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Development of a Failure Prediction System for Industrial Laser Diodes Based on Artificial Neural Networks

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ABSTRACT

Industrial laser diodes are essential devices used in semiconductor chip manufacturing, where the precision and stability of laser output strongly affect the process yield. However, under long-time operation and high thermal stress, these lasers tend to degrade slowly, sometimes leading to unexpected failure that causes production interruption and cost increasing. In this work, a data-driven fault prediction system is proposed for early detection of degradation behavior in industrial laser diodes. The experimental data were collected from a Monaco 517-40-30 femtosecond laser operating in an actual production environment. The proposed system monitors a set of electrical, thermal, and optical parameters that reflect the operational condition and degradation characteristics of the laser diode. After normalization, noise filtering and outlier removal, a feedforward neural network was trained using the Levenberg-Marquardt algorithm with Mean Squared Error (MSE) and regularization to reduce the overfitting problem. The model achieved above 98.9% for both training and testing accuracy, with minimum F1-score and Recall values of 0.9. This shows that the system can do early fault detection quite reliably even in industrial conditions. From these results, the system is considered a practical solution for predictive maintenance and can help improve uptime and reliability of laser equipment.

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1. Introduction

In modern semiconductor manufacturing, laser diodes play an important role in high-precision processes such as wafer marking, substrate engraving, and material cutting, where the positional accuracy often needs to be within several tens of micrometers. Figure 1 illustrates an example of Laser marking on a mobile processor of laptop. These devices are among the key components that decide both the precision and the throughput of the production system. However, because of their thermal sensitivity and continuous operation under high current and temperature, laser diodes tend to degrade gradually over time and sometimes fail suddenly, leading to unexpected downtime and considerable financial loss. As Vietnam is currently investing strongly in the semiconductor manufacturing industry, maintaining the reliability and operational stability of critical tools such as industrial lasers have become one of the national technology priorities.

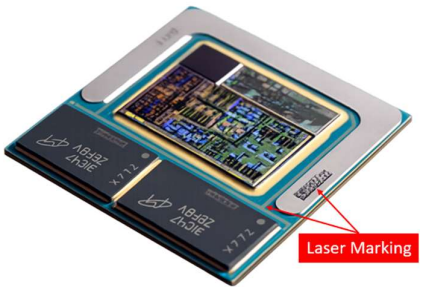


Figure 1. *Illustrative example of laser marking in advanced semiconductor packaging (adapted from [11]).*

Traditional maintenance approaches, like doing preventive checks on a fixed schedule, usually do not catch the early degradation because the equipment is quite complex and the issues start very slowly. In recent years, the rise of Machine Learning (ML) and Artificial Intelligence (AI) has made it possible to move toward Predictive Maintenance (PdM), where systems can be continuously monitored, and potential faults can be predicted before an actual failure happens. Among various ML techniques, Artificial Neural Networks (ANNs) have been widely applied because of their strong ability to model nonlinear relationships between multiple operating parameters and complex degradation patterns that occur in practice. Several international works have focused on laser reliability prediction using ML-based approaches. For instance, Abdelli et al. proposed multiple machine learning frameworks for lifetime estimation of semiconductor Lasers such as 1,550 nm DFB lasers [1]–[3], while Huang studied how temperature and current affect the degradation behavior of buried heterostructure semiconductor lasers [4]. However, most of these studies were carried out using laboratory or simulated datasets, which may not fully represent the real industrial conditions. In Vietnam, there is still a lack of research that uses actual factory data from operating laser systems as part of a predictive maintenance model.

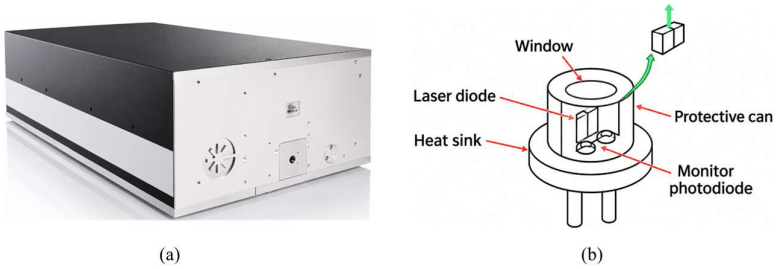


Figure 2. *(a) Industrial femtosecond laser system (Monaco 517-40-30, adapted from [5]); (b) Schematic illustration of a semiconductor laser diode structure.*

This research aims to address this gap by building an early fault-prediction system based on an artificial neural network for the Monaco 517-40-30 laser, Figure 2 illustrates the Laser System by Coherent with Semiconductor Diode [5]. The model was trained on data collected directly from equipment operating in a Vietnamese manufacturing site, so the inputs reflect real industrial behavior rather than only lab conditions. Based on the studies in [4] and [6] and on the application note in [7], the electrical, thermal, and optical parameters used in this study are indicators derived from the current-voltage behavior, temperature-related stress, and optical feedback characteristics of the laser diode. Using these signals, the proposed approach aims to identify developing faults before they lead to complete failure. The results are expected to provide a practical basis for predictive-maintenance solutions in Vietnam's growing semiconductor industry, helping to improve equipment reliability and reduce unexpected downtime.

