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RESEARCH ARTICLE OPEN ACCESS

# AN ARTIFICIAL NEURAL NETWORK FRAMEWORK FOR AUTOMATED FAULT DIAGNOSIS IN INDUSTRIAL DC-DC CONVERTERS

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**ABSTRACT**

The operational longevity of electrical equipment is often limited by gradual aging and degradation resulting from various stressors, which leads to a decrease in system reliability over time. In industrial environments, DC machines are commonly powered by chopper voltage sources, making them susceptible to a range of faults that affect switches, capacitors, and coils. Early detection and localization of such defects are crucial to ensure efficient maintenance and prevent faults. To address the risk of severe failures in DC-DC converters, advanced diagnostic techniques are required. This study explores the application of artificial neural networks (ANN) for automatic fault detection and diagnosis in DC-DC converters. The proposed ANN-based methodology demonstrates effective identification of converter faults, offering a reliable and practical solution for real-time monitoring and predictive maintenance in industrial settings.



## I. INTRODUCTION

Electric al equipment components inevitably lose efficiency during their operational life [1]. The duration and severity of this degradation depend on the nature and level of stress experienced by the components, ultimately leading to a decline in system performance [2]. To enhance the reliability of such systems, diagnostic practices and predictive maintenance are essential [3]. Several diagnostic approaches exist in the literature, broadly classified into two categories: model-based and model-free methods [4]. Model-based diagnostics detect failures by comparing the physical process with its associated analytical model [5]. In contrast, model-free approaches analyze information—typically signals such as current, voltage, or speed—collected by sensors installed on the system. Model-free methods can be further divided into two groups: pattern recognition-based diagnostics and statistical tools. While statistical techniques enable hypothesis testing on acquired signals, they do not always ensure fault detection. Pattern recognition methods, on the other hand, are more suitable and have been successfully applied in areas like speech recognition, handwriting recognition, machine vision, and industrial process control [6]. Neural networks, known for their ability to generalize knowledge to new inputs beyond their training data, are increasingly studied and applied for automatic classification tasks within this framework.

A simple perceptron can discriminate between two linearly separable classes; however, due to the complex nature and size of most training datasets, multilayer perceptron (MLP) architectures are preferred for their enhanced capability [7]. A recent industry survey on power converter reliability identified power semiconductors as the most vulnerable components. The major causes of stress on these devices include environmental factors, temporary disruptions such as load changes or faults, and significant load demands. In boost DC-DC converters, common component faults include open-circuit or short-circuit failures of power switches and capacitor degradation. Electrolytic capacitors may suffer structural failures, such as complete loss of function due to open or short circuits, or parametric faults that occur when the component is not replaced in a timely manner. Maintaining high performance in power conversion is critical to minimize power dissipation and prevent excessive heating within components. Consequently, power conversion primarily occurs around energy storage elements—such as inductors and capacitors—and switching devices. The selection of switching elements depends on the power level, with MOSFETs typically used for lower power applications, IGBTs for medium to high power, and thyristors employed at the highest power levels [8],[9]. This paper presents simulation results demonstrating the use of neural networks for diagnosing faults in

DC-DC boost converters. The methodology is outlined, covering both offline and online diagnostic techniques, and system performance is tested through various real-world scenarios.

## II. MATERIALS AND METHODS

### II.1 MATERIALS AND METHODS

Our diagnostic approach leverages artificial intelligence and involves two principal steps:

- Offline Testing: We first develop a detailed Simulink model of the DC-DC boost converter to simulate various fault scenarios, including short-circuits and open-circuits, affecting the key components: inductor, switch, and capacitor. The simulation generates extensive datasets that capture the converter's behavior under these fault conditions. This data serves as input for the neural network, where fault indicators (1 for a fault, 0 for no fault) are linked to system variables, such as output voltage and input current, for training purposes.
- Online Diagnosis: The second step involves deploying the trained neural network in an online simulation environment to detect and quantify the presence of faults in real-time across the three monitored components. Using the equivalent Simulink model of the power converter, we run simulations to evaluate the performance of the diagnostic system. The neural network output's real-time fault classifications as percentages, enabling continuous monitoring under dynamic operating conditions.

