A Trade-off Analysis of Quality of Service (QoS) Metrics Towards Routing in Mobile Networks: MOGA Based Approach

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Abstract The trade-off analysis between two QoS metrics towards efficient routing in mobile networks is proposed in this paper. For such analysis the behavioural natures of end-to-end transmission cost and hop-count as QoS metrics are accounted in discrete domain and subsequently, the probability density functions (*pdf*) of those important factors are determined. The *pdf* of these are transformed into continuous domain to perform mathematical operation and subsequent analysis is presented to obtain the optimal routing path(s). In this context, a multi objective optimization (MOO) on these parameters is proposed and more refined results among all possible solutions are obtained accordingly. The diverse set of possible solutions for such analysis is explored through a Multi Objective Genetic Algorithm (MOGA) based approach.

Keywords Trade-off · Optimization · Probability density function · Genetic algorithm · Mobile network

1 Introduction

In the past decade, wireless mobile networks have become increasingly popular in the computing domain. This class of network is commonly called mobile cellular networks, which has fixed switching sub-systems known as base stations that synchronize and control all wireless transmissions within their coverage area (or cell) [1]. A mobile node connects to and communicates with the neighbourhood

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BSs located within its transmission range [2]. The efficiency of such networks is characterised with different Quality of Service (QoS) metrics like delay, bandwidth, hop-count, transmission cost etc. [3]. The performances of these metrics are interrelated with each other. For example, if the number of hop is reduced, then the distance between two successive hops is increased accordingly. Subsequently, the transmission energy for sending data packet is increased, as it is directly proportional to the distance between hops. In real life application, it is necessary to optimize these QoS parameters to satisfy user requirements. Therefore, a trade-off analysis among these factors needs to be evaluated under such scenario.

The set of works related to the trade-off measurement and its applications spans several distinct areas of literature. The paper presented in [4] studies an optimization scheme for determining the trade-off between two routing cost metrics i.e., delay and bandwidth. Another application on determination of trade-off between the coexisting networks is accounted in [5] which is analysed in terms of transmission capacity. In [6], the fundamental trade-off among delay and infrastructure cost of epidemic routing in mobile networks is studied. The paper in [7] formulates a trade-off policy between energy consumption and other QoS parameters in the mobile grid environment. The performance of the energy QoS trade-off algorithm is compared with other energy and deadline constrained scheduling algorithm.

In [8] the authors discussed the selection of a caching policy by the network administrator based on hop-count and transmission cost with improved QoS. The works in [9, 10] show the trade-off between call arrivals and delay requirements i.e. target delay and delay probability. The trade-offs between two tree based routing strategies with respect to hop count and number of edges are described in [11, 12]. In short, several trade-off analyses of various QoS metrics on different aspects have been carried out. Most of them are resolved using some specific optimization technique. However, a new trade-off analysis for QoS metrics in mobile networks is proposed in this paper to facilitate more refined solutions. This is attempted in this work by proposing a probabilistic model in a comprehensive manner.

The trade-off performance between two QoS metrics in mobile networks namely end-to-end transmission cost (t_c) and hop-count (h_c) is proposed in this paper. Generally, the behavioural natures of these factors are accounted in discrete domain and subsequently, the probability density functions (pdf) of those important factors are determined. Due to the requirement of mathematical operations, the pdf of these factors are transformed into continuous domain and a trade-off analysis among these is presented to find out the optimal routing path(s).This is formulated using a multi objective optimization (MOO) where a simultaneous optimization on t_c and h_c is done. Further, more refined results among all possible solutions are obtained by using a bivariate distribution function involving t_c and h_c. Hence, the diverse set of possible solutions for these QoS metrics are explored through a Multi Objective Genetic Algorithm (MOGA) based approach.

The remainder of the paper is organized as follows. The problem addressed in this work is formulated in Sect. 2. The proposed solution for this problem is discussed in Sect. 3. Section 4 shows the simulation results to reflect the performance of the proposed model. Finally, we outline the conclusions of this paper in Sect. 5.

2 Problem Formulation

The problem addressed in this work begins with the computation of probability distribution for parameters t_c and h_c. Therefore, a two dimensional random walk [13] with random vector is used on cellular structure [1, 14] to determine the distribution function. The pdf of t_c and h_c describes the distribution of probability densities of these factors over the sample space. Here, the scatter plot for t_c and h_c for a given pair of source (s) and destination (d) is shown in the following Fig. 1.

