Chapter 9
Optimal Planning of Grid Reinforcement with Demand Response Control

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Abstract This chapter presents a hybrid methodology based on a local search algorithm and a genetic algorithm, used to address the multi-objective and multi-stage optimal distribution expansion planning problem. The methodology is conceived to solve optimal network investment problems under the new possibilities enabled by the smart grid, namely the new observability and controllability investments that will be available to enable demand response in the future. The multi-objective methodology is applied to an existing low-voltage electric distribution network under a congestion scenario to yield a Pareto-optimal set of solutions. The solutions are then projected onto the two investment possibilities considered: demand control investments and traditional network asset investments. The projected surface is then analyzed to discuss the merit of demand control with respect to postponing traditional asset investments.

Keywords Demand response · Distribution planning · Information and communications technology · Network optimization

9.1 Introduction

Distributed Generation (DG) and Electric Vehicles (EV) bring new challenges to the operation of electric distribution networks. New challenges involve dealing not only with peak load conditions, but also with potential reverse flows due to DG and

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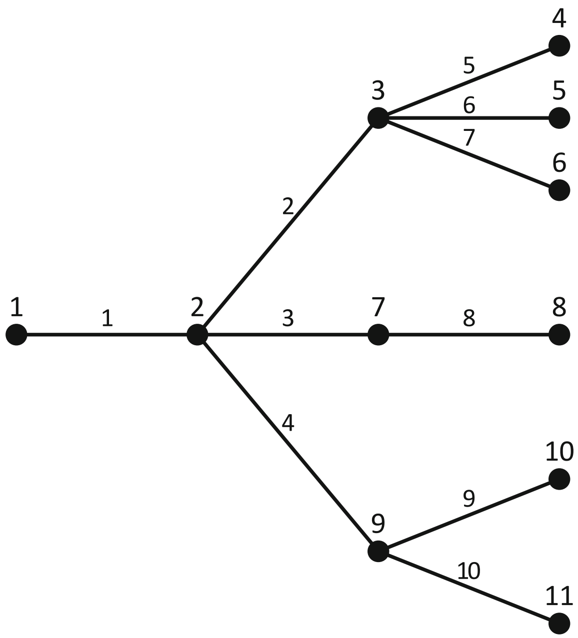

Fig. 9.1 Graph representation of an electric distribution network: circles represent network nodes (graph vertices), while lines connecting circles represent network branches (graph edges) that connect the network nodes

with the new active management possibilities enabled by the Information and Communications Technologies (ICT) such as demand response (DR) control.

Traditionally, distribution planning does not consider the investment and operational benefits of control as enabled by ICT. The benefits of additional controllability are currently not clearly identified and the impacts of ICT investments are not well understood.

A multi-objective optimization methodology is used to search for traditional network investments together with DR control investments, so that a set of investment projects and their corresponding time periods lead to a minimum overall value of a set of objective functions. A multi-objective formulation is quite valuable in this context since it allows projecting the Pareto surface onto the two investment dimensions of (i) investment on traditional network assets and (ii) investment on control equipment. Such a projection allows trading-off these two kinds of investments without speculating on the costs of ICT and control equipment, whose costs are currently difficult to predict.

Let us represent an electric distribution network by a graph G, where the vertices represent the network nodes, while the edges represent the existing lines and transformers (see Fig. 9.1). ICT (vertex) investments can be considered in order to reduce demand impact through demand and DER control, whereas line/transformer (edge) reinforcement investments can be considered in order to relieve overloads and avoid voltage drop or rise beyond predefined acceptable levels. Under such a solution space, the planning solution is a schedule of projects, both vertex and edge type projects, that aim to minimize investment and operational costs while respecting key planning criteria like adequate voltage levels under normal and contingency situations and loading limits for lines and transformers.

An overview of the existing literature shows that distribution planning used to rely on a set of methods to decide the location and type of reinforcements needed in order to cope with the traditional sources of uncertainty, such as expected load forecast, at minimum cost. Several approaches have been taken in the past to solve the problem [1–8].

Some models deal with a fixed horizon year and single network solution topology [9–16] and are thus known as single stage models. Other models deal with the dynamic nature of demand through time as well as with a sequence of network solution topologies (one per stage) and are hence known as multistage models [2, 3, 5, 8, 15].

In either single or multistage models, optimization techniques were used to solve the problem. These involve genetic algorithms [16], Benders' decomposition [17], simulated annealing [18], tabu search [19], greedy randomized adaptive search procedure (GRASP) [20] and game theory [21]. The common output of all these former approaches is the conception of a plan, i.e., a set of projects where the system reinforcements and equipment additions are scheduled.

A hybrid optimization strategy is presented in the following sections of this chapter, combining a local search algorithm with moderate search effort and a metaheuristic method to broaden the search space and to guide towards a close-to-optimum solution.

Finally, a realistic case study, where ICT reinforcements are traded off with conventional grid reinforcements, is analyzed through the application of the developed strategy.

9.2 Distribution Planning Methodology

9.2.1 Formulation of the Problem

Consider a vector of possible investment projects $P = [p_1, p_2, \ldots, p_N]$. A decision schedule can be represented by a vector of timings, $\bar{t}$, that index the projects of P, where $\bar{t} = [t_1, t_2, \ldots, t_N]$.

The optimal planning problem can then be formulated as the problem of finding the optimal timing for each investment project. As a multi-objective problem, the problem may be formulated as

$$\min_{(\bar{t})} \{f_1(\bar{t}), f_2(\bar{t}), \ldots, f_j(\bar{t})\} \tag{9.1}$$

$$\begin{aligned} s.t. \quad & \bar{t} = [t_1, t_2, \ldots, t_N] \\ & t_i \in \{1, 2, \ldots, T+1\}, i = 1, 2, \ldots, N \end{aligned}$$

where $f_j(\bar{t})$ represents the objective function j to be minimized for the planning horizon T, and the timing $T + 1$ is interpreted as the timing to be assigned to the projects that will not be undertaken within such an horizon.

9.2.2 Solution Approach

As decisions are multi-stage, the decision space is large-scale and the decision schedules are computationally expensive to evaluate, making the possible effective solution approaches very confined. Note that the scheduling problem alone is an NP-Hard problem [22] and therefore the search cannot guarantee the global optimum to be found. The solution approach must therefore be able to provide close-to-optimal plans involving short-term and longer-term investment decisions that need to be evaluated thoroughly.

Project schedules can be found by a classical local search algorithm (Gaussian-like search) with moderate search effort. However, such Gaussian algorithm is a local optimization approach, and being the stated problem a non-convex one [23], it does not guarantee close-to-optimum solutions [24]—solutions typically get trapped in local optima. The Gaussian Search (GS) is sensitive with respect to the order by which the different investment projects are analyzed [25]. Therefore, to find close-to-optimum schedules a specific Genetic Algorithm (GA) is presented to learn about the best order for analysis by the GS. The overall solution approach can then be formulated as a hybrid algorithm.

Thus, the GA is used to find the best order for the GS optimization, while GS is used to find the best project schedule given an order to analyze the projects. Within the GS evaluation, objective function values are updated based on the results of a DR optimized power flow, whose implementation is described in this chapter. The presented hybrid approach has proven to yield robust solutions in several planning contexts [25] and has been successfully implemented for a Medium Voltage feeder [26].

Within the application of this hybrid solution, if a multi-objective function is to be addressed explicitly, one may define GS and GA selection criteria to address search as multi-objective and return a set of Pareto non-dominated schedules.

The architecture of the overall algorithm is depicted in Fig. 9.2. The blocks represent the main methods, while the text and direction of the arrows represent, respectively, what information and the direction in which such information is exchanged between those methods. The methods of the hybrid solution approach are described in the following.

