# A Hierarchical Decision-Making Strategy for the Energy Management of Smart Cities

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***Abstract*— This paper presents a hierarchical decision-making strategy for the energy management of a smart city. The proposed decision process supports the city energy manager and local policy makers in taking energy retrofit decisions on different urban sectors by an integrated, structured, and transparent management. To this aim, in the proposed decision strategy, a bilevel programming model integrates several local decision-making units, each focusing on the energy retrofit optimization of a specific urban subsystem, and a central decision unit. We solve the hierarchical decision problem by a game theoretic distributed algorithm. We apply the developed decision model to the case study of the city of Bari (Italy), where a smart city program has recently been launched.**

***Note to Practitioners*—This paper addresses the emerging need of decision support tools for the energy management of smart cities. The proposed hierarchical decision-making strategy allows the city energy managers and local policy makers taking decisions on different urban sectors by a holistic view and a transparent planning. The presented strategy can be easily implemented in any engineering software, providing decision makers with an information and communication technology tool for the smart city energy management and the optimization of the city energy efficiency and environmental sustainability.**

***Index Terms*— Bilevel programming, energy efficiency, energy management, game theory, hierarchical decision making, optimization, smart city.**

## I. INTRODUCTION

IT IS expected that the percentage of world population in urban areas will grow up to 70% by 2050 [1]. At the same time, more than 80% of the world global GDP is generated in cities, which are responsible for over 70% of the world's greenhouse emissions. In such a scenario, the demand for a more efficient and sustainable model for cities is growing [2]–[4]. The concept of smart city has been introduced as a timely and proficient answer to the needs regarding key themes, such as sustainable development, business creation and employment, healthcare, education, energy and the environment, safety, and public services [5]. Various ambitious programs worldwide are promoting the development of smart cities [6]. Not surprisingly, the common feature is that the implementation of strategic plans to mitigate urban problems and make cities more efficient and sustainable steps through the realization of smart governance. This aspect is widely recognized as the core of all the smart city initiatives [7]. On the other hand, the success of smart governance relies on the increasing use of information and communication technologies (ICTs) in combination with other design tools. As a result, city planners, managers, and policy makers need efficient ICT tools to enable them take optimal or close-to-optimal decisions on the use of the available resources in order to reduce expenditure, consumption, and waste and improve performance and quality of service. For this reason, the need for smart cities decision support tools is emerging [5].

This paper presents a hierarchical decision-making strategy that helps the public administration (PA) define strategic and multisectorial retrofit action plans for the city energy management, aimed at improving the city energy efficiency and environmental sustainability. A novel bilevel programming model integrates several local decision-making units (decision panels), each focusing on the optimal energy retrofit of a specific urban subsystem, and a higher level central decision unit (CDU). We propose a game theoretic distributed algorithm and demonstrate that it allows solving the hierarchical decision problem. We apply the developed decision model to the case study of the city of Bari (Italy), where a smart city program has recently been launched. We report the obtained results for the integrated energy management of a public buildings portfolio, a private buildings portfolio, and the public street lighting panel. The presented decision-making strategy is the core of an innovative ICT platform called urban control center (UCC) that is being developed by IBM and Politecnico di Bari in the framework of the research project RES NOVAE [8]. The UCC is a dashboard and decision support tool for the energy management of smart cities. We highlight that the main focus of this paper lies in the integration, by the new bilevel programming model, of previously developed local decision models in [9] and [10] and in the coordination of their optimal action plans in accordance with common objectives imposed by a CDU. Note that this paper is a largely extended version of [10]: in this paper, we review and generalize the decision-making strategy of [10]; we present a novel distributed solution algorithm and demonstrate its convergence; we present a novel case study with a larger number of decision panels.

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The remainder of this paper is organized as follows. Section II provides a literature overview on decision techniques for city energy management, positioning the paper with respect to the related literature and showing its advancement. Section III presents the general framework of the decision-making strategy and the mathematical formulation of the problem statement. Section IV is focused on the distributed solution approach for the decision model. Hence, Section V presents the case study and results. Finally, Section VI provides the concluding remarks and discusses some future research lines.

## II. Literature Review and Paper Positioning

### A. Related Works

Researchers have recently made significant efforts toward the design and development of innovative technologies, enabling urban systems to be more operationally efficient, environmentally sustainable, and user friendly, in a cost effective manner [11]. In particular, several planning, management, and policy instruments based on ICTs are being experienced worldwide for improving cities' energy infrastructures and services.

In the related literature, the city energy management is traditionally addressed from the perspective of a single urban sector: the buildings sector, the public street lighting system, the urban infrastructures sector, the transportation system, the waste management, the water management, the land use, etc. In the sequel, we report the main related works, starting from the buildings' sector, which accounts for the most relevant research efforts, since the energy consumption of buildings accounts for around 40% of all energy consumed in advanced countries [12].

A wide variety of literature is available on decision support tools assessing existing building conditions and determining optimal retrofit or renovation actions. The interested reader is referred to the review in [9], which shows that most efforts concern the energy management of a single building [13]–[15], with only few contributions on optimal retrofit strategies for a stock of buildings [9], [16]. Moreover, numerous contributions focus on the real time energy management for single buildings [12], [17]–[21] and in some cases for a network of buildings [22].

Similarly to the buildings' sector, also the public street lighting is a key element in the development of urban districts, with high energy costs and impacts on the public expenditure. Several researchers are investigating tools for optimal street lighting that minimize energy consumption, while maintaining quality. The developed studies mostly focus on the optimization of the street lighting system design [23], [24]. Only a few works deal with the optimization of existing street lighting systems, addressing the benefits of replacing luminaries with LEDs [25], the potential savings from outdoor lighting installations with reference to different lighting systems and technologies [26], and retrofit interventions to reduce energy consumption, maintain comfort and quality of life, and minimize costs [10].

