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Damage detection of steel frames under fire using time-series acceleration and machine learning

Chẩn đoán hư hỏng khung thép chịu lửa sử dụng chuỗi gia tốc và học máy

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ABSTRACT

In this paper, a damage detection methodology for steel frame structures under fire load using time-history acceleration and machine learning (ML) is proposed. A randomly created dataset by finite element analysis (FEA) is utilized to develop deep neural networks (DNNs). In which, the inputs of the model are the time-dependent acceleration at limited degrees of freedom (DOFs) of a steel frame structure, while the outputs are damage ratios of frame members. The damage ratio of damage elements is defined by the reduction of material Young's modulus. The accuracy of DNNs is continuously upgraded by eradicating low-risk members after each iteration via a damage thresshold. A planar frame including damage detection scenarios with and without the fire effect programmed by Python are tested to confirm the validity of the proposed paradigm.

Keywords: Damage detection; frame structures; fire; time-series acceleration; machine learning (ML); Python.

TÓM TẮT

Trong bài báo này, một phương pháp chẩn đoán hư hỏng khung thép chịu lửa sử dụng chuỗi gia tốc và học máy được đề xuất. Một tập dữ liệu được tạo ra một cách ngẫu nhiên từ phân tích phần tử hữu hạn được sử dụng để xây dựng mạng thần kinh sâu (DNNs). Trong đó, dữ liệu đầu vào là gia tốc tại các bậc tự do của khung thép, trong khi đó dữ liệu đầu ra là tỉ lệ hư hỏng của các phần tử. Tỉ lệ hư hỏng của các phần tử được định nghĩa bằng cách giảm đi mô đun đàn hồi Young. Sự chính xác của các mô hình DNNs được cập nhật liên tục bằng cách loại bỏ các phần tử có nguy cơ hư hỏng thấp thông qua một ngưỡng phá hủy. Một khung phẳng được lập trình bằng Python bao gồm những kịch bản hư hỏng có và không có sự ảnh hưởng của lửa được kiểm tra để xác nhận giá trị của phương pháp pháp đề xuất.

Từ khóa: Chẩn đoán hư hỏng; kết cấu khung; lửa; chuỗi gia tốc; học máy; Python.

1. INTRODUCTION

In reality, there has been a notable observation that the increase in the number of civil engineering structures suffering significant damage caused by various adverse factors, including environmental effects, overloading, material deterioration, and inadequate maintenance. To prolong the service life of these structures and prevent catastrophic failure resulting from hidden local damage, it is crucial to accurately and quickly assess the prognosis of damage. This assessment enables the proposal of appropriate repair, reinforcement, or replacement strategies. In response to this need, the field of structural health monitoring (SHM) has emerged and attracted considerable attention from researchers in recent decades. In recent years, numerous articles related to this topic have been published. Especially, data mining (DM) techniques, such as artificial intelligence (AI), ML, and statistical methods, have been extensively employed in numerous applications of structural health monitoring (SHM) [1].

It is worthwhile indicating that in most of available publications existing in the open literature, free vibration properties including eigenvalues and eigenvectors are often utilized for damage detection in ML models. Nonetheless, those approaches require high-order free vibration features of at least the first five modes including eigenvalues and eigenvectors. And it is impossible to measure such properties in practice, especially for complex and large-scale structures. To deal this issue, Dang et al. [2] proposed a novel two-stage damage detection method for trusses using model order reduction (MOR) and time-series acceleration data from limited sensors.

In addition to optimization algorithms, AI techniques have gained significant attention in various scientific fields, including structural health monitoring. Lee et al. [3] introduced a surrogate model based on deep learning techniques to detect damaged states in truss structures. Fu et al. [4] developed a ML framework to quickly predict the failure mode of a fire-exposed simple steel frame and assess the progressive collapse resistance of the structure. This led to a new tool for evaluating the safety of steel multi-story buildings under fire conditions. Wu et al. [5] used an artificial intelligence framework with LSTM networks and large-scale data to predict the origin of the fire in a numerical model of a tunnel. Ji et al. [6] pioneered a real-time prediction method for diagnosing physical parameters and early warning of structural collapse in fire incidents using ML. Despite over two decades of research on machine learning applications in the field of civil engineering, there is still a small number of studies focusing on using machine learning for diagnosing fire-resistant frame structures. Therefore, this study aims to address this gap by using the example of fire-exposed Timoshenko frame structures subjected to dynamic or fire loads. A ML framework utilizing the DNN is constructed to detect the damage to steel frame structures through a surrogate model.