The execution of the algorithm starts with the initialization of a set of possible orders, O, for project evaluation by the GS. Within the context of this hybrid approach, a possible order is an order of N projects where each investment project $p_i \in P, i = 1, 2, \ldots, N$ appears exactly once in the order. For example, for $N = 6$

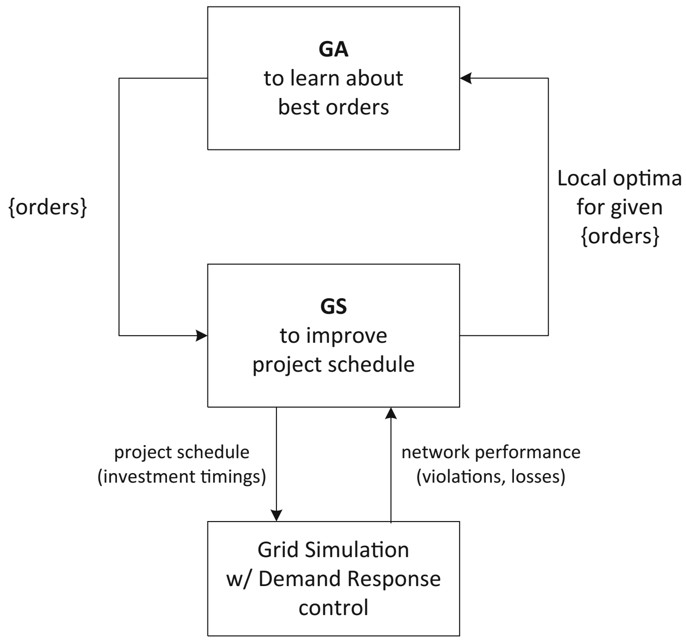

Fig. 9.2 Overview of the hybrid optimization methodology (GA and GS combination)

investment projects and an initial set of 4[1] orders, the initial population of orders could be the one illustrated in Fig. 9.3.

The population is then subjected to evaluation by the Gaussian Search, with each order o_k of O being evaluated separately. Throughout such evaluation, the optimal timings (stages) for allocation of the investment projects are continuously and iteratively updated so that a set of objective functions is minimized. When the set of optimal timings $\bar{t}$ of an order remains unchanged from the previous iteration, the process (GS) stops for that order. A possibility for the initial investment timings for the projects is $T + 1$ for all projects, meaning that at the beginning none of the projects has been allocated to the planning horizon.

More specifically, for a given order o_k of O, one iteration of the GS evaluation of such order corresponds to the update of the optimal investment timings for the $N = 6$ projects according to the relative positions of the projects in that order. As a convention, it is assumed that relative positions are established from left to right (referring to Fig. 9.3).

In the case of order o_1, this means that the GS starts by analyzing project p_3 and finding the optimal investment timing for such a project (t_3); then, it proceeds to the analysis of project p_5 and finding its optimal timing t_5. Similarly, the remaining

[1]Note that this value is relatively small and was chosen for demonstration purposes. The typical size of a genetic algorithm population is several tens or even hundreds of individuals.

o_1	p_3	p_5	p_2	p_4	p_1	p_6
o_2	p_1	p_5	p_6	p_3	p_2	p_4
o_3	p_2	p_4	p_3	p_5	p_6	p_1
o_4	p_4	p_1	p_2	p_3	p_6	p_5

Fig. 9.3 Example of an initial population of orders. The six projects of each order are highlighted in different colors for ease of recognition. Each project appears exactly once in each order

projects p_2, p_4, p_1 and p_6 are analyzed and the end of the order is reached. A certain set of investment timings $\bar{t}$ is obtained in this first iteration of the GS. The GS would then proceed to again analyzing all the projects of order o_1 in the aforementioned sequence, taking into account the optimal timings $\bar{t}$ of the previous iteration. When the end of order o_1 is reached again, the investment timings set is compared to that of the previous iteration. The GS procedure is repeated while the sets of investment timings of the last two iterations compare differently.

The GS determines the optimal investment timing of a project by making use of an Optimal Power Flow method, which considers, for all the other projects, those that have been added to the network graph G so far (investment timings between 1 and T) and, for the project being analyzed, all the possibilities of investment timings (1 to T + 1). Therefore, for the investment timings of all the other projects (unchanged) and the possibilities for the project under analysis (T + 1), T + 1 sets of objective function values are obtained.

From these objective function value sets (solutions), the (Pareto) non-dominated solutions are selected. A solution $a = \{f_1(\bar{t}_a), f_2(\bar{t}_a), \ldots, f_j(\bar{t}_a)\}$ is said to be non-dominated when there is no other solution $b = \{f_1(\bar{t}_b), f_2(\bar{t}_b), \ldots, f_j(\bar{t}_b)\}$ that satisfies $b \leq a$, i.e., the value of at least one objective function value in b is less than the value of the same objective function in a, while the values of the other objective functions in b are less or equal than the corresponding objective function values in a. In the latter case, b is said to dominate a and, conversely, a is said to be dominated by b.

Assume an electric distribution network, with a radial configuration and six branches (lines or cables) connecting the network nodes. The reinforcement of each network branch is considered ($N = 6$), and two objective functions to be minimized as well: network reinforcement and network losses. For the sake of simplicity, the cost of reinforcement is 1 unit (year zero), being discounted in the planning horizon stages with certain inflation and discount rates. Let us also suppose that, during the GS, some projects had already been analyzed and some of the optimal timings were between 1 and T (within the planning horizon), meaning that there were investment projects added to the network graph. When a certain reinforcement project was analyzed (suppose p_4), the results of the Optimal Power Flow for the T + *1* investment timing possibilities were the following (T = 3):

t_4 ($\bar{t} = [t_1, t_2, t_3, t_4, t_5, t_6]$)	$f_1(\bar{t})$ Present reinforcement cost	$f_2(\bar{t})$ Network losses
1	3.57	5
2	3.51	5
3	3.46	10
4	2.63	15

The impact of this reinforcement project on losses is the same whether it is allocated to stages 1 or 2. But, since its present cost decreases with time, the total reinforcement cost also decreases with time (the investment timings of the other projects, t_1, t_2, t_3, t_5 and t_6 remain unchanged). Therefore, the solution for $t_4 = 2$ dominates the solution for $t_4 = 1$. Thus, allocating project p_4 to stages 2, 3 or 4 leads to non-dominated solutions, since that postponing project p_4 means a decrease in the reinforcement cost but also a corresponding increase in the network losses.

We are then left with three possibilities for the optimal investment timing t_4. The criterion or criteria to select a value can vary. For example, one might want to invest as late as possible or simply choose a non-dominated solution randomly (the latter is used in the case study of this chapter).

The local optimization by the GS is heavily dependent on the Optimal Power Flow (OPF) method. The latter gives an indication to the GS of network performance (objective function values) considering the investments allocated so far within the planning horizon, and when the GS needs to decide on the investment timing of the project being analyzed, it does so based on the results of the OPF method. How investments affect network performance depends on how they impact network operation. More specifically, reinforcing a line or cable is different from ICT infrastructure investment intended to shed consumer load during congestion periods. The impacts and actions of network investments are simulated by the selected OPF method.

The OPF method presented in this chapter aims at simulating the actions facilitated by DR control investment, while still considering the impact of traditional reinforcement investments. If violations of network line or cable current ratings or of node voltage levels are detected, it tries to solve them by shifting (postponing) consumer load demand power. Priority is given to current rating violations over voltage level violations, since the former are more critical to network operation.

