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Deep Learning Neural Network for Chaotic Wind Speed Time Series Prediction

***Abstract**. Accurate wind speed forecasting is essential for wind energy systems, but it's difficult due to the wind's uncertainty. In this study, short-time wind speed prediction is done on the basis of phase space reconstruction and using neural network techniques. The BASEL (Switzerland) site wind speed data is collected. Firstly, the chaotic nature of the time series is ascertained to verify its short time predictability. Then training data is created by using the phase space reconstruction technique, i.e., using knowledge of embedding delay and embedding dimension. Using this data, two models of Artificial neural networks, i.e., Feedforward neural network (FFNN) and Convolution Neural Network (CNN) are trained to predict wind speed. The wind speed time series is categorized into seasons, respectively JUN-AUG (summer), SEP-NOV (autumn), DEC-FEB (winter), and MAR-MAY (spring), for both locations. Training accuracy of each model is compared on the basis of Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) & Symmetric Mean Absolute Percentage Error (SMAPE) metrics. Simulation results show the superiority of CNN over FFNN for the prediction of wind speed.*

Streszczenie. *Dokładne prognozowanie prędkości wiatru jest niezbędne dla systemów energetyki wiatrowej, ale jest trudne ze względu na niepewność wiatru. W tym badaniu krótkoterminowe prognozowanie prędkości wiatru odbywa się na podstawie rekonstrukcji przestrzeni fazowej i przy użyciu technik sieci neuronowych. Gromadzone są dane dotyczące prędkości wiatru w BAZYLEI (Szwajcaria). Najpierw ustala się chaotyczną naturę szeregu czasowego, aby zweryfikować jego krótkoterminową przewidywalność. Następnie tworzone są dane treningowe przy użyciu techniki rekonstrukcji przestrzeni fazowej, tj. wykorzystując wiedzę na temat opóźnienia osadzania i wymiaru osadzania. Przy użyciu tych danych trenowane są dwa modele sztucznych sieci neuronowych, tj. sieć neuronowa Feedforward (FFNN) i sieć neuronowa splotowa (CNN), aby przewidywać prędkość wiatru. Szeregi czasowe prędkości wiatru są kategoryzowane według pór roku, odpowiednio JUN-AUG (lato), SEP-NOV (jesień), DEC-FEB (zima) i MAR-MAY (wiosna), dla obu lokalizacji. Dokładność treningu każdego modelu jest porównywana na podstawie metryk średniego błędu kwadratowego (MSE), średniego błędu bezwzględnego (MAE), pierwiastka średniego błędu kwadratowego (RMSE) i symetrycznego średniego błędu procentowego bezwzględnego (SMAPE). Wyniki symulacji pokazują wyższość CNN nad FFNN w przewidywaniu prędkości wiatru.* (***Głęboka sieć neuronowa do przewidywania chaotycznych szeregów czasowych prędkości wiatru***)

Keywords: wind speed prediction, chaos theory, phase space reconstruction, Deep learning model.
Słowa kluczowe: prognozowanie prędkości wiatru, teoria chaosu, rekonstrukcja przestrzeni fazowej, model głębokiego uczenia się

Introduction

Recently, renewable energy sources have advanced as the world seeks sustainable solutions to its growing energy demands. Wind energy is an appealing option among these options due to its cleanliness, abundance, and significant potential. Accurate wind speed prediction models are crucial to fully use the potential of wind energy [1]. Wind energy production depends on wind speed forecasts, which affect wind farm efficiency and output. Accurate wind speed forecasting helps energy producers and grid operators optimize power output, schedule maintenance, and balance energy supply and demand.

Wind speed prediction estimates wind speed at a certain time and place. For wind energy generation, weather forecasting, aviation, agriculture, and environmental monitoring, this characteristic is essential [2]. Wind speed prediction entails using many data sources, mathematical models, and statistical approaches to approximate the velocity of wind at a certain place and time. Nowadays, having the ability to estimate wind speed is crucial for accurate weather predictions and effective planning of renewable energy resources [3]. Accurate wind speed forecasting enhances energy production, safety in several sectors, weather prediction, and climate research, making it a crucial tool in modern life. Short-term predictions exhibit greater accuracy compared to medium- and long-term forecasts. Several researchers have performed wind speed/power prediction utilizing both persistence and physical approaches [4], which rely on meteorological data. Additionally, traditional methods such as AR, ARMA, and ARIMA models [5-6] have been used. As the use of AI techniques improves the performance of systems [7], in order to enhance the accuracy of predictions, several researchers have used intelligent methodologies for prediction [8-9]. Researchers have used a combination of traditional and intelligent methods, such as ANN-ARIMA [10], PSO-ANFIS [11], WT-ANN [12-13], and WT-ANN-GA [14], to enhance prediction accuracy.

