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Research Article

Condition monitoring elements using integration model for wind turbine system

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Abstract

Due to the increasing unit capacity of wind turbines and development in wind power technology, the installed capacity is increased each year which leads to the poor working condition of the turbine and reduced transmission due to load changing complexity. Furthermore, there are several problems with the wind turbines due to the high force of wind blow, the blades may get damaged due to high vibration which results in the fatigue of main body of the wind turbine. In this paper, the wind turbine has been monitor using the integrated model using three stages such as preprocessing, fog computing, and fault classification. The secured data stored in the cloud is analyzed so as to provide an effective power generation so as to meet future demands. Moreover, it has been observed that the data undergoes a variation over the power generation due to fault detection caused by generation bearing, tip speed ratio noise, etc. The performance of the proposed method is analyzed by various parameters such as model performance.

1. Introduction

The generation of electricity from the wind turbine becomes one of the vital powers generating sources in recent years [1]. The change of wind energy into electrical energy happens with the assistance of wind turbines. The dynamic energy in the wind is changed into machine-driven energy by the wind turbines and afterward, they are changed over into electricity by the generator [2]. Furthermore, there are several problems with the wind turbines due to the high force of wind blow, the blades may get damaged due to high vibration which results in the fatigue of main body of the wind turbine [3]. They are complex electrochemical systems that consist of a large number of components and subsystems. The problems that occur in the wind turbine may also due to the harsh environmental conditions. Faults in the turbines must be pre-indicated to reduce the secondary damages and periodic diagnosis also helps to avoid catastrophic accidents [4]. The wind turbine fault may also cause, due to the abnormal working of the gearbox which connects the shaft and the generator.

The high-frequency vibration examination sensors for the assessment of the fundamental primary parts, for example, the turbine cutting edges, pinnacle, and establishment will be utilized. These will be applied along with oil temperature sensors, oil particle counters, current and pressure sensors to evaluate the general operating condition of the gearbox, generator bearing, yaw and braking mechanism, generator currents sensors, and electric power output measurements [5]. A single monitoring system, designed for modular use of the absolute measurement of the position of the wind turbine. Also, by consolidating and dissecting the information gathered through the various sensors, it will be conceivable to evaluate and address the faults by the framework and therefore, will empower the wind ranch administrators to refresh the support plan [6].

In [7], convolutional neural networks (CNN) and gated recurrent units (GRU) were proposed to create a creative wind turbine position measurement system focused on spatio-temporal properties fusion of SCADA data. The established technique's output was checked using SCADA data with a real wind farm's gear crack.In [8] aims to measure the effect of multiple cyber-attacks on a power grid and rate them in terms of seriousness. On a photovoltaic (PV) device in a hybrid power grid with a wind reactor, PV, synchronous generator, power generation, and loads, nine forms of cyber-attacks were identified.The Smart monitor (SM) in use establishes voltage and current signals to assess their amplitude and intensity enabling power quality (PQ) to be tracked using monitoring approaches that transmit only data about observed disruptions to the provider, minimizing internet traffic involved from PQ irregularities in smart grids [9].

In [10] examined the performance of compact and rigid Horizontal-Axis Wind Turbines (HAWTs) in a number of wind frequencies and pitch angles. The use of a compact rotor significantly expanded the operating scope and performance, with the cumulative anticipated benefit of more wind energy.Iso-geometric analysis (IGA), a computational approach from the above pitfalls identified with conventional finite element analysis (FEA), is used in [11] analysis. IGA uses the mathematical models developed by CAD software immediately, allowing less user input and removing the need to translate parametric geometries to FE meshes.Using supervisory control and data acquisition (SCADA) data, [12] proposes a novel general health surveillance system for wind turbines. The framework's main function was the clustering method which partitioned the turbine application into several sub-operation environments before constructing a standard turbine behavior design for through sub-operation condition.