2. Research Methodology and Experimental Setup

2.1. Data Acquisition and Modeling Strategy

This research combined electronics, optics, software, and AI to solve a practical problem in production: early failure detection in industrial laser diodes. The idea came from real challenges in semiconductor factories, where lasers are widely used for marking and micromachining. In these environments, unexpected laser failures can stop the entire production line, so predicting faults before breakdown is much more effective than fixing them afterward. To keep the study close to actual factory conditions, the Monaco 517-40-30 femtosecond laser was selected. This model is commonly used in semiconductor manufacturing and shows typical diode aging behavior. This research collected real sensor data, including optical power, threshold current, voltage, and diode temperature, to track degradation and estimate laser health over time. And then used an ANN as the main modeling tool because it handles nonlinear relationships between sensor signals and degradation quite well. The network was intentionally kept simple so that this model could run quickly, be retrained easily, and adapted to other laser types. MATLAB was used for simulation and training, and the results were then evaluated to assess the real-time applicability of this model. Going beyond pure simulation, this proposal

also sketched an implementation idea. The prediction model would feed into an IoT monitoring dashboard. In practice, that means continuous data collection, near-real-time prediction of the health state, and early warnings sent to engineers. In the long run the same setup could be moved to cloud platforms, which would make it easier to manage many machines and to build more advanced maintenance workflows.

2.2. Neural Network Modeling and Evaluation

A combination of data processing, statistical analysis, and machine learning was used to create a clear pipeline from data acquisition to model validation. This study first reviewed predictive maintenance methods and laser diode degradation behavior. The Monaco 517-40-30 datasheet served as the reference for model setup and performance limits. MATLAB was then used to process real laser data under both normal and degraded conditions, focusing on operating current, temperature, and optical power. These real measurements formed the training dataset. No synthetic data were used. Before training, the raw data were cleaned, filtered, and normalized using Min-Max scaling. The study found that this preprocessing step helped stabilize the training, even though some noise remained. The ANN model used was arranged in a simple way, with the usual input-hidden-output structure. The model was trained mainly with the Levenberg-Marquardt algorithm, since it converged faster than other tested options. Following the ANN failure-detection studies [1]–[3], model performance was evaluated using accuracy, recall, and F1-score, because the classes are not perfectly balanced. The training process also aimed to reduce overfitting using cross-validation and some early-stopping settings, plus a small amount of regularization. The results were mostly acceptable, although the training curves occasionally exhibited small fluctuations. These fluctuations were consistently observed during training, however, they did not adversely affect the overall stability or predictive performance of the model. Overall, the model produced stable predictions, and the observed behavior was considered acceptable for the intended application. It was also observed that adjusting the hidden neurons helped a bit, though not always in a predictable way, which is typical for these ANN setups. Based on previous study [2], the Accuracy is calculated by dividing the total number of successfully identified examples by the total number of test instances. While Precision measures how relevant the ML model's predictions are, the Recall gives the overall number of pertinent outcomes that the ML model properly classified. The F1-score is the harmonic mean of precision and recall. Precision is the proportion of samples predicted as degraded that are truly degraded; recall is the proportion of truly degraded samples that are detected.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

Where:

True Positive (TP) is number of damaged samples correctly predicted as damaged.

True Negative (TN) is number of non-damaged samples correctly predicted as non-damaged.

False Positive (FP) is number of non-damaged samples incorrectly predicted as damaged.

False Negative (FN) is number of damaged samples incorrectly predicted as non-damaged.

$$F1 - Socre = 2.\frac{Precision\ .\ Recall}{Precision + Recall} \tag{2}$$

Where:

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

Finally, the proposal supports industrial deployment by integrating the ANN with an IoT dashboard for real-time monitoring and early fault alerts. It shows strong potential for semiconductor manufacturing, though larger-scale validation is still needed.

