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Parameter Estimation of Cellular Communication Systems Models in Computational MATLAB Environment: A Systematic Solver-based Numerical Optimization Approaches

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Abstract: Model-based parameter estimation, identification, and optimisation play a dominant role in many aspects of physical and operational processes in applied sciences, engineering, and other related disciplines. The intricate task involves engaging and fitting the most appropriate parametric model with nonlinear or linear features to experimental field datasets priori to selecting the best optimisation algorithm with the best configuration. Thus, the task is usually geared towards solving a clear optimsation problem. In this paper, a systematic-stepwise approach has been employed to review and benchmark six numerical-based optimization algorithms in MATLAB computational Environment. The algorithms include the Gradient Descent (GRA), Levenberg-Marguardt (LEM), Quasi-Newton (QAN), Gauss-Newton (GUN), Nelda-Meald (NEM), and Trust-Region-Dogleg (TRD). This has been accomplished by engaging them to solve an intricate radio frequency propagation modelling and parametric estimation in connection with practical spatial signal data. The spatial signal data were obtained via real-time field drive test conducted around six eNodeBs transmitters, with case studies taken from different terrains where 4G LTE transmitters are operational. Accordingly, three criteria in connection with rate of convergence Results show that the approximate hessian-based QAN algorithm, followed by the LEM algorithm yielded the best results in optimizing and estimating the RF propagation models parameters. The resultant approach and output of this paper will be of countless assets in assisting the end-users to select the most preferable optimization algorithm to handle their respective intricate problems.

Index Terms: Numerical Optimisation, Model-based Parameter Estimation, Convergence Criteria, Precision Accuracy, Propagation Model, Radio Frequency, Attenuation.

1. Introduction

Model-based parameter estimation, identification, and tuning, play a dominant role in many physical and operational processes in applied sciences, engineering, and other related disciplines. The main concept is to search for the unknown model parameters that precisely describe the real condition, such that the gap existing between the known experimental data variables and the computed model parameters is minimized, via least square fit. In general, there exist many parametric models that are often engaged by the RF engineers either at the design stage to boost the system network planning or optimization stage to further enhance the operational systems network performance. An example of such a model is the Signal Propagation Loss model (SPLM). It is a special spatial model for determining the attenuation loss of propagated signals between the transmitters and receivers in cellular communication systems.

One main problem with existing SPLMs such Hata, Egli, Lee, Walficsh-Bertoni, Walficsh-Ikegami, Cost 231-Hata and ITU is that none of them can be used accurately in a given environment without optimizing the parameters with field signal data taken from the environment of interest. The process of optimizing the parameters of an existing SPLM with field data for an improved prediction or estimation performance in the desired environment (i.e., terrain wherein it is to be applied) is called propagation model optimization or tuning. In prior works, different numerical optimization algorithms have been explored to tune SPLM parameters as a means of enhancing their precision performance during application. The constituents of these algorithms differ in many aspects and as such, they generate different solutions under different or similar constraints, when they are engaged.

2. Related Works and Research Motivation

Predictive modelling for parameter identification using the trust-region method is presented in [1]. From the results, it was discovered that Quasi-Newton algorithm is more robust and computationally effective in identifying bolted joint parameters. Also, in [2], Quasi-Newton numerical based algorithm is proposed and explored to solve an unconstrained optimization problem. The results point out that the engaged algorithm is very viable as it achieved lesser function evaluations and iterations compared to the BFGS method. A new Dogleg algorithm is proposed in [3] to solve the trust-region sub problem by considering two paths construction method. The authors incorporated the paths conditions into the algorithm as a means of determining the best smooth function point. The numerical centered experiments results showed that the new dogleg algorithm was more robust and efficient when compared to the classic Dogleg algorithm.

Genetic algorithm is presented in [4] for parametric model tuning via Matlab-based test benchmarking. The experiment based global results point out the selecting the best method of tuning parameters for a specific application. The simplex algorithm is presented in [5], to search and identify the parameters of the Muskingum model. With the simplex algorithm, a near-optimum solution results 84.8% were achieved. The high sensitivity of the algorithm to the initial parameter values was also reported by the authors. A simplex modelling technique is investigated in [6, 7] to enhance parametric estimation of the Muskingum model and up to 29%parametric fitting was realized. The authors in [8] utilised two hybrid algorithms to resolve two NP-hard combinatorial optimisation problems. From the two algorithms, the authors reported that the merge, solve and adapt (CMSA) outperform the large neighborhood search (LNS). More specifically, different comparative study involving the, the weighted least square regression, global search, ordinary least square regression, Gauss-Newton and Levenberg-Marguardt algorithms are reported in [9-14].

In this paper, an expanded comparative study involving six numerical optimization algorithms is investigated for practical application. The algorithms include the Gradient Descent (GRA), Levenberg-Marguardt (LEM), Quasi-Newton (QAN), Gauss-Newton (GUN), Nelda-Meald (NEM), and Trust-Region-Dogleg (TRD). This has been accomplished by engaging them to solve intricate radio frequency propagation modelling and parametric estimation in connection with practical spatial signal data. The spatial signal data were obtained via real-time field drive test conducted around six eNodeBs transmitters, with case studies taken from different terrains where 4G LTE transmitters are operational. The comparative analysis of the six solvers has been actualized in terms of optimization errors and precision capabilities in solving the intended problem. Accordingly, provided below are the highlights of our key contribution attained in this thesis:

- Robust signal propagation loss data measurement in predefined environment to create room for an adept analysis of results
- Identification and application of six numerical based optimization algorithms for impact analysis in solving the real-time propagation model optimization problems
- Application of relevant key performance indicators to provide detailed performance strength and weakness of the each numerical optimsation algorithms

In the rest of the paper, the generic propagation model whose parameters are to be optimised is described in section 2. The list of the numerical optimization algorithms considered and their method of implementation for the propagation model tuning is provided in Section 3. The numerical optimization results, discussion, and the concluding part of the paper are contained sections in 4 and 5.

