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Algorithm for Electromagnetic Power Estimation in Radio Environment Map

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ABSTRACT

Perhaps the most important part of building a radio environment map is estimating the electromagnetic field strength. The more efficient the estimation algorithm used, the more accurate the radio environment map reached. A new hybrid algorithm to estimate electromagnetic power - using sensing data gathered by monitoring sensors - is proposed in this paper. A certain propagation model was used considering all physical phenomena along the whole path of the electromagnetic wave (including losses, attenuation).A theoretical variogram based on a certain propagation model was used and fitted using a real variogram through regression. This method simulates the real physical phenomenon more accurately. The proposed algorithm is mainly based on weighting parameters (that rely on the variogram method) and a factor taking the similarities because of the neighborhood. Experimental results showed close similarity between given and computed electromagnetic power through regression curves and objective evaluation indices. The proposed method's main contribution is gathering the merits of using a suitable propagation model and a theoretical variogram, besides getting merits of traditional methods(like Inverse Distance Weight) using new vision.

Keywords:

Radio environment map, Histogram, Propagation model

I. INTRODUCTION

The radio environment map is an integrated and intelligent database system that supports cognitive radio, Zhao [1]. This database contains different information from many different domains; including Geographical features, Services availability, Spectral regulations, rules, and procedures, Past, present, and expected future (by studying experience) situation of equipment, Locations and activities of radio equipment, and Policies of service providers and users through the environment. The main objective of the radio environment map is the efficient and optimized management of the radio spectrum. Many researchers like Ojaniemi [2] proved that the most important part of constructing an accurate radio environment map; is to develop an algorithm to estimate the radio parameter (electromagnetic power) since it is the main factor to be determined throughout the whole concept in order to make and take the right decision concerning both; primary and secondary users. This estimation problem is called by Pesko [3] as a radiofrequency layer. There have been extensive researches concerning this problem since 2012. Some researchers used the inverse distance method (IDW) like J.Riihijavri, P.Mahonen, W.Wellens, and M.Gordziel [4], 2008, .and Two pieces of research were held in 2012, one of them was introduced by D.Denkovski, V.Atanasovski, L.Gavrilovska, J.Riihijavri and P.Mhonen [5]. The other one was proposed by C.Phillips, M.Ton, D.Sicker, and D.Grunwald [6]. The authors used the Kriging method. In 2015, a paper was proposed by S.Ulanganathan, D.Deschrijver, M.Pakparvar, J.Coukuyt, W.Liu, D.Plets, W.Joseph, D.Dhaene, L.Martens and I.Moerman [7], used antiregressive Co Kriging model. In 2017, K.Sato and T.Fujii [8] proposed a new method for the concept of spatial spectrum sharing and radio environment maps; it was improved using Kriging interpolation. Although the Kriging method was thought of – by many researchers- as the most accurate method, many other researchers- on the other side- overviewed the limitations of the method, as Ojaniemi [2]. He proved the poorness of the method under certain conditions. Apparently Kriging model treats the whole data as normally distributed, which is not always the case. It does not take observations like sill and nuggets and generally all the outliers into consideration properly. Hence, to overcome this problem, a new model introduced, using both, Kriging and propagation model. The theoretical Kriging variogram is improved by using a certain propagation model suitable for considering outliers; then regression was used to optimize the variogram, resulting in a modified Kriging model that works much better than the traditional one.

II. RESEARCH METHOD (10 PT)

A. THE ALGORITHM

For any random process S(d),

$\{ S(d): d \in D \subset \mathbb{R}^n \}$ (1)

Where

d: Is a location in D

$\mathbb{R}^n$ (n=1,2,3) Is a dimensional Euclidean space.

Spatial data expressed as (p_i, d_i), i=1, 2, 3,…, N.

Where p_i : is the i^{th} observation of the phenomenon (here, it is the strength of electromagnetic field) of interest in location d_i .

For the process to be stationary random process:

i. $E(p(d)) = \mu, \forall d \in D$.
ii. $\operatorname{cov}(p(d_i), p(d_j)) = c(h) = c(d_i - d_j) < \infty$.
iii. $\operatorname{var}(p(d_i), p(d_j)) = 2\gamma(d_i - d_j) = 2\gamma(h)\ \forall d_j \in D$.