3. System Modeling and Failure Prediction Framework for Industrial Laser Diodes

3.1. Semiconductor Laser Diodes and Monaco 517-40-30 System

A semiconductor laser, often called a laser diode, produces coherent light through stimulated emission in semiconductor materials. Unlike ordinary LEDs, which emit spontaneous light, laser diodes generate highly directional, nearly monochromatic, and phase-coherent beams. Because of these properties, they are widely used in optical communication, precision measurement, biomedical systems, and industrial micromachining. Most laser diodes use a heterostructure design with multiple semiconductor layers of different bandgaps. This structure improves carrier confinement and recombination efficiency. This study found that even small changes in layer thickness or composition can noticeably affect performance. As shown in Figure 3, when forward current is applied across the p-n junction, electrons and holes recombine in the active region. Once population inversion is reached, stimulated emission amplifies photons inside the optical resonator, and the output rises rapidly above the threshold current. It was also observed that small variations in current or temperature can strongly influence laser performance, making accurate modeling and control essential.

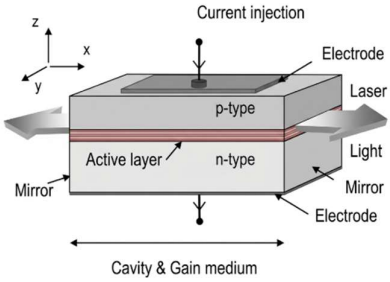


Figure 3. *Structural cross-section and components of a semiconductor laser diode [8].*

In this research, the proposal system focuses on the Monaco 517-40-30 industrial laser manufactured by Coherent. This system is not a direct diode laser but a diode-pumped solid-state laser (DPSS), where a high-power infrared laser diode (around 1,034 nm) is used as the pump source. The emitted infrared radiation excites a solid-state gain medium, and through a nonlinear crystal for second harmonic generation (SHG), the frequency is doubled to produce a green laser at 517 nm, as shown in formula (5). Although the output light does not directly come from a semiconductor junction, the degradation and failure phenomena still originate from the pump laser diode. Therefore, the same theories of semiconductor laser degradation can be applied for predictive modeling.

$$2 \times \lambda_{pump} \rightarrow \lambda_{output} \tag{5}$$

Where:

$$\lambda_{pump} \approx 1,034\ nm \rightarrow \lambda_{output} = 517\ nm$$

Its pulse width (below 350 fs), pulse energy (around 40 µJ) at a high-repetition rate of 750 kHz, average power (30 W) and wavelength (517 nm) make the Monaco ideal for semiconductor manufacturing that demands sub-micron precision with minimal damage to thermal material. However, prolonged high-power operation gradually introduces degradation. In this study, several mechanisms may appear, including rising threshold current due to material aging, reduced optical power from mirror contamination or nonlinear crystal wear, thermal buildup caused by insufficient cooling, and wavelength drift that can significantly affect machining accuracy. In severe cases, catastrophic optical damage (COD) may occur [9]. These degradation behaviors cause measurable changes in optical power, threshold current, forward voltage, and junction temperature, forming the physical basis for predictive maintenance using artificial neural networks.

3.2. Failure Prediction Basis for Industrial Laser Diodes

The degradation of industrial laser diodes usually happens slowly and accumulates over time. It is mainly driven by a combination of physical, thermal, and optical stresses that build up through

continuous high-power use. Observations indicate that in industrial environments, this degradation process occurs gradually rather than abruptly, subtly affecting laser efficiency over time. In high-precision fields like semiconductor fabrication or laser micromachining, even a small drop in performance can have a visible effect reduced machining accuracy, tiny defects on wafers or substrates, or sometimes unexpected downtime. For this reason, understanding how these degradation mechanisms occur, and how they can be detected through measurable parameters, becomes quite important when building a fault prediction model. From these observations, the main degradation tends to start in the active region and the optical cavity. Continuous current injection and high photon density for long periods accelerate the generation of crystal defects inside the semiconductor lattice, producing non-radiative recombination centers. These defects increase the threshold current (*Ith*) and gradually reduce slope efficiency [6] as shown in Figure 4. This is not a sudden failure, but rather a slow decline that shows up after long usage. Meanwhile, the optical parts for example, the laser facet or the nonlinear SHG crystal in the Monaco 517-40-30 configuration can also experience their own problems. Things like mirror contamination, slight oxidation, or thermal lensing might occur after long hours of operation. Over time, these small effects add up, leading to a visible drop in optical output power (Popt). In practice, it often takes many operation cycles before the drop becomes significant. Over time, these effects lead to a noticeable drop in optical output power (*Popt*). This reduction is often progressive it does not happen in a day but accumulates run after run. Thermal degradation is also a big factor. As the junction temperature increases, carrier mobility goes down, and thermal resistance rises. This combination causes wavelength drift and, in worse cases, can push the system into thermal runaway if the cooling is not managed properly. In short, heat management is one of the key factors to maintain long-term stability of such high-power laser systems.

