating prediction models in the absence of physics-based models and also for obtaining optimal process parameter combinations for optimization problems. Rajora et al. [2] used NNs, k-means clustering algorithm, and GA to create a forward prediction model and obtain multiple optimal solutions for the process of electrochemical micro-machining (µECM). Tansel et al. [3] used a cluster of NN to represent the friction stir welding operation. Rao and Pawar [4] used ABC, SA, and harmony search algorithms to minimize the production cost, maximize the production rate, and minimize the surface roughness of a grinding process. Ji et al. [5] used NN to model the process of minimum quantity lubrication (MQL) turning and then utilized GA to optimize its input process parameters. Lin et. al [6] developed a forward
prediction model between various inputs of turning operation and the surface roughness and cutting force. Benardos and Vosniakos [7] created an ANN to predict the surface roughness in computer numerically controlled (CNC) face milling. Mahesh et. al [8] used GA for the optimization of cutting parameters to minimize the surface roughness. Kumar et. al [9] used a hybrid Taguchi-ANN for predicting surface roughness during machining of titanium alloys. Ji et. al [10] used ANNs to predict surface residual stress in MQL face turning.

Though intelligent techniques have gained widespread usage in the traditional manufacturing industries, an area where traditional human decision-making process is still relied upon is in the production of stator cores. In this paper, NNs have been used to help the engineers with the decision-making process. The NNs are trained using a hybrid Genetic Algorithm (GA) – Levenberg Marquardt (LM) algorithm with the aim of increasing their prediction accuracy. Next, the trained NNs are used as the fitness function in an optimization model, using GA, to obtain optimal initial compensation sheet plan. The rest of the paper is organized as follows: the production of stator cores and decision making involved in their production is introduced. Next, the NN prediction model and optimization model are introduced. The results obtained when the trained NN is used to model the production of stator core process are presented followed by the optimization results. Lastly, some conclusions are drawn based on the results obtained.

2. Description of the Problem

A turbogenerator stator is comprised of two major components: 1) the stator windings, and 2) the stator core. A stator core is built up as laminations are placed side-by-side, to make a complete circular or ringed layer. The next layer is laid, offsetting each layer like a brick or cinder block wall. Along its back, the stator core is held in place by rails, which are bolted to so-called guide bars. Once the stacking is complete, the stator core is heated and pressed with a defined force. The process of stacking, heating and pressing needs to be repeated six times in the production to ensure the total height of the stator core reaches the desired value. To achieve uniform pressure distribution among the stator lamination layers, engineers align different shapes and sizes of compensation sheets between the layers of stator lamination per the measurement result of the lead extrusions, as seen in Fig. 1.

![Figure 1. Measurement points of the lead extrusion.](image)

In this study, there were nine different types and sizes of compensation sheets available that could be inserted among the stator lamination. Before the production of the stator laminations, experienced engineers make an initial guess on the number of each type of compensation sheets to be added after each pressure application process. Next, pressure is applied to the stator core for the first time and the value of four key performance indicators (KPIs), given by Equation (1) – (4) are measured. Based on the value of the four KPIs, the engineers use their experience to revise the initial compensation sheet assignment plan by either assigning more or fewer of each type of compensation sheets. Then, based on the revised compensation sheet assignment plan, the different compensation sheets are inserted at the eight location and the pressure is applied for the second time. The above process is repeated until the pressure application process is completed.
Average thickness \( \overline{t} \) can be calculated as the average of the thicknesses of each layer:

\[
\overline{t} = \frac{1}{8} \sum_{i=1}^{8} \left[ \text{avg}(\text{thickness}_{i}') - \text{avg}(\text{thickness}_{i} + \text{thickness}_{i}') \right]
\]  

(1)

Deviation \( \text{Deviation}_{i} \) can be calculated as:

\[
\text{Deviation}_{i} = \sqrt{\frac{1}{7} \sum_{i=1}^{8} \left( \text{avg}(\text{thickness}_{i}') - \overline{t} \right)^2}
\]  

(2)

Average thickness \( \overline{t} \) can be calculated as the average of the thicknesses of each layer:

\[
\overline{t} = \frac{1}{8} \sum_{i=1}^{8} \left[ \text{avg}(\text{thickness}_{i} + \text{thickness}_{i}') - \text{avg}(\text{thickness}_{i}') \right]
\]  

(3)

Deviation \( \text{Deviation}_{i} \) can be calculated as:

\[
\text{Deviation}_{i} = \sqrt{\frac{1}{7} \sum_{i=1}^{8} \left( \text{avg}(\text{thickness}_{i}' + \text{thickness}_{i}') - \overline{t} \right)^2}
\]  

(4)

During the production of the stator cores, the engineers also aim to create a correct initial compensation sheet assignment plan based on their years of experience. Additional complexities are added to the process of creating an optimal initial compensation sheet assignment plan since there is an upper limit on how many times each compensation sheet can be used during the production of the stator core.

