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Forecasting of weekly patient visits to emergency department: real case study

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Abstract

Emergency department (ED) is the most crowded entity in hospitals, because it is the access point of almost all patients looking for care without beforehand appointment. Accordingly, accurate forecasts of ED visits is increasingly required to bring up ED throughput. Hence, combining Artificial Neural Networks (ANNs) with a signal decomposition technique named Ensemble Empirical Mode decomposition (EEMD), to make one-ahead forecasting of patients arrivalstoED, is newly investigated in this paper. Seven years of aggregated weekly demand, from 2010 to 2016, has been collected from all services of emergency department of the University Hospital Hassan II of Fez city of Morocco. The time series (TS) of the demand was decomposed into several sub-signals, each of them was modeled using an ANN model. Then, their forecasting results were combined to produce the total forecast. Finally, the results of the used model were compared against the benchmarking models:ANN without signal decomposition, ANN with Discrete wavelet Transform (DWT) decomposition and ARIMA model. The results of this investigation show that, in forecasting ED weekly visits, ANN assisted with EEMD outperforms the benchmarking models for approximation and generalization capabilities, while overcoming the problem of overfitting. Thus, the used model can be employed to forecast efficiently ED arrivals, and to optimize human and material resources of hospitals.

Keywords: ANN; EEMD; DWT; ARIMA; Emergency department demand forecasting; Time series analysis.

1. Introduction and Background

Hospital is one of the prominent partners of healthcare system which aims to provide a quality service to

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patients [6].Emergency department (ED) is among the crucial entities within hospitals, which meets fundamental needs in society by delivering urgent healthcare especially in crisis time. ED is the access point of a majority of patients looking for immediate treatment without beforehand appointments.It is an area with resource constraints, because of various patient needs, different treatment levels, and different working times, unlike other hospital departments [42, 4, 17]. Therefore, this environment suffers from high pressure of patient visits, which make it one of the most crowded entities of hospitals.

ED crowding describes a discrepancy between healthcare supply of resources and patient demand of services[9].It is caused by many factors such as increase in patient arrivals without increase in hospital resources, bed insufficiency, delays in discharging patients, delays in tiding rooms after discharging hospitalized patients, and lack of staff resources (doctors, nurses,…)[5,13, 37].ED crowding has side effects on healthcare quality by causing harmful issues including: increase in waiting time, increase in queue length of patient, diversion in ambulance, increase in patients leaving hospital without receiving treatments, lack of patient satisfaction, increase in mortality, decrease in staff-to-patient ratios, and increase in poor treatment outcomes and treatment errors[7, 13, 14, 30]. Indeed, ED crowding remains an ambiguous term, that's why it is difficult to find appropriate solutions [8].
To overcome all these serious issues, it may be beneficial to bring up hospital resources, however, this strategic solution remains pricey and time consuming. As a result, it is a practical and costless solution to enhance the performance of ED from the operational level by opting for ED visits forecasting. In fact, the IOM report advocates hospitals to use demand forecasting in order to improve their efficiency and to guide decision makers in their planning. Accurateforecasting of ED visits can be a promising solution to increase ED throughput, by helping hospital staff to prepare resources for crisis situations, and by avoiding all possible problems that can affect the quality service, which would in turn hamper patient health and safety. Time series analysis has proved to be a useful tool to forecast demand levels in different fields [15,18-22, 31-36]. This tool is based on exploiting historical data of something that is changing over time, so as to build a mathematical model that can be used to discover the behavior of a sequence of observations in the future[2].It is widely used in strategic, tactical and operational levels of planning and management [3].Nevertheless, its usage in healthcare area still be limited.

Different methods in the literature have been proposed to predict ED visits, including statistical modeling [8, 27,43,1]. However, rare are the articles that deal with machine learning modeling[44, 41, 16]. Neural networks-based models have been broadly used with success to forecast time series in energy [28], finance [11], and meteorology fields, where other statistical models have revealed low efficiency.

