2018 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovations

A Hybrid MIP-based Heuristic for the Optimal Design of DVB-T2 Networks

Fabio D'Andreagiovanni[1,2]
Hicham Lakhlef [2]
Antonella Nardin[3]

[1]National Centre for Scientific Research (CNRS), France
Email: d.andreagiovanni@hds.utc.fr

[2]Heudiasyc UMR 7253, Sorbonne Universités, Université de Technologie de Compiègne, CNRS, CS 60319, 60203 Compiègne, France
Email: hicham.lakhlef@hds.utc.fr

[3]Università degli Studi Roma Tre, Via Ostiense 169, 00154 Roma, Italy
Email: nardin.an@gmail.com

Abstract—**Due to the ongoing introduction of the second generation of the Digital Video Broadcasting - Terrestrial standard (DVB-T2), television broadcasters that are already active and new broadcasters entering in the business will be required to (re)design their networks. This is generating a new interest for effective and efficient DVB optimization software tools. In this work, we propose a new fast hybrid heuristic for the design of DVB-T2 networks. The heuristic combines a genetic algorithm, adopted to efficiently explore the solution space of power emissions of DVB stations, with a (very) large neighborhood search formulated as a Mixed Integer Programming (MIP) problem solved exactly. Computational tests on realistic instances show that the new hybrid heuristic is able to identify solutions granting much higher user coverage than those identified by a state-of-the-art optimization solver.**

I. Introduction

Though the impressive evolution that telecommunications services have experienced in the last years, television broadcasting remains a fundamental service that is able to easily reach most of the population of a country and that is of high repute among national governments. A fundamental step in the evolution of the television technology has been represented by the switch from analogue to digital transmissions, which has allowed to increase the quality and the range of services. Among all the digital television technologies, the DVB-T Standard (Digital Video Broadcasting Terrestrial) [26] is the most popular and is adopted in the majority of world countries. The need for improving the efficiency of the standard in terms of exploitation of the radio spectrum has led to the development of a 2nd-generation DVB, which is commonly called DVB-T2 [27] and that was officially released by ETSI - the European Telecommunications Standardisations Institute - in 2009. The switch from DVB-T to DVB-T2 is currently ongoing in several European countries and is considered very important by the European Commission, since it will allow to increase the capacity of the television system of at least 30%, thus favouring more broadcasting companies to enter the market and enhance competition and media pluralism (see also [28]). The new broadcasting companies will be active through new networks that will require to be designed. At the same time, incumbent broadcasting companies will have to redesign their network in order to take into account the new features of the DVB-T2 and the interactions with the new deployed networks.

In this work, we address the question of developing a mathematical optimization algorithm in order to solve the challenging mathematical optimization models adopted for DVB-T2 networks. Specifically, our contributions are:

1) we discuss how to derive an optimization model to represent the problem of designing a DVB network, in particular modelling the power configuration of DVB stations and the association of users to a serving station. The model corresponds to a Mixed Integer Linear Programming (MILP) problem and employs signal-to-interference quantities recommended to be used for coverage evaluation by international regulatory bodies. After having introduced the model, we discuss its numerical drawbacks;
2) we define a new hybrid heuristic algorithm for solving the MILP problem associated with the design of DVB networks. In particular, we combine a *Genetic Algorithm (GA)* with a Mixed Integer Linear Programming heuristic. The aim of the GA algorithm is to efficiently explore the set of discrete power solution space that can be assigned to the DVB stations, whereas the aim of the MILP heuristic is to improve the best solution found by the GA algorithm, by executing a very large neighborhood search *exactly* (i.e., formulating the search through a MILP model that is solved through an MILP solver - see [6]).
We note that (nature-inspired and genetic) heuristics have been widely adopted to solve different versions of wireless network design problems. Referring to the case of GAs, we cite the case of: [11], which considers the transmitter location problem; [31], which considers the service assigment problem; [14], which considers the frequency assignment problem; [52], which considers power assignment problem; [15], which jointly considers power, frequency and modulation assignment for WiMAX networks. However, to the of our best knowledge, no hybrid algorithm combining GA and MIP heuristics has been yet developed to solve the DVB

978-1-5386-9380-3/18/$31.00 ©2018 IEEE
DOI 10.1109/SmartWorld.2018.00265

network design problem, in particular with the aim of tackling the numerical difficulties associated with the MILP model (see the next section).

More precisely, our hybrid algorithm is located between exact optimization algorithms and (bio-inspired) heuristics for DVB: exact algorithms, such as [17], [22], [45], theoretically guarantee convergence to an optimal solution, but, at the same time, they tend to present a slow convergence that is not suitable for tackling very large realistic instances; heuristics, such as [4], [15], [37], [40] are instead fast but cannot provide guarantees about the quality of the produced solution. In contrast, a hybrid heuristic like the one we present here runs fast, but also exploits the valuable information coming from (strengthened) linear relaxations of the problem, allowing to better guide the fixing of variables in the exact MILP search and also to derive a so-called *optimality gap* that can measure the quality of the produced solution. To the best of our knowledge, the only work that makes use of a hybrid metaheuristic for DVB design is [23], where an algorithm inspired by ant colony optimization strengthened through polyhedral considerations is developed. However, in contrast to the algorithm that we present here, the algorithm of [23] is not specifically developed to tackle the numerical difficulties of wireless network design and considers an approximated model for DVB network design problem where only one serving signal is considered for each user, instead of the composition of useful signals actually supported by the DVB-T Standard - see the next section for more details;

3) we present the results of computational tests based on realistic DVB instances, indicating that the new hybrid algorithm is able to return solutions of much higher quality than a state-of-the-art commercial optimization software.

