A Fast Metaheuristic for the Design of DVB-T2 Networks

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Abstract. In order to better exploit scarce radio spectrum resources, the second generation of the Digital Video Broadcasting - Terrestrial standard (DVB-T2) has been developed and is under adoption in many countries, especially in Europe, for providing digital television services. The switch from the first to the second generation of DVB-T will require new operators to design their new networks and old operators to reconfigure their existing networks to better adapt to the features and opportunities of the new services. In this work, we propose an optimization model and a fast metaheuristic for the design of DVB-T2 networks. The metaheuristic is based on combining a probabilistic variable fixing procedure with an exact large neighborhood search and is developed to tackle the unsatisfying performance of state-of-the-art optimization solvers when adopted to solve realistic instances. Computational tests on realistic instances show that our metaheuristic can find solutions of much better quality than those identified by a state-of-the-art optimization solver.

Keywords: Telecommunications · DVB · Network design
Mixed integer linear programming · Tight linear relaxations
MIP heuristics

1 Introduction

In recent times, digital telecommunications services provided through high-performance mobile networks and high-speed cable-based internet networks have become an essential part of our fast-moving everyday life and new technological paradigms like *cloud* and *5G* are going to offer even more performing

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connectivity experiences (see e.g., [1–3]). Notwithstanding the great expansion and diffusion of such new telecommunications services, the "dear old" television broadcasting services still constitute an extremely important telecommunication service that can easily reach the vast majority of the population and represents a crucial voice in the telecom agenda of national governments.

Thanks to the switch from analogue to digital television technology, the television market has known an increased competition between broadcasters that has stimulated the enlargement of programme variety and led to an increased quality of services and interactivity. Among the available digital television standards, the DVB-T (Digital Video Broadcasting – Terrestrial) [4] is the most widespread standard in the world and since its introduction in 1995 has been adopted in more than half of all world countries. Due to the need for better exploiting the scarce radio spectrum resources and provide services of higher quality, since 2006 the DVB Project has undertaken research projects to develop a 2nd-generation DVB, which is commonly called DVB-T2 [5]. DVB-T2 was standardized by the European Telecommunications Standardisations Institute (ETSI) in 2009. In Europe, since its first introduction in UK in 2010, it has been adopted by several European broadcasters. The full upgrade from DVB to DVB-T2 will take place in major European countries like Germany and Italy in the next few years.

A crucial benefit granted by the DVB-T2 is the increase in system capacity: for the same usage of spectrum, DVB-T2 provides an increase of capacity of at least 30% with respect to DVB-T, allowing the market entry of new broadcasters or the launch of new innovative services. On the other hand, adopting and implementing the new standard will translate into new costs for the broadcasters and users, which will need new broadcasting equipment and receiving devices.

Given the need for new DVB-T2 operators to design their new networks and for old DVB operators to reconfigure their existing networks to better adapt to the features and opportunities of the new services, we study here the question of developing an optimization model and algorithm for the design of DVB-T2 network. Specifically our contributions are:

1. We present a mixed integer linear programming problem for modelling fundamental decisions that must be taken in a DVB-T2 design problem (essentially, configure the network transmitters so to maximize the number of users covered with services) and discuss a way to strengthen the mathematical model through the insertion of additional valid inequalities. The model is based on signal-to-interference quantities recommended to be used for coverage evaluation by international regulatory bodies;
2. In order to fast solve the resulting challenging optimization problem, we propose a metaheuristic based on combining a probabilistic variable fixing procedure with an exact large neighborhood search. Our metaheuristic constitutes a solution approach that places itself in between exact (i.e., guaranteeing convergence to an optimum) but slow optimization approaches for DVB (e.g., [6–8]) and fast (bio-inspired) heuristics (e.g., [9–11]) which cannot provide guarantees about the quality of the produced solution: the metaheuristic indeed runs fast but also exploits the valuable information associated with

the linear relaxation of a strengthened formulation of the problem, using it to guide a variable fixing procedure (this allows to derive a so-called *optimality gap* that can measure the quality of the produced solution);
3. Computational experiments based on realistic DVB instances, showing that our metaheurisitc can produce solutions of much higher quality than a state-of-the-art optimization solver.

The remainder of this paper is organized as follows: in Sect. 2, we introduce an optimization model for DVB-T2 network design; in Sect. 3, we present a new metaheuristic to fast solve the design problem; in Sect. 4, we present our hybrid metaheuristic and computational results. Finally, in Sect. 5, we derive conclusions.

