Multi-objective Optimization Model for Network Selection in Multihomed Devices

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***Abstract*—Nowadays, the increasing diversity of wireless technologies opens the possibility for a mobile device to exploit the aggregated capacity of multiple wireless networks. This aggregated capacity gives different possible assignations of on-going flows to the available interfaces, that may depend on user-imposed restrictions, applications QoS or energy constraints. In this paper, we model the flow-to-interface assignation problem considering bandwidth and energy constraints as a multi-objective optimization problem and use genetic algorithms to search for optimal solutions. We discuss optimal solutions found through the proposed model.**

Keywords*—*Heterogeneous Networks; Multihoming; Network Selection; Energy Efficiency

I. Introduction

Nowadays, mobile users run different kind of applications over the Internet, e.g., messaging, web-browsing or multimedia streaming, which generate an important number of heterogeneous flows. These flows have different needs in terms of quality of service and may use different types of network. Nodes with multiple interfaces (e.g., smartphones, tablets, mobile routers) offer the possibility to be always best connected [1], by taking advantage of several networks. In this paper, we address the problem of choosing the most suitable network for each application flow.

In our recent work [2], we have shown that a mobile user currently has access to different technologies, either simultaneously, or alternatively. Such a mobile user could associate to more than one network, which is called multihoming, to gain in reliability or performance. Ideally, he/she could select the most appropriate network for a given flow and switch network when a connection loss occurs. However, the definition of the policies establishing how to map flows to interfaces, the so-called "network selection process", is still an open research topic. A number of works model the network selection process as a Multiple Attribute Decision-Making (MADM) problem. In MADM, the different alternatives (i.e., the flow-to-interface assignations) are characterized by multiple discordant attributes. In the context of network selection these attributes may include QoS (e.g., bandwidth, jitter, delay), cost, security or energy efficiency. In order to combine these different attributes and rate the different alternatives, a weighting vector is used to define the relative preference of the different attributes. The performance of each possible alternative (i.e., a potential solution to assign flow to interfaces) is evaluated in terms of each attribute and finally a ranking process is performed to determine the best alternative by aggregating the alternative's performance and weights. Some of the existing MADM aggregation mechanisms used in the context of network selection are the Simple Additive Weighting (SAW), the Multiplicative Exponential Weighting (MEW) and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). In SAW, each alternative is rated by calculating the weighted sum of its attributes, while in MEW the rating of each alternative is calculated as the exponentially weighted product of the attributes. In the case of TOPSIS, the best alternative is chosen to be the closest to the positive ideal alternative and the farthest from the negative ideal alternative.

These existing network selection mechanisms consider a large number of attributes that may be difficult to collect, including very detailed network performance parameters, user preferences and application QoS requirements. A second limitation is related to the logic to define attributes weights. In SAW, MEW or TOPSIS, the decision-maker manually sets the weights. The Analytical Hierarchy Process (AHP) [3] introduces a more complex logic to define weights, based on the relative importance of an attribute over the others. Even if the latter avoids manually setting the weights, which leads to subjectivity by nature, it may still introduce subjectivity and, even worst, inconsistency. In this order, a comparative study carried out by Stevens-Navarro et al. [4] shows that for the same weighting vector, there are up to $30\,\%$ of the cases in which the different MADM mechanisms select different interfaces. Moreover, they observe highly variable decisions for slight weight variations, which highlights the critical relevance of weights definition in MADM.

In this paper we propose to model in Section II the flow-to-interface assignation as a Multi-Objective Optimization (MOO) problem, and we propose using evolutionary algorithms to search for optimal solutions. The optimality of this assignation is measured in terms of the bandwidth dissatisfaction of a flow using a particular interface and its energy efficiency. In this way, we avoid subjectivity in giving weights to criteria and obtain a set of equivalent solutions, which provides a diversity for the final selection. An evaluation based on simulations is proposed in Section III. The paper is concluded in Section IV.