Thus t_c and h_c are correlated with each other as apparent from Fig. 1. The joint pdf of t_c and h_c follows bivariate Gaussian Distribution which is supported by the random walk. To determine such joint pdf, the mean (μ) and standard deviation (σ) of t_c and h_c for all possible routing paths between a pair of s and d are computed. Now, (1) expresses the discussed distribution as follows.

$$f(t_c, h_c) = \frac{1}{2\prod \sigma_{t_c}\sigma_{h_c}\sqrt{1-\rho^2}} e^{\left[-\frac{1}{2(1-\rho^2)}\left\{\left(\frac{t_c-\mu_{t_c}}{\sigma t_c}\right)^2 + \left(\frac{h_c-\mu_{h_c}}{\sigma h_c}\right)^2 - 2\rho\left(\frac{t_c-\mu_{t_c}}{\sigma t_c}\right)\left(\frac{h_c-\mu_{h_c}}{\sigma h_c}\right)\right\}\right]}, \quad -1<\rho<1 \tag{1}$$

where ρ denotes the correlation coefficient for bivariate Gaussian Distribution among t_c and h_c. The points with minimum probability would support the preference on t_c and h_c individually. However, the routing paths with minimum QoS metric values are usually different. Therefore, a path belonging to the set of solutions is selected with optimal values of the corresponding metrics to maintain a successful trade-off between these two. The optimal values of t_c and h_c are governed by the following partial differential equations.

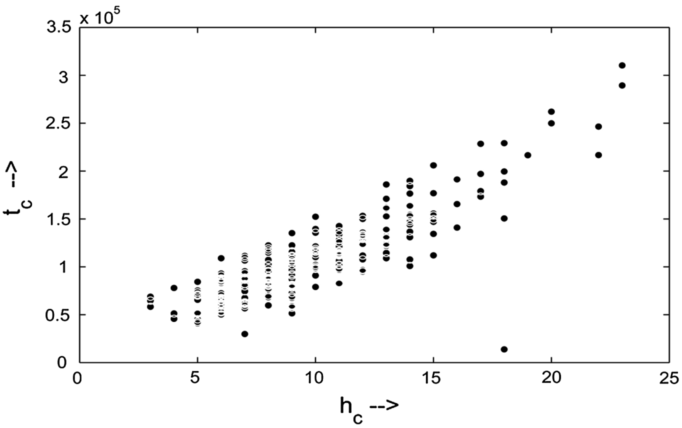

Fig. 1 Scatter plot for t_c and h_c

$$\frac{\partial f}{\partial Z_{\mathrm{t_c}}} = \frac{1}{2\prod\sqrt{1-\rho^2}} \mathrm{e}^{\left[-\frac{Z_{\mathrm{t_c}}^2 + Z_{\mathrm{h_c}}^2 - 2\rho Z_{\mathrm{t_c}} Z_{\mathrm{h_c}}}{2(1-\rho^2)}\right]} \left[-\frac{2Z_{\mathrm{t_c}} - 2\rho Z_{\mathrm{h_c}}}{2(1-\rho^2)}\right] = 0 \tag{2}$$

$$\frac{\partial f}{\partial Z_{\mathrm{h_c}}} = \frac{1}{2\prod\sqrt{1-\rho^2}} \mathrm{e}^{\left[-\frac{Z_{\mathrm{t_c}}^2 + Z_{\mathrm{h_c}}^2 - 2\rho Z_{\mathrm{t_c}} Z_{\mathrm{h_c}}}{2(1-\rho^2)}\right]} \left[-\frac{2Z_{\mathrm{h_c}} - 2\rho Z_{\mathrm{t_c}}}{2(1-\rho^2)}\right] = 0 \tag{3}$$

where $Z_{\mathrm{t_c}} = \frac{\mathrm{t_c} - \mu_{\mathrm{t_c}}}{\sigma_{\mathrm{t_c}}}$ and $Z_{\mathrm{h_c}} = \frac{\mathrm{h_c} - \mu_{\mathrm{h_c}}}{\sigma_{\mathrm{h_c}}}$.

