

Current Transformer Saturation Detection Bases On Artificial Neural Networks

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ABSTRACT

Protection and automation (PA) system is an integral part of electric power systems. The algorithms of the PA system operate based on the use of analysis of the electrical mode parameters - current and voltage - obtained from instrument transformers. As a rule, these transformers operate based on the electromagnetism laws. Operational experience shows that the current transformers (CT) core under fault conditions can be saturated. As a result, the shape of the measured current is distorted, which can lead to maloperation of the PA system. In this paper, a method for solving the problem of CT core saturation based on the use of artificial neural networks for classification problems is proposed. The saturation problem is reduced to a binary classification problem, a description of the synthesis of DATASET is given. Computational experiments were carried out for the cases of balanced (the number of CT modes with and without saturation are the same) and imbalanced classes. The experimental results show that the accuracy of the model can reach 99%

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1. INTRODUCTION

In relay protection and automation systems (PAS), electromagnetic voltage and current transformers are most often used as a source of information. The core of the current transformers (CT) during faults, due to the peculiarities of the magnetic circuit, can be saturated. This leads to malfunctioning of the algorithms of the PAS system [1]. For example, during a fault in the differential protection zone with saturation of one of the CT, the operating current may remain below the threshold, which leads to failure to operate. And in the case of a fault outside the protection zone with CT saturation, a false operation may occur. When the CT is saturated, the algorithms of PAS system can work: false; with slowdown; with decreased sensitivity [2]. CT saturation also negatively affects fault location algorithms.

In differential protection, to consider CT errors, including those caused by low saturation of the core, operate-restrain characteristics are used [3]. Also, to avoid the influence of CT saturation on the operation of differential protections, many methods have been proposed [4-6]. These methods have not found wide practical development. In conditions of deep CT saturation, these methods are unable to ensure the correct functioning of the relay protection and PAS system.

The problem of CT saturation, as a rule, is solved in two ways: saturation detection with subsequent restoration of distorted current values [7–23] and saturation detection with subsequent blocking of the PAS algorithms [24–39]. The application of methods of the first way is limited to theoretical development, and it consists of the following stages: recognition of changes in the network mode and its segmentation into before and after fault; selection of good measurements from bad ones obtained in fault mode; replacement of distorted measured current values with calculated ones close to the reference current. If one considers the harmonic components and noise in the fault current, the practical application of the methods from the first way is impossible. A more detailed analysis of the properties of these methods and their numerical assessment is proposed in [40].

Several methods of the second way have found wide practical development due to their reliability and ease of implementation. They are based on the application of the follow: the theory of mathematical analysis [24–32], statistical signal processing [33–38] and the use of neural networks in classification problems [39].

The basis of the methods of the first group is the use of the derivative of the current. In the case of CT saturation with a sharp current cutoff, large bursts appear in the derivative of the current. Based on these bursts, CT saturation is detected. Most methods [24–31] use the method proposed in [32].

Their positive side includes a small computational load and signal processing at the rate of information receipt. The negative side of these methods is their sensitivity to noise and harmonics. To reduce the sensitivity of methods to noise, the Savitzky–Golay “smoothing” filter [40] is used in [29] and [30]. When a CT with a large reactive load is saturated, the distorted current shape does not contain sharp cuts. In this case, the effectiveness of methods [24–32] sharply decreases.

The methods of the second group operate based on follow: analysis of extremes of the measured current of one period [33], correlation analysis between the measured and calculated current [34], correlation analysis of the measured currents of the high and low sides of a two-winding power transformer [35], analysis of the shape of the differential current in the circuit differential protection of a power transformer [36], dispersion analysis of measured current data of one period [37] and calculated values of magnetic density of $\frac{1}{4}$ period [38].

The positive aspects of the methods of the second group include their robustness with respect to noise and harmonic components. Their disadvantage is signal processing with a delay.

The methods of the third group [39] use machine learning algorithms, consisting of stages: data generation and collection, data preprocessing, training and evaluation of the model and its further application.

Methods of the third group at the data preprocessing stage require fault currents with the beginning and end of a homogeneous process, which can last up to hundreds of milliseconds or more. In this case, the use of these methods considering data preprocessing procedure turns out to be ineffective due to the large time delay.