The OPF method ensures that the minimum number of controllable consumers is affected when trying to solve violations. On the one hand, it tries to solve current (and later voltage) violations by first looking at problematic branches (nodes) at the most downstream locations in the network topology and only affecting controllable consumers downstream such branches (nodes). Only when violations are solved or when no further reduction in demand power of downstream controllable consumers is possible it moves upstream the network to solve current (voltage) violations. On the other hand, in a given time period only the minimum number of consumers is affected as the demand power of controllable consumers that contribute most to violations (highest demand power) is reduced first, and only then controllable consumers with lower demand power may have their demand power reduced in order to solve violations.

After all the orders of population O are evaluated by the GS, a set of investment timings $\overline{t}$ for each order o_k is determined, as well as the corresponding objective function values. Following GS evaluation, individuals (orders) of the population are selected and then manipulated through genetic operators in order to create a new population. The process of selection and manipulation is described next.

The orders are selected considering how interior the Pareto fronts to which their solutions (objective function values) belong is. From a Pareto-optimal point of view, the more interior the solution front is the better—corresponding to lower overall values of the objective functions, in the case of a problem formulated as a minimization. To determine the Pareto fronts to which each solution belongs, the non-dominated sorting of the NSGA-II [27] is used.

Essentially, the NSGA-II sorting works in the following way: initially, considering all the solutions obtained, the subset of solutions that are not dominated by any other solution belongs to the most interior Pareto front of solutions (with rank equal to one); discarding this first subset of solutions, the remaining solutions that belong to the next most interior Pareto front (not dominated by any other solution) are determined, resulting in a second subset of solutions (with rank equal to two). This process of ranking solutions according to the Pareto front they belong to is repeated until there are no more solutions to be ranked. There can be as much Pareto fronts (ranks) as solutions (in the case of one solution per Pareto front).

Following rank determination, the orders are selected for genetic manipulation using binary tournaments. For each order of the population, an opponent order is selected. Each of these order-opponent order pairs corresponds to one tournament round. For each tournament round, it is decided if the existing population order is kept or is replaced by the opponent order: if the orders solutions have different ranks, the order with the lowest ranked solution wins; if the solution ranks are equal, then one order is randomly chosen as winner. In the case the opponent order wins, it replaces the existing population order. This way of selecting individuals for genetic manipulation ensures that the global search by the GA is guided towards a more Pareto-optimal population.

Genetic manipulation follows order selection. The genetic operators to be applied to the selected orders are order recombination and mutation. The goal of the recombination process is that information regarding relative project positions in the orders that lead to more interior Pareto solutions is exchanged between population orders (note that the selection that precedes manipulation favors lower ranked, more Pareto-optimal solutions). In turn, the mutation process aims at introducing randomness that might contribute to improve the Pareto-wise quality of the solutions (i.e., more interior solutions, namely non-dominated solutions).

The recombination works in the following way: the population of orders is divided into pairs, with each order only being present in one pair; for each pair, recombination will be undertaken (or not) according to a given probability; if a pair is to be recombined, a crossover point is chosen; finally, the positions of the projects

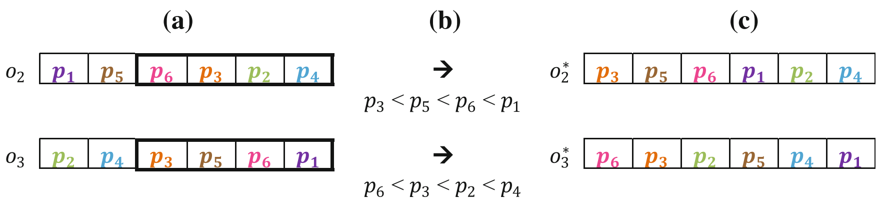

Fig. 9.4 Example of order recombination, starting from the third project position (**a**): relative project positions to be respected in each order (**b**) and offspring orders that result from recombination (**c**)

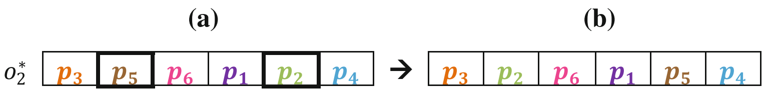

Fig. 9.5 Example of order mutation: chosen project positions (**a**) and resulting order (**b**)

in one order of the pair are altered in order to satisfy the relative project positions imposed by the other order of the pair, starting from the crossover point of the latter.

As an example, suppose that the orders of Fig. 9.3 have been divided into the pairs (o_1, o_4) and (o_2, o_3). According to the recombination probability, it was decided that the orders of the pair (o_2, o_3) were to be recombined. Also, a crossover point was randomly chosen[2] so that recombination takes place starting from the third project position. The relative project positions in one order of the pair, starting from the crossover point, impose relative project positions to be respected in the other order (Figs. 9.4a, b). The orders would have then been changed, with the resulting project positions being the ones in the offspring orders (indicated in Fig. 9.4c).

The next step is the mutation of the orders. This process occurs for each order of the population with a given probability. If it is decided that an order is to be mutated, then two distinct project positions need to be chosen (e.g. randomly). The projects in such positions are then swapped. An example of order mutation is shown in Fig. 9.5.

After genetic manipulation of the orders, a new genetic population is created (population of the next generation). This population will then be subjected to evaluation by the GS and to selection and manipulation in order to create another population. The whole process of population evaluation, selection and manipulation is repeated until some stop or convergence criteria is met.

The steps of the various methods described (Hybrid Genetic Algorithm, Gaussian Search, Optimal Power Flow, Binary tournaments, Recombination and Mutation) are presented below.

[2]For N projects, meaningful values of the crossover point are in the range of 2 to N-1.

(M1) Hybrid GA search

Step 1 Initialize a set O of possible orders for project evaluation (population of project orders).
Step 2 Evaluate the population of orders by running GS (method M2) on each order k of O (o_k).
Step 3 Determine the rank of each order of O according to the non-dominated sorting described in [27].
Step 4 Select the best orders from the population using binary tournaments (sub-method S1).
Step 5 Subject the best orders to genetic manipulation: recombination (sub-method S2) and mutation (sub-method S3).
Step 6 Go back to Step 2 until convergence is achieved.

(M2) Gaussian Search

Step 1 Initialize i ($i = 1$).
Step 2 Take the ith project of project order o_k and choose the optimal timing for its implementation, t_i, according to an OPF method considering DR control (method M3);
Step 3 If the optimal timing t_i is not $T + 1$, add the project to the network graph G.
Step 4 Increment i ($i \leftarrow i + 1$); go back to Step 2 until the Nth project of o_k is reached.
Step 5 If the end of the project order is reached, go back to Step 1 until the project timing array $\bar{t} = [t_1, t_2, \ldots, t_N]$ remains unchanged from the previous GS iteration (Steps 1–4).

(M3) DR optimized power flow

Step 1 Run power flow for unconstrained network loading.
Step 2 If the current rating of a network branch (line or cable) is violated, go to Step 3, otherwise go to Step 7.
Step 3 Select the most downstream branch (or one of the most downstream branches) with current rating violations.
Step 4 For all consumers downstream the selected branch having a control enabling device, decrease demand power of the consumers with highest demand power according to a predefined rate; the shed demand power is postponed (load shifting); if no (further) decrease of demand power is possible, go to Step 6.
Step 5 Run power flow. If the current rating of the branch is still violated, go back to Step 4, otherwise continue.
Step 6 If there is a branch with current rating violations at the same network topology level of the branch being considered that has yet not been selected, select that branch; otherwise, if there is at least one branch with current rating violations at a level upstream the branch that was being

considered, select a branch at the closest level upstream that branch. If a branch is selected, go back to Step 4.

Step 7 If the voltage level at a node is violated, go to Step 8, otherwise stop.

Step 8 Select the most downstream node (or one of the most downstream nodes) with voltage level violations.

Step 9 For all consumers downstream the selected node having a control enabling device, decrease demand power of the consumers with highest demand power according to a predefined rate; the shed demand power is postponed (load shifting); if no (further) decrease of demand power is possible, go to Step 11.

