A wavelet neural network assisted framework for active fault detection and diagnosis of process systems

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Abstract: Modern day industries invest heavily on looking for various methods for timely and accurate fault detection and diagnosis. Since training a model to learn all possible faults is challenging and impractical, developing an active learning based methodology which is capable of learning about any new faults arriving in the plant in the due course of operation is the main objective of this paper. This objective is achieved through a two staged methodology where in, an unsupervised learning strategy using one-class SVM is considered in the first stage to detect the presence of a new fault. In the second stage a multi-class classifier of Wavelet Neural Network is utilized to detect the nature of fault. The efficacy of the proposed method is demonstrated on a benchmark Tennessee Eastman Process and the results are compared with the existing methods.

Keywords: Active Learning ,Fault Detection and Diagnosis, Wavelet Neural Network, Artificial Neural Network, Tennessee Eastman Process.

1. INTRODUCTION

In recent years, many process-industries want to minimize their costs associated with the process safety and focus on maximizing their profits while using the available resources at the most optimal level and ensuring the safe operation of process. To achieve this goal, early detection of fault(s) and providing the root cause for the same (diagnosis) becomes very crucial. Fault detection and diagnosis is the process of identifying deviation from normal behavior caused in the process plant, along with finding the root cause of this deviation. This identification is carried out using various techniques like model based (Gupta et al., 2022; Venkatasubramanian et al., 2003c), rule based (Xing and He, 2023; Venkatasubramanian et al., 2003a) and process history or data driven based (Yadav et al., 2020; Venkatasubramanian et al., 2003b). The early research focused on model based approaches which involved development of a mathematical model to replicate the normal behavior of the plant and any deviation from this would raise a fault (Raveendran et al., 2018). While the rule based methods relied on defining a thresholds over various process parameters or variables and once these thresholds were exceed it was flagged as fault.

As the emergence of more reliable data acquisition systems along with the boom of modern techniques like Artificial Intelligence in the Industries (Industry 4.0) became evident, researchers started to look into the possibilities of implementing data-driven methods in the field of fault detection and diagnosis (Mahadevan and Shah, 2009; Jack and Nandi, 2002; Don and Khan, 2019; Amin et al., 2018). Based on the conclusions from (Goetz et al., 2015), data-driven approaches are further classified into statistical and novel learning based methods. The traditional statistical methods involve methods like Principal Component Analysis (PCA) (Qin, 2012) and Dynamic Principal Component Analysis (DPCA) (Kodamana et al., 2017) for fault detection and diagnosis. Novel learning based approaches used various machine learning algorithms like Support Vector Machines (SVM) (Yin and Hou, 2016) and also some deep learning methods like use of Neural Networks (NNs) (Sorsa and Koivo, 1993; Chalapathy et al., 2018).

It was observed that although majority of data-driven methods for fault diagnosis are based on supervised learning, the problem lies in generating the dataset for all possible faults that may occur in the process plant. As it is utterly impossible and impractical for process industries to generate this datasets for all possible faults and as the range of fault categories are wide and different, training a model apriori incorporating all the categories would be challenging (Arunthavanathan et al., 2020). Hence, it is necessary to develop an active learning based methodology which is capable of learning about any new faults arriving in the plant in the due course of operation and is the main ideology behind this study.

In this paper, a two staged methodology inspired from the approach presented in Arunthavanathan et al. (2020) is proposed. In the first stage, an unsupervised learning strategy using one-class SVM is considered in this paper to detect the presence of an existing or new fault. The second stage involves use of a multi-class classifier using Neural Network like Wavelet Neural Network (WNN) to detect the nature of fault. The novelty for this work over Arunthavanathan et al. (2020) holds in using a special kind of single hidden layer feedforward neural network known as Wavelet

Neural Network(WNN) as a classifier for identifying the type of fault. The advantage of the proposed WNNs are unique in the way that the parameters in the hidden layer are assigned using Wavelet decomposition, thereby the model becomes linear-in parametric form. WNNs can handle non-linearity while the structure being linear with respect to their parameters, making them faster to train and implement. Hence, in this study WNN is used as a classifier. A comparison between the two classifiers (NN and WNN) is also made to demonstrate the efficacy of the proposed approach.