2 An Optimization Model for DVB-T2 Network Design

For modelling purposes, we can essentially describe a DVB-T2 network as a set S of *DVB Stations (DSs)* that provide a broadcasting television service to a set of customers located in a territory of interest. Following the recommendations of major international and national regulatory bodies in the field of telecommunications (e.g., [12,13]), we discretize the territory into a raster of small elementary squared areas of identical size: the point at the center of each area is called *testpoint (TP)* and is assumed to be representative of all the points inside the elementary area. We denote by T the set of all testpoints in the territory.

Each DS is characterized by a location (its geographical coordinates) and a number of radio-electrical parameters (e.g., power emission, antenna diagram, frequency channel). The *DVB-T2 Network Design Problem* (DND) consists in choosing the location and setting the parameters of the DSs in order to maximize an objective function that typically represents the total number of people in testpoints covered with service.

As it is common in wireless network design problems, the optimization does not aim at optimizing all the parameters of the DSs, but just focuses on a subset of them. In the vast majority of studies, the two critical design decisions that are included in the optimization models are: (1) setting the power emissions of the transmitters providing the wireless telecommunication service (in our case the DSs); (2) assigning testpoints covered with service to a deployed transmitter. These are indeed two critical decisions that must be taken by a network administrator, as indicated in several real studies (e.g., in DVB [6–8,14], 5G [15–17], in FTTx [18], in UMTS [19,20], in WiMAX [21,22], in WLANs [23,24] and in other wireless network design problems such as [8,25–30]).

We now proceed to discuss how service coverage is assessed, focusing on a generic TP $t \in T$: when t is covered with service (or shortly, *served*), the service is provided by one single DS $\sigma \in S$, which acts as *server* of t. All the remaining DSs, i.e. all $s \in S \backslash \{\sigma\}$, act as interferers for t, reducing the quality of wireless service obtained from the server σ. More formally, if we denote the power emission of a DS $s \in S$ by $p_s > 0$, a TP $t \in T$ is served by $\sigma \in S$ when the ratio of the *received* service power and the sum of the *received* interfering powers (so-called *signal-to-interference ratio - SIR*) is above a threshold $\delta > 0$ [31,32]:

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

Here, the value of δ depends upon the desired quality of service and $N > 0$ is the noise of the system. The *received* power that t gets from any DS $s \in S$ is expressed as the product of the power p_s emitted by s and a factor $a_{ts} \in [0, 1]$ that is commonly called *fading coefficient* and expresses the power reduction that a wireless signal undergoes when propagating from s to t [32].

The inequality (1) can be easily transformed into the following linear inequality, commonly called *SIR inequality*:

$$a_{t\sigma} \cdot p_\sigma - \delta \sum_{s \in S \setminus \{\sigma\}} a_{ts} \cdot p_s \geq \delta \cdot N. \tag{2}$$

Since assessing service coverage constitutes a crucial issue when designing any kind of wireless network, the SIR inequalities are at the basis of most mathematical optimization models adopted for wireless network design (see e.g., [22,29]. In order to model the two fundamentals decisions exposed above, namely setting the power emissions of DSs and assigning served TPs to activated DSs, two kind of decision variables are introduced:

– a continuous *power variable* $p_s \in [0, P^{\max}]$ that represents the power emission of each DS $s \in S$;
– a binary *service assignment variable* $x_{ts} \in \{0, 1\}$, $\forall t \in T, s \in S$, which is set equal to 1 if TP $t \in T$ is served by DSs $s \in S$ and equal to 0 otherwise.

Through these two kind of decision variables the problem of designing a DVB-T2 network can be cast as the following Mixed Integer Linear Programming problem (DVB-MILP):

$$\begin{aligned}
\max \quad & \sum_{t \in T} \sum_{s \in S} r_t \cdot x_{ts} && && \text{(DVB} - \text{MILP)} \\
& a_{t\sigma} \cdot p_\sigma - \delta \sum_{s \in S \setminus \{\sigma\}} a_{ts} \cdot p_s + M \cdot (1 - x_{t\sigma}) \geq \delta \cdot N && t \in T, \sigma \in S && (3) \\
& \sum_{s \in S} x_{ts} \leq 1 && t \in T && (4) \\
& 0 \leq p_s \leq P^{\max} && s \in S && \\
& x_{ts} \in \{0, 1\} && t \in T, s \in S. &&
\end{aligned}$$