3. Methodology

In this paper, a systematic-stepwise approach has been employed to review and benchmark six numerical-based optimization algorithms in MATLAB computational Environment. The algorithms include the Gradient Descent (GRA), Levenberg-Marguardt (LEM), Quasi-Newton (QAN), Gauss-Newton (GUN), Nelda-Meald (NEM), and Trust-Region-Dogleg (TRD). This has been accomplished by engaging them to solve an intricate radio frequency propagation modelling and parametric estimation in connection with practical spatial signal data. The spatial signal data were obtained via real-time field drive test conducted around six eNodeBs transmitters, with case studies taken from different terrains where 4G LTE transmitters are operational. The work flow is shown in Figure 1 and the implementation steps involved in using solver-based approach is as follows:

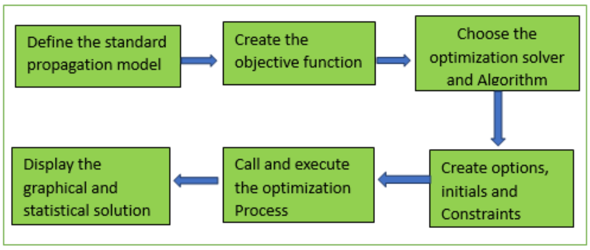

Fig.1. A Stepwise Methodology and implementation workflow

- define the problem objective function in MATLAB format
  - problem.objective = @(p) p(1)+p(2)* log10(X)+p(3)*log10(2600)
  - objFun = @(p) norm(fun(p)-Y);
- create the options, initials and constraints required to solve or unbundle the problem structure
  - options = optimoptions('fminunc');
  - a = [];
  - b = [];
  - Intials, p_0 = [0,0,0];
- select the problem solver to use.
  - problem.solver = 'fminunc';
- select the optimization algorithm to solve the problem.
  - optimoptions('Algorithm','Algorithm-name');
- define the metric to evaluate the performance of the chosen algorithm as shown in equation (6)
- iteratively display the entire solution
- statistically display the objective function value attained at the solution
  - fvals = [fgn; flm; fgd; fqn; ftr; fnm];
  - fevals = [ogn.funcCount;olm.funcCount; ogd.funcCount; oqn.funcCount; otr.funcCount; onm.funcCount];
  - stats = table(sols,fvals,fevals);
- track the problem with a different optimization algorithm, until all the algorithms are examined
- examine the respective solution of the optimization algorithm for comparative analysis

3.1. Standard Propagation Model

The standard propagation model consisting of three key parameters to be estimated is considered in this paper. The model is expressed in equation (2). For the purpose of clarity, we represent the model parameters as the spatial distance independent variables and the measurement values belonging to the acquired field data through the drive test as the dependent variables.

The objective function, which is to be optimized using the various numerical-based optimization algorithms is revealed in equation (6). The objective function connects the standard propagation model parameters and the values measured field data values. It is expected that the objective function or model is solvable using the various optimization algorithm with respect to the modeling the parameters to be estimated

The parametised Hata model is considered is this paper, and it is given by

$$PL_p(dB) = P_1 + P_2 log10(f) - P_3 log10(H_e) - c(h_r) + (P_4 - P_5 log10(H_e))log10(d) \\ +(P_4 - P_5 log10(H_e))log10(d) \tag{1}$$

PL_p, h_r,$H_e$and f represent the propagation loss, the receiver height, the eNodeB height and carrier frequency.

In a generalized form, equation (1) can be rewritten as:

$$PL_p(dB) = V_1 + 10.V_2 log10(f) + V_3 log10(d) \tag{2}$$

$$V_1 = P_1 + c(h_r) - P_3 log10(H_e) \tag{3}$$

$$V_2 = P_2 \tag{4}$$

$$V_3 = P_4 - P_5 log10(H_e) \tag{5}$$

The unknown parameter: V_1, V_2 and $V_3$of the standard propagation model expressed in Equation (2), are key focused parameters that need to be estimated in connection with field data, using numerical based optimization algorithms.