2. Proposed method

The secured data stored in the cloud is analyzed to provide an effective power generation to meet future demands. Moreover, it has been observed that the data undergoes a variation over the power generation due to fault detection caused by generation bearing, tip speed ratio noise, etc. Thus, to overcome the fault detection in wind turbines the work has proposed a complete system monitoring under a multi-fault scenario. The overall diagram of the proposed method is given below,

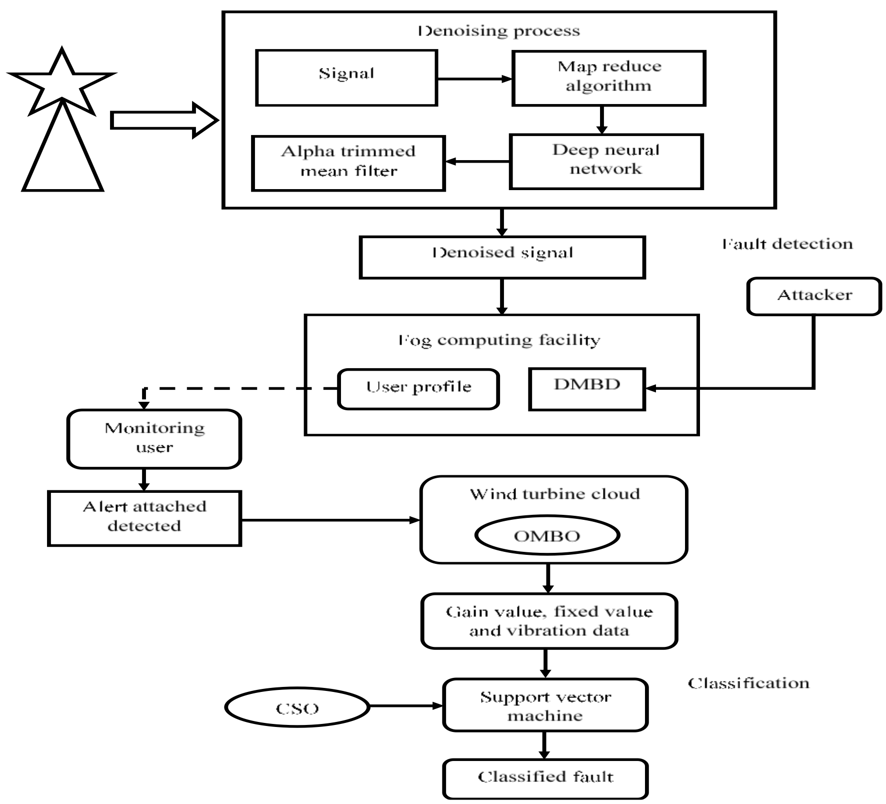


Figure 1: Overall diagram of the proposed method

Step 1: Data initialization

Initially, data are obtained from each individual turbine and these details are given to user profile and DMBD. A user profile consists of user details and the details include id number, photo, and biodata. These details are obtained from each individual person and stored in the profile station. DMBD and user profile are combined called a fog computing facility.

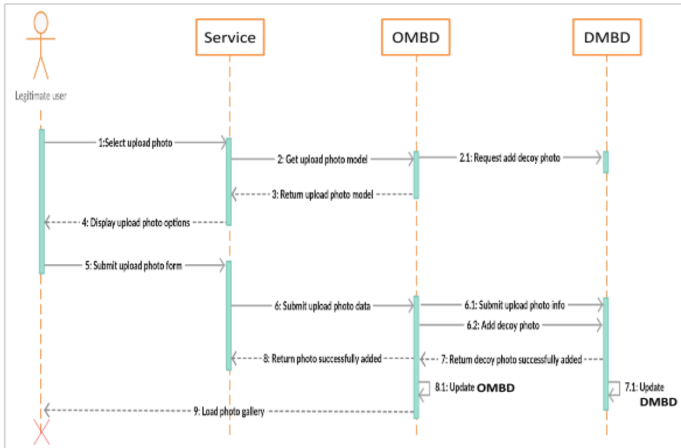


Figure 2: Upload photo/image process

As a result, the intruder will be unable to differentiate between the true and false consumer images. As a consequence, in the system, the client is not responsible for including the interruption image in his or her DMBD because it would be done automatically when the user is transferring the key photograph to the OMBD. DMBD is used as a gadget demonstration, but it doesn't occur to the legitimate user straight away. Instead, it's used to protect their OMBD by redirecting the attacker. It's hidden in the fog as a honeypot to keep an eye on the first, which is set up in the cloud.