With deep saturation, methods of the first group are not able to detect CT saturation, since in the measured current a sharp cut occurs at an early stage, in the region near zero current values. In this case, the methods of the second and third groups work well due to the appearance of a large stable section of the measured current caused by CT saturation.

The work presents the solution of the problem of CT saturation based on the use of ANN for classification problems. Detection of CT saturation is carried out when the level of the secondary load and its components were varied.

2. PROPOSED METHOD BASED ON ANN

2.1. DATASET generating and ANN architecture selecting

It is known that training an ANN requires a set of statistical data called DATASET. In classification problems ANNs are models that are trained on the basis of reference data – supervised learning. Therefore, when synthesizing data in DATASET, each sub-set of input data must have a corresponding reference value. In relation to the task of CT saturation detection, the measured current values obtained both in the CT saturation mode and under its normal operation conditions will be used as input data to the ANN.

To synthesize the data, the TT mathematical model proposed in [42] was used. This model in accordance with a single-phase CT can be described by the system:

$$\begin{cases} N_2 A \frac{dB}{dt} = (R_2 + R_b) i_2 + (L_2 + L_b) \frac{di_2}{dt} \\ Hl = N_1 i_1 - N i_2 \\ \lambda = f(H) \end{cases} \quad (1)$$

where R_b and R_2 – the active load of secondary devices and the secondary winding of the CT, respectively; L_2 and L_b – the inductance of the secondary winding and CT load, respectively; A – cross-section of magnetic core steel; l – average length of the magnetic line of the CT magnetic circuit; i_1 , i_2 – primary and secondary currents of the CT, respectively; N_1 , N_2 – number of turns of the primary and secondary windings of the CT; B and H – magnetic induction and magnetic field strength, respectively; $B = f(H)$ – magnetization characteristic of the magnetic circuit.

Model (1) included the parameters of CT with an accuracy class 10P: $A = 19.1 \times 10^{-4} \text{ m}^2$; $l = 90 \times 10^{-2} \text{ m}$; $N_1 = 2$ and $N_2 = 239$; $R_b = 0.98 \text{ Ohm}$ and $R_2 = 0.48 \text{ Ohm}$; $L_b = 0$ and $L_2 = 3.666 \times 10^{-5} \text{ H}$. The specified CT has a non-aired-gap core.

A current consisting of a normal:

$$i'_1(t) = I_{m1} \sin \omega t \quad (2)$$

and fault conditions:

$$i'_1(t) = k I_{m1} \sin(\omega t + \varphi) + I_{m2} e^{-\frac{(t-t_0)}{T}} \quad (3)$$

was supplied to the input of model (1),

where k – fault gain coefficient; I_{m1} – amplitude of the nominal mode current; φ – angle of fault occurrence; I_{m2} and T – initial value and the rate of decay of the DC component in the fault, respectively; t_0 – the moment of transition of the mode from one characteristic to another.

The factors that influence the moment of CT saturation are:

- amplitude and angle of fault;
- initial flux density of the core;
- decay rate of the aperiodic component of the fault;
- secondary active load;
- secondary inductive load.

Taking into account the variation of all factors, a series of 44,000 faults curves was simulated:

$$M = M_1 \cdot M_2 \cdot M_3 \cdot M_4 \cdot (M_5 + M_6) = 11 \cdot 40 \cdot 10 \cdot 1 \cdot (5 + 5) = 44,000 \quad (4)$$

where M_1 and M_2 – the total number of fault amplitudes and angles; M_3 – the number of initial flux of the CT; M_4 – the decay rate of the DC component, M_5 and M_6 – the number of active and reactive loads of the CT, respectively.

The next factor is the location of the saturated regions in the measured current. When a fault occurs, CT saturation can occur in the first cycle or in one of the subsequent cycles. To take into account this point, data will be received at the ANN input according to the window function principle with a width of one current cycle. The window sliding step is one packet (5 ms). Figure 1 shows an example of a sliding window of data with a sampling rate of 16 points/ cycle. In this figure, the reference and measured currents are shown as blue and red curves, respectively. The red squares (on the measured current curve) highlight its samples. In the lower part of the figure, black rectangles highlight the actual corresponding current samples (16 points), taking into account their batch offset (4 points). After each batch offset, the first batch is thrown away - rectangles shaded in red. Then 4 new dimensions of the “fresh” package are added. Vertical blue arrows indicate the end of each data window. From Figure 1 it can be seen that a complete transition from one period to the second requires 5 steps. As a result, 5 modes (mode1-mode5) are formed to detect CT saturation.