3.2. Optimisation Algorithms

Parametric model-based problem solving via optimization techniques is geared toward the determination or identification of the intended model parameters through maximization or minimization of an objective function. In this paper, we consider solving an unconstrained objective function problem expressed through minimizing the residual standard error (RSE):

$$min_{\boldsymbol{V}}\, RSE = \left[\sum_{i=1}^{n}[y_i - f(d_i, \boldsymbol{V})]^2 / df\right]^{0.5} \tag{6}$$

$$Subject\ to: RSE^c \le \varepsilon \tag{7}$$

where

$$f(d_i, \boldsymbol{V}) = V_1 + V_2 log10(f) + V_3 log10\ (d_i) \qquad \text{i=1, 2, …, n} \tag{8}$$

with $\boldsymbol{V} = (V_1, V_2 \text{and } V_3)$ representing the unknown parameters vector, $y$the measured field data, and c the constraint modes number. df =(n-N) indicates the degree of freedom. N and n indicate the number of unknown parameters and the measured field dada number

The gradient and Hessian of the residual function are as follows:

$$\boldsymbol{g}(V_j) = \frac{\partial RSE(\boldsymbol{V})}{\partial V_j} = -2\sum_{i=1}^{n}[y_i - f(d_i, \boldsymbol{V})]\frac{\partial f_i(\boldsymbol{V})}{\partial V_j} \tag{9}$$

$$\boldsymbol{H}[V]_{jk} = \frac{\partial^2 RSE(\boldsymbol{V})}{\partial V_j \partial V_k} = -2\sum_{i=1}^{n}\frac{\partial f_i(\boldsymbol{V})}{\partial V_j}\frac{\partial f_i(\boldsymbol{V})}{\partial V_j} - (y_i - f(d_i, \boldsymbol{V}))\frac{\partial^2 f_i(\boldsymbol{V})}{\partial V_j \partial V_k} \tag{10}$$

In terms of Jacobian, J, the expression in equations (9) and (10) as:

$$g(\boldsymbol{V}) = \frac{\partial RSE(\boldsymbol{V})}{\partial \boldsymbol{V}} = -2J\boldsymbol{r}(\boldsymbol{V}) \tag{11}$$

$$H(\boldsymbol{V}) = \frac{\partial^2 RE(\boldsymbol{V})}{\partial V_j \partial V_k} = 2(J^{\mathrm{l}}J - \sum_{i=1}^{n} r_i(\boldsymbol{V}))\boldsymbol{H}_i^*(V)) \tag{12}$$

where

$$\boldsymbol{r} = (y_i - f(\boldsymbol{V}) \tag{13}$$

With exception to Nelder-Mead (NEM) which is a non-derivattive optimizer, other onesnamely the Gauss-Newton (GUN), Levenberg-marguardt (LEM, Gradient Descent (GRA), Quasi-Newton (QAN), and Trust-Region-Dogleg can be explored to estimate the unknown parameters iteratively in terms of the Jacobian,Gradient and Hessian expressions in table 1. Iteratively" implies that it utilises a sequence of computations (based on chosen initial ues) to find the solution

Table 1. A

SN	Algorithm	Description	Iteration update procedure
1	Gauss-Newton (GUN)	The GUN is an approximation or a simplification of the Newton method for iteratively solving the optimization problem	$V_{z+1} = V_z - (J_z J_z^T)^{-1} J_z^T(\boldsymbol{r})$
2	Gradient Descent (GRD)	The GU uses the 1st order derivative to carry out theiterative update in determining the itsin determining the unknown parameter vector, ***V***	$V_{z+1} = V_z - J^T(\boldsymbol{r})$
3	Levenberg-Maguardt (LEM)	The unknown parameter vector, ***V*** is determined iteratively by the LEM algorithm using the combined strength of GUN and GRD	$V_{z+1} = (J_z J_z^T + I\omega)^{-1} J_z^T(\boldsymbol{r})$
4	Quasi-Newton (QAN)	The QAN explores the approximate Hessian matrix version in place of the full Hessian matrix for its iterative update in determining the unknown parameter vector, ***V***	$V_{z+1} = u^T J^T S(\boldsymbol{r}) + \frac{1}{2} u^T J^T J$
5	Trust-Region-Dogled (TRD)	With TRD, the unknown parameter vector, ***V*** is determined iteratively by emploing the combined strength of the Hesian matrix and GRD	$V_{z+1} = \gamma_z - \alpha(B_z)^{-1} J_z^T(\boldsymbol{r})$
6	Nelder-Mead (NEM)	NEM is non-derivative direct search method wherein the unknown parameter vector, ***V*** is determined iteratively using a sequence of simplices, S, and vertices function $f(V_z)$ evaluations	$S_{z+1} = f(V_1) \leq f(V_2) \ldots, f(V_{z+1})$

In table 1, where *z* indicates the iteration number and the QAN approximate hessian, B_z is given by:

$$B_{z+1} = D_z^T B_z D_z + q_z s_z^T s_z \frac{B_z K_z^T}{q_z^T s_z} \tag{14}$$

$$q_{tz} = \frac{1}{q_z^T s_z} \tag{15}$$

$$D_z D_z^T = 1_z + q_z s_z^T s_z \tag{16}$$

3.3. *Field Measured Data*

Conducting a real-time field test signal measurements in an area as a means of optimizing the parameters of existing propagation loss model, clearly, has an added advantage of involving the terrain effects. The signal propagation loss data utilised in this paper was obtained from a commercial cellular communication system service provider, operating in Akwa, Anambra State, Nigeria. The cellular system operates the fourth generation (4G) LTE networks. In the networks, three eNodeB antennas whose heights ranged from 30-34m were engaged for the signal propagation loss collection. Each eNodeB transmits with the following parameters: antenna gain, Gt=17.5dBi, transmit power, Tp=20w, carrier frequency=2600MHz, and bandwidth, B=10MHz with professional TEMS empowered tools, involving the connected to Samsung Galaxy phone, Sony Ericson phone, scanner, Dwell laptop, cell info, Dongle and GPS, the field data was conducted via drive test around the terrains of interest. With the testing tools locked to 4G LTE frequency and running on the TEMS software mode, automated calls were made and save in log-files.