Several decision support tools have also been proposed in the context of urban infrastructures' management, addressing the urban infrastructure planning phase [27], and the maintenance phase in the life-cycle management of urban infrastructure [28]. In particular, Liu and Li focus on smart grid optimization presenting a new energy-saving dispatch problem based on emission-reduction potentials of generation and demand sides, as well as their interaction [29].

Not surprisingly, decision support systems have also been broadly applied for the energy management of urban transport, which is a threat against environmental sustainability and energy efficiency if not monitored and managed appropriately [30]. For instance, since many cities will electrify their transportation systems in their future smart city plans, Lam *et al.* formulate an optimization model for the electric vehicle charging station placement problem [31]. Moreover, Domínguez *et al.* propose a metropolitan railway substation model in order to assess the energy savings due to possible investments, such as installing power inverters or storage devices [32].

In the context of waste management, several studies are available defining tools assisting city planners and managers in decisions concerning the waste management at a municipal scale to minimize the carbon footprint of the whole city collecting system [33]. More generally, a wide literature presents decision support tools for natural resources management. In this context, water management [34], brownfield redevelopment [35], and land use [36] are examples where the development of ICTs and decision support tools helps prioritize local policies in terms of energy efficiency and environmental sensitivity.

All the mentioned works address the city energy management by a sectorial approach, i.e., considering the energy management of an urban sector in a stand-alone way. Instead, a city is a system of systems, i.e., a set of task-oriented systems that pool their resources and capabilities together to create a more complex system. Hence, in order to produce higher performance, with more functionalities and services than simply the sum of the individual composing systems, a smart city should aim at integrating and simultaneously optimizing the ensemble of its interdependent and interacting systems [37]. This objective may be realized only by an appropriate decision-making process based on a holistic awareness and global knowledge of the dynamics of all the city components. The resulting complexity in the city decision process is exacerbated by the typical organization of the city administration into a collection of entities (municipal agencies, departments, divisions, etc.) that are responsible of specific services and infrastructures. As a result, the design of a supporting tool for decision makers in a smart city is as much a challenging as an attractive task.

Only minor efforts have been devoted in the related literature to propose decision tools aimed at determining the optimal strategies for the energy management of a city as a whole. Calvillo *et al.* review energy-related works on planning and operation models within the smart city by classifying their scope into five main intervention areas: generation, storage, infrastructure, facilities, and transport [38]. Bartlett *et al.* are among the first to envision the advantages of a city command center that optimizes the dynamics of individual urban services while concurrently optimizing actions for goals associated with the city as a holistic entity [39]. Even though they do not develop any specific tool, their work highlights how the availability of advanced technologies allows integrating information and processes to efficiently coordinate urban operations. In the same direction, Mattoni *et al.* propose a holistic methodological approach to identify the appropriate actions to obtain a smart city by considering its specific features and developing different specific strategies in urban areas [40]. The proposed scheme provides policy makers and city managers only with guidelines to define and drive their strategy actions toward the most appropriate domains of implementation. However, the model in [40] does not deal with the decision and planning problem of choosing the optimal alternative from the set of identified strategy actions. Moreover, Suakanto *et al.* propose an ICT platform to help the local government monitor what currently happens in the city [41]. In addition, Adepetu *et al.* develop a decision support system that measures the performance of the water, waste, energy transportation, and buildings systems to predict the city's long term sustainability [42]. However, the proposed applications in [41] and [42] are just focused on monitoring the city in a single indicators' dashboard to help decision makers analyze the current urban conditions: no analytical, simulation, business intelligence, or decision tool is provided.

In the context of city energy management, only few literature contributions offer some integrated energy management tools. For instance, Yamagata and Seya propose a simulation tool that combines land use (based on a compact city model with energy efficient buildings and photovoltaic panels), transportation (electric vehicles and public transportation system), and energy systems (smart grid systems) [43]. The proposed integrated model aims at assessing the impacts at an urban scale of energy efficiency measures implementation, such as renewable energy sources installation. Similarly, Kim *et al.* define an energy management system called the energy integrated urban planning and managing support system [44]. The platform is not only for use by energy management specialists, but also by general energy consumers. Useful information is extracted from sensors installed throughout the city in order to enhance the notion of energy-aware consumption. By accumulating periodical data, the system is able to provide a statistical foundation to predict and design the future city energy plan. Moreover, Phdungsilp develop an integrated approach to study the city energy utilization and development based on the so-called long-range energy alternatives planning system model, used to simulate a range of policy interventions and predict how these would change energy and carbon development [45]. However, the recalled contributions in [43]–[45] mainly focus on simulating and forecasting the city energy consumption, while the emerging concept of smart city management and its opportunities seem to be missing.

In the direction of proposing integrated solutions for the energy management of the various city subsystems, Juan *et al.* [46] develop a decision support system that uses the well-known analytic hierarchy process to assess multidimensional levels of smartness for the current solutions to environmental problems of a city and recommend an optimal set of improvement strategies. Furthermore, Gironès *et al.* develop a new modeling framework, designed to support decision makers by improving their understanding of the energy system [47]. The goal is to show the effect of the policy and investment decisions on final energy consumption, total cost, and environmental impact [47]. However, both in [46] and [47], the decision process is defined as a single problem, so that only centralized policies may be applied and no structural interventions on a single urban subsystem may be conceived.

### B. Paper Contribution

The discussed literature clearly shows a prominent gap in the context of strategic approaches for the energy management of smart cities. In most of the related works, the city energy management is addressed from the perspective of a single urban sector. There is an apparent lack of techniques that look at the existing urban subsystems in an integrated way rather than on a subsystem by subsystem basis. In order to fill the highlighted gap in the existing literature, this paper develops a hierarchical decision-making strategy to identify an optimal set of retrofit action plans in an urban area aimed at improving globally the city energy performance by the given budget.