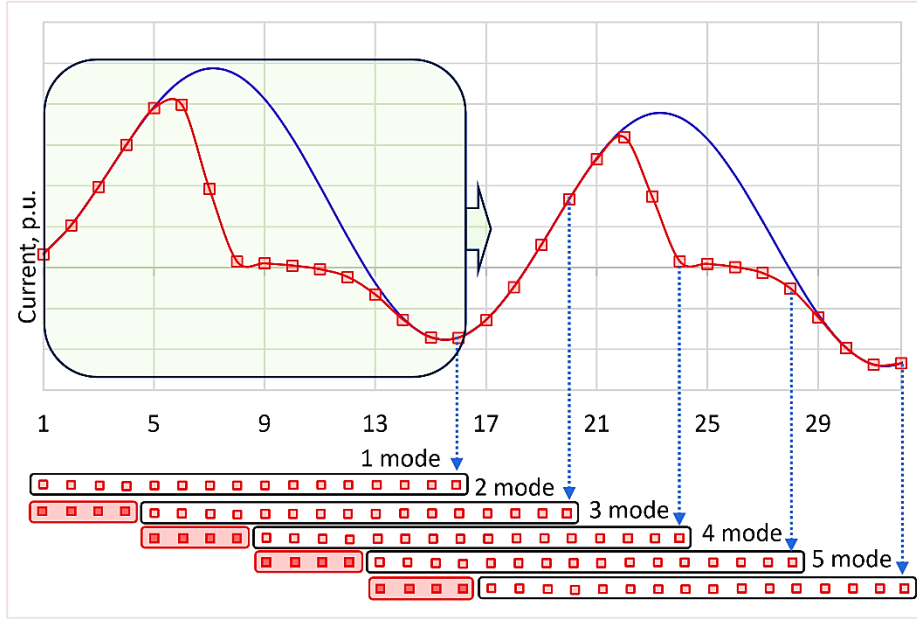


Figure 1. An example of a sliding window with a complete transition from the first cycle to the second.

Thus, taking into account all factors, the number of input data of DATASET is:

$$INP = M \cdot WndStep = 440\,00 \cdot 5 = 220,000 \quad (5)$$

where WndStep – the number of window sliding step for full transmission from one cycle to the another.

Within this work, when solving the problem of saturation detection, the presence and absence of CT saturation is taken into account. In this case, the inrush of the magnetizing current of the power transformer, harmonic components and noise, as well as frequency fluctuations of the AC component are not taken into account. Therefore, the task of detecting CT saturation is reduced to the task of binary classification and it uses two classes $y = \{1, 0\}$. $y = 1$ indicates the presence of CT saturation, and $y = 0$ its absence. Now, for each input from the INP, a corresponding class label is needed at the output of the ANN. For this purpose, based on the assessment of the total CT error, the following criterion is formulated:

$$error = \frac{I_\mu}{I} 100 = \frac{100}{I} \sqrt{\sum_{k=1}^K \left(\frac{i_1(k)}{n} - i_2(k) \right)^2} \quad (6)$$

$$Y = \begin{cases} 1 & \text{if } error \geq Th \\ 0 & \text{if } error < Th \end{cases} \quad (7)$$

where I and I_μ – the effective values of the primary and magnetizing currents of the CT reduced to the secondary side, respectively, i_1 and i_2 – the instantaneous values of the reference and measured currents; n – CT transformation ratio; K – signal sampling frequency, samples/cycle, Th – threshold. In the case of a CT with an accuracy class of 10, the threshold value is set to $Th = 10$. Depending on the depth of CT saturation and the sensitivity of the PAS algorithms to the CT error, the threshold values can be set individually.

Expression (6) is the total error of the CT, expression (7) is the label of the true class Y .