The objective function pursues the maximization of the number of users covered with service (for each TP $t \in T$, $r_t > 0$ is the number of users located in t). Constraint (3) constitutes a slightly modified version of the SIR inequality (2) and it is called *SIR constraint*: it includes a sufficiently large value M (so-called, *big-M coefficient*) multiplied by $(1 - x_{t\sigma})$ in order to activate/deactivate the constraint: if $x_{t\sigma} = 1$, then TP t is served by DS and the corresponding SIR inequality must be satisfied; if instead $x_{ts\sigma} = 0$, then the big-M coefficient "activates" and makes the constraint satisfied for any valorization of the power variables, thus actually making it redundant. Finally, constraints (4) impose that each TP must be served by at most one DSs.

2.1 Strengthening the Formulation DVB-MILP

The formulation DVB-MILP represents a very natural way for modelling the problem of designing a DVB network. However, it is known that the presence of the big-M coefficients combined with the presence of the fading coefficients, which may vary in a very wide range thus causing numerical instabilities, may reduce the effectiveness of commercial state-of-the-art MILP solvers, as discussed in [7,8,22,26,33].

With the aim of reducing these computational issues, we adopt a strengthening method proposed in [7,22]. The method is based on considering a discretization of the continuous power emissions of DSs, which follows the practice of networking professionals. To this end, the continuous power variable p_s of each DS $s \in S$ is replaced by a non-negative integer power variable $\bar{p}_b \in \mathcal{P} = \{P_1, \ldots, P_{|\mathcal{P}|}\}$, with $P_1 = 0$ (*switched-off value*), $P_{|\mathcal{P}|} = P_{\max}$ and $P_l > P_{l-1} > 0$, for $l = 2, \ldots, |\mathcal{P}|$. This integer variable can be expressed as the linear combination of the power values P_l and suitable binary variables: specifically, for each $s \in S$ a binary power variable z_{sl} is introduced and is equal to 1 if s emits at power P_l and 0 otherwise. Denoting by L the set of feasible power levels, formally we have:

$$\bar{p}_s = \sum_{l \in L} P_l z_{sl}$$

Such linear combination must be accompanied by the *generalized upper bound (GUB)* constraints:

$$\sum_{l \in L} z_{sl} \leq 1,$$

expressing that each DS may emit at a single power level.

Using what introduced above, we can define the following SIR constraints based on binary variables, which replaces their continuous form (3):

$$a_{t\sigma} \cdot \left(\sum_{l \in L} P_l \, z_{\sigma l} \right) - \delta \sum_{s \in S \backslash \{\sigma\}} a_{ts} \cdot \left(\sum_{l \in L} P_l \, z_{sl} \right) + M \cdot (1 - x_{t\sigma}) \geq \delta \cdot N t \in T, \sigma \in S \tag{5}$$

We denote by DVB-01 the resulting model based on binary power variables.

In order to operate the strengthening, we exploit the presence of the GUB constraints to replace the SIR constraints (5) including the binary power variables with a set of *GUB cover inequalities*. For an exhaustive introduction to the concept of cover inequalities and to their GUB version, we refer to [34,35]. We concisely recall here the main theoretical results about the well-known general *cover inequalities*: a *knapsack constraint* $\sum_{j \in J} a_j x_j \leq b$ with $a_j, b \in \mathbb{R}_+$ and $x_j \in \{0,1\}$, $\forall j \in J$, can be replaced by its cover inequalities $\sum_{j \in C} x_j \leq |C| - 1$, where C is a *cover*. A cover is a subset $C \subseteq J$ such that the summation of the coefficients a_j with $j \in C$ violates the knapsack constraint, i.e. $\sum_{j \in C} a_j > b$. The cover inequalities thus identify combinations of binary variables x_j that cannot be activated at the same time (we can activate at most $|C| - 1$ variables in each cover C). The GUB cover inequalities represent a stronger version of the simple cover inequalities, which are defined by exploiting the presence of GUB constraints $\sum_{j \in K \subseteq J} x_j \leq 1$, which allows to set to 1 at most one variable in K.

