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Wavelet transform and ANFIS network-based prediction technique for forecasting confirmed cases of Covid-19 in Iran

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Abstract Coronavirus disease 2019 (COVID-19) is a contagious disease caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). The first case was identified in Wuhan, China, in December 2019. The number of confirmed cases is increasing daily and reached 101 million on 28 January 2021. This paper attempts to propose a new hybrid intelligent method for the prediction of confirmed cases of COVID-19 in the upcoming ten days based on the previously confirmed cases recorded. To forecast future cases, wavelet full decomposition of time series analysis served as input data for Adaptive Network-based Fuzzy Inference System (ANFIS). In addition, to tune the ANFIS membership functions, Quantum-behaved Particle Swarm Optimization (QPSO) was used. During the data preprocessing phase, all kinds of Wavelet Transform functions were tested for the best result. The proposed method was found to be very efficient in forecasting confirmed cases of COVID-19 in the upcoming ten days.
The proposed model is an improved adaptive neuro-fuzzy inference system (ANFIS) using QPSO and Wavelet Decomposition. The WT-QPSO-ANFIS model is evaluated using the World Health Organization (WHO) official data on the outbreak of COVID-19 to forecast the confirmed cases in the upcoming ten days. More so, the WT-QPSO-ANFIS model is compared to several existing models, and it showed better performance in terms of Mean Absolute Percentage Error (MAPE), Root Mean Squared Relative Error (RMSRE), Root Mean Squared Relative Error (RMSRE), coefficient of determination (R2), and computing time.

Keywords: COVID-19; Wavelet Transform, Adaptive Neuro-Fuzzy Inference System (ANFIS); Forecasting; QPSO Algorithm.

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1 Introduction

As serious pathogens for human beings, and known as coronaviruses, a big family of viruses can bring about respiratory, hepatic, gastrointestinal, and neurologic diseases, which are common among people, and different species of domestic and wild animals and birds [1–3]. The transmission of the disease from human to human and animal to animal has already been approved by prevalence of SARS-CoV (in 2003) and MERS-CoV (in 2012), [4].

In December 2019, China informed the World Health Organization (WHO) about several cases of respiratory illness associated with people consuming seafood in Wuhan [5], which is now suffering from a new version of coronavirus, called COVID-19 (previously known as 2019-nCoV).

In [6], based on ensemble adjustment Kalman filter for seasonal outbreaks of influenza, a forecasting model was proposed and it was evaluated through the influenza seasons data of New York City from 2003 to 2008. In an attempt by Shaman et al. [7], there was another model which used susceptible-infected-recovered-susceptible, ensemble adjustment Kalman filter, and influenza-like illness to make weekly forecasts.

Moreover, in [8], there was a dynamic model with Bayesian inference for the prediction of the outbreaks of Ebola in such African countries as Liberia, Sierra Leone, and Guinea. In their mathematical model, Massad et al. [9] analyzed and forecast J. Clin. Med. 2020, 9, 674 3 of 15the infection of the SARS epidemic for two different communities, Hong Kong and Toronto and found that the reproduction numbers were 1.2 and 1.32, respectively.
A monitoring and forecasting model was proposed by Ong et al. [10] for influenza A (H1N1-2009).

In [11], a probability-based model was proposed by Nah et al. for the prediction of the spread of the MERS. In time series prediction and forecasting problems, the Adaptive Neuro-Fuzzy Inference System (ANFIS) [12] has a widespread application and has proven to be efficient in many existing applications. In addition to the ability to combine the properties of both artificial neural networks (ANN) and fuzzy logic systems, it can flexibly determine nonlinearity in the time series data and has been found useful in many different forecasting applications such as [13], where a stock price forecasting model was proposed via employment of ANFIS and empirical mode decomposition.

In another instance, based on a hybrid of ANFIS and ordered weighted averaging (OWA) a TAIEX time series forecasting model was proposed by Chen et al. [14]. In [15], based on ANFIS, a time series forecasting method was proposed for electricity prices.

