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Estimation of Prediction Intervals for Time Series by Neural Network Constructed with Particle Swarm Optimization

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Abstract. In the present work, Particle Swarm Optimization (PSO) is applied to determine the weight connections of an Artificial Neural Network (ANN) trained to estimate Prediction Intervals (PIs) of time series forecasting. Three case studies are implemented to evaluate the performance of PSO and PIs, in terms of accuracy (coverage probability) and efficacy (width). Results indicate that the utilized method reveals efficiency in constructing high quality PIs in a simpler and faster manner. According to them, the algorithm built narrow PIs, with a (mean±st.dev.)% for the coverage probability of (85.85±1.01)%, (92.77±1.50)% and (87.63±1.15)%, to the first, second and third. And it took 0.022 seconds on average for PI construction time for all cases.

Keywords. Prediction Interval, Artificial Neural Network, Particle Swarm Optimization, Time Series Forecasting.

1 Introduction

Accurate forecasts of future events are an important input into many types of planning and decision making processes in many study areas, especially for times series [2] in the energy field [1]. There is a vast quantity of reports discussing the successful application of Artificial Neural Networks (ANNs) in times series forecasting, due to strong approximation capacity and learning ability, through adjusting connection weights between neurons [3].

However, in forecasting application of ANNs, they have been mainly used for point

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forecasting, which gives none or little information about the uncertainty in the data and carries no indication of their reliability. Datasets may contain uncertainties related with noise or due to the nature of the event modelled on the data series. It is important to know how well were the predictions made of by the ANN models, if they match the real targets and how large the risk of un-matching them [3].

In contrast with point forecasting, Prediction Intervals (PIs) are suitable to address uncertainties. PIs consist of lower and upper bounds that a future unknown value will lie within, with a predetermined probability. PIs are more reliable and informative for decision-makers, giving support to select the best action for the problem. Several ANN-based methods are used for the construction and assessment of PIs, such as Delta, Bayesian, Bootstrap and Mean Variance Estimation (MVE) techniques. Khosravi *et al* [3] compared these complex methods in his work, and propose a new method, called Lower Upper Bound Estimation (LUBE), that applies an ANN with two outputs to directly generate the bounds of PIs.

In this paper, PSO is utilized to minimize the proposed cost function [3], as it is highly nonlinear and complex, and train the ANN model. Results from three real-world case studies shown that the algorithm builds narrow PIs, with a (mean±st.dev.)% of coverage probability of (85.85±1.01)%, (92.77±1.50)% and (87.63±1.15)%, to the first, second and third cases. Section 2 introduces the methodology and its implementation. Section 3 presents the results and discussions. Finally, the section 4 concludes the paper and introduces the future work.

2 Methodology

2.1 Evaluation indices of PIs

A PI is described by an interval, with upper and lower bounds, that include an unknown target value with a certain probability, called confidence level $(1 - \alpha)$. The PICP index indicates the probability that targets values will lay within the upper and lower bounds, measured in percentage and it is considered as the calibration of the PI quality.

Equation 2.1. $\text{PICP} = \frac{1}{n_p}\sum_{i=1}^{n_p} c_i$

where n_p is the number of samples, and c_i is a Boolean variable, which shows the coverage behavior of PIs. If $y_i \in [L(x), U(x)]$, c_i will be equal 1, otherwise $c_i = 0$. In practice, to consider the PIs as valid, the PICP should be equal or greater than the nominal confidence level.

The width of intervals needs to be smaller enough to allow the requirement for high PICP can be satisfied. If the width of intervals is too large, they convey little information about the targets. According to [3], Prediction Interval Normalized Average Width (PINAW) has been used in order to evaluate the width of PIs, and it measures the average width of PIs, for all points in the dataset, as a percentage of the underlying target range.

Equation 2.2. $\text{PINAW} = \frac{1}{n_p R}\sum_{i=1}^{n_p}(U_i - L_i)$

Where L_i and U_i are the boundaries of PIs, lower and upper, respectively, and R is the range of the underlying targets. Quan *et al* [5] proposed a new width assessment index that can be similar to the Mean Square Errors (MSE), utilized for training ANNs models. The PI Normalized Root-Mean-Square Width (PINRW) is described in Equation 2.3.

