Placement of Base Stations in Broadband Power Line Communications Access Networks by Means of Multi-criteria Optimization

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Abstract. Broadband Power Line Communications (B-PLC) technology is an alternative for broadband access networks, allowing bit rates up to currently 200Mbps. This technique uses the wiring of the low-voltage grid in order to offer to the users the telecommunications services, such as Internet, VoIP, VoD, etc. The B-PLC design process is sub-divided into two parts: the *Generalized Base Station Placement* (GBSP) problem and the *PLC Channel Allocation Problem* (P-CAP). This paper focuses on GBSP that is modeled as multi-criteria combinatorial optimization problem. Based on our published mathematical modeling, this paper supplies more numerical experiments for the evaluation of Multi-Objective Evolutionary Algorithms (MOEAs) in solving GBSP. Their performance is compared with the single-objective optimization.

Keywords: network costs, uplink delay, Broadband Power-Line Communications (B-PLC), access network planning, generalized base station placement, multi-criteria optimization.

1 Introduction

The Internet is becoming more dominated by complex applications such as video (video-on-demand, video-broadcast or streaming) and the audio streaming, etc. These applications consume large portions of bandwidth and demand high a quality of service. This forces network operators to seek for new promising access alternatives, which try to realize an optimal trade-off between network costs and high bit rates. One of such alternatives is the Broadband Power Line Communications (B-PLC). This technology uses a frequency band [3-30 MHz] of the already existing power cables of the Low-Voltage Network (LVN) to build a B-PLC Access Network (B-PLC AN). Through this resources reuse, huge savings in the investment costs are possible. Recent advances in the development of the PLC system hardware have reached bit rates up to 200Mbps; [1]. This has pushed B-PLC on the way of standardization, which is organized in the framework of the Open PLC European Research Alliance (OPERA) Project [2], or HOMEPLUG Powerline Alliance in North America; [3].

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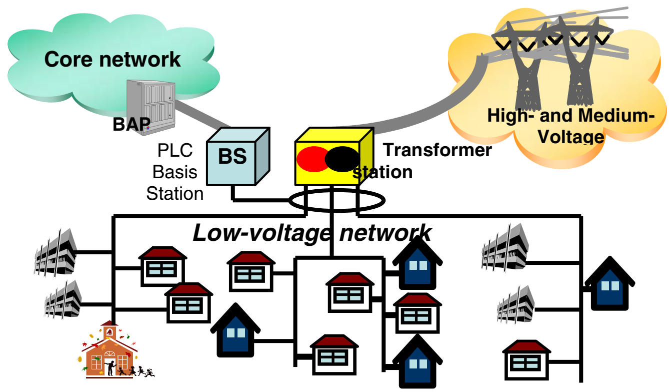
In the field trials where the network size is very small, the planning tasks are done with simple empirical rules. However, since the PLC technology is starting to spread in different countries and application fields become larger, deep investigations of the planning process become necessary. First investigations concerning the design of the B-PLC AN have been done in [4]. In [4], the B-PLC planning problem is subdivided into two main parts: the Generalized Base Station Placement (GBSP) problem and PLC Channel Allocation Problem (P-CAP). However, these have been simplified by avoiding the usage of PLC repeaters, which has a big influence on the problem complexity. In this paper, we analyze and solve the GBSP by considering the use of repeaters. For solving the GBSP problem, two objectives have to be achieved: minimization of network costs and delay. These are conflicting objectives, because the optimization of one of them leads to the penalization of the other. Therefore, the GBSP is a Multi-criteria (or multi-objective) Optimization Problem (or MOP), which can be solved by two different approaches. The classical approach consists in scaling the different objectives into one general objective in a linear way by the means of weighting factors. Then, this general objective is solved by any one of the known algorithms of the combinatorial Single-Objective Optimization (SOO). Recent class of algorithms has been developed, called Multi-Objective (or Criteria) Optimization Algorithm (MOA), to optimize the different objective without scaling them. Firstly, we evaluate the performance of the MOO and then we compare it with the SOO. This paper is based on our previous work from [5], where detailed theoretical analysis of GBSP with initial results can be found. In this paper, we avoid this detailed mathematics, in order to focus more on the analysis and the evaluation of the numerical results for the evaluation of MOO and SOO algorithm and their comparison; and their impacts from the network planner/operator point of view.

The remaining of the paper is organized as follows: The process of building a broadband access network on the low-voltage grid is described in the next section. Overview on the optimization approaches is given in the third section. Exact definition of the GBSP is given and its optimization objectives are modeled in the fourth section. In the fifth section, numerical experiments and results are discussed.