Step 2: Attacker: When a fault is identified, the types and area of the fault are interpreted for basic assistance. The rapid gearbox, generator bearing, and disappointments that occurred in various sections trigger faults in wind turbines. Wind turbine performance testing is used in wind farms to minimize maintenance costs while also improving efficiency.

Flood attack (FA): It causes damage to the objective system by sending numerous amounts of traffic through zombies. So, data transmission usage is knowingly extended with traffic. All the wind data packets are affected by FA, carrying about UDP flood, ICMP flood flow attacks.

Common Gateway Interface (CGI) Request attack: As a result of the assailant issuing a sufficient number of CGI demands that consume the casualty’s computer's CPU cycles, the contingency computer ceases issuing demands.

2.1 Architecture

For the most part, in wind turbine gearbox condition observing utilizing a sensor is a beneficial technique to screen wind turbine execution and fault. In order to that, it also deals with denoising the data using different techniques which additionally involves the PD measurement analysis in which there does not occur any wastage of wanted signal while applying denoising techniques. It assigns a strategy to choose the boundaries for SVM in wind turbines called CSO. The mix of optimization method with order procedure is assessed. In order to obtain a robust accurate model, the data are further classified for obtaining a predictive solution under a strong classifier known as Deep Recurrent Neural Network (DRNN) which helps to retain the noiseless original data by removing noises from the signal and also predicting the faults before its existence. Infomax ICA algorithm employed here maximizes the entropy to remove the faults from the data. The optimization of the task design of Map and Reduce results in quicker and more accurate retrieval.

2.2 SVM Classifier

SVM is a procedure for design acknowledgment, and this strategy is by and large used in characterization issues. This calculation is used to tackle the optimization issue. Finding the hyperplane that protects three capacities: direct power, nonlinear capacity, and kernel work, completes the arrangement. In the element space, SVM finds a separating hyperplane and configures depends on it. The SVM technique can be used to track wind turbine faults.

2.3 Deep learning Algorithm:

It is a one-of-a-kind layer within the Neural Network (NN), which consists of three layers: knowledge, yield, and veiled layers. For NN, the product of the AE (Auto Encoder) is called information. A coding and decoding process refers to the plotting transition from the I/P layer to the hidden layer and from the inconspicuous layer to the output layer.

$$y(x) = h(W_1 x + b_1) \quad (1)$$

$$z(x) = f(W_2 y(x) + b_2) \quad (2)$$

Where y(x) is a data given to hidden layer. z(x) is a processed data from the hidden layer. It gives the output of the wind status. For an training process three class of data is given to hidden layer such as $(N_1, N_2, \dots, N_L \ or \ P_1, P_2, \dots, P_L, or \ R_1, R_2, \dots, R_L,)$. The processed data is obtained by the output layer $z(x)$= normal class or Pre-attack class or attack class.

Table1. Weighting factor for the Neural Network

W_{ij}	W(1)	W(2)	W(3)	W(4)	………	W(n)
Initial weight by ANN	0.3	0.42	0.45	0.53	………	……..

Table. 6. 1 shows the weighting factor for the initial steps, after that the value are calculated based on the obtained values. Where, W_1 →the weight factor from I/P layer to the covered-up layer, W_2 →the weight factor from covered-up layer to yield layer, $b_1$and b_2 →bias of the covered-up layer to yield layer, *h(.)* and *f(.)*→ activation functions

$$prederror(L) = EX, Y\{1(Y = L(X))\} = P(Y = L(X)) \quad (3)$$

The generalization error of the model becomes

$$prederror(L) = EX, Y\left\{\left(Y - L(X)\right)^2\right\}(4)$$

$$predicted = \sum_{i=1}^{n}(prederror(L) = \mathrm{X, Y\{L(Y, L(X))\}}) \quad (5)$$

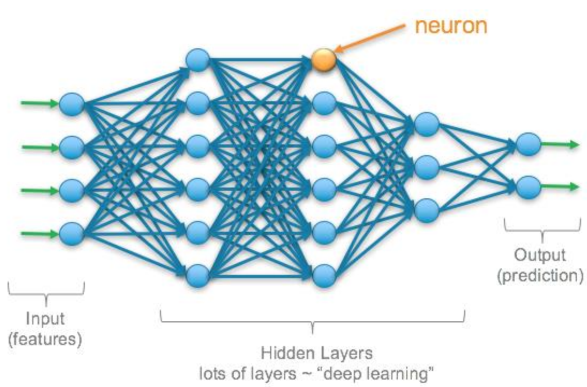


Figure 3: Structure of Deep Neural Network (DNN)