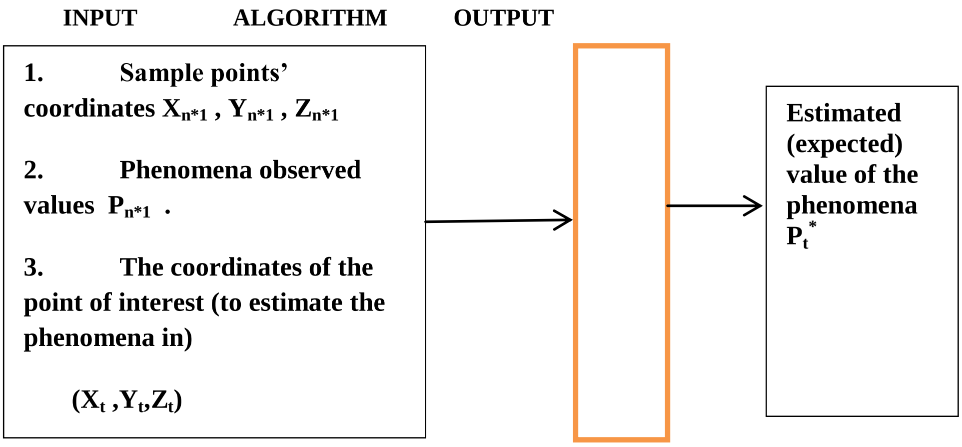
Where:

μ: is the expected value of the phenomena.

c(h) And 2ɤ(h) are the covariance and variogram for distant h pair of points, respectively.

A block diagram for the algorithm is shown below in figure (1).

Figure (1)



B. THE VARIOGRAM

It is an autocorrelation measure used in geostatistics, given by:

$\gamma(h) = 1/N(h) \sqrt{\sum_{i=1}^{N} (P(d_i) - p(d_i + h))^2}$ (2)

Where

$\gamma(h_j)$: is the variogram function.

N(h): is the number of data pairs with lag distance h.

$p(d_i)$: is the value of electromagnetic power at position d_i.

$p(d_i+h)$: is the value of electromagnetic power at position d_i+h .

N: is the total number of data points.

C. THE THEORETICAL VARIOGRAM

A variogram based on Longely – Rice model (sometimes called the irregular terrain model) is introduced.

Since:

i. Heights of antennae are known.
ii. Loss of free space propagation considered.

Theoretical variogram will be:

$\gamma(h) = \alpha_1 + \alpha_2 d + \alpha_3 \ln(h/\varphi + \delta) + \alpha_4 \log(h + \delta)$ (3)

Where

h: is the distance between two data points.

δ: is a very small constant (to overcome division by zero problems)

φ: used to simulate distance of sight (taken as 14000).

α_1, $\alpha2$, $\alpha3$, andα_4: are the coefficients to be determined.

D. FITTING ALGORITHMS

Three weight coefficients used to overcome certain three problems as follows:

a. Random distribution of sampling points :

A weight coefficient $\lambda = N/N_i$ (4), is used to overcome the sampling randomness, where:

N_i: is the number of sample point pairs that correspond to a certain lag.

N: is the total number of sample number pair.

b. Inconsistencies and Inaccuracies

This problem is caused by electromagnetic shadowing and reflections of buildings, multipath, and radio propagation diffractions(abnormally large or small sampled values).to deal with this issue; a second weighting coefficient is used,

$\lambda_2 = \tilde{\imath}(h_) / \gamma(h_i)$ (5)

Where

$\tilde{\imath}(h_)$: is the mean value of the variogram.

$\gamma(h_{i)})$: Is the value of the variogram at lag distance h_i.

c. Reflection of the variability of the regionalized variable

This is achieved by considering points of smaller lag distance. Hence, a third weighting coefficient used, which is $\lambda_3 = \hat{h} / h_i$ (6), where:

$\hat{h}$: is the mean value of the lag distance.

h_i: is the corresponding lag distance.