2 Building Broadband Access over Low-Voltage Grid

The B-PLC AN is realized by placing a Base Station (BS), which plays the role of a bridge between telecommunications backbone network and the low-voltage network. The end user device uses a PLC modem to communicate with the BS. Because the PLC systems have a limited coverage, one or several repeaters can be sued to reach user (or users) above this distance. A general structure of a B-PLC AN and its environment is shown in Figure 1. In the practice, one or several BSs have to be installed in the LVN to serve all the users. Therefore, the LVN must have potential locations, where BSs could be installed. Generally, the BSs are installed in the transformer station and the street cabinets. This makes the LVN structure important information for the B-PLC network planner. Because of that the different LVN structures have been investigated and modeled in [6]. These investigations are based on the European LVN (especially the German) with underground wiring. North America, Asia and Oceania have another structure of LVN, which makes the GBSP easily solvable, as shown in Figure 2. For this case, a practical solution consists in using B-PLC in low-voltage network for serving the last meters towards the subscribers and in the Medium-Voltage (MV) network to cover the last mile. The information signal is injected/extracted by the MV Head End (or BS) in/from the Metropolitan Area Network of the city.



Fig, 1. Structure of Broadband Power Line Communications (B-PLC) access networks over an underground infrastructure; example of Europe

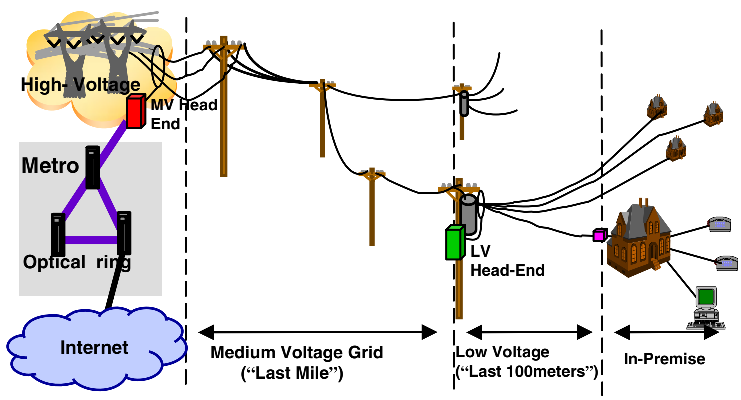


Fig. 2. Example of broadband access networks over aerial infrastructure (North America)

The first task of B-PLC AN design is the placement of the BSs. An optimal placement consists in defining the optimal number of the needed BSs and to place them in the optimal locations in the LVN. A second planning subtask consists in defining which users have to be served by which BS. This is strongly affected by the distance between user and BS. Because the LVN wirings were not designed to use their high frequencies, the distortions affecting PLC signals are too strong. This makes the BS coverage (L_{max}) very short, typically about the 300m. Therefore, if a user is apart from BS by more than L_{max}, one or several PLC repeaters have to be used. After that, each BS has to be connected with the backbone network. We assume that in the LVN environment different possible access points to the WAN are available, which we refer to them as Backbone network Access Points (BAPs). A BAP can be for example an optical line termination. The problem to solve in this phase is to determine over which BAP each BS can access the backbone network. These sub-tasks defined above can be classified under a general problem, called *Generalized Bas Station Placement* (GBSP) problem. This is of same class than problem of base station placement in wireless networks, which is NP-hard. The solution of GBSP builds a *PLC site*, which contains a set of PLC cells. A PLC Cell is built by: a BS j, its sub-set of allocated users $U^{(j)}{}_{S}$, its repeaters and its BAP $W^{(j)}{}_{BAP}$.

3 Optimization Paradigms

Usually network planning related optimization problems are modeled as one objective function (mostly the costs), which has to be minimized in presence of constraints. Such problems are said to be single-objective optimization problems. The GBSP is modeled in this work as Multi-Objective Optimization Problem (MOP). A MOP consists in optimizing simultaneously a vector of objectives under certain constraints, and has the general form in Eq.1. Generally all or some of those objectives are conflicting, where the optimization of one results in deterioration of other(s).

$$. \textit{minimize} \qquad \mathbf{z} = \mathbf{f}(\mathbf{x}) = [f_1(\mathbf{x}), f_2(\mathbf{x}), ..., f_k(\mathbf{x})] \tag{1}$$

The classical method for solving the MOO problems consists in aggregating the different objectives into a single general objective function, which is then optimized by the means of the traditional SOO algorithms. This method is called "*scaling method*" that achieves the conversion by forming a linear combination of the objectives using weights or scaling factors w_k's, with $\sum w_k=1$. Another classical approach takes into consideration only one objective for the optimization, where the remaining ones are converted into constraints. Another solving paradigm for MOPs is gaining an increasing interest, both in engineering as well as in academic fields. This is the Multi-objective Optimization (MOO), which is known also as Multi-Criteria Optimization (MCO), where the different objectives are optimized quasi-independently. Most of the research in MOO is oriented towards the Metaheuristics. These have three main advantages: *i)* find good (but not necessarily the best) solution; *ii)* require acceptable computation time; and *iii)* have a generic form that makes them adaptable to any engineering optimization problem.