The technique chosen for our neural system is pattern recognition. Pattern recognition is the process of categorizing input data into distinct classes or categories based on specific distinguishing features. Two main classification methods exist in pattern recognition: supervised and unsupervised classification. Supervised classification relies on labeled data for training, while unsupervised classification identifies inherent structures in unlabeled data. Pattern recognition has widespread applications in computer vision, radar processing, speech recognition, and text classification. This approach is well-suited for fault detection as it enables the system to automatically identify and classify faults by learning patterns inherent in the input signals [10].

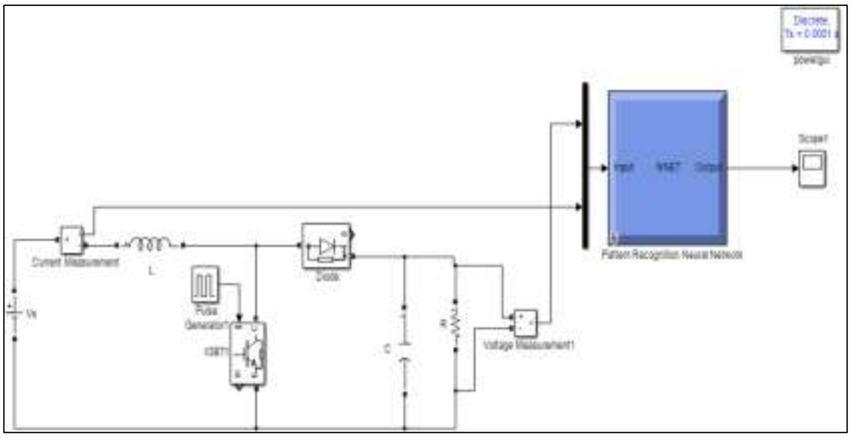


Figure 1: Online diagnosis Matlab.
Source: Authors, (2026).

### II.2 CONVERTER PARAMETERS:

The power boost converter parameters can be summarized in the following Table 1:

Table 1: DC-DC converter parameter.

| Parameter | Value |
|---|---|
| Input Voltage | 100 V |
| Output voltage (desired) | 200V |
| Inductance | 150e-6 H |
| Capacité | 820e-6 F |
| PWM Frequency | 50000 Hz |
| Resistance (load) | 10 Ohm |

Source: Authors, (2026).

### II.3 ANNS PARAMETERS:

The input and target vectors versus their parameter size and data type are shown below:

Table 2: ANNs parameter.

| Component | Parameter | Size | Data type |
|---|---|---|---|
| Input vector | Input current | 100001 | Analogical |
| | Output voltage | 100001 | |
| Target victor | Coil fault vector | 100001 | digital |
| | IGBT fault vector | 100001 | |
| | Capacitor fault vector | 100001 | |

Source: Authors, (2026).

- After many trials, we have found that the best results were obtained with the use of 10 neurons in one hidden layer.
- The other parameters are defaults.

### II.4 IMPLEMENTATION STEPS:

- The figure below shows the distribution of the validation and test datasets, each set to 15% of the original data. With these settings, the input and target vectors are randomly divided into three distinct subsets as follows:
- 70% of the data is used for training the neural network.
- 15% is reserved for validation, which helps assess whether the network is generalizing well and allows stopping training early to prevent overfitting.
- The remaining 15% forms an independent test set, used to provide an unbiased evaluation of the network's generalization performance.
- This split ensures a balanced approach to training, validation, and testing, promoting reliable model performance and robustness.