Equation 2.3. $\text{PINRW} = \frac{1}{R}\sqrt{\frac{1}{n_p}\sum_{i=1}^{n_p}(U_i - L_i)^2}$

L_i and U_i and R are the same as in PINAW. In this paper PINRW is used for train the ANN model while PINAW is chosen for testing. The cost function proposed in [3] is called Coverage Width-based Criterion (CWC), which presents a comprehensive balance between PICP and PINRW (PINAW for testing). It is defined as

Equation 2.4. $\text{CWC} = PINRW(1 + \gamma(PICP)e^{-\eta(PICP-\mu)})$

Where μ and η are the nominal confidence level and the scaling factor that magnifies the difference between PICP and μ, respectively. The function $\gamma(PICP)$ is equal to one during training, while in testing it is a step function whose value depends upon the satisfaction of PICP: $\gamma(PICP) = 0$ when measurement of PICP is not less than μ, and $\gamma(PICP) = 1$ otherwise, penalizing the function CWC.

2.2 PSO and LUBE algorithm

The Lower Upper Bound Estimation (LUBE) proposed in [3] is a method that adopts a fully connected feedforward ANN model with two outputs to directly construct PIs in one step. These two outputs corresponding to the upper and lower bound of the PI, and the application of the method is easy and straightforward. The mainly advantages of this method relay in its simplicity and takes less computational costs than others traditional methods. For a graphical representation of the ANN model utilized in LUBE method, the interested reader is referred to [3].

The implementation of the LUBE method trained by PSO is described in Figure 1. Regarding implementation details the interested reader is referred to [4]. The parameters sets of PSO - C_1, C_2, ω_{max} and ω_{min} - are configured with the values 1.22, 1.49, 0.9 and 0.7, respectively. To the cost function CWC, α is 0.1, μ and η are 0.9 and 50.

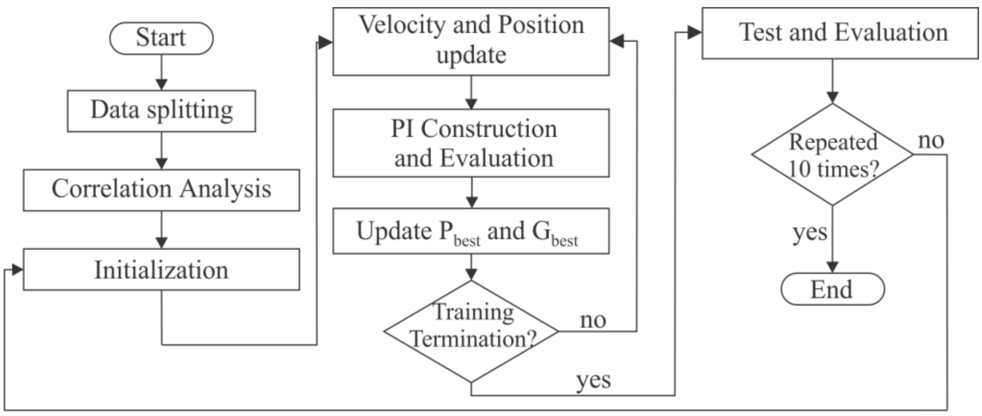


Figure 1: Implementation of the PSO-based LUBE algorithm.

Table 1 shows the three case studies are used in order to examine the performance of the LUBE method trained by PSO. Since the definition of the ANN structure utilized to construct PIs is related to the LUBE method performance, the determination of the ANN architecture for each case study followed related research or a trial-and-error process. The number of input neurons is determined based on ACF analysis. Then, to the Wind Speed case, the ANN structure is configured with 3 input neurons and 10 hidden neurons. The number of output neurons is 2, one for the lower bound and one for the upper bound values of PIs. The corresponding ANN structures for Load and Solar Irradiance cases are 3-6-1-2 and 2-12-2, respectively.