2. FINITE ELEMENT MODEL OF STEEL FRAME STRUCTURES

2.1. Dynamic analysis

In the work, the Timoshenko beam theory proposed by Friedman et al. [7] is employed to construct the stiffness matrix for beam and colum elements of a frame structure. The governing equation for the dynamic analysis of a frame is given by

$$\mathbf{M}\ddot{\mathbf{x}}(t)+\mathbf{C}\dot{\mathbf{x}}(t)+\mathbf{K}\mathbf{x}(t)=\mathbf{f}(t) \tag{1}$$

where **M**, **C**, **K** are the lumped mass, proportional damping, and global stiffness matrixes, respectively; $\ddot{\mathbf{x}},\dot{\mathbf{x}}$ and $\mathbf{x}$ are the global acceleration, velocity and displacement vector, in turn; $\mathbf{f}(t)$ is the global time-series force.

The damping matrix **C** given in the above equation is defined as follows

$$\mathbf{C}=\alpha\mathbf{M}+\beta\mathbf{K} \tag{2}$$

where α and β denote the mass- and stiffness-proportional damping factors, and they are given by the Rayleigh coefficient as follows

$$\alpha=\xi\frac{2\omega_1\omega_2}{\omega_1+\omega_2};\ \beta=\xi\frac{2}{\omega_1+\omega_2}, \tag{3}$$

where $\xi=5\%$ is the damping ratio; ω_1 (rad/s) and ω_2 (rad/s) are the first two frequencies, having the same direction of the applied loading.

2.2. Fire-induced temperature curve

A temperature curve [8] which represents the relationship between the temperature and fire time is adopted. Its mathematical expression is given as follows

$$\Theta_{\mathrm{g}}=20+345\log_{10}(8t+1) \tag{4}$$

where Θ_{g} is the mean furnace temperature in Celsius degree, and *t* is the time (minute).

2.3. Fire-induced material mechanical properties

The properties of steel regarding strength and deformation are obtained from the Eurocode standard [8]. The reduction factors for the stress-strain relationship for steel at elevated temperatures are defined as follows: (i) effective yield strength, relative to yield strength at 20°C: $k_y=f_{y,\theta}/f_y$; (ii) proportion limit, relative to yield strength at 20°C: $k_p=f_{p,\theta}/f_y$, and (iii) slope of linear elastic range, relative to slope at 20°C: $k_E=E_{\mathrm{a},\theta}/E_{\mathrm{a}}$. In which, $f_{\mathrm{y},\theta}$ is the effective yield strength; $f_{p,\theta}$ is the proportional limit; $E_{a,\theta}$ is the slope of the linear elastic range; f_y and E_a are the yield and Young's modulus at 20°C, respectively.

2.4. Thermal elongation

Also in the Eurocode standard [8], the relative thermal elongation of steel $\Delta l/l$ is determined from the following

$$\Delta l/l=1.2\times10^{-5}\theta_{\mathrm{a}}+0.4\times10^{-8}\theta_{\mathrm{a}}^{2}-2.416\times10^{-4},\ \text{for } 20°C\le\theta_{\mathrm{a}}<750°C \tag{5}$$

$$\Delta l/l=1.1\times10^{-2},\quad \text{for } 20°C\le\theta_{\mathrm{a}}<750°C \tag{6}$$

$$\Delta l/l=2\times10^{-5}\theta_{\mathrm{a}}-6{,}2\times10^{-3},\quad \text{for } 20°C\le\theta_{\mathrm{a}}<750°C \tag{7}$$

where l is the lenghth at 20°C; Δl is the temperature-induced elongation, and θ_{a} is the steel temperature in Celsius degree.