Under the current settings of the production of stator cores, coming up with the final compensation sheets assignment plan in which no additional adjustments are required is very crucial to help reduce the dependency on the experienced engineers and improve the efficiency. Therefore, it is important to create a prediction model that can accurately map from the inputs to the key performance indicators (KPIs) in the production of stator core and a corresponding optimization model that can create an optimal initial compensation sheet assignment plan which deviates very little from the adjusted compensation sheet assignment plan while meeting all the constraints of the process.

### 3. Modelling

#### 3.1. Prediction Model

To map from the inputs to the outputs of the stator lamination production process NNs were utilized. Instead of Gradient Descent (GD), Levenberg-Marquardt (LM) algorithm was used for training as it has shown to outperform GD in a variety of problems. To overcome the drawback of gradient based algorithms (only local convergence), it was used in conjunction with GA, a metaheuristic algorithm. During the training procedure, GA was first used to search the function space for the optimal or sub-optimal weight and bias values. These values were then used as a starting point for the LM algorithm, which then fine-tuned the weight and the bias values to improve the results.

Since the pressure application was performed in six stages, five different NN models were created. Each NN had 13 inputs, four corresponding to the value of the KPIs obtained after a pressure application and the other nine corresponding to the number of each type of compensation sheet to be added before the next pressure application. The nine outputs were the revised compensation sheet plan based upon the experience of the engineers.

#### 3.2. Optimization Model

The optimization objective in this study was to minimize the number of incorrectly predicted compensation sheets to be added before each force application. The four inputs corresponding to the KPI values were used as reference inputs (their values were not changed during optimization) while the nine inputs corresponding to the number of each type of compensation sheet to be added before each pressure application were the design variables. The NNs created in the previous step were used as the fitness function during the optimization process and GA was used to find the optimal values of the design variables.

### 4. Results

#### 4.1. Training Results

Due to the lack of actual production data, 20 simulated data sets were generated with the help of experienced engineers. Of the 20 data sets available, 14 of them were used for training, three for
validation, and three for testing the trained NN. The best NN structure, selected through trial-and-error, for each NN was a 13-12-9 structure. For each trained NN, its prediction accuracy was measured by observing how many outputs for each testing data set it could predict correctly. These results are shown in Figure 2, each column for a NN represents the number of outputs predicted correctly for a testing data set by that NN.

![Correctly Predicted Outputs for the Testing Data Set](image)

**Figure 2.** Prediction results obtained using the trained NNs.

### 4.2. Optimization Results

Once the NNs had been trained sufficiently, they were used as the fitness function for the GA optimization process. To test the optimization model, three different sets of four KPI value for the reference inputs were generated for each pressure application and given as inputs to the NNs. Next, the optimization algorithm was used to find the optimal values of the initial compensation sheets. The optimization objective was to minimize the difference between the initial compensation sheet plan and the adjusted compensation sheet plan, so that the optimized initial compensation sheet plan could be used in the production with little to no adjustment. The corresponding optimization result are calculated based on Equation (5) and are shown in Table 1.

\[
\text{% difference} = \left( \frac{\text{number of incorrectly predicted compensation sheets}}{\text{total compensation sheets predicted}} \right) \times 100\%
\]

(5)

|   | Percentage of difference using Settings A (%) | Percentage of difference using Settings B (%) | Percentage of difference using Settings C (%) |
|---|---------------------------------------------|---------------------------------------------|---------------------------------------------|
| Simulation 1 | 26.7                                         | 26.7                                         | 26.7                                         |
| Simulation 2 | 22.2                                         | 26.7                                         | 33.3                                         |
| Simulation 3 | 33.3                                         | 33.3                                         | 33.3                                         |

Based on the results, the results obtained using setting A provides a slight improvement comparing to the results obtained by setting B and C. However, in general, the percentage of difference between the initial plan and the adjusted plan is around 22.2-33.3%, which may due to the relatively high number of optimization variables.

### 5. Conclusion

In this study, a prediction and optimization approach was proposed to solve the problem in the production of stator core that the assignment and adjustment of compensation sheets between each pressure application. In the proposed approach, a NN model was first trained with simulated training data with the aim of capturing the decision-making capabilities of experienced human engineers. Then,
a GA based optimization model, which utilized the built NN as the fitness function, was created to minimize the difference between the initial assignment plan and the adjusted one. The results of the prediction model showed that the NN trained using the hybrid LM-GA algorithm had a prediction accuracy of 90% indicating that the NN model can capture the decision-making capabilities of experienced human engineers. However, the optimization result shows that the algorithm is unable to find an optimal plan and the adjusted one was generally around 30%. Future research will be focused on improving the optimization process to narrow down the difference between the initial plan and the adjusted one. Possible solutions include combining simulated and historical data and selecting alternative inputs for the prediction model that might be better suited for the optimization purpose.

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