The condition for obtaining the trade-off between $\mathrm{t_c}$ and $\mathrm{h_c}$ by solving (2) and (3) is expressed as in the following.

$$Z_{\mathrm{t_c}} - \rho Z_{\mathrm{h_c}} = 0 \tag{4}$$

$$Z_{\mathrm{h_c}} - \rho Z_{\mathrm{t_c}} = 0 \tag{5}$$

Hence, (4) and (5) are combined to provide the required condition for trade-off by the following.

$$\frac{\mathrm{t_c} - \mu_{\mathrm{t_c}}}{\sigma_{\mathrm{t_c}}} = \frac{\mathrm{h_c} - \mu_{\mathrm{h_c}}}{\sigma_{\mathrm{h_c}}} \tag{6}$$

The inter-twining of cost metrics is expressed in terms of ρ as shown in (1). As the extreme values of pdf would have the lowest probability, minimizing $f(t_c, h_c)$ would lead to the maximization or minimization. However, for a trade-off in routing metrics, we are interested only with the minima values. Therefore, both $\mathrm{t_c}$ and $\mathrm{h_c}$ needs to be minimized as shown below in (7) respectively. The problem is now formulated as MOO with consideration of the set of all possible routing paths $P = [\{p_1, p_2, \ldots, p_n\} | \forall p_i \in P]$ between s and d as follows.

$$objectives \begin{cases} \min f(t_c, h_c) \\ \min g(p_i) = |p_i|_{t_c} \\ \min h(p_i) = |p_i|_{h_c} \end{cases} \tag{7}$$

$$subject\ to \begin{cases} |p_i|_{t_c} \in t_c, \forall p_i \in P \\ |p_i|_{\mathrm{h_c}} \in \mathrm{h_c}, \forall p_i\, P \end{cases} \tag{8}$$

The constraints in (8) ensure that $\mathrm{t_c}$ and $\mathrm{h_c}$ of a specific path is selected during trade-off analysis.

3 Proposed Solution

The model proposed in this work is evaluated with the application of MOGA. The ability of MOGA to search different regions of the solution space makes it suitable to find optimal solutions of multi objective problems in a single run. We use a non-dominated sorting approach NSGA-II [14] to determine the Pareto optimal front. In this context, transformation of network characteristics to GA paradigm and the function of genetic operators for creating offspring population are discussed next.

- **Chromosome encoding**: A chromosome in our proposed MOGA based methodology is a sequence of positive integers corresponding to the IDs of nodes that represent a routing path and each gene of the chromosome provides the order of the nodes in that routing path. The length of the chromosome is variable, but it should not exceed the maximum length N, where N denotes the total number of nodes in the network. A chromosome encodes the problem by listing up node IDs from s to d based on an information database like routing table of the network. In our work, this information is obtained and managed by using an adjacency matrix.
- **Population Initialization**: There are two ways to generate the initial population such as heuristic initialization and random initialization. Although the mean fitness of the heuristic initialization is already high so that it may help the GAs to find solutions faster, it may explore a small part of the solution space and never find global optimal solutions because of the lack of diversity in the population. Therefore, 80:20 combinations of random initialization and heuristic initialization are effected in this work to take the advantages provided by both methods. The various graph traversal methods are used as heuristics. Thus initial population is now generated with the encoding method described earlier.
- **Selection**: The selection operator is intended to improve the average quality of the population by providing the high-quality chromosomes to get a better chance to be copied into the next generation. As elitism is applied here, ξ best solutions are forwarded into the next generation where ξ denotes the elitism count. To fill rest of the population, tournament selection [15] without replacement is perceived in our approach. However, the same chromosome should not be picked twice as a parent. The use of Crowded-Comparison Operator ($\prec_n$) [14] drives the procedure towards a better spread of population in attaining the true Pareto-optimal front.
- **Crossover**: The crossover procedure is used to generate offspring chromosomes from dominant parent chromosomes. In the proposed model, a single point crossover is used to exchange genetic materials between the parent chromosomes. One random site is selected as the crossover site out of the several potential crossing sites. In our problem, the crossover between two paths from s to d is shown in Fig. 2.
- **Mutation:** Mutation not only helps to recover any lost gene but also helps to stay away from local optima and head for global optima. The mutation function has the ability to generate a path which has a very different fitness from the

original path, thus preserving diversity in the population. For path with *s* and *d*, the mutation procedure is shown in Fig. 3.

- **Loop Repair:** The crossover and mutation procedure may give rise to loops in the generated path. The loops are removed from the path with the help of repair function [15].