The remainder of this paper is organized as follows: in Section II, we introduce an optimization model for DVB-T2 network design; in Sections III and IV, we present the new hybrid algorithm and the computational tests, respectively. Finally, in Section V, we derive conclusions.

II. DVB-T2 Network Design

In order to derive a mathematical optimization model, a DVB-T2 network can be described as a set of DVB transmitting stations S that broadcast a signal associated with a television service to users located in a target territory. Each station is associated with a geographical location and a number of parameters (e.g., power emission, modulation scheme, frequency channel), which define its radio-electrical configuration. In accordance with recommendations and requirements for DVB network design released by major international and national regulatory bodies (e.g., [1], [9]), we decompose the target territory into a grid of elementary (small) squares, called *testpoints* (TPs). Each TP can be seen as a kind of "superuser" that is located at the center of the square and is representative of all the users located in the square. The set of all TPs is denoted by T.

The general *Wireless Network Design Problem* (WND) (see e.g., [16], [22], [36], [50]) can be described as the optimization problem consisting of establishing the location and the configuration of each transmitter in a telecommunication network in order to optimize an objective function, typically representing the profit of the operation or the coverage of users, while guaranteeing a desired level of quality of service. Though in principle all the parameters of a transmitter can be simultaneously optimized and be considered as decision variables of a WND, all works considering the WND focus their attention on just a subset of the parameters. In particular, most of the works consider only the setting of the power emission of each transmitter together with establishing the transmitter that serves each user (user-serving transmitter association). Indeed, these constitute two crucial questions to be considered when designing networks, as indicated and taken explicitly or implicitly into account in several (real) studies (e.g., in DVB [28], [22], [42], [45], 5G [10], [33], [43], [44], [51], in FTTx [18], [48], in Mesh Networks [25], [32], in UMTS [2], [3], in WiMAX [5], [16], in WLANs [20], [19], [29] and in other wireless network design problems such as [7], [8], [17], [34], [36], [39], [38], [50], [54]).

Optimizing the power emission of transmitter and the user-trasnmitter association leads to the so-called *Scheduling and Power Assignment Problem (SPAP)*, a version of the WND that is known to be NP-hard [45]. In a hierarchy of WND problems identified in [16], [45], [46], the SPAP plays a crucial role. In order to model the SPAP for DVB-T2 network design, we introduce two typologies of decision variables, namely:

- a continuous power variable $p_s \in [0, P_{\max}]$ representing the power emission for each transmitter $s \in S$;
- a binary service assignment variable $x_{ts} \in \{0, 1\}$ defined in the following way:

$$x_{ts} = \begin{cases} 1 & \text{if } s \in S \text{ is the serving station of TP } t \in T \\ 0 & \text{otherwise} \end{cases}$$

for each TP $t \in T$ and station $s \in S$.

Concerning the evaluation of the quality of service, we can first note that each TP $t \in T$ receives signals from all the stations $s \in S$ and the power $P_t(s)$ that t gets from s is proportional to the power p_s emitted by s by a factor $a_{ts} \in [0, 1]$ (i.e., $P_t(s) = a_{ts} \cdot p_s$). The factor a_{ts} is indicated by the name of *fading coefficient* and represents the reduction in power that a signal experiences while propagating from s to t [49].

In canonical wireless networks, if we focus on a specific frequency channel, each user/testpoint receives signals from all the stations, but the service is provided by the signal of one single station, chosen as *server* of the user, while all the other stations emit signals that interfere with the serving station, thus reducing the quality of service. In contrast, the DVB-T(2) standard adopts Orthogonal Frequency Division Multiplexing (OFDM) and this allows to treat as useful signals received by distinct stations transmitting on the same channel (we recall indeed that in a DVB-T(2) network, the stations are broadcasting the same information and the signal of each station reaches a testpoint at different time - see [41], [45] for more details). Specifically, a user/testpoint must decide where to position a *time window* for signal detection: all the signals received within the time window are useful and strengthen the quality of service, whereas all the signals received outside the time window are interfering and deteriorate the quality of service.

Notwithstanding the fact that a time window could be placed in a theoretically unlimited number of positions on the time axis, it is common to let start the time window in correspondence with the instant in which a signal is received from a station. As a consequence, for each testpoint, we assume that the number of possible time windows is equal to the number of stations in the network. Given a a tespoint $t \in T$, if the detection time window of t starts when the signal of station $s \in S$ is received, we say that s is the *serving station* (or *server*) of t.