Feedforward Neural network is the most famous ANN type, it has been widely employed in the domain of time series, due to its flexibility and generalization ability. Despite its flexibility, FFNN may be unable to deal with non-stationary time series if data preprocessing is not applied [10]. In existing studies [44, 16], ANN was used without focusing on performant techniques of data preprocessing. However, dealing with time series data before learning helps ANN model to capture the real patterns (trend, seasonality…) in the signal, to avoid learning noise, and to enhance its predictive performance. It is universally acknowledged through several past studies, that data decomposition is one of the most prominent techniques of data preprocessing that helps to deal with nonstationary data. In fact, data decomposition plays a functional role in analyzing seasonality, trends, cycles and irregular components in time series [29]. As a result, in order to enhance their forecasting accuracy, numerous hybridizations [38,25,23]of decomposition techniques and other forecasting models have been approached in different fields.

Accordingly, the main objective of this study is to forecast weekly arrivals of patients to ED. In line with that, we had used FFNN model combined with the decomposition technique EEMD, the motivation behind the usage of these two methods consists in denoising the TS signal and removing its stochastic volatility using EEMD, then predicting its future values using FFNN. From our best knowledge, this article is the first to use the combination of FFNN and EEMD to predict ED visits of patients. The remainder of this paper is organized as follows: section 2 introduces the used models. Section 3 describes the models in details and implement them within a real case study. Section 4 evaluates the models, compares their performances based on statistical metrics and discuss the obtained results. Finally, section 5 draws conclusions and sheds light on future works.

1. Material and Methods

1.1. Overview of Multilayer Neural Networks

ANN is a machine learning paradigm which mimics the human brain functioning through learning complex data patterns. MLP is one type of supervised feedforward neural networks. It owns three types of layers, input layer with

N input nodes, output layer of m output nodes, and one or more hidden layers. Even though, it is preconized in most applications to use only one hidden layer of L hidden nodes. The mathematical representation of this framework for one pattern $(x^{(p)}, y^{(p)})$, where $p \in \{1, \dots P\}$ is presented by Eq.1:

$$\hat{y}_k^{(p)} = f_M(\theta_k + \sum_{j=1}^{L} w_{kj}.f_L(\theta_j + \sum_{i=1}^{N} w_{ji}x_i^{(p)})) \tag{1}$$

The objective of ANN, is to find an approximation of the unknown function (target), represented by the data, through weights adjustment. This adjustment is performed by means of a learning process, there exist various optimization algorithms used for this purpose. The objective function of the optimization process is to minimize the cost function defined in Eq.2:

$$E = \frac{1}{2P}\sum_{p=1}^{P}\sum_{k=1}^{m}(y_k^{(p)} - \hat{y}_k^{(p)})^2 \tag{2}$$

Where:

Pnumber of patterns.
$\hat{y}_k^{(p)}$actual output value of output node k of pattern p.
$y_k^{(p)}$desired output value of output node k of pattern p.
$x_i^{(p)}$input value of input node i of pattern p.
f_M, f_L activation function of output layer and hidden layer, respectively.
θ_k, θ_j threshold of output node k and hidden node j, respectively.
w_{kj}weight from hidden node j to output node k.
w_{ji}weight from input node i to hidden node j.
E: cost function.

1.2. Overview of ensemble empirical mode decomposition (EEMD)

Ensemble empirical mode decomposition (EEMD) developed by [40]is an extension of Empirical mode decomposition (EMD) to solve the problem of mode-mixing. This technique enables to process non-linear and non-stationary time series. It decomposes the original time series based on its local scale characteristics, into a finite set of oscillatory modes. Each mode is presented by an independent intrinsic mode function IMF. Each independent IMF describes the noise, the cycles of different periods and trend components [39]. Therefore, an IMF should satisfy the following two conditions:

- IMFs should be symmetric with zero mean.
- IMFs should have the same number of zero-crossings and extrema (minima and maxima) or can at most differ by one.

The main advantage of this method is that no prior knowledge of functions are presumed, which is different from wavelet transform decomposition. Further, it defines the true IMFs as the mean of an ensemble of trials. Each trial consists of signal plus white noise with finite amplitude [39].

