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A Comparison of a Radial Basis Function Neural Network with other Methods for Estimating Missing Values in Univariate Time Series

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Abstract

Missing values in the time-series data set have an impact on the correct decision-making in the future. Since complete data helps to obtain high accuracy in the estimation process, the reason for missing values is a malfunction of the measuring device or an error in the data entry process by the person. The research aims to compare the radial basis function methods with other methods to estimate missing values in univariate time series data. the simulation method was used to compare the methods to estimate the missing values, and that was used the Box-Jenkins model AR(1) once with the value of $\alpha = 0.5$ and once with the value of $\alpha = 0.9$ and with different sample sizes (60,100,300), assuming four percentages of missing from data values are missing at random MAR (5%,10%,15%,20%) . The accuracy of the estimation of the methods was evaluated by using the standard of accuracy, the mean sum of squares error (MSE). from the results obtained using simulation, it was found that the(RBF) method is the best method for estimating the missing values in both values, in all sizes, and all loss ratios, because it produces the lowest value of the average square error compared to other methods.

Paper type: Research paper

Keywords: univariate time series, Radial Basis Function, Bi-directional Recurrent Neural Networks, Adaptive response rate exponential smoothing, Next observation carried backward.

1. Introduction

Time series is a collection of observations or digitally recorded measurements of a statistical indicator that are arranged chronologically and can be observed over successive periods of time with equal distances (daily, weekly, monthly, ...) (Mohammed and Mousa, 2020). There are two types of time series according to the number of variables (the first type: univariate time series, the second type: Multivariate time series). In this paper, we use the first Univariate time series is a time series that contains only one variable in the data, meaning that we will deal with the previous values of the variable with the time variable. Most researchers in various scientific fields such as (medicine - engineering - science....) face a real problem when collecting data, which is the presence of missing values in the data set. It is meant by (the loss of a value or a set of values from the data). It is considered one of the common and recurring research problems that directly affect the process of building statistical and mathematical models, and this in turn affects the accuracy of the final results and reduces the ability to make decisions. There are three types of mechanisms for losing missing values (non-missing random (not missing at random NMAR, missing at random MAR, missing completely at random MCAR). In this paper, we assume that the data is missing at random MAR, meaning that the missing observation value does not depend on the missing observation value itself but depends on other variable values. In recent years, there has been remarkable progress and researchers' interest in developing many methods and improving methods in estimating missing values in time series data before the process of statistical analysis in order to obtain correct and complete data on which to make accurate and correct decisions. (Moustris *et al.*, 2012) used artificial neural network (ANN) models to estimate the missing values of the average daily concentration substances (PM10), and it was found that the models are excellent predictive methods for estimating the missing values in the time series data of atmospheric pollutants. In the same year, (Aydilek and Arslan, 2012) presented methods for estimating the missing values as they used a novel hybrid neural network and weighted nearest neighbors (KNN), and high accuracy results were obtained and the results were compared with the algorithm estimation method genetics of neural networks.(Moritz *et al.*, 2015) used (Decompositions, Kalman filtering, linear/nonlinear Interpolation) to treat the missing values in irregularly spaced univariate time series and the results showed that the estimate using Kalman filter Linear interpolation was one of the most effective ways to deal with missing values. (Yi *et al.*, 2016)proposed a spatio-temporal multi-view-based learning (ST-MVL) method to estimate missing values for geosensory time series data. (Yen *et al.*, 2020) used linear regression, support vector regression, artificial neural networks, and long short-term memory to estimate missing values in the time series. Deep learning models achieved great performance. Better compared to traditional models. (Ding *et al.*, 2020) focused on estimating missing values in time series of Internet of Things data using Radial Basis Function (RBF), Moving Least Squares (MLS), and Adaptive Inverse Distance Measurement. (AIDW) Adaptive Inverse Distance Weighted found that the estimation by MLS of Lancaster's function is the best compared to other methods.(Li *et al.*, 2020) introduced a Multimodal Deep Learning Model (MMDL) to estimate missing values in traffic data. They found that the model had the best performance.(Saeipourdizaj, Sarbakhsh and Gholampour, 2021) used the methods of moving average, K-nearest

neighbor (KNN) and predictive mean matching (PMM) to estimate the values and the missing concentrations of PM10 and O3 air pollutants. Through the results, it was found that the PMM method did not have good performance compared to other methods.