For a given TP $t \in T$ and serving station $s \in S$ of t, we denote by $U(s,t) \subseteq S$ the subset of useful stations for t and by $I(s,t) \subseteq S$ the subset of interfering stations. We remark that such two subsets constitute a partition of the set of stations, i.e. $S = U(s,t) \cup I(s,t)$ and $U(s,t) \cap I(s,t) = \emptyset$. Once that the subsets of useful and interfering signals are established, we say that TP t is served by station s if the ratio of the sum of the useful powers to the sum of the interfering powers (the Signal-to-Interference Ratio - SIR) is above a threshold $\delta > 0$, whose value depends on the wanted quality of service [41], [49]:

$$SIR_{ts}(p) = \frac{\sum_{\sigma \in U(s,t)} a_{t\sigma} \cdot p_\sigma}{N + \sum_{\sigma \in I(s,t)} a_{t\sigma} \cdot p_\sigma} \ \geq \ \delta \ . \tag{1}$$

Here, $N > 0$ represents the noise of the system. Serving a TP t generates a revenue r_t (in the case of DVB-T networks, we set r_t equal to the number of users located in a testpoint). Through simple operations of linear algebra, we can rewrite the SIR (1) as the following inequality, which we call SIR inequality:

$$\sum_{\sigma \in U(s,t)} a_{t\sigma} \cdot p_\sigma - \delta \sum_{\sigma \in I(s,t)} a_{t\sigma} \cdot p_\sigma \ \geq \ \delta \cdot N \ . \tag{2}$$

Since part of the decision process consists of deciding which is the serving station of a TP, for each TP $t \in T$ we have to consider one SIR inequality (2) for each potential server $s \in S$. This implies that we actually face the following disjunctive constraint, including one SIR inequality for each potential server:

$$\bigvee_{s \in S} \left(\sum_{\sigma \in U(s,t)} a_{t\sigma} \cdot p_\sigma - \delta \sum_{\sigma \in I(s,t)} a_{t\sigma} \cdot p_\sigma \ \geq \ \delta \cdot N \right) . \tag{3}$$

By following a well-known approach in Mixed Integer Programming (see e.g., [47], [22]), this disjunctive constraint can be expressed as a family of linear constraints, by relying on the introduction of a sufficiently large positive value M, commonly known by the name of *big-M coefficient*. To this end, besides the big-M coefficient, we also employ the binary service assignment decision variable x_{ts}, introducing the following constraint for each potential server $s \in S$:

$$\sum_{\sigma \in U(s,t)} a_{t\sigma} \cdot p_\sigma - \delta \sum_{\sigma \in I(s,t)} a_{t\sigma} \cdot p_\sigma + M(1 - x_{ts}) \ \geq \ \delta \cdot N \ . \tag{4}$$

It is easy to check that if $x_{ts} = 1$, then the big-M term disappears and the SIR inequality corresponding with TP t served by station s must be satisfied. If instead $x_{ts} = 0$, then the big-M activates and the inequality is satisfied by any valorization of the power variables p_σ, thus becoming redundant. The inequality (4), which we call *SIR constraint*, constitutes the core of any wireless network design problem including service quality under the form of a signal-to-interference ratio.

On the basis of the system elements and notation introduced above, we can define the problem of designing a DVB network as follows.

Definition 1 (The DVB Network Design Problem - DVB-ND): Given a set of stations S, a set of TPs T, the fading coefficients a_{ts} $\forall t \in T, s \in T$, the testpoint population r_t $\forall t \in T$, the maximum power emission P^{max} of each station, the system noise N and the SIR threshold δ, the DVB Network Design Problem consists of establishing the power emission of each station $s \in S$ and the serving station of each TP $t \in T$, so that the TP population covered with service is maximized, while the corresponding SIR constraints are satisfied, each TP is served by at most one station and the power limits of the stations are respected.

The DVB-ND problem can be modelled through the following Mixed Integer Linear Programming problem, which we denote by the acronym DVB-MILP:

$$\max \ \sum_{t \in T} \sum_{s \in S} r_t \cdot x_{ts} \tag{DVB-MILP}$$

$$\sum_{\sigma \in U(s,t)} a_{t\sigma} \cdot p_\sigma - \delta \sum_{\sigma \in I(s,t)} a_{t\sigma} \cdot p_\sigma + + M(1 - x_{ts}) \geq \delta \cdot N \qquad t \in T, s \in S \tag{5}$$

$$\sum_{s \in S} x_{ts} \leq 1 \qquad t \in T \tag{6}$$

$$0 \leq p_s \leq P^{\max} \qquad s \in S$$

$$x_{ts} \in \{0,1\} \qquad t \in T, s \in S \ .$$

Here, the objective function models the target of maximizing the number of users covered with service, expressed as the summation of the population of served TPs. The constraints (5) are the SIR constraints, whereas the constraints (6) model that each TP can be served by at most one station.

In what follows, for algorithmic purposes, we consider a purely binary version of DVB-MILP including discrete power values. To this end, we introduce a set $\mathcal{P} = \{P_1, \ldots, P_{|\mathcal{P}|}\}$ of feasible power values on which a DVB station may emit and we replace each continuous power variable with the linear combination of 0-1 power level activation variables $z_{sl} \in \{0,1\}$ and the power values, namely p_s is replaced with

$\sum_{l=1}^{|\mathcal{P}|} P_l \cdot z_{sl}$. A generic variable z_{sl} is equal to 1 if s emits at power level P_l and 0 otherwise. Additionally, each station must be activated on a single power level, so we must also include the constraint $\sum_{l=1}^{|\mathcal{P}|} z_{sl} = 1$ for each station s.