The procedure to get Pareto optimal solutions is thus described by the following MOGA and subsequently it is discussed in detail.

Algorithm: procedure MOGA $(N,\ t_{max},\ p_{crossover},\ p_{mutation})$

/**N* is the population size, t_{max} is the desired number of generations, $p_{crossover}$ and $p_{mutation}$ denote crossover and mutation probabilities respectively */

```
t ← 1
P_1 ← create a new random population of size N
Q_1 ← ∅
while (t <= t_max ) do
    R_t ← P_t ∪ Q_t
    P_{t+1} ← ∅
    Q_{t+1} ← ∅
    F ← non_dominated_sort (R_t)
    i ← 1
    while( |P_{t+1}| + |F_i| ≤ N )do
        assign_crowding_distance (F_i)
        P_{t+1} ← P_{t+1} ∪ F_i
        i ← i + 1
    end while
    if( |P_{t+1}| < N )
        sort(F_i, ≺_n)
        P_{t+1} ← P_{t+1} ∪ F_i[1 : (N - |P_{t+1}|)]
    end if
    while( |Q_{t+1}| ≤ N )do
        individual_A ← tournament_selection( P_{t+1} )
        individual_B ← tournament_selection( P_{t+1} )
        rand_no ← choose a random number between 0 and 1
        if (rand_no ≤ p_crossover )
            Q_{t+1} ← crossover (individual_A , individual_B )
        else
            Q_{t+1} ← individual_A or individual_B
        end if
        rand_no ← choose a random number between 0 and 1
        if ( rand_no ≤ p_mutation )
            individual_to_mutate ← select a random individual from Q_{t+1}
            mutated_individual ← mutate (individual_to_mutate )
            replace individual_to_mutate with mutated_individual in Q_{t+1}
        end if
    end while
    t ← t + 1
end while
end procedure
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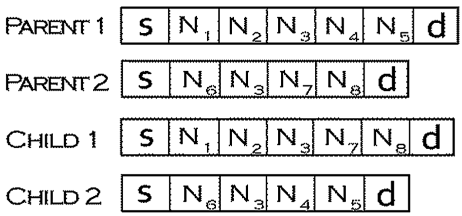

Fig. 2 Crossover used in the proposed work

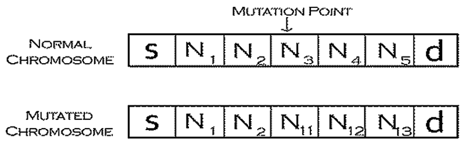

Fig. 3 Mutation used in the proposed work

- Line 1: Generation count (t) is initialized.
- Line 2: Initial population (P_1) is initialized as discussed previously with N individuals.
- Line 3: Offspring population (Q_1) is initialized to null.
- Line 4–36: Loop controls the number of generations.
- Line 5: Parent and offspring population are combined into R_t.
- Line 6–7: Next generation populations are initialized to null.
- Line 8: All non-dominated fronts of the combined population are searched and assigned to F.
- Line 9: Front count i is initialized to 1.
- Line 10–14: Loop is executed until new parent population is filled up.
- Line 11–12: Crowding distance in ith front is computed and included as part of parent population.
- Line 13: The front count is incremented.
- Line 15–18: Check if parent population is filled yet or not.
- Line 16: Sort only the ith front by using Crowded-Comparison Operator ($\prec_n$).
- Line 17: The first ($N - |P_{t+1}|$) elements of the ith front are selected and placed into P_{t+1}.
- Line 19–34: The offspring population is generated and filled up using selection, crossover and mutation as discussed earlier.