2. Material and Method

2.1. Radial Basis Function Neural Networks (RBF)

RBF is a type of artificial neural network (ANN) and one of the most important methods of supervised machine learning used to estimate missing values in time series; the network has three layers:

- **input layer: Dedicated to input vector input values**
- **hidden layer: Contains activation function Gaussian ‹Its equation can be computed using Eq. (1).(Jinkun, 2013)**

$$G_j = exp\left(-\frac{\|Z_i - C_p\|^2}{2\sigma_j^2}\right) \qquad \sigma > 0 \qquad \dots (1)$$

where: σ_j^2 represent the distance value of Gaussian function for neural net j, y_i represent input values, C_p represent the center vector of the Radial Basis Function whose value is determined using the k- means clustering algorithm that will be mentioned in the following paragraphs.

- **Output layer: in this layer, the final output of the network is calculated; the output of RBF can be computed using Eq. (2).**

$$\hat{Z}_m = \sum_{i=1}^{m} w_{ji}\left[exp\left(-\frac{\|Z_i - C_p\|^2}{2\sigma_j^2}\right)\right]^T \qquad \dots (2)$$

where: w_{ji} represent the weight in the output sum, m represent the number of neurons in the hidden layer that each contains a Gaussian activation function . The other symbols have already been explained.

Each value of the input vector in the input layer is connected to n neurons in the hidden layer between these two layers and calculated as the Euclidean distance between the center of the activation function and the input vector then this distance is used to apply the radial basis function in the hidden layer, which has a non-linear character. The neurons in the hidden layer are connected with the neurons in the output layer to get the output values of the radial basis function network, which are linear. The network’s work is reduced to transforming a non-separable linear problem into a linearly separable problem.

2.2. Bi-directional Recurrent Neural Networks (Bi-RNN)

It is a distinctive and developed type of recurrent neural network, which can exploit the previous and subsequent long-term time steps in estimating the missing values. The network consists of the combination of two separate hidden layers of a network (Cao *et al.*, 2018)

- **The output of the forward hidden layer $\overrightarrow{h_t}$**

$$h_t{}^f = \sigma_{sig}\left(z_t * W_{zh}^f + h_{t-1}{}^f * W_{hh}^f + b_h^f\right) \quad \dots (3)$$

where z_t input observations, σ_{sig} activation function, W_{zh}^f and W_{hh}^f weight parameter, b_h^f bias, $h_{t-1}{}^f$ The hidden state in the previous time step.

- **The output of the background hidden layer $\overleftarrow{h_t}$**

$$h_t{}^b = \sigma_{sig}\left(z_t * W_{zh}^b + h_{t-1}{}^b * W_{hh}^b + b_h^b\right) \quad \dots (4)$$

where z_t input observations, σ_{sig} activation function, W_{zh}^b and W_{hh}^b weight parameter, b_h^b bias, $h_{t-1}{}^b$ The hidden state in the previous time step.

- **The output bi-directional recurrent neural network**

$$\widehat{Z}_t = \sigma_{sig}(w_{\hat{z}h} h_t + b_{\hat{z}}) \quad \dots (5)$$

2.3. Adaptive response rate exponential smoothing (ARRES)

The ARRES is a developed method to overcome the value of the fixed exponential smoothing constant by making this value α change from one period to another according to the nature of the data in order to obtain accuracy in the estimation process. The ARRES technique comprises of the following basic equations:

- **The basic equation for calculating the estimation of the lost value**

- In the initial time period:

$$\widehat{Z}_1 = Z_1 \quad \dots (6)$$

- In the time period t+1 (Nazim and Afthanorhan, 2014):

$$\widehat{Z}_{t+1} = \alpha_t Z_t + (1 - \alpha_t)\widehat{Z}_t \quad \dots (7)$$

where $\widehat{Z}_t$ represents the missing value in the time period t , $\widehat{Z}_{t+1}$ represents the missing value in the time period t+1 , α_t value of the exponential smoothing constant in time period t, Z_t time series variable.