Figure3 explains the deep learning structure where information sources are assault subtleties from different casualty joins. They're generally referred to as highlights. The veiled plate, which is accompanied by an info layer, refines the operation of order and highlight extraction. An arbitrary woodland measurement is implemented in the veiled layer, and the result of this veiled layer is supplied to a third layer known as the yield layer or predictor layer. The forecasting operation is carried out here in order to characterize the data.

Let consider, the labeled data is expressed as $X_L = (N_1, N_2, \dots, N_L) = (P_1, P_2, \dots, P_L) = (R_1, R_2, \dots, R_L,) = \left(X_{L_1}, X_{L_2}, \dots, X_{L_M}\right)$ With M labels $Y_L = \left(Y_{L_1}, Y_{L_2}, \dots, Y_{L_M}\right)$ similarly unlabeled statistics set is expressed as $X_U = \left(X_{U_1}, X_{U_2}, \dots, X_{U_N}\right)$ without M labels. Sigmoid functions are *h(.)* and *f(.)*, and it is expressed as,

$$h(x) = f(x) = s(x) = \frac{1}{1+\exp(-x)} \qquad (6)$$

$$LS(\theta_1) = LA\big(x, z(x)\big) + \alpha \sum_{j=1}^{H} KL(\rho||\hat{\rho}_j) \qquad (7)$$

$$LA\big(x, z(x)\big) = \frac{1}{2N} \sum_{i=1}^{N} \left\| X_{U_i} - z\left(X_{U_i}\right) \right\|^2 \qquad (8)$$

$$KL(\rho||\hat{\rho}_j) = \rho log \frac{\rho}{\hat{\rho}} + (1-\rho) log \frac{1-\rho}{1-\hat{\rho}_j} \qquad (9)$$

$$\hat{\rho}_j = \frac{1}{\mathrm{N}} \sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{Y}_{\mathrm{U_j}}\left(\mathrm{X}_{\mathrm{U_i}}\right) \qquad (10)$$

$$\theta_1 = (\mathrm{W}_1, b_1), \qquad (11)$$

W_1 *and* b_1 →weight and bias vector, *LA(.)*→renovation error made by training samples *α*→weight coefficient, H →Hidden nodes, *KL(.)*→Kullback-Leibler divergence function.If $\rho = \hat{\rho}_j$, *then the* $KL(.)$ *value is* 0, ρ → the sparsity parameter, $\hat{\rho}_j$ → the typical initiation of *j*th unseen node, n→ *N*umber of input nodes, θ_{ij} → Weight 7bias value of SM layer, M → Total amount of samples. While setting up the SoftMax (SM) classifier, a definitive yield of the SAE (Stack Auto Encoder) is sustained as the approaching information of the SM j node. The SM relapse layer is set up by using the learning calculation (managed). The probability value $P(\mathrm{Z_i} = j \mid \mathrm{X_{L_i}})$,

$$\mathrm{h}_{\theta_2}\left(\mathrm{X}_{\mathrm{L_i}}\right) = \begin{bmatrix} P(Z_1 = 1|\mathrm{X}_{\mathrm{L_i}}; \theta_2) \\ P(Z_2 = 2|\mathrm{X}_{\mathrm{L_i}}; \theta_2) \\ \vdots \\ P(Z_K = K|\mathrm{X}_{\mathrm{L_i}}; \theta_2) \end{bmatrix} \qquad (12)$$

$$= \frac{1}{\sum_{j=1}^{K} e^{\theta_j^T \mathrm{X}_{\mathrm{L_i}}}} \begin{bmatrix} e^{\theta_1^T \mathrm{X}_{\mathrm{L_i}}} \\ e^{\theta_2^T \mathrm{X}_{\mathrm{L_i}}} \\ \vdots \\ e^{\theta_K^T \mathrm{X}_{\mathrm{L_i}}} \end{bmatrix} \qquad (13)$$