Signal frequency $N = 32$ samples/cycle. Consequently, DATASET of $X = \{i_2(j), Y(j) \mid i_2 = i_2(1), i_2(2), \dots, i_2(32), Y = \{0; 1\}\}_{j=1}^{220,000}$ with two classes at the ANN output is formed. An ANN architecture with 32 inputs and 1 output is selected. Figure 2 shows the architecture of the selected ANN classifier. The results of intermediate calculations showed that the most suitable is an ANN classifier with two hidden layers $h1$ and $h2$ of 200 neurons each. Depending on the input data, the only output neuron of the network $a(x)$ can take two states $a \approx \{1, 0\}$.

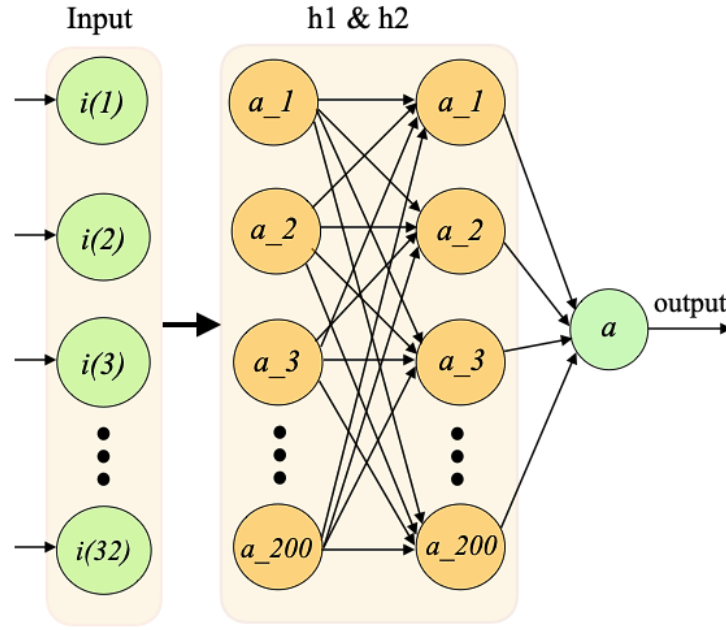


Figure 2. Architecture of the ANN classifier.

Since the task of detecting CT saturation is reduced to a binary classification problem, the loss function is described as:

$$Loss = -[y \cdot \log(a) + (1 - y) \cdot \log(1 - a)] \quad (8)$$

where y – the true class labels; a – the class labels at the output of the ANN.

2.2. Selection of ANN activation function

As a rule, to increase the learning speed of an ANN data scaling is used. It is worth noting that to process data using existing scaling methods is impossible. This is caused by the short input window, deep CT saturation, diversity of fault currents and window offset. There are faults whose extrema are not in the first window(s) of data.

When using the Max, Min-Max and Z-scaling methods, the scale of the current data in each data packet will change as the window is shifted. In this case, with each window step, the data scale of the same packet can change until it is excluded from the window (5 times). Moreover, when scaling using the Max method, near-zero current values turn into an infinitesimal number. All this complicates the task and negatively affects the representativeness of the data.

Based on the above, scaling methods will not be used at the data preprocessing stage.

Another point during ANN modeling and evaluation is the activation function of neurons. In the ReLU function, the values of neurons change in the range of $[0; \infty)$. In this case, for negative current values the “dead neurons” are formed. Solving the problem of detecting CT saturation in negative half-cycles becomes impossible.

In the Leaky ReLU function, the “dead neurons” task is absent and the output values of neurons change in the range $(-\infty; \infty)$. However, using a linearly separable function to take into account the diversity of all faults with CT saturation is impossible.

In the Softmax function, the input values of neurons are turned into a probability distribution at the output. This function is actively used in the output layers of ANNs in multi-class classification problems. Therefore, its direct use in binary classification problems is impossible.

The most suitable for the CT saturation detection task is the sigmoid function. It is used both in the hidden and output layers of the network. In all neurons of the network, the sigmoid will be used as the activation function:

$$a(x) = \frac{1}{1 + e^{-x}} \quad (9)$$

where x is the announced input amount.

2.3. Optimizer selection for ANN training and visulisation of CT saturation detection prosedure

Another key point of the ANN at the training stage is the speed of convergence and exclusion of the local extrema influence of the function. For this point several optimization methods have been proposed:

- Stochastic gradient decent (SGD);
- Momentum;
- Adaptive momentum;
- Root mean squared, etc.

