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Uncovering Hidden Causes of Turbine Bearing Vibration Using Neural Network

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Abstract
This paper presents a practical application of Artificial Intelligence (AI) to identify the root cause of excess vibration in a turbine bearing at a conventional power plant. For several years, the vibration occurred sporadically without any physical explanation. Traditional diagnostic methods failed to determine the cause of this excessive vibration in the 5th bearing of the turbine shaft. To address this, we applied a neural network program, using all available measured data from the plant to train the AI system. After training, the AI revealed that the unexpected eigenfrequency of the condenser, combined with the rotational frequency of the shaft, was the actual cause of the event.

Introduction
In recent years, Artificial Intelligence (AI) methods have increasingly been applied to the mathematical modeling of industrial processes. Many studies have explored the development of neural network software packages, yet fewer reports highlight successful implementations of these techniques in real-world industrial applications. This paper presents a notable case where AI was applied to solve a long-standing vibration issue in a conventional power plant.

The problem persisted for years despite repeated attempts using traditional diagnostic methods, including vibration measurements, calculations, and finite element analyses. None of these methods succeeded in identifying the root cause of the excessive vibration observed in one of the turbine bearings. Given the complexity of the system and the limitations of physical models, we turned to AI for a solution, leveraging neural network techniques to model the behavior of the system and uncover the underlying cause.

Description of the Problem
Many conventional power plants operate with turbine-generator systems that consist of components from different manufacturers. In this case, the turbine was purchased from Brown-Boveri, while the generator was from Ganz-Huslet. To connect the two components, a coupling without an additional bearing was initially suggested, based on the original design from Brown-Boveri. However, since the components were sourced from different manufacturers, an additional bearing (referred to as t5) was introduced near the coupling (see Figure 1).

Under normal conditions, the system operated without major issues. However, excessive vibration in the t5 bearing was occasionally observed during power reductions to around 50% of the unit's capacity. These vibrations sometimes exceeded the allowed limits, particularly during unloading of the unit. Despite multiple attempts to resolve the issue, including vibration measurements, calculations, and finite element analysis, the root cause of the vibration could not be identified. Resonance between the shaft's rotational frequency and the bearing's eigenfrequency was suspected, leading to the addition of masses to the bearing base to avoid this resonance. While this eliminated some resonance peaks, the specific vibration occurring during unloading persisted, and its occurrence was inconsistent, making the problem even more difficult to diagnose.

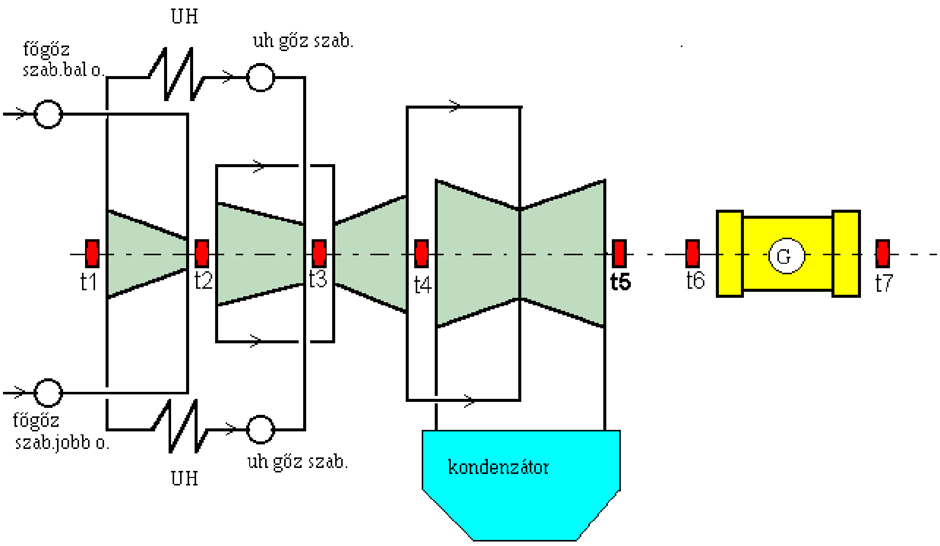

Figure 1: Schematic Representation of Turbine-Generator Ensemble. Main Components, Signals and Bearings are Marked. The Bearing Marked T5 Went to Excess Vibration

Since the cause of the problem was not found we decided to use an Artificial Intelligence (AI) program for searching the cause.