In particular, the contribution of this paper with respect to the related literature is twofold.

First, this paper defines a decision-making strategy for the smart city energy management that is able to deal with complexity, such as conflicting objectives and requirements, fragmented decision making, and difficult subsystem cross optimization. In particular, the strategic decision model is hierarchical and reflects the PA organization structure. On the one side, it integrates a set of sectorial decision support tools for specific interventions on a single urban subsystem; on the other hand, it provides a mechanism to design and coordinate all the decisions distributed over multiple urban decision units participating in the energy optimization problem. As a result, differently from the related literature, the proposed model tackles the smart city energy management problem addressing different urban sectors with an integrated, structured, and transparent planning. We highlight again that the focus of this paper lies on the integration and coordination of already developed local energy retrofit decision models and is not intended to address any energy management issues of a specific urban subsystem.

Second, this paper defines a comprehensive resolution technique based on bilevel programming that simultaneously pursues an optimal resources distribution and an optimal planning of each urban subsystem achievement. The technique is based on a game theoretic algorithm that allows a multisectorial intervention on an urban scale so as to ensure the integrated achievement of conflicting objectives in the energy management of the complex city system.

Finally, we remark that, differently from the centralized approaches proposed in [46] and [47], the chosen energy management strategy is hierarchical, allowing urban sectors to cooperate but keep their independence, which is an essential requirement for the effective governance of a smart city.

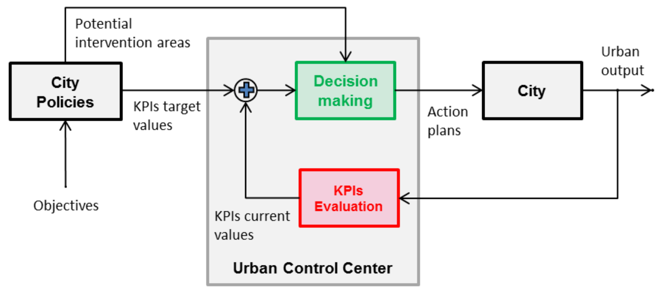


Fig. 1. Scheme of the smart city energy management.

## III. Proposed Decision-Making Strategy

A general scheme representing the smart city energy management process is shown in Fig. 1. Based on the PA objectives, the energy manager first determines the energy policies in terms of a set of key performance indicators (KPIs) target values and of a list of potential intervention areas (e.g., transport, facilities, infrastructure, etc.). Obviously, KPIs differ with the city and with its political program (for instance, some cities may select KPIs related to the installed renewable energy power, rather than other KPIs measuring the average buildings' energy rating). In addition, the definition of potential intervention areas is specific to the city. In fact, each city may exhibit unique architectural, technical, and/or structural characteristics, and customized retrofit options must be individually investigated (e.g., subsidizing photovoltaic panel installations). Moreover, the energy manager continuously surveys the current state of urban performances. In general, indicators' dashboards are used as quantitative tools for measuring the performance of urban infrastructures and services [11]. After establishing the measureable objectives and feasible options to deliver results in accordance with the expected level, the core activity of the energy manager is the decision making for the strategic energy management [48]. More in detail, the energy manager aims at controlling the urban dynamics, i.e., enforcing the energy performance to follows the desired KPIs. To this purpose, the energy manager may rely on decision-making tools that support him in determining, in the possible intervention areas, the action plans that the PA has to implement.

As previously mentioned, a city is composed by many interacting subsystems and it can be hardly managed by a unique centralized control structure. As a result, a hierarchical approach for an integrated decision process is more suitable than a centralized one, since it reflects the PA organizational structure and allows decisions to be made at different levels with different goals. In particular, the hierarchical decision-making scheme, as the name implies, relies on a set of independent decision units arranged in a hierarchy. This is obviously possible if the physical system of systems can be characterized by a finite set of subsystems with a clear and fixed interface between them, as it is verified in the system of systems' view of a city. Each decision unit can thus be separately designed and optimized, reducing the complexity of the overall decision-making process. Nevertheless, optimizing the performance of the whole system requires all

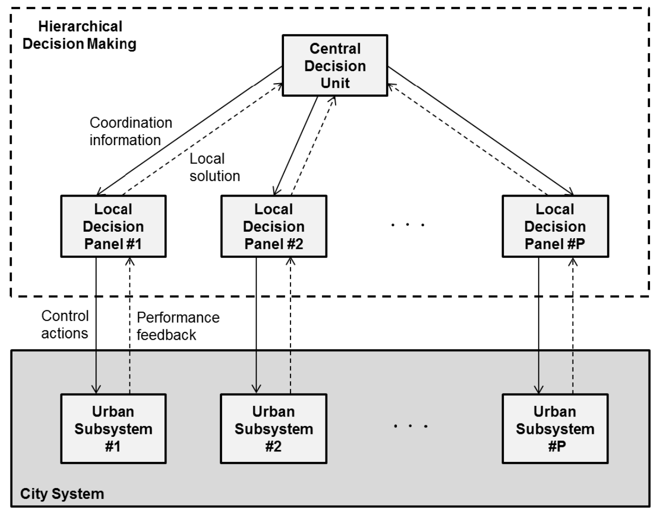


Fig. 2. Scheme of the hierarchical decision-making architecture.

decision-making units to be coordinated and their interactions to be accurately modeled.

Based on these considerations, the proposed model for an integrated urban energy decision process has the hierarchical structure shown in two levels in Fig. 2. The upper-level decision unit (CDU) takes care of the energy manager preferences and guidelines, while the lower-level decision units [local decision panels (LDPs)] are related to different urban sectors that may be affected by specific energy efficiency and retrofit policies dictated by specific facility managers. The CDU has a broad view; but at the same time, it has no detailed knowledge of the special problems that are known to the sectors (e.g., the specific conditions limiting choices within the sector). Instead, LDPs see many details, but they have no ability to realize the broader interrelations which only the CDU is aware of [49].