Among the proposed optimizers, SGD is the most commonly used. Other optimizers are most often combined with it. Elimination of the influence of local extrema of the function in SGD is performed by averaging the errors obtained as a result of running a series of several observations through an ANN classifier. This series is called a mini batch. SGD together with Momentum will be used as an optimizer.

The data processing with CT saturation detection process is shown in Fig. 4.

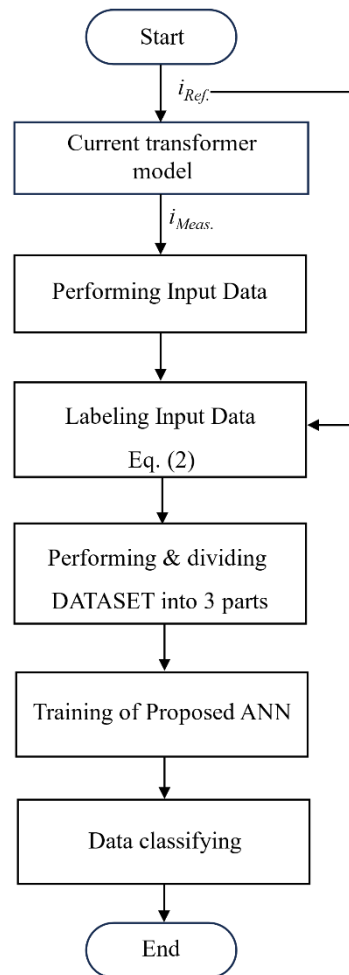


Figure 3. CT saturation detection process

From Figure 3 it is clear that the procedure for solving the CT saturation detection problem using an ANN classifier consists of synthesizing input data (measured currents) based on the mathematical model of CT, forming a class label for each of the input data, forming DATASET and its dividing into sub-sets, ANN training and data classification (CT saturation detection).

3. EXPERIMENTAL RESULTS

Before training an ANN classifier, to configure its internal architecture and hyperparameters is required. To train the selected ANN classifier, DATASET with a size of 220,000 were divided into parts: training, validation and test sub-sets. To increase the model learning speed, the SGD optimizer was used with a combination of Momentum. After applying Momentum to SGD, the network learning was increased. The values of the internal architecture of the ANN classifier and its hyperparameters are given in Tables 1 and 2, respectively.

Table 1. Internal architecture of the model

Parameter name	Parameter value
Network architecture	Feedforward
Number of input nodes and output neurons	32 and 1
Number of neurons in hidden layers h_1, h_2	200
Layer activation functions	Sigmoid
Distribution of initial values of weight links	Normal

Table 2. Model hyperparameters

Parameter name	Parameter value
DATASET size	220,000
Training set	0.8 DATASET
Testing set	0.1 DATASET
Validating set	0.1 DATASET
Learning rate	0.07
Number of epochs	200
Minibatches size SGD	128
Damping coefficient β Momentum	0.7
Sampling rate of input data	32 samples/cycle

In the CT saturation detection task, the number of modes with saturation is greater than the number of modes without it. This leads to an imbalance between classes. Consequently, direct assessment of the quality of an ANN classifier distorts the true effectiveness of its work. To eliminate this point, a confusion matrix with four elements is used:

- correct detection of CT normal operation – TP;
- correct detection of CT saturation – TN;
- false detection of CT normal operation – FP;
- false detection of CT saturation – FN.

Based on the elements of the confusion matrix, two indicators are calculated – Precision and Recall. The first shows the proportion of true classes among the predicted classes, in other words, this indicator answers the question “What is the model accuracy?” The second indicator determines the proportion of correctly classified modes with and without CT saturation, and it answers the question “what proportion of modes with and without CT saturation were classified correctly?” Therefore, these indicators are defined as:

$$Precision = \frac{TP}{TP+FP} \quad (10)$$

$$Recall = \frac{TP}{TP+FN} \quad (11)$$

where TP, FP and FN are the correct CT normal operation detection, false CT normal operation detection and false CT saturation detection, respectively.

Since two classes are used in the work to determine the precision and recall of the model for each of them is required. Class 0 corresponds to normal CT operation, and class 1 to CT saturation. The precision and recall of class 0 are denoted as Precision_0 and Recall_0, and class 1 are denoted as Precision_1 and Recall_1, respectively.