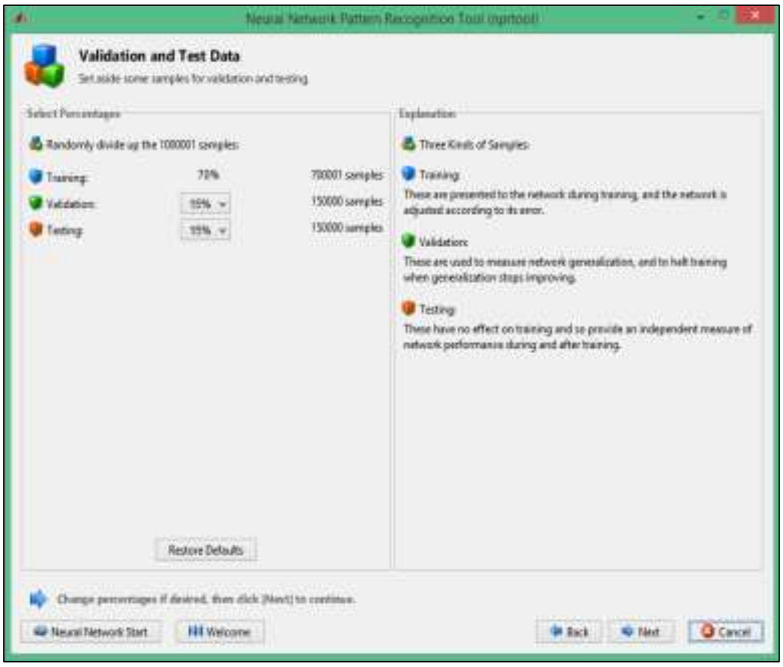


Figure 2: Training, Testing, and Validation.
Source: Authors, (2026).

The figure below shows the architecture of the chosen neural network we have:

- Two inputs
- One hidden layer consists of 10 neurons.
- One output layer consists of three outputs.
- We use sigmoid transfer functions in both the hidden layer and the output layer.

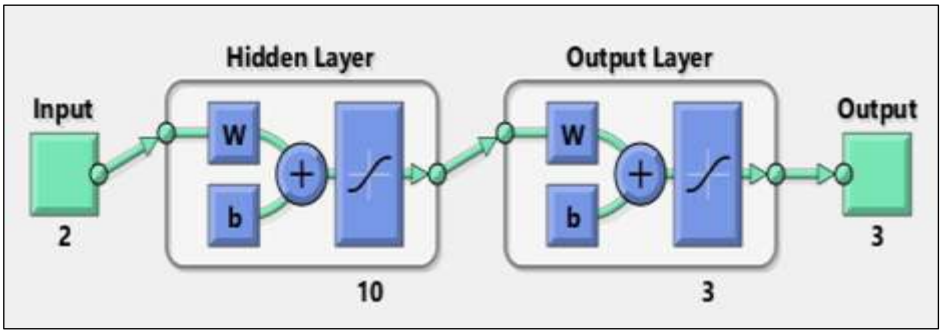


Figure 3: Architecture of Trained Neural Network.
Source: Authors, (2026).

The figure above represents the neural network training:

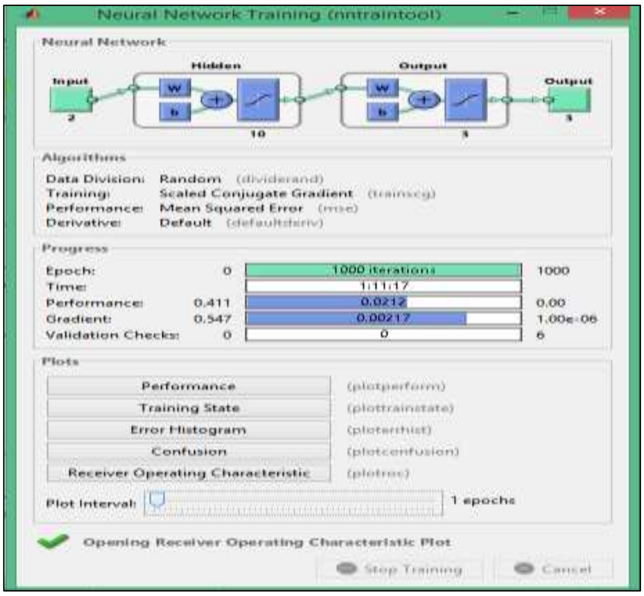

Figure 4: Neural Network Training.
Source: Authors, (2026).

1. Data Division: Random (dividerand) divide the target into three sets using random indices. In our case, 1000001 samples are divided into 70% for training, 15% for validation, and 15% for testing.
2. Scaled Conjugate Gradient (trainscg): is a network training function that updates weight and bias values according to the scaled conjugate gradient method.
3. Mean squared error performance function (MSE): mse (net, targets, outputs, error Weights, parameters...) calculates a network performance given targets, outputs, error weights, and parameters as the mean of squared errors.