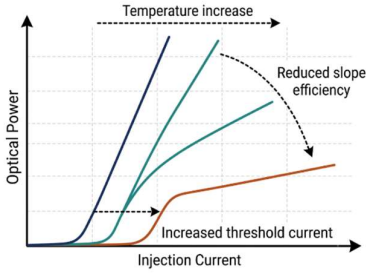


Figure 4. *Thermal effects on laser diode threshold current and slope efficiency [10].*

The parameters with the most vulnerability to degradation are optical output power, threshold current, forward voltage and junction temperature. These variables represent the internal condition of the diode and can be tracked to discover potential breakdowns. As an example, increased threshold current with decreased optical power is typically associated with gain degradation or mirror effect. An unusual forward voltage may be due to increasing series resistance, and higher junction temperature generally means poor cooling. Such gradual changes, if left unaddressed, can eventually lead to catastrophic optical damage (COD). By combining sensor data with intelligent models, predictive maintenance can predict failures before they happen, unlike traditional corrective or preventive maintenance. Based on the temporal changes of these important parameters, artificial neural networks can learn the nonlinear mapping between operating conditions and degradation, which is one prerequisite for building the fault prediction system proposed in this work.

3.3. Artificial Neural Network Modes for Laser Diode Failure Prediction

Artificial Neural Networks (ANNs) offer a practical and powerful way to model the nonlinear degradation behavior of laser diodes, which traditional statistical or analytical tools usually cannot capture accurately. In industrial platforms like the Monaco 517-40-30 laser, the connection between measured signals such as optical output, threshold current, voltage, and junction temperature and the actual internal wear-out state of the diode is highly nonlinear and also changes over time. Noticed that ANNs can learn these complicated patterns directly from sensor data without the need to build an explicit mathematical description of the physical process, which is often difficult in real systems. The proposed concept is shown in Figure 5.

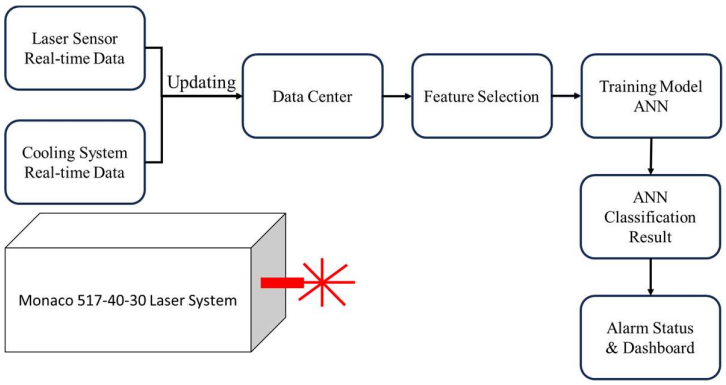


Figure 5. *Proposed architecture of the ANN-based failure prediction system for the Monaco laser.*

In this study, the model employs a Feedforward ANN mainly because it remains simple, has reasonable generalization ability, and can be integrated into near-real-time workflows. The network includes an input layer that receives the monitored diode parameters (*Popt*, *Ith*, *Vf*, *T*), followed by one or more hidden layers using nonlinear activation functions like Sigmoid or Tanh-sigmoid, as shown in Equations (6) and (7). The final output layer consists of a single neuron with a logistic sigmoid (logsig) activation function, which outputs the probability that the laser diode is operating in a degraded state. The network is trained using the Backpropagation algorithm together with the Levenberg-Marquardt optimization scheme, the Equations showed in (8) and (9). In simple terms, this combination aims to minimize the Mean Squared Error (MSE) between what the model predicts and the actual degradation state, and was found to work effectively for this problem, as defined in Equation (10). This optimization method was chosen mainly because, in our experiments, it tends to reach convergence faster and is a bit more stable than the usual gradient-descent approaches. It also works reasonably well with medium-sized datasets, which are commonly encountered in real industrial measurement setups.

$$Sigmoid: f(x) = \frac{1}{1+e^{-x}} \tag{6}$$

$$Tanh - sigmoid: f(x) = \frac{2}{1+e^{-2x}} - 1 \tag{7}$$

The Backpropagation algorithm calculates the gradient using:

$$\delta^{(l)} = (W^{(l+1)})^T \delta^{(l+1)} . g'(z^{(l)}) \tag{8}$$

Where:

$W^{(l+1)}$ is weight matrix connecting layer l to layer $l+1$.