II. Energy-Efficient Network Selection using Genetic Algorithms

We consider network selection as a load spreading problem in a per-flow granularity, i.e., each flow is individually assigned to a single interface. We propose to model this network selection mechanism as an MOO problem and use Genetic

Algorithms (GA) [5] to search for optimal solutions. GA can provide a set of optimal flow-to-interface assignations (i.e., the solutions of the MOO), which is called the Pareto Optimal Front (POF). GA iteratively approaches the POF through a variable number of generations, which allows to manage the trade-off between the calculation time and the proximity to the POF. Our approach differs from preference-based algorithms (like the SAW or MEW algorithms), since it avoids subjectivity related to the definition of weights and provides a set of optimal solutions instead of a single solution. In order to instantiate our MOO model, we consider two criteria: the total energy consumption of the interfaces and the bandwidth usage. So, the MS can have a complete view of the energy-bandwidth trade-off to select the most suitable flow-to-interface assignation for each particular scenario. To model the problem, we use a binary-coded decision space where each decision vector X represents the flow-to-interface assignations that are evaluated in a two-dimensional objective space (e.g., Fig. 1) that considers the overall energy consumption of the interfaces ($E(X)$) and the total bandwidth dissatisfaction ($B(X)$), i.e., the difference between the demanded bandwidth by the applications and the offered bandwidth of the interfaces. Both objectives are minimized.

Interface Model - We consider that an interface i_j, $j \in [1, m]$ is characterized by three parameters: the available bandwidth bw_j, the power consumption of its different operating states e_j and the timeouts values to switch to low power consumption states t_j. e_j and t_j are estimated by using energy models for 3G [6] and WLAN [7].

Application Flow Model - As it has been previously proposed in [8], we consider two different types of application flows: non-real-time and real-time. The non-real-time traffic is modeled as the web-browsing traffic model suggested by the 3GPP [9]. It considers a number of browsing sessions, including one or more packet calls (i.e., a sequence of packets after a web-request). Between two consecutive packet calls there is an idle time, corresponding to the reading time). These model variables follow different random distributions. On the other hand, real-time traffic is modeled as video streaming flows in an On/Off approach, in which the duration of the video streaming (On periods) and the time between video requests (Off periods) follow exponential distributions.

Energy Consumption objective - $E(X)$ is calculated as the sum of the average power consumption (in Watts) of all the interfaces, i.e., $E(X) = \sum_{j=1}^{m} p_j(X)$. To calculate $p_j(X)$, we estimate, using e_j and t_j, the time the interface remains on each operating state for a given set of flows that are assigned to each interface.

Bandwidth Dissatisfaction objective - $B(X)$ is calculated as the difference between the applications' bandwidth demand and the available bandwidth. We define the bandwidth dissatisfaction on each interface, $B_j(X)$ with $j \in [1, m]$ as the difference between the bandwidth demand and the available bandwidth of the interface (if this difference is positive) or zero for the rest of the cases. Then, the overall bandwidth dissatisfaction is $B(X) = \sum_{j=1}^{m} B_j(X)$. The bandwidth demand on each interface is equal to the sum of the bandwidth of each application assigned to that particular interface (that depends on the particular decision-vector X).