In this work, the evolutionary algorithms have been chosen for the application, in its both variants (SOO and MOO). This choice has been motivated by two facts. Firsts, these metaheuristics have been widely and successfully used in different engineering fields. Especially, these algorithms are the mostly used in different telecommunications fields, as stated in [7] and [8], where more than 450 references are listed. Seconds, the evolutionary algorithm is the most investigated and developed variant in the multi-objective optimization; [9]. A metaheuristic MOA is an algorithm that samples the solution space, in a random-controlled way. These samples are evaluated separately and compared in all optimization dimensions. With this comparison, the dominated (i.e. the worst in all dimensions, like S_2 in Figure 3 (*left*))

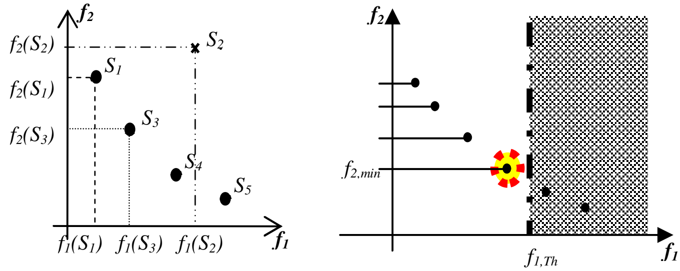


Fig. 3. Example of Pareto front or approximation set for a minimization problem (left, for a MOP: minimize **f**=*[f1,f2]*) and the front reduction (right)

solutions are eliminated and only the non-dominated (i.e. relative good) ones are kept. These will build a *Pareto front* or *Approximation Set*, which is referred as $\mathbb{A}=\{S_1,S_3,S_4,S_5\}$. Further examples and details can be found in [10] [11].

SOO supplies exactly one optimal solution to the considered problem, while the MOO supplies a set of trade-off solutions. Therefore, they can not be directly compared. Because of that, the approximation set (or front) is reduced to one solution. Firstly, a threshold for one objective dimension is set (like in Figure 3 *(right)*). This threshold is set by the best solution of SOO. The sub-space above this threshold is considered as unfeasible. Among the remaining solutions of the MOO, we choose the solution with the minimum value according to the other objective dimension. This solution is then considered as the best MOO solution. Then the comparison of SOO and MOO is done according to this second dimension. Practical examples are given in the section with numerical results.

4 Definition and Modeling of GBSP Problem

4.1 Problem Description

Generally, the GBSP is a combinatorial optimization problem that can be summarized as follows:

Given: LVN topology; set of available BAPs (W_S); BAP-BS cost matrix (M_{BS-BAP}); users traffic demand; PLC element costs (BS and TDR); and an access scheme to the medium;

Tasks: Place an optimal number of BSs; allocate each user; place repeaters where needed; and connect BSs to backbone over the BAPs;

Objectives: **minimize** costs, **minimize** delay;

Constrained by: in-sight constraints; system coverage (BS and repeaters); and BAP capacities.

4.2 Network Costs

The total GBSP costs include the BSs, TDRs and BS-BAP costs. Generally, the costs of BSs and TDRs contain the hardware as well as the installation costs. The potential locations for placing these PLC network elements (namely the transformer stations and the street cabinets) are very hostile for communications devices, because of their characteristics. Among such hostile characteristics are: the temperature that varies between -10C° and 70C°, the weak ventilation, humidity <95%, very dusty, risk of flooding, etc. Because of the complexity of modeling the installation costs, only the hardware costs are taken into consideration in this work. Example of BS placements are given in Figure 4, where BS is placed in an on-the-ground transformer station – example form Europe- and another BS (i.e. head end) placed on a pole near to the aerial transformer; example from Asia. Detailed mathematical formulation of the costs minimization as function of network decision variables and all the optimization constraints can be found in [5]. Among the main constraints, we have:

i) The in-sight condition, represented by the variable $\hat{y}_{ij}$, guarantees the free sight between user *i* and his BS *j*. A user and BS are said to be in-sight if they are not separated by any other BS. This variable is equal to one if the in-sight constrained is fulfilled, as it is the case between user 1 (*u1*) and BSs *j* and *k* in Figure 5. Otherwise it is zero; which is the case of user u1 and BS *m*. This constraint is very important, because if there is another BS between the user and his BS, to which he is allocated, the communication between them is impossible. Each BS transmits only its signal, while it sees other BS signals as noise, which is filtered out. The in-sight constraint is also valid in case of BS-TDRs and TDR-user;

ii) Because of the reachability limitation, the distances (BS and its adjacent TDR), (BS and its adjacent user), (TDR and its adjacent TDR) and (TDR and its adjacent user) must remain below the distance limit (L_{max});

Fig. 4. Example of practical placement of base station (i.e. head end) in on-the-ground transformer station (left – Source: Drewag, Dresden, Germany) and on a pole near to the aerial transformer; example form Asia (right - Source: Kepco, Jeju Island, South Korea)