Thus the total weight will be $\lambda_{total} = \lambda_1 . \lambda_2 . \lambda_3$ (7)

Now Γ and Γ_t calculated using theoretical variogram model

$$\Gamma = \begin{pmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} & \dots & \gamma_{1n} & 1 \\ \gamma_{21} & \gamma_{22} & \gamma_{23} & \dots & \gamma_{2n} & 1 \\ \dots & & \dots & & \dots & \\ \gamma_{n1} & \gamma_{n2} & \gamma_{n3} & \dots & \gamma_{nn} & 1 \end{pmatrix} \quad \textbf{(8)}$$

$$\Gamma_t = \begin{bmatrix} \Upsilon_{1t} \\ \Upsilon_{2t} \\ \dots \\ \Upsilon_{nt} \\ 1 \end{bmatrix} \quad (9)$$

$$\begin{bmatrix} \lambda 1 \\ \lambda 2 \\ \lambda 2 \\ \lambda n \\ \zeta \end{bmatrix} = \quad \dots \quad (10)$$

Where ζ is Lagrange constant.

$\Gamma * \lambda = \Gamma_t$**, hence** $\lambda = \Gamma^{-1} * \Gamma_t$

$$P_t^* = \sum_{i=1}^{N} (\lambda_i * pi) \quad (11)$$

Where:

p_i is the power at point i.

Γ is the augmented total histogram matrix (between any points he whole n sampling points).

Γ_t is the histogram matrix (between every point of the n sampling point and the point of interest t).

Finally, the expected power at point t ($P_{expected} = a * P_t^* + b*$ (average neighborhood power)).

Where: P_t^* is the expected power in point t due to applying the weighted algorithm only. Neighborhood average power is the power in the nearest point or the average in the nearest points' powers (if there is more than one point). Given: a + b = 1.

In this paper: a =b 0.5 were used.

E. DATA
Two sets of data were taken at two certain frequencies, 263.2148 MHz and 600 MHz, at a calibrated chamber.

F. SIMULATION AND IMPLEMENTATION
Python version 3.4.0 was used to implement the proposed algorithm.

III. RESULTS AND DISCUSSION

3.1 Two cases were studied: 263.2148 MHz, and 600 MHz

3.2 The resultant expected power at the point of interest is taken as half of the power using the weighted parameters algorithm and the other half using the nearest points' average power.

3.3 The results were compared with the well-known two algorithms of Inverse Distance Weight and Inverse Distance Weight Squared.

3.4 Comparisons are held using regression graphs similarities between each of the three methods (Algo (proposed whole algorithm), IDW (Inverse distance weight algorithm), and IDWSQU (Inverse Distance Weight Squared) compared with the real points' powers.

3.5 Also, five objective evaluation indices were used :

3.5.1Average Estimation Error Percentage:

AEEP =1/(Avgpgiven) ∑i=1N (Pexpected-(pgiven)i) (12)

3.5.2Relative Mean Square Error:

RELMSE =1/(N * S2) ∑i=1N (Pexpected-(pgiven)i)2 (13)

3.5.3Root Mean Square Error:

RMSE =((1/(N) ∑i=1N (Pexpected-(pgiven)i)2)0.5 (14)

3.5.4Maximum Error:

Max_Err = Maximum Value of(Pexpected-(pgiven)i (15)

3.5.5Average Error

Av_Err = Average Value of(Pexpected-(pgiven)I (16)

Where:

N: is the total number of sampling points.

Avgpgiven: is the average value of the real sampling points' powers.

Pexpected: is the estimated power of the point at position i.

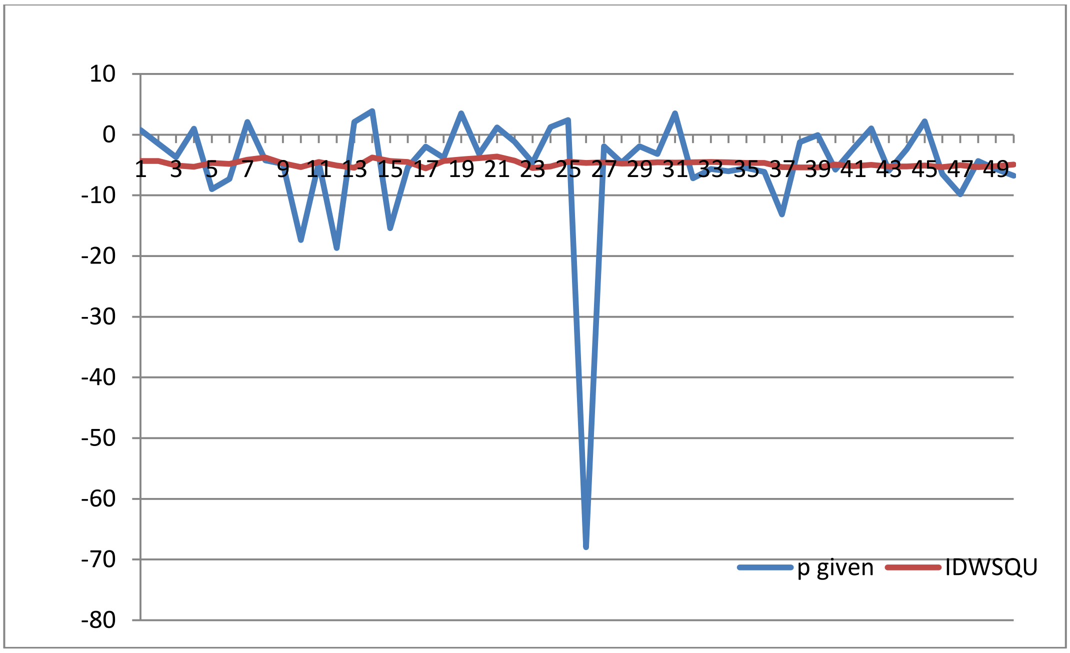
(pgiven)i : is the real power of the point at positions i.