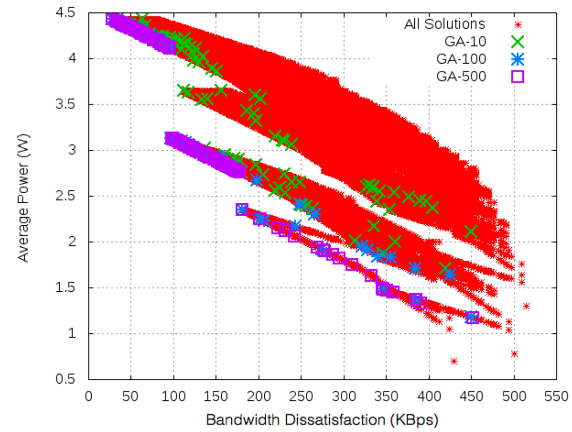


Fig. 1: Simulation Event for 16 Chromosomes

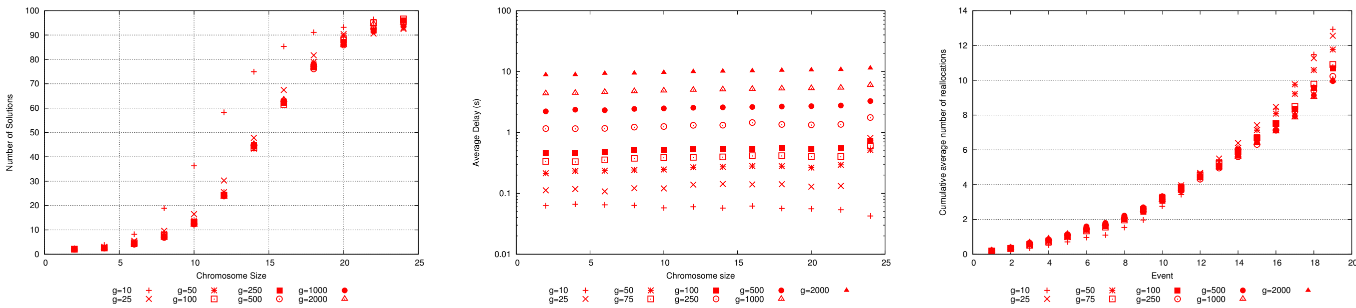
III. Evaluation

We have implemented our own simulator that generates random scenarios and solves the MOO problem using an ideal approach based on the NSGA2 [10] GA. The scenarios generated by our simulator are composed of an application flow arrival process and an interface availability process. We consider the application flow arrival process as a Poisson process of parameter λ_a. Each application flow is a non-real-time flow with probability $p_{nrt} = 0.6$ or a real-time flow with probability $p_{rt} = 0.4$. The interface availability is calculated by interleaving exponentially distributed connected and disconnected times. In our simulator, a decision-making process (i.e., an event in the simulation) is triggered on each application arrival time in order to assign the application flows over the different interfaces. Regarding the GA implementation, we based our implementation on the PISA framework [11], which allows defining an MOO problem (the *Variator* in PISA) and solving it using an existing *Selector* (NSGA2 in our case).

A. Simulation Results

1) Approximation of the POF: We illustrate in Fig. 1, a representative case of a single simulation event. An event in the simulation corresponds to the arrival of a new application flow. As said before, each event is treated as a single and independent optimization problem, which corresponds to a given chromosome size and has been solved using the GA with different generation values (i.e., number of iterations). For the GA, we consider a population size of 100, a number of parents of 50 and an offspring size of 50 individuals. We consider in Fig. 1 the case of 8 flows to be assigned to 4 interfaces (i.e., a chromosome size of 16). Note that depending on the number of generations, there are a high number of solutions that have $B(X) > 0$, meaning that the bandwidth demand is greater than the total available bandwidth for some assignations. Using a low number of generations (e.g., GA-10) the GA finds sub-optimal solutions, i.e., some dominated solutions are observed. But for GA-100 and GA-500 the algorithm provides solutions in the POF.

2) Diversity of Solutions: We measure the diversity in Fig. 2(a) as the average number of different solutions found using the GA for different problem sizes. We observe that the



(a) Diversity of solutions

(b) Calculation time

(c) Number of reallocations

Fig. 2: GA performance evaluation

diversity increases with the chromosome size independently from the number of generations. This is because an increasing chromosome size indicates a large number of applications to assign, which gives more possible solutions and then a larger range for $E(X)$ and $B(X)$.

3) Calculation Time: Mobile devices and routers are usually on the move and need to take decisions as fast as possible in order to prevent impacting the on-going applications. We compute in Fig 2(b) the time spent between the initialization of the random population and the last iteration in the GA (i.e., the last generation of solutions). We observe that, for GA, the calculation time mostly depends on the number of generations rather than on the chromosome size (i.e., the problem size), which means that GA is a good approach even if the problem scales (i.e., more number of applications and interfaces).

4) Number of Reallocations: We observe in Fig. 2(c) that, in the long term, using a mid and high number of generations for GA can provide optimal solutions with the lowest number of reallocations. When performing flow-to-interface assignation, it is not desirable for a given flow to be assigned to different interfaces each time a new event in triggered (i.e., each time a new decision-making problem is solved), since performance may degrade. The POF should provide optimal solutions that minimize the number of reallocations, i.e., the number of flows that have to be assigned to a new interface different than the previous one.

IV. Conclusion

In this paper, we have considered the network selection problem in multihomed mobile devices. Existing network selection mechanisms are commonly based on MADM problems that consider different criteria, including the QoS required by the applications and provided by the interfaces, the security level and energy cost. This high number of heterogeneous criteria gives very complex and non-scalable solutions, that are not easy to solve for the decision-maker since a high level of subjectivity have to be added (i.e., by using weighting vectors) to prioritize all the criteria and reduce the problem to a single dimension. We proposed a simple MOO problem that aims at finding multiple optimal flow-to-interface assignations by considering two antagonistic objectives, the energy consumption and the bandwidth dissatisfaction. After obtaining the POF, the MS must select one particular solution and enforce it. At this point, the decision-maker can use high level information to take the final decision (e.g., depending on the remaining battery of the device, to minimize the number of reallocations). We propose to solve the problem using GA, which avoids introducing subjectivity to the decision-making and increases the scalability (i.e., more applications and interfaces do not impact the delay to obtain the optimal solutions). Note that in the case of a mobile network (i.e., composed of several nodes connected to a mobile router), the problem size scales and so our MOO approach can provide optimal assignations in a relatively short delay.

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