3.1. Experiment 1. Imbalance between classes 0 and 1

There was a large imbalance between classes in this experiment. The percentage of class 0 and class 1 in DATASET was 5% (11,533) and 95% (20,8462), respectively. The size of the DATASET test subset was 22,016. The result of the ANN classifier based on the test subset is shown in Figure 5. From Figure 5 it can be seen that among 22,016 modes, the precision of the ANN classifier and its recall for class 0 is Precision₀ = 92.7% and Recall₀ = 97.6% respectively. These figures for class 1 are Precision₁ = 99.9% and Recall₁ = 99.6%.

True Class	0	1110	88	92.7%	7.3%
	1	27	20791	99.9%	0.1%
		97.6%	99.6%		
		2.4%	0.4%		
	0	1			
	Predicted Class				

Figure 4. The result of an ANN classifier with class imbalance

3.2. Experiment 2: Balanced classes

It is worth noting that high precision and recall for modes with CT saturation in Figure 4 can be caused by a strong imbalance between classes towards class 1. In this case, class 1 becomes dominant. To achieve balance between classes, some modes with CT saturation are removed from the DATASET. As a result, the size of DATASET is reduced from 220,000 to 23,066. Then, dividing the data into a training (0.8DATASET), testing (0.1DATASET) and test (0.1DATASET) subsets, an ANN classifier is trained and tested.

In the case of class balance, the dominance of class 1 ceases. Therefore, for it there should be a decrease in the accuracy of the model. As for recall, it shouldn't change much. The result of the trained ANN classifier for the test subset is shown in Figure 5. The accuracy of the ANN classifier for class 1 decreased Precision₁ = 99.2%, and its recall increased and became Recall₁ = 98.8%. The accuracy of the ANN classifier and its recall for class 0 have increased and become Precision₀ = 98.8% and Recall₀ = 99.2%, respectively.

True Class	0	1115	14	98.8%	1.2%
	1	9	1166	99.2%	0.8%
		99.2%	98.8%		
		0.8%	1.2%		
	0	1	Predicted Class		

Figure 5. The result of the ANN classifier with balanced classes

3.3. Comparison of the results of experiments 1 and 2

For clarity of data, the results of the experiments are shown in Table 3. The last column of the table shows the difference in the assessment of the effectiveness of the ANN classifier before and after forming a balance between classes 0 and 1.

Table 1. Comparative analysis of experiments 1 and 2.

	Experiment 1	Experiment 1	Experiment 1
Precision_0	92.7%	98.8%	6.1%
Recall_0	97.6%	99.2%	1.6%
Precision_1	99.9%	99.2%	-0.7%
Recall_1	99.6%	98.8%	-0.8%

From the last column of Table 3 one can see that the precision and recall of the model for class 0 in the balanced classes improved by 6.1% and 1.6%, respectively. And for class 1, on the contrary, when establishing a balance across classes, these indicators decreased by - 0.7% and - 0.8%, respectively. The negative difference for class 1 does not in any way indicate a deterioration in the efficiency of the model. This means a decrease in the dominance of class 1 over class 0.

4. CONCLUSIONS

An analysis of existing methods for CT saturation detection was carried out. Their positive and negative sides are described. A systematization of these methods is given. A method for detecting CT saturation using artificial neural networks for binary classification is proposed. The properties of the activation function ReLU, Leaky ReLU, softmax and sigmoid are described in relation to the CT saturation detection task. The task of CT saturation detection is reduced to the binary classification problem. The advantage of using the sigmoidal activation function is given.

A neural network with a fully connected forward propagation architecture is proposed for CT saturation detection. A description of the data synthesis method is given. A method for forming a class label is proposed in relation to the CT saturation detection problem with the ability to tune out shallow saturations. Computational experiments were carried out with a large imbalance between classes 1 (CT saturation) and 0 (normal CT operation) and with their balance. The results of the first experiment show that with a large imbalance between classes the precision of the ANN classifier and its recall for class 1 were 99.9% and 99.6%, respectively. These figures for class 0 were 92.7% and 97.6%, respectively. In the second experiment, with balanced classes, the precision of the ANN classifier and its recall for class 1 relative to the first experiment fell by 0.7% and 0.8%, respectively. In the case of class 0, these indicators relative to the first experiment increased by 6.1% and 1.6%, respectively.

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