EEMD algorithm is based on the following steps:

1- Generate a new time series Y_t, by adding white noise to the original signal X_t.
2- Identify local extrema of the time series Y_t.
3- Join all local maxima and all local minima with cubic splines interpolation, to form lower envelop $e_{min}(t)$ and upper envelop $e_{max}(t)$.
4- Compute the mean of envelops:$m_1(t) = (e_{min}(t) + e_{max}(t))/2$
5- Evaluate the difference:$h_1(t) = Y(t) - m_1(t)$
6- Check if $h_1(t)$ satisfies the two conditions of IMF according to stopping criteria. If the conditions are satisfied, $h_1(t)$ is called $IMF_1(t)$. Otherwise, Y_t is replaced by $h_1(t)$ and the steps from 1 to 4 are repeated, until the two conditions are met by $h_1(t)$.
7- Compute the value of the residue:$r_1(t) = Y(t) - IMF_1(t)$
8- Repeat the whole process by considering $r_1(t)$ as a new $Y(t)$, until the residual $r_n(t)$ becomes monotonic or constant, or has at most one local extremum from which no IMF can be extracted (stopping criteria). Thus, the time series $Y(t)$ can be decomposed in: $Y(t) = \sum_{i=1}^{n} IMF_i(t) + r_n(t)$. Where n is the number of IMFs.

1.3. The proposed model

Real world time series always depict a nonlinear and a nonstationary behavior, because they are affected by complex factors. This results in poor generalization ability of many models, since nonstationary time series are characterized by pseudo-variations which mistaken the model understanding of the right data variations[39]. Therefore, so as to enhance the forecasting abilities of ANN model, EEMD decomposition technique has been tackled. In the present research, EEMD was employed to decompose the time series signal into multi-level of sub-signals so as to discover the real patterns behind the approached time series. This process is referred to as Data Decomposition. Second, to make one-ahead forecasting of ED patients visits, several models of ANN were created, where the outputs of each decomposition technique were used as the input of each ANN model. This process is termed Data Modeling. Finally, the forecasting results of ANN models were combined to generate the ensemble forecast. This process is called Data Ensemble. The three processes of the proposed model are described in details in the Algorithm of Fig. 1.

2. Empirical Analysis

2.1. Study Design

The present research is a retrospective study based on historical data of weekly patient's visits to emergency department services. This data was collected from the information systems of the University Hospital of Hassan II of Fes city in Morocco. This hospital was chosen because it is considered as the bigger hospital of the region of Fes-Meknes, it owns five hospitals: Oncology Hospital, Specialty Hospital, Mother-Child Hospital, Psychiatric Hospital and Otorhinolaryngology Hospital. So it is the most likely to suffer from ED crowding.

Algorithm :

Load TS signal X_t .
Decompose TS signal into k sub-signals $X_t(k)$.
Identify the variables by creating several scenarios.
Normalize each sub-signal.
Partition sub-signals into training, validation and testing sets.
  For each sub-signal k.
    For each scenario j = {1,2,3}.
      For each ANN configuration i ={2,4,6,8,10}.
        Train each sub-signal k using ANN_i^j .
      End
    End
  Validate the trained $ANN_i^j(k)$ and choose the best $\{i, j\}$.
  De-normalize each sub-signal.
  End
Summate forecasts from $ANN_i^j(k)$ models to generate the forecast of the original signal.
Compute the approximation and the generalization error of the ensemble model.
End

Fig. 1. The algorithm of the proposed EEMD-ANN model.

2.2. Data collection

In this study, we had investigated the aggregated demand of the six services working under the emergency department, namely: adult emergency (C0, B0), Gynecology and obstetrics emergency, Pediatric emergency, and three emergency operating rooms of the mentioned services. The weekly aggregated data were collected from January 2010 to December 2016. The time series is shown in Fig. 2.

2.3. Data preprocessing

Before modeling this data, and trying to construct an ANN based-model in order to predict future values, the data should be preprocessed so as to help the forecasting model capture the real patterns within the time series.

Table 1 indicates that the used data is characterized by significant variations around the mean, due to the high difference between the Min and the Max. Additionally, the value of the kurtosis$K$, which is less than 3, reveals that the tackled time series is less outlier-prone. Moreover, the value of skewness$S$ is positive, which means that the data are spread out more to the right of the mean. Furthermore, the high value of the standard deviation implies that the data are not concentrated around the mean.