S2: is the variance of the real sampling points' powers.

3.6 3.6 figure (2) shows the curves of real powers and expected powers using the Inverse Distance Squared algorithm of the whole fifty points (treated as unknowns and then estimated using the Inverse Distance Squared algorithm) taken at a frequency of 263.2148 MHz.

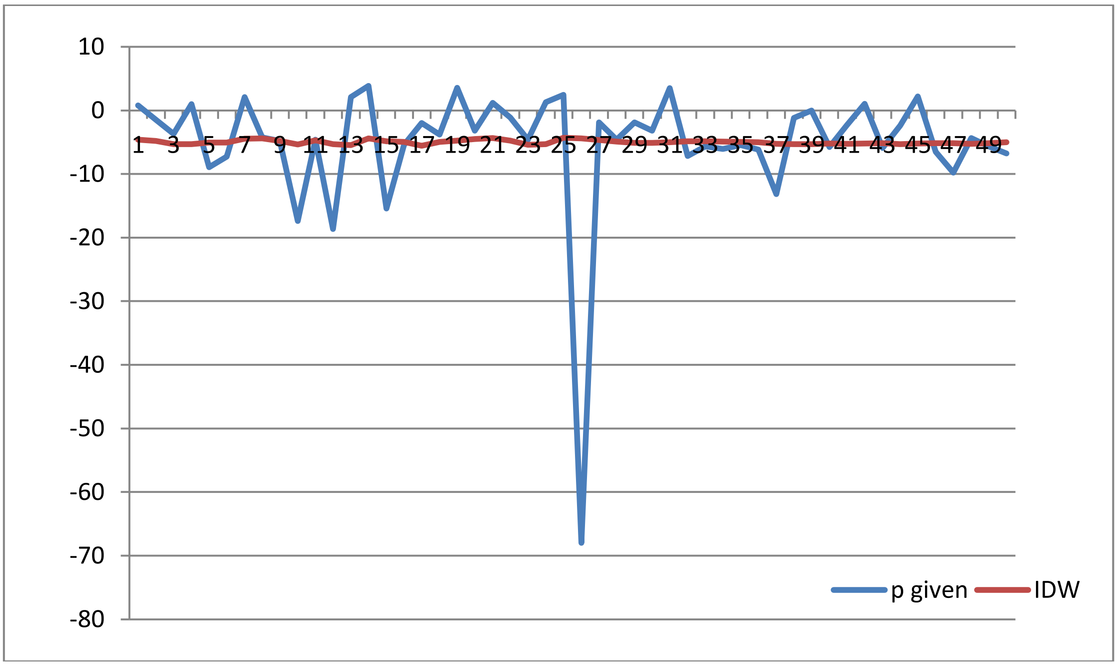
Figure (2)

Shows the curves of real powers and expected powers using IDWSQU at f=263.2148MHz.