Proceeding as in [7], we can define the general form of the GUB cover inequalities (GCIs) needed to replace the binary SIR constraint (5):

$$x_{t\sigma} + \sum_{l=1}^{\lambda} z_{\sigma l} + \sum_{i=1}^{|\Gamma|} \sum_{l=q_i}^{|L|} z_{sl} \leq |\Gamma| + 1, \tag{6}$$

with $t \in T$, $\lambda \in L$, $\Gamma \subseteq S \backslash \{\sigma\}$, $(q_1, \ldots, q_{|\Gamma|}) \in L^I(t, \sigma, \lambda, \Gamma)$, with $L^I(t, \sigma, \lambda, \Gamma) \subseteq L^{|\Gamma|}$ representing the subset of interfering levels of DSs in Γ that deny the service coverage of t provided by the server σ, emitting with power level λ. Intuitively, for given TP, server DS and subset of interfering DSs, a GCI is defined by fixing the power of the server DS and defining a power setting of the interfering DSs that deny the coverage of the considered TP.

By replacing the SIR constraints (5) with the GCIs (6) in the model DVB-01, we obtain *Power-Indexed* model (DVB-PI) that has the big advantage of eliminating the big-M and fading coefficients, thus greatly strengthening and stabilizing the formulation [7]. On the other hand, DVB-PI presents an exponential number of constraints that should be generated dynamically as in a typical *cutting plane* method [34]: initially, the model just contains a subset of GCIs (6) and then additional required GCIs are added by solving an auxiliary separation problem (see [7] for a detailed discussion about the separation of GCIs for Power-Indexed formulations).

In the metaheuristic that we propose in the next section to solve the DVB network design problem, we limit our attention to the following subset of GCIs:

$$x_{t\sigma} + \sum_{l=1}^{\lambda} z_{\sigma l} + \sum_{l=q}^{|L|} z_{sl} \leq 2, \tag{7}$$

which are defined by considering a relaxed version of the SIR constraints (5) obtained by breaking the SIR constraints containing multiple interfering DSs into multiple single-interferer SIR constraints. Such single-interferer relaxation comes from the observation that in real-world networks it is common to find one interfering DS that is much stronger than all the other interefering DS and thus service coverage just depends on the power emitted by it (see [7,22]). The GCIs (7) of the relaxed SIR constraints can be added to DVB-MILP in order to strengthen it.

3 A Metaheuristic for DVB-T2 Network Design

DVB-MILP, as a mixed integer linear programming problem, can be solved in principle by adopting a commercial optimization solver, such as IBM ILOG CPLEX [36]. Nevertheless, even instances of DVB-MILP of moderate size may result very challenging to be optimally solved even by a state-of-the-art solver like CPLEX. This is especially due to the presence of the fading and big-M coefficients in the SIR constraints.

In order to overcome such unsatisfying performance of commercial solvers, we propose to adopt a metaheuristic that first executes a *probabilistic fixing procedure*, guided by the solution of suitable linear relaxations of the design problem, and then executes an MILP heuristic, based on an *exact very large neighborhood search*. The probabilistic fixing is partially inspired by the algorithm ANTS (*Approximate Nondeterministic Tree Search*) [37] an improved ant colony algorithm that aims at exploiting the information about bounds available for the specific optimization problem. In particular, we follow the principle of using suitable linear relaxations of the problem at hand, instead of generic bounds, that has been originally proposed in the works [38–40] and extended in further works such as [41].

Ant Colony Optimization (ACO) is a metaheuristic inspired by the behaviour of ants, which has been initially proposed in [42] and then been object of uncountable further studies and applications (e.g., [37,43–47] - see also [48,49] for an overview). The essential pseudocode of an ACO algorithm (ACO-alg) is presented in Algorithm 1.

Algorithm 1. General ACO Algorithm (ACO-alg)

```
while an arrest condition is not satisfied do
    ant-based solution construction
    pheromone trail update
end while
local search
```

In an ACO, a number of *ants* are defined and each ant iteratively builds a feasible solution until an arrest condition, such as a time limit, is met. At every iteration, the ant is in a *state* that corresponds to a *partial solution* for the optimization problem and can execute a *move* to further complete the partial solution. The move consists of fixing the value of a decision variable that is still not fixed and such variable is probabilistically chosen, using a formula that mixes an *a-priori* and an *a-posteriori* measure of fixing attractiveness. The a-priori attractiveness measure is called *pheromone trail value* in an ACO-alg context and is updated at the end of the construction phase: the updates aim at penalizing variable fixing of bad quality and rewarding good quality fixing. When the arrest condition is reached, it is common to execute a local search in order to bring the current best solution to a locally optimal solution.