### A. Bilevel Programming Decision Model

The global decision problem shown in Fig. 2 may be formulated as a bilevel programming problem, assuming that a multicriteria decision-making process is executed in both the upper and lower levels [50]

$$\max_{\mathbf{Y}} \mathbf{F}(\mathbf{Y}, \mathbf{x}^{(1)}, \ldots, \mathbf{x}^{(p)}, \ldots, \mathbf{x}^{(P)}) \tag{1}$$

$$\text{s.t. } G(\mathbf{Y}, \mathbf{x}^{(1)}, \ldots, \mathbf{x}^{(p)}, \ldots, \mathbf{x}^{(P)}) \leq 0 \tag{2}$$

where each $\mathbf{x}^{(p)} (p = 1, \ldots, P)$ solves

$$\max_{\mathbf{x}^{(p)}} \mathbf{f}^{(p)}(\mathbf{Y}, \mathbf{x}^{(p)}) \tag{3}$$

$$\text{s.t. } g^{(p)}(\mathbf{Y}, \mathbf{x}^{(p)}) \leq 0 \tag{4}$$

where the meaning of the notation is as follows:

1) $p = 1, \ldots, P$ is the integer index of the $p$th LDP;
2) $P$ is the number of LDPs;
3) $\mathbf{F}$ is a vector multiobjective function of the upper-level problem;
4) $\mathbf{Y}$ is the decision variables' vector of the upper-level problem;

5) $G$ is the constraint set of the upper-level problem;
6) $\mathbf{f}^{(p)}$ is a vector multiobjective function associated with the $p$th lower-level problem;
7) $\mathbf{x}^{(p)}$ is the decision variables' vector of the $p$th lower-level problem;
8) $g^{(p)}$ is the constraints' set of the $p$th lower-level problem.

Note that 1) and 2) identify the so-called upper-level decision problem, while 3) and 4) define the lower-level decision problem of the $p$th subsystem.

The sequel details the proposed bilevel programming model for supporting the city energy manager to solve the following decision problem: optimally dividing a predefined budget between urban sectors for energy retrofitting actions planning in multiple different sectors of a given urban area. We suppose that the PA has a total budget $E_T$ allocated to the whole city energy management programs implementation and it must address the problem to distribute it through $P$ local panels acting as many urban subsystems.

Sections III-B and III-C present the models of LDPs (summarizing results published in [9] and [10]) and CDU, respectively, while Section IV addresses the solvability of the bilevel programming problem and presents a distributed game theory resolution approach.

### B. Local Decision-Making Model

Each LDP aims at helping sector-specific decision makers select the optimal actions to take in order to maximize the energy efficiency related performance of a particular urban subsystem (e.g., public buildings, private buildings, public street lighting, etc.) against a set of conflicting criteria within a given budget. All the activities involved in the proposed local decision-making process may be ideally divided into two macrophases: a first part that comprises activities regarding the urban sector status acquisition as well as identification of convenient retrofitting measures activities, and a second phase which consists in the actual multicriteria decision making resulting in the identification and selection of the possible optimal actions. We remark that no inaccuracy is considered in the first phase, since we assume to have the perfect knowledge on model parameters. Furthermore, we highlight that we do not consider dynamic models. As it is well known, see, for instance [51], the energy management decision-making models may be divided into off-line and online models, respectively, focusing on long-term and short-term goals. In the case of off-line models, just as the proposed framework, typically dynamical models are not used, since the focus is on energy retrofit long-term strategies. Moreover, operational online changes (e.g., behavioral changes, such as running appliances when electricity prices are lower, set-point optimization, etc.) are here disregarded, because they may be optimally determined on a single subsystem scale and do not require a holistic approach for the city as the one we adopt.

With no loss of generality, Sections III-B1 and III-B2, respectively, present the local decision-making model for each of the following $P = 3$ urban subsystems: the public buildings decision panel ($p = 1$), the private buildings decision panel ($p = 2$), and the public street lighting decision panel ($p = 3$). Note that the considered LDPs are typical urban subsystems to be governed by an energetic point of view. However, the selected decision panels list may be incremented with additional urban subsystems to be governed from an energetic point of view with analogous considerations. The proposed framework is scalable for energy retrofit of all other urban subsystems: grid infrastructures (e.g., district heating and cooling), generation infrastructures (combined heat and power generation), waste systems (e.g., biogas recovery), and transportation systems.

*1) Public Buildings and Private Buildings Local Decision Panels:* All the activities involved in the decision process of the public buildings LDP (PuBLDP) and the private buildings LDP (PrBLDP) are similar. Hence, this section formulates the multicriteria problem devoted to determining the energy efficiency strategy for the renovation of a generic stock of buildings. Subsequently, we use index $p$ in superscript to distinguish parameters, variables and objective functions concerning different LDPs: PuBLDP ($p = 1$) and PrBLDP ($p = 2$). The decision model is based on a method proposed in [9] and is summarized hereafter.