A. Discussing the strength of the DVB-MILP model

The optimization model DVB-MILP constitutes a very natural way to model the DVB-ND problem by directly including the SIR constraints. Such direct inclusion has been largely adopted in literature for nay different types of WND problems (see, for example, [16], [22], [36], [50]). However, this generates the following difficulties:

- the fading coefficients may vary in a (very) wide range and thus define (very) ill-conditioned coefficient matrices that make the solution process unstable from a numerical point of view;
- the big-*M* coefficients are known to lead to "mathematically weak" formulations associated with bounds of low quality, which greatly reduce the effectiveness of state-of-the-art optimization solvers [13];
- the resulting coverage plans are often unreliable and may contain errors (see e.g., [8], [22], [34]), that is, if we post-process solutions returned by solvers like IBM ILOG CPLEX [12] it is very likely to find SIR constraints that are actually not satisfied by the computed power assignment (for a more technical discussion about why this happens due to the floating-point arithmetic adopted in commercial optimization solver, we refer the reader to [21])

.

In practice, models based on SIR constraints like DVB-MILP can be solved to optimality only in the case of instances of small size. In contrast, as the size of instances increases, the identification of feasible solutions may constitute a very difficult task, even for state-of-the-art commercial optimization solvers like CPLEX. Though these drawbacks are well-known, it is interesting to note that just a relatively small part of the wide literature devoted to WND has tried to overcome them (see [16], [22] for a review). In the next section, we proceed to introduce a fast hybrid heuristic that is able to take into account such numerical difficulties.

III. A Hybrid Heuristic for the DVB-MILP

In order to develop an effective and efficient algorithm for solving DVB-MILP, we combine a construction phase based on a Genetic Algorithm (GA) with an improvement phase consisting of an MIP heuristic. The GA phase adapts algorithmic consideration made in [15].

Genetic algorithms are widely-known bio-inspired heuristic algorithms originally developed for solving combinatorial optimization problems. Specifically, they take inspiration from the evolution process of a population of individuals (for an exhaustive introduction to theory and applications of GAs, we refer the reader to [30], [35], [53]). Essentially speaking, a GA maintains a population of individuals and each individual corresponds to a feasible solution of the considered optimization problem. The value that the decision variables assume in a solution is encoded in the so-called *chromosome* of an individual. The *genetic strength* of an individual is assessed through the adoption of a *fitness function* that measures the quality of the solution associated with the chromosome. In a typical GA, there is an initial population that evolves iteratively through individual crossover, mutation and death mechanisms that mimic natural selection and evolution. More in detail, the general structure of the GA that we consider is depicted in Algorithm 1.

Algorithm 1 General Genetic Algorithm (GA-alg)

```
1: Creation of the initial population
2: while an arrest condition is not satisfied do
3:    Selection of individuals who generate the offspring
4:    Generation of the offspring by crossover
5:    Mutation of part of the population
6:    Death of part of the population
7: end while
8: Improving MIP Heuristic
```

We now proceed to discuss in detail the features of all the steps of the algorithm.

A. Characteristics of the population

1) Representation of the individuals: The central decision that we encode in the chromosome of an individual is the power setting of the DVB stations. In our algorithmic setting, the chromosome of an individual thus corresponds to a power vector p of size $|S|$. The generic position $s \in \{1, 2, \ldots, |S|\}$ in the chromosome stores the discrete power level $p_s \in \mathcal{P}$ emitted by station $s \in S$.

Once that a power vector/chromosome is defined, we still have to decide how to select the server for a TP (i.e., deciding the value of the service assignment variables x_{ts}, in order to compute the associated coverage). In order to do this, for each TP $t \in T$ and server $s \in S$, we compute the value of the signal-to-interference ratio $SIR_{ts}(p)$ using the power vector p and the distinction between useful and interfering signals induced by the server s. Let us denote now by $\Sigma(t, p) \subseteq S$ the subset of serving stations that can guarantee service coverage to TP t for power p by satisfying the corresponding SIR inequality, i.e.:

$$\Sigma(t, p) = \{s \in S : SIR_{ts}(p) \geq \delta\}$$

If $\Sigma(t, p)$ is not empty, we choose as server σ of t, the station $\sigma \in \Sigma(t, p)$ associated with the highest SIR value $SIR_{ts}(p)$. Then, looking at the service assignment variables, we set $x_{t\sigma} = 1$ and $x_{ts} = 0 \; \forall s \in S \setminus \{\sigma\}$.

2) Fitness function: Since our objective is to maximize the population covered with service, it is natural to adopt a fitness function $COV(p)$ that computes the coverage granted by an individual as a function of the power vector/chromosome p. Specifically, $COV(p)$ is obtained as the summation of the population of TPs whose SIR constraints are satisfied by p, with servers established according to the rules defined in the previous subsection.

3) Initial population: We define the initial population by including power vectors where a single station is activated and, for each station, we define one power vector for each discrete power level except the null one. Formally, for each $s \in S$, the initial population POP contains the following vectors:

$$
\begin{array}{ccc}
(0,0,\ldots, & p_s = P_2 & ,\ldots,0,0) \\
(0,0,\ldots, & p_s = P_3 & ,\ldots,0,0) \\
 & \vdots & \\
(0,0,\ldots, & p_s = P_{|\mathcal{P}|} & ,\ldots,0,0)
\end{array}
$$

thus including $|S| \cdot (|\mathcal{P}| - 1)$ initial individuals in total.

B. Evolution of the population

1) Selection: The selection of individuals whose chromosomes are combined in order to create the new generation of individuals takes place through a *tournament selection*. Specifically, given the current population POP of individuals, we first create $k > 0$ subgroups by randomly selecting $\lfloor \alpha \cdot |P| \rfloor$ individuals from POP, with $\alpha \in (0, 1)$. Then we select a number $m < \lfloor \alpha \cdot |P| \rfloor$ of individuals presenting the best fitness value in each group. Such individuals are those employed to give birth to the new generation through crossover.

