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Hybrid Irradiation Forecasting Method Using Neural Network To Reduce Exponential Smoothing Error

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Abstract: *Now a days talking about renewable energy is getting more common as long as researches are trying to come up with new ideas and updating previous approaches. One of the most common way to study and planning for increasing efficiency is forecasting demand and available resources. For forecasting different variables, different methods experimented. However, none of the approaches could minimize the forecasting error to the suitable point in renewable energy field such as, irradiation and wind prediction. In this paper one of the most frequent method for forecasting solar radiation were studied and examined which is exponential smoothing and the result of calculation were trained by neural network (feedforward). Neural network always used as an approach for forecasting separately but in this paper it is going to be used as part of the main calculation. Meaning to say that, neural network can be combined any method which in this case is exponential smoothing. The results was noticeable improved. Normally the average exponential smoothing errors would be around ten percent based on calculated results. But after applying neural network for completing the process, average error was declined to six percent.*

Keywords*: solar radiation, hybrid forecasting, historical data, exponential smoothing, neural network, feedforward.*

I. Introduction

Forecasting non-linear variable especially for solar radiation which depends on weather conditions by using historical data is one of the challenge recently.There are many approaches to predict irradiation, such as exponential smoothing, seasonal method and neural network. But based on studies [1-4], average error in the best review was around ten percent which was improved over time [3]. However, applying these method in real project or designing, out of calculation will be noticeable.One of the main reason that these calculations are facing these errors, is because weather conditions are changing over time, for example climate changes year by year. More specifically, for irradiation, other substance will effect on receiving irradiation by solar panels, such as, density of clouds which is changing constantly because of clouds motion.

For this case, it would be a thought of using any forecasting method few times to get more accurate results. In another words, applying one method and then use the outcome and doing it again to reduce the error [5-12]. But the fact about exponential smoothing is that, the prediction will be always on average of few day before and after. For having a better image figure 1 was provided. Furthermore, the graph won't change noticeably. For other methods such as seasonal method, it cannot be applied on a result because this method requires few dataset for particular day or period. Meaning to say that, after seasonal calculation, the result would be only a day or a period which the same method can't be applied for just only one dataset of specific day or duration.

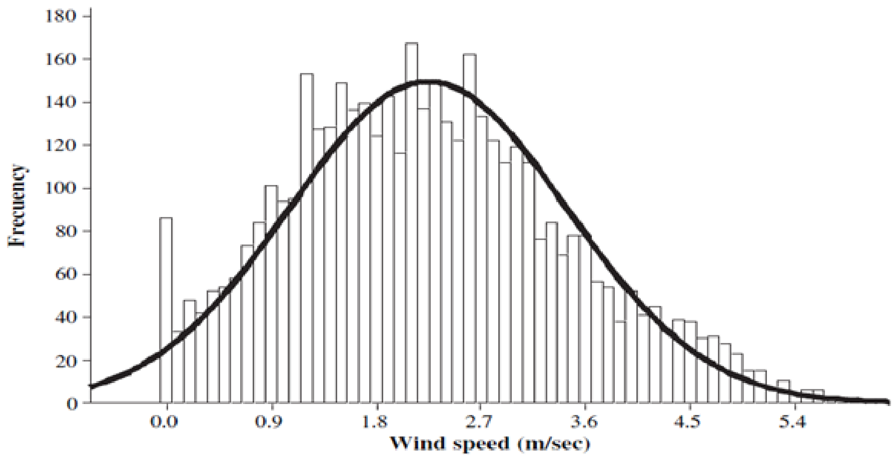


Figure 1. Sample of exponential smoothing graph [1].

In this paper one of the most suitable approaches was selected for solar radiation forecasting which is exponential smoothing meanwhile in this method the most accurate trial was selected and examined. After comparing the result with actual data, neural network was used to learn the pattern of the difference between exponential method result and actual data to improve further forecasting with more accuracy.