*a) Phase 1 (Decision Analysis):* The first phase is focused on the decision design and is performed by the buildings' decision maker in conjunction with energy buildings' practitioners. We indicate the buildings in the stock as the set $\mathcal{K}^{(p)} = \{B_1^{(p)}, \ldots, B_k^{(p)}, \ldots, B_{K^{(p)}}^{(p)}\}$ whose cardinality is $K^{(p)} = |\mathcal{K}^{(p)}|$. Primarily, the joint analysis with technical experts identifies the sector-specific decision criteria that are denoted as the set $\mathcal{H}^{(p)} = \{1, \ldots, h, \ldots, H^{(p)}\}$ whose cardinality is $H^{(p)} = |\mathcal{H}^{(p)}|$. Second, the current status of each building in the portfolio is estimated through various surveys and on-site measures. Third, considering the existing operating conditions of buildings, a feasibility study on potential retrofitting intervention addressing both technical and architectural constraints is carried out. The outcome of the evaluation of renovation and energy efficiency measures is the list of actions to be possibly implemented in the buildings. We denote this list as the set $\mathcal{J}^{(p)} = \{1, \ldots, j, \ldots, J^{(p)}\}$ whose cardinality is $J^{(p)} = |\mathcal{J}^{(p)}|$. Each action is successively characterized from two perspectives: its cost and its payoff. The cost for implementing the $j$th action on the $k$th building is denoted by $C_{\mathrm{jk}}^{(p)}$. Note that in the case of the PuBLDP, this is a full cost for the PA, while for the CoBLDP and the ReBLDP, $C_{\mathrm{jk}}^{(p)}$ represents the cofunding cost that the PA transfers to the $k$th private building owner (that is in charge of the residual action cost) in order to incentivize the application of the $j$th action. Since an action could impact on different criteria, a payoff estimation for each indicator is provided. For the $k$th building, the $j$th action produces the payoff $P_{\mathrm{hjk}}^{(p)}$ for the $h$th criterion.

*b) Phase 2 (Decision Making):* The second phase of the decision process consists in the actual decision making. The decision model relies on several decision variables reflecting the choices on actions. To this aim, the binary decision variables $x_{\mathrm{jk}}^{(p)}$ for each action $j = 1, \ldots, J^{(p)}$ and each building $k = 1, \ldots, K^{(p)}$ have to be determined. In other words, the local decision maker has to choose whether the $j$th action has to be applied to the $k$th building (i.e., $x_{\mathrm{jk}}^{(p)} = 1$) or not (i.e., $x_{\mathrm{jk}}^{(p)} = 0$). The $J^{(p)}K^{(p)}$ decision variables of the local decision-making model are collected in the decision variables vector $\mathbf{x}^{(p)}$. Hence, the multiobjective optimization (MOO) problem is defined to determine the Pareto frontier collecting all possible optimal retrofit strategies. In particular, the MOO is concerned with the maximization of the payoff for all the criteria

$$\max_{\mathbf{x}^{(p)}} f_h^{(p)}(\mathbf{x}^{(p)}) = \sum_{k=1}^{K^{(p)}} \sum_{j=1}^{J^{(p)}} x_{\mathrm{jk}}^{(p)} P_{\mathrm{hjk}}^{(p)}, \quad \forall h = 1, \ldots, H^{(p)}. \tag{5}$$

Of course, the main constraint for the previously defined problem comes from the financial resources limitation. Hence, the following inequality must be verified:

$$\sum_{k=1}^{K^{(p)}} \sum_{j=1}^{J^{(p)}} x_{\mathrm{jk}}^{(p)} C_{\mathrm{jk}}^{(p)} \leq Y^{(p)} \tag{6}$$

where $Y^{(p)}$ is the budget cumulatively allocated to the refurbishment of the whole stock of buildings. In addition, the following constraints for the actions' mutual exclusion are introduced, indicating which actions cannot be simultaneously implemented for technical reasons:

$$\sum_{j \in M_\delta^{(p)}} x_{\mathrm{jk}}^{(p)} \quad \leq 1, \forall k = 1, \ldots, K^{(\mathrm{p})}, \quad \forall \delta = 1, \ldots, \Delta^{(p)} \tag{7}$$

where $M_\delta^{(p)}$ is the set of indices of the $\delta$th given group (with $\delta = 1, \ldots, \Delta^{(p)}$) of mutually exclusive actions. An example of mutually exclusive actions consists in the external walls insulation with different materials: only one of these actions may be obviously selected for the building retrofit.

Decision problem (5)–(7) is a vector maximization problem with binary variables, known as multiobjective knapsack problem (MOKP). For the sake of simplicity, we assume that the public buildings decision maker provides an *a priori* articulation of criteria preferences. Hence, the PuBLDP is devoted to solve the reformulated optimization problem

$$\max_{\mathbf{x}^{(p)}} f^{(p)}(\mathbf{x}^{(p)}) = \sum_{h=1}^{H^{(p)}} \frac{\pi_h^{(p)}}{f_{h,0}^{(p)}} \cdot f_h^{(p)}(\mathbf{x}^{(p)})$$
$$\text{s.t. (6) and (7)} \tag{8}$$

where non-negative real weights $\pi_h^{(p)}$ indicate the importance of each objective as assigned by the local decision maker. Moreover, in (8), the values $f_{h,0}^{(p)}$ with $h = 1, \ldots, H^{(p)}$ are the so-called utopia points, each representing the optimal value of the $h$th objective function (5) with respect to the $h$th criterion only.

Summing up, (8) is the optimization problem of the $P = 2$ LDPs: PuBLDP ($p = 1$) and PrBLDP ($p = 2$). It is a 0/1 knapsack problem and may be solved by several techniques [52].

*2) Street Lighting Local Decision Panel:* This section presents the multicriteria problem formulation of the street lighting LDP (StLLDP), dedicated to determining the energy efficiency strategy for the retrofitting of a public street lighting area. The decision model is based on the method proposed in [10] and here summarized.

