Multi-Objective Cross-Layer Optimization for Selection of Cooperative Path Pairs in Multihop Wireless Ad hoc Networks

Nyoman Gunantara, and Gamantyo Hendrantoro

Abstract: **This paper focuses in the selection of an optimal path pair for cooperative diversity based on cross-layer optimization in multihop wireless ad hoc networks. Cross-layer performance indicators, including power consumption, signal-to-noise ratio, and load variance are optimized using multi-objective optimization (MOO) with Pareto method. Consequently, optimization can be performed simultaneously to obtain a compromise among three resources over all possible path pairs. The Pareto method is further compared to the scalarization method in achieving fairness to each resource. We examine the statistics of power consumption, SNR, and load variance for both methods through simulations. In addition, the complexity of the optimization of both methods is evaluated based on the required computing time.**

Index terms: **multi-objective optimization, Pareto method, scalarization method, selection of the path pair, multihop wireless ad hoc networks**

I. Introduction

An ad hoc network is a collection of nodes that communicate dynamically without a fixed infrastructure. Each node can act as a source, relay, and destination. The nodes have limitations in terms of transmission range and battery capacity [1]. To overcome aforementioned limitations, it requires cooperative communication techniques. Cooperative communication is a system where the source nodes cooperate and coordinate with the nodes functioned as relay before reaching the destination node to improve transmission quality. Cooperative communication using a single antenna in multinode scenario can make beneficial use of antenna from each node so that it can create multiple antenna communication systems such as the multi input multi output (MIMO) [2].

Selection of nodes that will act as relays is a problem that must be solved by considering several criteria. In [1] and [3-6] relay selection is based only on the resources at the physical layer. Selection of relay that meets targets and constraints on multiple layers need to take into account the resources in the higher layers, so it is necessary to apply a cross-layer optimization [7-10]. If the optimization problem involves the compromise of more than one resource, where some of them are contradictory, it is needed to apply MOO (multi-objective optimization) [11]. The application of MOO to optimize wireless networks in [11-13] is solved by scalarization. However, the problem of resources optimization can not be done separately because the problems are inter-related with each other. An alternative to overcome this weakness is the Pareto method.

Runser et al [14] is one of the first to apply the Pareto method in solving MOO problems in wireless ad hoc networks. The result is a tradeoff characteristic of three parameters, namely robustness, energy consumption and delay for 2 hop ad hoc networks. Gunantara and Hendrantoro [15] further develop optimal relay selection for single multihop paths based on cross-layer optimization for power consumption, throughput, and load variance. In [15], the work deals with finding the optimum single path with multiple hops, whereas the problem at hand is on finding a pair of multihop paths that is optimum for cooperative diversity applications. This paper is motivated by those results, as well as to address the limitations of the study in [9] for wireless networks with relays where energy efficiency and load balance can not be achieved at the same time.

To determine the performance of Pareto method, we compare it with the scalarization method. Scalarization method has been applied on the manipulator where each resource is normalized by the standard deviation method [16] and the priority method [17]. Normalization using standard deviation and priority method tends to separate prioritized objects and ignore other objects. In this study, each object is given equal weight and normalized by the square root of average power of the performance indicator quantity. Normalization is used to provide a sense of fairness among the objectives.

The main contribution of this paper is, firstly, the optimization method for ad hoc network model that is dynamic that can be done simultaneously for all optimized resources based on path in order to obtain an optimal pair of paths with the help from MOO with Pareto method. Secondly, it describes scalarization method with fairness for all three resources. Thirdly, this paper describes the complexity of both methods of optimization and also to obtain cumulative value for all three resources.

Section II of this paper gives a description of ad hoc networks, radio propagation, and MOO. Section III describes the model configuration, parameter simulation, and analysis of simulation results, with conclusions given in Part IV.

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II. Cooperative Communications

Cooperative communication can be explained by graph $G = (V, L)$, where $V = \{1,2,\ldots,N\}$ is the set of nodes and $L = \{(1,2),(1,3),\ldots,(N-1,N)\}$ is the set of links/hops. In multihop ad-hoc networks, there are pairs of source and destination node that communicate by involving other nodes as relays to form multihop paths. If the total number of nodes (including the source and destination pair) is N, then there is one single-hop solution, $(N-2)$ 2-hop solutions, $(N-2)(N-3)$ 3-hop solutions, $(N-2)(N-3)(N-4)$ 4-hop solutions, and so on, for the source and destination pairs.