In this work, we emphasize that we do not propose an ACO-alg, but we propose a metaheuristic that can be in some sense seen as a stronger and improved version of the ANTS algorithm, based on the principles formalized in the works [38–40], which heavily exploit the valuable information coming from suitable linear relaxations of the problem. Specifically, in our case, the a-priori measure is given by a strengthened linear relaxation of the problem (we use the model DVB-01 strengthened by adding the inequalities (7)), while the a-posteriori measure is given by the linear relaxation of DVB-MILP including the partial fixing of power variables. The essential structure of our algorithm can be thus stated as in Algorithm 2.

Algorithm 2. General metaheuristic (META)

1: **while** a time limit is not reached **do**
2: linear relaxation-based probabilistic variable fixing
3: variable fixing measures update
4: **end while**
5: MILP improvement heuristic

We now describe in detail the new metaheuristic for DVB-T2 network design.

3.1 Feasible Solution Construction

Before describing how the solution construction work, we make some preliminary considerations. The model DVB-01 employs 2 types of variables: (1) binary power variables z_{bl}; (2) binary service assignment variables x_{ts}. Once that the power variables are fixed, it is easy to check which SIR constraints (5) are satisfied and thus which service assignment variables x_{ts} can be set to 1 contributing to increase the value of the objective function. As a consequence, in the solution construction phase we can just limit the attention to power variables and we introduce the concepts of power state.

Definition 1. *Power state (PS): A* power state *represents the activation of a subset of DSs on some power level $l \in L$ and excludes that the same DS is activated on two power levels. Formally: $PS \subseteq S \times L : \nexists (s_1, l_1), (s_2, l_2) \in PS : s_1 = s_2$.*

We say that a power state PS is *complete* when it specifies the power configuration of every DS in S (i.e., $|PS| = |S|$). Otherwise the PS is said *partial* and such that $|PS| < |S|$. Furthermore, for a given power state PS, we denote by $S(PS)$ the subset of DSs whose power is fixed in PS (we call such DSs *configured*), i.e. $S(PS) = \{s \in S : \exists (s,l) \in PS\}$.

In order to reach a complete power state, a sequence of partial power states is defined. Specifically, the execution of a move brings from a partial power state PS_i to a new partial power state PS_j such that:

$$PS_j = PS_i \cup \{(s,l)\} \text{ with } (s,l) \in S \times L : s \notin S(PS_i).$$

We remark that, by definition of power state, the added couple (s, l) may not contain a DS whose power is already fixed in a previous power state. Every move adds one new element to the partial solution. Once that the construction phase ends, the value of the decision variables z_{sl} is completely specified and, as previously explained, we can deduce the value of the variables x, therefore defining a complete feasible solution (x, z) for the model DVB-01.

Given a *partial*, the probability π_{sl} of operating an additional move/fixing $(s, l) \notin PS$ is established through the formula [37,39,40]:

$$\pi_{sl} = \frac{\alpha\ \tau_{sl} + (1-\alpha)\ \eta_{sl}}{\sum_{(\sigma\lambda)\notin PS} \alpha\ \tau_{\sigma\lambda} + (1-\alpha)\ \eta_{\sigma\lambda}}\ , \tag{8}$$

which combines the a-priori attractiveness measure τ_{sl} with the a-posteriori attractiveness measure η_{sl} through a coefficient $\alpha \in [0, 1]$. In our case, τ_{sl} is given by the optimal value of the linear relaxation DVB-01 including the strengthening inequalities (7), while η_{sl} is the value of the linear relaxation of DVB-MILP with included the variable fixing associated with the current partial power state.

At the end of a solution construction phase, we update the a-priori measures τ on the basis of the quality of fixing, adopting a formula proposed in [18] partially based on that originally proposed in ANTS [37]. To define the formula, we first introduce the concept of *optimality gap* ($OGap$): given a feasible solution of value V and a lower bound B that is available on the optimal value V^* of the problem (note that it must hold $B \leq V^* \leq V$): the $OGap$ allows to evaluate the quality of the feasible solution and is defined as $OGap(V, B) = (V - B)/V$. The a-priori attractiveness measure that we use is:

$$\tau_{sl}(h) = \tau_{sl}(h-1) + \sum_{\mathrm{SOL}=1}^{\Sigma} \Delta\tau_{sl}^{\mathrm{SOL}}$$