*a) Phase 1 (Decision Analysis):* The first phase is focused on the decision design and is performed by the local decision maker in conjunction with street lighting practitioners. We assume that the number of lighting units in the given public street lighting area is $N$ and their types belong to the set $\mathcal{T} = \{1, \ldots, t, \ldots, T\}$ whose cardinality is $T = |\mathcal{T}|$. Moreover, we divide the given urban area into different zone lighting subsystems that are collected in the set $\mathcal{S} = \{1, \ldots, s, \ldots, S\}$ whose cardinality is $S = |\mathcal{S}|$. The lighting units of a given zone lighting subsystem are energized by their own power substation that is also provided with a control unit aimed at automatically turning lights ON or OFF by a timer switch. Furthermore, we call $N_{st}$ ($\forall s = 1, \ldots, S$, $\forall t = 1, \ldots, T$) the number of lighting units of the $t$th type installed in the $s$th zone lighting subsystem. Primarily, the joint analysis with technical experts allows identifying the sector-specific decision criteria that are denoted as set $\mathcal{L} = \{1, \ldots, l, \ldots, L\}$ whose cardinality is $L = |\mathcal{L}|$. Without loss of generality, here the following $L = 3$ street lighting area performance indicators to be improved are defined: total energy consumption, total uplight luminous flux, and mean color rendering index. Second, the current status of each zone lighting subsystem is estimated through various surveys and on-site measures. Third, considering the existing operating conditions of the street lighting area, a feasibility study on potential retrofitting intervention addressing both technical constraints is carried out. The outcome of the evaluation of renovation and energy efficiency measures is the list of possible actions to be implemented in the given urban area lighting system. In particular, we identify the following three retrofitting actions: replacement of luminaires, installation of energy harvesting modules, and installation of dimming devices. Each action is successively characterized by two perspectives: the cost and the payoff.

*b) Phase 2 (Decision Making):* The second phase consists in the actual decision making. An MOO problem is defined to determine the characteristic Pareto frontier collecting all the possible optimal retrofit strategies. The decision model relies on several decision variables reflecting the choices on actions. To this aim, the following decision variables are considered.

1) Decision variables regarding the luminaire replacement. Let $u_{st}$ be a variable representing the quantity of $t$th type lamps to be replaced in the $s$th zone subsystem. This is a nonnegative integer variable that is upper bounded by the number of lighting units of the $t$th type deployed in the $s$th zone

$$u_{st} \in \{\mathbb{N}\}, 0 \leq u_{st} \leq N_{st}, \ \forall s = 1 \ldots, S, \quad \forall t = 1, \ldots, T. \tag{9}$$

2) Decision variables regarding energy harvesting modules installation. Let $v_s$ be the quantity of energy harvesting

equipment to be installed in the $s$th zone subsystem. This is a nonnegative integer variable that is upper bounded by the number of all the lighting units deployed in the $s$th zone

$$v_s \in \{\mathbb{N}\}, 0 \leq v_s \leq \sum_{t=1}^{T} N_{st}, \quad \forall s = 1, \ldots, S. \quad (10)$$

3) Decision variables regarding zonal dimming devices installation. Let $w_s$ be a binary variable assuming unitary value if dimming has to be integrated in the control station of $s$th zone lighting subsystem (zero value otherwise)

$$w_s \in \{0, 1\}, \quad \forall s = 1, \ldots, S. \quad (11)$$

All the defined $S \cdot (T+1)$ integer variables and $S$ binary variables are collected in the vector $\mathbf{x}^{(3)}$ of length $S \cdot (T+2)$.

Now, the application of retrofit actions to the lighting system leads to the formulation of the three criteria objective functions of the optimization problem

$$f_1^{(3)}(\mathbf{x}^{(3)}) = \sum_{s=1}^{S}\left(\sum_{t=1}^{T}((\gamma_t - \gamma_t^{'}) \cdot u_{st} - \alpha_s \cdot (\gamma_t - \gamma_t^{'}) \cdot u_{st} \cdot w_s + \alpha_s \cdot \gamma_t \cdot N_{st} \cdot w_s) + \Omega \cdot v_s\right) \quad (12)$$

$$f_2^{(3)}(\mathbf{x}^{(3)}) = \sum_{s=1}^{S}\sum_{t=1}^{T}((\varphi_t - \varphi_t^{'}) \cdot u_{st} - \alpha_s \cdot (\varphi_t - \varphi_t^{'}) \cdot u_{st} \cdot w_s + \alpha_s \cdot \varphi_t \cdot N_{st} \cdot w_s) \quad (13)$$

$$f_3^{(3)}(\mathbf{x}^{(3)}) = \sum_{s=1}^{S}\sum_{t=1}^{T}(\rho_t^{'} - \rho_t) \cdot u_{st} \quad (14)$$

where $\gamma_t$, $\varphi_t$, and $\rho_t$ are the annual energy consumption, the uplight luminous flux, and the color rendering index of lighting units of $t$th type, respectively; $\gamma_t^{\prime}$, $\varphi_t^{\prime}$, and $\rho_t^{\prime}$ are the energy consumption, uplight luminous flux, and color rendering index of the $t$th substitute luminaire of $t$th type, respectively; $\Omega$ is the estimated annual amount of energy provided by the single energy harvesting module; $\alpha_s$ is the relative total annual energy saving factor of the $s$th subsystem equipped with a dimming device with respect to the original deployment. The objective functions in (12)–(14) represent the reduction in the total energy consumption, the reduction in the total uplight luminous flux, and the increase in the mean color rendering index, respectively.

Hence, the MOO problem consists in determining the $S \cdot (T+2)$ decision variables in $\mathbf{x}^{(3)}$ that maximize the three objective functions in (12)–(14) and meet the constraints

$$\max_{\mathbf{x}^{(3)}} \begin{bmatrix} f_1^{(3)}(\mathbf{x}^{(3)}) \\ f_2^{(3)}(\mathbf{x}^{(3)}) \\ f_3^{(3)}(\mathbf{x}^{(3)}) \end{bmatrix} \quad (15)$$

s.t. (9)–(10)–(11) and

$$\sum_{s=1}^{S}\left(\sum_{t=1}^{T}(c^{u,t} \cdot u_{st}) + c^{v} \cdot v_s + c^{w} \cdot w_s\right) \leq Y^{(3)} \quad (16)$$

where $c^{u,t}$, $c^{v}$, and $c^{w}$ are, respectively, the unitary cost of replacement of a $t$th type lighting unit, the unitary cost of installation of an energy harvesting module, and the unitary cost of installation of a dimmer. Furthermore, $Y^{(3)}$ is the budget for the retrofit actions plan of the whole street lighting system.