- Line 35: The generation count is incremented.

4 Experimental Results

The simulation of the proposed model has been carried out using MATLAB 7.6 and JAVA on a server with two Intel Xeon processor (2.33 GHz) and 12 GB memory. Now the trade-off analysis is carried out with $N = 250$ (initial population), $p_{crossover} = 0.8$ (crossover probability) and $p_{mutation} = 0.1$ (mutation probability). The Pareto optimal solutions for the optimization of both t_c and h_c is obtained through the proposed MOGA and is shown in Fig. 4. Here, it is observed that the transmission cost is increased for reduced hop count and vice versa.

The solution obtained in Fig. 4 is further refined by the expression (1) and are shown with variation against t_c and h_c in Figs. 5 and 6 respectively. In these

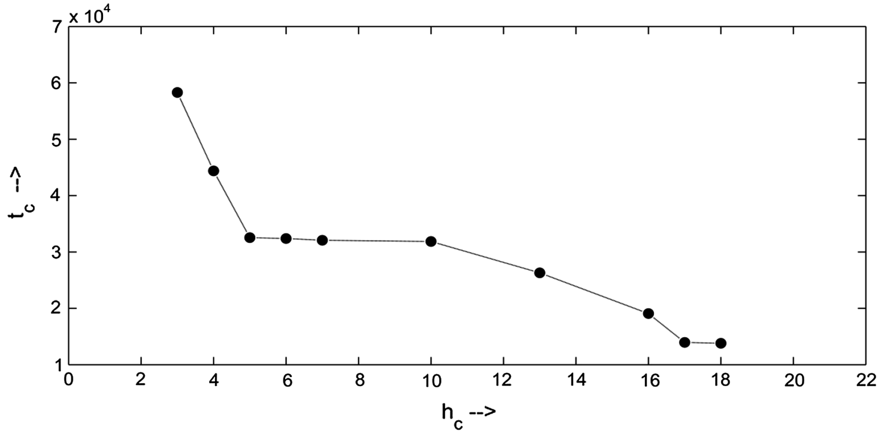

Fig. 4 Pareto optimal solutions for t_c and h_c

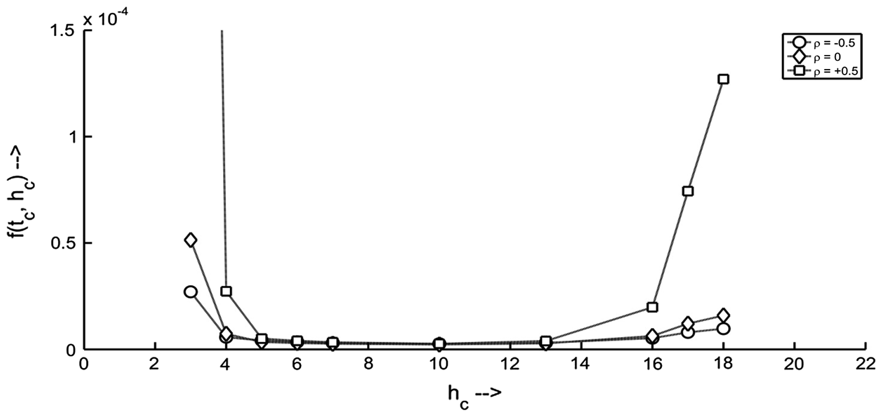

Fig. 5 Refinement for h_c achieved by varying $f(t_c, h_c)$

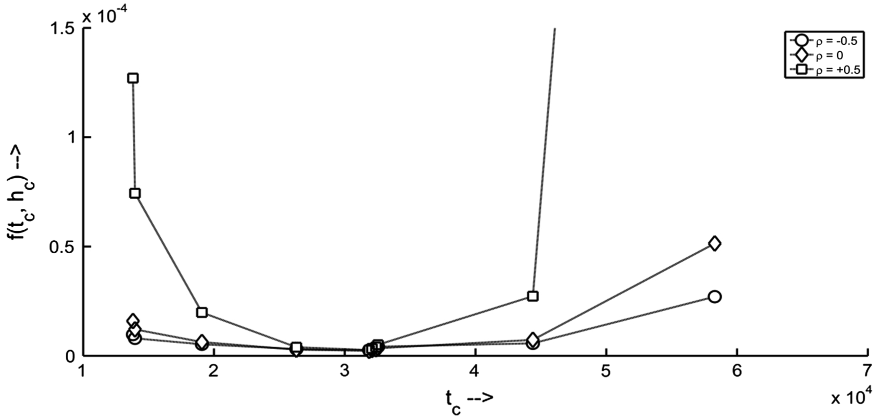

Fig. 6 Refinement for t_c achieved by varying $f(t_c, h_c)$

experiments, the refined solutions are obtained for different values of ρ. It is observed in Fig. 5 that the more perfect solutions for reducing h_c lie in the lower portion of the curve which was not apparent from Fig. 4. Similarly, Fig. 6 points out the perfect candidates for reducing t_c and its variation with the same. It is significant that the extreme points in Fig. 4 provide the better results only for any one among t_c and h_c, whereas the solutions obtained in both Figs. 5 and 6 provide better trade-off involving both t_c and h_c. In addition, resemblance in nature of the curves obtained in Figs. 5 and 6 are apparent from (6). Thus for each route, the deviation of t_c and h_c from their mean values are similar which preserves the balance between these QoS metrics from trade-off perspective.

5 Conclusions

The efficiency of mobile cellular network is measured with the help of different QoS parameters. The inter-twining of these parameters requires a trade-off performance among these factors. Here, the performance and its effectiveness is established for the metrics end to end transmission cost (t_c) and hop-count (h_c). In this work, pdf of those factors is determined and subsequently, the analysis on trade-off measurement converges to a MOO problem. Further, the selection of improved solutions is obtained by satisfying another objective after simultaneous minimization of both t_c and h_c. The introduction of MOGA based approach is used to obtain the Pareto optimal solutions. In addition, the effectiveness of our proposed model is verified through experimental analysis.

References

1. Banerjee, S., Roy, S., Thakurta, P.K.G.: Coordinate based directed routing protocol. Int. J. Inf. Electron. Eng. **2**(2):170–173 (2012)