$$\text{with } \Delta\tau_{sl}^{\mathrm{SOL}} = \tau_{sl}(0) \cdot \left(\frac{OGap(\bar{V}, L) - OGap(V_{\mathrm{SOL}}, B)}{OGap(\bar{V}, B)} \right) \tag{9}$$

where $\tau_{sl}(h)$ is the a-priori attractiveness of fixing (s, l) at fixing iteration h, B is a lower bound for the optimal value of the problem (in our case we use as lower bound the strengthened formulation DVB-01 with included the inequalities (7)), V_{SOL} is the value of the SOL-th feasible solution built in the last construction cycle and $\bar{V}$ is the (moving) average of the values of the Σ solutions produced in the previous construction phase. $\Delta\tau_{sl}^{\mathrm{SOL}}$ is the reward/penalization factor for a fixing and depends upon the initialization value $\tau_{sl}(0)$ of τ (in our case, based upon the linear relaxation of DVB-01), combined with the relative variation in the optimality gap that V_{SOL} implies with respect to $\bar{V}$.

3.2 MILP Improvement Heuristic

Given a feasible solution defined in the construction phase, we operate a search for better solutions by adopting an MILP heuristic that executes a very large neighborhood search *exactly*, by formulating the search as a mixed integer linear programming problem that is solved through an MILP solver [49]. More formally, given a feasible solution $(\bar{x}, \bar{z})$ to the problem DVB-01, we define the neighborhood by allowing to switch the binary value of at most $U > 0$ power variables $\bar{z}$ and allowing all the other variables to vary freely. Expressing such condition can be done by introducing the following hamming distance constraint to DVB-01:

$$\sum_{(s,l):\bar{z}_{sl}=0} z_{sl} + \sum_{(s,l):\bar{z}_{sl}=1} (1 - z_{sl}) \leq U$$

The modified problem is then solved through an MILP solver like CPLEX, running with a time limit.

3.3 The Complete Algorithm

The complete algorithm for solving the model DVB-01 is presented in Algorithm 3. We base the algorithm on the execution of two nested loops: the outer loop runs until a global time limit is reached and contains an inner loop inside which has the task of building Σ feasible solutions. In more detail, the first task of the algorithm is to solve the linear relaxation of DVB-01 strengthened by (7) for the possible fixings of the power variables z_{sl}, obtaining the corresponding optimal value and using it to initialize the a-priori measure of attractiveness $\tau_{sl}(0)$. This is followed by the definition of a solution (x^*, z^*) that represents the best solution found during the execution of the algorithm. Each run of the inner loop is aimed at deriving a complete power state that is then used as basis to check which SIR constraints are satisfied. At the end of the inner loop, the a-priori measures τ are updated according to formula (9), considering the quality of the produced solutions, and the global best solution (x^*, z^*) is updated, if necessary. After having reached the global time limit, the MILP improvement heuristic is executed with the aim of improving the best solution found (x^*, z^*).

4 Computational Tests

We tested the performance of our metaheuristic on 20 instances that refer to realistic DVB regional networks potentially deployable in Italy. The network represented in an instance is constituted by a set of DVB stations that broadcast the same telecommunication service in a synchronized way using the same frequency in a given territory. Each station can emit at a power that lies in the range $[-40, 26]$ dBkW. The experiments were performed on a 2.70 GHz Windows machine equipped with 8 GB of RAM and adopting IBM ILOG CPLEX 12.5 as MIP solver. The code implementing the optimization model and the solution algorithm was written in C/C++ and interacts with CPLEX through Concert Technology.

A global time limit of 3600 seconds was adopted for solving each instance. In the case of the metaheuristic, the available time budget is distributed in this way: the construction phase loop is associated with a time limit of 3000 s, whereas

Algorithm 3. - Metaheuristic for DVB-01

compute the linear relaxation of DVB-01 for all $z_{sl} = 1$ and initialize the values $\tau_{sl}(0)$ with the corresponding optimal values
let (x^*, z^*) be the best feasible solution found
while a global time limit is not reached **do**
  let (x^B, z^B) be the best solution found in the inner loop
  for $SOL := 1$ to Σ **do**
    build a complete power state PS
    check the SIR constraints satisfied by PS
    derive a feasible solution $(\bar{x}, \bar{z})$
    if the coverage granted by $(\bar{x}, \bar{z})$ is better than that of (x^B, z^B) **then**
      update the best solution found $(x^B, z^B) := (\bar{x}, \bar{z})$
    end if
  end for
  update τ according to (9)
  if the coverage granted by (x^B, z^B) is better than that of (x^*, z^*) **then**
    update the best solution found $(x^*, z^*) := (x^B, z^B)$
  end if
end while
run the MILP improvement heuristic for (x^*, z^*)
return (x^*, z^*)