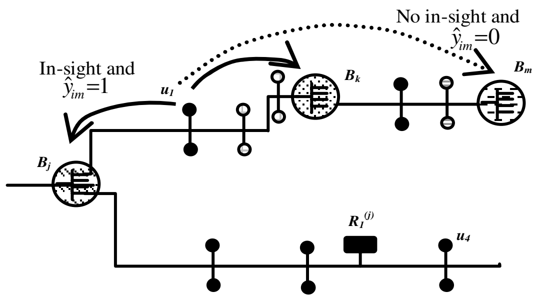


Fig. 5. Example of in-sight constraint between PLC subscriber and BS

In this paper, we consider that B-PLC systems (BS and TDR) coverage (L_{max}) is a constant. However, this is not true in the practice. In fact, the system coverage is influenced by several parameters at the same time; such as the medium size, number of connected users, their activities, the age of the cable, etc. For example, if the transmitted signal crosses a street cabinet, which contains generally different coupling of the outgoing segments. This results in considerable lost of signal energy. On the other hand, if a higher number of households is connected to the, then line impedance is higher. Furthermore, these households connect different household appliances, which generate stronger noise over this medium segment; [12]. The consideration of all those factors in one model for the channel model to compute the system coverage in each line segment makes the problem too complex. However, in future works the coverage has to be taken as function of most important parameters affecting the attenuation, such as cable characteristics (length, type, impedance, number of connected households, etc.), multi-path effect, number/types of coupling inside the street cabinets, used frequency, etc.

4.3 Downlink and Uplink Delay in B-PLC Access Networks

The packet delay in the b-PLC AN represents the time required by the packet to arrive from it source (BS or user) to its destination (user or BS). Here we differentiate two-types of delay; the downlink (from BS to end user – referred as $\boldsymbol{D_{BS2e}}$) and the uplink delay (from user to BS - $\boldsymbol{D_{e2BS}}$). In the downlink, the BS gets the packet from the backbone (or metro network) and broadcast it over the access network; as illustrated in the queuing system in Figure 6. The service time is the time needed by the packet to arrive to the ser destination, and represents the propagation/transmission time over all network segments between the BS and the targeted user. The uplink delay is more complex, because each user willing to send a packet to the BS hat to get the right to access the medium. The power line is used by several users at the same time, because of that it is pointed out as shared medium and a Medium Access Control (MAC) mechanism is needed, in order to guarantee a good utilization of the medium.

In this paper, we focus only the uplink delay that is also called *End-user-to-BS* Delay (D_{e2BS}). For the computation of the delay, the B-PLC cell is assumed as an *M/G/1*-queuing system. Such system assumes that users (or user packets) arrive in memory-less fashion with rate λ. The service X is assumed to be memory-less random

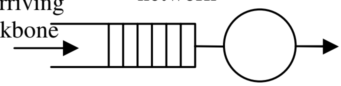


Fig. 6. Queuing model for the B-PLC AN downlink

variable *($X_1, X_2, \ldots, X_i, \ldots$)* with an arbitrary distribution. The total delay affecting user packets in such system contains a waiting time in the queue, plus a service time. The mean value of the total delay can be written as; [13]:

$$E\{D_{Total}\} = E\{X\} + \frac{\lambda \cdot E\{X^2\}}{2(1-\rho)} \tag{2}$$

With $E\{X\} = 1/\mu$ is the average service time, $E\{X^2\} = \sum_i p(X_i) X_i^2$ is the second moment of service time, and $\rho = \lambda/\mu$. Thus, the next step consists in calculating the first and the second moment of the service time by firstly modeling the service time in the uplink.

The service time of a packet of user *i* contains two components. Firstly, this waits in the queue until it arrives to the front of the queue. Even if it is in the front of the queue, this packet can not be automatically served, because it must wait until the station gets the right to access the medium by the means of a polling message. This delay is called polling waiting time that a user packet must wait in the queue ($D_i^{(poll)}$). Seconds, when the packet has the right to access the medium, then a transmission time ($D_{(i \to j)}^{(Tx)}$) is needed so that the packet goes from the user *i* to the BS *j*. In this case, the service time has the form:

$$D_{(i \to j)}^{(Serv)} = D_i^{(poll)} + D_{(i \to j)}^{(Tx)} \tag{3}$$

Transmission Delay: A PLC repeater extends the coverage of BS, which reduces the network costs, because the BS is more expensive than repeater. However, its utilization results in some drawbacks, such increase of delay and/or reduction of the available bit rate. Because the BS and its repeaters use the same medium, their transmissions must be multiplexed, either in time, or in frequency, or in time and frequency. Based on some technical and costs considerations, the Time Division-based Repeaters (TDR) are considered as the best solution. Therefore, only TDRs are considered in this work. In a network using TDRs, the time is organized in Time Slots (TS). Any packet transmission must occur at the beginning of a TS and the packet arrives to its destination in this same TS. An example of the effect of the TDRs is shown in Figure 7, where a data packet has to be sent from BS to user #3. At a 1st time TS, data packet is sent by the BS and will be received by repeater #1 (R1). At the 2nd TS, R1 sends the packet further to arrive to R2. At the beginning of the 3rd TS, R2 sends further the packet to R3. At 4th TS, R3 sends the packet further. The

