Prediction of Solar Radiation According to Aerosol Optical Depth

F. Chabane[1]*, A. Arif[2], N. Moummi[1], A. Brima[1]

[1] *Department of Mechanical, Faculty of Technology, University of Biskra, Biskra, Algeria*
[2] *Department of Electrical Engineering, Faculty of Technology, University of Biskra, Biskra, Algeria*

PAPER INFO	ABSTRACT
	The dependencye of aerosol optical depth on wavelength as well as the fit of the humidity, temperature and pressure approximation under atmoshperic condition at Biskra city of Algeria has been investigated. Our work consists of measuring and modeling solar radiation on the horizontal area to create a mathematical model of global solar radiation which depends on the aerosol optical depth data between two wavelengths: 550 and 1250 nm. Simultaneous measurements of global solar radiation were carried out and recorded on the horizontal zone on an urban site (Biskra, Algeria) to characterize the radiative effect of atmospheric aerosols from January to December 2013. In addition, the effect of meteorological parameters such as: humidity, ambient temperature, and time durations were studied. This relationship constitutes an alternative tool to estimate AOD at the routine lighting measurements available at many radiometric stations around the world. Finally, a comparative study was established between the theoretical results and the experimental data which leads at an excellent correlation by a low relative error which is limited by the interval 2 and 15%.

NOMENCLATURE

ANN	artificial neural network	ε	depending to number of day
SVR	vector support regression	h	sun elevation angle
GSR	global solar radiation	BCAOD	aerosol of black carbon
ML	machine learning model	DUAOD	aerosol of dust
MLP	multilayer perceptron	OMAOD	aerosol of organic matter
GSR	global solar radiation(W/m²)	SSAOD	aerosol of sea salt
AOD	aerosol optical depth	SUAOD	aerosol of sulfate
H_r	relative humidity (%)	N_d	number of the day
T	ambient temperature (°C)	μ, Ψ, β, m and α	constants relate to Y_0
A	constant depending to number of the day	A_2, b_2, c_2 and d_2	constants relate to A and ε
Y_0	constant relate by relative humidity and ambient temperature and aerosol optical depth	A_a, B_a, C_a	constants corresponding to aerosols optical depth of BC, DU, OM, SS and SU with μ =550 nm

INTRODUCTION

Pollution screamed by the consumption of energy in the world, leads us to reflect on the problem caused by fossil fuels and the solutions to be accepted to have a healthy environment. The large deposit of solar energy abandoning in nature leads us to think about how to extract it and how to use this solar radiation. Several researchers have worked on the modeling, forecasting, and estimation of solar radiation.

Ghardaïa (Algeria) is a site very recognized for its solar deposit. Guermoui et al. [1] worked on this site and wrote an article on the estimation of solar radiation. They estimated and developed an SVM model to correct the error of solar radiation.

In Finland, Tuononen et al. [2] carried out a forecast study to see the influence of the cloud on the accuracy of solar radiation forecasts. To locate these clouds and see their influence on the accuracy of solar radiation forecasts in Helsinki, they have developed methods and

*Corresponding Author E-mail: fouedmeca@hotmail.fr (F. Chabane)

algorithms to evaluate their performance on cloud and radiation forecasts.

There are several prediction models based on the artificial neural network (ANN), support vector regression (SVR), fuzzy logic, and the Gaussian process. Basaran et al. [3] and Ghimire et al. [4] have exploited the learning techniques in predicting the irradiance solar. To estimate the irradiance solar, Basaran et al. [3] have used a set of support vector regression (SVR) and artificial neural networks (ANN). On the other hand, Ghimire et al. [4] used the convolutional neural network and the short-term memory network to determine the global solar radiation (GSR) as a function of time. Beyaztas et al. [5] carried out a study based on the modeling, analysis, and prediction of global solar radiation in Africa and more precisely Burkina Faso. Using the concept of functional data analysis, they found a new mathematical model that predicts daily global solar radiation.

On some continents, there are significant amounts of solar radiation. For different types of the sky, we can estimate global solar radiation by using several models such as genetics, artificial neural network (ANN), machine learning model (ML), fuzzy logic, and multilayer perceptron (MLP). Ghimire et al. [6], Khatib [7], Kuhe et al. [8], Wang et al. [9], Kumar Yadav and Chandel [10], Neelamegam and Amirtham [11] artificial neural networks for predicting solar radiation.