Chaos theory has been used to forecast many complex and nonlinear time series recently. This involves developing short-term predictions based on chaotic time series data [15-16]. The paper in [17] proposes significant attributes of chaotic properties for short-term wind speed prediction. A chaotic system has extreme sensitivity to initial scenarios and exhibits predictable behaviour in the short-term period. The accuracy of wind speed forecasting may be significantly enhanced by using the chaotic forecasting model. Several researchers have used the chaotic properties of wind to forecast outcomes using models such as RBFNN [18], Bernstein Neural Network [19], GABP [20], etc.

This study first determines the chaotic properties of wind time series by the use of the 0-1 test technique, approximation entropy calculation, correlation dimension analysis, and Lyapunov exponent estimation. Subsequently, the time series phase space reconstruction was performed using the delay coordinates approach, and a training dataset was generated to train the models.

CNN utilizes convolutional layers with filters/kernels for local patterns, whereas FFNN uses fully connected layers with linked neurons. CNN is Well-suited for grid-like or sequential data but FFNN is used for More general-purpose, suitable for various data types. FFNN training may be slower for large networks than CNN training due to parameter sharing. Due to weight sharing, CNNs are translation-invariant, however, FFNNs lack translation invariance, sensitive to pattern position [21-22]. In this research, FFNN and CNN are used for a Chaotic wind time series prediction (short term) & their prediction accuracies are compared.

Analysis of chaotic characterization for wind speed Time series

The chaotic characteristics are verified by using following methods:

- *Determination of chaotic characteristics by 0-1 test method*

The zero-one (0-1) test is a recently introduced method that aims to ascertain when deterministic nonlinear dynamic systems exhibit chaotic or periodic behavior. This method allows for the differentiation between regular and chaotic movements by calculating the parameter Kc, which tends to approach either zero or one asymptotically. If the asymptotic growth rate Kc of the wind speed time series is approximately 1 or equal to 1, then the wind speed is considered chaotic based on this test. Otherwise, it is determined to be non-chaotic [23]. It is calculated by eqn. 1.

(1) $$K_c = \lim_{i\to\infty} \log X(i)/\log(i)$$

K_c= incremental growth rate ; X= mean shift function; i = length of time series

- *Approximate entropy*

The degree of unpredictability in changes in a time series is measured using a regularity metric known as approximation entropy. An estimated entropy number that is much bigger reflects the probability that identical patterns of observations are not followed by more similar observations. An estimate of entropy is used as a measure of regularity to determine the degree of complexity inside a time series. It evaluates how disorganized or chaotic a system's motion is calculated by eqn. 2.

(2) $$N_i = \sum_{i=1, i\neq k}^{N} D(\|Y_{i-}Y_j\|)_\infty > R$$

Where D = indicator function; R= radius of similarity
Approximate entropy is given by eqn. 3
approxEn

(3) $$t = \emptyset_m - \emptyset_{m+1}$$

where $\emptyset_m = (N-m+1)^{-1} \sum_{i=1}^{N-m+1} log(N_i)$
m = embedding dimension; N= length of time series; $|Y_i - Y_j|$= distance between Y_i and Y_j vector

- *Largest Lyapunov exponent*

The most crucial factor in chaotic systems is the Lyapunov exponent, it is useful in quantifying the level of chaos in a system because a positive maximal Lyapunov exponent is a potential indicator of disorder. On the other hand, a maximal Lyapunov exponent of zero indicates a stationary point while a maximal exponent of minus one indicates a limit cycle or quasiperiodic orbit. A system with m dimensions has m Lyapunov exponents with declining values of 1, 2, … m. In this work, a practical method proposed by Rosenstein [24] for calculating Lyapunov exponent is used. Using this method eqns. 4 & 5 are used to estimate the greatest lyapunov exponent for the wind speed data. Because of the finite nature of this value, which ranges from 0 to 1, the chaoticity of time series of wind speed data and its short-term predictability is ascertained. Firstly, the nearest neighbor point Y_j is found by searching for the point that minimizes the distance to the particular reference point Y_i and is calculated by eqn. 4.