II. Forecastin gliterature

For applying any forecasting method, there are few details that is required to be identified. The main of them is the purpose of the prediction. Because it will help to indicate what kind of dataset is required in terms of linear and non-linear available information. Besides, the duration of forecasting. In another words, does this prediction is for hourly, daily, weekly and etc. by knowing all the mentioned criteria, it helps the researcher to narrow down number of methods. In addition, Forecasting techniques can be divided in to two main general class: based on numbers which is called quantitative and qualitative or subjective. The strategies in the quantitative class incorporate numerical models, for example, moving average, straight-line projection and exponential smoothing. In the subjective classification subjective or intuitive models such as jury or executive opinion, sales force composite, and customer expectations is the strategy [15].

In addition, the two classes those were specified, there are different variables that will impact on forecasting, for example, time or duration which are called as time-series, causal, and judgmental [4]. A time-series relies on the previous recorded information for computation of forecasting [5]. The idea of a causal model is that, for particular expected result which is specifically influenced by other participate variable. These techniques include regression models. Judgmental procedures are essentially lies on probability and calculation, so that anytime that this method is about to use, it won't show the same results or numbers [4].

III. Methodology

Exponential forecasting: based on the duration and amount of data, different formula need to be used, but generally for this paper, exponential smoothing was selected and applied by Excel. For forecasting the first approach was exponential smoothing, which is suggested for time series forecasting, that weather can be included as well. This paper is continues of previous journal paper, which means the same dataset and calculation were used [3-4].

$F_{t+1} = \alpha D_t + (1 - \alpha) F_t$ (1)

Where;

F_{t+1} = the forecast for the next period.

D_t = actual data in the present period.

F_t = the previously determined forecast for the present period.

α = a weighting factor referred to as the smoothing constant.

Neural network: In this paper, ANN in terms of feed forward method has been tried based completing exponential smoothing method forecasting. Which means for specific periods that is required to be forecast, calculation of mentioned method by historical data observation for predicting that specific duration is needed. In here the idea was to examine whether combining these to method based on the real data would increase the accuracy of forecasting or it will increase the average error. But how does ANN will help on this forecasting. It will be explained on figure 2.

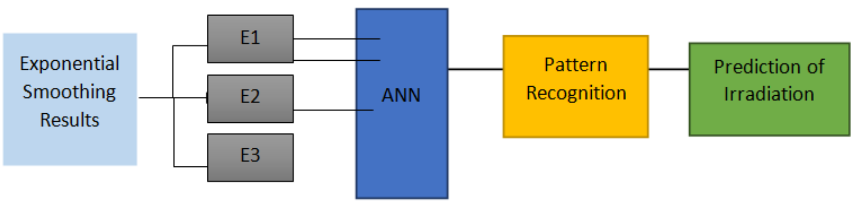


Figure 2. Combination of neural network and exponential method.

What above all else has showed is, ANN has been used to learn the error patterns and increase the accuracy of approach. At the end the result of combination of both method and exponential smoothing alone will be compared.

IV. Discussion

The main aim is to create and train a network that can predict the solar radiation. For a specific location and for specific day or week which is going to be the output and the historical data for that specific location and duration would be the input for our exponential smoothing method. In this paper, examine and studying about how neural network can be effective to improve any methods which is exponential smoothing in this case.Data was selected from the previous work [13]. Mentioned dataset was plotted in excel for four years continuously from 2010 till 2014. All the calculation was done by formulating excel and after that, the result was keyed in MATLAB. For neural network, 80% of data was selected for training, 10% for validation and same percentage for testing.

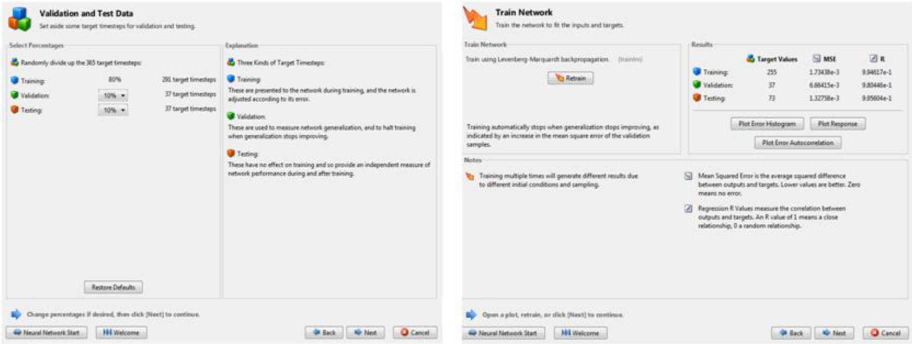


Figure 3. Training and checking R and MSE after training.