- **Calculate the value of the exponential smoothing constant**

- In the initial time period:

$$\alpha_1 = 0 \quad \dots (8)$$

- In the time period t:

$$\alpha_t = \left|\frac{E_t}{S_t}\right| \quad \dots (9)$$

where E_t the mean smoothing error represents the exponential at time period t , S_t the absolute exponential smoothing error at time period t.

- **Calculates the mean error for exponential smoothing**

- In the initial time period:

$E_1 = 0$ **… (10)**

- In the time period t:

$E_t = \beta e_t + (1-\beta)E_{t-1}$ **… (11)**

where E_t average error of exponential smoothing per time period t, E_{t-1} average error of exponential smoothing over the previous time period , β A constant for the exponential smoothing and its value is between 0< β<1 .

- **Calculate the absolute exponential smoothing error**

- In the initial time period:

$S_1 = 0$ **… (12)**

- In the time period t:

$S_t = \beta|e_t| + (1-\beta)S_{t-1}$ **… (13)**

where S_t absolute exponential smoothing error at time period t , β A constant for the exponential smoothing and its value is between 0< β<1, S_{t-1} absolute exponential smoothing error at time period t-1, e_t The random error of the true value in the time period .

- **Calculate the random error of the true value**

- In the initial time period:

$e_1 = 0$ **… (14)**

- In the time period t:

$e_t = Z_t - \hat{Z}_t$ **… (15)**

2.4. Double exponential smoothing / Holt (DES/Holt)

Holt's method is a classic method for estimating missing values in univariate time series. This method is used when the demand is influenced by the trend but is not influenced by the seasons (Risteski, Kulakov and Davcev, 2004) (Cadenas, Jaramillo and Rivera, 2010) (Rachmat and Suhartono, 2020) . This method gives trend values with new parameters different from the parameters used in the original time series, and these parameters are two parameters (a parameter for measuring the trend and a parameter for the level of the variable).

- **The basic equation of the Holt method is as follows:**

$$\widehat{Z}_{t+r} = L_t + T_t(r) \qquad r = 1, 2, \dots, n \qquad \dots (16)$$

where $\widehat{Z}_{t+r}$ the estimate of the missing value in the subsequent t + r time intervals ,r the number of time periods to estimate in the future , L_t the variable level parameter in time period t , $T_t$trend measurement parameter in time period t.

- **The equation of the variable level parameter (Level) is as follows:**

- Initial variable level parameter

$$L_1 = Z_1 \qquad \dots (17)$$

- Parameter of the level of the variable in the time period t

$$L_t = \alpha Z_t + (1-\alpha)(L_{t-1} + T_{t-1}) \qquad \dots (18)$$

where α the exponential smoothing coefficient and its value is 0<α<1, Z_t time series variable, L_{t-1} Parameter of the level of the variable in the previous time period t-1, T_{t-1} Trend measurement parameter in the previous time period t-1 .

- **Parameter equation for measuring trend (Trend) as follows:**

- Initial Trend measurement parameter

$$T_1 = \frac{(Z_2 - Z_1) + (Z_4 - Z_3)}{2} \qquad \dots (19)$$

- Trend measurement parameter in time period t

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1} \qquad \dots (20)$$

where β the exponential smoothing constant has a value between 0<β<1.The other symbols have the same interpretation as above .

2.5. Recurrent Neural Networks Long Short-Term Memory(RNN-LSTM)(Petneházi, 2019)

RNNs - LSTMs are a special type of advanced recurrent neural network (RNN) that is a type of neural network that uses hidden units to analyze data streams(Ashour, 2022) that are used in deep learning. He was the first to discover it (Hochreiter and Schmidhuber 1997) to overcome the vanishing gradient problem in traditional RNNs that are unable to relate information to the current time step for a long-term period. LSTM consists of cells connected in chains. These cells are called (memory blocks). These blocks contain the input gate, the output gate, and the forgetting gate. Through these gates, it can be known what data should be stored in memory, how long it should be stored, and when it should be read, so the network learns how it should be acting on its memory; these gateways are responsible for monitoring internal operations on the network.