(4) $$d_i(0) = \min_{Y_j} ||Y_i - Y_j||$$

Where $d_i(0)$ is the initial distance from the ith point to the nearest neighbor and $|i-j|$ greater than the mean period of time series, is the reciprocal of the mean frequency. And it is calculated by eqn. 5.

(5) $$\lambda_{(x)} = \frac{1}{x\Delta t} \frac{1}{(M-x)} \sum_{i=1}^{M-x} \ln \frac{d_i(x)}{d_i(0)}$$

Where Δt is the sampling period of time the series, is the distance between the ith pair of nearest neighbors after x discrete-time steps, i.e., xΔt sec. In order to improve convergence with respect to x, it may be calculated by eqn. 6 [25].

(6) $$\lambda_{(x,k)} = \frac{1}{k\Delta t} \frac{1}{(M-k)} \sum_{i=1}^{M-k} \ln \frac{d_i(x+k)}{d_i(x)}$$

Where *k* is held constant and λ is largest Lyapunov exponent.

- *Correlation Dimension*

The correlation dimension measures the dimensionality of a random collection of points' spatial distribution. The calculation involves plotting the gradient of the correlation integral against the range of similarity. The correlation dimension may be used for recognizing problems and distinguishing between deterministic chaos and random noise. The presence of robust stochastic characteristics in the time series contributes to a rise in the correlation dimension as the embedding dimension increases, without reaching a saturation point. Equation 7 is used to define the correlation integral.

(7) $$C(r) = \lim_{N=\infty} \frac{2}{N(N-1)} \sum_{i,j=1}^{X} H(r|Y_i - Y_j|)$$

Where N= length of time series; r = radius of sphere centered on the vector Y_i or Y_j; $|Y_i - Y_j|$= distance between Y_i and Y_j ; H = Heaviside function.

Phase space reconstruction (PSR)

The univariate time series can represent all the variable information in a dynamic system and can be used to restore the phase space of a chaotic system [26]. Taken's delay embedding theorem forms the basis of phase space reconstruction. It asserts that by choosing a delay time and embedding dimension m such that m > 2*d + 1 is generally accomplished, the reconstructed m-dimensional state space will possess the identical topological structure as the original chaotic dynamic system. PSR is beneficial in situations when the dimensions and delay are uncertain. Phase space for chaotic time series Z_1,, Z_2,,..., Z_{N-1},, Z_N can be represented by eqn. 8.

(8) $$Y_j = [Z_j, Z_{j+\tau} \dots \dots \dots Z_{j+(m-1)\tau}]$$

for j = 1,2,3, … N, N = n-(m-1) τ
Where m = Embedding Dimension,τ = Embedding delay,
N= length of time series.
Following procedure is used to choose the suitable values of E & τ.

- *Embedding Delay (τ)*

The MI (mutual information) method is an efficient method for estimating the delay constant in the PSR. Average mutual information (AMI) is calculated by comparing two time series, $\text{i.e.}, Z(k)$ and a time-shifted version of the same time series, i.e., $Z(k+\tau)$.

(9)

$$AMI(\tau) = \sum_{k=1}^{N} p\big(Z(k), Z(k+\tau)\big) log_2 \left[\frac{p\big(Z(k),Z(k+\tau)\big)}{p\big(Z(k),p(Z(k+\tau)\big)}\right]$$

....

For the chaotic time series Z_1 , Z_{2} ,..., Z_{N-1} , Z_N, AMI may be calculated by eqn. 9.
Where N = length of series, τ = delay or lag of series,
p= probability

- *Embedding Dimension (E)*

False nearest neighbor's approach is used to determine the ideal embedding dimension. If the distance between two points x_q and x_p in Euclidean space is less than a very tiny value, they are considered to be close by (less than standard deviation of test data). If the normalized distance between $x_{p's}$ (m+1)th embedding coordinate and $x_{q's}$ is more than a certain threshold, x_p is then said to have a false nearest neighbor [26]. For a certain time delay, a sufficiently large embedding dimension must be chosen so as to minimize the fraction point with false nearest neighbors, where, in a d-dimensional phase space, the phase point vector is defined as

$$x(i) = \ (x(i), x(i+\tau), \dots, x(i+(d-1)\ \tau))$$

and the adjacent point $x^{NN}(i)$ within a certain distance is defined by eqn. 10.