The rest of paper is organized as follows. Section 2 explains about the proposed approach starting with the problem statement in Section 2.1 and Section 2.2 briefly explains about the preliminaries required for the paper. In Section 2.3, the details of the proposed methodology for Data-based adaptive fault detection and diagnosis is detailed followed by a case study on Tennessee Eastman Process in Section 3 and finally the paper ends with Section 4 as Conclusions.

2. DATA-BASED FAULT DETECTION AND DIAGNOSIS

2.1 Problem Statement

Developing an effective methodology for fault detection and diagnosis which is able to adapt to any new faults occurring during the operation of a process becomes essential and is the main objective of this paper. Inspired by the work in Arunthavanathan et al. (2020), a two staged strategy is adopted, wherein the first step involves utilization of an unsupervised learner like one-class SVM for detecting the presence of any new fault in the due course of operating a plant. The second step involves a multi-class classifier using Wavelet Neural Network (WNN) for identifying the class of a given fault. A brief introduction about the one-class SVM and WNN and detailed proposed methodology is provided in the subsequent sections of the paper.

2.2 Preliminaries

One-class SVM: Soft margin classifiers or Support Vector machines (SVMs) is traditional machine learning algorithm generally used for the tasks of regression and classification. SVM's primary objective is to find line or hyperplane that classifies the features of a dataset such that the features between different classes have maximum margin. The term margin refers to the minimum distance between the data points from the hyper-plane. SVMs are a good linear and non-linear classifiers (Gholami and Fakhari, 2017; Hearst et al., 1998). Researchers searched for various ways to incorporate standard SVMs for the task of fault detection but fell short to the problem of supervised learning as mentioned earlier in Section 1.

One-class SVM (OCSVM) is a special variant of the traditional Support Vector Machine (SVM) majorly used for the purpose of adaptive fault detection or abnormality detection. Unlike the standard SVMs, OCSVMs are an unsupervised learning algorithm specifically tailored for anomaly detection with the help of training using only normal or non-faulty dataset. One-class SVM tries to learn a boundary such that it has a maximum margin between the non-faulty data points and origin (Yin et al., 2014). Whenever, a new data is presented lies outside this boundary the OCSVM flags it as fault.

Numerous researchers opted this idea of One-class SVM to solve the problem of Fault detection. As an example, the authors in Sotiris et al. (2010) utilized the idea of OCSVM to detect faults and combined the results with output to calibrate the posterior probability to look for false alarms. The authors in Yin et al. (2014) proposed a robust one-class SVM which is insensitive towards outliers for fault detection. For a detailed description of one-class SVMs, the reader is requested to refer to Erfani et al. (2016).

Wavelet Neural Network: A Wavelet Neural Network is a special kind of neural network in which wavelets are used as activation functions. A Wavelet Neural Network (WNN) typically consists of three layers: the input layer, the hidden layer, and the output layer as seen in Fig.1

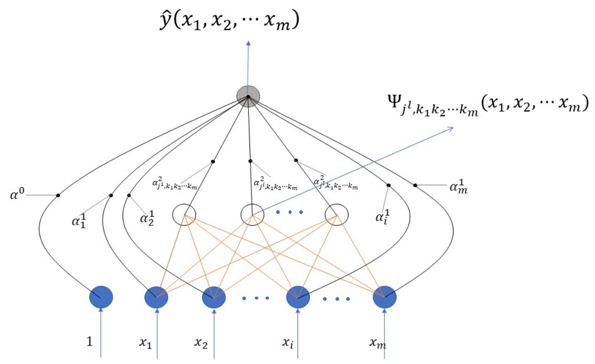


Fig. 1. Wavelet Neural Network

In the input layer, the network receives explanatory variables, also called inputs. The hidden layer contains nodes, known as wavelons, which transform these input variables into a non-linear space. The output layer then uses the transformed variables to approximate the target values. The authors in Alexandridis and Zapranis (2013) proposed a wavelet network that incorporates a multi-dimensional basis and linear connections between the input and output layers, as depicted in Fig. 1, to enhance training performance in highly linear settings.