2) Crossover, mutation and death: The individuals that have been selected in the previous step are paired in a random way with the aim of forming $\lfloor k \cdot m/2 \rfloor$ couples. Every couple then generates two offspring by means of chromosome crossover. Specifically, given a couple of individuals (the *parents*) associated with power vectors p^1, p^2, the crossover operation mixes the power levels in the same position of p^1, p^2 to generate two offspring with power vectors p^3, p^4 of possibly higher fitness value.

To evaluate the effect of a crossover operation, we introduce the measure $\Delta\text{COV}(p, p_s = P_l) \in \mathbb{Z}$ to denote the variation in the number of covered users induced by changing the power value p_s in position s of a power vector p to a value $P_l \in \mathcal{P}$, while maintaining all the other power values unchanged. By using this measure, we adopt the following crossover operation, which attempts at making $p3$ the best individual in the offspring. At the beginning of the crossover, p^3 and p^4 have all elements equal to 0. Then, by following an increasing order of the index s from 1 to $|S|$, each value 0 inherits the power value of one of the two parents in the same position. More in detail, let us assume to focus on the crossover procedure for a position $\sigma \in \{1, \ldots, |S|\}$: for values of $s \in \{1, \ldots, |S|\}$ such that $s < \sigma$, the crossover has been operated and thus the vectors p^3, p^4 include power levels inherited by the parents p^1, p^2; in contrast, positions corresponding to values $s \geq \sigma$ have not yet been processed and are thus still equal to 0.

In order to establish the inheritance of power values of p^3 and p^4 from their parents p^1 and p^2, we adopt the following rules:

$$
p_s^3 = \begin{cases} p_s^1 & \text{if } \Delta\text{COV}(p^3, p_s^3 = p_s^1) \geq \Delta\text{COV}(p^3, p_s^3 = p_s^2) \\ p_s^2 & \text{otherwise} \end{cases}
$$

$$
p_s^4 = \begin{cases} p_s^1 & \text{if } \Delta\text{COV}(p^3, p_s^3 = p_s^1) < \Delta\text{COV}(p^3, p_s^3 = p_s^2) \\ p_s^2 & \text{otherwise} \end{cases}
$$

which guarantee that the new power vector p^3 inherits the power levels that grant the best variation in coverage ΔCOV.

Besides crossover operations, we include the possibility to vary the values of power vectors by *mutation*, since this favours a better exploration of the solution space and helps to avoid to get trapped in locally optimal solutions. To this end, at every iteration, we randomly choose a number of individuals $\lfloor \gamma \cdot |POP| \rfloor$ with $0 < \gamma < 1$. Then, still by random selection, $|\mathcal{P}|$ power levels corresponding with different frequencies are reduced to the immediately lower power level allowed in $\mathcal{P}$. This mutation operation attempts at creating individuals that grant the same coverage at lower power emission, thus reducing interference effects of a station.

Finally, after having executed crossover and mutation, the weakest individuals *die* and are removed from POP. Specifically, we choose to select and remove the $2 \cdot \lfloor k \cdot m/2 \rfloor$ individuals presenting the worst values of the fitness function. We remark that, due to the specific number of individuals generated and removed from *POP* at every iteration, the size of the population is maintained constant throughout the execution of the algorithm.

C. MIP improvement heuristic

Given the best feasible solution identified in the GA construction phase as starting point, we try to find feasible solutions of higher value through an MIP heuristic corresponding to operating a very large neighborhood search *in an exact way*, namely formulating the search as a MILP problem that is solved through a state-of-the-art MILP solver [6]. The rationale beyond this heuristic is that, while a state-of-the-art solver like IBM ILOG CPLEX can have difficulties in finding good quality solutions for the complete design problem, it can instead fast provide good quality solutions to subproblems obtained by fixing the value of a consistent number of decision variables.

Specifically, we adopt a modified *Relaxation Induced Neighborhood Search* (RINS) (see [24] for a complete and formal definition of this algorithm). Also in this heuristic, we adopt a power-indexed version of DVB-MILP, where the continuous power variables are replaced by binary variables representing the activation of a station on a discrete power level. Let $(\bar{p}, \bar{x})$ be a feasible solution of the problem and let (p^{TLR}, x^{TLR}) be an optimal solution of the linear relaxation, strengthened by the cuts found by CPLEX in the root node of the branch-and-bound tree. Furthermore, let $(\bar{p}, \bar{x})_j, (p^{TLR}, x^{TLR})_j$ denote the j-th component of the vectors.

The modified RINS algorithm that we adopt and that we denote by *(mod-RINS)* consists of solving a subproblem where we set the value of decision variables whose value in $(\bar{p}, \bar{x})$ and (p^{TLR}, x^{TLR}) differs of at most a positive quantity $\rho < 1$, in accordance to the following rules:

$$(\bar{p}, \bar{y})_j = 0 \ \wedge \ (p^{TLR}, x^{TLR}) \leq \rho \implies (p, x)_j = 0$$

$$(\bar{p}, \bar{y})_j = 1 \ \wedge \ (p^{TLR}, x^{TLR}) \geq 1 - \rho \implies (p, x)_j = 1$$

.

The resulting problem is then passed to the state-of-the-art solver, which solves it with a time limit.