2.5. Heat transfer analysis

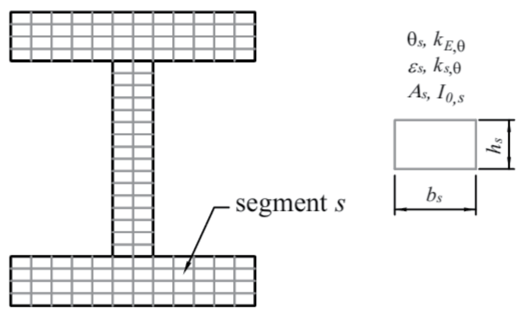


Figure 1. 1D segmentation process of the cross-section for temperature analysis

This approach employs a two-end nodes thermal element to simulate each cross-section segment [9]. As depicted in Figure 1, each linear element is transformed into a segment *s*. Accordingly, the equivalent cross-section area A_θ can be calculated as follows

$$A_\theta=\int_A k_{E,\theta}\mathrm{d}A=\sum_{s=1}^{n}k_{E,\theta,\mathrm{s}}A_s \tag{8}$$

where $k_{E,\theta}$ is the elastic reduction factor of the effective area of each segment A_s.

The equivalent moment of inertia I_θ can also be computed by

$$I_\theta=\int_A k_{E,\theta}y_s^{\,2}\mathrm{d}A=\sum_{s=1}^{n}(k_{E,\theta,\mathrm{s}}I_{0,\mathrm{s}}+k_{E,\theta,\mathrm{s}}b_sh_sy_s^{\,2}) \tag{9}$$

The magnitude of the axial P_θ and the flexural M_θ restoring force can be calculated as follows

$$P_\theta=\int_A \varepsilon_\theta k_{E,\theta}E\mathrm{d}A=\sum_{s=1}^{n}\varepsilon_{\theta,k}k_{E,\theta,\mathrm{s}}Eb_sh_s \tag{10}$$

$$M_\theta=\int_A \varepsilon_\theta k_{E,\theta}Ey_s\mathrm{d}A=\sum_{s=1}^{n}\varepsilon_{\theta,\mathrm{s}}(k_{E,\theta,\mathrm{s}}E)y_sb_sh_s \tag{11}$$

where ε_θ is the thermal elongation defined in sub-section 2.4.

3. DEEP NEURAL NETWORK

DNNs denote a remarkable breakthrough in the field of ANNs. It has captured considerable attention and witnessed a surge in popularity in recent years. DNNs are a group of ML models, which have been meticulously crafted to emulate the structure and functionality of the human brain's intricate neural networks. These layers are thoughtfully organized in a hierarchical manner, where each layer extracts and transforms features from the input data before passing the result to the subsequent layer. The layers closer to the input layer are responsible for cap-turing low-level features, while the deeper layers capture higher-level concepts. From several other points of view, DNNs can be used interchangeably to represent Multi-layer Perceptron (MLP). DNNs are designed to learn and improve iteratively. Once these DL algorithms are fine-tuned for accuracy, they become powerful tools in computer science and artificial intelligence, enabling us to perform tasks such as classification, data clustering, and high-speed regression approximation in various fields. Several applications of DL techniques to the structural field could be found in Refs. [10], [11], [12].

4. TEST EXAMPLES

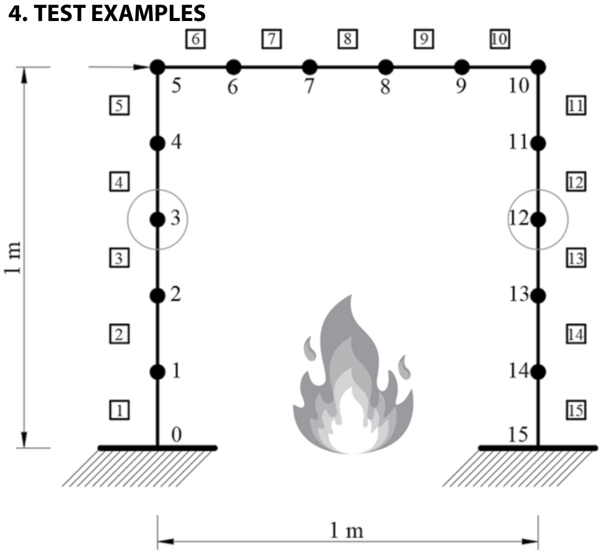


Figure 2. A 15-element frame model

A planar frame [13] as sketched in is examined. The number of elements and the index of each node are also indicated in the above figure. In which, the height and width of all column and beam elements are 0.00635 m and 0.0760 m, respectively. All elements are of the same Young's modulus E=210 GPa, and their material density ρ =7860 kg/m^3.