Step 10 Run power flow. If the voltage level of the node is still violated, go back to Step 9, otherwise continue.

Step 11 If there is a node with voltage violations at the same network topology level of the node being considered that has yet not been selected, select that node; otherwise, if there is at least one node with voltage level violations at a level upstream the node that was being considered, select a node at the closest level upstream that node. If a node is selected, go back to Step 9, otherwise stop.

(S1) Binary tournaments

Step 1 For each individual of the population (order o_k), randomly select an opponent order from the same population.

Step 2 For each individual of the population and its opponent order, decide the winner of the tournament round: if the orders have different ranks, the order with the lowest rank is the winner, otherwise the winning order is one of the two orders chosen at random.

Step 3 For each individual of the population (order o_k), if the winning order of the corresponding tournament round is the opponent order, it replaces the existing order.

(S2) Recombination

Step 1 Randomly divide the population in pairs, with each individual of the population (order o_k) only being present in one single pair.

Step 2 Select the first pair.

Step 3 Decide if the pair is to be recombined with a probability of p_{recomb}; if the pair is to be recombined, go to Step 4, otherwise go to Step 6.

Step 4 Randomly determine the crossover point of the pair.

Step 5 Change the positions of the projects in each order of the pair so that the exchanged relative positions of projects, beginning from the crossover point position to the last project position, are respected.

Step 6 Select the next pair and go back to Step 3 until there are no more pairs left to recombine.

(S3) Mutation

Step 1 Select the first order of the population (order o_1).
Step 2 Decide if the order is to be mutated with a probability of p_{mut}; if the order is to be mutated, go to Step 3, otherwise go to Step 5.
Step 3 Select two distinct project positions at random.
Step 4 Swap the projects in the selected positions.
Step 5 Select the next order of the population and go back to Step 2 until there are no more orders left to mutate.

9.3 Case Study

A Low-Voltage (LV) electric distribution network is considered as an investment case study. The network has a nominal voltage of 400 V and is comprised of thirty six nodes and thirty five cables (underground network with radial topology, see Figs. 9.6 and 9.7). Several network reinforcement and ICT investments are considered as possible projects:

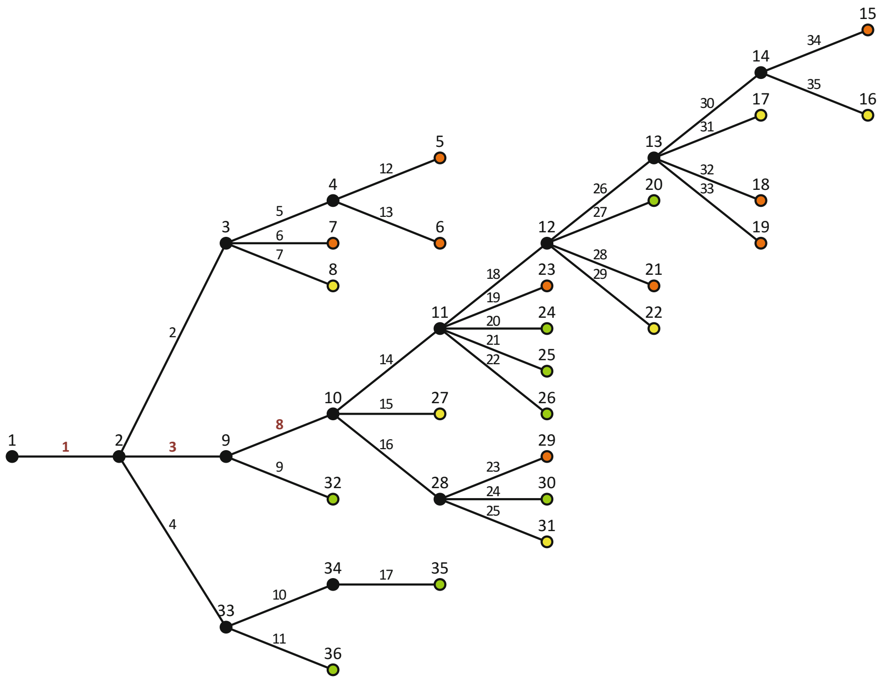

Fig. 9.6 Schematic representation of the network nodes, cables and consumers. Current rating violations are observed for cables 1 (feeder), 3 and 8, hence their numbers are highlighted in color. Nodes with connected consumers are colored according to the combined contracted power at the node: less or equal to 20 kVA (green), greater than 20 kVA and less or equal to 40 kVA (yellow), greater than 40 kVA (orange)

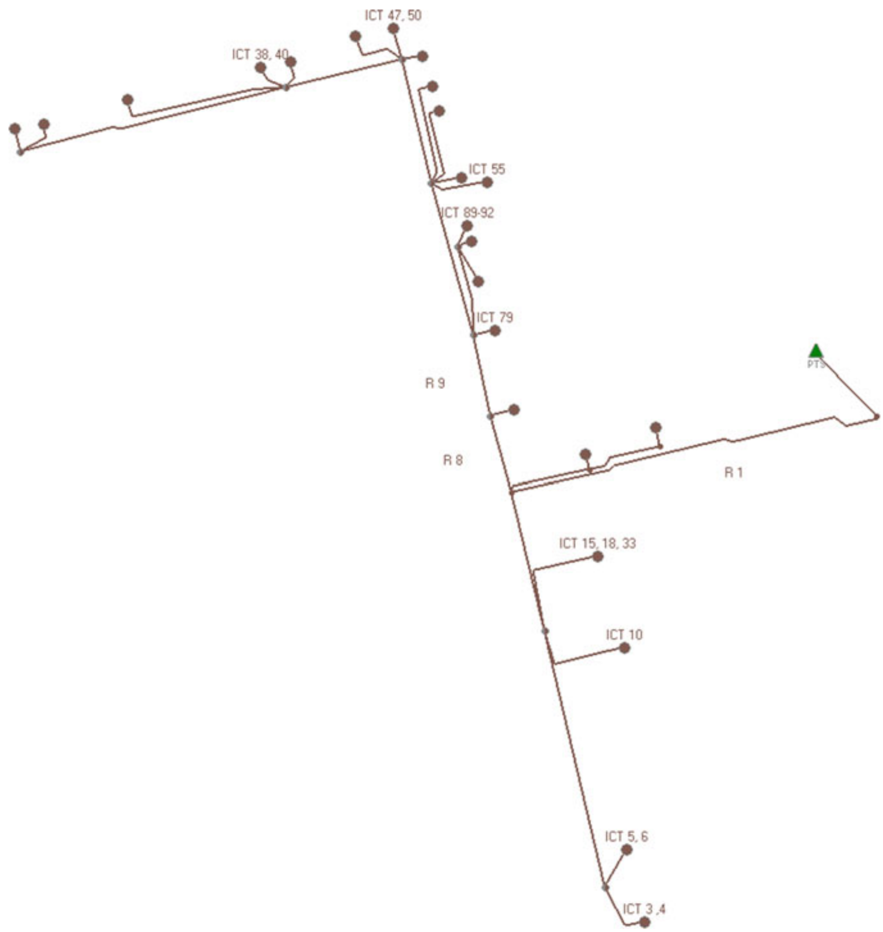

Fig. 9.7 Geographic view of the LV network of the case study, in which possibilities for investment in grid reinforcement (R) and DR reinforcements (ICT) are marked. The triangle refers to the secondary MV/LV substation

- The reinforcement projects are the replacement of three existing weak cables by 185 mm^2 Aluminum conductors (reinforcements denoted by R's in Fig. 9.7).
- The ICT projects are smart meter investments at the premises of every consumer, capable of enabling DR control of such consumers (smart meters denoted by ICT's in Fig. 9.7).