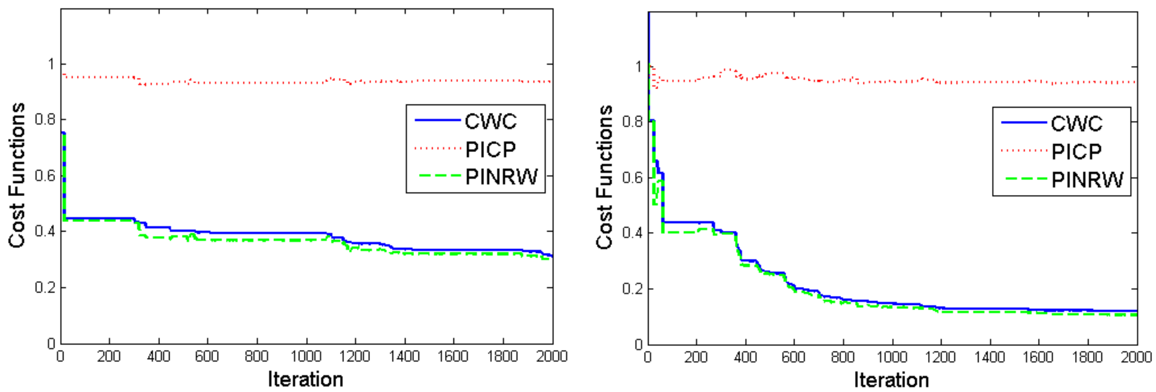
Table 1: Datasets for case studies

Dataset	Time Period	Website	Reference
Wind Speed	Feb 1 – Mar 31, 2012	http://www.weatheroffice.gc.ca/canada_e.html	[1]
Load	Jan 1 2010 – Mar 30 2011	https://www.emcsg.com/MarketData/Priceinformation	[4]
Solar Irradiance	Jan 1 2012 – Mar 31 2013	http://rredc.nrel.gov/solar/old_data/nsrdb/	Present work

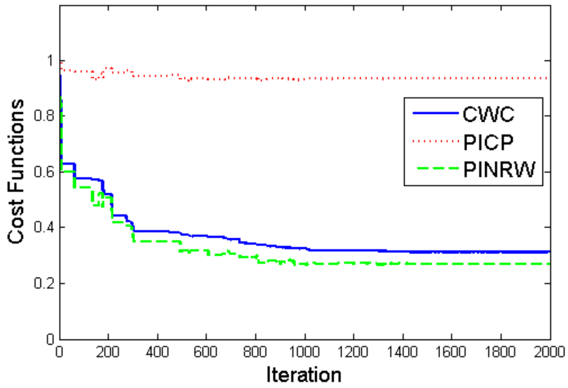
3 Experiments and Results

The training process shows the convergence of the PSO algorithm over the iterations. The number of particles is 50 and the maximum iteration is 2000, for all case studies. Figure 2 shows CWC, PICP and PINRW in each generation of the algorithm, in each case. At the beginning of the minimization process, CWC (blue line) decreases sharply after a few iterations. The same behavior can be seen in the PINRW (green dotted line) function, and both of them decrease gradually until the end.

The PICP (red dashed line) presents little fluctuations during the whole training process. For each case study, the algorithm converges, especially in the cases of Wind Speed and Load that are compared with [1] and [4], which use the same datasets, respectively. The utilization of PSO algorithm for training the ANN model showed good convergence.



(a) (b)



(c)

Figure 2: Cost functions (CWC, PICP and PINRW) of the G_{best} in each generation of the PSO algorithm: (a) Wind speed; (b) Load; and (c) Solar irradiance.

3.1 Test results

To evaluate the quality of the constructed PIs for testing data it was used the PINAW index, as mentioned before, and CWC and PICP. The results of the ten times for each case are shown in Table 2, as well as the average computational time for construction PIs. For each case study the constructed PIs cover the targets in a great percentage, which implies that the PICP indices for the test samples are very satisfactory, reaching close or more than to 90% for all cases. The mean and standard deviation of the indices over all cases studies indicate that algorithm is consistent.