- Forget gate equation as follows:

$$f_t = \sigma_{sigmoid}\left(W_{fh}h_{t-1} + W_{fz}z_t + b_f\right) \qquad \dots (21)$$

where W_{fh}, W_{fz} .The set of weights parameters is adjustable in the Forget gate , b_f The set of bias parameters is adjustable in the forget gate. $\sigma_{sigmoid}$ Nonlinear activation function , h_{t-1} The hidden state vector of the previous time step , z_t A vector from the input at the time step t with dimension m , t is the time step associated with the gate.

- Input gate equation as follows:

$$i_t = \sigma_{sigmoid}\,(W_{ih}h_{t-1} + W_{iz}z_t + b_i) \qquad \dots (22)$$

where W_{ih}, W_{iz} , The set of weights parameters is adjustable in the input gate , b_i The set of bias parameters is adjustable in the forget gate. $\sigma_{sigmoid}$ Nonlinear activation function. The other symbols have the same interpretation as above .

- Output gate equation as follows:

$$O_t = \sigma_{sigmoid}\,(w_{oh}h_{t-1} + W_{oz}z_t + b_o) \qquad \dots (23)$$

where w_{oh}, W_{oz} , The set of weights parameters is adjustable in the output gate , b_o The set of bias parameters is adjustable in the forget gate. $\sigma_{sigmoid}$ Nonlinear activation function . The other symbols have the same interpretation as above .

- Cell state equation as follows:

$$C_t = f_t * C_{t-1} + i_t * \widetilde{C}_t \qquad \dots (24)$$

$$\widetilde{C}_t = \sigma_{tanh}\,(W_{ch}h_{t-1} + W_{cz}z_t + b_c) \qquad \dots (25)$$

where $\widetilde{C}_t$ new memory cell vecto ,C_{t-1} Previous cell state (stored information) which will be forgotten ($f_t$value will be 0) and which will be preserved ($f_t$value will be 1) , σ_{tanh} The hyperbolic tangent function through which the output of each cell is enlarged as it maintains values between -1,1 to ensure that the network is constant and stable, W_{ch} , W_{cz} Adjustable weight matrices.

- Compute the new hidden state (Output vector) equation as follows:

$$h_t = O_t * \sigma_{tanh}(C_t) \qquad \dots (26)$$

where C_tThe state of a cell is the sum of the inputs at a time step t that can store information unchanged over a long period of time, O_t output gate , h_t output at a time step t .

2.6. Next observation carried backward(NOCB)

The NOCB algorithm is considered one of the simplest methods used with univariate time series to estimate missing values, as each missing value is replaced by the subsequent observation value known back (Moritz *et al.*, 2015) :

$$\widehat{Z} = Z_{i+1} \qquad \dots (27)$$

3. Discussion of Results

Matlab program was used to generate data and build simulation models in order to compare the methods used to estimate the missing values in different sample sizes and with four loss ratios in the variable values. Simulation experiments were carried out using three sample sizes (n = 300, 100, 60) and with a repetition of (r = 500) value for each experiment, where it was:

i. Generate variable X into numbers following the standard normal distribution .

ii. Generate random errors that have a standard normal distribution (mean = zero , variance = 1) e_t~N(0,1) .

iii. Simulation Model used the Box-Jenkins model AR (1) once with the value of α=0.5 and once with the value of α=0.9. model / first-order autoregressive(Gorgess, 2017) AR(1) $\widehat{Z}_t = \alpha_1 Z_{t-1} + e_t$ α_1=0.5 و α_1=0.9

iv. **Taking four missing ratios, which are (5%, 10%, 15%, and 20%). The type of data missing is missing at random (MAR), meaning that the value of the missing observation does not depend on the value of the missing observation itself, but rather depends on the time point of this observation.**

v. **Using the standard of accuracy, mean square error, to compare the methods of estimating missing values(Firas A. Al-Mohana, and Noor Saleem, 2018), and to indicate the best method for estimation**

$$MSE = \frac{\sum_{t=1}^{n}(Z_t - \hat{Z}_t)}{n}$$

Table (1) summarizes the results (MSE) for a model AR (1) at α=0.5 at the methods used to estimate the missing values when the sample size is (60,100,300) with missing (5%,10%,15%,20%) and with repetition (r=500)