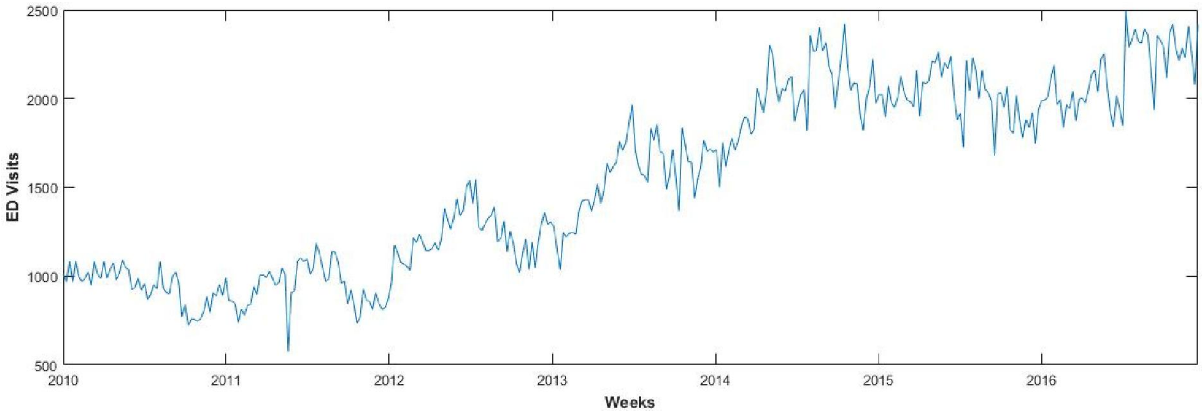

Fig. 2. Time series plot of historical weekly ED visits.

Table 1
Statistical properties of the time series data

Min	Max	Mean	Std. deviation	Skewness	Kurtosis
575	2496	1545	508.60	0.02	1.57

2.3.1. Signal decomposition

This step consists of decomposing the time series signal into several sub-signals using EEMD. This process of signal decomposition aims to analyze the time series patterns and to discover its right variations, which cannot be done using only ANN model, provided that it is considered as a black box. Thereafter, the original signal (X_t) was decomposed into several independent IMFs and one residual signal using EEMD technique. Fig. 3illustrates the results of this decomposition. This figure shows that EEMD had generated seven independent IMFs and one residue where the frequency becomes smoother as we go down to other IMFs. The first IMF component presents the high frequency noise. The remaining sub-signals of the IMFs components depict periodic variations, which prove the existence of cyclic pattern that last one year. Further, the residual component displays the overall trend of the weekly visits time series. The time series is presented in Eq.3:

$$X_t = IMF1 + IMF2 + IMF3 + IMF4 + IMF5 + IMF6 + IMF7 + Residual \quad (3)$$

2.3.2. Variable identification

A time series (X_t) is an ordered number of observations, collected at consecutive time periods t. In this study, a real world univariate time series with discrete values ($t \in \mathbb{N}$) of patient's weekly visits to ED was used. When ANN is used to tackle univariate time series, past values of (X_t) should be used as ANN inputs.
Thus, several combinations of past values of each sub-signal$X_t(k)$ have been tried to forecast weekly ED visits, these combinations have produced three types of scenarios presented in Table 2.

2.3.3. Data partition

After decomposing the original signal X_t into the sub-signals $X_t(k)$, the next step is to divide each sub-signal into three subsets: 70% of the data were used to train each ANN model to discover their approximation abilities, 15% of the data were used to validate the explored models, so that to choose the best one, and the remaining data were used to evaluate the generalization performance of the selected model. This decomposition was done by respecting the order of observations, for the reason that random partition of time series data leads to loss of information.

2.3.4. Data normalization

Before starting the modeling process, sub-signals $X_t(k)$were normalized using standardization technique, soas each sub-signal has zero mean and unity standard deviation.
The standardization is described in Eq.4:

$$X_i^n = (X_i - \bar{X})/\sigma \quad (4)$$

Where:
X_i: the observation at time $t = i$ of the sub-signal $X_t(k)$.
X_i^n: the normalized value of the observation X_i.
$\bar{X}$: the mean of the sub-signal.
σ: the standard deviation of the sub-signal.