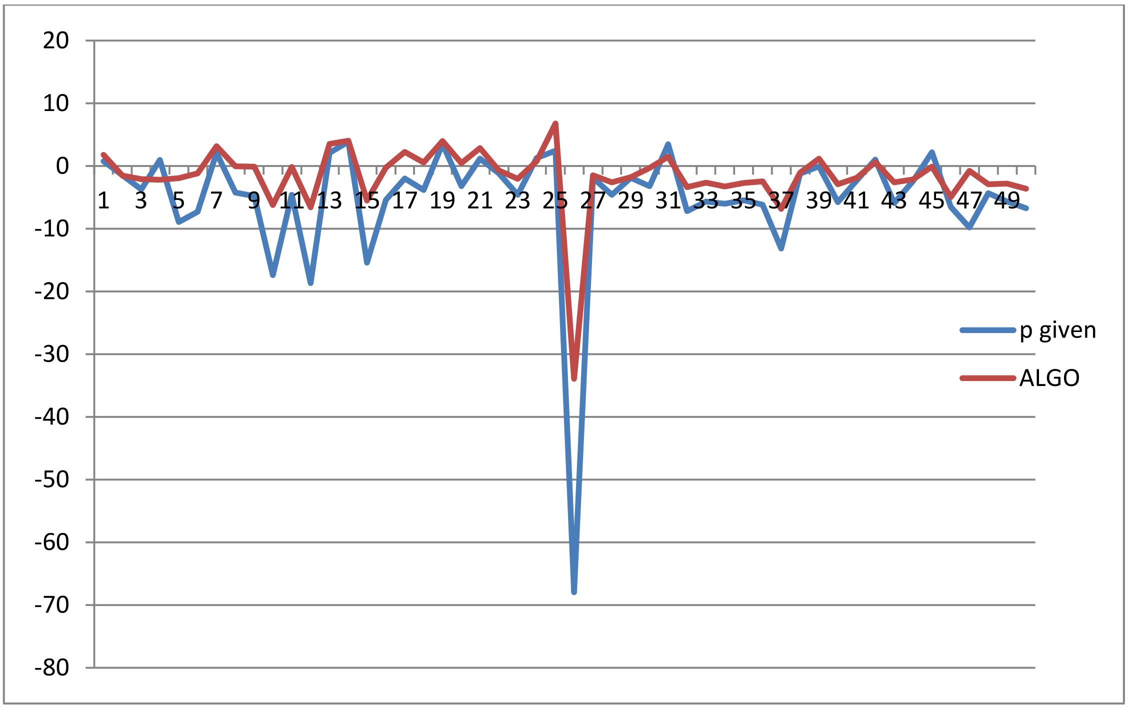
3.7 figure (3) shows the curves of real powers and expected powers using Inverse Distance algorithm of the whole fifty points(treated as unknowns and then estimated using Inverse Distance algorithm) taken frequency of 263.2148 MHz.

Figure (3)
Shows the curves of real powers and expected powers using IDW at f=263.2148MHz.



3.8 figure (4) shows the curves of real powers and expected powers using the Hybrid algorithm proposed in this paper of the whole fifty points (treated as unknowns and then estimated using the proposed algorithm)taken at a frequency 263.2148 MHz.

Figure (4)
Shows the curves of real powers and expected powers using ALGO at f=263.2148MHz.



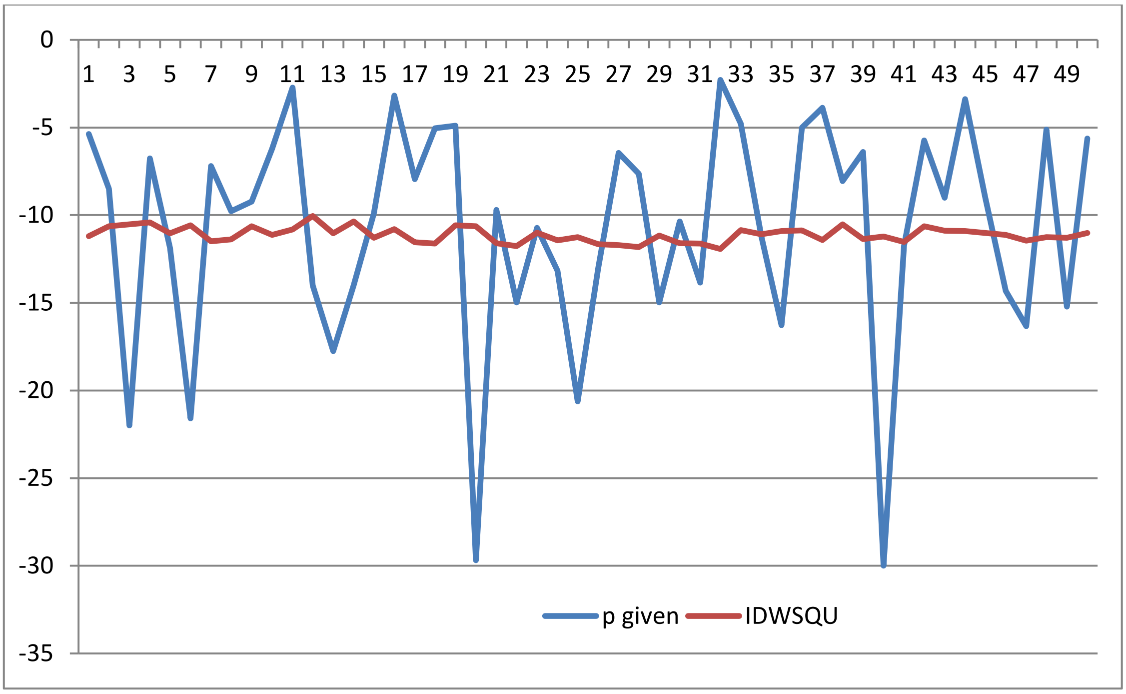
3.9 table (1) compares the five objective evaluation indices defined in 3.5 for the three algorithms at a frequency of 263.2148 MHz.