Since any non-linear function can be approximated using wavelet frame decompositions (Billings and Wei, 2005), similar to the work considered in (Varanasi et al., 2022), the main objective of this work is to represent the parameters in the input-hidden layer using these decompositions. This type of approximation helps us in ensuring the model in linear-in-parametric form thereby making the learning faster, accurate and require less amount of data to train when compared to a traditional single hidden layer feed-forward neural network. Further, with the appropriate selection of the dilational and translational parameters associated with the wavelet frame decompositions (Billings and Wei, 2005), the number of neurons to be considered in the hidden layer will be automatically fixed, thereby avoiding the trial and error approach for selection of optimal number of neurons in the hidden layer. The output equation of the wavelet neural network is given as

$$\hat{y}(x_1, x_2, \cdots, x_m) = \alpha^0 + \sum_{i=1}^{m} \alpha_i^1 x_i$$
$$+ \sum_{j=j_0}^{j_M} \sum_{k_1 \in K_j} \cdots \sum_{k_m \in K_j} \alpha^2_{j,k_1,\ldots,k_m} \psi^{[m]}_{j,k_1,\ldots,k_m}(u_1, u_2, \cdots, u_m)$$

where,

$$\psi^{[m]}_{j,k_1,\ldots,k_m}(x(t)) = 2^j \times (m - \|2^j x(t) - v\|^2) \times \exp(-0.5 * \|2^j x(t) - v\|^2) \tag{1}$$

denote the Mexican hat wavelet function with $j \in \mathbb{Z}$ and $(k_1, k_2, \ldots, k_r) \in \mathbb{Z}^r$ denote the dilation and translation parameters respectively and $v = [k_1, k_2, \cdots, k_m]$. The terms j_0 and and j_f denote be the coarsest resolution and the finest resolution respectively. The term k_i has to be selected in such a way that $-(s_2 - 1) \leq k_i \leq 2^j - s_1 - 1, i = 1, 2, \ldots, r$ where, s_1 and s_2 control the range of the translations. Typical choice of s_1 and s_2 for the Mexican hat wavelet function are -3 and 3 respectively (Billings and Wei, 2005).

2.3 Proposed Methodology for FDD

Inspired by the work presented in Arunthavanathan et al. (2020), an adaptive and real-time based framework for fault detection and diagnosis is presented. The main idea of the proposed methodology is to adopt one-class SVM as an unsupervised method to detect the existence of known/new fault and then use WNN in a supervised way to classify the faults and provide diagnosis for it. In the proposed methodology, it is assumed that only one fault exists in the process at any given point in time and the time horizon of the presence of fault is significant enough for training/updating the model. The overall workflow for the proposed methodology is presented in Fig. 2 and the details are presented as follows:

The first step of training involves training a one-class SVM (OCSVM) using non-faulty or normal dataset. The OCSVM tries to learn a boundary that classifies faulty data from normal data points. Once the training is completed, whenever a dataset with fault is introduced, the one-class SVM will raise a flag and will label it (for example, as fault-1). This labeled faulty data and non-faulty data will be used to train WNN in a supervised manner. The second stage of training involves re-training the one-class SVM with the help both non-faulty and fault-1 datasets. By doing so, one-class SVM was successfully trained and would now let non-faulty or fault-1 data to pass and be able to detect the presence of any new fault and label it as fault-2. WNN will then classify the data point into non-faulty and fault-1. After receiving enough amount of dataset for fault-2 from OCSVM, one-class SVM and WNN will be updated using all the datasets to detect the presence of non-faulty or fault-1 or fault-2 data points. Since it is assumed that the time horizon of the fault is significant, it can be noted that whenever a new fault is detected by the one-class SVM, is labeled as