Among them, $\theta_2 = (W_2, b_2)$, W_2 *and* b_2 denotes the weight & bias of SR node, correspondingly. The classifier function is defined as

$$LSM(\theta_2) = -\frac{1}{M}\left[\sum_{i=1}^{M} \sum_{j=1}^{K} 1\{Z_i = j\} log \frac{e^{\theta_j^T \mathrm{X}_{\mathrm{L_i}}}}{\sum_{s=1}^{K} e^{\theta_s^T \mathrm{X}_{\mathrm{L_i}}}}\right] + \frac{\beta}{2} \sum_{i=1}^{K} \sum_{j=1}^{n} \theta_{ij}^2 \qquad (14)$$

$$LSM(\theta) = -\frac{1}{M}\left[\sum_{i=1}^{M} \sum_{j=1}^{K} 1\{Z_i = j\} log \frac{e^{\theta_j^T \mathrm{X}_{\mathrm{L_i}}}}{\sum_{s=1}^{K} e^{\theta_s^T \mathrm{X}_{\mathrm{L_i}}}}\right] + \frac{\gamma}{2} \sum_{i=1}^{K} \sum_{j=1}^{n} \theta_{ij}^2 + \frac{\gamma}{2} \sum_{h=1}^{H} \theta_h^2 \ (15)$$

Among them, $\theta = (\theta_1, \theta_2)$. *H*→amount of SAE hidden layer. θ_h → SAE weight &bias value.

2.4 NN-Training procedure

The training set data (attack, pre-attack, natural status) are given to the input of the deep neural network to form the classifier. To train the classifier, there are two kinds of layers are presented in the deep neural network. The first one is the autoencoder, second is the soft regression layer. Hence the parameters for this layer should be initialized to calculate the value of bias (b) and weight factors (z). The bias and weight values of the autoencoder are given to the soft regression layer, which calculates its own weight and a bias value. The final weight and bias value are given to the deep neural network to form the classifier. Based on the output, it detects the attacks. Ultimately, the BP (Back Propagation) algorithm is used to refine the weighting variables.The weighting factor of the neural network is determined using Cuckoo search Optimization (CSO) Algorithm.

3. Result Analysis and Discussion

In this section, the wind turbine can be monitor by using integrated model.The proposed methodology is implemented in MATLAB simulation platform.Table 2 demonstrates that exploratory for gearbox in different working circumstances.

Table 2: Models for challenging

Status	Model scope	Running ailment	State encoding
Regular gear	104	13	1
Injured gear	112	14	2
Fractured gear	114	18	3

The methods presentation is articulated as,

$PE = \sum_{i=1}^{n}|X(i) - X^{\wedge}(i)|/n$(16)

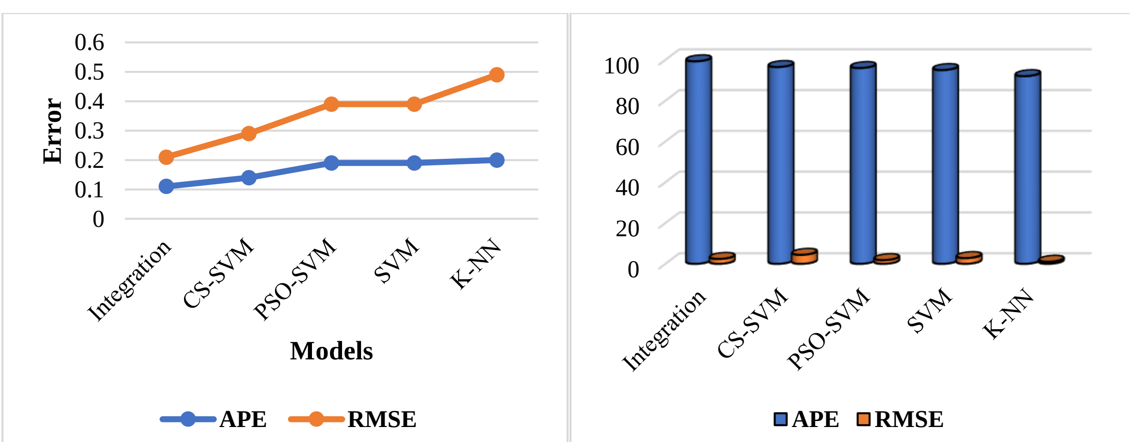
$$MSE = \sum_{i=1}^{n}\sqrt{(Xi - X^{\wedge}i)^2}/n \qquad (17)$$

Where X^(i) is the demonstrating rate, X(i) is the genuine rate and n is the challenging illustrations.