Table (1)
Compares the five objective evaluation indices defined in 3.5 for the three algorithms at a frequency of 263.2148 MHz.

	ALGO	IDW	IDWSQU
AEEP	-7.979787889	-20.83185285	-20.56436201
RELMSE	0.003658915	0.009551882	0.009429231
RMSE	6.384915063	10.31628663	10.24983964
Max_Err	34.04258976	63.62412487	63.35257744
Avg_Err	4.365355635	6.204105244	4.995278133

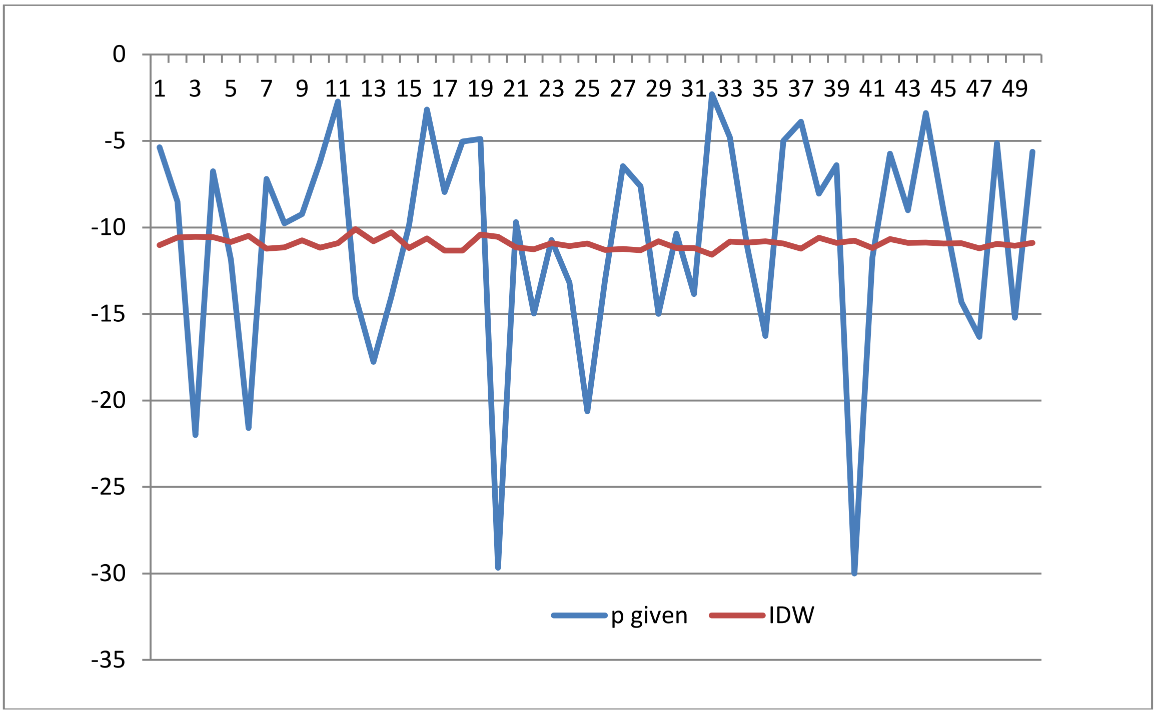
3.10 figure (5) shows the curves of real powers and expected powers using the Inverse Distance Squared algorithm of the whole fifty points (treated as unknowns and then estimated using Inverse Distance Squared algorithm)taken at a frequency of 600 MHz.