In this study, the maximum number of hops to be considered for one path is limited to three. From the set of paths with three hops maximum, there are several possible combinations that form a pair of paths between the source and destination. Suppose $R(a,b)$ denotes the set of all path pairs having a and b hops, P_l^k states permutations of l out of k, and |•| specifies the number of path pairs in the set. The number of combinations can be obtained such as $|R(1,2)| = (N-2)$ solutions consisting of two paths, each with one and two hops for each path, $|R(1,3)| = (N-2)(N-3)$ solutions consisting of two paths, each with one and three hops, |R (2,2)| = (N-2) (N-3) solutions consisting of a pair of paths, each with two hops, $|R(2,3)| = (N-2)P_2^{(N-2)-1}$ solutions consisting of two paths, each with two and three hops, and $|R(3,3)| = (N-2)(N-3)P_2^{(N-2)-2}$ solutions with a pair each having three hops. At the receiver, the signals received from the selected pair are combined with maximal ratio combining (MRC).

Broadcast routing is assumed using amplify-and-forward (AF) relays, where the source sends the information to all nodes potential to be relays, so that information can arrive at the destination [18]. Broadcast routing is selected so that the transmitted data can be received by all adjacent nodes simultaneously to save transmission time.

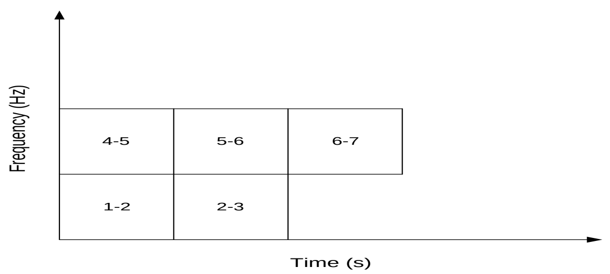

Fig. 1. OFDMA Method for Path (1-2-3) and (4-5-6-7)

The protocol mechanism of the system model can be described as follows:

- The source can identify the destination position by each node detecting other nodes connected directly via a single hop and sending information to all nodes within one hop [19].
- To avoid interference and collisions among nodes, OFDMA (orthogonal frequency division multiple access) is used as in [20]. Each path uses a different sub-carrier, whereas each hop in a path uses a different time slot. Fig. 1 illustrates an example of frequency/sub-carrier time slot division for two paths, namely path (1-2-3) consisting of two hops and path (4-5-6-7) that consists of three hops.

III. Problem Formulation

A. *Radio Propagation*

A.1 Outdoor

It is assumed that the transmit power P_t for all nodes is identical and gain of the transmitter and receiver antenna, G_t and G_r are the same. Therefore the received power P_r through a wireless hop of length d meters can be calculated by the following equation [15]:

$$P_r = P_t\ G_t\ G_r \left(\frac{\lambda}{4\pi}\right)^2 d^{-\alpha}\ 10^{\frac{X_\varphi}{10}} \tag{1}$$

where X_φ denotes shadowing loss (dB) which is normally distributed with a standard deviation of φ.

A.2 Indoor

In indoor condition, the nodes in an ad-hoc network are well positioned in rooms separated by walls. The walls can cause partial reflection of the transmitted signal so that only some portion of the energy is transmitted through the wall, which is represented by a transmission coefficient [21]. Power received at a node from another node in a different room via a link/hop can be determined using (1) by introducing the influence of the transmission coefficient:

$$P_r = P_t\ G_t\ G_r \left(\frac{\lambda}{4\pi}\right)^2 d^{-\alpha}\ 10^{\frac{X_\varphi}{10}} \prod_{m=1}^{M} |\Gamma_m|^2 \tag{2}$$

where Γ_m and M respectively denotes the transmission coefficient of the m-th wall that is passed by the direct propagation path and the number of walls.