			MSE					
			Method					
	Missing	Sample size	RBF	Bi-RNN	ARRES	DES/HOLT	RNN-LSTM	NOCB
α=0.5	5%	60	0.0000149	0.12980	0.000454	0.0183	0.01620	0.0470
		100	0.00000313	0.1653	0.000507	0.0121	0.0271	0.0467
		300	0.00000101	0.1262	0.000627	0.0124	0.0176	0.0502
	10%	60	0.0000327	0.25360	0.000651	0.0334	0.02570	0.0978
		100	0.00000448	0.2534	0.000532	0.0297	0.0459	0.1102
		300	0.00000057	0.15656	0.000724	0.0359	0.03540	0.0958
	15%	60	0.0000119	0.30600	0.000661	0.0401	0.03500	0.1502
		100	0.00000708	0.30213	0.000683	0.0374	0.0289	0.1503
		300	0.00000192	0.18789	0.00011	0.0333	0.01762	0.1438
	20%	60	0.0000133	0.2904	0.0021	0.0420	0.0435	0.1744
		100	0.00000102	0.14310	0.0014	0.0445	0.01780	0.2091
		300	0.00000107	0.09218	0.000938	0.0358	0.01410	0.1823

Table (2) summarizes the results (MSE) for a model AR (1) at α=0.9 at the methods used to estimate the missing values when the sample size is (60,100,300) with missing (5%,10%,15%,20%) and with repetition (r=500)

			MSE					
			Method					
	Missing	Sample size	RBF	Bi-RNN	ARRES	DES/HOLT	RNN-LSTM	NOCB
α=0.9	5%	60	0.0000702	0.5520	0.0003255	0.0142	0.0161	0.0463
		100	0.00000409	0.1618	0.0022	0.0137	0.0360	0.0552
		300	0.00000064	0.2450	0.0023	0.0138	0.1149	0.0449
	10%	60	0.0000245	0.2266	0.0006804	0.0326	0.0264	0.0860
		100	0.00000443	0.2236	0.0006657	0.0319	0.0552	0.1186
		300	0.00000088	0.4037	0.0010	0.0291	0.1678	0.0960
	15%	60	0.0000249	0.2980	0.0007205	0.0363	0.0359	0.1519
		100	0.00000355	0.4188	0.000989	0.0330	0.0608	0.1302
		300	0.00000055	0.10648	0.0009346	0.0355	0.19040	0.1542
	20%	60	0.00000877	0.1881	0.0091	0.0409	0.0493	0.1822
		100	0.00000847	0.2659	0.0029	0.0464	0.0796	0.2409
		300	0.00000012	0.7562	0.0012	0.0676	0.2365	0.1327

In the two tables above:

i. **We note from Table (1), when α=0.5, in the state stable and Table (2), when α=0.9 in the state a semi- stable that the best methods for estimating the missing values are RBF at the missing ratios (5%,10%,15%,20%) and for all sample sizes (60,100,300) because they have the lowest value of MSE and followed by a method ARRES, which gave less value than MSE compared to other methods.**

ii. **From Table (1), when α=0.5، shows that the method (Bi-RNN) showed its efficiency because it gave the lowest value of MSE at the sample size of (300) at the largest loss percentage (20%) but it did not perform well at the sizes of small samples, and this confirms its efficiency at the sizes of large samples when the percentages of the missing are also great.**

iii. **From Table (2), when α=0.9, the (Bi-RNN) method gave the least (MSE) at the sample size of (60) at the lowest missing ratio of (15%), but it gave the largest value of (MSE) at the sample size (300) in the missing ratios (10%, 20%) and also at the sample size (100) at the ratio (15%).**

iv. **From Table (1), when α=0.5، shows that the method (RNN-LSTM) showed its efficiency has been proven at all sample sizes (60,100,300) and for all missing ratios (5%,10%,15%,20%), but from Table (2), when α=0.9، shows that the method (RNN-LSTM) showed that it was not good at large sample sizes (300) in all missing ratios (5%,10%,15%,20%), but it was efficient at small sample sizes (60,100) and in all missing ratios (5%,10%,15%,20%).**