4.1. *Damage detection without fire*

Table 1. Damage scenario without fire effect assumed for 15-element frame

Damage scenarios	Damaged elements	Damaged ratio
1	5,13	0.2, 0.2

Firstly, the above-examined frame is presumed to have a damaged scenario as presented in Table 1. In order to measure time-series accleration data, a trapezoid-shaped impulse load applied at node 5 is given as follows

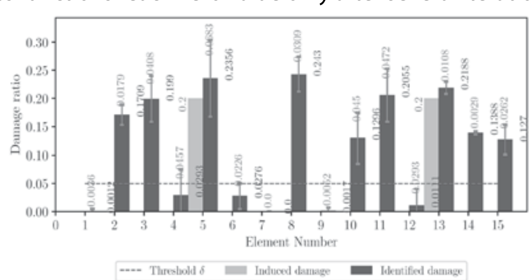
$$\begin{cases} F(t) = 500(1-0.01t) & \text{when } t \le 0.1s \\ F(t) = 0 & \text{when } t > 0.1s \end{cases} \quad (12)$$

All time-series accleration data are horizontally mearsured at nodes 3 and 12, and they are randomly noised by a 2% level. In order to obtaint the corresponding data for creating the data by FE simulation to feed into the learning model, the Newmark-beta method is adopted to acquire acceleration data at the measuring DOFs in the time domain of 15e-4 s with the time step 5e-5 s. Now, the DNN model is now employed as a surrogate model to learning damage-sensitive properties of frame structure. From that, the learning model can preliminarily predict both the severity and location of damaged element. In order to build such a model, hyper-parameters of the DNN are set up as those given in Table 2. It is worthwile highlighting that all values of those hyper-parameters are chosed by the trial and error method after careful investigations. The output of the dataset is randomly created in a uniformly distributed range of [0, 0.5]. Note that, higher damaged ratios of column and beam elements may lead to the whole collapse of a structure. And this is out of the SHM field. Therefore, they are assumed to be less than or equal to 0.5 in this work.

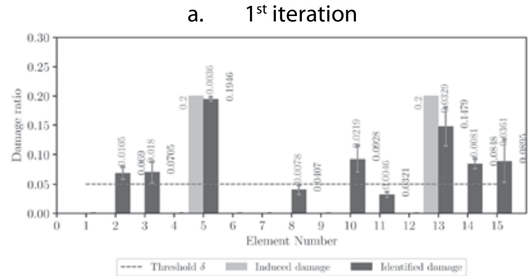
Table 2. Hyper-parameters of DNN for the 15-element frame

Hyper-parameters	Value
Train/Test ratio	0.9
Activation function	Relu, LeakyRelu
Optimizer	Adam
Hidden Layer	2
Epoch	1500
Mini batch size	256

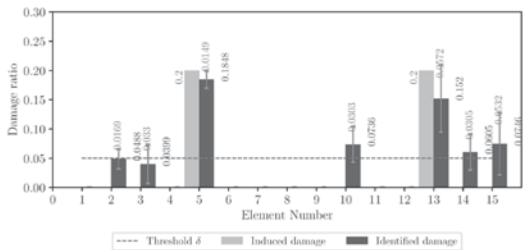
In this study, a series of DNN models is utilized for the damage detection proccess. More concretely, in the first step, only a small datatset of 2000 samples is employed to construct the DNN in each iteration. Then, this learning model is used to predict the location and extent of damage elements. It is clear that the accuracy of this DNN is not high with false alerts as indicated in Figure 3a. This is because only a small dataset is used instead of a big one as that done by other studies. In order to improve the accuracy of the current DNN, a damage thresshold of 5% is applied. Accordingly, the damage ratios predicted by this DNN which are less than or equal to this thresshold are eliminated. This performance helps to reduce the number of output neuros of the next DNN model. As a consequence, its accuracy is naturally enhanced with only four iterations. By repeating such a simple manner, both the location and extent of damage eleements can be detected with high accuracy as shown in Figure 3b, c and d. The loss convergence history of the damage detection process is plotted in Figure 4. It is obvious that the loss functions reach zero value only after several iterations.