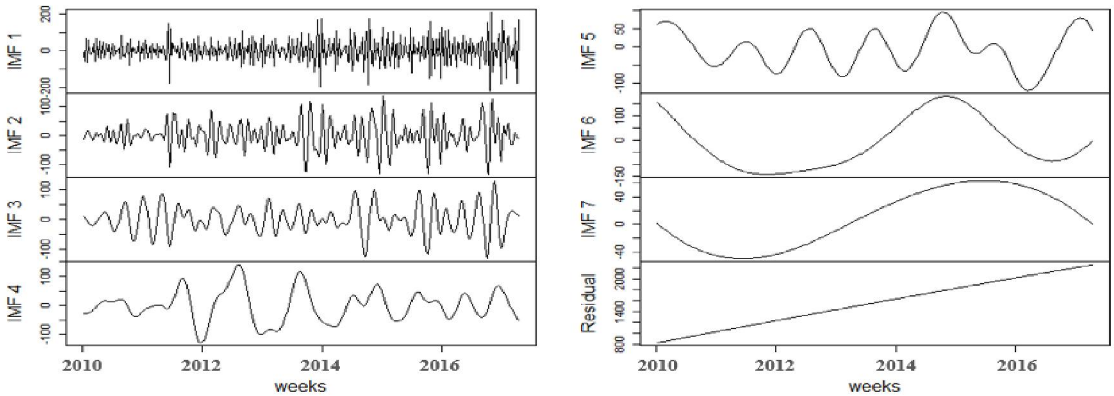

Fig. 3. Sub signals after TS decomposition through EEMD with.

Table 2

Scenarios of ANN inputs of a sub-signal k

	ANN inputs
Scenario 1	$X_t(k) = ANN(X_{t-1}(k), X_{t-2}(k), X_{t-3}(k))$
Scenario 2	$X_t(k) = ANN(X_{t-1}(k), X_{t-2}(k))$
Scenario 3	$X_t(k) = ANN(X_{t-1}(k))$

2.4. Data modeling

ANNs are self-adaptive nonlinear data-driven models, which do not demand any specific assumptions. The ANN topology used in this study is MLP, this network is the most popular ANN paradigm. The architecture of ANN is one of the most crucial step in ANN modeling, it has a direct impact on ANN performance. The architecture of any machine learning model is shaped by the values of the hyper parameters and parameters.

The hyper parameters are a configuration variables whose values cannot be estimated from the data, they are determined manually by the practitioner, and they help estimate the model parameters. In this study, the hyper parameters used to construct the ANN model are referred to as the number of hidden nodes, the number of hidden layers, and the type of activation function in hidden and output nodes. In the literature, complex optimization processes were introduced to determine the number of hidden layers and hidden neurons, nevertheless, we had adopted the simple trial and error approach. Notably, linear function was used for output layer nodes, and thanks to its sensitivity to noise, tangent sigmoid function was used for hidden nodes.

On the other hand, machine learning model parameters are a configuration variables whose values can be directly estimated from the data through the learning process of the model. In artificial neural networks, the parameters are represented by the values of the weights. Those weights were determined by the combination of the Backpropagation algorithm that computes the gradient of the cost function, and Levenberg Marquardt algorithm, which gives the optimum set of weights by finding the local minimum of the cost function. Each sub-signal $X_t(k)$ of the two decomposition techniques was modeled using $ANN_i^j(k)$, accepting a certain scenario j of inputs and a certain configuration i of ANN hidden nodes.In fact, we had used only one hidden layer, and a set of five configurations $\{2,4,6,8,10\}$ have been evaluated.To forecast the number of weekly ED visits of the original time series, the forecasted values of each sub-signal had been aggregated according to Eq.5:

$$\hat{y}_{TS}^{EEMD} = \sum_{k=1}^{8} \hat{y}_k \tag{5}$$

2.5. Performance evaluation

To evaluate the performance of the proposed two models and to compare the accuracy of their different scenarios and configurations, several performance metrics were used.
Here,the studied models have been evaluated using the performance metrics cited in Eq.6, 7 and 8:
Root mean square error ($RMSE$):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(T_i - O_i)^2}{n}} \tag{6}$$

Mean absolute error (MAE):

$$MAE = (\sum_{i=1}^{n} |T_i - O_i|)/n \tag{7}$$

Correlation coefficient (R):

$$R = \sqrt{1 - \frac{\sum_{i=1}^{n}(T_i - O_i)^2}{\sum_{i=1}^{n} {T_i}^2}} \tag{8}$$

Where O_i are predicted values and T_i are real values.