ICT investment is considered as a separate and normalized investment. Being considered as a separate normalized investment (and not minimized together with traditional investment) allows us to trade-off the two types of investment without establishing a cost for ICT, which would be very difficult as the use of ICT for DR control is not yet widespread as a mature technology.

The network has both single- and three-phase consumers (70 single-phase and 30 three-phase consumers) with contracted power values ranging from 1.15 to 20.7 kVA. The most common contracted power values for single-phase consumers are 3.45 and 6.9 kVA (28% and 22% of all the consumers), while for three-phase consumers these values are 10.35 and 17.25 kVA (12% and 8% of all the consumers).

Consumer load demand power is calculated for each consumer using historical smart meter data of a consumer with the same characteristics (identical number of connection phases and contracted power). Both single- and three-phase consumer demand power is evenly distributed among the three phases (for balanced load flow). Unity power factor is assumed. Consumer locations at network nodes are taken from real network data.

The operational conditions in which the case study is run are

- DR simulation starts at peak load time; whenever there is ICT equipment (smart meters) installed at the consumers' premises, the allowed demand power of control enabled consumers can be decreased in steps of 1.15 kVA, as much as needed in order to minimize violations of cable current ratings or node voltage levels.
- DR is simulated for a whole day in each stage of the planning horizon. Such days are assumed to be representative of the corresponding years (stages).
- The MV/LV substation secondary voltage is set to 1.05 pu.
- Monitoring equipment is assumed to be installed at secondary substation level so that cable currents can be measured and communicated to the ICT control system. The costs associated with the installation and operation of monitoring equipment are not considered.

A ten year planning horizon is considered with 11 possible investment stages ($T = 10$), being the investment stages evenly distributed in time (one stage per planning horizon year, plus one stage outside the planning horizon meaning that the project is not to be undertaken within the horizon). Two objective functions are optimized (minimized) together:

- Network reinforcement investment
- ICT (smart meter) investment

The inflation and discount rates considered are 3 and 10%, respectively.

The optimization algorithm is run for an initial population of fifty random project orders and five population generations, and for recombination and mutation probabilities of 80 and 10%, respectively.

From the obtained set of solutions (one optimized project schedule per project order), the non-dominated solutions were selected, and those with current or voltage violations were excluded, as they were considered unfeasible. The remaining non-dominated solutions were projected onto the objectives of ICT investment and reinforcement investment. Four zones corresponding to four project allocation modes were identified. The projected non-dominated solutions and the identified zones are shown in Fig. 9.8.

The solution with highest network reinforcement cost (2400 €) and no ICT investment corresponds to the reinforcement of all the three cables where current

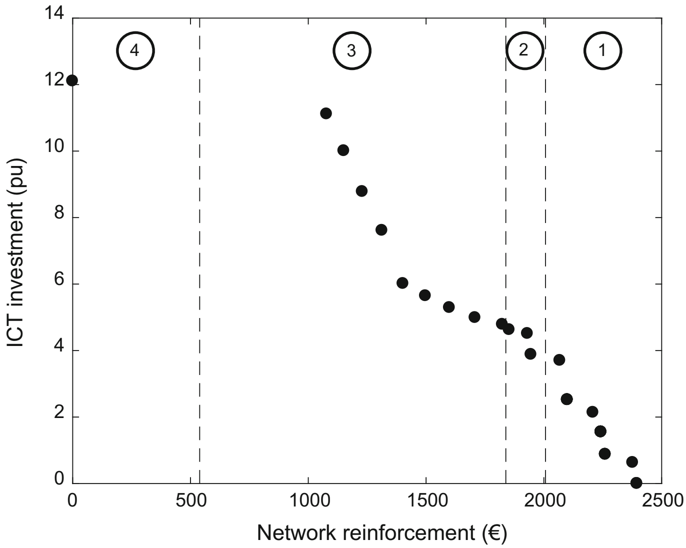

Fig. 9.8 Projection of the obtained non-dominated solutions onto the objectives of ICT investment and reinforcement investment for the LV electric distribution network

rating violations occur (cables 1, 3 and 8, referring to Fig. 9.6). The reinforcement of such cables is enough to ensure violation-free operation of the network within the planning horizon.

As ICT projects are allocated, DR control is possible and the reinforcement projects are postponed, making the reinforcement cost lower (considering inflation and discount rates, the present cost is lowered). The transition from zone 1 to 2 occurs when the allocated ICT projects are enough to avoid one reinforcement project (reinforcement of cable number 8).

Cables number 3 and 8 are almost identical (in length and cross section), and therefore when the OPF method reduces demand power downstream cable number 8, solving its current rating violations and thus avoiding its reinforcement, it also removes most of contributions to the violations of the current rating of cable number 3. As more ICT projects are allocated and more consumer demand power is shifted by the OPF, the reinforcement of cable number 3 is also avoided and transition from zone 2 to 3 occurs.

With the reinforcement of cables 3 and 8 avoided, what is left is the reinforcement of cable number 1 (feeder cable). Similarly to what happens in zones 1 and 2, allocating more ICT projects and shifting consumer demand allows postponing the reinforcement of cable 1. Since there are only ten stages (years) in the considered planning horizon, the reinforcement of cable 1 can only be postponed up to the last stage of the planning horizon.

Having enough ICT projects allocated and enough consumer demand power to be shifted makes the transition from zone 3 to 4 possible—the reinforcement of the feeder cable (and of the other two cables) is avoided. The optimal solution where all cable reinforcements are avoided corresponds to about 12 pu of investment in ICT projects (present cost) and 18 consumers (18% of all consumers) with DR enabling devices.

In Figs. 9.9 and 9.10, the distribution of the reinforcement and ICT investments according to their optimal timings for the two extreme solutions is illustrated. In Fig. 9.9, the allocation of the three reinforcement projects matches the stages when violations would first occur in each of the cables. On the other hand, it can be observed from Fig. 9.10 that the allocation of ICT projects is gradual and not abrupt, varying between 0.9 and 2.0 pu per stage of the planning horizon. This can also be verified through the cumulative ICT investment cost, whose evolution is very well fitted to a first-degree polynomial curve.

Figures 9.11, 9.12 and 9.13 correspond to the solutions preceding the transitions from zone 1 to 2 (Fig. 9.11), from zone 2 to 3 (Fig. 9.12) and from zone 3 to 4 (Fig. 9.13). From such figures, one can observe which reinforcement projects have been postponed or avoided so far, the limits for postponing reinforcement projects in the solutions found by the described hybrid approach and, similarly to Fig. 9.10, that ICT project allocation is gradual.