4. Results and Discussions

Here, the performance of the respective six numerical optimization algorithms is examined in terms of their capacity to solve the parametric path loss modelling problem. The first contains the estimated model parameters attained using the six numerical optimization algorithms. The second contains the precision performance attained by each algorithm in connection with the estimated parameters. To quantitatively benchmark precision performances, we employ two indicators namely mean percentage error (MAPE) and root mean square error (RMSE). The third part concentrates on the function evaluation value achieved in connection with rate of convergence. The first is function evaluation number achieved as defined in equation (2). For reference purpose, all codes, computations and graphics were accomplished using the standard laptop computer with 3.00 GHz processor, 16 GB RAM and Intel(R) Core(TM) i5-8500 CPU features.

4.1. Estimated Propagation Model Parameters

Each optimizer begins iteratively at the suggested initial guess values, [1, 4] intended for parameter V1, V2, V3, and then the progresses to perform more transitional computations and successive approximations that finally results to new parameters of the local minimum as reported in Table 1-3. Shown in Tables1-3 are the estimated propagation model parameter values for V1, V2 and V3 obtained using the respective numerical optimization algorithm (Optimiser) in connection with the expression in equation (2). Among other ones, V2 is an important cellular network planning parameter called the propagation-loss exponent and it expresses the rate of signal power fluctuation and attenuation with respect to terrain profile and communication distance. V1 represents the collective value average over the signal power plus terrain offsets and its value depends on a given carrier frequency and reference distance. The parametric estimation error attained by each numerical optimizer is shown in subsection (2) for further analysis.

Table 1. Estimated Parameters by each Optimiser in location 1

Algorithm	P1	P2	P3
GUN	10.00	20.00	22.56
LEM	6.62	26.86	18.46
GRA	8.40	18.20	24.56
QAN	6.58	27.02	18.35
TRD	6.62	26.86	18.47
NEM	10.67	22.33	20.00

Table 2. Estimated parameters by each optimiser in location 2

Algorithm	P1	P2	P3
GUN	10.00	20.00	22.59
LEM	6.78	26.29	19.01
GRA	6.91	25.68	19.44
QAN	6.71	26.60	18.78
TRD	6.72	25.61	19.50
NEM	10.37	22.04	22.22

Table 3. Estimated parameters by each optimiser in location 3

Algorithm	P1	P2	P3
GUN	10.00	20.00	22.00
LEM	6.32	27.98	17.37
GRA	8.16	19.03	23.71
QAN	5.49	31.84	14.62
TRD	7.13	23.99	20.21
NEM	10.67	22.33	20.00

4.2. Analysis of Precision Performance Using Some Standard Indicators

Here, firstly, we employ a number of standard metrics such as MAE, RMSE, MSE and MAPE, to assess the precision performance of each numerical optimizer, as shown in Figures 2 - 4 and summarized in Tables 4 - 6. The challenge with these indicators is that they often provide same performance results for optimizers with close similarities, even when they possess different problem-solving capacities. For example, Figures 4-6 and Tables 4-6 both reveals that LEM, QAN and TRD achieve the same performance with MAPE, MAE, SE, and RMSE values. To solve the problem, we introduced two more key performance distinguishing indicators such as RSE and objective function value. The details performance of each optimizer with these two indictors are shown in the next subsections. In Figure 2, LEM, TRD and QAN attained the best MAPE values of 2.03 dB each, while NEM, GRD and GRA attained the poorest performance with MAPE values of 2.71, 2.41 and 2.31 dB respectively. Similar performance is also achieved by LEM, TRD, QAN and NEM, GRD, GRA in locations 2 and 3.

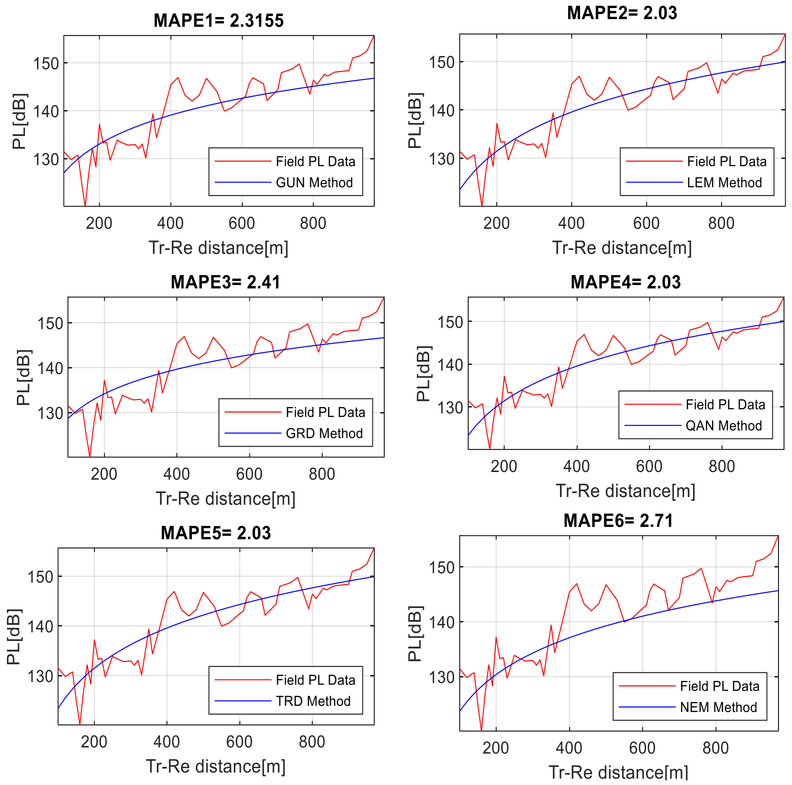

Fig.2. Optimised model fitting analysis with mean percentage error (MAPE) in location 1