The Measured Signals

Modern power plants record numerous signals from various components through automated data collection systems, typically at sampling rates of 1 to 3 seconds. These signals include temperature, pressure, flow rates, vibration parameters (such as velocity and acceleration), shaft eccentricity, power production and losses, oil consumption, and bearing temperatures, among many others.

In our case, the signals recorded by the plant's data collection system were used for training the AI model. Figure 2 shows a typical plot of the recorded data. The topmost curve displays the changes in power production, which dropped to 50% between 6:30 AM and 8:30 AM. Notably, during this period, two additional signals, corresponding to the horizontal and axial vibrations of the t5 bearing, began to oscillate with long periods.

Despite the wealth of available data, identifying the interconnections between the signals and understanding their causal relationships was challenging. Traditional physical models were no longer sufficient to handle such complex problems, and it became clear that a mathematical approach leveraging AI was needed. By training an AI model with this data, we aimed to uncover the root cause of the excessive vibration.

To explore this, we selected two different sets of signals. The first set included 12 input signals, while the second set comprised 30 inputs. The outputs were initially limited to the vibration of the 5th bearing, the starting point of our investigation. Later, we expanded the outputs to include multiple vibration sensors (up to 7*2) across the turbine shaft.

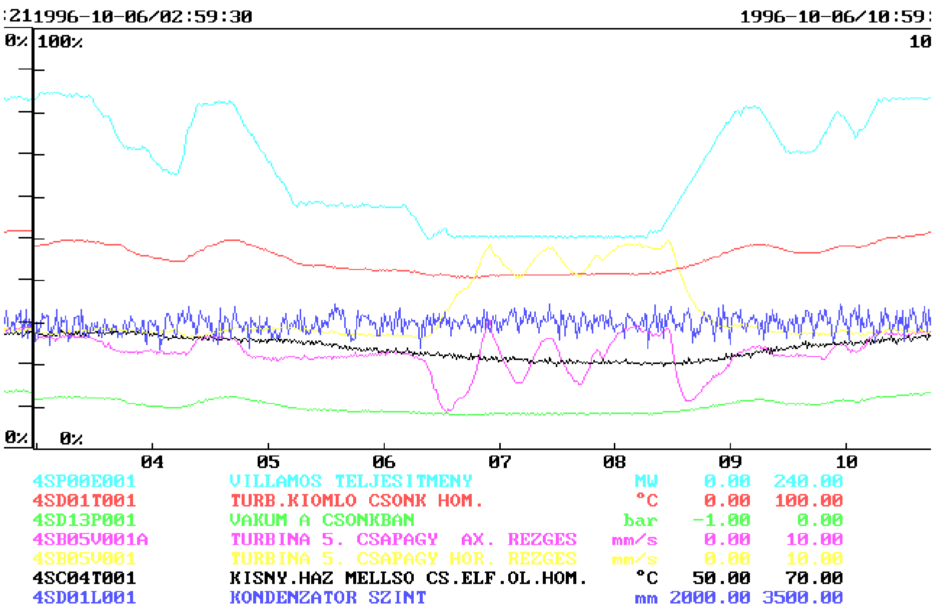

Figure 2: Records of Signals from Plant Data Collection System Used for Training

Description of the software used in our modeling

The software used in our analysis, AiNet, is a semi-commercial program available as a shareware product. While AiNet is not a traditional neural network in the strictest sense, it functions as an artificial intelligence tool that fits a matrix to the measured data [1,2]. Once the optimal fit is found, the model is ready for prediction purposes.