Ghimire et al. [4] used the Queensland site in Australia to predict global solar radiation an artificial neural network (ANN) model. They established models based on the neural network such as the machine learning model, they also used genetics to estimate and calculate solar irradiation. Khatib [7] has deduced a new prediction model based on artificial neural networks. The variables used were humidity, temperature, and energy from the sun. His model gave very satisfactory errors, as an example the mean square error. In Nigeria, more precisely in the city of Makurdi, Kuhe et al. [8] used several forms of artificial neural networks such as the generalized regression model to predict global solar radiation. Wang et al. [9] studied three forms of ANN to predict daily global solar radiation. Wang et al. [9] used three forms of artificial neural networks to predict solar radiation. They used the radial-based neural network, the multilayer perceptron, and the generalized regression neural network. To model daily solar radiation, they applied these three different techniques. In several countries, there is a lack of radiation database. To overcome this problem and predict solar radiation Kumar Yadav and Chandel [10], have used the models found in the literature based on artificial neural networks. To predict solar radiation, Neelamegam and Amirtham [11] used several algorithms. The results obtained by the predictive artificial neural network model used gave very high accuracy.

In Morocco (Marrakech), a new fuzzy model has been established by Iqdour and Zeroual [12]. They predicted daily global solar radiation. The neuro -flou proposed by Parsaei et al. [13], they improved the prediction model by using intelligent algorithms. Voyant et al. [14] employed machine learning methods for the global prediction of solar radiation. Rabehi et al. [15] predicted modeling based on methodologies such as linear regression and the multilayer perceptron. These models have been applied in southern Algeria to predict global solar radiation. The interest in solar energy led us to seek new methods of prediction of solar radiation. Reikard [16] tested some methods like the autoregressive integrated moving average and the networks of artificial neurons (ANN). He found that the ANN model is not optimal, especially in terms of computing time.

In semi-arid regions, Samadianfard et al. [17] studied several models using the adaptive neuro-fuzzy inference, gene expression programming, vector support regression (SVR), and empirical relationships. According to their results, the SVR model is the most efficient. In India, Suthar et al. [18] estimated solar radiation by taking into account atmospheric pollution, they predicted daily global solar radiation independent of location by the exponential quadratic system. They concluded that air pollution is more important than location.

Some works were used the different meteorologic parameters such as humidity, temperature, pressure, and angle of sun elevation for determined the global solar radiation [19–23]. The aim of our study was to measure and model solar radiation on the horizontal area to create a mathematical model of global solar radiation which depends on the aerosol optical depth data between two wavelengths: 550 and 1250 nm.

MATERIAL AND METHOD

Solar irradiation
We chose the total solar irradiance equation in the form of Siberian and variable according to the angle of solar elevation accompanied by a constant.

We noticed that each constant of the chosen equation is variable by month change, and for this, we tried to connect it with the optical spray according to the wavelengths of 550 and 1250 microns taking into account the climate values, for example, moisture and temperature.

About the impact of the aerosol optical depth onto solar radiation; we trying to find the relationship between forecast the variation of global solar radiation on a horizontal area as a function of the Meteorology parameters based on Equation (1):

$$G(AOD_{550}, AOD_{1240}) =$$
$$Y_0(AOD_{550}, AOD_{1240}, Hr, T) + A(n) \times exp\left(\frac{h}{\varepsilon(n)}\right) \quad (1)$$

Table 1 summarized the constants of the relationship of global solar radiation, we can determine from equation 1. The residual become a perfect value between 0.93 and 0.94.

At this point, we tried to create a new approach corresponding to weather parameters and aerosols optical depth between two wavelengths 550 nm and 1240 nm, and another parameter as a function to many months;

$$Y_0 = \mu \times T^{\psi} \times Hr^{\beta} \times AOD_{1240}^{m} \times AOD_{550}^{\alpha} \qquad (2)$$

For determined Y_0 easily taken out of Tables 1 and 2 help us to give all constants which relate by each month of the year. Table 2 summarized the average aerosol optical depth corresponding to two wavelengths.