(10) $$Rd(i) = ||xd(i) - x^{NN}\, d\ (i)||$$

Prediction Models

- Feed Forward Neural Network

A neural network, often known as an artificial neuron network, is a computational model of the way human brain cells communicate with one another. The artificial neural networks often have three or more levels of convolutional neurons. The first layer, which consists of neurons, is the input layer. The information processed by these neurons is transmitted to the next layer, where it is processed further before being sent to the output layer as shown in Fig. 1.

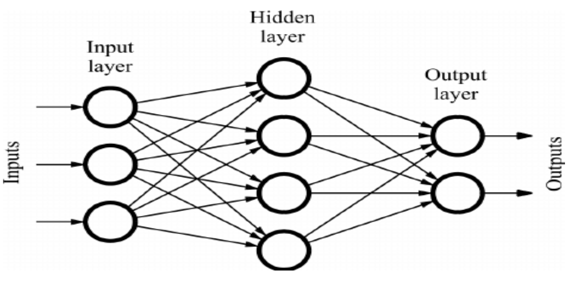

Fig.1. Basic structure of FFNN

The inner layers' hidden units transform information as it moves from layer to layer in an adaptive manner. The capacity of each layer to function as both an input and an output layer enables the FFNN to deal with objects that are more and more complicated. By increasing or decreasing the weight assigned to specific inputs in accordance with the internal logic of the FFNN, the units in the neural layer attempt to learn about the information. According to these rules, individual units can produce a modified outcome that is subsequently output to the layer ahead. FFNN model (evolved via extensive hit & trial) used in this work is given in Table 4.

- Convolution Neural Network (CNN)

A CNN is an advanced form of ANN mostly utilized for extracting features from datasets organized in a grid-like matrix format. For instance, visual datasets such as photos or films where data patterns have a significant impact. The architecture comprises various levels, including the input layer, Convolutional layer, Pooling layer, and fully connected layers as shown in fig.4. The input is filtered by the Convolutional layer, which then uses the Pooling layer to down sample the data from the convolutional layer and decrease computation. The fully connected layer makes the final prediction. The network acquires the most effective filters by employing backpropagation and gradient descent. Pooling layers decrease the spatial dimensions of the input volume, efficiently down sampling the features. Max pooling and average pooling are often employed methods to preserve the most salient information while decreasing computational intricacy.

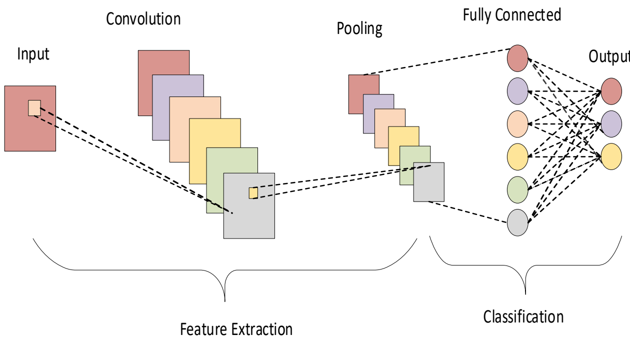

Fig. 2. Structure diagram of CNN

Following the convolutional and pooling layers, the fully connected layers analyze the retrieved high-level characteristics from the preceding layers in order to generate predictions. The presence of these layers allows the network to acquire knowledge about intricate connections within the data.

Performance evaluation metrics

Performance evaluation metrics play a critical role in ensuring the reliability, accuracy, and effectiveness of wind speed prediction models. Various evaluation performance metrics, on the basis of which the prediction models' performance is compared are given in Table.1.