the MILP-based improvement phase is associated with a time limit of 600 s. For the metaheuristic parameter setting, we impose $\alpha = 0.5$ (i.e., we balance the a-priori and a-posteriori attractiveness measure) and $\Sigma = 5$. The results of the computational tests are presented in Table 1, where: ID identifies the instance; *COV-CPLEX%*, *COV-Meta% (best)* and *COV-Meta% (avg)* are the percentage of population covered by the best solution found by CPLEX, by the best solution found by the metaheuristic and by the metaheuris-tic on average within the time limit, respectively; *ΔCOV% (best)* and *ΔCOV%(avg)* are the percentage increase in population coverage that the metaheuristic grants with respect to CPLEX in the best case and on average, respectively.

Concerning the results of the computational tests, it is clear that in all cases the coverage granted by CPLEX is sensibly lower than that granted by the metaheuristic on average, lying in the range between 52 and 75% (in contrast, the metaheuristic offers a coverage between 56 and 86%). The better performance of the metaheuristic is more evident when looking at the best solutions found, which offer a percentage coverage between 63 and almost 89%. The percentage increase in coverage is equal to 15.1% on average and, for the best cases, increases to the very remarkable value of 21.8%. The performance of the metaheuristic is particularly good in the case of instances like I11 and I16, which almost reach the remarkable coverage of 90%. We note that the improvement in the value of solutions that we get are very significative, since in region-wide network instances improving a solution even by a small percentage can lead to an additional coverage of population of the order of thousands of people, thus being practically very attractive for the planning of television service broadcasters.

Table 1. Experimental results

ID	COV-CPLEX%	COV-Meta% (avg)	ΔCOV% (avg)	COV-Meta% (best)	ΔCOV% (best)
I1	53.3	61.0	14.5	63.2	18.6
I2	62.9	74.3	18.16	77.1	22.7
I3	57.4	69.3	20.8	73.5	28.2
I4	71.6	81.1	13.2	85.2	19.0
I5	66.5	78.6	18.2	83.8	26.1
I6	51.1	61.0	19.3	63.7	24.8
I7	54.1	60.4	11.6	63.2	19.5
I8	63.8	67.4	5.6	64.6	13.4
I9	68.2	79.3	16.3	72.3	20.3
I10	66.0	78.7	19.2	82.0	29.0
I11	74.4	83.0	11.5	85.1	17.8
I12	52.0	56.3	8.2	87.6	15.6
I13	60.6	69.0	13.8	60.1	19.4
I14	59.4	68.6	15.5	72.3	20.2
I15	56.8	70,3	23.7	71.3	27.8
I16	74.7	85.5	14.4	72.5	18.4
I17	67.3	80.2	19.2	88.4	27.0
I18	63.5	71.5	12.6	85.4	23.5
I19	64.8	75.6	16.6	82.1	26.8
I20	58.0	63.6	9.7	67.8	16.9

5 Conclusion and Future Work

In this paper, we have derived an optimization model for the design of digital television broadcasting networks adopting the second generation of DVB-T standard, i.e. the DVB-T2. Since even a state-of-the-art optimization solver may have difficulties in finding good quality solutions for real-sized instances, due to the presence of complicating wireless coverage signal-to-interference constraints, we have proposed a metaheuristic that combines a probabilistic variable fixing procedure with an exact large neighborhood search formulated as a Mixed Integer Linear Programming problem. Computational tests on realistic instances show that the metaheuristic is able to identify solutions that guarantee a much larger service coverage than those identified by a state-of-the-art optimization solver.

As future work, we plan to further strengthen the performance of the solution algorithm by considering the integration with other heuristic (specifically, cutting plane methods exploiting conflicts between variables, similarly to [50], and sequential heuristics as in [51])). Furthermore, we plan to consider variants of the problem including multiple objectives, taking into account trade-off between user coverage and power consumption, in a way similar to [52]. Last but not least, we plan to address the uncertainty of signal propagation and system capacity, by adopting Multiband Robust Optimization [25,53] and robust cutting plane methods [54].

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