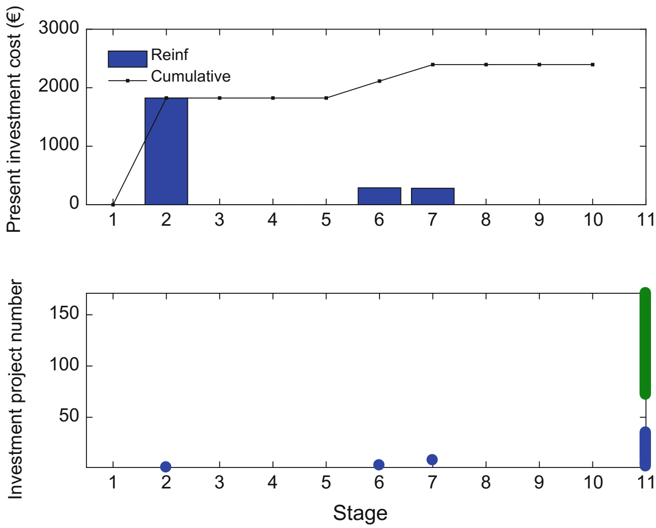

Fig. 9.9 Optimal investment stages and investment costs for reinforcement projects (blue dots and bars) of the solution where all the necessary reinforcement projects and no ICT projects are allocated

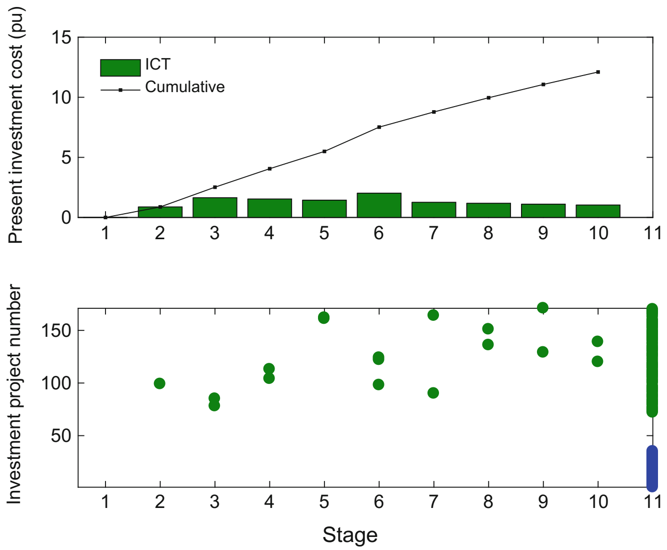

Fig. 9.10 Optimal investment stages and investment costs for ICT projects (green dots and bars) of the solution where the allocation of enough ICT projects avoids all cable reinforcements

The projection of the solutions in Fig. 9.8 can be looked at from another point of view: by doing a translation of the horizontal axis, the solutions can be seen from the perspective of avoided network reinforcement (due to the investment in ICT equipment) instead of required network reinforcement. The result of this translation is shown in Fig. 9.14. In this figure, the dashed lines connect the axes origin to the projection of certain solutions (marked within circles). These are the four solutions where ICT is most valuable in terms of avoided network reinforcement per installed ICT unit (€/pu of ICT)—the more horizontal the line connecting the solution projection to the axes origin, the higher the average ICT unit value.

For the extreme solution where enough ICT investment leads to complete avoidance of traditional network reinforcement, the current profile of the cables whose reinforcement is avoided, before and after investment optimization with DR, is shown in Figs. 9.15 and 9.16. It can be observed from these figures that DR control affects load demand power (and thus cable current) in two essential periods: from 14 to 16 h, when the current rating of the feeder cable would be violated, and from 20 to 24 h, when the ratings of the three cables would also be exceeded (blue lines). The excess demand power is shifted to later periods, decreasing cable loading in those two periods, which is offset by a slight increase in cable loading in the period of 17 to 19 h and a significant increase of such loading in the period of 1 to 5 h.

Changes occur in the load demand profiles of the consumers with DR enabling devices. Two groups of profile changes are identified: consumers whose profiles are affected by demand power shed in the period of 20 to 1 h and shifted to the period

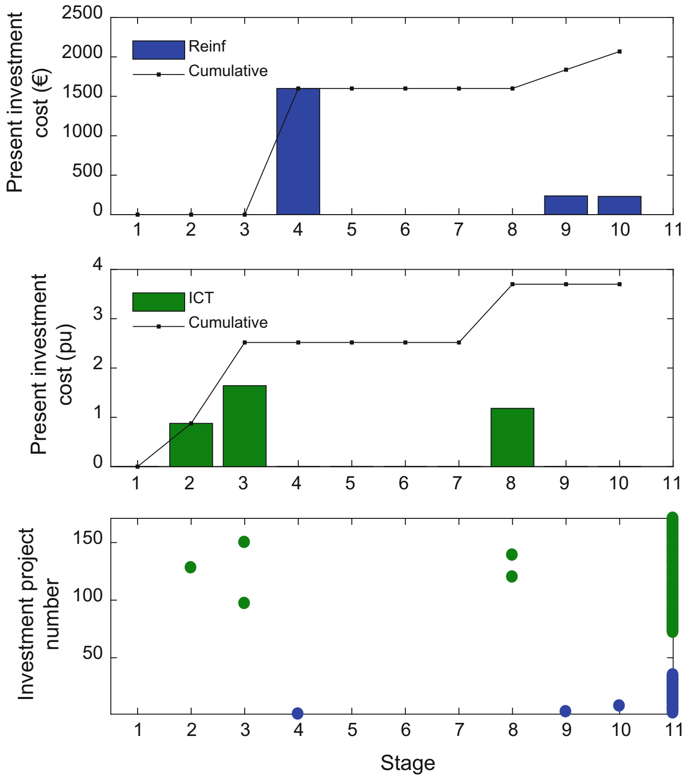

Fig. 9.11 Optimal investment stages for reinforcement and ICT projects (blue and green dots, respectively) and investment costs for reinforcement and ICT projects (blue and green bars, respectively) of the solution preceding the transition from zone 1 to 2 in Fig. 9.8. This solution corresponds to the limit found for postponing the reinforcement of cable number 8 (stage 10), while also reinforcing cables number 1 and 3

of 1 to 5 h (named DR pattern number 1) and consumers whose profiles, besides being affected by the same demand power shifting, are also affected by the postponing of demand power in the period of 14 to 17 h to the period of 16 to 19 h (named DR pattern number 2).

In Table 9.1, for the consumers affected by DR control (eighteen out of the total of one hundred), their network connection node, contracted power and DR pattern number are summarized. Figure 9.19 is similar to Fig. 9.6, with the differences being that the colored network nodes represent the nodes where consumers affected by DR patterns number 1 (blue) and number 2 (yellow) are located. In Figs. 9.17 and 9.18, two examples of optimized consumer demand profiles due to DR control (one example per DR pattern) are shown.

By comparing Figs. 9.6 and 9.19, it can be observed that there is a correlation between nodes with higher combined contracted power and the corresponding

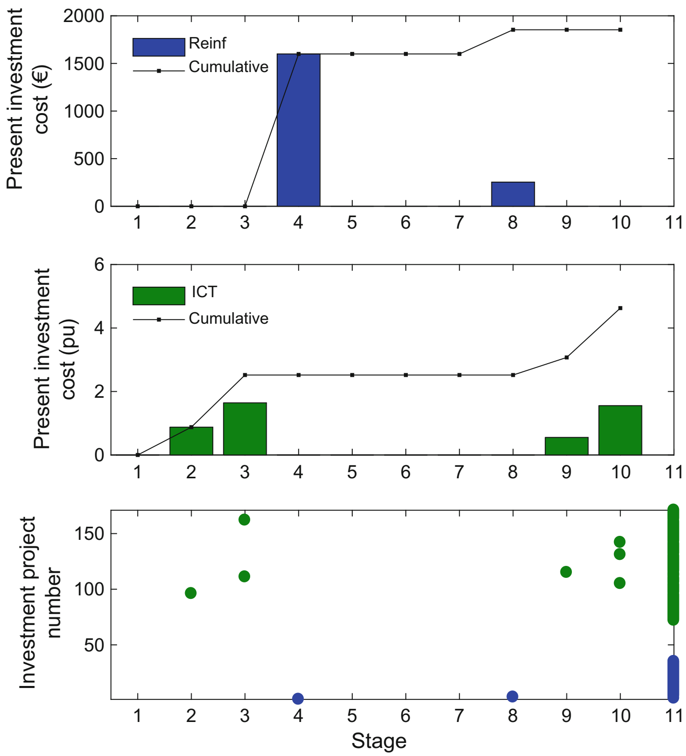

Fig. 9.12 Optimal investment stages for reinforcement and ICT projects (blue and green dots, respectively) and investment costs for reinforcement and ICT projects (blue and green bars, respectively) of the solution preceding the transition from zone 2 to 3 in Fig. 9.8. This solution corresponds to the limit found for postponing the reinforcement of cable number 3 (stage 8), while reinforcing cable number 1 and avoiding the reinforcement of cable number 8

consumers having DR enabling equipment—most of the nodes concerning consumers with DR equipment (blue and yellow colored nodes in Fig. 9.19) correspond to nodes with a combined contracted power greater than 20 kVA (yellow and orange colored nodes in Fig. 9.6). This is expected, as more consumers connected to the same node (higher combined contracted power) means higher aggregate loading demand power, thus enabling DR control for consumers at such nodes will decrease upstream cable loading when violations would occur.