IV. Computational tests

In order to test the performance of the new algorithm, we considered 15 instances based on regional DVB network data from Italy. Each instance corresponds to a single-frequency DVB network and includes stations emitting power in the range $[-40, 26]$ dBkW. The computational tests have been conducted on a Windows-based notebook with 2.70 GHz and 8 GB of RAM. The optimization solver IBM ILOG CPLEX 12.5 was employed as MIP solver. The code implementing the optimization model and the solution algorithm was written in C/C++, adopting IBM ILOG CPLEX Concert Technology to interface with CPLEX.

When solving a DVB-MILP instance through CPLEX, a time limit of 3600 seconds was imposed. In the case of the new algorithm, the genetic construction phase runs with a time limit of 3000 seconds and the improvement MIP phase based on mod-RINS runs with a time limit of 600 seconds. The parameters of the algorithm were set as follows: for each tournament selection we define $k = 10$ groups that include a fraction $\alpha = 0.1$ of the population POP; the $m = 10$ individuals with the highest fitness of each group are selected for crossover; following the creation of new individuals, a fraction $\gamma = 0.2$ of the population is subject to mutation. In RINS, we impose $\rho = 0.1$.

In Table 1, we present the results of the computational tests. ID is the identifier of the instances. *COV-CPLEX%* is the percentage of population covered by the best solution found by the optimizer CPLEX within the time limit. *COV-GMIP% (best)* and *COV-GMIP% (avg)* are the percentages of population covered on average and in the best case by our new hybrid algorithm, which we denote by GMIP, within the time limit. Finally, Δ*COV% (best)* and Δ*COV%(avg)* denote the percentage coverage increase, on average and in the best case, that GENMIP is able to grant with respect to CPLEX.

Looking at the results, it is evident that the performance of GMIP is much better than that of CPLEX, granting a percentage increase in coverage that on average is equal to 22% and in the best cases can range from 25 to 52%. Such improvements are really satisfying and remarkable, considering that, in instances corresponding to regions, even small increases in coverage can translate into thousands of additional users getting the service. We believe that the problem results so challenging for CPLEX due in particular to the composition of multiple useful and interfering signals that is present in the SIR constraints.

TABLE I
COMPUTATIONAL RESULTS

ID	COV-CPLEX%	COV-GMIP% (avg)	ΔCOV% (avg)	COV-GMIP% (best)	ΔCOV% (best)
I1	48.6	63.5	30.6	67.5	38.8
I2	55.3	71.1	28.5	73.8	33.4
I3	54.7	64.6	18.0	73.7	34.7
I4	49.2	63.9	29.8	66.2	34.5
I5	50.0	59.7	19.4	69.1	38.2
I6	56.4	66.4	17.7	75.2	33.3
I7	53.9	65.0	20.5	74.9	38.9
I8	62.4	68.0	8.9	78.0	25.0
I9	55.5	72.3	30.2	80.6	45.2
I10	46.3	59.4	28.2	67.4	45.5
I11	57.2	65.2	13.9	73.3	28.1
I12	57.7	68.6	18.8	75.8	31.3
I13	51.4	72.8	41.6	78.2	52.1
I14	62.5	76.9	23.0	79.4	27.0
I15	58.8	65.4	11.2	77.6	31.9

V. Conclusion and future work

The optimal design of television broadcasting networks based on the DVB-T(2) standard is a challenging task, which can prove difficult even for a state-of-the-art optimization solver. In order to tackle the unsatisfying performance of commercial solvers, we presented a new hybrid algorithm for DVB network design, based on combining a genetic algorithm with an exact large neighborhood search formulated as a Mixed Integer Linear Programming problem. Computational tests on realistic instances show that the new hybrid algorithm can find solutions of much better quality than those computed by a commercial solver, thanks to a more efficient exploration of the power emission solution space. As future work, we intend to further enhance the performance of the hybrid algorithm, considering in particular a better integration with valid inequalities from Power-Indexed formulations [22]. Moreover, it would be also interesting to investigate the adoption of hyperheuristics for finding more effective tuning of the various parameters of the hybrid algorithm.

References

[1] Italian Authority for Telecommunications (AGCOM). Specifications for a DVB-T planning software tool. http://www.agcom.it/Default.aspx?message=downloaddocument&DocID=3365 (in Italian), 2009. Retrieved 01.04.2018.

[2] E. Amaldi, A. Capone, F. Malucelli, F. Signori, "UMTS radio planning: optimizing base station configuration". In: Proceedings IEEE 56th Vehicular Technology Conference. vol. 2, pp. 768–772 vol.2, 2002.

[3] E. Amaldi, P. Belotti, A. Capone, F. Malucelli, "Optimizing base station location and configuration in UMTS networks". Ann. Oper. Res. 146, 135–151, 2006.

[4] M. Anedda, J. Morgade, M. Murroni, P. Angueira, A. Arrinda, J. R. Prez, J. Basterrechea, "Heuristic optimization of DVB-T/H SFN coverage using PSO and SA algorithms". 2011 IEEE International Symposium on Broadband Multimedia Systems and Broadcasting (BMSB), 1-5, 2011.

[5] J. Andrews, A. Ghosh, R. Muhamed, *Fundamentals of WiMAX*, Prentice Hall, Upper Saddle River, 2007.