Similarly, using forecasting model for close price indices for a stock market, Svalina et al. [16] introduced an ANFIS for five days. In [17], a hybrid algorithm that is called FPASSA was proposed for the improvement of the ANFIS model by determining the parameters of ANFIS using FPASSA to forecast the confirmed cases of the upcoming ten days.

In this study, based on a modified quantum particle swarm optimization (QPSO) and using empirical mode decomposition (EMD), we proposed an improved ANFIS model. The QPSO was proposed by Yang [18] and it is an optimization algorithm, which was inspired by the particle swarm process. The EMD was used in such wavelet decomposition as the reduce noise. The proposed method, EMD-ANFIS-QPSO, involves EMD, ANFIS, and the QPSO tunes weights for ANFIS training. This method starts by receiving the historical COVID-19 dataset. Then there will be generated a set of solutions each of which represents the value for the parameters of the ANFIS model.

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Next, by means of the fitness value, the quality of each solution is calculated. After that, the solution bearing the best fitness value is selected to represent the best solution. The next stage is the computation of the probability of each solution. Finally, the solution will be updated. Regarding the local strategy, however, the operators of WT or EMD will be employed following the probability of the fitness value for each solution.

The update continues until the stop condition is achieved, and the best parameter configurations are employed to predict the number of confirmed cases of COVID-19.

2 Material and Methods

2.1 Adaptive Neuro-Fuzzy Inference System (ANFIS)

Zadeh first implemented fuzzy logic and Fuzzy Inference Systems (FIS) in 1965. In fuzzy logic, a member of more than one set may be data. Models are represented in fuzzy logic by if-then rules and linguistic variables. There are three key aspects of a fuzzy inference system: fuzzy rules, membership functions and a reasoning process. The Mamdani method, where the fuzzy output needs to be defuzzified, the Takagi-Sugeno system, which provides a real number as output, and the Tsukamoto system, which uses monotonous operations, are three kinds of fuzzy inference schemes. The 1993 Adaptive Network-based Fuzzy Inference Method (ANFIS) was introduced by Jang. A Takagi-Sugeno style fuzzy framework is used in the ANFIS architecture. In forecasting applications, ANFIS performs well and is also used widely.

2.2 QPSO

Proposed by Sun, Feng, and Xu (2004a) and Sun, Xu, & Feng (2004b, 2005), QPSO (Quantum-behaved Particle Swarm Optimization) has particles with quantum behavior, revolving around the potential field. QPSO does not assign each particle with position and velocity, but with Q a wave function w(x, t), instead. There is a difference between the behavior of particles in QPSO and PSO. The probability density function w(x, t) determines the probability of the appearance of the particle i in position x. Each particle moves following Eqs. (1) and (2)

$$Pid = \varphi \cdot Pid + (1 - \varphi) \cdot Pgd \qquad \varphi = rand() \qquad (1)$$

$$Xid = Pid \pm \alpha \cdot | mbestd - xid | \ln(1/u) \qquad u \sim U(0.1) \qquad (2)$$

where, mbest is the mean best position of the particles.

$$Mbest = \frac{1}{M}\sum Pi = \left(\frac{1}{M}\sum Pi1, \frac{1}{M}\sum Pi2, \dots\dots\dots\dots\dots \frac{1}{M}\sum Pin\right) \qquad (3)$$

Pid is a random point between Pid and Pgd and a local attractor for the i-th particle on the d-th dimension. u and u are random numbers in [0 1] and a is one of the QPSO parameters, called the contraction-expansion coefficient(Bagheri et al., 2014).

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2.3 EMD

As a method for analyzing a signal without leaving the time domain, EMD can be compared with other methods like Fourier Transforms and wavelet decomposition. This is a useful process for the analysis of natural signals, nonlinear and nonstationary data sets. This approach decomposes a signal into a series of intrinsic mode functions (IMFs) and a residual signal using a sifting process and the signal geometrical characteristics. EMD eliminates functions that shape a complete and partly orthogonal basis for the original signal. The basis of completeness depends on the EMD method and how it is decomposed. Even though the functions, commonly referred to as Intrinsic Mode Functions (IMFs), are not necessarily orthogonal, they can sufficiently be used for the description of the signal.