v. **We note from Table (1), when α=0.5, in the state stable and Table (2), when α=0.9 in the state a semi- stable that the method (DES/HOLT) showed its efficiency has been proven in all missing ratios (5%,10%,15%,20%) and for all sample sizes (60,100,300).**

vi. **We note from Table (1), when α=0.5, in the state stable and Table (2), when α=0.9 in the state a semi- stable that the method (NOCB) was good when the missing ratio (5%) in all sample sizes (60,100,300), but its performance declined at the ratio (10%) in the sample size (100), as the value of (MSE) increased. It also increased when the missing ratios (15%,20%) were in all sample sizes, which confirms that (NOCB) is efficient when the missing ratios are small (5%).**

4. Conclusion

i. **Simulation results showed that the method (RBF) has proven its efficiency in estimating the missing values, as well as (ARRES) as it achieved the lowest MSE compared to the other methods.**

ii. **The sample size had a significant and clear effect on the accuracy of the results RBF because the value gradually decreases with increasing sample size.**

iii. **The method (Bi-RNN) has proven its efficiency when the series is stable and when the sample sizes are large and the missing ratios are also large.**

iv. **The method (NOCB) proved effective in estimating the missing values when the missing ratio (5%) is in all sample sizes because it achieved a small percentage of the MSE values.**

v. **The method (RNN-LSTM) proved its efficiency in the case of the series being stable, as it gave a low value of MSE in all sample sizes and for all missing ratios, but in the semi-stable series, it did not prove its effectiveness at large sample sizes, but it gave MSE results with small sizes.**

vi. **The method (DES/HOLT) proved its efficiency in the case of the series being stable or semi-stable because it achieved a small percentage of (MSE) with all missing ratios and for all sample sizes.**

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مقارنة بين الشبكة العصبية دالة الأساس الشعاعي RBF وطرائق أخرى لتقدير القيم المفقودة في السلاسل الزمنية أحادية المتغير

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مستخلص البحث

تؤثر القيم المفقودة في مجموعة بيانات السلاسل الزمنية في اتخاذ القرار الصحيح بالمستقبل . حيث أن البيانات الكاملة تساعدنا في الحصول على الدقة العالية في عملية التقدير ، السبب في وجود القيم المفقودة هو عطل جهاز القياس أو خطأ في عملية أدخال البيانات من قبل الشخص . يهدف البحث الى مقارنة طريقة دالة الأساس الشعاعي مع طرائق أخرى لتقدير القيم المفقودة في بيانات السلاسل الزمنية أحادية المتغير . وتم أستخدام أسلوب المحاكاة للمقارنة بين الطرائق لتقدير القيم المفقودة وتم أستخدام نموذج بوكس جنكيز AR(1) مرة مع قيمة $\alpha = 0.5$ ومرة مع قيمة $\alpha = 0.9$ وبأحجام عينات مختلفة (300,100,60) بأفتراض أربع نسب فقدان للقيم مفقودة عشوائياً MAR (5% ، 10% ،15% ،20%) . وتم تقييم دقة تقدير الطرائق بواسطة أستخدام معيار الدقة متوسط مجموع مربعات الخطأ(MSE). ومن النتائج التي تم الحصول عليها بأستخدام المحاكاة وجد أن طريقة (RBF) أفضل طريقة لتقدير القيم المفقودة في كلا القيمتين وبكافة الأحجام وبكل نسب الفقدان لأنها تنتج أقل قيمة من متوسط مجموع مربعات الخطأ مقارنة بالطرائق الأخرى.

نوع البحث: ورقة بحثية .
المصطلحات الرئيسة للبحث: سلاسل زمنية أحادية المتغير ، دالة الأساس الشعاعي، الشبكة العصبية المتكررة ثنائية الأتجاه، التمهيد الأسي (المعامل التكيفي)، الشبكات العصبية المتكررة الذاكرة طويلة المدى، ترحيل المشاهدة التالية للخلف.

*البحث مستل من رسالة ماجستير

(2)
(1)