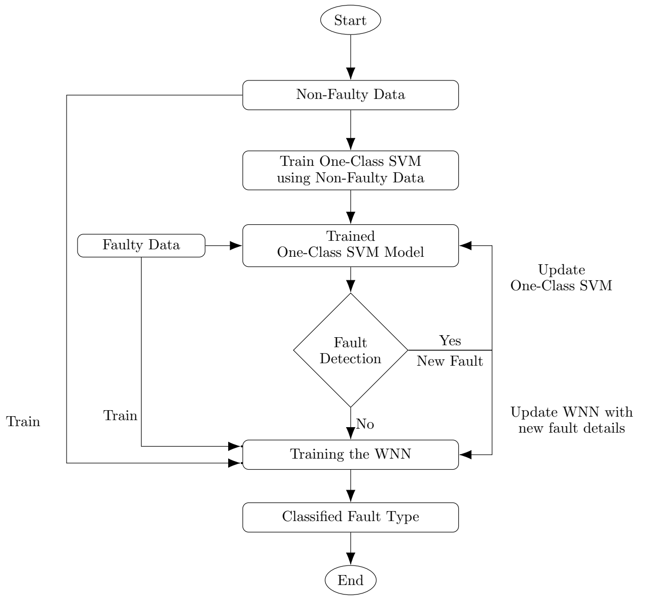


Fig. 2. Workflow of Fault Detection and Classification

fault-i and the re-training of one-class SVM and WNN will take place. Due to this active re-training of the models, the approach is capable of detecting and diagnosing any new faults that might arise in the due course of operation of a process.

3. TENNESSEE EASTMAN PROCESS - FAULT DETECTION AND DIAGNOSIS

The Tennessee Eastman Process (TEP) is considered for testing the efficiency of the methodology proposed earlier. TEP is a benchmark case study used for developing and testing various monitoring and control schemes, FDD strategies (Downs and Vogel, 1993). The corresponding section provides a brief process description of the TEP which will be followed by results of the FDD.

3.1 Process Description

A TEP process have five main process units: reactor, condenser, separator, stripper and compressor as shown in the Fig.3.

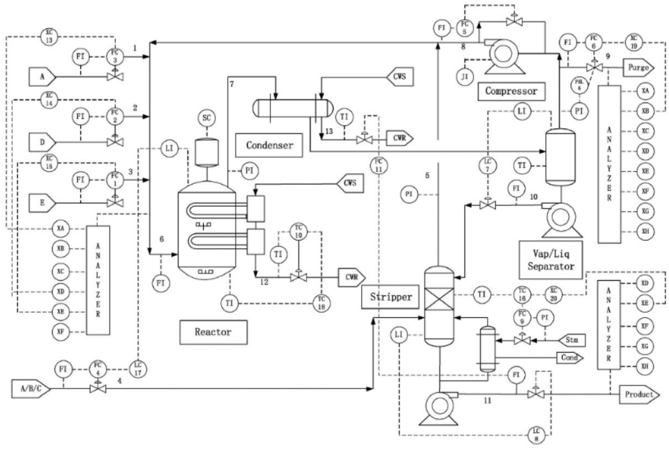


Fig. 3. TEP flow diagram (Downs and Vogel, 1993)

Such a process has a total of 51 variables out of which 41 are measurable variables (22 input variables are continuous process measurements and 19 are composition measurements) and the rest 12 are manipulable variables (11 valves and 1 speed of stirrer). The process mainly has 8 various feed components labeled as A-H to produce two products from four reactants. The gaseous reactants A,C,D and E reacted along inert component B to form liquid products G and H, along with F as by-product in the reactor.

During the operation of such a process, there are 21 different possible faults that might occur (Downs and Vogel, 1993; Zhang et al., 2014). From these 21 faults, IDV 1, IDV 4, IDV 9 and IDV 11 as detailed in Table 1 are an accurate representations of overlapping information and are considered to be challenging to detect in general (Zhang et al., 2014). Owing to these reasons, the faults $IDV1$ and $IDV4$ were considered in this study to test the accuracy of the proposed methodology. Extension of this work may involve incorporation of all other remaining faults which would be studied in future.

Table 1. Tennessee Eastman process faults (Downs and Vogel (1993))

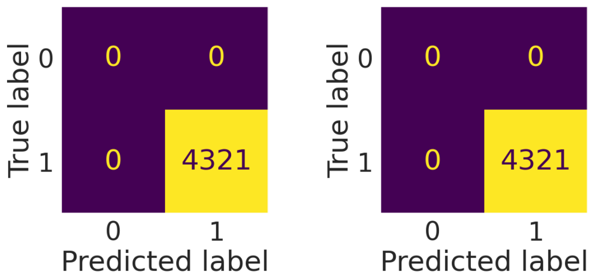
Variable	**Description**	**Type**	**Fault ID**
IDV 0	Non-faulty data	-	0
IDV 1	A/C feed ratio, B composition constant (Stream 4)	Step	1
IDV 4	Reactor cooling water inlet temperature	Step	2
IDV 9	D feed temperature (Stream 2)	Random Variable	3
IDV 11	Reactor cooling water inlet temperature	Random Variable	4