The varying frequency in time can be preserved because the functions into which a signal is decomposed are of the same length as the original signal and are in the time-domain. It is important to obtain IMFs from real world signals because there are often multiple causes for natural processes, and these causes are likely to occur at specific time intervals. This type of data cannot be seen in Fourier domain or in wavelet coefficients but is completely visible in an EMD analysis. The EMD method may effectively be applied in sea-surface height (SSH) readings, seismic readings, results of neuroscience experiments, gastroelectrograms and electrocardiograms (Huang and Wu, 2008; Wei, 2016).

3 The Proposed Method

This section explains the proposed EMD-ANFIS-QPSO method. It is a new approach for forecasting the confirmed cases of COVID-19, as given in figure 1.

Applying EMD to historical Covid-19 cases data to remove noise begins the data preprocessing process. In the data preprocessing section, we first use the EMD method, whose threshold is a number between 0 and 1. Results for values 0.1 and 0.2 give the best input for ANFIS. So after checking, the threshold is set to 0.1(threshold value=0.1).

The EMD-ANFIS-QPSO starts by denoising the input data in time series form. The training data contains of 80% of the dataset, whereas the testing data contains 20% of them. The output of EMD method constructs the ANFIS model. In training phase. The calculation error (as in Equation (4)) between the real data and the predicted data is used to evaluate the parameters' quality.

$$MSE = \frac{1}{Ns} \sum_{i=1}^{Ns} (Ti - Pi)^2 \qquad (4)$$

Where T is the real data, and P is predicted data. N_s is the sample length. The smaller values of the objective function indicate good ANFIS's parameters. On the other hand, the tuning of weight factors in ANFIS training phase update with QPSO algorithm. This is the best solution that passed to train the parameters of ANFIS model. After ending the training phase, the testing stage is started with the best solution to computer the final output. The performance of the proposed method is evaluated by comparing the real data with the predicted data using the performance measures. Finally, EMD-ANFIS-QPSO produces a forecasted model for confirmed cases of Covid-19 in IRAN in the next day