Decision problems (15) and (16) are integer nonlinear programming (NLP) problems, since (16) contains product $u_{st} \cdot w_s$. As shown in [10], using an appropriate variable replacement, an equivalent linear program may be defined, resulting in an MOKP. Also, in this case, assuming that the street lighting decision maker provides an *a priori* articulation of criteria preferences, (15) and (16) are reformulated as

$$\max_{\mathbf{x}^{(3)}} f^{(3)}(\mathbf{x}^{(3)}) = \sum_{l=1}^{L} \frac{\pi_l^{(3)}}{f_{l,0}^{(3)}} \cdot f_l^{(3)}(\mathbf{x}^{(3)})$$
$$\text{s.t. } (9)\text{–}(10)\text{–}(11)\text{–}(16) \quad (17)$$

where weights $\pi_l^{(3)}$ indicate the importance of each objective. Moreover, in (17), the values $f_{l,0}^{(3)}$ with $l = 1, \ldots, L$ are the so-called utopia points, i.e., the optimal values of the $l$th component of objective function (15) determined with respect to the $l$th criterion only. It is a bounded knapsack problem (BKP) and may be solved by means of several techniques [52].

Summing up, (17) is the optimization problem of the third LDP, the StLLDP.

We close this section remarking that here we prefer to detail the criteria and actions adopted for the StLLDP instead of using a more general formulation as in the two previous panels. This choice allows improving readability, since a more general formulation, although feasible, would request many more variables with respect to those actually used in practice.

### C. Central Decision-Making Model

We now detail the central decision-making model (1) and (2) solved by the energy manager. The CDU addresses the goal of distributing the budget while improving the city energy performance by the following criterion: allocating the budget to the panels proportionally to their achieved payoffs. To this aim, $P$ positive decision variables are defined, reflecting the amount of financial resources allocated to the LDPs, such that

$$Y^{(p)} \geqslant 0, \quad \forall p = 1, \ldots, P. \quad (18)$$

All the upper-level decision variables are collected in the vector $\mathbf{Y} = [Y^{(1)}, \ldots, Y^{(p)}, \ldots, Y^{(P)}]$. The main constraint in the choice of these variables comes from the overall financial resources limitation. Hence, calling $E_T$ the budget allocated to the retrofit actions plan of all the urban sectors, the following inequality must be verified:

$$\sum_{p=1}^{P} Y^{(p)} \leq E_T. \quad (19)$$

Having defined as efficiency metric of each LDP action plan the ratio between the overall payoff actually achieved by the given panel and the assigned panel budget, the CDU objective function may be modeled by a distance function, measuring the mutual square deviations between the efficiency ratios of the panels, as follows:

$$F(\mathbf{Y}, \mathbf{x}^{(1)}, \ldots, \mathbf{x}^{(p)}, \ldots, \mathbf{x}^{(P)}) = \sum_{p=1}^{P-1} \sum_{q=p+1}^{P} \left( \frac{f^{(q)}(\mathbf{x}^{(q)})}{Y^{(q)}} - \frac{f^{(p)}(\mathbf{x}^{(p)})}{Y^{(p)}} \right)^2. \quad (20)$$

This objective function has to be minimized in order to allocate the budgets to the LDPs proportionally to their achieved payoffs. Hence, for a given choice of LDP action plans $\mathbf{x} = [\mathbf{x}^{(1)}, \ldots, \mathbf{x}^{(p)}, \ldots, \mathbf{x}^{(P)}]$, the decision-making problem of the CDU is formulated as follows:

$$\min_{\mathbf{Y}} \{F(\mathbf{Y}, \mathbf{x}^{(1)}, \ldots, \mathbf{x}^{(p)}, \ldots, \mathbf{x}^{(P)}) : \mathbf{Y} \in \mathcal{Y}\} \quad (21)$$

where $\mathcal{Y}$ denotes the upper-level feasible region in accordance with the defined constraints (18) and (19)

$$\mathcal{Y} = \left\{ \mathbf{Y} \in \mathbb{R}^P : Y^{(p)} > 0 \quad \forall p = 1, \ldots, P, \sum_{p=1}^{P} Y^{(p)} \le E_T \right\}. \quad (22)$$

Assuming that the LDP action plans are fixed, (21) and (22) are NLP problems and may be solved by means of several techniques [53].

### *D. Global Smart City Energy Management Model*

Having modeled the set of lower-level optimization problems and the upper-level optimization problem that concur to the global smart city energy management problem, this section summarizes how the aforementioned models are fully combined into a global optimization problem.

Equation (21) for the CDU, together with (8) and (17) for the $P = 3$ described LDPs, defines the hierarchical decision-making problem as follows:

$$\text{“}\min_{\mathbf{Y}}\text{”} \left\{ \begin{array}{l} F(\mathbf{Y}, \mathbf{x}^{(1)}, \ldots, \mathbf{x}^{(p)}, \ldots, \mathbf{x}^{(P)}) : \mathbf{Y} \in \mathcal{Y}, \\ \mathbf{x}^{(1)} \in \Psi^{(1)}(Y^{(1)}), \ldots, \mathbf{x}^{(P)} \in \Psi^{(P)}(Y^{(p)}) \end{array} \right\} \quad (23)$$

with

$$\Psi^{(p)}(Y^{(p)}) = \underset{\mathbf{x}^{(p)}}{\operatorname{argmax}} \{ f^{(p)}(\mathbf{x}^{(p)}) : \mathbf{x}^{(p)} \in \mathcal{X}^{(p)}(Y^{(p)}) \}, \quad \forall p = 1, \ldots, P \quad (24)$$

where $\Psi^{(p)}(Y^{(p)})$ denotes the set of all optimal solutions of the $p$th lower-level problem for the parameter $Y^{(p)}$ and $\mathcal{X}^{(p)}(Y^{(p)})$ denotes the $p$th lower-level feasible region in accordance with the defined constraints.