## III. RESULTS AND DISCUSSIONS

### III.1 WITHOUT FAULST:

In the following figure, we present the variation of desired output voltage and input voltage in Figure 5 and input current in Figure 6:

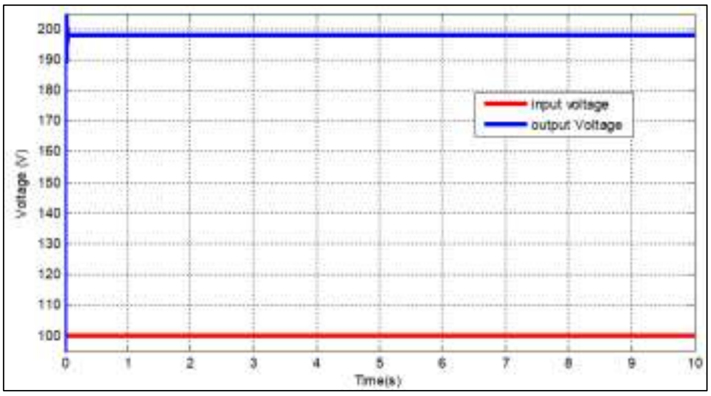

Figure 5: output Voltage.
Source: Authors, (2026).

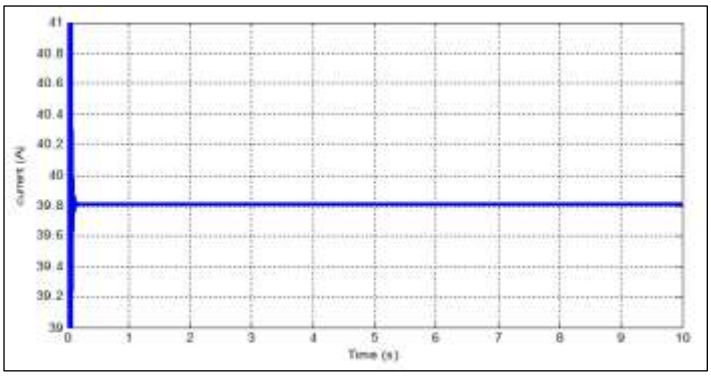

Figure 6: Input current.
Source: Authors, (2026).

### III.2 WITH FAULT (OFFLINE):

❖ Confusion matrix

As a classifier and predictor, four cases are possible:

- True positive: positive instance, classified positive
- False positive: negative instance, classified positive
- True negative: negative instance, classified negative
- False negative: positive instance, classified negative

Summarizes the results of a classifier on test data in a **confusion mat**

Table 3: Classification Results Matrix.

| Actual Class \ Predicted Class | Predicted Positive | Predicted Negative |
|---|---|---|
| **Actual Positive** | True Positive (TP) | False Positive (FP) |
| **Actual Negative** | False Negative (FN) | **True Negative (TN)** |

Source: Authors, (2026).

True Rate/False Rate:

$$\text{Rate TP} = \frac{\text{positive although classified}}{\text{total positive}} \tag{1}$$

$$\text{Rate FP} = \frac{\text{negative misclassified}}{\text{total negative}} \tag{2}$$


Figure 7: All confusion matrices in training, validating, and testing of N.N. performance.
Source: Authors (2026).

The accuracy in the training confusion matrix is approximately 39.9%, the validation confusion matrix's prediction accuracy is almost 40%, and the test confusion matrix shows an accuracy of 39.8%. After training, validation, and testing, we collected 100,001 individual samples for overall performance evaluation.


Figure 8: All confusion matrix of diagnosis converter, DC-DC results by scaled conjugate gradient back propagation Neural Network.
Source: Authors (2026).

The diagonal cells of the confusion matrix represent the number of correctly classified instances for each class, while the off-diagonal cells indicate misclassified cases. The blue cell at the bottom right displays the overall accuracy (in green) and the total misclassification rate (in red). These results demonstrate strong recognition performance. Specifically, within the red circle, the neural network successfully identified 39.9% of fault events. In each confusion matrix: The top-left green cell shows the absolute number and percentage of true positive (TP) cases, representing correctly identified fault instances. The central green cell indicates the true negative (TN) cases, correctly identifying the absence of faults. The top red cell reflects false positive (FP) cases — instances incorrectly classified as faults (Type I error). The middle left red cell represents false negative (FN) cases — faults that were missed or classified as normal (Type II error).