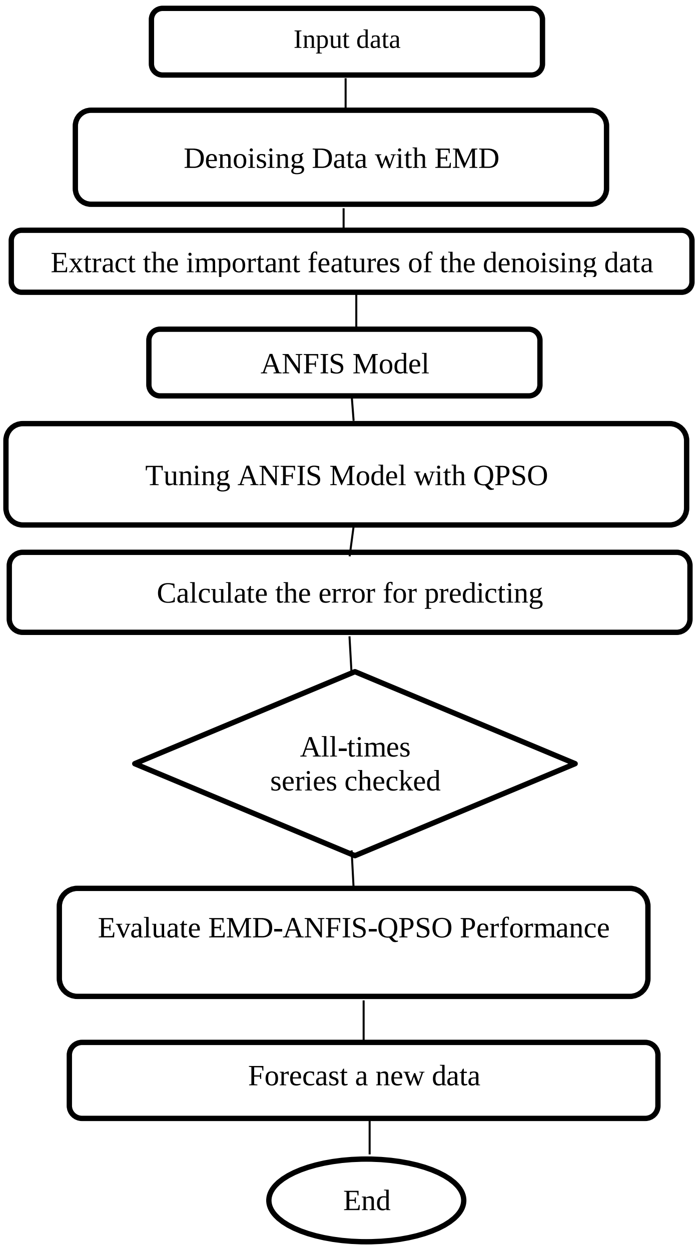

Fig. 1 The proposed EMD-ANFIS-QPSO

4 Experiment

In this section, the EMD method is first applied to input dataset that causes the noise is reduced. In Fig 2, real data vs. deniosed data are showed.

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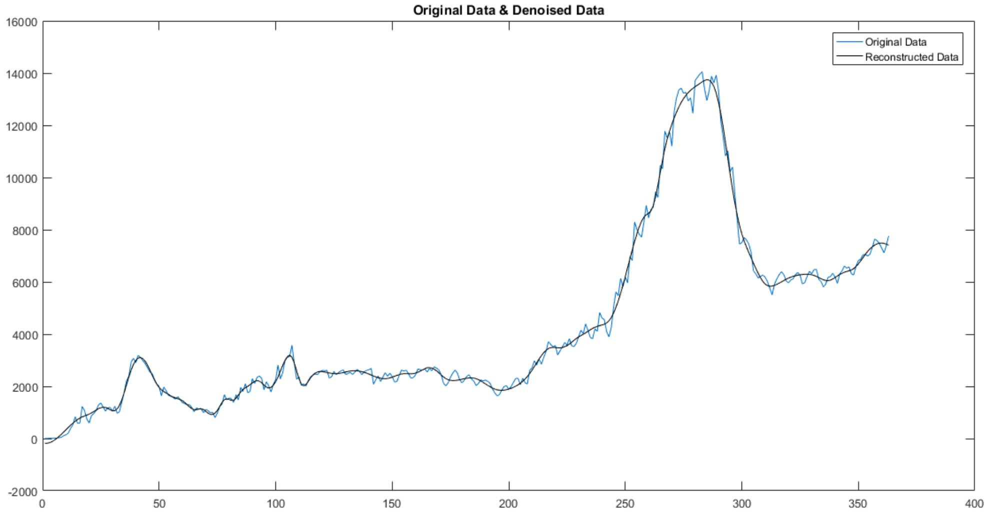

Fig. 2 The real data against the denoised data

In this step, we decomposed the training data by using EMD. EMD is a method of breaking down a signal without leaving the time domain. The full decomposition of the historical confirmed Covid-19 cases vs. days are shown in Fig. 3.