$\delta^{(l+1)}$ is error signal propagated backward from the next layer.

$z^{(l)} = W^{(l)} a^{(l-1)} + b^{(l)}$ is pre-activation input to layer l

The weights are updated using the Levenberg–Marquardt rule:

$$w_{k+1} = w_k - (J^T J + \mu I)^{-1} J^T e \tag{9}$$

Where:

J is the Jacobian matrix.

e is the error vector.

μ is the damping factor.

The Mean Squared Error (MSE) computed as:

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \tag{10}$$

Where:

y is the target output of the i^{th} sample.

$\hat{y}_i$ is the predicted output produced by the ANN.

ANNs were used as the main framework for predicting laser-diode failures, mostly because they can approximate the nonlinear relationships between sensor inputs and the actual physical degradation happening inside semiconductor lasers. In this work, the ANN model is arranged into three principal layers an input layer, two hidden layers, and finally an output layer. The input layer contains 14 neurons, corresponding to the 14 features extracted from the laser system, such as optical power, threshold current, forward voltage, and diode temperature. These variables reflect the internal operating condition of the device, as observed, they correlate strongly with the degradation behavior over time. The number of neurons in the hidden layers was determined dynamically according to the expression. The expression (11) defines how the number of neurons in the two hidden layers changes as the configuration index I varies. In this work, the term $[i + 5, i / 2]$ is simply the way the model changed the size of the two hidden layers during the tests. When i increases, the first layer grows a bit faster because of the "+5" part, while the second layer grows slower since it only uses "$[i / 2]$". This architecture was selected to ensure a gradual progression in network complexity, avoiding significant discontinuities in model performance during testing. It also helps evaluate whether the model really improves when the number of neurons gets larger, or if it stops bringing any benefit.

$$\left[i+5, \frac{i}{2} \right] \tag{11}$$

Where: $i = 1 \rightarrow 20$

This setup allows the model's complexity to change during our testing phase, making it possible to identify which architecture actually works best for the prediction problem. For the first hidden layer, model applied the hyperbolic-tangent sigmoid (tansig), whereas the output layer uses a logistic sigmoid (logsig). With this setup, the network's output remains roughly in the (0, 1) range, which matches the simple binary scheme we use in the study (0 for Healthy and 1 for Degraded), the network structure is shown in Figure 6.

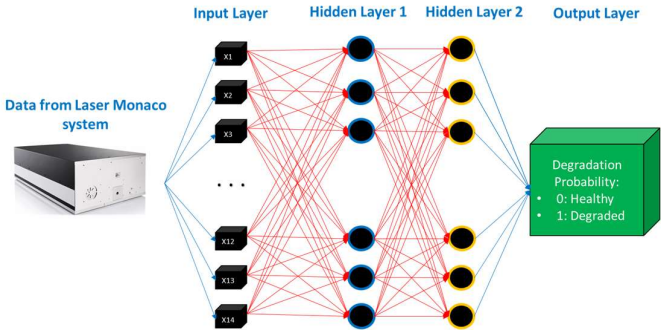


Figure 6. *Proposed ANN architecture for laser diode failure prediction in the Monaco laser system.*

The Levenberg-Marquardt (LM) backpropagation algorithm (trainlm) was chosen as our main training approach, as it offers good trade-off between fast convergence and reasonable accuracy. In practice, this study found that this method works very well for medium-sized neural networks, even though it sometimes requires a bit more memory than other algorithms. To reduce the chance of overfitting, the dataset was automatically split into 70% for training, 15% for validation, and the remaining 15% for testing. The MATLAB program also introduced a small regularization term (with a coefficient of approximately 0.1), mainly to avoid the model getting too "attached" to the training data. In the conducted trials, this approach generally improved generalization, although not in every single run. As a result, the ANN configuration achieved relatively high prediction accuracy while keeping the computation time manageable. One practical advantage noticed is that the model can be retrained for other laser-diode setups with only a few parameter tweaks. However, in some cases the tuning phase took longer than expected, which is something we had to work around.

4. Deployment of ANN Model and Result Analysis

4.1. ANN Feature Selection

Feature selection plays a significant role in improving both the learning efficiency and the generalization ability of our ANN model. The dataset collected from the Monaco 517-40-30 industrial laser system contains a mix of sensor-derived parameters that reflect electrical, thermal, and optical behaviors of the laser-diode modules. These signals were taken directly from real semiconductor production lines, therefore the dataset captures actual degradation patterns rather than the more "clean" laboratory-type measurements. To build a prediction model that is reasonably efficient and still physically meaningful, we carried out a feature-selection step using domain knowledge together with correlation analysis and a simple variance-based filtering. From the original dataset, fourteen (14) representative variables were chosen. The intention was to keep enough information to cover the critical aspects of laser operation drive current, optical efficiency, temperature stability while avoiding too much redundancy among parameters that are strongly correlated.