[6] C. Blum, J. Puchinger, G. R. Raidl, A. Roli, "Hybrid metaheuristics in combinatorial optimization: A survey". Applied Soft Computing 11, 4135-4151, 2011.

[7] A. Bouabdallah, H. Lakhlef, M. Raynal, F. Taiani, "Providing Collision-Free and Conflict-Free Communication in General Synchronous Broadcast/Receive Networks". Proc. of IEEE AINA 2017, 2017.

[8] A. Capone, L. Chen, S. Gualandi, D. Yuan, "A New Computational Approach for Maximum Link Activation in Wireless Networks under the SINR Model". IEEE Trans. Wireless Comm. 10, 1368–1372, 2011.

[9] The Chester 1997 Multilateral Coordination Agreement. Technical criteria, coordination principles and procedures for the introduction of terrestrial digital video broadcasting. http://www.archive.ero.dk/132D67A4-8815-48CB-B482-903844887DE3?frames=no&5, 1997. Retrieved 01.04.2018.

[10] L. Chiaraviglio, F. D'Andreagiovanni, G. Sidoretti, N. Blefari-Melazzi, S. Salsano, "Optimal design of 5G superfluid networks: Problem formulation and solutions", 2018 21st Conference on Innovation in Clouds, Internet and Networks and Workshops (ICIN), Paris, 2018, pp. 1-8.

[11] Y.S. Choi, K.S. Kim, N. Kim, "The Displacement of Base Station in Mobile Communication with Genetic Approach". EURASIP J. Wireless Comm. and Net. Vol. 2008, 2008.

[12] IBM ILOG CPLEX: http://www-01.ibm.com/software

[13] G. Codato, M. Fischetti, "Combinatorial Benders' Cuts for Mixed-Integer Linear Programming". Oper. Res. 54 (4), 556–766, 2006.

[14] G. Colombo, "A Genetic Algorithm for Frequency Assigment with Problem Decomposition". Int. J. Mob. Net. Des. and Innov. 1 (2), 102–112, 2006.

[15] F. D'Andreagiovanni, "On Improving the Capacity of Solving Large-scale Wireless Network Design Problems by Genetic Algorithms". In: Di Chio C. et al. (eds.) Applications of Evolutionary Computation. Lecture Notes in Computer Science, vol. 6625, pp. 11-20. Springer, Heidelberg, 2011.

[16] F. D'Andreagiovanni, "Pure 0-1 Programming Approaches to Wireless Network Design". 4OR-Q. J. Oper. Res. 10 (2), 211–212, 2012, DOI: 10.1007/s10288-011-0162-z.

[17] F. D'Andreagiovanni, "A hybrid exact-aco algorithm for the joint scheduling, power and cluster assignment in cooperative wireless networks". In: Di Caro G., Theraulaz G. (eds) Bio-Inspired Models of Network, Information, and Computing Systems. BIONETICS 2012. Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering vol. 134, 3-17. Springer, Cham 2014.

[18] F. D'Andreagiovanni, F. Mett, A. Nardin, J. Pulaj, "Integrating LP-guided variable fixing with MIP heuristics in the robust design of hybrid wired-wireless FTTx access networks". Applied Soft Computing 61, 1074- 1087, 2017.

[19] F. D'Andreagiovanni, R. Garroppo, M.G. Scutellà, "Power Savings with Data Rate Guarantee in Dense WLANs". In: 2017 International Conference on Selected Topics in Mobile and Wireless Networking (MoWNet), 2017.

[20] F. D'Andreagiovanni, R. Garroppo, M.G. Scutellà, "Green Design of Wireless Local Area Networks by Multiband Robust Optimization". Electronic Notes in Discrete Mathematics 64, 225-234, 2018.

[21] F. D'Andreagiovanni, A. Gleixner, "Towards an accurate solution of wireless network design problems". In: Combinatorial Optimization - 4th International Symposium, ISCO 2016, Spriner Lecture Notes in Computer Science vol. 9849, 135-147, 2016.

[22] F. D'Andreagiovanni, C. Mannino, A. Sassano, "GUB Covers and Power-Indexed Formulations for Wireless Network Design". *Management Science* 59 (1), 142-156, 2013,

[23] F. D'Andreagiovanni, A. Nardin, "A Fast Metaheuristic for the Design of DVB-T2 Networks". In: Sim K., Kaufmann P. (eds) Applications of Evolutionary Computation. Lecture Notes in Computer Science, vol. 10784, 141-155, 2018.

[24] E. Danna, E. Rothberg, C. Le Pape, "Exploring relaxation induced neighborhoods to improve MIP solutions". *Math. Progr.* 102, 71-90, 2005.

[25] P. Dely, F. D'Andreagiovanni, A. Kassler, "Fair optimization of mesh-connected WLAN hotspots". Wirel. Commun. Mob. Com. 15, 924–946, 2015.

[26] DVB Project: DVB-T. https://www.dvb.org/standards/dvb-t. Retrieved 01.04.2018.

[27] DVB Project: DVB-T2. https://www.dvb.org/standards/dvb-t2. Retrieved 01.04.2018.

[28] European Broadcasting Union, "Frequency and Network Planning Aspects of DVB-T2", 2014. https://tech.ebu.ch/docs/tech/tech3348.pdf. Retrieved 01.04.2018.

[29] B. Gendron, M.G. Scutellà, R. Garroppo, G. Nencioni, L. Tavanti, "A branch-and-benders-cut method for nonlinear power design in green wireless local area networks". Eur. J. Oper. Res. 255, 151–162, 2016.