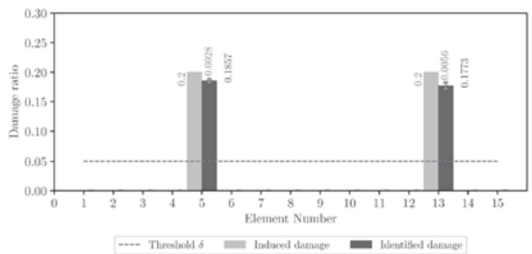
a. 1st iteration



b. 2nd iteration



c. 3rd iteration



d. 4th iteration

Figure 3. The damage detection process for the 15-element frame without fire

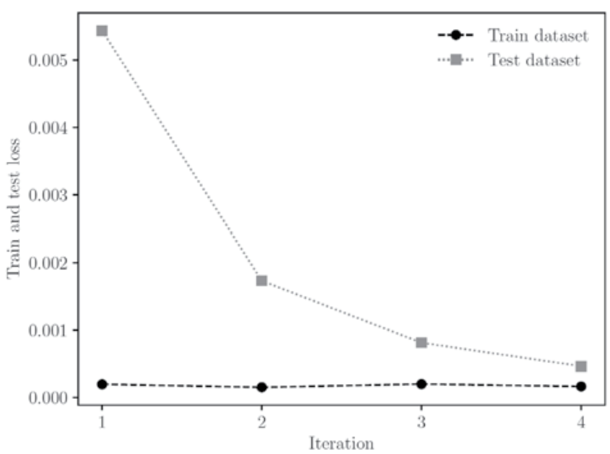


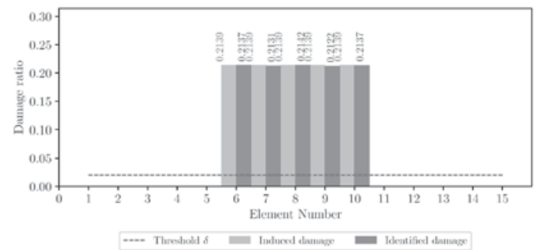
Figure 4. The loss convergence history of the damage detection process for the 15-element frame without fire

4.2. *Damage detection with only fire*

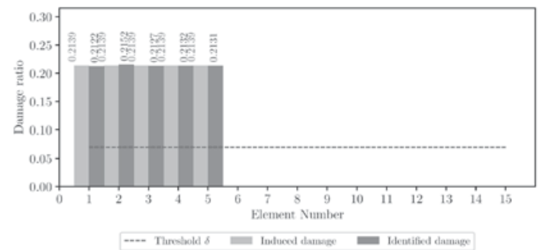
In this case, the damage only caused by fire load is taken into account. For this, a binary classification model using the DNNs is proposed to recognize damaged elements in the 15-element frame. The hyper-parameters of DNNs are similar to those of the foregoing case. Damage cases induced by fire load are given in Table 3. Note that if longer time is considered, the fire-induced material mechanical properties presented in Section 2.3 will be dramatically reduced. This may lead to the whole collapse of a structural system. This issue is out of the scope of this study, and it is not therefore investigated. Damage prediction results of the 15-element frame under fire load are reported in Figure 5. As seen from the above figure, damage outcomes identified by the proposed methodology can be achieved with high accuracy and reliability.

Table 3. Damage scenarios with only fire effect assumed for 15-element frame

Fire scenarios	Fired elements	Fire Time
1	1, 2, 3, 4, 5	5 min
2	6,7, 8, 9, 10	5 min



a. Scenario 1



b. Scenario 2

Figure 5. Damage prediction results of the 15-element frame with only fire for different scenarios

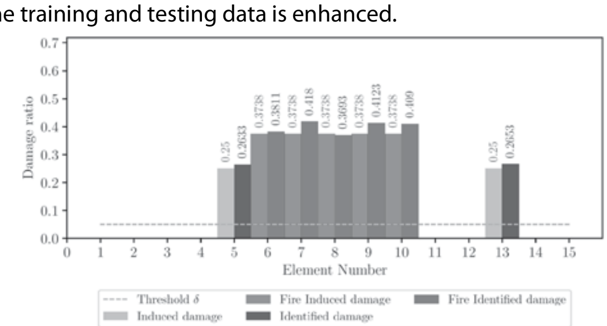
4.3. *Damage detection induced by fire and others*