The selected features include BT, BT2, D1T, D2T, D3LLV, DSC, DSLLV, PD1V, PD2V, PD4V, PDSV, SHGT, STR2T, and STRT. Together, they make up a fairly balanced and easy-to-interpret feature set for training the ANN. For convenience, we grouped them and listed everything in Table 1.

Table 1. *Initial Features.*

Group	Parameters	Description
Electrical Parameters	*DSC, DSLLV, D3LLV*	Current and light-loop voltage of seed and diode stages, indicating electrical drive and modulation response
Thermal Parameters	*BT, BT2, D1T, D2T, SHGT, STR2T, STRT*	Operating and set-point temperatures of diode and stretcher modules, correlated with thermal stress and degradation
Optical Parameters	*PD1V, PD2V, PD4V, PDSV*	Photodiode voltages used for optical feedback control, representing laser output power stability and optical efficiency.

This selection also helps make sure that the ANN is trained on inputs that are reasonably good in quality, not overly repetitive, and still consistent with the expected physical behavior of the laser system. As a result, the convergence tends to be faster and the fault-prediction accuracy improves in most cases, although the effect varies a bit depending on the dataset. By combining parameters from different domains, the model is able to capture the nonlinear degradation behavior of laser diodes in a more holistic manner, which is generally aligned with common practices reported in laser-reliability studies.

4.2. Activation Function Configuration in ANN

In developing the ANN model for predicting laser-diode degradation, the study found that the choice of activation function was one of the factors that noticeably affected how the network learned and eventually converged. The activation function basically defines how each neuron reacts to the weighted inputs, and this reaction ends up shaping how well the model can capture the nonlinear relationships among electrical, thermal, and optical parameters. This research evaluated two activation-function setups to see which one fits this application better. In the first setup, the ANN used tansig (hyperbolic tangent sigmoid) for the hidden layer, and logsig (logistic sigmoid) for the output layer. Since the tansig function gives outputs in the range (-1, 1), the neurons can react more evenly to both positive and negative changes. This is useful when we try to model small variations around a stable operating point. Meanwhile, logsig compresses outputs into (0, 1), so it is suitable for distinguishing between healthy and faulty diode states. The second setup used the logsig function for both hidden and output layers, giving the network a more uniform activation behavior. This makes the training process simpler and tends to improve numerical stability, although the gradient flow can be somewhat limited when dealing with stronger nonlinear effects. Both configurations were trained with the Levenberg-Marquardt (trainlm) optimization method and are shown in Table 2. This optimizer generally provided stable and fast convergence for the medium-scale dataset. The dataset was split into 70% training, 15% validation,

and 15% testing, as listed in Table 3, to make sure the generalization behavior was properly monitored. By comparing these two architectures, the objective is to determine which activation-function combination offers the most reasonable balance between stability, training efficiency, and prediction accuracy.

Table 2. *ANN models with two methods of activation function selection.*

Method	Hidden Layer	Output Layer
Configuration 1	tansig (hyperbolic tangent sigmoid)	logsig (logistic sigmoid)
Configuration 2	logsig (logistic sigmoid)	logsig (logistic sigmoid)

Table 3. *Dataset of ANN training model.*

Dataset	Training dataset	Validation dataset	Testing dataset
7,289 data	5,103 data (70%)	1,093 data (15%)	1,093 data (15%)

4.3. Model Training and Evaluation Results

To check how the two activation setups in Table 2 perform, the study ran training and testing on both ANN models using the same dataset and roughly the same hyperparameter settings. For evaluation, it mainly looked at a few indicators: Accuracy, F1-score, and Recall. Sometimes these numbers give slightly different impressions, but they help to understand both the model's prediction performance and general behavior. These metrics are used to check not only how good the classification is, but also to see if the model can work well on new data. Accuracy shows the overall correctness of predictions, while the F1-score gives an idea of the balance between Precision and Recall. The results are shown in Figures 7 and 8, presenting the training and testing accuracies for Configuration 1 and Configuration 2, respectively. These figures also show how the training and testing accuracies change as the number of hidden neurons increases from 1 to 20. For Configuration1 (tansig-logsig), the results are very stable, with training and testing accuracies mostly above 98.5%, especially from the 9th neuron onward, with an accuracy of up to 99.8%. The small difference between the two lines shows that the model can generalize well and does not overfit too much. It also means that using tansig in the hidden layer helps the network catch nonlinear patterns better, while still keeping the convergence more or less stable.