B. *Performance Indicators of Cooperative Communications*

To optimize the performance of cooperative communications, function or duty of each communication layer needs to be adapted by including the parameters and criteria on more than one layer of the architecture of the communication system. This is known as cross-layer optimization. The purpose of cross-layer optimization depends on the quantity of the layer to be made adaptive. In this paper, the layers of interest are the physical and the network layer. The following describes the parameters of these two layers.

B.1 Power Consumption

Power consumption on path is overall power requirements needed in transmitting data from the source to destination through multiple relays in each path. If it is assumed that all nodes have the same transmission power P_t, then power consumption in the p-th path consisting of L hops are:

$$P_{t,p} = L\, P_t \tag{3}$$

While the amount of power consumption for path pair is obtained from the following equation:

$$P_{t,R(a,b)} = P_{t,R(a)} + P_{t,R(b)} \tag{4}$$

where $P_{t,R(a)}$, $P_{t,R(b)}$ and $P_{t,R(a,b)}$ denote the power consumption of the path with a hops, the path with b hops, and the pair of paths with a and b hops, respectively. The optimal path pair is thus the one with the smallest value of power consumption:

$$\begin{aligned} P_{t,R,opt} = \min(&P_{t,R}(1,2), P_{t,R}(1,3), P_{t,R}(2,2), \ldots \\ &P_{t,R}(2,3), P_{t,R}(3,3)) \end{aligned} \tag{5}$$

where $P_{t,R,opt}$ represents the power consumption of the optimal path pair.

B.2 Signal-to-Noise Power Ratio

SNR at each hop is the ratio between the received power with the noise power at the node, $\gamma = P_r/N_0$, where N_0 represents noise power assumed identical for all nodes. It is assumed that each relay does amplify and forward, so that the overall SNR on a path depends on the SNR of each hop [22]:

$$\gamma = \left(\sum_{i=1}^{L} \gamma_i^{-1}\right)^{-1} \tag{6}$$

with γ_i is the value of SNR at the i-th hop.

The SNR for a path pair after maximal-ratio combining is obtained from the following equation:

$$\gamma_{R(a,b)} = \gamma_{R(a)} + \gamma_{R(b)} \tag{7}$$

where $\gamma_{R(a)}$, $\gamma_{(b)}$, and $\gamma_{R(a,b)}$ represent SNR of the path with a hops, that of the path with b hops, and that of the maximal-ratio combined paths with a and b hop.

For an ad hoc network, the optimal pair of paths is the one giving the maximum value of SNR among all path pairs determined by the following equation:

$$\begin{aligned} \gamma_{R,opt} = \max\ (&\gamma_R(1,2),\ \gamma_R(1,3), \gamma_R(2,2), \ldots \\ &\gamma_R(2,3), \gamma_R(3,3)) \end{aligned} \tag{8}$$

with $\gamma_{R,opt}$ denotes the SNR of the optimal path pair.

B.3 Load Variance

Load variance is the variance of traffic load over all nodes, which is inversely proportional to the load balance or fairness [23]. In wireless ad hoc networks, load balance is very important because some node may have greater opportunity to be chosen as a relay when energy consumption alone is considered, but might not be so when the traffic load it carries is taken into account. In a path pair, where node i is used as a relay, the load of node i becomes:

$$B_i = B_{oi} + B_{di} \tag{9}$$

with B_{oi} and B_{di} respectively denoting its own traffic load and the incoming traffic load into node i.

After the load of each node is known then the variance of traffic load of nodes in the whole network can be evaluated for each possible path pair with the following equation [23]:

$$V_R = \frac{1}{N}\sum_{i=1}^{N}\left(B_i - \left(\frac{1}{N}\sum_{i=1}^{N} B_i\right)\right)^2 \tag{10}$$

Based on variances obtained for all possible path pairs, the optimal path pair in terms of load fairness can be determined by finding one with the lowest traffic load variance:

$$\begin{aligned} V_{R,opt} = \min\ (&V_R(1,2), V_R(1,3), V_R(2,2), \ldots \\ &V_R(2,3), V_R(3,3)) \end{aligned} \tag{11}$$

where $V_{R,opt}$ denotes the load variance of the network with the optimal path pair and $V_{R(a,b)}$ denotes the load variance obtained for a path pair with a and b hop.