Figure 3 presents the graphical layout of AiNet, showing its resemblance to other Artificial Neural Networks (ANNs). AiNet operates in two phases: training (or modeling) and prediction. During the training phase, the model vectors (from the recorded data) are presented to the network. This process is rapid, similar to the presentation of data in other supervised neural networks, such as Probabilistic Neural Networks (PNNs) [3].

The prediction phase follows, where the AI system calculates the unknown output values for either prediction or verification purposes, ensuring the model's accuracy. Prediction phase corresponds to the calculation of values of processing elements and calculating the unknown output values of prediction vector (in case of prediction). Or it calculates output values of model vectors (in case of filtration of verification for determination of penalty coefficient value).

Training (or learning) the aiNet ANN corresponds to the presentation of the model vectors to the net. The weights on connections are either equal to one or equal to zero. The expression for weight adaptation can be written as:

$$w_{ij} = \overline{w}_{ij}\delta_{kj},$$

This structure allowed us to efficiently model and analyze the system's behavior, identifying key patterns and predicting outcomes based on the data from the plant. The following expressions describe feedforward - prediction mode of the aiNet. It should be noted that such network has two hidden layers (layer B and layer C). The number of neurons in layer B is equal to the product of the number of all model vectors N and the number of input variables M (N M), while the number of neurons in the layer C is equal 2 times the number of model vectors. For the sake of simplicity, we will assume that we have only one output (unknown) variable in the output layer D.

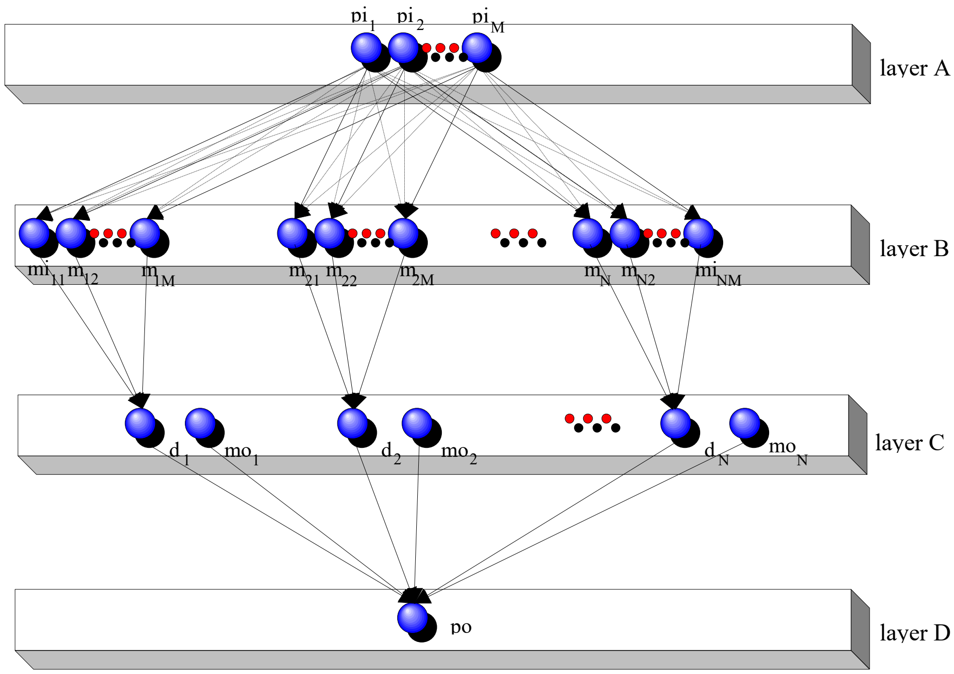

Figure 3: Graphical Presentation of the aiNet

Notations in Figure 3 have the following meaning:

- p prediction vector.
- m model vector.
- i indicate the neuron, belonging to the input variable.
- o indicates the neuron, belonging to the output variable.
- N number of model vectors.
- M number of input variables of the phenomenon.
- K number of output variables of the phenomenon (K is equal to 1 in presented case, and is omitted).
- Pc penalty coefficient.