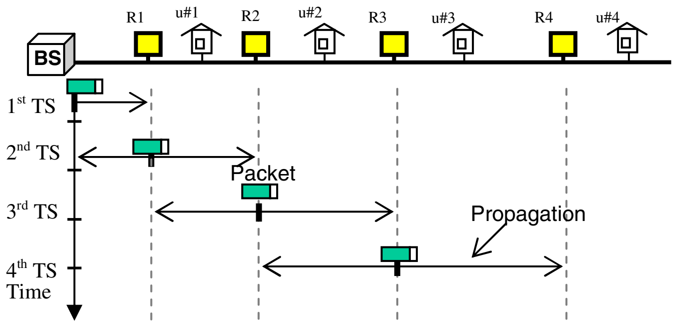


Fig. 7. Effect of time division repeaters in the B-PLC access networks

transmission time of packet from/to user i is a function of the number of TDRs separating this user from his BS j ($R_{(j\rightarrow i)}$), and can be written in the following form:

$$D^{(Tx)}_{(i\rightarrow j)} = (1 + R_{(j\rightarrow i)}).T_{TS} \tag{4}$$

MAC-related Delay: Because several energy users share the same wiring, the PLC medium is called "*shared medium*", and the BS should also realize the Medium Access Control (MAC) tasks. Different MAC mechanisms have been investigated to be implemented for PLC systems; [14]. In this work, we consider a master-salve mechanism that is used in some commercialized PLC systems. This works according a *Round Robin Polling* scheme, where the BS polls its users in a cyclic deterministic way. When the packet of user i arrives to the front of the queue, the access right (i.e. polling message) can be at any one of the $|U^{(j)}_S|$ user stations of the cell. Because the polling message is sent to stations in a deterministic cyclic way without priorities, then the probability that the polling message is at station i' is equal for all stations. This probability is $p^{(poll)}_{i'} = 1/|U^{(j)}_S|$. If we assume that the BS polls its users in a cyclic way in the following succession $\{u\#1, u\#2, \ldots, u\#|U^{(j)}_S|\}$, then the BS has to poll the subset of users $\overline{U}^{(j)}_{(i'\rightarrow i)} = \{u\#i', u\#(i'+1), \ldots, u\#(i-1)\}$ before to arrive to poll the user i. The time $D^{(poll)}_{(j\rightarrow i'\rightarrow i)}$ represents the time required to poll each user $i'' \in \overline{U}^{(j)}_{(i'\rightarrow i)}$ and to receive back a message of "*no-data-to-send*" from this user. This message is sent by the user, when he has no data to send. After that, a delay $(R_{(j\rightarrow i)}+1).T_{TS}$ is required by the BS to transmit the polling message to user i. In this case, the mean value of the polling waiting time for user i becomes as follows:

$$\begin{aligned} E\{D^{(poll)}_i\} &= \sum_{i'\in U^{(j)}_S} p^{(poll)}_{i'} . D^{(poll)}_{(j\rightarrow i'\rightarrow i)} \\ &= \frac{1}{|U^{(j)}_S|-1} \sum_{\substack{i'\in U^{(j)}_S \\ i'\neq i}} \left(\sum_{i''\in \overline{U}^{(poll)}_{(i'\rightarrow i)}} 2.(R_{(j\rightarrow i'')}+1).T_{TS} \right) + (R_{(j\rightarrow i)}+1).T_{TS} \end{aligned} \tag{5}$$

Combining (4) and (5) in (3), it becomes:

$$E\{D_{j,UL}^{(Serv)}\} = \frac{1}{|U_S^{(j)}|}\sum_{i\in U_S^{(j)}}\left(E\{D_i^{(poll)}\} + D_{(i\to j)}^{(Tx)}\right)$$

$$= \frac{1}{|U_S^{(j)}|}\sum_{i\in U_S^{(j)}}\left(\begin{array}{l}\frac{1}{|U_S^{(j)}|-1}\cdot\sum_{\substack{i'\in U_S^{(j)}\\ i'\neq i}}\left(\sum_{i''\in \overline{U}_{(i'\to i)}^{(poll)}} 2.(R_{(j\to i'')}+1).T_{TS}\right)\\ +2.(R_{(j\to i)}+1).T_{TS}\end{array}\right) \tag{6}$$

The mean value of the uplink delay in cell j becomes as follows (more details can be found in [5]):

$$E\left\{D_{e2BS}^{(j)}\right\} = E\left\{D_{(j,UL)}^{(Serv)}\right\} + \frac{|U_S^{(j)}|.\lambda^{(UL)}.E\left\{\left(D_{(j,UL)}^{(Serv)}\right)^2\right\}}{2\left(1-|U_S^{(j)}|.\lambda^{(UL)}.E\left\{D_{(j,UL)}^{(Serv)}\right\}\right)} \tag{7}$$

A PLC site is constituted by several cells. Therefore, to model the delay in the site, either the average delay over all cells is taken or the maximum one. In later case, the mean uplink delay in the site can be written as:

$$minimize \qquad f_{Delay} = E\left\{D_{e2BS}^{(Site)}\right\} = \max_{j\in P_S^{(BS)}}\left(E\left\{D_{e2BS}^{(j)}\right\}\right) \tag{8}$$