TABLE 1. The constants corresponding to global solar radiation

Months	Y_0	A	ε	R^2
1	-19.926	109.262	-0.32405	0.94345
2	-38.863	151.536	-0.42782	0.94344
3	-85.422	221.455	-0.58797	0.94308
4	-151.723	272.879	-0.78343	0.93987
5	-288.937	405.313	-1.10223	0.94011
6	-517.329	645.115	-1.49439	0.94095
7	-504.323	642.525	-1.45532	0.94343
8	-260.896	397.926	-1.01372	0.94103
9	-79.727	177.283	-0.61313	0.94475
10	-36.457	122.491	-0.44097	0.94612
11	-22.583	109.884	-0.34927	0.94261
12	-15.814	94.232	-0.29758	0.9432

TABLE 2. The average aerosol optical depth corresponding to AOD_{1240} and AOD_{550}

Months	AOD_{1240}	AOD_{550}
1	0.05229	0.08099
2	0.07732	0.11396
3	0.112	0.15846
4	0.20837	0.27519
5	0.23148	0.29649
6	0.39862	0.4401
7	0.2912	0.36352
8	0.19095	0.24978
9	0.24102	0.31277
10	0.21926	0.24232
11	0.04851	0.087
12	0.04916	0.09295

Table 3 reported the constants corresponding to Y_0 according to the relationship between the metrology values.

$$(A, \varepsilon) = a_2 + b_2 \times exp\left[-0.5 \times \left(\frac{(N_d - c_2)}{d_2}\right)^2\right] \qquad (3)$$

The constants corresponding to A and ε according to the relationship between the number of months are given in Table 4.

$$(BCA, DU, OM, SS, SU) = A_a + B_a \times N_d + C_a \times N_d^2 \qquad (4)$$

The constants corresponding to aerosols optical depth of BC, DU, OM, SS, and SU with $\mu = 550$ nm are reported in Table 5.

RESULTS AND DISCUSSION

Figures 1 and 2 show the variation of global solar radiation as a function to the true solar time corresponding to the site of Biskra. In the record points, the global solar radiation varying according to relative

TABLE 3. The constants corresponding to Y_0

Constants	Y_0
μ	-275121
ψ	0.5855
β	-2.719
m	-1.121
α	2.303
R^2	0.9498

TABLE 4. The constants corresponding to A and ε

Constants	A	ε
a2	124.846	-0.343
b2	546.707	-1.158
c2	6.404	6.321
d2	1.351	1.645
R^2	0.962	0.983

TABLE 5. The constants corresponding to aerosols optical depth of BC, DU, OM, SS, and SU with $\mu = 550$ nm

	BCAOD	DUAOD	OMAOD	SSAOD	SUAOD
A_a	0.00151	-0.1481	8.56E-04	0.05036	0.01772
B_a	0.00186	0.11859	0.00459	-0.00869	0.00984
C_a	-1.41E-04	-0.0088	-3.66E-04	4.25E-04	-6.46E-04
R^2	0.8424	0.70756	0.8294	0.8345	0.75665
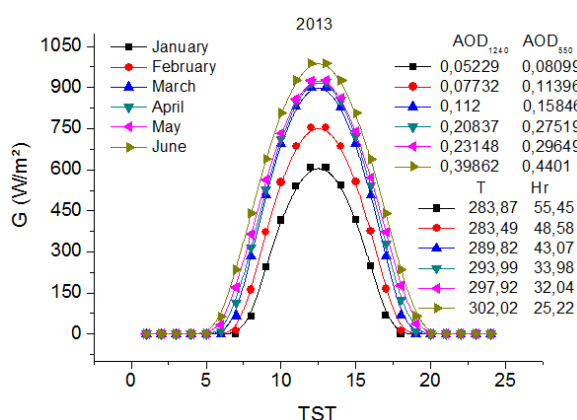
Figure 1. Global solar radiation from January to June
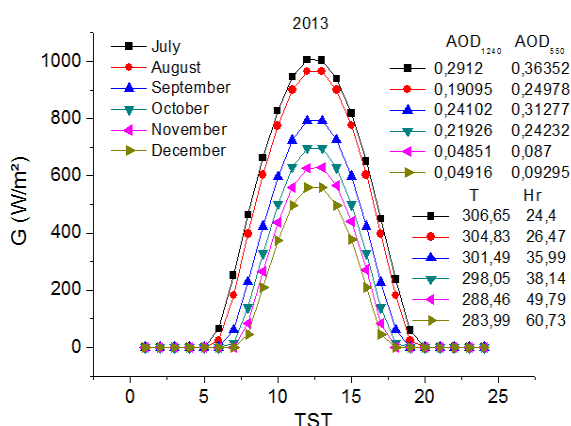
Figure 2. Global solar radiation from July to December