Network works in prediction mode according to the following scheme:

- *layer A:* value of the neuron: $X_i^A = p_i$,
  transfer function: *linear*
  output value of the neuron: $Y_i^A = f(X_i^A) = X_i^A$.

- *layer B*: value of the neuron: $X_{ij}^B = \sum_{k=1}^{M} \left(Y_k^A - mi_{ij} \right) \delta_{kj}$
  transfer function: *linear*
  output value of the neuron: $Y_{ij}^B = f\left(X_{ij}^B\right) = \left(X_{ij}^B\right)^2$

- *layer C:* value of the neurons <u>type d</u>: $X_i^C = \sum_{j=1}^{M} Y_{ij}^B$
  transfer function: *linear*
  output value of the neuron: $Y_i^C = f\left(X_i^C, pc\right) = e^{\frac{-X_i^C}{pc}}$
  value of the neuron <u>type mo</u>: $\overline{X}_i^C = mo_i$,
  transfer function: *linear*
  output value of the neuron: $\overline{Y}_i^C = f(\overline{X}_i^C) = \overline{X}_i^C = mo_i$.

layer D: value of the neuron: $X^D = \sum_{i=1}^{N} Y_i^C$,

$$\overline{X}^D = \sum_{i=1}^{N} Y_i^C \; \overline{Y}_i^C$$

transfer function: *linear*

output value of the neuron: $po = Y^D = f\left(X^D, \overline{X}^D\right) = \dfrac{X^D}{\overline{X}^D}$

Testing the Software

We began by testing the AiNet software step by step to ensure its reliability.

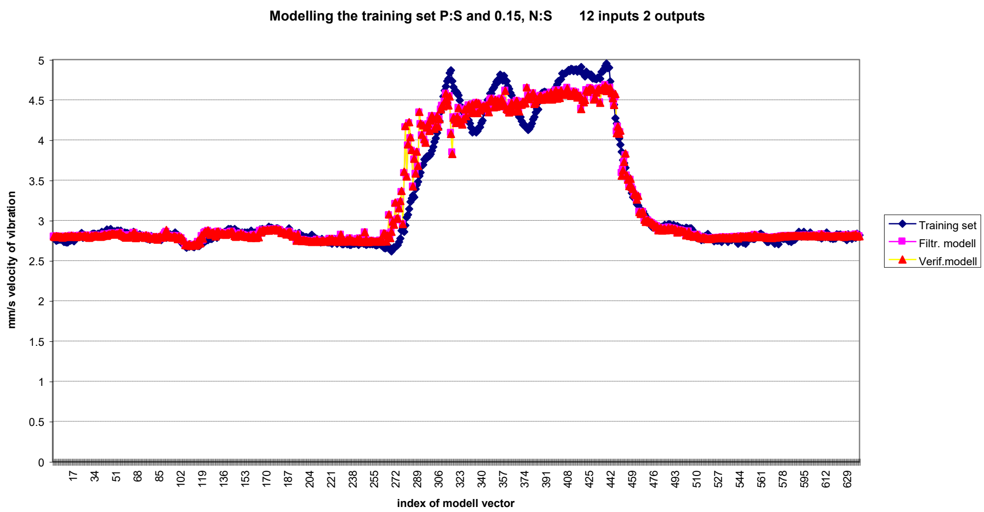

Figure 4: Trained with 12 Inputs and 2 Outputs Data the Fit was Not Perfect

The first test involved using artificial data, which allowed us to assess the software's ability to predict outcomes when different amounts of white noise were added to the data. The results showed that the fitted model was effective for predictions, as long as the predicted values stayed within the range of the training data. However, extrapolation beyond the training range proved to be less accurate. This highlighted the importance of keeping the AI's predictions within the limits of the training dataset, a well-known limitation in many AI-based classification models, including neural networks.

