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Path Loss Minimization in GSM Networks - A study of 2 Metaphorless Optimization Approaches

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ABSTRACT

The problem of existing modern path loss minimization AI models borders on the aspect of needless complexity and unwarranted use of metaphors. This research proposes an alternative strategy that is purely mathematical based and very simple to apply. The strategy employs the Rao-type optimizer (RaoO) and the Sine Cosine Optimizer (SCO) proposed. The approach is applied to modeling a case study dataset with the integration of Cost-232 Hata model in an error-loss minimization objective. The results agree with those reported in similar studies and using available case data. The results further show that the SCO approach gives better fit with lower path loss when compared to the RaoO.

Key words: *Dynamic Programming, GSM, Path loss, MetaphorlessOptimization*

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I. Introduction

The transmission and reception of signals in GSM networks typically faces the problem of propagation loss or attenuation. This is mainly attributed to both operational and structural issues; for instance the frequency of operation, height and type of transmitter tower in addition to the presence of obstacles (such as is in found in high rise buildings in urban centers) on path of propagation.In this regard, researchers have sought a variety of approaches – both classical (Dalela et al., 2012; Okorogu et al., 2013) and modern (Sah & Kumar, 2009) to minimize these losses.Jadhav and Kale (2015), developed an optimized path loss model for the Maharashtra city in India using different path loss models. Their model fitting process was described as a sum-of-deviation squares function for which the minimum (least) state is desired. Furthermore researchers have explored the use of Artificial Bee Colony (ABC) technique to optimize base transceiver locations (Singh & Kaur, 2013). Their key idea was to determine the minimum number of BTSs based on their location(s) that can serve a large number of subscribers at lower infrastructural cost.Nadir &Suwailam(2014)had developed non-optimal path loss predictions for the Okumura-Hata model and applied to the semi-urban and urban environments.

While several of the aforementioned researches are statistical – they do not employ a dynamic structure in the solution process and hence will always get stuck in local-minima. The modern dynamic approaches have been found to be mainly nature inspired and a great many exist that may not necessarily give the optimum or less complex solution.

In this research study, an alternative approach to solving the PLMP based on two metaphorlessdynamic approaches called the Rao Optimizer (RaoO) and the Sine Cosine Optimizer (SCO) are proposed.

II. Methodology

The study methods considered in this research employs the techniques of mathematical optimization that dynamically solves the given PLMP problem – in this case the identification of the best set of operational parameters that minimizes the path loss.

The data employed for model simulations were obtained from the research on path loss optimization of urban and semi-urban environmentsconducted earlier in (Marderni&Priya, 2010).

The RaoO and SCO methods are described in the sub-sections that follow.

2.1. RaoO Technique

Rao Optimizer (RaoO)is a best-worst approach that employs a population search strategy using purely mathematical formula (Rao, 2020; Jagun et al., 2020).

The solution process is mathematically described as follows:

$$X_{j,k,i}^{new} = X_{j,k,i}^{old} + r_{1,j,i}\left(X_{j,best,i} - X_{j,worst,i}\right). \quad (1)$$

where,
$X_{j,k,i}^{old}$ = the initial or past candidate value of *j-th* variable for *k-th*candidate at *i-th* iteration

$r_{1,j,i}$ = a random perturbation factor of *j-th* variable at *i-th* iteration

$X_{j,best,i}$ = the best (minimum) candidate value of *j-th* variable at *i-th* iteration

$X_{j,worst,i}$ = the worst (maximum) candidate value of *j-th* variable at *i-th* iteration

The model process requires only two tuning parameters: the population size, and the number of generations (iterations) as described in (Rao, 2020).

2.2. SCO Technique

Sine Cosine Optimization Algorithm (SCO) is a mathematical population based optimizer that was introduced earlier in (Mirjalili, 2016). Interestingly, it is very fast and performs very well and easy to implement. Rather than use metaphors such as bio-inspiration (e.g. genetic algorithms), swarming behavior (e.g. bee colony algorithms) it exploits a mixture of sine and cosine functions to find good solutions to optimization problems. For the SCO, it's search and update strategy is as defined following the convention of explorative and exploitative phases (Mirjalili, 2016):

$$X_i^{t+1} = \begin{cases} X_i^t + r_1 \times \sin(r_2) \times \left| r_3 P_i^t - X_i^t \right|, r_4 < 0.5 \\ X_i^t + r_1 \times \cos(r_2) \times \left| r_3 P_i^t - X_i^t \right|, r_4 \geq 0.5 \end{cases} \tag{3.2}$$

where,
X_i^t = current solution position in i-*th*dimension and at *t-th* iteration

r_1, r_2, r_3 = random numbers

r_4 = random number in the range 0 and 1

As in RaoO, the SCO equally emphasizes two parameters namely the number of search agents and the number of iterations.