Figure 3. Comparison of global solar radiation both experimental data and prediction

humidity, ambient temperature, wind speed, air pressure, rainfall, and aerosols optical depth corresponding to wavelength 550 and 1240 nm. We can observed that the maximum top global solar radiation would be in June, July and August with (G = 989.78W/m², AOD_{550} = 0.4401 and AOD_{1240} = 0.3986), (G =1006.37 W/m², AOD_{550} = 0.3536 and AOD_{1240} = 0.2912) and (G = 964.81 W/m², AOD_{550} = 0.2497 and AOD_{1240} = 0.1909), respectively. About the minimum top global solar radiation would be in November, December and January with (G = 627.48W/m², AOD_{550} = 0.087 and AOD_{1240} = 0.04851), (G =560.49 W/m², AOD_{550} = 0.09295 and AOD_{1240} = 0.04916) and (G = 606.10 W/m², AOD_{550} = 0.08099 and AOD_{1240} = 0.05229), respectively. From all of these data we can conclude that when the top global solar radiation take a maximum value is the aerosol optical depth at maximum point. On the other hand, when the global solar radiation takes a minimum value having a minimum aerosol optical depth. Finally that means the global solar radiation has positive relationship with aerosol optical depth.

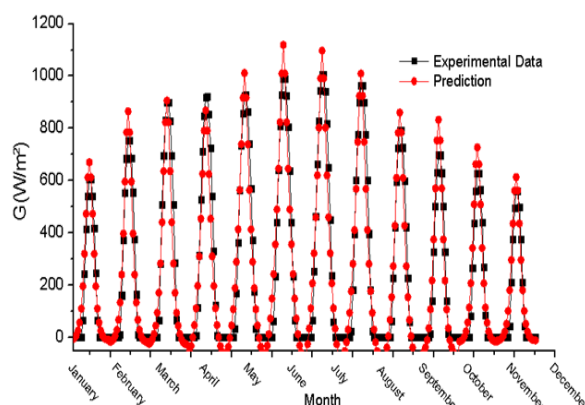Figure 3 shows the variation in the curves of the global solar radiation as a function to the number of months. According to experimental data we established desired model. Through the two curves, we notice a convergence and convergence between the two curves, which makes the chosen model ideal. We can see that June and July estimated the symmetrical axes of the global solar radiation which partitions the values of the number of the months in the year. The global solar radiation started with minimum variation in January by 600 W/m² and continues to increase to June and July with 1100 W/m² and decrease to respectively to December with 600 W/m².

Figure 4 represents the relative errors of global solar radiation as a function to numbers of the day. Remark that the maximum relative error has been selected in the number of the day 33, 125, and 300 which estimated the values of 11%, 13%, and 15%, respectively. The minimum relative error has been selected in the number of the day 75, and 200 which estimated the values of 5% and 2%. That means the prediction model gives a perfect curve of the global solar radiation.
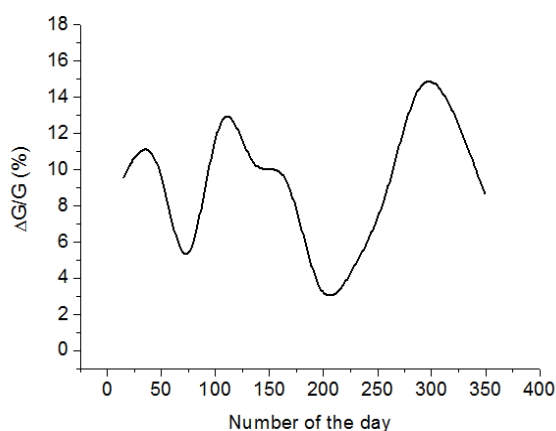

Figure 4. Relative errors of global solar radiation both experimental data and prediction

CONCLUSION

The researchers today need to predict some parameters before they do the experimental study, such as the simulation or numerical modeling of some physic phenomena. So at these points trying to create a good approximate of global solar radiation with a perfect relationship between many parameters such as weather climate and some components of pollution in the atmosphere like the aerosols optical depth.

In conclusion that has a good result between measured data and predicted model; which resulted in a perfect approximation with a great convergent.