The GBSP problem can be then formulated as a multi-objective optimization problem in the following standard form:

$$minimize \qquad \mathbf{f}_{GBSP} = \left[f_{Costs}, f_{Delay}\right] \tag{9}$$

5 Experiments and Numerical Results

5.1 Parameters Setting

Generally the performances of any algorithm are depending on several factors, like the characteristics of the planning problem that are generally referred as instance size. This is represented in this work by the LVN structure and its environment. In order to check how hard the algorithm performances can be affected by the problem (i.e. LVN) characteristics, two problem instances with different sizes (a small and a large network) are used for the generation of numerical results. Two main characteristics of the instances can be seen as basic parameters, namely the users' density and the LVN size. Therefore, the small instance has short distances and a lower number of users (7 potential locations for BSs placement and 45 users, as shown by the solution samples depicted in Figure 8). The large network instance has 14 potential BS locations and 934 users. For the realization of the B-PLC access network in the practice, there are different PLC systems that are available, where each offers a kind of tradeoff between the costs and the system performances. Generally, the recent systems still have relative high prices, but they are offering better characteristics. Different characteristics are interdependent, such as the total bit rate, the time slot duration and the number of channels. Because of that, two possible B-PLC systems are used as reference for the planning of B-PLC in this work, which characteristics are listed in Table 1. Time slot duration must be equal or larger than the time needed to transmit one packet with maximum length. In B-PLC the Ethernet packets are used to transmit the data, with a maximum length of 1500Bytes.

Table 1. Characteristics of two different used B-PLC systems

--	Bit rate	TDR cost	BS cost	T_{TS}	Coverage
System#1	30Mbps	100cu	300cu	0.5ms	500m
System#2	15Mbps	50cu	150cu	1ms	500m

From numerous possible Multi-Objective Evolutionary Algorithms (MOEAs), two versions of Non-dominated Sorting Genetic Algorithm (NSGA and NSGA-II) and Strength Pareto Evolutionary Algorithms (SPEA) have been selected. These are called Pareto-based MOEA and are more powerful than the other ones, according to their performances in solving other engineering MOO problems; [10] [11]. A solution violating one or more constraints is applied to some repair mechanisms. If in spite of the repair the solution is still violating a constraint, then it will be discarded and another one is generated. The evolutionary search uses the following parameter: 100 generations, population of 100 individuals, crossover probability $p_c=1$ and mutation probability $p_m=0.01$.

5.2 Pareto-Based Multi-objective Evolutionary Algorithm Solving the GBSP

Different possible quality indicators (i.e. performance metrics) of multi-objective algorithms can be used for the performance evaluation; [11]. However, in this section we focus only on two metrics; namely *front cardinality* (or approximation set cardinality) and *the coverage of two sets*. Concerning the front cardinality, this does not play a big role in the comparison in case of GBSP. The numerical results show similar cardinality in case of all three MOEAs for all problem instances, which average varies between 5 and 7 solutions. This very low cardinality seems to be normal, because of the high number of optimization constraints (i.e. boundary conditions). During the simulation also the infeasible solutions belonging to the front have also saved separated of the feasible ones. An infeasible solution is a solution that violates at least one solution in spite of the use of some repair mechanisms. Their number was very large in the case of the large network instance. In this case, only the coverage of two sets is used to compare the algorithms. The results related to this metric are given in Tables 2 and 3 for the small and the large network; respectively. This metric measures the percentage of solutions in front A_1 that are dominated by at least one solution from front A_2. It shows how good is the solutions convergence towards the optimal front in comparison to solutions of the other front.

A first remark that can be made concerns the clear variation of the values of this metric in case of small and large network instances. For example, $\boldsymbol{C}(A_{NSGA},A_{NSGA\text{-}II})=0.43$ in case of small network with system#1, while $\boldsymbol{C}(A_{NSGA},A_{NSGA\text{-}II})=0.03$ in

Table 2. Coverage of two sets for evaluation of different MOEAs for small network

Small network – System#1			
	NSGA	NSGA-II	SPEA
NSGA	#	0.43±0.05	0.23±0.04
NSGA-II	0.37±0.05	#	0.14±0.03
SPEA	0.51±0.104	0.68±0.05	#
Small network – System#2			
	NSGA	NSGA-II	SPEA
NSGA	#	0.46±0.06	0.26±0.04
NSGA-II	0.31±0.05	#	0.14±0.04
SPEA	0.52±0.05	0.68±0.05	#

Table 3. Coverage of two sets for evaluation of different MOEAs for large network