This detailed breakdown provides insight into the network's classification strengths and areas for improvement. The top right gray square with green letters describes the positive predictive value [TP/(TP+FP)] ×100, and with the red letters the [FP/(TP+FP) ×100. The middle right gray square with green letters describes the negative predictive value [TN/(TN+FN)] ×100, and with the red letters the [FN/(TN+FN)] ×100. The bottom left gray square with green letters describes the sensitivity [TP/(TP+FN)] × 100, and the red letters describe the [FN/(TP+FN)] × 100. The bottom middle gray square with green letters describes the specificity [TN/(TN+FP)] × 100, and the red letters indicate the [FN/(TN+FP)] × 100. Finally, the bottom right blue square with green letters indicates the correctly classified incidents, [(TP+TN)/total incidents used] × 100, and the red letters indicate the incorrectly classified incidents, [(FP+FN)/total incidents used] × 100. The curve below gives us the overall performance of the network:

The y-axis represents the mean squared error, where a lower error indicates better performance. The x-axis demonstrates the epochs, which represent a step in the training of the NN. The best results were achieved at epoch 1000 in our NN.

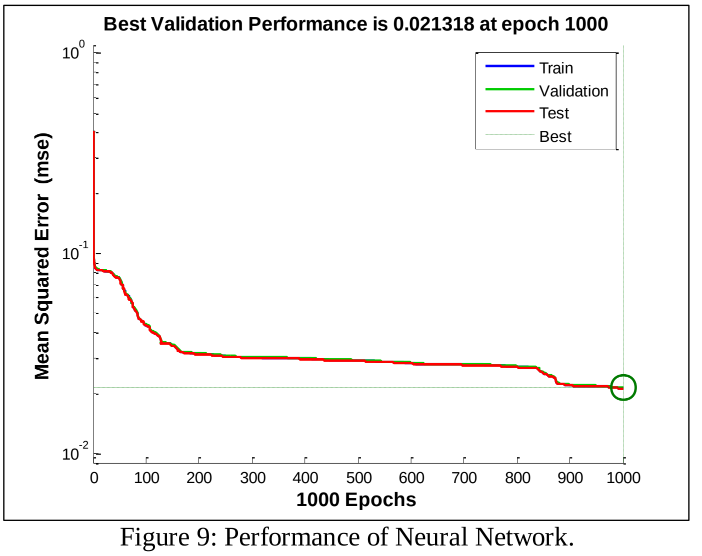


Figure 9: Performance of Neural Network.
Source: Authors (2026).

Figure 9 clearly shows that around 1000 epochs, the training, testing, and validation errors stabilize. After epoch 1000, the training error reaches a very low value of 0.0301, indicating a highly successful training process with a close match between actual and predicted outputs. The best validation performance is achieved at epoch 1000, with a mean squared error (MSE) of 0.0213. Initially, the MSE is relatively high, but it decreases steadily during training, reaching its minimum at epoch 1000. This demonstrates that the network's performance improves progressively with training, as further supported by Figure 3.5, where training and testing results closely align.

## III.3 FAULTY CONDITION (ONLINE):

- The following figure represents the variation of the output voltage caused by faults.

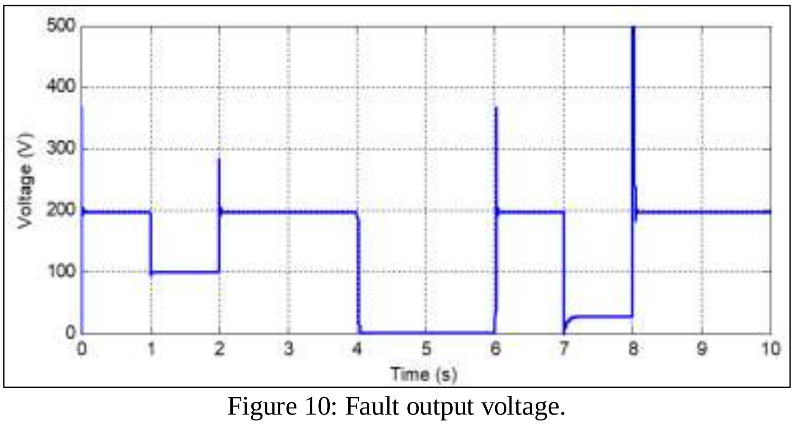


Figure 10: Fault output voltage.
Source: Authors (2026).