For training neural network, 364 calculated data from the exponential smoothing was the input and result would be 365 days after learning the error graph. But before starting the neural network, it is required to check the R and MSE, as much as MSE is closer to zero the result would be more suitable and based one readings on papers, as long as R is near or above 0.9, the data sets are suitable [13]. As long as the MSE is near to zero and at the same time, R is more than 0.9. Convenient result can be expected. Next graph is provided to show the validation and error of the whole actual data and forecasted value provided by neural network.

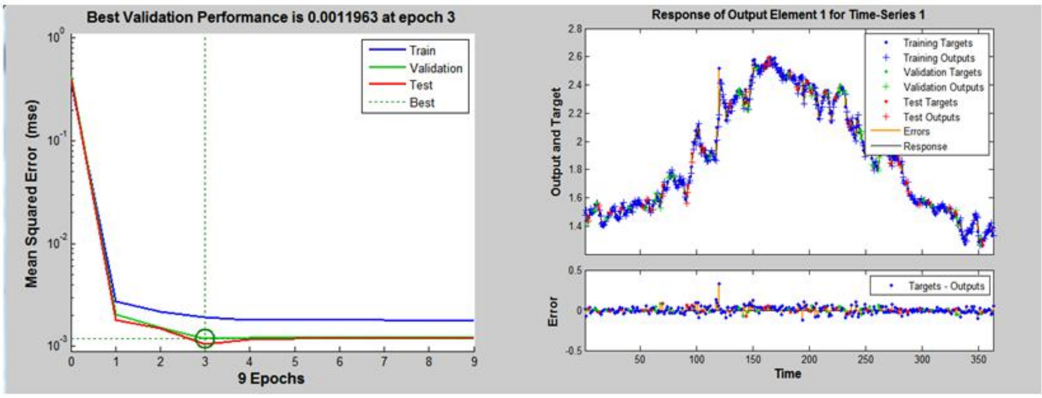
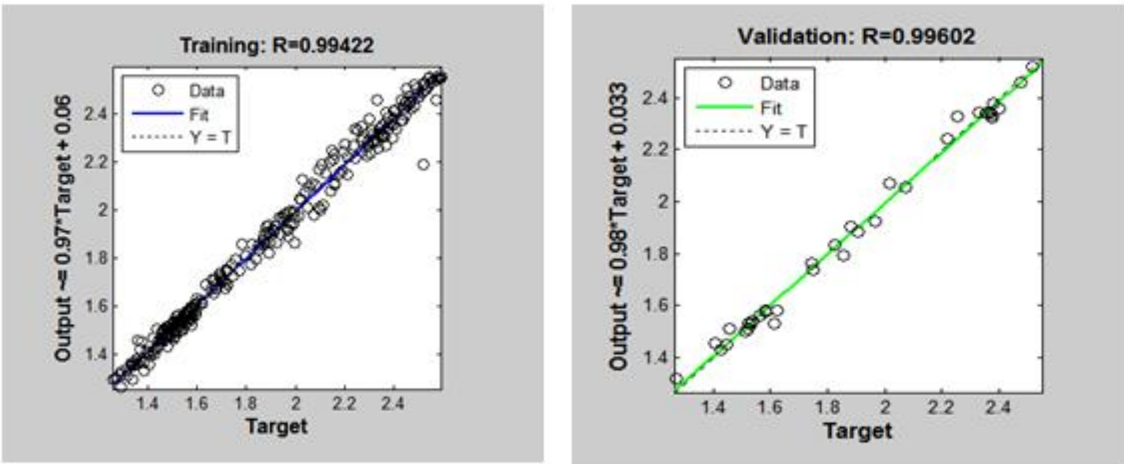


Figure 4. Validation, testing and errors.

The average error of neural network, after exponential smoothing was six percent. In figure 6 and 7, the result of exponential alone and combination of this method with neural network is displayed.