Figure 4 shows an early attempt to fit the training data set, focusing on the t5 bearing's oscillations. The model was trained with 12 input signals and 2 output signals (for horizontal and axial vibration), using a static penalty coefficient of 0.15. While the model fit the training data reasonably well, the filtration and verification curves deviated slightly, and the oscillations were smoothed out in comparison to the raw data.

After refining the parameters, a much better fit was achieved using 30 input signals and 2 output signals, with the nearest-neighbor penalty coefficient set at 0.15 and a normalized statistical model (see Fig. 5). This model provided excellent agreement with both the filtration and verification datasets, capturing both the rise in amplitude and the oscillations observed during reduced power. With this model, we were able to move forward with confidence in the training phase and begin applying the AI for predictive analysis.

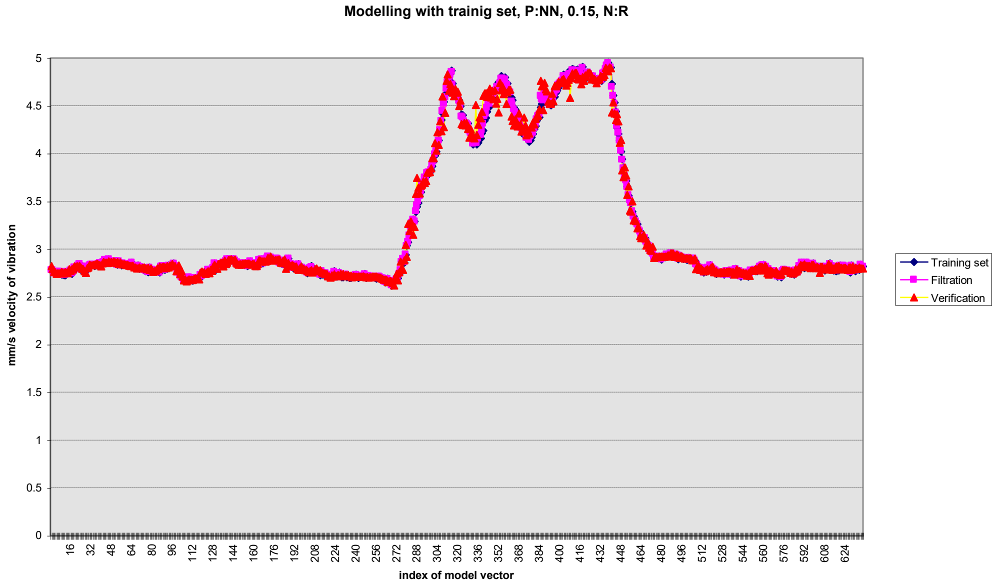

Figure 5: Good fit of the Model Was Achieved with 30 Inputs and 2 Outputs Using the Nearest Neighbour Penalty Coefficient with Value of 0.15

Analyzing the Given Case: Prediction

Once we achieved a good fit with the model, we proceeded to the prediction phase. The goal here was to simulate how the system would behave if certain parameters were adjusted, which would allow us to explore potential solutions to the excessive vibration problem. Our first simulation involved reducing the power from 100% to 50%, as shown in Figure 6. This mirrored the operational conditions under which the t5 bearing's excess vibration typically occurred. According to the trained AI model, the excess vibration was predicted to emerge when the power reached around 50%, which matched the actual data.