Table 2: PI evaluation indices for test samples.

	Wind Speed			**Load**			**Solar Irradiance**		
	CWC	PICP (%)	PINAW (%)	CWC	PICP (%)	PINAW (%)	CWC	PICP (%)	PINAW (%)
1	17.79	85.26	39.32	0.17	91.62	17.15	0.95	88.53	30.68
2	38.73	84.21	37.35	0.12	90.88	11.69	1.12	87.94	29.51
3	13.87	85.61	40.32	0.16	94.25	15.71	0.36	90.18	36.30
4	12.48	85.61	36.28	0.12	94.52	12.06	1.29	87.31	26.71
5	13.33	85.61	38.73	0.15	93.63	15.22	1.54	87.31	31.79
6	27.15	84.56	34.57	0.14	94.34	13.53	1.74	86.72	28.24
7	13.09	85.61	38.05	0.17	93.95	17.18	1.83	86.76	30.21
8	5.17	87.02	43.53	0.32	91.96	31.58	1.27	87.82	31.95
9	19.31	85.26	42.68	0.17	91.62	17.15	2.30	86.02	27.65
10	17.79	85.26	39.32	0.12	90.88	11.69	1.31	87.71	31.50
Mean	**14.09**	**85.85**	**41.84**	**0.16**	**92.77**	**16.30**	**1.37**	**87.63**	**30.46**
St. Dev.	**7.76**	**1.01**	**2.23**	**0.06**	**1.50**	**5.82**	**0.53**	**1.15**	**2.73**
Time (s)	**0.022**			**0.023**			**0.022**		

Figures 3-5 show the constructed PIs for all case studies estimated by the trained LUBE model, corresponding to the run results with the smallest PINAW value. We can observe that the test samples (blue line) lie within the constructed lower and upper (red and green dashed lines) bound in most cases. The width of PIs is determined by the uncertainty level present of the datasets, and because of that PINAWs vary from one case study to another. They can be very narrow, such as the PINAWs in the case 2, and much wider in the case 1 and 3, wind speed and solar irradiance, both characterized by intermittent changes according to weather conditions in different time scales. Under a hardware configuration of Intel® Core™ i3-2350M CPU 2.30 GHz and 8 GB of RAM, the average PIs construction time for the test set is 0.34, 0.022, 0.023 and 0.022 seconds, implies that the LUBE method is very fast.

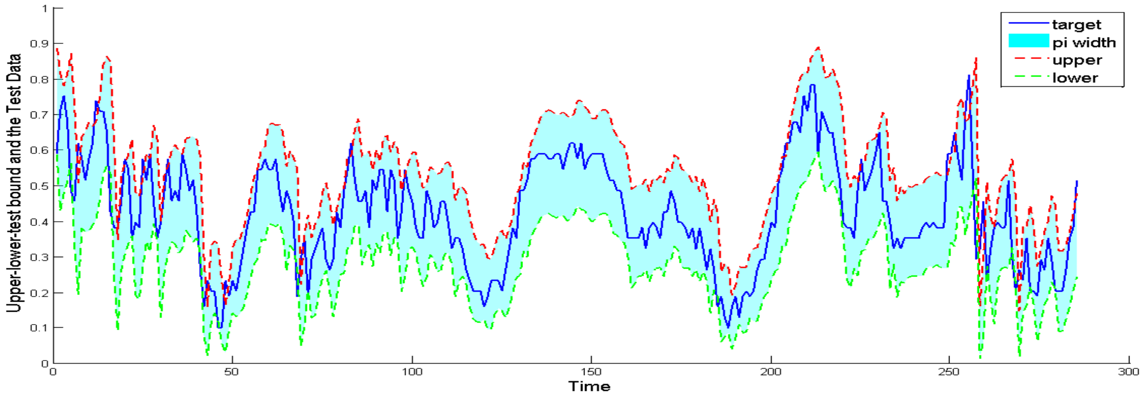


Figure 3: Estimated PIs for the Wind Speed dataset.