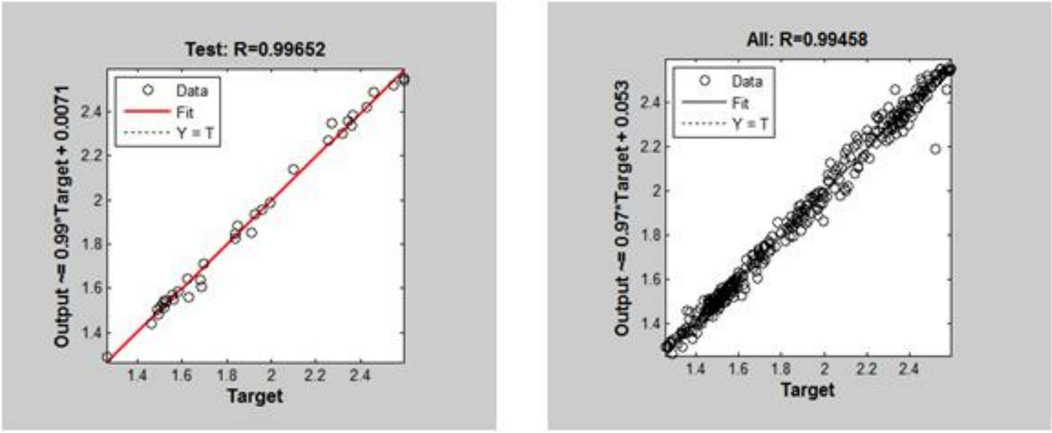


Figure 5. Regression analysis of the network outputs with respect to targets for training, validation and test sets.

Further, the network outputs with respect to the target for training, validation, and test sets are shown in figure 5, the dashed line in each axis represents the perfect result, that is: outputs = targets. The solid line represents linear best fit between the outputs and targets. For this problem, the fit is reasonably good for all data sets, with the overall regression values as high as 0.98 [2].

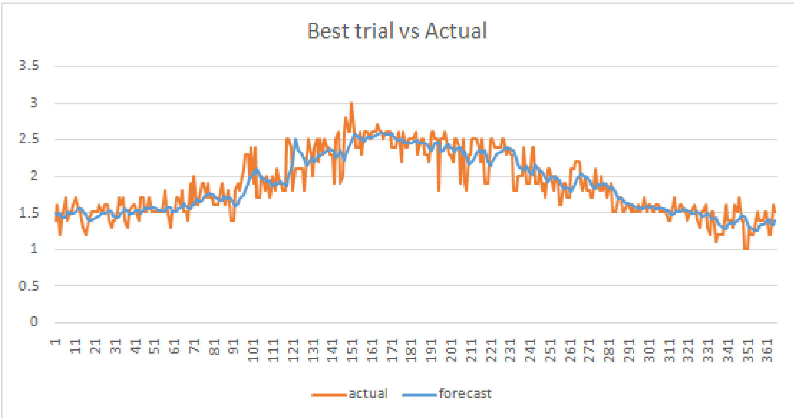


Figure 6. Exponential smoothing, best trial vs actual values.