The result conducted that the global solar radiation has a relationship with the aerosol optical depth in both wavelengths 550 nm and 1240 nm. When the global solar radiation on the horizontal area takes a maximum value is parallel with a maximum aerosol optical depth in both waves the opposite is true.

Finally, we made the global solar radiation varying between many parameters; such as temperature, relative humidity, wind speed, air pressure, and rainfall, and aerosols optical depth. AODs increases with decreasing wavelength for all meteorological conditions.

REFERENCES

1. Guermoui, M., Abdelaziz, R., Gairaa, K., Djemoui, L., & Benkaciali, S., 2020, New temperature-based predicting model for global solar radiation using support vector regression, International Journal of Ambient Energy. https://doi.org/10.1080/01430750.2019.1708792

2. Tuononen, M., O'Connor, E. J., & Sinclair, V. A., 2019, Evaluating solar radiation forecast uncertainty, Atmospheric Chemistry and Physics, 19(3): 1985–2000. https://doi.org/10.5194/acp-19-1985-2019

3. Basaran, K., Özçift, A., & Kılınç, D., 2019, A New Approach for Prediction of Solar Radiation with Using Ensemble Learning Algorithm, Arabian Journal for Science and Engineering, 44(8): 7159–7171. https://doi.org/10.1007/s13369-019-03841-7

4. Ghimire, S., Deo, R. C., Raj, N., & Mi, J., 2019, Deep solar radiation forecasting with convolutional neural network and long short-term memory network algorithms, Applied Energy, 253: 113541. https://doi.org/10.1016/j.apenergy.2019.113541

5. Beyaztas, U., Salih, S. Q., Chau, K.-W., Al-Ansari, N., & Yaseen, Z. M., 2019, Construction of functional data analysis modeling strategy for global solar radiation prediction: application of cross-station paradigm, Engineering Applications of Computational Fluid Mechanics, 13(1): 1165–1181. https://doi.org/10.1080/19942060.2019.1676314

6. Ghimire, S., Deo, R. C., Downs, N. J., & Raj, N., 2019, Global solar radiation prediction by ANN integrated with European Centre for medium range weather forecast fields in solar rich cities of Queensland Australia, Journal of Cleaner Production, 216: 288–310. https://doi.org/10.1016/j.jclepro.2019.01.158

7. Khatib, T., 2015, A Novel Approach for Solar Radiation Prediction Using Artificial Neural Networks, Energy Sources, Part A: Recovery, Utilization and Environmental Effects, 37(22): 2429–2436. https://doi.org/10.1080/15567036.2012.713080

8. Kuhe, A., Achirgbenda, V. T., & Agada, M., 2019, Global solar radiation prediction for Makurdi, Nigeria, using neural networks ensemble, Energy Sources, Part A: Recovery, Utilization and Environmental Effects. https://doi.org/10.1080/15567036.2019.1637481

9. Wang, L., Kisi, O., Zounemat-Kermani, M., Salazar, G. A., Zhu, Z., & Gong, W., 2016, Solar radiation prediction using different techniques: Model evaluation and comparison, Renewable and Sustainable Energy Reviews, 61: 384-397. https://doi.org/10.1016/j.rser.2016.04.024

10. Yadav, A. K., & Chandel, S. S., 2014, May 1, Solar radiation prediction using Artificial Neural Network techniques: A review, Renewable and Sustainable Energy Reviews, 33: 772-781. https://doi.org/10.1016/j.rser.2013.08.055

11. Premalatha, N., & Valan Arasu, A., 2016, Prediction of solar radiation for solar systems by using ANN models with different back propagation algorithms, Journal of Applied Research and Technology, 14(3): 206–214. https://doi.org/10.1016/j.jart.2016.05.001

12. Iqdour, R., & Zeroual, A., 2007, Prediction of daily global solar radiation using fuzzy systems, International Journal of Sustainable Energy, 26(1): 19–29. https://doi.org/10.1080/14786450701265371

13. Reza Parsaei, M., Mollashahi, H., Darvishan, A., Mir, M., & Simoes, R., 2020, A new prediction model of solar radiation based on the neuro-fuzzy model, International Journal of Ambient Energy, 41(2): 189–197. https://doi.org/10.1080/01430750.2018.1456964