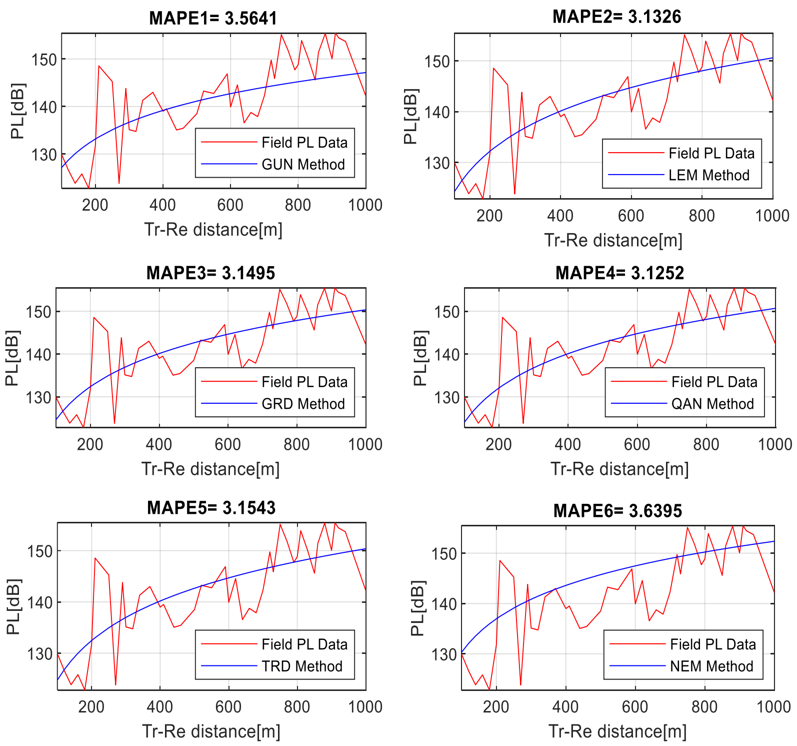

Fig.3. Optimised model fitting analysis with mean percentage error (MAPE) in location 2

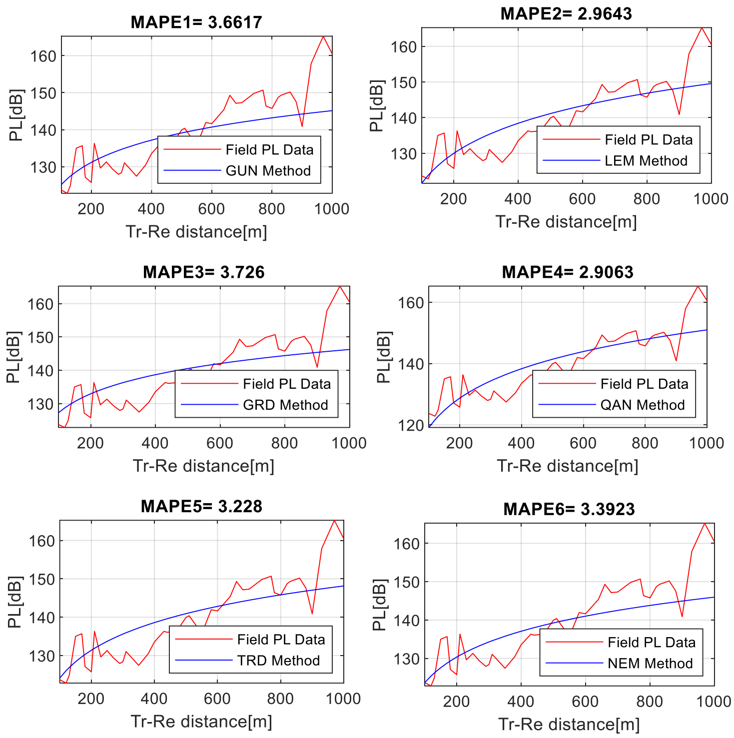

Fig.4. Optimised model fitting analysis with mean percentage error (MAPE) in location 3

Table 4. Precision performance of algorithm using some standard indicators

Location	Metric	GUN	LEM	GRD	GAN	TRD	NEM
1	MAE	3.21	2.79	3.36	2.79	2.79	3.73
	MAPE	2.31	2.93	2.41	2.03	2.03	2.03
	RMSE	3.98	2.44	3.19	3.44	3.44	4.49
2	MAE	5.00	4.41	4.44	4.40	4.44	5.23
	MAPE	3.56	3.13	3.14	3.12	3.15	3.15
	RMSE	6.02	5.57	5.58	5.57	5.58	6.51
3	MAE	5.09	4.13	5.19	4.02	5.51	4.72
	MAPE	3.66	2.96	3.72	2.90	3.22	3.22
	RMSE	6.37	5.33	6.36	5.22	5.67	6.06