3. Results and Discussion

EEMD gave birth to seven IMFs and one residual, which were modeled through different $ANN_i^j(k)$ models. Table 3 shows that almost all ANN models required the three past values, except $ANN(7)$ that had only two inputs. Further, according to the values of $R$and $RMSE$, the frequency of the sub-signals have a great impact on the forecasting performance of the ANN models. For instance, if we compare the validation and the training results of the two models $ANN(1)$ of the high frequency IMF1 and $ANN(8)$ of the monotonic residual signal, results ($R_{val} =$ 1and $RMSE_{val} = 0.0001$) of $ANN(8)$ outperform those ($R_{val} = 0.75$ and $RMSE_{val} = 0.65$) of $ANN(1)$.
After modeling the sub-signals, the resulting forecasts had been combined to generate the total forecast of the original signal. Then the used EEMD-ANN model was compared against DWT-ANN, ANN model without decomposition, and ARIMA model. In this study, the discrete wavelet transformation was selected since we tackle a discrete time series which consists of the number of ED visits. Daubetchies wavelet mother with two vanishing moments (db2) and with two decomposition levels was selected to decompose the time series. On the other hand, the used ANN model without decomposition had performed better with scenario 2 and configuration 1. Further, ARIMA(1,1,1) model was used to estimate 80% of data and the remaining data were used to test its forecasting.

Table 4 shows that according to the performance metrics of the training set, the four models have close training results for R metric, while EEMD-ANN is better than DWT-ANN and ANN models for $RMSE$ and MAE metrics. And those three models outperform widely ARIMA model for the same metrics ($RMSE$and MAE). Hence, the first three models have high approximation capabilities. Furthermore, the test results proves that EEMD-ANN have better generalization performance than the three other models. Therefore, we can assert that ANN and ARIMA have bad generalization abilities, because there is a large gap between their approximation and generalization errors. Therefore, we can say that ANN and ARIMA models are prone to overfitting phenomenon (high variance), for the reason that the generalization errors of EEMD-ANN is broadly lower than those of ANN and ARIMA models.
These results are depicted in Fig. 4, 5 and 6, which show the evolution of real and estimated values of ED visits for the three best models (EEMD-ANN, DWT-ANN and ANN). Indeed, they point out that, the estimated values of the training data, follow perfectly the evolution of the real values, while ANN represents a slight under forecasting. Alternatively, Fig. 4 demonstrates that ANN testing values are largely different from real values, with a certain

amount of under forecasting. Albeit, the testing values of EEMD-ANN and DWT-ANN are very approximate to the real values, while the former outperforms the latter. Therefore we can say that, signal decomposition techniques help increase the generalization performance of ANN model and prevent overfitting phenomenon, by creating a tradeoff bias-variance.

4. Conclusions

In this study, we had investigated the combination of ANN model with EEMD decomposition technique to predict weekly arrivals of patients to the emergency department of a University hospital. First we had decomposed the signal of weekly ED visits into multi sub-signals, using EEMD. Then we had learned the patterns behind each sub-signal using different ANN models with different combinations of (scenarios, configurations), aiming at varying the number of inputs and hidden nodes. Finally, we had combined the forecasting results of all sub-signals, in order to generate the total forecasting of the original undecomposed signal.

Table 3
Results of modeling EEMD sub-signals.

			EEMD-ANN					
			Training			Validation		
Sub-models	Scenarios	Configurations	$RMSE$	MAE	R	$RMSE$	MAE	R
ANN(1)	1	10	0,57	0,43	0,81	0,65	0,53	0,75
ANN(2)	1	8	0,28	0,21	0,96	0,35	0,28	0,95
ANN(3)	1	2	0,05	0,04	0,99	0,05	0,04	0,99
ANN(4)	1	4	0,004	0,004	0,99	0,01	0,008	0,99
ANN(5)	1	6	0,001	0,001	1	0,007	0,005	0,99
ANN(6)	1	6	0,0003	0,0003	1	0,002	0,001	1
ANN(7)	2	4	0,0002	0,0002	1	0,018	0,01	0,99
ANN(8)	1	8	0,0001	0,0001	1	0,0001	0,0001	1

Table 4
Performance comparison between EEMD-ANN, DWT-ANN, ANN and ARIMA models.