IV. Multi-Objective Optimization

Methods to solve MOO problems can be classified into two, Pareto and scalarization [24]. The following describes each of these methods.

A. Pareto Method

Optimization is the process of finding the best solution of a problem. For issues that contradict each other, such as the problems of smallest power consumption and the largest SNR, Pareto method can be used in searching the best solution. Mathematically, three issues in section III can be written as follows [25]:

$$\begin{aligned} &P_{t,R,opt} = \min(P_{t,R}(1,2), \ldots, P_{t,R}(3,3)) \\ &\gamma_{R,opt} = \max\ (\gamma_R(1,2),\ \ldots, \gamma_R(3,3)) \\ &V_{R,opt} = \min\ (V_R(1,2), \ldots, V_R(3,3)) \\ &\text{subject to :} \\ &\qquad R = 2, \quad R_1(i,k) \neq R_2(i,k) \end{aligned} \tag{12}$$

where R represents the number of cooperative paths and $R_1(i,k) \neq R_2(i,k)$ indicates that the paths constituting a cooperative path pair cannot share any hop.

Pareto optimization method maintains the solutions of both problems in the Pareto Optimal Front (POF) apart during optimization. In POF, there is the dominance concept to distinguish the dominated (inferior) and the non-dominated solution (non-inferior). For the optimization of two problems, non-dominated solution can be described on a POF plane (two dimensions), as illustrated in Fig. 2 for two problems Z_1 and Z_2 [26]. As for the optimization of three problems, non-dominated solution can be described in POF surface (three dimensions) [27].

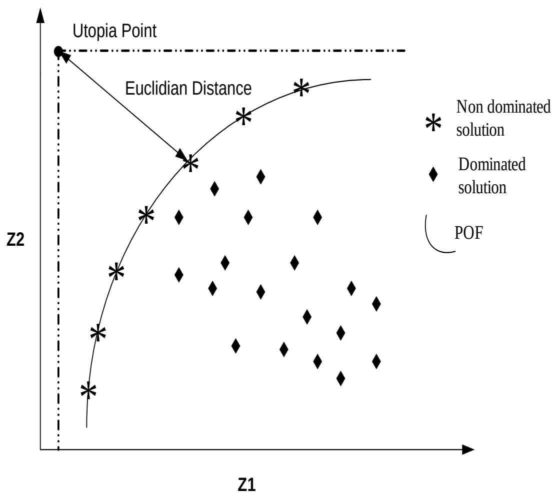

Fig. 2. POF for Two Objectives

In searching for the optimal value of a POF, the utopia point should be set first. For the case involving two objective functions that should be minimized and maximized, respectively, the utopia point is the intersection of the minimum value of the first objective function and the maximum value of the other. The optimal value can be determined by finding the shortest Euclidian distance [28] by equation [29]:

$$d_E = \min \sqrt{\left(\frac{Q_1 - Q_1^*}{Q_{1\,norm}}\right)^2 + \left(\frac{Q_2 - Q_2^*}{Q_{2\,norm}}\right)^2} \tag{13}$$

where $\{Q_1^*, Q_2^*\}$ is the coordinate of the utopia point for variable Z_1 that should be minimized and variable Z_2 that should be maximized and $\{Q_1, Q_2\}$ is the coordinate of the points on POF on the objectives plane. The normalizing value $Q_{1\,norm}$ is determined based on the mínimum value of Q_1, while $Q_{2\,norm}$ is determined by the maximum value of Q_2. In the simulation results reported in section V, this method is applied to three problems in (12).

B. Scalarization Method

In the scalarization method, all objectives are organized into a scalar by giving weight to each of them. Objective functions that should be minimized are marked negative, while those that should be maximized are marked positive. To gain a sense of fairness all objectives are given equal weight and are each normalized by its square root of average power (SRAP). For example, SNR is normalized by the SRAP of SNR, which simply can be seen in the denominator of equation (14), namely $\sqrt{E(\gamma^2)}$.