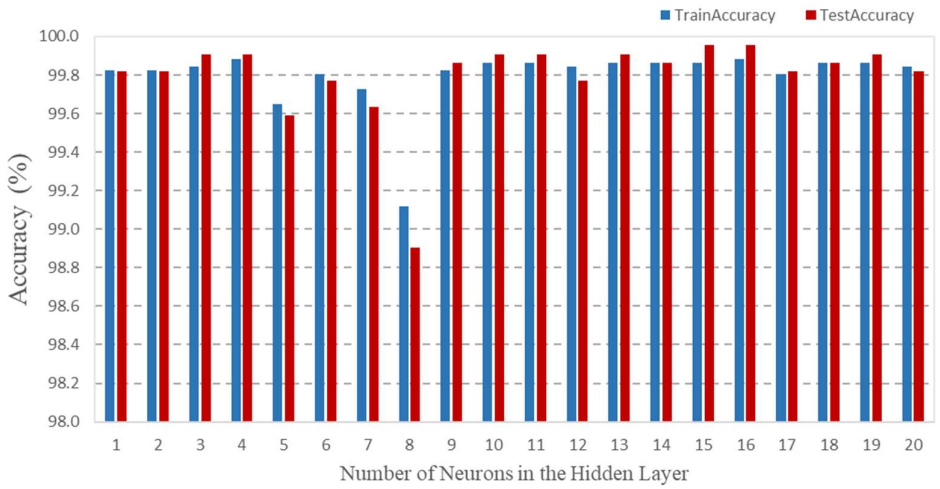


Figure 7. *Training and Test Accuracy results of Configuration 1.*

For Configuration 2 (logsig-logsig), the results show noticeable fluctuations. The accuracy changes a lot, ranging from around 90% up to 100%, depending on how many hidden neurons are used. This kind of instability indicates that using logsig in both layers might limit the gradient flow, which can make learning slower or less consistent in some setups. From the observations, overall, Configuration 1

still performs more reliably, giving faster convergence and better robustness for predicting laser diode degradation.

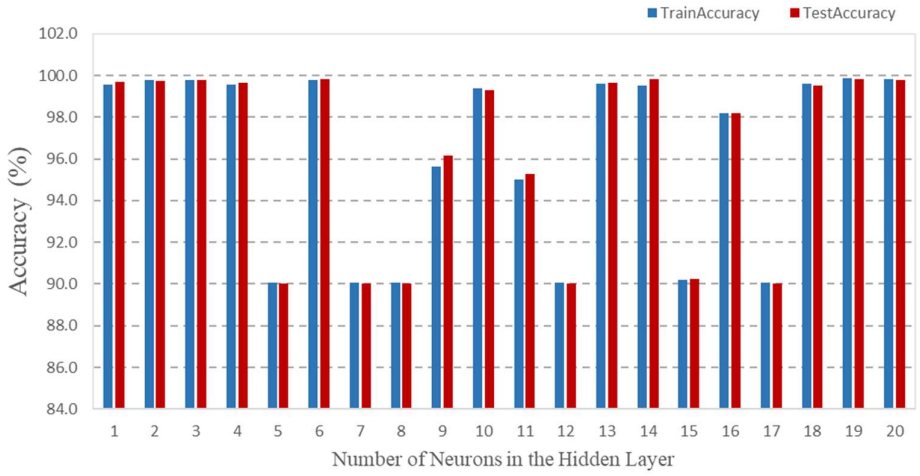


Figure 8. *Training and Test Accuracy results of Configuration 2.*

Figure 9 compares the F1-score values of the two ANN configurations as the number of hidden neurons increases. Configuration 1 (tansig-logsig) keeps a high F1-score almost all the time, close to 1.0, showing good stability and a balanced between precision and recall. On the other hand, Configuration 2 (logsig-logsig) shows large fluctuations, with the F1-score sometimes dropping below 0.8, and in some neuron counts even close to zero. This kind of unstable behavior suggests that using the same sigmoid function in both layers reduces the model's learning capacity and makes classification less consistent. Overall, the results indicate that Configuration 1 is more robust and reliable for predicting degradation in the laser diode dataset.