3.2 FDD results

This section highlights the results acquired when the proposed methodology was applied on the TEP. For the sake of simplicity, this study considers the datasets of Non-faulty data (Fault ID: 0), IDV1 (Fault ID: 1) and IDV4 (Fault ID: 2) with each of size 7201 × 53. Out of this 7201 data-points 60% is used for training, and the remaining 40% is used for validation and testing purposes. The dataset is taken from Liu et al. (2024). The entire computations are performed using scikit-learn package of python with a laptop having Intel i5 11th Gen processor running at 3.1GHz using 8GB of RAM. The kernel utilized is **Radial Basis Function (RBF)** and the selection of hyper-parameters for training are: gamma set as **Auto** (This is a parameter for non-linear hyperplanes. It highlights the extent of influence exerted by an individual training example. gamma parameter is specific to the RBF kernel and is typically set to 'auto,' which defaults to 1 / no. of features) and nu set as $1e-6$ (the nu value is an upper bound on the fraction of training errors and a lower bound of the fraction of support vectors).

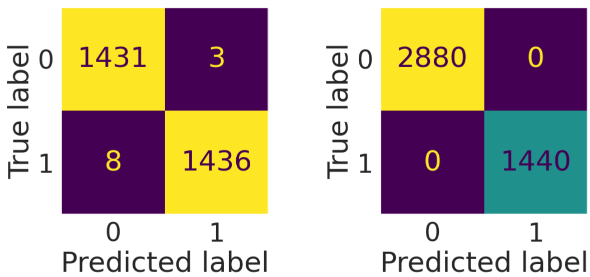
For training the first step, 60% of the Non-faulty data (Samples from 1 to 4321) was considered to train the one-class SVM. Once the training of OCSVM is completed, 60% IDV 1 faulty data (4321 samples) were introduced to test the accuracy of Fault detection by the One-class SVM, the accuracy of fault detection turned out to be 100%. Now the faulty data identified by OCSVM is labeled as fault-1 and One-class SVM is retrained with the combination of data from non-faulty and fault-1. Alongside this, a Wavelet Neural Network (WNN) was trained for detection of non-faulty and fault-1 datasets. The accuracy of training for WNN is 99.51%. Now a dataset of 2878 samples (20% of validation data from non faulty and fault-1) is considered for testing purpose and the accuracy of the proposed method with test data set is 99.79%.

In the next step, 60% of IDV 4 dataset is introduced and the fault detection accuracy of one-class SVM was calculated and it turned out to be 100% . The faulty dataset detected by one-class SVM is then labeled as fault-2 and the one-class SVM and WNN are re-trained using the 60% datasets of non-faulty, fault-1 and fault-2. A dataset of 4320 samples (20% of validation data from non faulty, fault-1 and fault-2) is considered for testing purpose and the accuracy of the proposed method with test data set is 100 %. To further demonstrate the significance of the proposed method, the classifier was replaced with a regular neural network and the same steps above are repeated this time by considering a SLFN with the number of neurons in hidden layer as **50**, **100** and **150** and the activation function as **ReLU**. The overall results with the proposed method using WNN and the method where in SLFN is considered are reported in Table 2 and the corresponding confusion matrices are shown in Figs. 4, 5 and 6.



(a) Step 2 (b) Step 6

Fig. 4. Confusion matrix of classification with One-class SVM i.e., Steps 2 and 6 of Table 2.

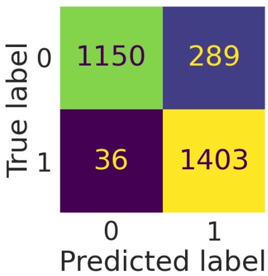


(a) Step 5 - WNN (b) Step 8 - WNN

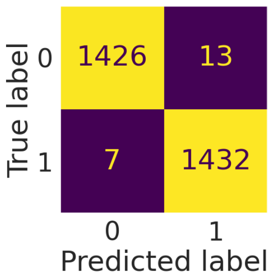
Fig. 5. Confusion matrix of classification with WNN i.e., Steps 5 and 8 of Table 2