14. Voyant, C., Notton, G., Kalogirou, S., Nivet, M. L., Paoli, C., Motte, F., & Fouilloy, A., 2017, May 1, Machine learning methods for solar radiation forecasting: A review, Renewable Energy, 105: 569-582. https://doi.org/10.1016/j.renene.2016.12.095

15. Rabehi, A., Guermoui, M., & Lalmi, D., 2020, Hybrid models for global solar radiation prediction: a case study, International Journal of Ambient Energy, 41(1): 31–40. https://doi.org/10.1080/01430750.2018.1443498

16. Reikard, G., 2009, Predicting solar radiation at high resolutions: A comparison of time series forecasts, Solar Energy, 83(3): 342–349. https://doi.org/10.1016/j.solener.2008.08.007

17. Samadianfard, S., Majnooni-Heris, A., Qasem, S. N., Kisi, O., Shamshirband, S., & Chau, K., 2019, Daily global solar radiation modeling using data-driven techniques and empirical equations in a semi-arid climate, Engineering Applications of Computational Fluid Mechanics, 13(1): 142–157. https://doi.org/10.1080/19942060.2018.1560364

18. Suthar, M., Singh, G. K., & Saini, R. P., 2017, Effects of air pollution for estimating global solar radiation in India, International Journal of Sustainable Energy, 36(1): 20–27. https://doi.org/10.1080/14786451.2014.979348

19. Foued Chabane, Guellai, F., Michraoui, M. Y., Bensahal, D., Bima, A., & Moummi, N., 2019, Prediction of the Global Solar Radiation on Inclined Area, Applied Solar Energy (English translation of Geliotekhnika), 55(1): 41–47. https://doi.org/10.3103/S0003701X19010055

20. Chabane, F., Khadraoui, Z., & Bensahal, D., 2019, Prediction of Global Solar Radiation on the Horizontal Area with the Effect of Ambient Temperature Part: II, TECNICA ITALIANA-Italian Journal of Engineering Science, 63(1): 73–77. https://doi.org/10.18280/ti-ijes.630110

21. Chabane, F., Laznek, I., & Bensahal, D., 2018, Prediction of global solar radiation on the horizontal area with the effect of relative humidity part: I, TECNICA ITALIANA-Italian Journal of Engineering Science, 61+1(2): 115–118. https://doi.org/10.18280/ti-ijes.620209

22. Chabane, F., Ghedhifi, M. A., Bensahal, D., Bima, A., & Moummi, N., 2018, Forecast of global solar irradiation with a perfect model according to incline angle, Journal of Power of Technologies, 98(3): 245–254.

23. Chabane, F., Moummi, N., & Brima, A., 2016, Predictions of solar radiation distribution: Global, direct and diffuse light on horizontal surface, European Physical Journal Plus, 131(4): 1–8. https://doi.org/10.1140/epjp/i2016-16106-7

Persian Abstract

DOI: 10.5829/ijee.2020.11.04.04

چکیده

در وابستگی عمق نوری آئروسل به طول موج و همچنین تناسب رطوبت، دما و تقریب فشار در شرایط جوی در شهر بیسکرا الجزایر بررسی شده است. کار ما شامل اندازه‌گیری و مدل‌سازی تابش خورشید در منطقه افقی برای ایجاد یک مدل ریاضی از تابش خورشید جهانی است که به داده‌های عمق نوری آئروسل بین دو طول موج: ۵۵۰ و ۱۲۵۰ نانومتر بستگی دارد. اندازه‌گیری همزمان تابش خورشید جهانی در منطقه افقی در یک مکان شهری (بیسکرا، الجزایر) و برای توصیف اثر تابشی ذرات معلق در هوا از ژانویه تا دسامبر ۲۰۱۳ انجام شد. علاوه بر این، اثر پارامترهای هواشناسی مانند: رطوبت، دمای محیط و مدت زمان مورد بررسی قرار گرفت. این رابطه ابزاری جایگزین برای برآورد AOD در اندازه‌گیری‌های معمول روشنایی است که در بسیاری از ایستگاه‌های رادیومتریک در سراسر جهان موجود است. سرانجام، یک مطالعه تطبیقی بین نتایج نظری و داده‌های تجربی ایجاد شد که منجر به یک همبستگی عالی با یک خطای نسبی کم می‌شود که با فاصله ۲ و ۱۵ درصد محدود می‌شود.