4.3. Analysis of Precision Performance using Residual Standard Deviation (RSE) Indicator

The RSE is introduced as a key indicator here to enable us use to choose an optimizer with a better solution. Each optimizer performance is classified as follows: The solution quality is 'Excellent' if the RSE value is less than 0.001, 'Good' if it is greater than 0.01, 'Poor', if is greater than 0.1 and 'Mediocre' if it is greater than 1. Accordingly, Figure 5-7 display the RSE values achieved by six the optimization algorithms. The QAN achieved 0.000001, 0.00005, and 0.0045 RSE values to provide the best solution qualities in locations 1-3. The LEM and TR achieved 0.001, 0.005, 0.003, and 0.0051, 0.002, 0.0033 RSE values to provide good solution qualities in the same locations. The GUN and GRD achieved 0.664, 0.5, 1.536, 1.606and 0.51, 0.106, 0.05, 0.0 4RSE values to provide poor solution qualities in the same locations. The worst solution quality is achieved by the NEM as seen in Figures 5-7, with 2.23, 3.23, and 2.51 RSE values. The NEM yielded poor solution because its optimization approach is without derivative information. For the GRD, its single derivative optimization approach could not boost its performance. These results could imply that the hessian and gradient-based approach with derivative enough inbuilt derivative information are better solution providers to solving the optimization problems. The QAN explores the approximate Hessian matrix version in place of the full Hessian matrix for its iterative update in determining the unknown parameter vector, V. This empowers algorithm to converge to the optimum more quickly and in turn yielding better solutions.