Scalarization of the three objectives becomes:

$$F = \frac{-w_1 P_{t,R}}{\sqrt{E\left(P_{t,R}^2\right)}} + \frac{w_2 \gamma_R}{\sqrt{E(\gamma_R^2)}} - \frac{w_3 V_R}{\sqrt{E(V_R^2)}} \tag{14}$$

where F denotes the fitness function, $P_{t,R}$, γ_R, and V_R denote the 1st, 2nd and 3rd objective function, respectively, and w_1, w_2, w_3 denote the corresponding weights. $P_{t,R}$, γ_R, and V_R are respectively calculated by equation (4), (7), and (10). Weights w_1, w_2, w_3 are determined randomly, selected, and changed gradually and periodically [30]. In our study, w_1, w_2, and w_3 are all set equally to 1/3.

Due to the large number of searches over existing cooperative path pairs, optimization methods such as genetic algorithm (GA) can be applied to determine the optimal value.

V. Numerical Results

A. Model Configuration

We review ad-hoc networks in two conditions, i.e. outdoor and indoor. Results discussed in this and the next part are taken from one out of 500 configurations generated with randomly positioned nodes in our simulations. The exemplary configuration can be seen in Figs. 3 and 4. For outdoor condition, all the nodes are in an open space with an area of 40 m × 40 m. As for indoor condition, the building area of 40 m × 40 m is divided into 16 rooms bounded by walls. In both configurations there are 32 nodes with random positions. Node 1 acts as a source, whereas node 32 as destination, and the other nodes might act as relays if considered necessary. Simulation parameters are taken based on the application of WLAN in ad-hoc wireless networks as shown in Table I.

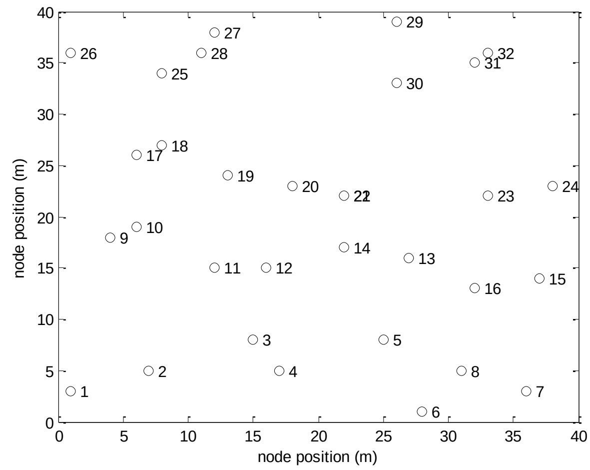

Fig. 3. Outdoor Configuration

To calculate the load variance of a path, it is assumed that aside from node 1 acting as the source that send data to a destination, there are five other nodes that transmit data simultaneously to their respective destination nodes. As a result, there might be some nodes with better chance to become a relay due to their relatively low traffic loads. In this example, these five node pairs are using path 4-12-29-32, 7-11-19-25, 10-19-22-23, 16-12-14-2, and 25-20-12-6. It is assumed that the sources, i.e., nodes 4, 7, 10, 16 and 25, each send data at a rate of 5 Mbps, 3 Mbps, 8 Mbps, 7 Mbps, 2 Mbps, and 11 Mbps, respectively. Whereas other nodes are each assumed to have a random load of 2 Mbps, 7 Mbps, 12 Mbps, or 17 Mbps.

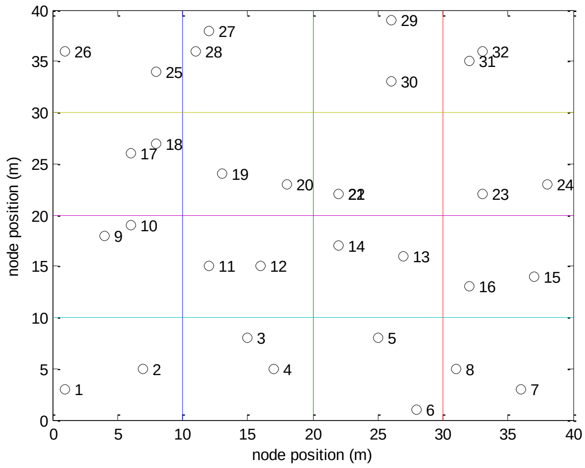

Fig. 4. Indoor Configuration

TABLE I
PARAMETERS OF SIMULATION

Parameter	:	Value
Outdoor path loss exponent , $\propto_o$	:	4
Indoor path loss exponent, $\propto_i$	:	2
Standard deviation of shadowing, φ	:	8 dB
Wall transmission coefficient, Γ	:	0.3
Power Transmit, Pt	:	1 W
Transmit antenna gain, G_t	:	2 dB
Receive antenna gain, G_r	:	2 dB
Frequency, f	:	2.5 GHz
Bandwidth, W	:	20 MHz
Noise, N_0	:	- 101 dBm