It should be noted that these results were obtained for given reference costs of cable reinforcement and a given load density (respectively, around 40k € per kilometer of cable replacement and a contracted power density of 1900 kVA per kilometer of feeder length). For different cable reference costs and contracted power densities, the valuation of ICT investment would also be different.

If the same load density is considered with varying reference reinforcement costs, the ICT valuation would be directly proportional to such costs. If not, if the

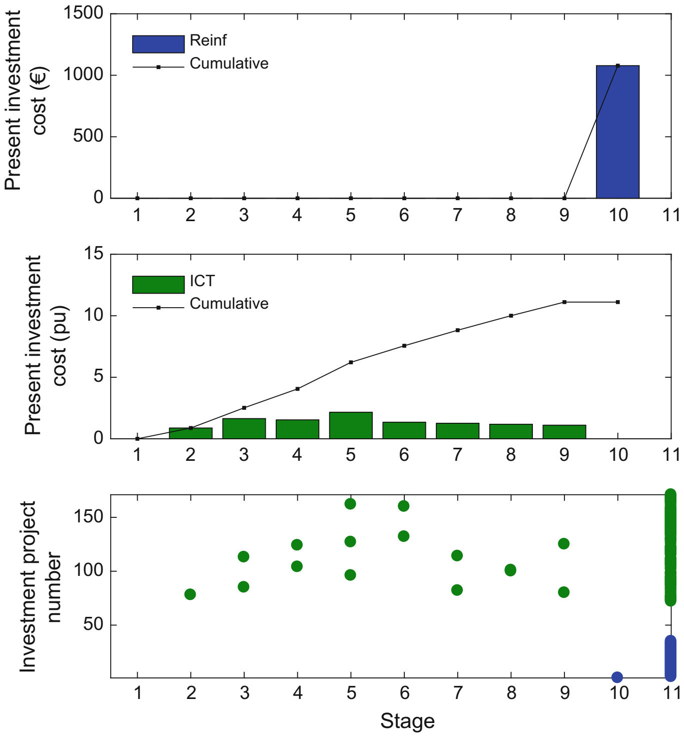

Fig. 9.13 Optimal investment stages for reinforcement and ICT projects (blue and green dots, respectively) and investment costs for reinforcement and ICT projects (blue and green bars, respectively) of the solution preceding the transition from zone 3 to 4 in Fig. 9.8. This solution corresponds to the limit found for postponing the reinforcement of cable number 1 (stage 10), while avoiding the reinforcement of cables number 3 and 8

network has the same reference costs but different load density, the ICT valuation would be inversely proportional to the load density. For instance, with a higher load density (same aggregate contracted power and lower network length) the installation of ICT infrastructure enables the management of the same load demand power as in a lower load density situation (higher network length), while the reinforcement expected to cope with that load demand power would be lower in length (lower in cost), and in that way the ICT valuation would be lower.

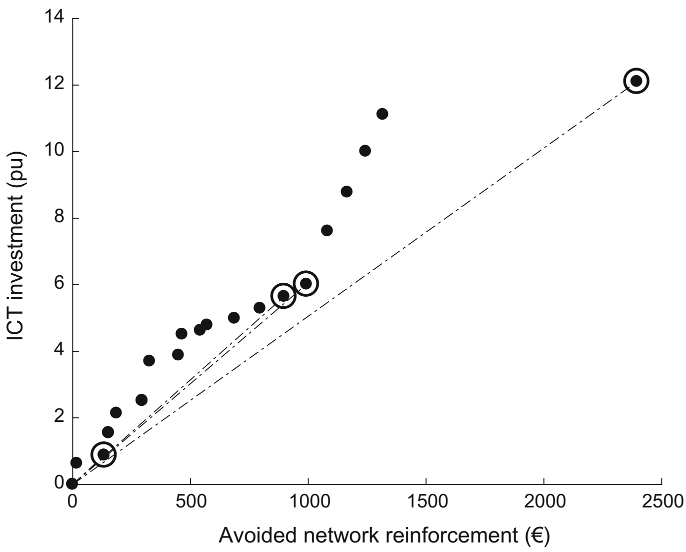

Fig. 9.14 Projection of the obtained non-dominated solutions onto the objectives of ICT investment and reinforcement investment for the LV electric distribution network

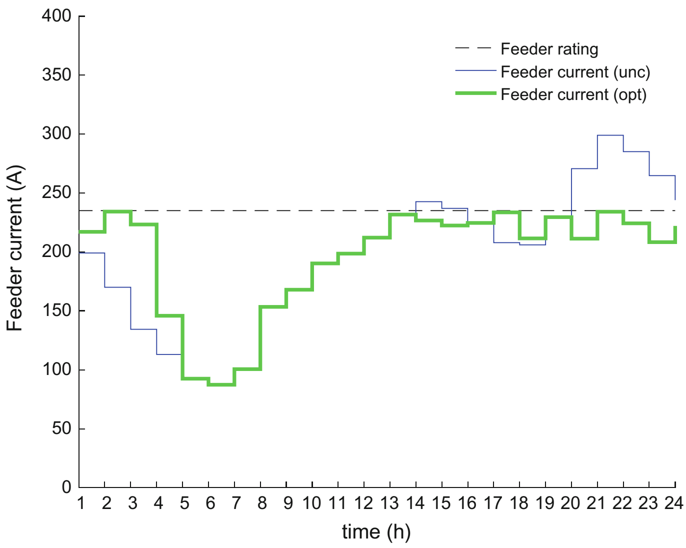

Fig. 9.15 Current in the feeder cable (year 10); due to the combination of network monitoring with DR control as enabled by ICT (peak shifting), feeder cable current does not exceed the cable current rating (dashed line), allowing its reinforcement to be avoided