Table 3: Evaluation of Methods presentation

Models	APE (%)	RMSE (Degree Celsius)
Integration	0.1145	0.2138
CS-SVM	0.1356	0.2867
PSO-SVM	0.1874	0.3710
SVM	0.1879	0.3800
K-NN	0.1910	0.4880

Table 3 demonstrate the routine of the Integration model consumes APE worth 0.1145 and RMSE worth 0.2138 improved than the PSO-SVM, SVM, and K-NN method. PSO-SVM have APE rate 0.1874 as well as RMSE rate 0.3710, SVM contains APE rate 0.1879 besides RMSE charge 0.3800, in addition K-NN contains APE worth 0.1910 then RMSE price 0.4880.



(a) (b)

Figure 6: a) Graphical representation of model's performance and b) Performance Analysis

Comparison Analysis

Take a look at the results of the intensive work with elliptic bend cryptography schemes that were reported in the evaluation. It has made use of a few documents that are available to define the number of assignments that are used.

Table4: Comparison Based on the Computational Cost

Structures	**MUL**	**DIV**	**ADD**	**ECPM**	**ECPA**	**HASH**
Hwang	2	1	2	6	2	1
Zheng	4	2	2	4	2	5
ID based sign encryption	4	1	2	6	1	2
P2PDMS	1	0	1	1	0	5
Integration scheme	0	0	0	1	0	3

MUL represented as modular multiplication operation, DIV denotes modular division operation, ADD represented as modular addition operation and ECPM denoteselliptic curve point multiplication operation.ECPA representselliptic curve point addition operation.

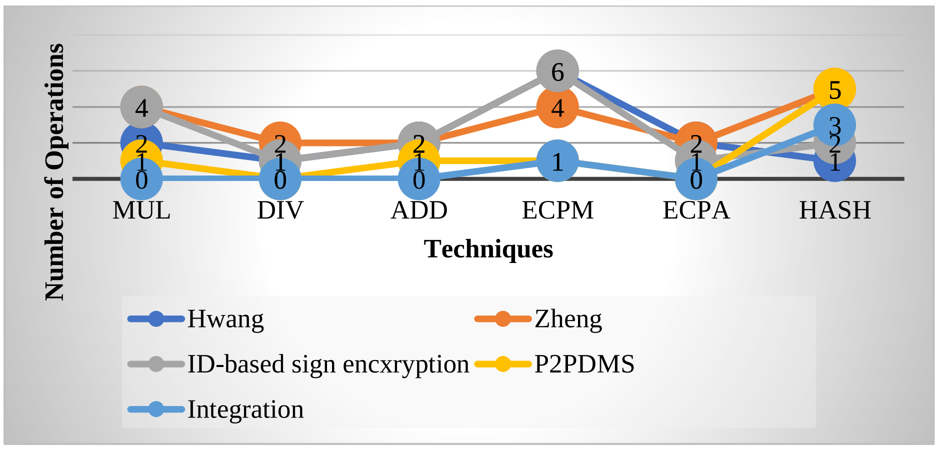


Figure7: Comparison graphs between existing and proposed schemes

This paper uses fog computing to verify wind energies' sight and sound data within the cloud as a way of proving the cloud data function. The OMBD is saved in the cloud without fanfare, while the DMBD is used by a nectar pot and then saved in the fog.

4. Conclusion

With the end goal of best-in-class condition checking and fault detection in wind turbines, immense and profound research and diagram of foundation work and flow innovations should be thought of. A superior method of understanding specific framework practices or assisting with arranging created applications can often be given by numerical models of the framework and its subsystems. Despite the fact that displaying has its impediments, an adequate model will prompt significant results and ends. Wind turbine frameworks are normally unique frameworks, which contain subsystems with the various arrangement of time constants: wind, turbine, generator, power gadgets, transformer, and so forth. The detecting framework will be connected to a distant SCADA unit, which will gather and investigate the procured information through the introduced sensors on every turbine of the wind ranch. Additionally, the dissected sign will be put away just as the state of each wind turbine and the entire wind ranch.

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