B. *Optimization Results*

In determining the results of this optimization we perform simulations 500 times. This section describes one of the simulation results. Optimization by Pareto method for all three performance indicators in outdoor configuration results in cooperative path pair R_1 (1-32) and R_2 (1-11-20-32) having the smallest Euclidean distance of 0.6499. Performance components produced in the process are power consumption of 3 W, SNR of 43.21 dB, and load variance of 56.91 Mbps^2.

As for the indoor configuration, cooperative path pair R_1 (1-14-32) and R_2 (1-18-28-32) are obtained with the smallest Euclidean distance of 0.5467. The values achieved of performance components are power consumption of 4 W, SNR of 45.3 dB, and load variance of 48.91 Mbps^2.

In our reviewed example, optimization with scalarization for all three performance indicators outdoors produces fitness value of 2.4858. The selected cooperative path consists of R_1 (1-3-22-32) and R_2 (1-4-14-32). As for indoor configuration, the cooperative path pair are found to be R_1(1-26-6-32) and R_2(1-10-14-32) with the fitness value of -9.0105.

The result of the entire 500 times simulation is shown in Figs. 5 through 10. Beside the comparison between Pareto and scalarization method, we also compare the results for outdoor and indoor configurations.

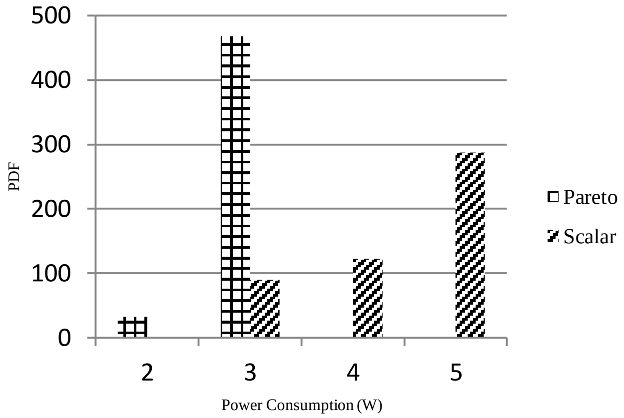

Fig. 5. PDF of Power Consumption Outdoor

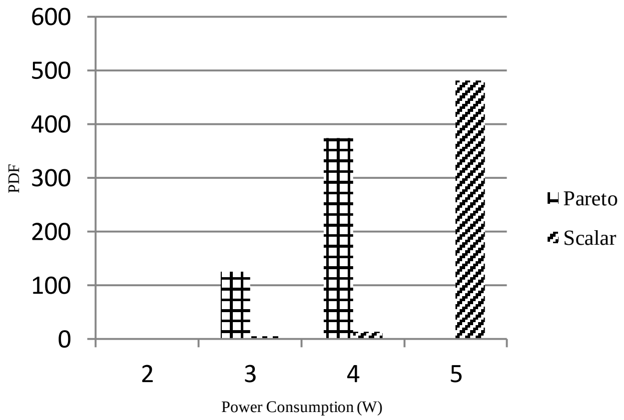

Fig. 6. PDF of Power Consumption Indoor

Fig. 5 shows the PDF (probability density function) of power consumption for outdoor configuration. From Fig. 5 it can be seen that the largest value of power consumption with Pareto method in outdoor configuration is 3 W while the result from scalarization method varies between 3 W, 4 W, and 5 W. On the other hand, Fig. 6 shows that the power consumption in indoor configurations based on the Pareto method varies between 3 W and 4 W, while the scalarization results in an accumulation at 5 W.