Figure(5)
Shows the curves of real powers and expected powers using IDWSQU at f=600MHz.



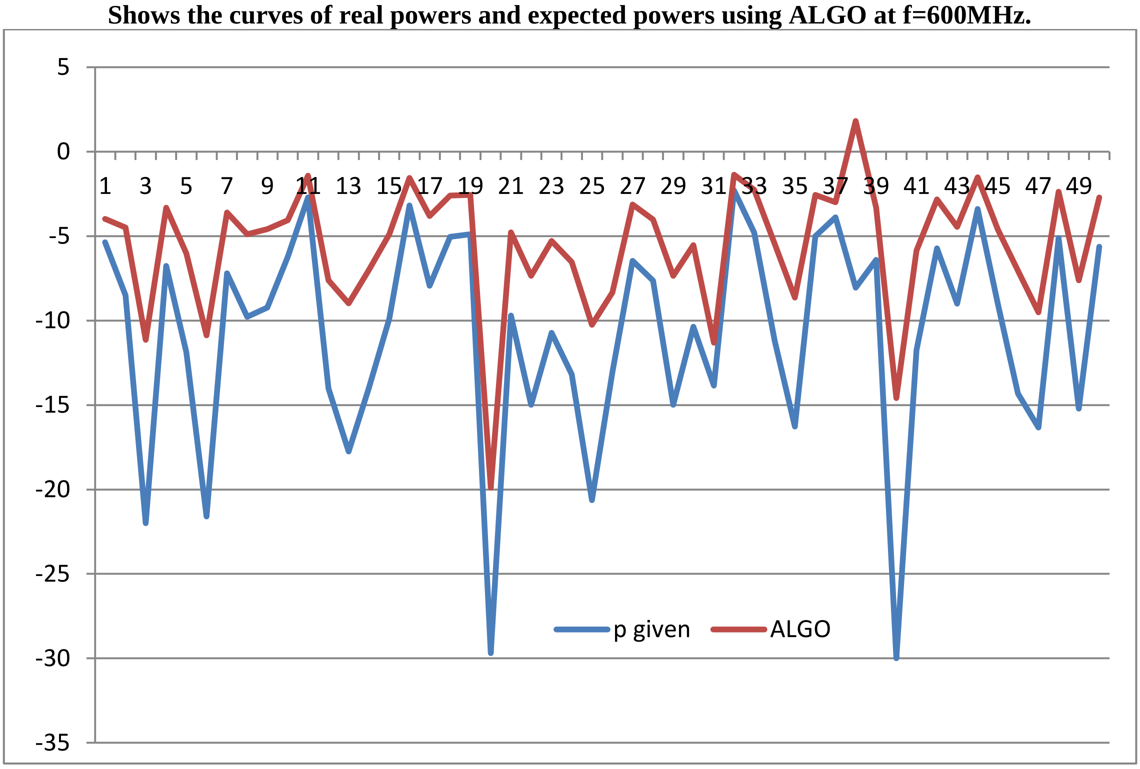
3.11figure (6) shows the curves of real powers and expected powers using the Inverse Distance algorithm of the whole fifty points (treated as unknowns and then estimated using Inverse Distance algorithm)taken frequency of 600 MHz.

Figure (6)
Shows the curves of real powers and expected powers using IDW at f=600MHz.



3.12 figure (7) shows the curves of real powers and expected powers using the Hybrid algorithm proposed in this paper of the whole fifty points(treated as unknowns and then estimated using the proposed algorithm) taken frequency of 600 MHz.

Figure (7)
Shows the curves of real powers and expected powers using ALGO at f=600MHz.



3.13table (2) compares the five objective evaluation indices defined in 3.5 for the three algorithms at a frequency of 600 MHz.