Table 2. Framework and Results

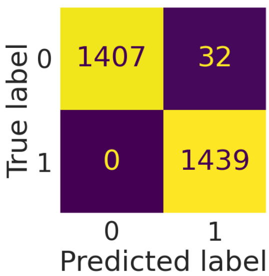
Step	**# of Samples**	**Fault ID**	**Model update and Results**
1	4321	0	Trained One-class SVM
2	4321	1	Unknown Fault detected with 100% accuracy 4(a)
3	4321	0 & 1	Updated One-class SVM with new Fault
4	4321	0 & 1	Trained both WNN and NN. Training accuracies are 99.24% and 97.20% respectively.
5	2878	0 & 1	Best Testing accuracy of fault-1 classification with WNN and NN are 99.79% 5(a) & 100% respectively 6(c). fault-1 classified.
6	4321	2	Unknown Fault detected with 100% accuracy 4(b).
7	4321	0 & 1 & 2	Updated One-class SVM & WNN.
8	4320	0 & 1 & 2	Best Testing accuracy of fault 4 classification with WNN and NN are 100% 5(b) & 80.06% respectively 7(b). Fault 4 classified.



(a) Step 5 - NN-1 (50)



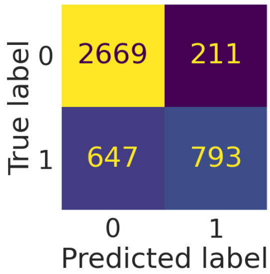
(b) Step 5 - NN-1 (100)



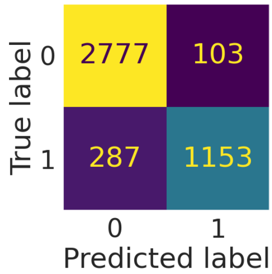
(c) Step 5 - NN-1 (150)

Fig. 6. Confusion matrix of classification with NN for Step 5 of Table 2 for different number of neurons

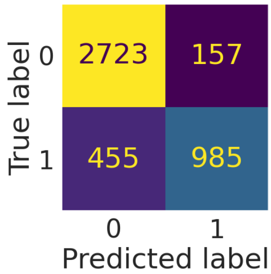
Observing from the results mentioned in the Table 2 and the corresponding confusion matrices, it is clear that One-class SVM was highly accurate with an accuracy of 100% in both the cases when Fault-1 and Fault-4 were introduced. WNN proved to be more efficient than NN for



(a) Step 8 - NN-2 (50)



(b) Step 8 - NN-2 (100)



(c) Step 8 - NN-2 (150)

Fig. 7. Confusion matrix of classification with NN for Step 8 of Table 2 for different number of neurons

various architecture with 50,100 and 150 # of neurons with an accuracy of around 99.79% and 100% for Steps 5 and 8 respectively. On the other hand, the NN suffered to reflect high accuracies with 97.49%, 99.51% and 100% for 50,100 and 150 neurons respectively for Step 5. It can be observed that in case of 150 neurons even though the accuracy with respect to fault-1 was 100% but the confusion matrix in Fig. 6(c) indicates a significant cases of false alarms which may be not desirable for active FDD. Even for Step 8 no improvement was observed with accuracies of 55.06%, 80% and 68% for 50,100 and 150 neurons respectively. Further it was also observed that as # of neurons were increased the NN suffered with the problem of over-fitting which signifies its poor performance on testing dataset.

4. CONCLUSIONS

In this paper, an active learning based methodology which is capable of learning about any new faults arriving in the plant in the due course of operation is considered. achieved through a two staged methodology where in, an unsupervised learning strategy using one-class SVM is considered in the first stage to detect the presence of a new fault. In the second stage a multi-class classifier of Wavelet Neural Network (WNN) is utilized to detect the nature of fault. The advantage of the proposed WNNs are unique in the way that the parameters in the hidden layer are assigned using Wavelet decomposition, thereby the model becomes linear-in parametric form. WNNs can handle non-linearity while the structure being linear with respect to their parameters, making them faster to train and implement. Hence, in this study WNN is used as a classifier. The efficacy of the proposed method is demonstrated on a benchmark Tennessee Eastman Process and the results are compared with the existing methods. From the results it can be concluded that the proposed approach to be more accurate than the traditional SLFN and also provided with an advantage over hyper-parameter tuning as the # of neurons required in hidden layer are pre-defined from wavelet decompositions rather than it being a hyper-parameter as in case of standard NNs.

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