From Figs. 5 and 6, it is known that Pareto method for the outdoor configuration results in selected cooperative path pair consisting of one and two hops, while for the indoor configuration the selected pair may consist of paths having one to three hops. This is because the received power at nodes obstructed by walls for indoor configuration is under the threshold power so that more hops are required in selection of cooperative path pair. A similar story also happens with the scalarization case, that is, the number of hops constituting the selected cooperative path pair is greater for the indoor than that for the outdoor configuration. Consequently, cooperative diversity in the indoor scenario tends to consume more energy than in the outdoor, which can be expected due to the presence of walls separating rooms inside the building.

The CDF (cumulative distribution function) of SNR in outdoor configuration for both methods can be seen in Fig. 7. It shows that optimization by Pareto method produces values of SNR slightly greater than those obtained by scalarization method. However, both methods have the same range of SNR, that is, 40.5 - 51 dB. The SNR median difference between Pareto and scalarization method for the outdoor configurations is approximately 0.5 dB.

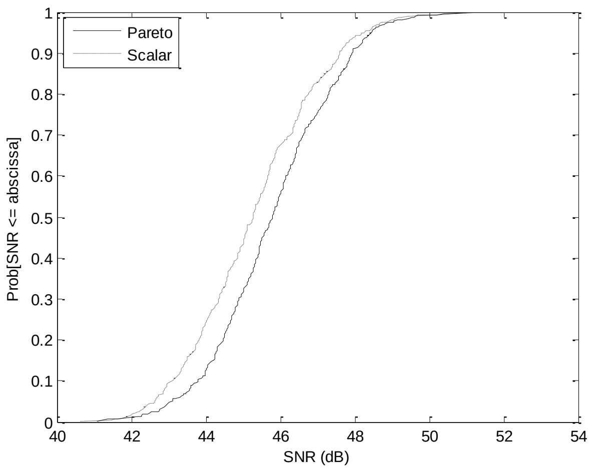

Fig. 7. CDF of SNR Outdoor

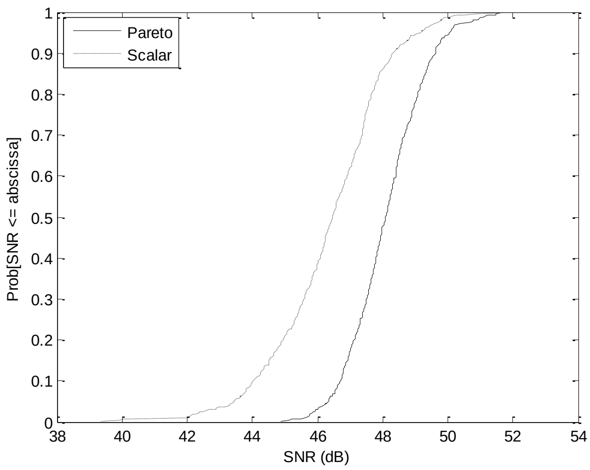

Fig. 8. CDF of SNR Indoor

Fig. 8 shows the CDF of SNR for indoor configurations and demonstrates that by using Pareto method the achieved SNR values are greater compared to those from the scalarization method. The range of SNR for the Pareto method is between 45 - 51.5 dB, while for the scalarization method, SNR value is in the 39 - 51.5 dB range. In this case, the median difference of SNR between the two methods is roughly 2 dB. Comparing the median differences from the outdoor and indoor configurations, it can be observed that the indoor case benefits more than the outdoor case does from the use of Pareto method over the scalarization.

Fig. 9 shows the CDFs of load variance for outdoor configuration. The values of load variance resulting from the use of Pareto method is found to be smaller than those produced by the scalarization method. For the Pareto method the load variance ranges from 45.05 - 60 Mbps^2, whereas using scalarization method, it ranges from 45.05 - 67.5 Mbps^2.

The CDFs of load variance for the indoor scenario are given in Fig. 10, which shows again that the load variance acquired by employing the Pareto method tends to be smaller than that produced by the scalarization method. The range of load variance obtained by Pareto is from 41.5 - 56 Mbps^2, whereas the scalarization method results in the range between 47.5 - 59.5 Mbps2. This observation confirms that the Pareto method outperforms the scalarization in balancing the traffic loads among the nodes.