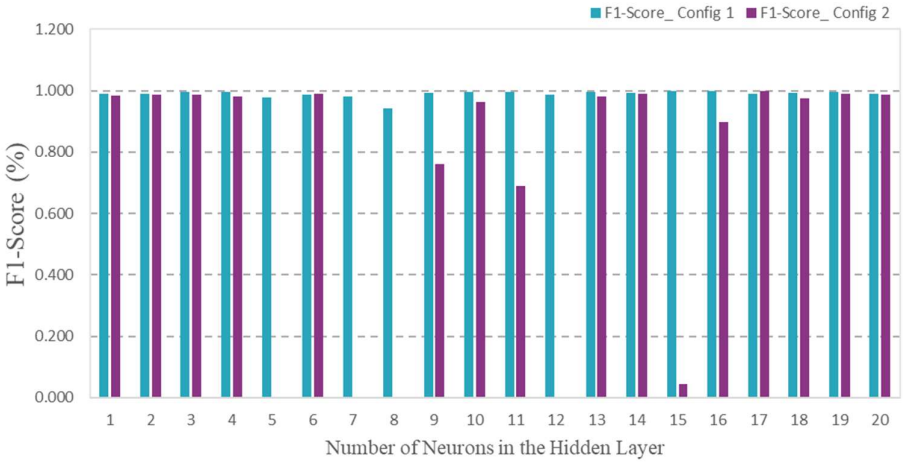


Figure 9. *F1-Score comparison result of two configurations.*

As shown in Figure 10, The Recall results are quite similar to what observed for the F1-score in Figure 9. Configuration 1 (tansig-logsig) still shows strong performance, keeping a high Recall value, almost 1.0, across most neuron configurations. This means the model can catch positive samples quite well and stays mostly stable, even if the network structure changes a little. But for Configuration 2 (logsig-logsig), the Recall is very unstable, and in some cases like with 5, 7, 8 or 15 hidden neurons it drops very low or zero. It seems the model with Configuration 2 has trouble keeping positive detection consistent, maybe because using the same sigmoid in both layers makes the feature representation less diverse.

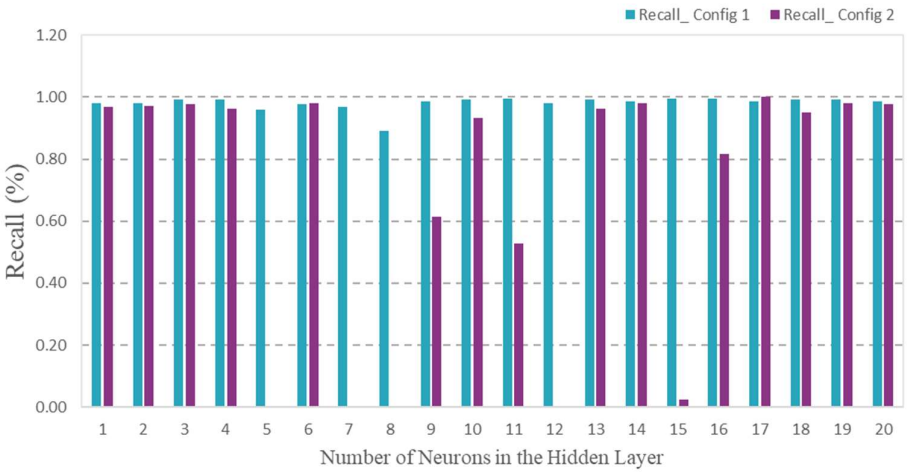


Figure 10. *Recall comparison result of two configurations.*

5. Conclusion

In this study, a data-driven fault prediction model was developed and tested for industrial laser diodes used in precision manufacturing systems. Using operational datasets collected from the Monaco 517-40-30 femtosecond laser, the model relied on artificial neural networks (ANN) to capture the nonlinear degradation relationships between electrical, optical, and thermal parameters. From the comparison of two activation-function setups, it was found that using tansig in the hidden layer and logsig in the output layer gave the most stable and accurate results. The final ANN model uses two hidden layers, both employing the tansig activation function, followed by a single output neuron with logsig activation for binary classification of healthy and degraded laser-diode conditions. This architecture corresponds to Configuration 1 and was selected as the final network used for all reported results. The model reached an average training accuracy of 99.86% and testing accuracy of 99.82%, with F1-score and Recall values close to 1.0, which suggests very reliable classification performance. Unlike current industrial maintenance practices, which are largely based on run-to-failure or reactive detection of diode faults, the proposed ANN-based model enables early prediction of degradation trends before functional failure occurs. These results show that neural network-based approaches are suitable for predictive maintenance of laser systems under real industrial conditions. Besides proving technical feasibility, the study provides a practical framework for early fault detection, which could help push maintenance practices toward more data-informed strategies in semiconductor laser applications. In the future, the dataset can be expanded include longer degradation cycles, additional network architectures can be evaluated, and explainable components can be incorporated to improve model interpretability and facilitate deployment in real industrial environments.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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