❖ The following figure represents the variation of the input current caused by the faults:

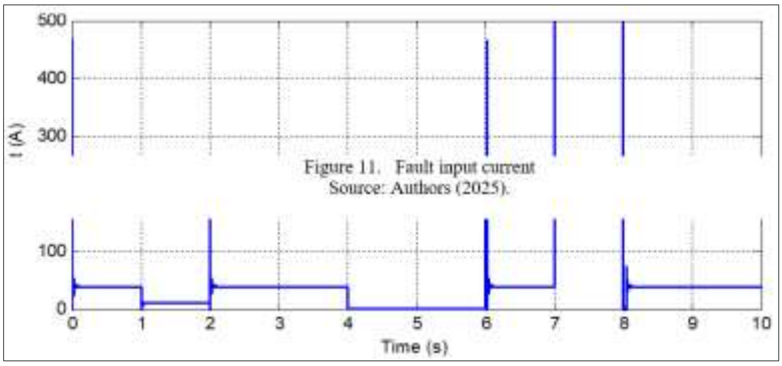


Figure 11: Fault input current.
Source: Authors, (2026).

In the preceding figures, we clearly see the variation in output voltage and input current due to the faults generated in the converter components. These variations will be used later for the detection.

❖ The following figure represents the ANN fault indicator (Observing and indicating faults)

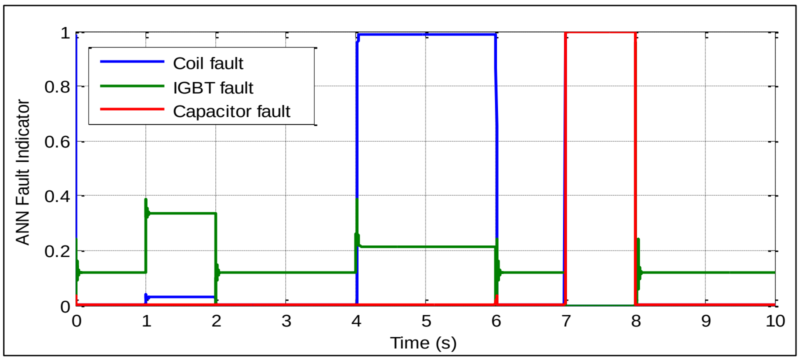


Figure 12: Online ANN fault indicator.
Source: Authors (2026).

The figure illustrates the performance of our fault smart indicator following the detection of defects. The diagnosis of serous neurons can easily locate the default by percentage signals. Product failure is most likely the one with the highest failure percentage (%).

## IV. CONCLUSIONS

The purpose of this study is to apply an artificial neural network (ANN) technique for fault diagnosis in power converters. We aimed to address the challenge of online diagnosis by focusing on the identification and localization of component faults within DC-DC converters. Our approach involves implementing neural network structures tailored for this task. We reviewed basic topologies of DC-DC converters, including buck, boost, and buck-boost configurations. For each converter type, we analyzed the behavior of voltage and current through power switches, voltage gains, voltage and current ripples, and typical applications. We also surveyed existing fault diagnosis techniques for DC-DC converters.

An introduction to artificial neural networks was provided, covering fundamental concepts such as architecture, operational principles, learning mechanisms, and various types of neural networks and learning methods. We concluded with a discussion on their applications and reliability in challenging conditions.We detailed the key steps of our diagnosis system, utilizing a pattern recognition approach and selecting parameters validated numerically. Based on the obtained results, this diagnostic method has proven effective, especially in online operations.Following training, the ANN system can accurately detect and localize various faults in real time, supporting proactive maintenance and improving the reliability of the converter components.]

## V. AUTHOR'S CONTRIBUTION

**Conceptualization:** Naas Djeddaoui.
**Methodology:** Naas Djeddaoui.
**Investigation:** Naas Djeddaoui.
**Discussion of results:** Naas Djeddaoui.
**Writing – Original Draft:** Naas Djeddaoui.
**Writing – Review and Editing:** Naas Djeddaoui.
**Resources:** Naas Djeddaoui.
**Supervision:** Naas Djeddaoui.
**Approval of the final text:** Naas Djeddaoui.

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