Table. 1. Performance Evalauation

Metrics	***Definition***	***Equation***
MSE	mean squared error	$\frac{1}{n}\sum_{i=1}^{n}(Y_i - X_i)^2$
MAE	mean absolute forecasting error	$\frac{1}{n}\sum_{i=1}^{n}\lvert Y_i - X_i \rvert$
RMSE	root mean squared error	$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - X_i)^2}$
SMAPE	Symmetric mean absolute percentage forecasting error	$\frac{1}{n}\sum_{i=1}^{n}\frac{\lvert y_{i-x_i}\rvert}{\lvert y_i\rvert + \lvert x_i\rvert/2}$

Simulation Results and Discussion

- Data Collection

The data has been collected from BASEL site, of one year [27], i.e., from Jun 2022- May 2023.

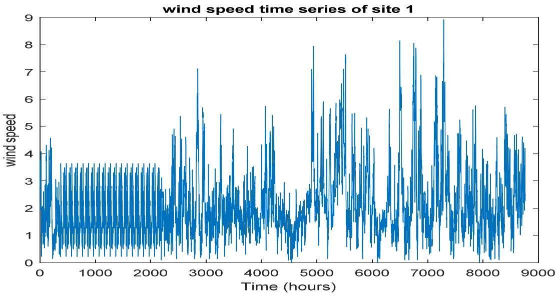

Fig. 3. Wind Speed time series Data.

Wind speed time series data are shown in Fig. 3. The data consists seasonal time series daily hourly wind speed data from JUN 2022 to MAY 2023. The length of all wind speed time series is divided according to seasons such as summer (JUN-AUG), Autumn (SEP-NOV), winter (DEC-FEB) and spring (MAR-MAY) seasons. The statistical parameters value such as observing the no. of samples, minimum, maximum, median and standard deviation of each season are shown in table 2, we can know data sets have great volatility.

Table. 2. Statistical value of the experimental datasets

Seasons	**No. of Samples**	**Min.**	**Max.**	**Median**	**Std.Div**
Summer	2208	0.1000	4.7854	1.7464	0.9972
Autumn	2184	0.1414	7.1176	1.7464	1.0039
Winter	2160	0	8.1394	1.9416	1.4344
Spring	2208	0	8.9157	2.0125	2.0125

- Chaotic Characterization

For Chaotic characteristics, methods discussed in section 2 are used and the results for various tests are listed in Table 3. For a chaotic timeseries, the results for 0-1 test must be close to 1, approximate entropy lies between 0 to 1 and the largest lyapunov exponent should be positive. The correlation dimension is directly related to the extent of chaos in the system. Therefore, a higher correlation dimension indicates a greater degree of chaotic complexity in the system. All these conditions are satisfied as shown in Table 3, so wind speed time series used in this work is chaotic in nature and short term predictable. Phase space reconstruction parameters i.e., embedding dimension (E) and embedding delay(τ), also shown in Table 3, is used to create the training data.

Table.3. Chaos parameters

Seasons	**Chaotic Analysis Methods**				**PSR**	
	0-1 test	App.ent.	(lyapnov exponent)	Corr.Dim	E	τ
Summer	0.9714	0.2684	0.0007	0.0070	8	3
Autumn	0.9965	0.5517	0.0012	2.8694	5	4
Winter	0.9972	0.5969	0.0030	1.3406	7	4
Spring	0.9963	0.6248	0.0017	4.2071	5	4

- Creation and Splitting of Training and Testing Data

The total no. of samples of each season, 70% are used for training and 30 % are used for testing. Creation of training data is based on phase space reconstruction parameters. For the prediction of wind speed time series FFNN and CNN model is used.

- Training of Models

Two Neural Network models which employed in this work are ANN and CNN. The dimensions of the input, the maximum number of epochs, iterations and other parameters for both models are given in Table. 4.

Table 4. Training parameter of all models

Parameters	**Techniques**	
	FFNN	**CNN**
Ratio of training Samples	0.7	0.7
Ratio of testing Samples	0.3	0.3
Neurons in input layer	Lag dependentent	Lag dependent
Neurons in hidden layer	5-7-15	-
Neurons in output layer	1	1
Net	Feedforward	Xception
Training function	trainbr	-
Activation function of hidden layer	tansig	tansig
Activation function of output layer	Linear	Linear
Learning rate	0.00611	0.00611
Momentum rate	0.25	-
Maximum epochs	600	600
Performance goal	1e-6	-
Normalized range	-1 to 1	-1 to 1

- Prediction by FFNN and CNN Model

For FFNN, we combine a Bayesian regularization training function that adjusts the weights and biases of the network with the Levenberg-Marquardt optimization technique. By minimizing the sum of squared errors and the sum of weights, it determines the optimal combination from which a generalizable network can be constructed. Bayesian regularization helps to control overfitting and leads to better generalization. It automatically determines the network complexity during training. Prediction by both models for each seasons are shown in figure 4-7.