2.3. Objective Function Formulation

The PLMP objective function is described as follows:
Minimize:

$$f_{obj} = \sum \left| P_{l(measured)} - P_{(\cos t-231)} \right| \tag{3.3}$$

s.t. constraints:

$$h_{cpe}^{\min} \leq h_{cpe} \leq h_{cpe}^{\max} \tag{3.4}$$

$$h_{base}^{\min} \leq h_{base} \leq h_{base}^{\max} \tag{3.5}$$

$$f_{base}^{\min} \leq f_{base} \leq f_{base}^{\max} \tag{3.6}$$

where,
$P_{l(measured)}$ = measured path-loss

$P_{(\cos t-231)}$ = estimated path-loss based on Cost-231 Hata

h_{cpe} = customer premise equipment height, m

h_{base} = height of base station (BS), m

f_{base} = base station transmitting frequency, MHz

III. Results and Discussion

3.1. Simulation Details

Simulation experimentshave been conducted on an Intel i-core-5 PC and using the MATLAB R2007b software algorithm programming.

For the RaoO approach the population size and number of iterations were set to 5 and 100 respectively while for the SCO, the number of search agents and number of iterations were similarly set to 5 and 100 respectively. This ensures that both techniques had un-biased parameterization settings.

3.2. Comparative Simulation Results

The results showing the optimal performance of the RaoO and SCO at first trial run are as shown in Figure 1.

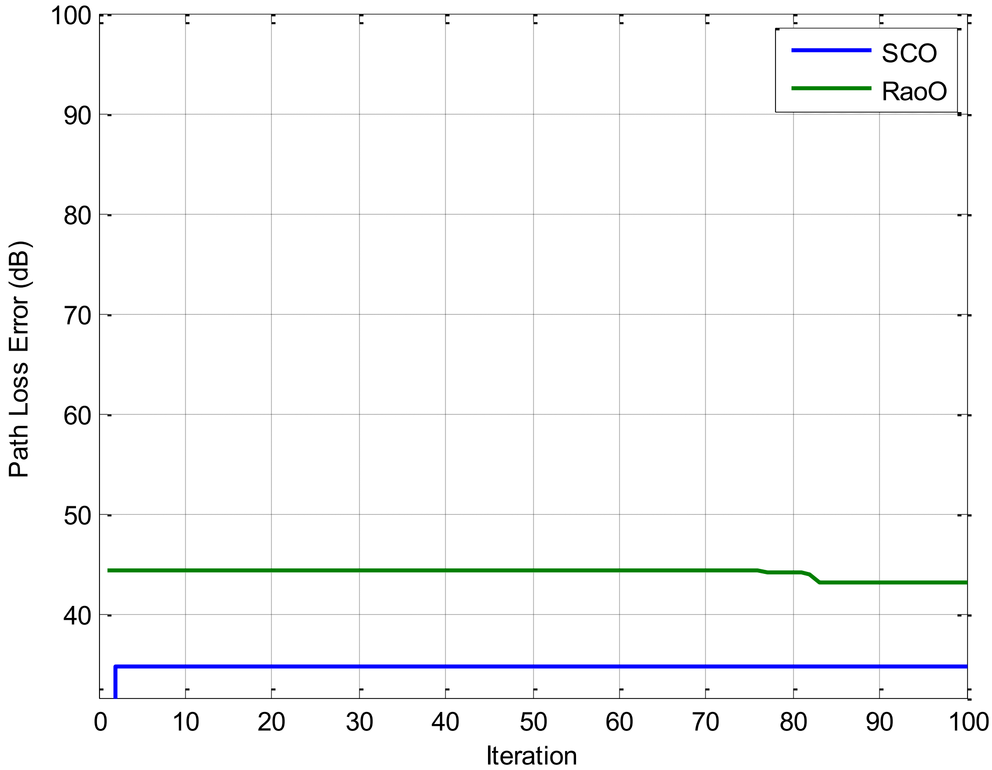

Figure 1: Predicted Path-loss for SCO andRaoO techniques

As can be seen from Figure 1, the SCO path loss estimate is much lower than that of RaoO (< 40dB). Thus, the SCO should be considered for this study case.

The optimal decision variables (DV's), after search are as provided in Table 1.

Table 1: Optimized Results Using Default Parameters

Technique	h_{cpe}	h_{base}	f_{base}
SCO	1	40.00	1500
RaoO	10	30.82	1500

As can be seen, the height of the CPE should be much smaller to assure a better fit.

IV. Conclusions and Future Work

The research has shown the performance of using mathematical based optimizer strategies for solving the PLMP. The approach based on the RaoO and SCO algorithms and assures a simpler and fast optimization strategy.

In future, it will be desirable to compare with other kinds of methaporless techniques for the solution of PLMP. Also, other wireless models apart from the Cost-231 Hata should be studied.

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