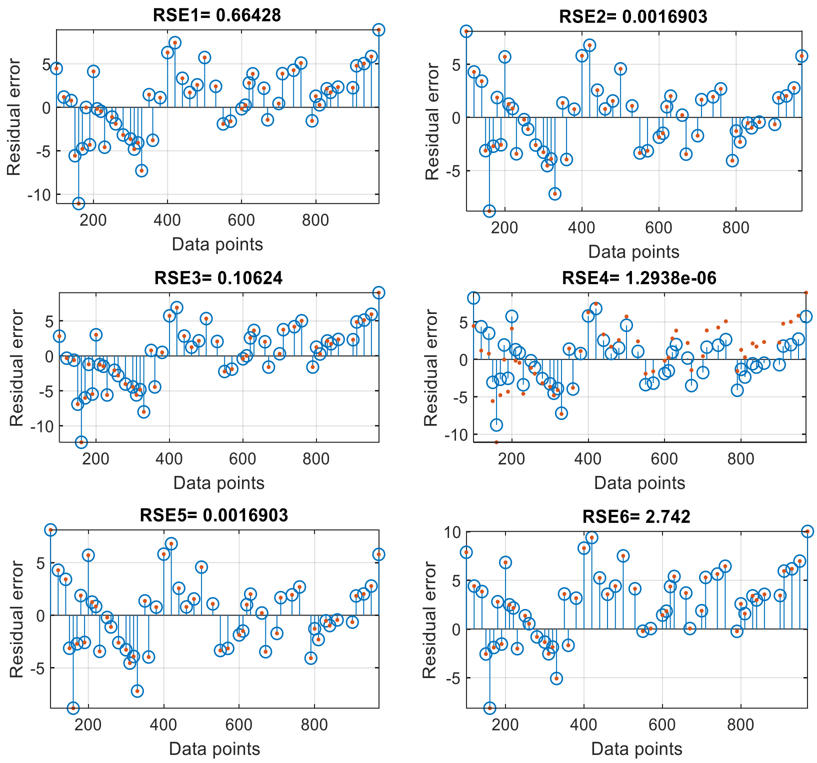

Fig.5. Precision error analysis with residual standard error (RSE) in location 1

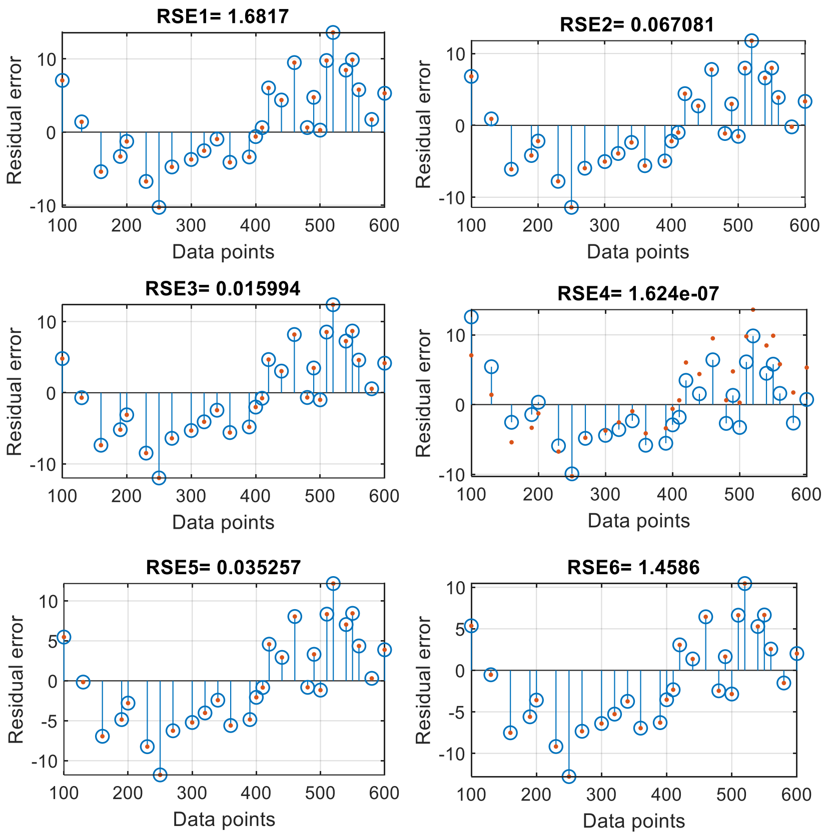

Fig.6. Precision Error Analysis with Residual Standard Error (RSE) in location 2

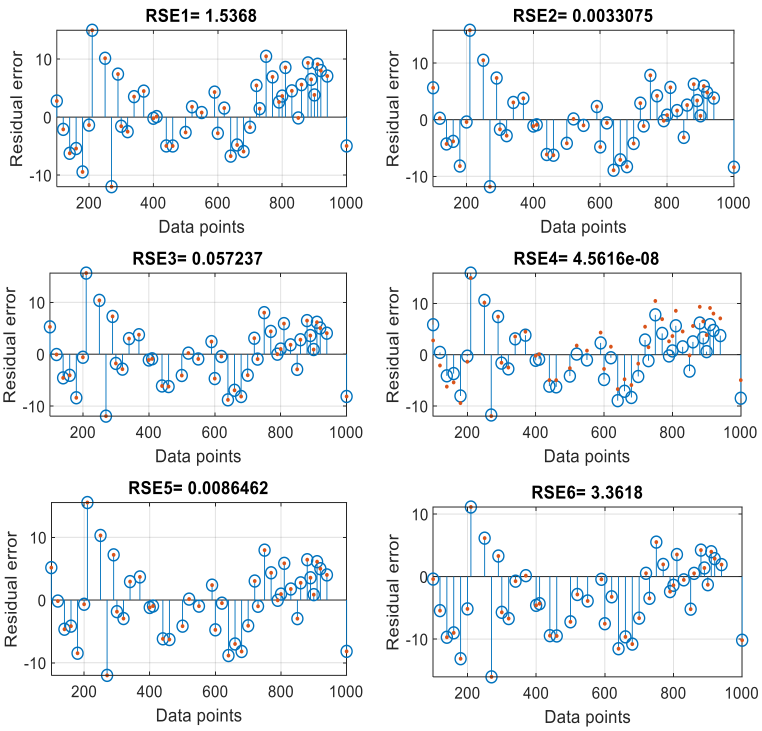

Fig.7. Precision error analysis with residual standard error (RSE) in location 3

4.4. Analysis of Function Evaluation Value (Fval) Versus Number of Evaluations (NumEval)

Figures 8-10 display the computed Number of evaluated (NumEval) versus function evaluated value (FVal) during the optimization process. The FVal is key term in MATLAB for evaluating objective function output. As the numerical opimiser (algorithm) is lunch, the FVal iteratively decreases and moves towards feasible direction (zero value) until the optimization is completed. Hence, with FVal, lower value is mostly preferred, irrespective of the NumEval value. The graphical figures below shows that QAN provides best optimisation performance as it attains the least objective function value of 24.866, 37.394, and 33.47 in locations 1-3.LEM and TRD also achieved similar low objective function values but by taking over four to five times as function evaluations of QAN. The worst objective function values are provided by GUN, GRD, and NEM algorithms.

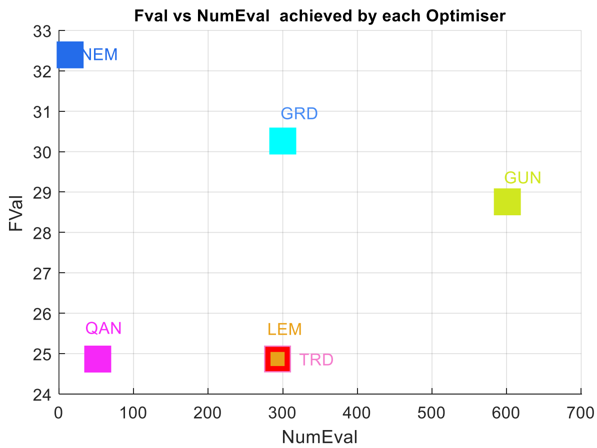

Fig.8. Function evaluation value (Fval) achieved by each numerical optimiser in location 1

The entire performance summary of the six algorithms in terms of solution quality, RSE values, FVal and NumEval are shown in Tables 5-7. An algorithm with the smallest RSE and FVal value is most preferred. Tables 5-7 shows that the QAN yield excellent solution quality with lowest RSE and FVAL values of 1.29e-06 and 24.866 in location 1, 4.56e-08 and 37.394 in location 2, 3.791e-07 and 33.47 in location 3. The LEM, GRD and TRD yielded good solution qualities with RSE values of 0.00169, 0.106, 0.00169, and FVAL values of 24.866, 24.866, 24.866 in location 1; with RSE values of 0.00330, 0.057, 0.0086 and FVAL values 37.39, 37.43, 37.43 in location 2, with RSE values of 0.0091, 0.042, 0.0487, and FVAL values 34.18, 36.34in location 3. The GUN and NEM yielded poor solution qualities with RSE values of 0.664, 2.74, and FVAL values of 40.40 43.69 in location 1; with RSE values of 1.53, 3.36 and FVAL values 40.40, 43.69 in location 2, with RSE values of 1.60, 1.64 and FVAL values 40.82, 38.84 in location 3.