[30] D.E. Goldberg, *Genetic Algorithms in Search, Optimization & Machine Learning*. Addison-Wesley, Reading, 1988.

[31] T. Hu, Y.P. Chen, W. Banzhaf, "WiMAX Network Planning Using Adaptive-Population-Size Genetic Algorithm". In: C. Di Chio et al. (eds.) EvoApplications 2010. Lecture Notes in Computer Science, vol. 6025, 31–40. Springer, Heidelberg, 2010.

[32] K. Kamimura, H. Hayashi, "Optimization of power-efficient wireless mesh networks in outdoor and indoor environments in Japan". IEEJ Transactions on Electrical and Electronic Engineering 10(6), 2015.

[33] M. Kang, Y. Chung, "An Efficient Energy Saving Scheme for Base Stations in 5G Networks with Separated Data and Control Planes Using Particle Swarm Optimization". Energies 10, 2017.

[34] J. Kalvenes, J. Kennington, E. Olinick, "Base station location and service assignments in w-cdma networks". INFORMS J. Comp. 18, 366–376, 2006.

[35] S. Karakatic, V. Podgorelec, "A survey of genetic algorithms for solving multi depot vehicle routing problem". Applied Soft Computing 27, 519 -532, 2015.

[36] J. Kennington, E. Olinick, D. Rajan, *Wireless Network Design: Optimization Models and Solution Procedures*, Springer, Heidelberg, 2010.

[37] G. Koutitas, "Green Network Planning of Single Frequency Networks". IEEE Trans. on Broadcasting 56 (4), 541-550, 2010.

[38] H. Lakhlef, A. Bouabdallah, M. Raynal, J. Bourgeois, "Agent-based broadcast protocols for wireless heterogeneous node networks". Computer Communications 115, 51-63, 2018.

[39] H. Lakhlef, M. Raynal, F. Taiani, "Vertex Coloring with Communication and Local Memory Constraints in Synchronous Broadcast Networks". Algorithms for Sensor Systems, Springer LNCS vol. 10050, pp. 29-44, 2017.

[40] M. Lanza, A. Gutierrez, J. Perez, J. Morgade, M. Domingo, L. Valle, P. Angueira, J. Basterrechea, "Coverage Optimization and Power Reduction in SFN Using Simulated Annealing". IEEE Trans. on Broadcasting 60 (3), 474-485, 2014.

[41] A. Ligeti, J. Zander, "Minimal cost coverage planning for single frequency networks". IEEE Trans. Broadcasting 45(1), 78-87, 1999.

[42] G. Martinez, J. Sanchez, D. Barquero, N. Cardona, "Optimization of the Digital Terrestrial Television Transmission Mode of DVB-T2 in Colombia". IEEE Latin America Transactions 13 (7), 2144–2151, 2015.

[43] A. Marotta, F. D'Andreagiovanni, A. Kassler, E. Zola, "On the Energy Cost of Robustness for Green Virtual Network Function Placement in 5G Virtualized Infrastructures". Computer Networks 125, 64–75, 2017.

[44] A. Marotta, E. Zola, F. D'Andreagiovanni, A. Kassler, "A Fast Robust Approach for Green Virtual Network Functions Deployment". Journal of Network and Computer Applications 95, 42–53, 2017.

[45] C. Mannino, F. Rossi, S. Smriglio, "The network packing problem in terrestrial broadcasting". Oper. Res. 54, 611–626, 2006.

[46] C. Mannino, F. Rossi, S. Smriglio, "A Unified view in planning broadcasting networks". DIS Tech. Rep. 08-07, Sapienza Università di Roma, Roma, Italy, 2007.

[47] G. Nehmauser, L. Wolsey, *Integer and Combinatorial Optimization*. John Wiley & Sons, Hoboken, 1988.

[48] D. Novak, R. B. Waterhouse, A. Nirmalathas, C. Lim, P.A. Gamage, T.R. Clark, M.L. Dennis, J.A. Nanzer, "Radio-Over-Fiber Technologies for Emerging Wireless Systems". IEEE J. Quantum Electronics 52, 2016.

[49] T. Rappaport, *Wireless Communications: Principles and Practices*. Prentice Hall, Upper Saddle River, 2001.

[50] M. Resende, P. Pardalos, *Handbook of Optimization in Telecommunications*, Springer, Heidelberg, 2006.

[51] M. Shojafar, L. Chiaraviglio, N. Blefari-Melazzi, S. Salsano, "P5G: A Bio-Inspired Algorithm for the Superfluid Management of 5G Networks", GLOBECOM 2017, 2017.

[52] W.J. Song, W.H. Kim, S.J. Kim, B.H. Ahn, B.G. Kim, M. Choi "Evolutionary Computation and Power Control for Radio Resource Management in CDMA Cellular Radio Networks". IEEE PIMRC 2002, 2002.

[53] M. Srinivas, L.M. Patnaik, "Genetic algorithms: a survey". Computer 27 (6), 17 - 26, 1994.

[54] A. Zakrzewska, F. D'Andreagiovanni, S. Ruepp, M.S. Berger, "Biobjective optimization of radio access technology selection and resource allocation in heterogeneous wireless networks". 2013 11th International Symposium and Workshops on Modeling and Optimization in Mobile, Ad Hoc and Wireless Networks, WiOpt 2013, 652-658, 2013.