2. Wu, Z., Song, H., Jiang, S., Xu X.: A grid-based stable routing algorithm in mobile ad hoc networks. IEEE First Asia International Conference on Modeling and Simulation, pp. 181–186, 27–30 Mar 2007
3. Chen, L., Heinzelman, W.B.: A survey of routing protocols that support QoS in mobile ad hoc networks. IEEE Network **21**(6):30–38 (2007)
4. Lu, J., Cheng, W.: A genetic-algorithm-based routing optimization scheme for overlay network. In: Third International Conference on Natural Computation—(ICNC '07), vol. 04, pp. 421–425, 24–27 Aug 2007
5. Huang, K., Lau, V.K.N., Chen, V.: Spectrum sharing between cellular and mobile ad hoc networks: transmission-capacity tradeoff. IEEE J. Sel. Areas Commun. Spec. Issue Stoch. Geom. Random Graphs Anal. Des. Wirel. Netw. **27**(7):1256–1267 (2009)
6. Zhou, S.,Ying, L., Tirthapura, S.: Delay, cost and infrastructure tradeoff of epidemic routing in mobile sensor networks. In: 6th International Wireless Communications and Mobile Computing Conference (IWCMC '10), pp. 1242–1246, June 28–July 2, 2010
7. Li, Chunlin, Li, Layuan: Tradeoffs between energy consumption and QoS in mobile grid. J. Supercomputing **55**(3), 367–399 (2011)
8. Guha Thakurta, P. K., Mallick, N., Dutta, G., Bandyopadhyay, S.: A new approach on caching based routing for mobile networks. In: International Conference on Communication, Computing and Security 2011(ICCCS '11), pp. 32–35, 12–14 Feb 2011
9. Soret, B., Torres, M.A., Entrambasaguas, J.T.: analysis of the trade-off between delay and source rate in multiuser wireless systems. EURASIP J. Wirel. Commun. Networking **2010,** 12 (2010)
10. Vasef, M.: Effective capacity of a rayleigh fading channel in the presence of interference. Int. J. Wirel. Mob. Networks **4**(3):1–19 (2012)
11. Meghanathan, N.: Performance comparison of minimum hop and minimum edge based multicast routing under different mobility models for mobile ad hoc networks. Int. J. Wirel. Mob. Networks **4**(3), 1–14 (2011)
12. Meghanathan, N.: Benchmarks and tradeoffs for minimum hop, minimum edge and maximum lifetime per multicast tree in mobile ad hoc networks. Int. J. Advancements Technol. **1**(2), 234–251 (2010)
13. Keqin, L.: Performance analysis and evaluation of random walk algorithms on wireless networks parallel and distributed processing. IEEE international symposium on workshops and Ph.D. forum (IPDPSW), 19–23 Apr 2010, pp. 1–8
14. Deb, K., Pratap, A., Agarwal, S., Meyarivan, T.: A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Trans. Evol. Comput. **6**(2), 182–197 (2002)
15. Poddar, R., Banerjee, S., Thakurta, PKG.: Shortest path routing for co-ordinate based mobile networks: a genetic algorithm approach. In: International Conference on Advances in Mobile Network, Communication and its Applications (MNCAPPS), pp. 50–53, 1–2 Aug 2012