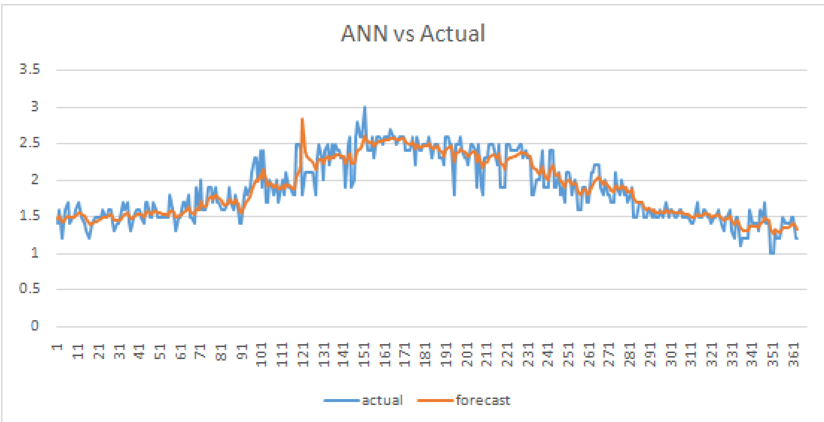


Figure 7. ANN vs actual data

Exponential smoothing always involves days before forecast as reference. Which means, whatever happened in pass, it will happen in future, that's why, if in few days the numbers increases, the next day prediction would increase as well. This is one of the main reason to make the forecasting less accurate. However, this method is useful for non-linear dataset because for few days the actual value might be more than what has been predicated and in other hand the next few days the actual value might be less than what has been predicted.By looking at figure 6. The blue line which is the calculated forecast, is mostly in middle of actual values. The point, those are not in middle located exactly after or before any sudden drops or rise. By comparing figure 6 and 7, it is possible to see that ANN graph is more curvy in respect to exponential graph, even the gap between actual and forecast become less. However at one point or another, the difference was even higher. In overall the average error was reduced from 10% to 6%.

	February					
1	32	1.8	1.440595		0.35940546	20%
2	33	1.8	1.452476		0.34752437	19%
3	34	1.4	1.501981		0.10198051	7%
4	35	1.4	1.521584		0.12158441	9%
5	36	1.3	1.557268		0.25726752	20%
6	37	1.3	1.525814		0.22581402	17%
7	38	1.8	1.480651		0.31934878	18%
8	39	1.8	1.484521		0.31547903	18%
9	40	1.7	1.497617		0.20238322	12%
10	41	1.8	1.518093		0.28190658	16%
11	42	1.9	1.534475		0.36552526	19%
12	43	1.6	1.52758		0.07242021	5%
13	44	1.6	1.502064		0.09793617	6%
14	45	1.5	1.541651		0.04165107	3%
15	46	1.5	1.573321		0.07332085	5%

	February			
1.5	1.456965		0.043035	3%
1.7	1.50684		0.19316	13%
1.6	1.524749		0.075251	5%
1.7	1.558794		0.141206	9%
1.4	1.5112		0.1112	7%
1.3	1.468687		0.168687	11%
1.5	1.488473		0.011527	1%
1.55	1.502024		0.047976	3%
1.6	1.521748		0.078252	5%
1.6	1.535423		0.064577	4%
1.5	1.523216		0.023216	2%
1.4	1.495429		0.095429	6%
1.7	1.545234		0.154766	10%
1.7	1.572314		0.127686	8%
1.5	1.545094		0.045094	3%

Figure 8. Exponential smoothing vs ANN errors.

Figure 8 has been provided to show how effectively combining this two methods can be. This was part of excel file where calculation were done, randomly for comparison the first 15th days of February were selected or 32 – 46 days of a year. On first day of this month the error for exponential is 20% but the same day for ANN is 3%. However, on day 12 and 13, exponential smoothing was more accurate. By observing other months errors, for example January, exponential smoothing was more accurate comparing to ANN but in overall of year ANN was more suitable. All these calculated forecast was compared with the next year actual value.

V. Conclusion

In this paper, combination of one the most common forecasting method which was exponential smoothing with neural network was used to get more accurate data. This idea was came up after doing previous article review regarding to three main forecasting method which were, exponential smoothing, seasonal method and artificial neural network. As it was mentioned exponential smoothing had the less average errors comparing with the rest methods and at that time neural network was classified as a single approach. Even though, exponential was more accurate comparing to the rest, but still the result wasn't satisfying enough. For getting in more detail, other articles regarding to exponential smoothing were studied and at the end, they faced the same problem. That's why combining this method and ANN was suggested and examined. For forecasting, the dataset was used from the similar database for previous work.

It is known, artificial intelligence can be used for more complex situation such as satellite image for forecasting any related variables to weather. As long as satellite figures and images are not easy to access, and at the same time neural network was suggested to use for more complex conditions, learning patterns of the exponential smoothing and actual data. Before starting to work on this hybrid method, the expectation was lesser than what actually happened. To having a clear image, previously the best accuracy of exponential was lacking 10 percent in average and applying ANN would decrease average errors by 2% approximately, but after doing this review the total average error was reduced down to 6% which was surprisingly effective. Even in provided figure, some of the errors were reduced from 20% to 3%. Meanwhile, in somedays, errors were increased.After doing this review, it brings the idea of using this pattern learning not just only for exponential smoothing method, it can be combined with other forecasting method such as seasonal forecasting in case of radiation or any weather related prediction.

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