Large network – System#1			
	NSGA	NSGA-II	SPEA
NSGA	#	0.03±0.04	0.05±0.08
NSGA-II	0.68±0.22	#	0.41±0.37
SPEA	0.59±0.26	0.23±0.21	#
Large network – System#2			
	NSGA	NSGA-II	SPEA
NSGA	#	0.3±0.14	0.14±0.1
NSGA-II	0.31±0.14	#	0.19±0.12
SPEA	0.42±0.15	0.43±0.14	#

case of large network with system#1. This considerable changes in this relative behavior can be explained by the exponentially increase of the search space, which requires longer computation time to allow the algorithms to converge. In this experiment, the small number of generation (100 generations) has been used in case of both instance sizes. In case of small network, NSGA and NSGA-II show similar relative performances. This means, that the mechanisms introduced by NSGA-II to conserve the population diversity do not make a major difference. This could be explained by the very low number of the feasible solutions; and therefore, the very low number of solutions in the partial fronts. In this case, the solutions are not crowded in narrow regions of the objective space. This explains why the NSGA-II which mechanisms are based on the crowded-distances measurements does not show higher performances in comparison to its original version (i.e. NSGA). However, the advantage of NSGA-II became clearer in the case of large network. Furthermore, the use of elitism by this variant allows preserving the good solutions found in the early generations. In fact, in larger problem the MOEA needs longer time for the convergence, and it is possible that the good solutions found at the beginning of the search get lost, because the genetic operators (esp. crossover) can destroy them. The SPEA, which solution samples from the front of one run are shown in Figure 8, shows better performances than both NSGA variants.

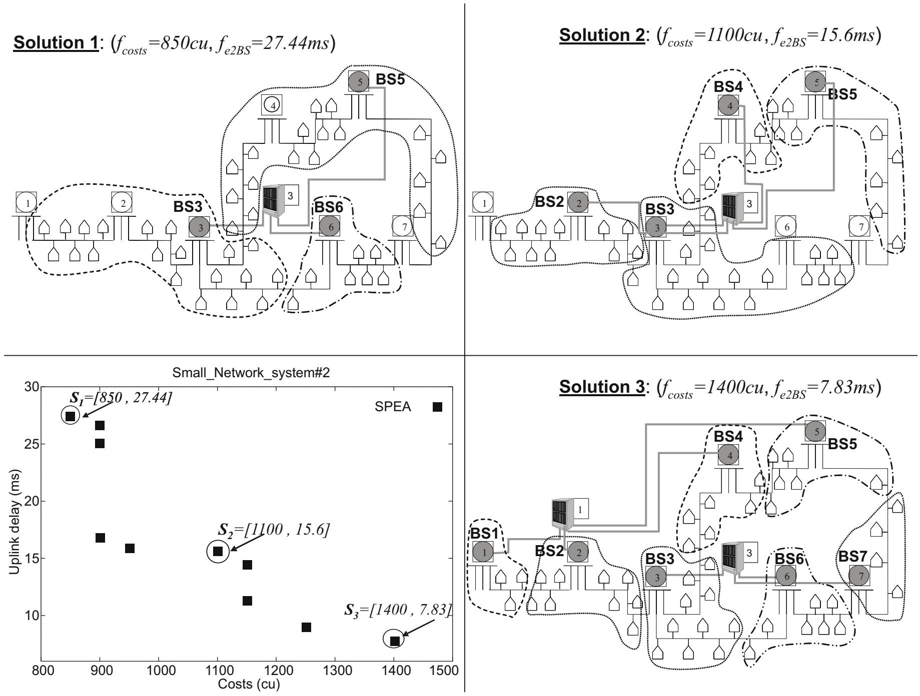


Fig. 8. Example of SPEA solutions for GBSP -small network and system#2

5.3 Comparison of Single- and Multi-objective Optimization

A single-objective optimization algorithm supplies a unique solution as output, while a multi-objective optimization algorithm supplies a set (or front) of optimal solutions. Because of that, such front has to be reduced into one solution, in order to make any comparison between SOO and MOO possible. The front reduction is done by fixing a threshold to one objective. The surface above this threshold is considered as infeasible in the objective space. In the remaining feasible part, we choose the solution that realizes the best value according to the second objective. In the GBSP, we define a delay threshold (D_{Thr}). This threshold is the best value realized by the SOO. The numerical results for the SOO and MOEAs comparison are given in Tables 4 and 5 for small and large network; respectively. In case of small network using system#1, the delay threshold is 5.8ms. This delay is realized by the SOO by the means of 2051cu, while the SPEA realizes it with less costs; namely 2001cu. The other MOEAs algorithms can also realize a delay under this threshold with lower costs that SOO; namely 2006cu and 2009cu for NSGA-II and NSGA; respectively. However, this advantage of MOO toward the SOO is not so large, since it disappears in the case where the small network is designed with system#2. In this case, the costs form the different optimization approaches are closer. A remark can be done concerning the stability of the algorithms convergence. The results show very small confidence intervals of the costs values achieved by MOEAs in comparison to the SOO. However, this characteristic is deteriorated for all MOEAs in the experiments with

Table 4. Comparison of SOO and MOO costs for given delay threshold DThr – Small network