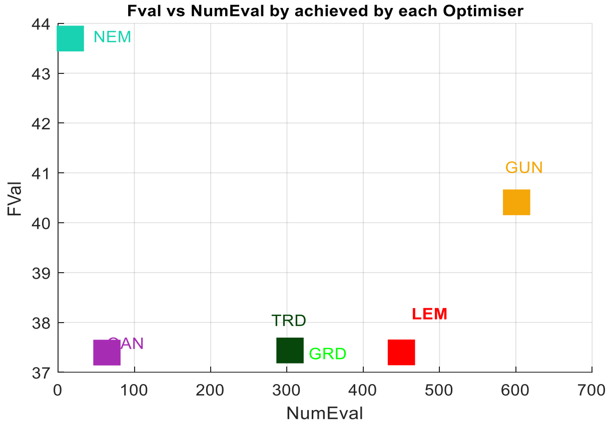

Fig.9. Function evaluation value (FVal) achieved by each numerical optimiser in location 2

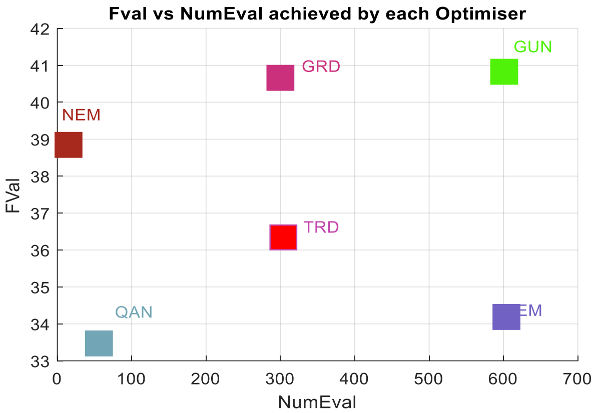

Fig.10. Function evaluation value (Fval) achieved by each numerical optimiser in location 3

Table 5. Performance summary of the six algorithms with four different indicators in location1

Algorithm	Solution-Quality	RSE	FVal	NumEval
'GUN'	'Poor'	0.66428	28.758	601
'LEM'	'Good'	0.00169	24.868	293
'GRD'	'Poor'	0.10624	30.262	300
'QAN'	'excellent'	1.29e-06	24.866	52
'TRD'	'Good'	0.00169	24.868	293
'NEM'	'Poor'	2.742	32.395	15

Table 6. Performance summary of the six algorithms with four different indicators in location 2

Algorithm	Solution-Quality	RSE	FVal	NumEval
'GUN'	'Poor'	1.5368	40.409	601
'LEM'	'Good'	0.00330	37.398	450
'GRD'	'Good'	0.05723	37.433	300
'QAN'	'excellent'	4.56e-08	37.394	64
'TRD'	'Good'	0.008646	37.437	304
'NEM'	'Poor'	3.3618	43.695	16

Table 7. Performance summary of the six algorithms with four different indicators in location 3

Algorithm	Solution-Quality	RSE	FVal	NumEval
'GUN'	'Poor'	1.6062	40.825	601
'LEM'	'Good'	0.00915	34.187	604
'GRD'	'Good'	0.042562	40.661	300
'QAN'	'excellent'	3.791e-07	33.47	56
'TRD'	'Poor'	0.048732	36.341	304
'NEM'	'Poor'	1.6423	38.846	15

5. Conclusions

Optimization of predictive modelling parameters plays key decisive roles in many areas of physical sciences and engineering applications. A key example is in the area propagation model tuning to fit into field measured signal data during cellular network design, analysis, and management. There exist numerous optimization solvers (algorithms) that has been developed at different point in time for resolving complex problems. The design constituents or elements these algorithms depend largely on the specific problem to be solved by them. In general, there is no optimization algorithm that has the capacity to handle all kinds of real-time problems.

Thus, the need to conduct an in-depth performance application analysis of these optimization algorithms is self-evident and justified. Accordingly, this paper was motivated to identify some key numerical-based optimisation algorithms and analyses their performance in solving parametric propagation loss model problem over cellular network interface.

Specifically, this paper offered a thorough benchmarking analysis of six different numerical based optimization algorithms and their prognostic identification capacity on propagation loss model parameters have been revealed using different performance metrics. Consequently, three criteria in connection with rate of convergence were explored to quantitatively benchmark the respective six optimization algorithms. The first is precision accuracy attained by each algorithm in the parametric estimation process using standard key performance metrics such mean percentage error (MAPE) and root mean square error (RMSE). The second is residual standard error (RSE) which has a better dimension to reveal each algorithm precision performance. The third is function evaluation number achieved during the parametric estimation process. Results show that the six algorithms achieved good precision outcome, However, the approximate hessian-based Quasi-Newton and Levenberg-Marguardt (damped Gauss-Newton) algorithms yielded the best results in optimizing the RF propagation models parameters with most preferred computational times. The approach and the resultant output of this paper can aid to guide end-users in pick out the best choice of algorithm to solving specific real-world multipart problems.

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