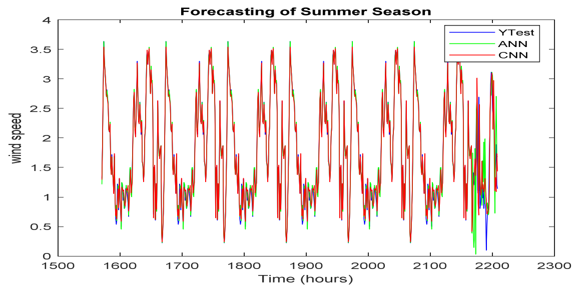

Fig.4. Prediction of Summer Season

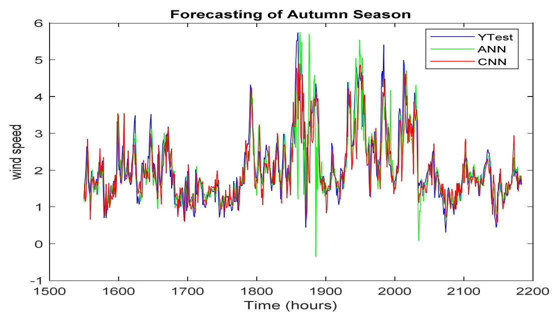

Fig.5. Prediction of Autumn Season

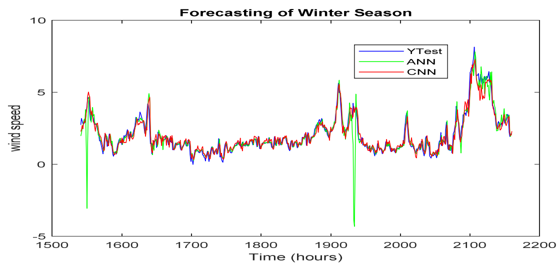

Fig.6. Prediction of Winter Season

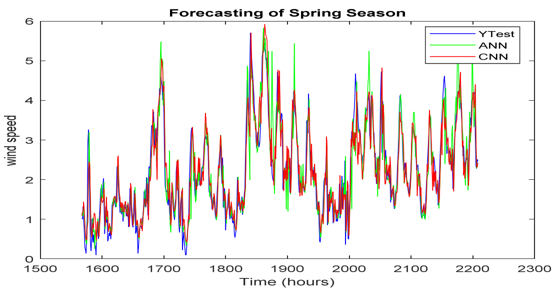

Fig.7. Prediction of Spring Season

- Comparison of Models

The comparison of prediction results by FFNN and CNN methods are shown as the value of metrics. The values of four evaluation metrics (MSE, MAE, RMSE and SMAPE) shows that the CNN model outperforms the FFNN.

Table v. Comparison of models performance

Seasons	Tech.	MSE	MAE	RMSE	SMAPE
Summer	ANN	0.0346	0.0746	0.0023	0.0157
	CNN	0.0257	0.0698	0.0019	0.0141
Autumn	ANN	0.3471	0.3705	0.0538	0.0454
	CNN	0.2728	0.3702	0.0590	0.0469
Winter	ANN	0.4952	0.3250	0.0543	0.0433
	CNN	0.1567	0.2918	0.0084	0.0431
Spring	ANN	0.2789	0.3770	0.0042	0.0502
	CNN	0.2229	0.3572	0.0060	0.0496

conclusion and future scope

A prediction model for the short-term prediction of wind speed time series has been developed. This model makes use of chaos theory and Deep Learning model. In terms of errors such as MSE, MAE, RMSE, MAPE, and SMAPE, it has been confirmed that the prediction has a good level of accuracy for the test data. in this paper, the use of CNN model enhances the wind speed prediction accuracy. In future, the accuracy of wind speed predictions may be enhanced by adopting hybrid methodologies.

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