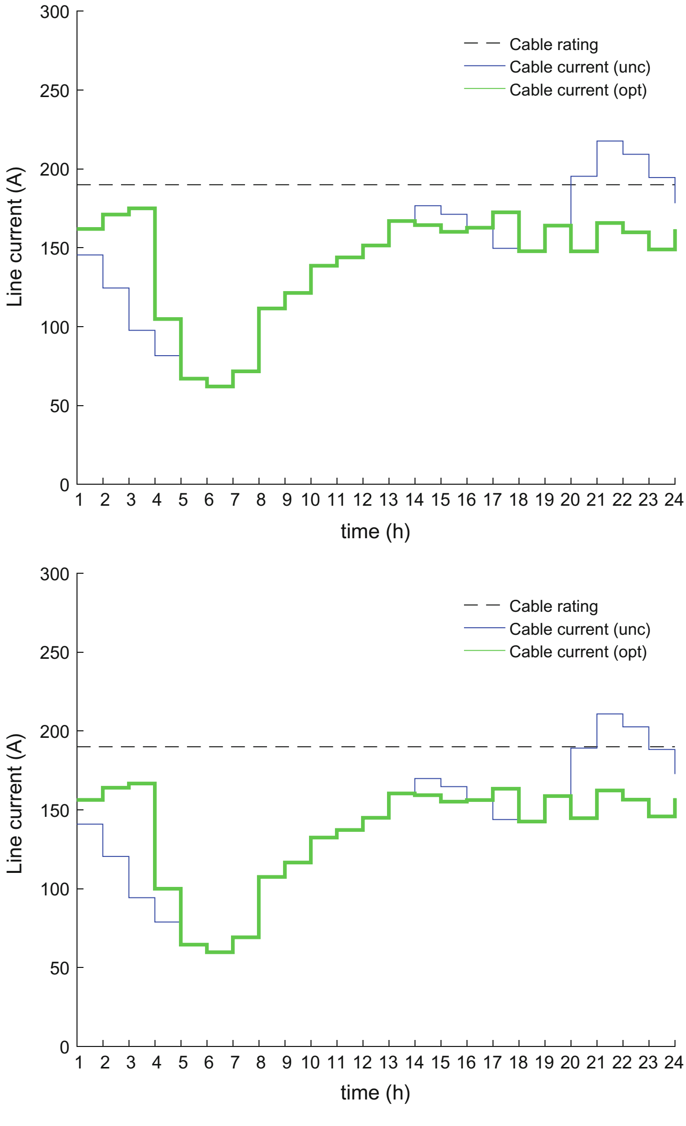

Fig. 9.16 Current in cables number 3 (top) and 8 (bottom), in the last stage of the planning horizon (year 10); due to the combination of network monitoring with DR control as enabled by ICT (peak shifting), cable current does not exceed cable current rating (dashed line), allowing the corresponding reinforcements to be avoided

Table 9.1 Summary of the network connection nodes, contracted power and DR pattern number of the consumers affected by DR control (eighteen consumers)

Consumer	Connection node	Contracted power (kVA)	DR control pattern
7	6	20.70	2
14	7	13.80	1
19	15	6.90	2
27	16	6.90	2
28	16	6.90	2
33	17	10.35	1
42	18	10.35	1
49	21	17.25	1
51	22	5.75	1
53	22	10.35	1
58	23	17.25	1
65	25	4.60	1
68	25	4.60	1
80	27	6.90	2
90	31	6.90	2
91	31	6.90	2
93	32	6.90	2
100	36	4.60	1

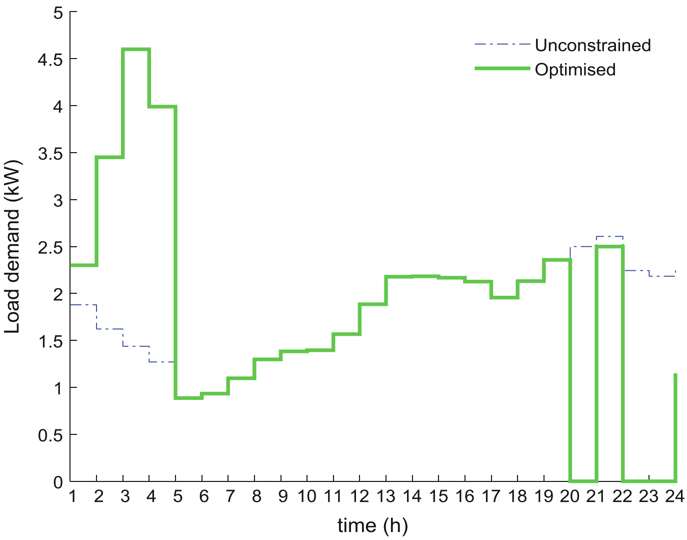

Fig. 9.17 Consumer load demand profile optimization (year-10) as a result of DR as enabled by ICT (smart meters): consumer 58 as an example of DR pattern number 1

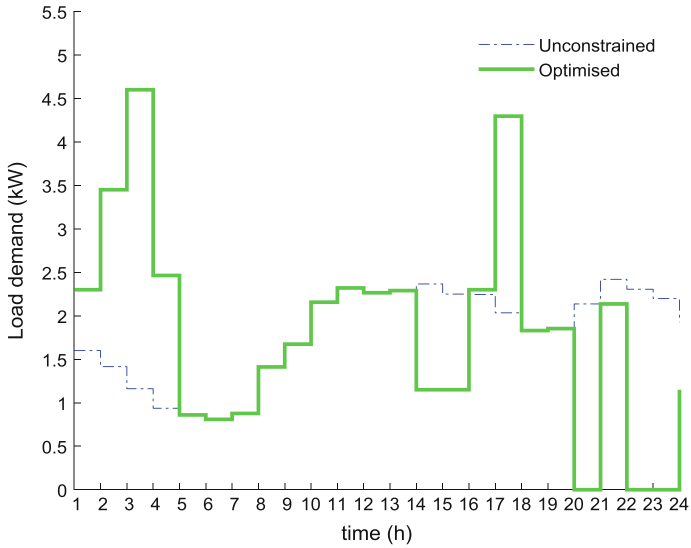

Fig. 9.18 Consumer load demand profile optimization (year-10) as a result of DR as enabled by ICT (smart meters): consumer 80 as an example of DR pattern number 2

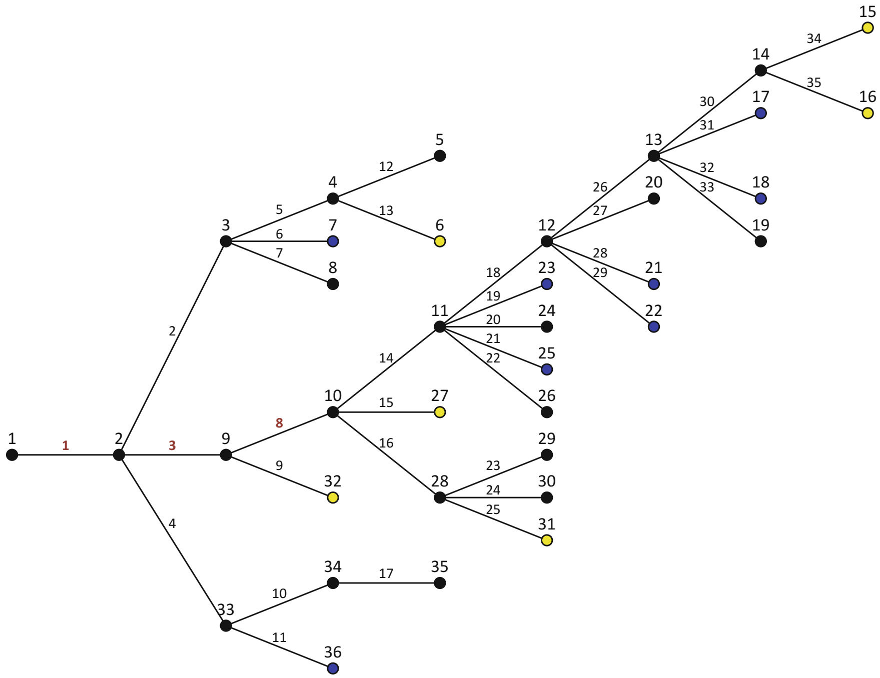

Fig. 9.19 Schematic representation of the network nodes, cables and consumers affected by DR control. Current rating violations are observed for cables 1 (feeder), 3 and 8, hence their numbers are highlighted in color. Nodes with DR enabled consumers are colored according to the DR control pattern: pattern number 1 (blue) and pattern number 2 (yellow)

Appendix

The notations used throughout this chapter are listed below:

f_j Objective function j
P Set of investment projects
O Set of orders for project analysis (population)
p_i Project i of P
o_k Order k of O (individual of the population)
t_i Timing of project p_i, $t_i \in \{1, 2, \ldots, T+1\}$
$\bar{t}$ Decision schedule: indexed array of timings t_i for projects p_i
N Number of projects
T Number of stages of the planning horizon
G Graph of the electric distribution network

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