Table (2)
Powers and three-dimensional coordinates of fifty different points at a frequency of 600 MHz

	ALGO	IDW	IDWSQU
AEEP	-3.332002	-3.773065	-3.753388938
RELMSE	0.8918367	1.009891	1.004624179
RMSE	5.9798869	6.363375	6.346760598
Max_Err	1.8242065	-10.10416	-10.05338129
Avg_Err	-0.448179	-10.50261	-10.53823175

3.14 Discussion and Analysis

3.14.1 from 3.6, it was noticed that: the curve represents the estimated values of powers using the IDWSQU algorithm compared with the curve of real powers at a frequency of 263.2148 MHz, does not resemble nor the pattern neither the values in any way. The estimated values of powers curve using the IDWSQU algorithm is more like a linear curve rather than a regression curve following a certain pattern of distribution using a certain regression algorithm that depends on the inverse relationship with the squared distance contribution, i.e., near points powers contribute effectively into an estimation of the unknown point's power while far distant points' powers have neglectable contributions.

3.14.2 from 3.7, the same notice as in 3.14.1 is valid except that the curve of IDW estimated powers is supposed to follow a certain distribution depending on the inverse relationship with the distance (rather than the square of the distance as above) contribution, i.e., far distant points' powers have less more contribution than above. However, again the curve seems to be more linear and does not follow the pattern of the real powers' curve.

3.14.3 Now, from3.8 using the proposed Hybrid algorithm: the curve represents the estimated powers using the Hybrid algorithm has the same pattern of the curve representing the real powers, and even the values seem to be more like their analogous values in the other curve. However, it appears as if the Algo curve needs a mathematical electromotive force to push it up to match the Pgiven curve exactly.

Again we can notice that the similarity in the pattern appears everywhere except at the very beginning of the curve and the end of the curve, i.e., at so far distant points, although the similarity still exists.

Also, it must be noticed that: for similarity of values, it appears to be very clear in the range of powers between 10 and -10; and clearly, the maximum error appears to happen at the point where the power is near -70, which is far in the powers axis.

3.14.4 The table in section 3.9 shows that using those five objective evaluation indices, Algo has the lowest value for the five indices. Although for the Av_Err, the IDWSQU algorithm has a very close value to Algo, whereas, for Max_Err, both IDWSQU and IDW have nearly twice the value of that of Algo. Again for RMSE, both IDWSQU and IDW have nearly one and a half of that of Algo. For RELMSE, it is apparent that both well-known algorithms IDWSQU and IDW, have nearly three times that of Algo.

For AEEP, the two algorithms IDWSQU and IDW values have even more than twice that of our proposed algorithm Algo.

3.14.5 From 3.10, it is clear that the same discussion as in 3.14.1 could be repeated here; however, the operating frequency is 600 MHz instead of 263.2148 MHz.

3.14.6 Interpreting the graph in section 3.11, again, the same comments in section 3.14.2 could be repeated, taking in mind that the frequency is 600MHz.

3.14.7 Investigating the graph in section 3.12, we can repeat the same comments as in section 3.14.3; however, here, even for the far distant points, the pattern's similarity is pretty apparent. Also, even for odd values of powers, the similarity in values is clear.

3.14.8 For the table in setion3.13 we noticed the following:

For the AEEP, although the value for Algo is the lowest, the other two values for IDWSQU and IDW are very close to it.

Also for RELMSE the same above comment is valid.

One more time the same above comment could be repeated for RMSE.

However, for Max_Err, the value for both IDWSQU and IDW appears to be nearly six times that of Algo.

Again, for the Av_Err, the value for both algorithms IDWSQU and IDW reaches twenty-five multiples of Algo's.

IV. CONCLUSION AND RECOMMENDATIONS

The overall conclusion from the above discussion is the clarity of superiority of our proposed algorithm over the traditional algorithms (as in this paper IDWSQU and IDW) in so many ways, as pattern, values, evaluation indices, and also in dealing with odd points in both axes location and power.

Apparently, in our proposed algorithm, we introduced a new weighted algorithm depending on histogram concept, with an eye on traditional algorithms' concepts that take distance contribution into account in order to estimate the missing parameter, but in a new way by taking another weight of the average power of the nearest points to the point of interest, and the result is pretty good.

As a recommendation, different values for a and b could be taken (instead of a= b 0.5 as taken in this paper) and studied carefully in different frequencies and circumstances.

Also, it is recommended to use different techniques for the regression of the powers' curve and estimated value; for example, machine learning is a powerful tool that could be used extensively in this matter, leading to more accurate results.

Finally, our proposed algorithm could be used in so many applications besides power parameter estimation in Radio Environment Map.

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