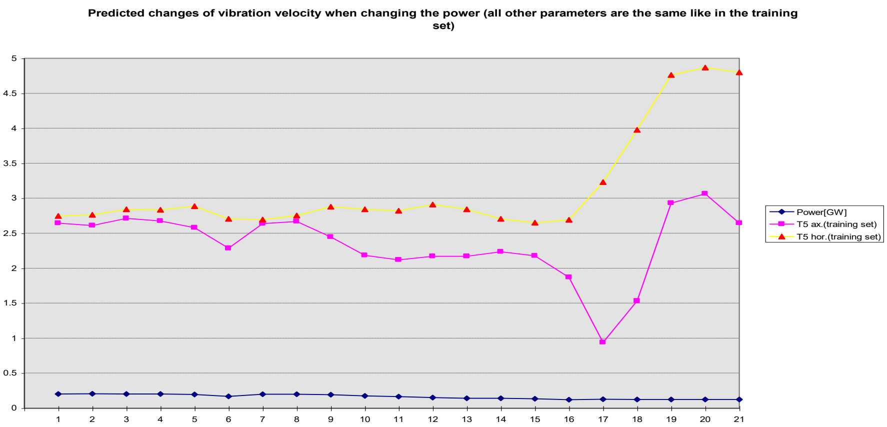

Figure 6: Prediction of Changes of Vibration Velocities for Different Power Level Using Original Data

With this baseline established, we began to systematically vary the input parameters to determine their effect on the vibration. One hypothesis was that the axial vibration of the t5 bearing might be connected to the elongation of the small pressure turbine housing. From a technical perspective, this made sense because changes in the turbine's elongation could impact the bearing's gap. However, when we simulated a reduction in elongation, no significant reduction in the t5 bearing's vibration was observed, as shown in Figure 7. The curves for both the horizontal and axial vibrations were nearly identical to the original dataset, leading us to conclude that elongation was not the root cause of the excess vibration

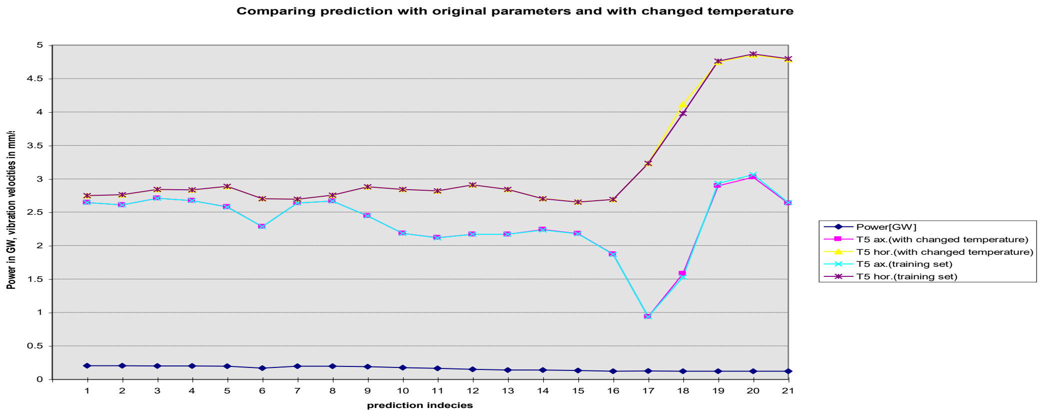

Figure 7: Comparison the Predictions Using Original Data and the Modified Temperature Data

After testing several parameters with limited success, the most promising results were achieved by varying the water level in the condenser. Initially, there was no indication that this parameter could be directly related to the excess vibration of the t5 bearing, as the condenser does not have a direct mechanical connection to the turbine axis. However, since all input parameters could be varied within the AI model, we decided to test this hypothesis as well.

The results were surprising. At specific water levels in the condenser (which, incidentally, corresponded to the most frequent operating conditions in the plant), we observed the excess vibration of the t5 bearing, as shown in Figure 8. By either raising or lowering the water level, the AI model predicted a significant reduction in the vibration, bringing it within acceptable limits according to national standards. While the reduction was not enormous, it was sufficient to lower the vibration to a permitted level.