Algorithm	System#1		System#2	
	D_{Thr}(ms)	Costs(cu)	D_{Thr}(ms)	Costs(cu)
SOO	5.8	2050.98±40.58	12.5	1137.47±28.88
NSGA	5.8	2009.33±7.35	12.5	1154.33±2.39
NSGA-II	5.8	2006.33±5.95	12.5	1151.33±0.0
SPEA	5.8	2001.33±0.0	12.5	1151.33±0.0

Table 5. Comparison of SOO and MOO costs for delay threshold D_{Thr}– case of large network

Algorithm	System#1		System#2	
	D_{Thr}(ms)	Costs(cu)	D_{Thr}(ms)	Costs(cu)
SOO	175	6275.27±86.29	323	4092.08±297.36
NSGA	175	8718.64±823.25	323	4401.11±273.02
NSGA-II	175	8290.65±380.7	323	4383.78±191.2
SPEA	175	8790.69±978.3	323	4308.91±256.82

large network, especially when using system#1. The large network instance does not only cause an instable behavior of MOEAs convergence, but also a bad convergence, as this is reflected by the numerical results. For example, SOO supplies solution for the large problem with system#1 and threshold of 175ms by costs of 6275cu, while the SPEA solution costs are of 8790cu for a same delay. A cause of this behavior can be the convergence time that is longer in case of MOO.

A general advantage of the MOO lies in the diversity of the output. In fact, if the network planner would like to have different possible solutions for his problem, and then to decide which one to keep according either to delay or costs or both, then MOO is advantageous. If the network planner lets the SOO runs several times, then he will mostly get two or three completely different solutions. But this is possible with the MOO in one run. As an example, Figure 9 is given, where the solutions resulting form 10 different SOO runs and solutions from one SPEA run are plotted in the objective space. In case of system#1, the 10 runs of SOO supply only 4 different solutions, in the time where one SPEA run reaches 8 different solutions. Furthermore, the front of MOO covers all the solutions found by SOO in different runs. Similar is the remark concerning the network using system#2, where 4 and 10 different solutions are found by 10 SOO runs and one SPEA run; respectively. Also in this case, the SOO results are covered by the unique SPEA run. Another advantage of the MOO is that it allows to find a solution for extreme cases. For example, if the network has to be designed to transport a service that constraints hardly the delay, then MOO is the best approach to solve this problem. The problem of SOO to deal with such scenario lies in the fact that it is generally hard to model correctly the preference in the optimization weighting factors (i.e. w_i's), which are used for objectives scaling. The MOO supplies front of solutions that can be used to design B-PLC AN for any scenario (independently of service desired to transport). Such front will allow choosing the solution that is adequate for any faced scenario. This option is not possible with SOO,

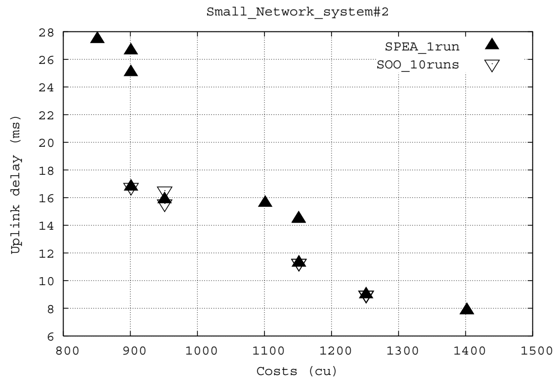


Fig. 9. Comparison of solutions from 10 SOO runs and 1 MOO run in objective space

as it is stated in Figure 9, where the MOO reaches the shortest delay. This effect is clear also in larger networks.

6 Conclusions

The Generalized Base Station Placement (GBSP) problem consists of the following: *a)* finding the optimal locations where an optimal number of BSs has to be placed; *b)* allocating in an optimal way a number of PLC subscribers to each BS; *c)* placing time division PLC repeaters where this is necessary; and *d)* to connect each placed BS to the backbone network over an available Backbone network Access Point (BAP). This optimization problem is a Multi-objective Optimization Problem (MOP) because different conflicting objectives have to be optimized at the same time. The main GBSP optimization objectives that have been considered are the network costs, network delay (in uplink and downlink). For the solution of the mathematically formulated MOP, two optimization paradigms have been used: the single objective optimization (SOO) where the MOP is converted into a single-objective problem and the Multi-objective Optimization where the objective are optimized separated from each other. In the numerical experiments two problem instances have been used (small and large low-voltage networks) with two possible B-PLC systems (system#1 and system#2), which differ in the costs and performances. The used optimization algorithms, for both SOO and MOO, are based on the evolutionary search.

The MOO can perform better than the SOO; however, it must have enough computation time to be able to converge as it was the case with the small network instance. In large problem instance, the SOO supplies the best results, because it needs short time for the convergence. However, The MOO has the major advantage to offer wider choice to the decision making. In this way, the network planner gets a deeper sight into the optimization process. In fact, the use of MOO allows the network planner to find solution even for hardly constrained objectives. For example, the MOO found in each run network solutions where the uplink delay is less than 5ms, while this case is rare if the SOO is used.

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