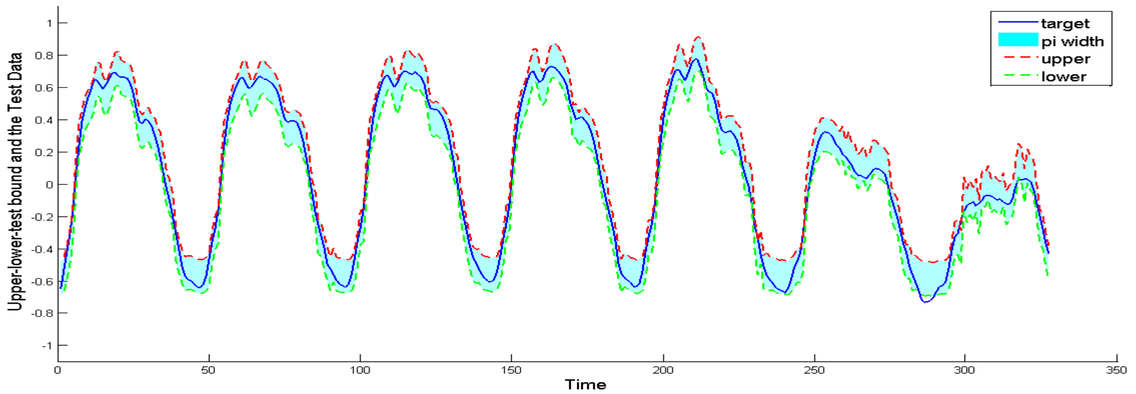


Figure 4: Estimated PIs for the Load dataset.

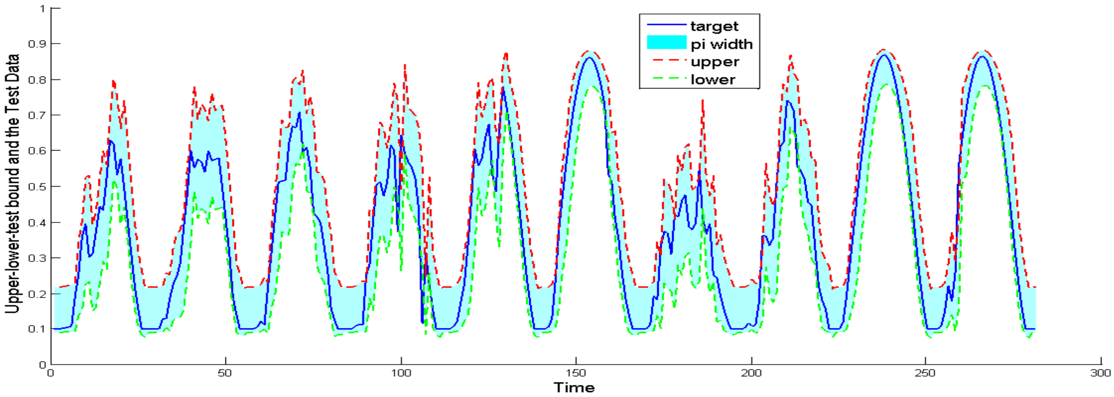


Figure 5: Estimated PIs for the Solar Irradiance dataset.

4 Conclusions

In this paper, three real-word case studies are implemented to validate the recently introduced PI construction method called LUBE integrated with PSO algorithm. PI evaluation indices for coverage probability and width are utilized to assess the quality of PIs. It was demonstrated that the algorithm is effective and reliable for forecasting prediction intervals for the three cases presented. The results show that make forecast in PIs with LUBE method is a faster manner without any assumption about the data distribution. The utilization of PSO to minimize the cost functions and trains the ANN model, reaching optimal values, give more reliability to the PI forecasting with a short computation time.

For future research, the use of new ANN architectures will be implemented to increase the accuracy of the predictions and the approach to power availability from renewable power sources and load forecasting will be pursued to optimize the management of dispatch energy in an off-grid solar photovoltaic system.

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