Table 4. Damaged scenarios induced by fire and others assumed for the 15-element frame

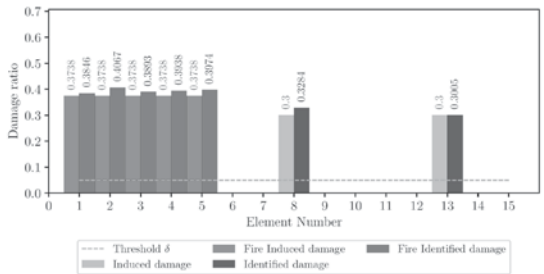
Fire scenarios	Fired elements	Fire Time	Typical damaged elements	Damaged ratio
1	6,7, 8, 9, 10	10 min	5,13	0.25, 0.25
2	1, 2, 3, 4, 5	10 min	8,13	0.3, 0.3

Practically, two kinds of damaged elements can occur in a structure under fire. The first is typical damage caused by various common factors such as environmental conditions, earthquakes, etc., and the fire triggers the second one. Due to the abovementioned reason, this study presents an algorithm or paradigm to resolve it. This model has such detectors that predict the damage ratio of elements and the damage-causing factor. Furthermore, when fire is considered in dataset creation, that changes the damage ratio of a element created in the dataset from uniform to normal distribution. Table 4 presents damaged scenarios examined in this part. Hypothesize that no noise effect on recorded data exists.

Due to the complexity of damage scenarios caused by fire, the number of epochs is set up to be 2000 instead of 1500 as that of the previous two cases. It can be found from Figure 6 and Figure 7, the suggested paradigm can be detected both the location and extent of damaged elements with high reliability and accuracy. As expected, the accuracy of the subsequent learning models on both the training and testing data is enhanced.

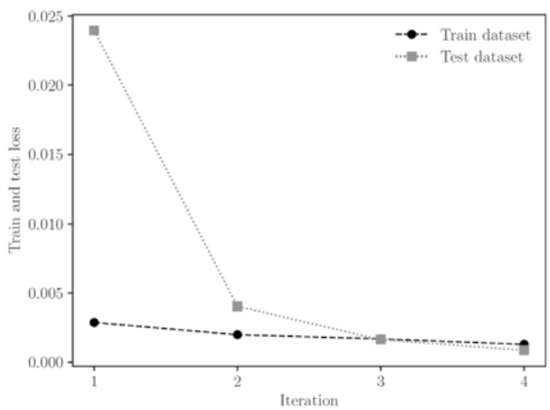


a. Scenario 1

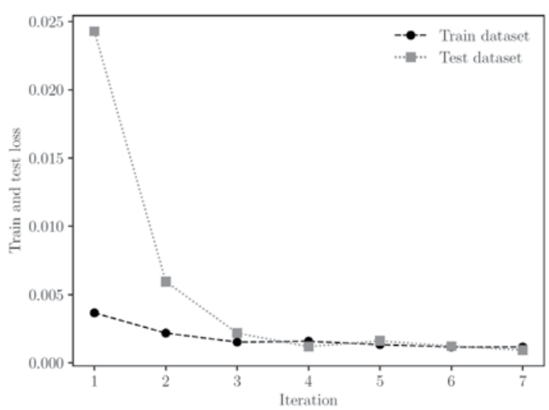


b. Scenario 2

Figure 6. Damage prediction results of the 15-element frame induced by fire and others for different scenarios



a. Scenario 1



b. Scenario 2

Figure 7. The convergence history of the damage detection process for the 15-element frame induced by fire and others for different scenarios

5. CONCLUSIONS

This article presents a ML-based damaged detection approach for steel frames under fire using time-history responses. A surrogate model grounded in ML architecture is developed with an input dataset employing time-dependent acceleration at limited measuring points. A reduction of material Young's modulus is assumed as the damage ratio of elements. By eliminating low-risk members by a suggested thresshold, the accuracy of DNNs is continuously enhanced. Through the cases investigated with and without the fire influence, the proposed methodology demonstrates remarkable performance for damage detection purposes in simple structures under local dynamic or fire loads. Therefore, the developed surrogate ML-based model is promising to its application to damage detection of frame structures considering nonlinear inelastic behavior in furture works.

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