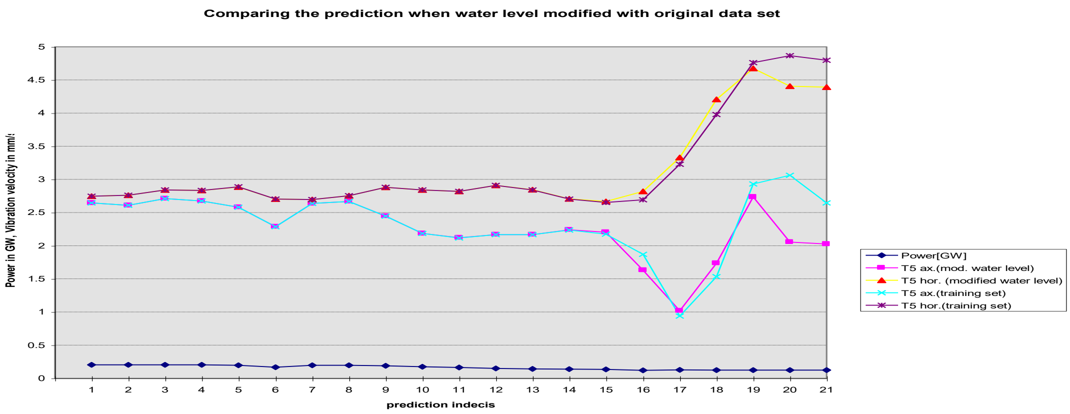

Figure 8: Comparison Using Original Data and Changed Water Level in the Condensator

This unexpected finding provided a key insight: the water level in the condenser influenced the system's resonance. By altering the water level, the overall mass of the turbine support structure was changed, which in turn affected the resonance conditions. This behavior closely resembled a classic case of resonance, where adjusting a single parameter – in this case, the water level – could mitigate unwanted vibrations.

A Physical Explanation to the AI Result

The results of the AI analysis pointed to a resonance phenomenon between the condenser and the turbine bearing system. Specifically, at certain water levels in the condenser, the mass of the entire support structure changes, which in turn alters the natural frequencies of the system. When the eigenfrequency of the condenser matches the rotational frequency of the turbine shaft, the system experiences resonance, leading to the observed excess vibration in the t5 bearing.

By either raising or lowering the water level, the overall mass distribution changes, thus shifting the resonance away from the problematic frequency. This explains why adjusting the water level helped reduce the vibration amplitude. Before the AI model identified this, the relationship between the condenser water level and the turbine bearing's vibration was not considered, as the condenser was not directly connected to the turbine shaft. However, the AI model highlighted this indirect connection, offering a new perspective on how seemingly unrelated parameters can influence turbine behavior.

This AI-driven discovery illustrates the value of machine learning in industrial applications, where complex systems have many interdependent variables. In this case, the AI model helped to uncover a hidden relationship that would have been difficult to detect using traditional diagnostic methods alone.

Conclusions

This study demonstrates the potential of artificial intelligence to solve complex, long-standing industrial problems. By applying AI to model the multi-variable dynamics of a power plant system, we were able to identify the root cause of excessive vibration in a turbine bearing, which had evaded traditional diagnostic methods for years.

The AI model successfully predicted that the resonance between the condenser's eigenfrequency and the turbine shaft's rotational frequency was responsible for the vibration. Adjusting the water level in the condenser provided a simple yet effective solution by shifting the resonance frequency, reducing the vibration amplitude to within acceptable limits. This discovery showcases how AI can reveal hidden relationships within complex systems that are often overlooked by conventional approaches.

Moreover, the success of this model highlights the importance of experimenting with different combinations of variables, even those that may seem unrelated at first glance. With modern computing power, such simulations are increasingly accessible and can be used to address a wide range of industrial challenges. We believe that similar AI-based modeling approaches can be applied to other persistent problems in industrial environments.

Acknowledgements

In this work a purchased AiNet software was used [1]. The problem was raised and partly the testing was carried out by J. Vasko in his diploma work [4].

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