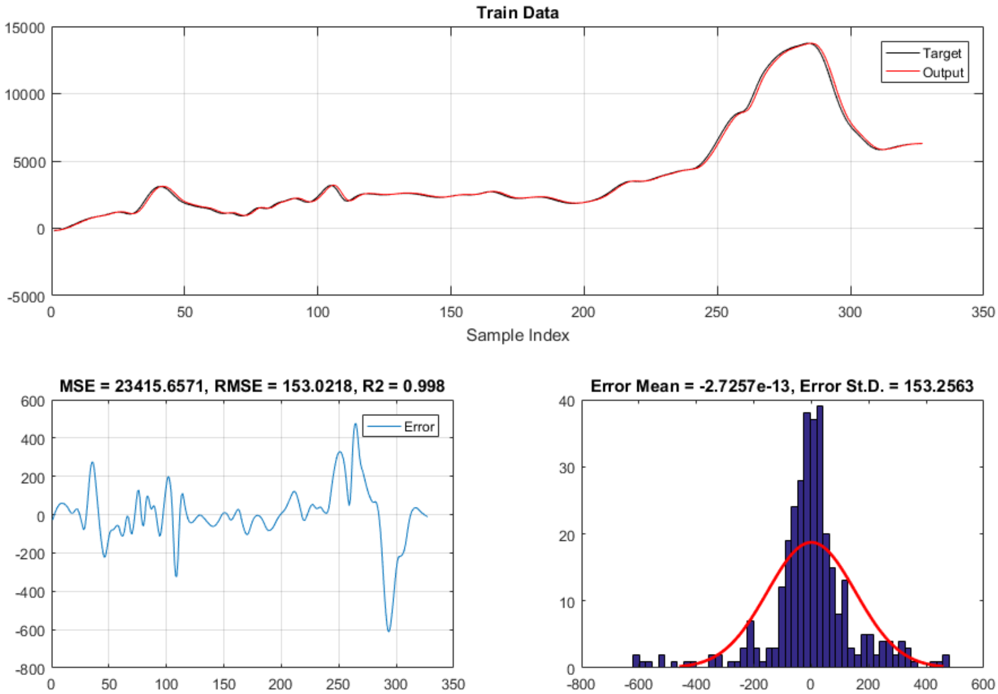

Fig. 3 Confirmed Covid-19 cases vs. days in training phase

After the training phase and error calculating, the proposed method is applied to test dataset. The figure 4 is showed it.

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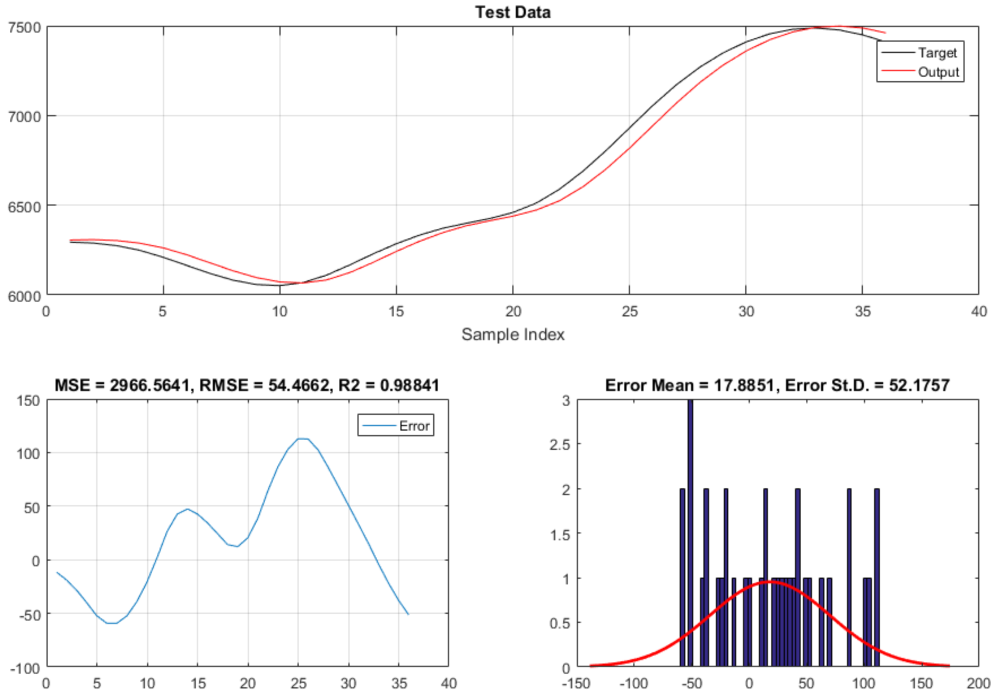

Fig. 4 Confirmed Covid-19 cases vs. days in test phase.