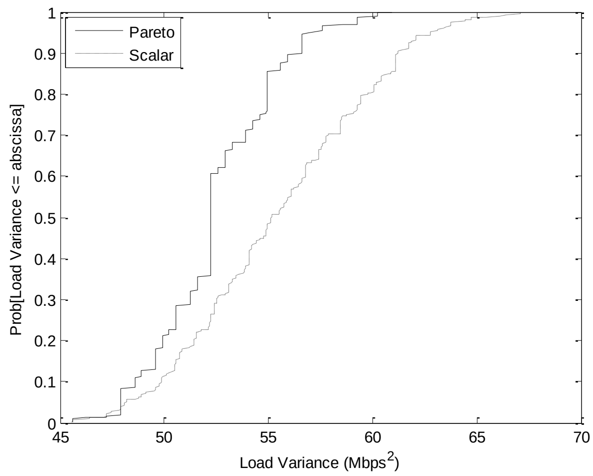

Fig. 9. CDF of Load Variance Outdoor

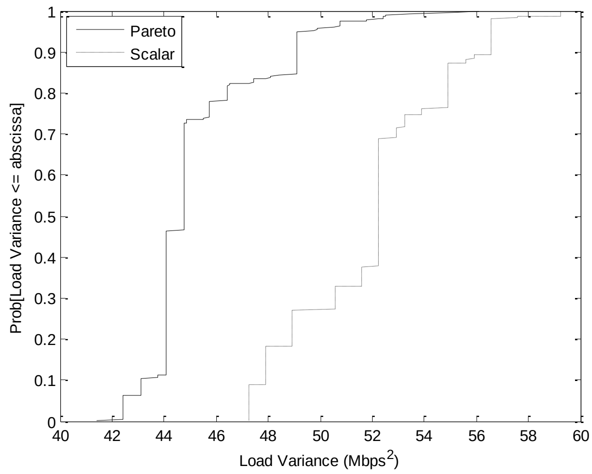

Fig. 10. CDF of Load Variance Indoor

In addition, from Figs. 9 and 10, it is known that the median difference in load variance between the Pareto and scalarization method in outdoor configuration is equal to 3 Mbps^2, while in indoor configuration, the median difference is 7 Mbps^2. As in the case of SNR, the indoor scenario appears to benefit more than the outdoor from the use of the Pareto method in reducing the load variance.

C. Computation Time

The Pareto method is found to take a longer time to complete in the simulation compared to scalarization method. For a total of 500 times simulation, the Pareto method takes 61.1 hours to complete (7.3 minutes per simulation), while the scalarization method only takes about 13.96 hours (about 1.7 minutes per simulation). It means that Pareto method takes on average 4.4 times longer than the scalarization method. This is because Pareto method takes into account all possible cooperative pairs in the optimization. On the other hand, with the scalarization method, the optimization is done iteratively and randomly, depending upon the population and the number of iterations. This computational results are obtained for simulations on Matlab 7.8.0.347 (R2009a) run on a computer with Core 2 CPU 4400 (2 GHz) and 4 GHz RAM. A computer with higher specifications can be used to get faster computation.

VI. Conclusions

From the analysis of the optimization results, several points can be highlighted. Firstly, in selecting cooperative path pair using MOO with the Pareto method, performance indicators under consideration are taken care of separately. With the scalarization method, performance indicators of interest are incorporated in the scalar fitness function. It is therefore expectable that the results of the Pareto method give a better compromise of the performance indicators. Secondly, the optimization results obtained with the Pareto method are better than those obtained using scalarization, as shown by the three performance indicators of cooperative diversity networks considered herein, i.e., power consumption, signal-to-noise power ratio and load variance.

Thirdly, the advantage of the Pareto method over scalarization is more prevalent for indoor cooperative diversity networks than for their outdoor counterparts. This is supported by the finding that the median difference of SNR between the Pareto and scalarization is greater for indoor than for outdoor scenario, and similarly so for load variance. Lastly, Pareto method requires a longer computing time than scalarization does because Pareto method is enumerative while scalarization method is random. Hence, if the problem of computation time can be alleviated by employing a fast computing processor, the use of Pareto method in MOO for cooperative diversity paths selection is recommendable.

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