		Models			
		EEMD-ANN	DWT-ANN	ANN	ARIMA
Training	$RMSE$	30,84	37,4	32,39	110.04
	MAE	24,04	28,84	25,19	82.22
	R	0,99	0,99	0,96	0.97
Test	$RMSE$	52.86	59.32	149.23	201.73
	MAE	39.88	46.75	104.87	160.70
	R	0.96	0.95	0.67	0.62

In accordance with the results of this study, EEMD-ANN exhibits the best results with respect to the selected benchmarks. Indeed, we believe that data decomposition is a powerful tool of data preprocessing that provides better insights into time series structure. Consequently, it enables to improve the generalization abilities of ANN while mitigating the problem of overfitting. This, by assisting ANN model to avoid learning stochastic noise (irreducible error due to data measurement and representation of the unknown target function) and to focus on real variations in the data. The results of this research can be used by hospital managers, while forecasting ED weekly visits, in order to optimize their human resources (doctors, nurses…) and material resources (beds, drugs, blood…), as well as to enhance their preparedness for crisis periods so as to provide a quality care services for most of patients. Future research could be directed to improving the forecasting performance of EEMD-ANN model by using adaptive parameters and hyper-parameters of neural networks, and by increasing the amount of data.

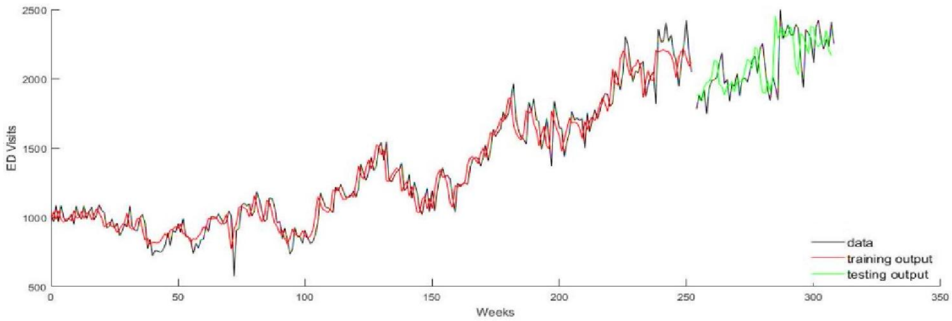

Fig. 4. Training and testing results of ED visits forecasting by ANN model.

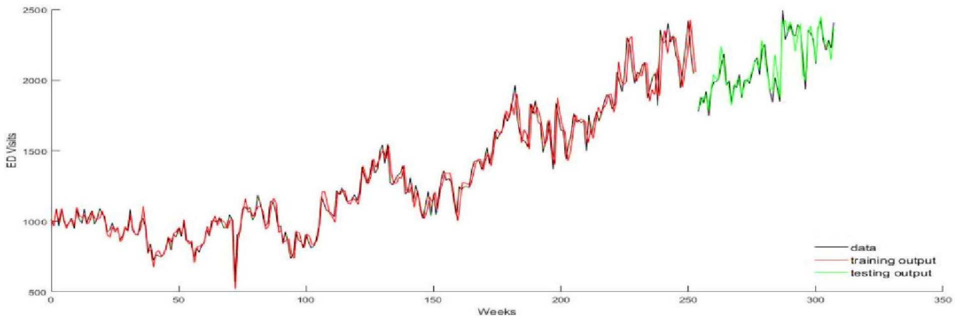

Fig. 5. Training and testing results of ED visits forecasting by DWT-ANN model.

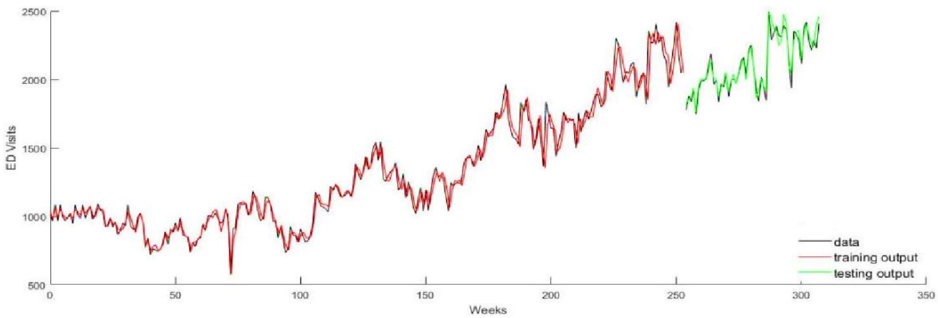

Fig. 6. Training and testing results of ED visits forecasting by EEMD-ANN model.

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