Comparison results between the proposed method, EMD-ANFIS-QPSO and standard ANFIS model to forecast Covid-19 are showed in table 1.

Table 1 Computational results for COVID-19

Method	RMSE	R2	Time
FPASSA	5779	0.9645	23.30
EMD-ANFIS-QPSO	**5446**	**0.9684**	**6.45**

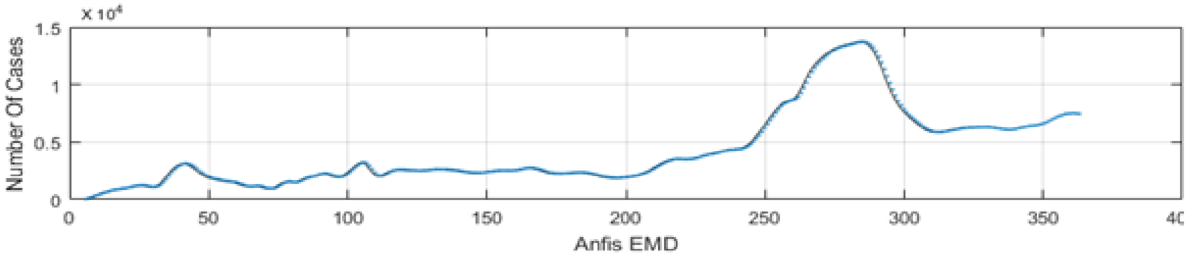

Fig. 5 The real data(target) against the forecasted data(output) for ANFIS method

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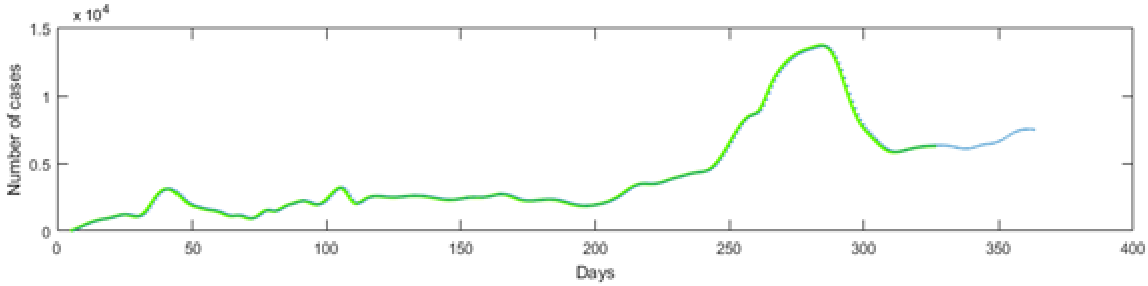

Fig. 6 The real data(target) against the forecasted data(output) for proposed method.

5 Conclusions

This paper proposed a new approach that combined Adaptive Neural Fuzzy Inference System with Quantum Particle Swarm Optimization and Empirical Method Decomposition, called EMD-ANFIS-QPSO algorithm. The proposed method improves the performance time of the FPASSA algorithm to predict the number of confirmed cases in Covid-19. Two datasets of daily Covid-19 confirmed cases in IRAN and China were used to evaluate the proposed new approach. Based on obtained results by proposed new method, it can be applied in different forecasting models that need low time consuming method.

References

1. Chen, Y., Liu, Q., & Guo, D. (2020). Emerging coronaviruses: genome structure, replication, and pathogenesis. *Journal of medical virology*, *92*(4), 418-423.
2. Ge, X. Y., Li, J. L., Yang, X. L., Chmura, A. A., Zhu, G., Epstein, J. H., ... & Shi, Z. L. (2013). Isolation and characterization of a bat SARS-like coronavirus that uses the ACE2 receptor. *Nature*, *503*(7477), 535-538.
3. Wang, L. F., Shi, Z., Zhang, S., Field, H., Daszak, P., & Eaton, B. T. (2006). Review of bats and SARS. *Emerging infectious diseases*, *12*(12), 1834.
4. Cauchemez, S., Van Kerkhove, M. D., Riley, S., Donnelly, C. A., Fraser, C., & Ferguson, N. M. (2013). Transmission scenarios for Middle East Respiratory Syndrome Coronavirus (MERS-CoV) and how to tell them apart. *Eurosurveillance*, *18*(24), 20503.
5. WHO Organization. Novel Coronavirus (2019-nCoV) 2020. Available online: https://www.who.int/ (accessed on 27 January 2020).
6. Shaman, J., & Karspeck, A. (2012). Forecasting seasonal outbreaks of influenza. *Proceedings of the National Academy of Sciences*, *109*(50), 20425-20430.
7. Shaman, J., Karspeck, A., Yang, W., Tamerius, J., & Lipsitch, M. (2013). Real-time influenza forecasts during the 2012–2013 season. *Nature communications*, *4*(1), 1-10.
8. Shaman, J., Yang, W., & Kandula, S. (2014). Inference and forecast of the current West African Ebola outbreak in Guinea, Sierra Leone and Liberia. *PLoS currents*, *6*.
9. Massad, E., Burattini, M. N., Lopez, L. F., & Coutinho, F. A. (2005). Forecasting versus projection models in epidemiology: the case of the SARS epidemics. *Medical Hypotheses*, *65*(1), 17-22.
10. Ong, J. B. S., Mark, I., Chen, C., Cook, A. R., Lee, H. C., Lee, V. J., ... & Goh, L. G. (2010). Real-time epidemic monitoring and forecasting of H1N1-2009 using influenza-like illness from general practice and family doctor clinics in Singapore. *PloS one*, *5*(4), e10036.
11. Nah, K., Otsuki, S., Chowell, G., & Nishiura, H. (2016). Predicting the international spread of Middle East respiratory syndrome (MERS). *BMC infectious diseases*, *16*(1), 1-9.
12. Bagheri, A., Peyhani, H. M., & Akbari, M. (2014). Financial forecasting using ANFIS networks with quantum-behaved particle swarm optimization. *Expert Systems with Applications*, *41*(14), 6235-6250.
13. Wei, L. Y. (2016). A hybrid ANFIS model based on empirical mode decomposition for stock time series forecasting. *Applied Soft Computing*, *42*, 368-376.

[DOI: 10.71885/ijorlu-2023-1-632]

14. Cheng, C. H., Wei, L. Y., Liu, J. W., & Chen, T. L. (2013). OWA-based ANFIS model for TAIEX forecasting. *Economic Modelling, 30*, 442-448.
15. Pousinho, H. M. I., Mendes, V. M. F., & Catalão, J. P. D. S. (2012). Short-term electricity prices forecasting in a competitive market by a hybrid PSO–ANFIS approach. *International Journal of Electrical Power & Energy Systems*, *39*(1), 29-35.
16. Svalina, I., Galzina, V., Lujić, R., & Šimunović, G. (2013). An adaptive network-based fuzzy inference system (ANFIS) for the forecasting: The case of close price indices. *Expert systems with applications*, *40*(15), 6055-6063.
17. Abd Elaziz, M., Ewees, A. A., & Alameer, Z. (2019). Improving adaptive neuro-fuzzy inference system based on a modified salp swarm algorithm using genetic algorithm to forecast crude oil price. *Natural Resources Research*, 1-16.
18. Yang, S., & Wang, M. (2004, June). A quantum particle swarm optimization. In *Proceedings of the 2004 Congress on Evolutionary Computation (IEEE Cat. No. 04TH8753)* (Vol. 1, pp. 320-324). IEEE.

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