The mathematical model (23) and (24) is a mixed-discrete bilevel programming model. The quotation marks in (23) express the uncertainty in the definition of the problem, i.e., the case when any set $\Psi^{(p)}(Y^{(p)})$ is not reduced to a singleton.

Clearly, the upper-level decision maker has control over its own level decision variables only; this may cause some ambiguity in the selection of the lower-level decision strategies $\mathbf{x}^{(p)} \in \Psi^{(p)}(Y^{(p)})$, since different such decision strategies may solve the problem, thus leading to different values of the upper-level objective function. To avoid this ambiguity, usually two approaches are proposed in the literature: the optimistic approach (each LDP chooses an optimal solution, which is the best one for the CDU) and the pessimistic approach (each LDP chooses an optimal solution, which is the worst one from the point of view of the CDU) [54].

Introducing the optimistic solution function, we define

$$\Phi_b(\mathbf{Y}) = \min_{\mathbf{x}} \{F(\mathbf{Y}, \mathbf{x}) : \mathbf{x}^{(p)} \in \psi^{(p)}(Y^{(p)}) \quad \forall p = 1, \ldots, P\}. \quad (25)$$

Hence, problem (23) is replaced by

$$\min_{\mathbf{Y}} \{\Phi_b(\mathbf{Y}) : \mathbf{Y} \in \mathcal{Y}\} \quad (26)$$

and, consequently, (24)–(26) define the optimistic bilevel programming problem.

Similarly, introducing the pessimistic solution function, we determine

$$\Phi_w(\mathbf{Y}) = \max_{\mathbf{x}} \{F(\mathbf{Y}, \mathbf{x}) : \mathbf{x}^{(p)} \in \Phi^{(p)}(Y^{(p)}) \forall p = 1, \ldots, P\} \quad (27)$$

problem (23) is replaced by

$$\min_{\mathbf{Y}} \{\Phi_w(\mathbf{Y}) : \mathbf{Y} \in \mathcal{Y}\} \quad (28)$$

and, consequently, (24), (27), and (28) define the pessimistic bilevel programming problem.

For the bilevel programming problem defined in (27) and (28), the following result holds.

*Proposition 1:* In optimization problem (23) and (24), the optimistic and the pessimistic approaches coincide.

*Proof*: In case the set $\Psi = \Psi^{(1)}(Y^{(1)}) \times \cdots \times \Psi^{(P)}(Y^{(P)})$ is a singleton, the demonstration is trivial.

Consider the case when $\Psi$ is not a singleton and choose arbitrarily $\mathbf{x}_b = [\mathbf{x}_b^{(1)}, \ldots, \mathbf{x}_b^{(p)}, \ldots, \mathbf{x}_b^{(P)}]$ and $\mathbf{x}_w = [\mathbf{x}_w^{(1)}, \ldots, \mathbf{x}_w^{(p)}, \ldots, \mathbf{x}_w^{(P)}]$ in $\Psi$. First, we note from (24) that

$$f^{(p)}(\mathbf{x}_b^{(p)}) = f^{(p)}(\mathbf{x}_w^{(p)}), \quad \forall \mathbf{x}_b^{(p)}, \mathbf{x}_w^{(p)} \in \Psi^{(p)}(Y^{(p)}), \quad \forall p = 1, \ldots, P. \quad (29)$$

Combining (29) with (20), we get

$$F(\mathbf{Y}, \mathbf{x}_b) = F(\mathbf{Y}, \mathbf{x}_w), \quad \forall \mathbf{x}_b, \mathbf{x}_w \in \Psi. \quad (30)$$

Without loss of generality, suppose that $\mathbf{x}_b$ and $\mathbf{x}_w$ are the optimal solutions of the optimization problem defined in the right-hand side of (25) and (27), respectively

$$\begin{aligned} \Phi_b(\mathbf{Y}) &= F(\mathbf{Y}, \mathbf{x}_b) \\ \Phi_w(\mathbf{Y}) &= F(\mathbf{Y}, \mathbf{x}_w). \end{aligned} \quad (31)$$

Combining (31) with (30) we conclude that $\Phi_b(\mathbf{Y}) = \Phi_w(\mathbf{Y})$. Thus, Proposition 1 is proved.

Based on the previous result, the quotation marks in (23) can be dropped, keeping the problem well-posed

$$\min_{\mathbf{x}} \{F(\mathbf{Y}, \mathbf{x}) : \mathbf{x}^{(p)} \in \Psi^{(p)}(Y^{(p)}), \quad \forall p = 1, \ldots, P\}. \quad (32)$$

Summing up, the upper-level optimization problem (32) and the set of lower-level optimization problems (24) compactly define the global smart city energy management problem.

### E. Existence of Solutions to Bilevel Programming Model

In general, it is difficult to solve a bilevel programming problem, even for small instances. One reason for this is that a bilevel programming problem is an NP-hard problem, due to its nonconvex nature [54]. An additional difficulty in solving the bilevel programming problem (24) and (32) presented in this paper lies in fact that it involves decisions for both discrete and continuous variables. In particular, since the sets of inner continuous and outer integer variables are empty, and the sets of inner integer and outer continuous variables are nonempty, problems (24) and (32) are mixed-integer bilevel programming problems of type III (see the classification reported in [55]) that has been shown to be a difficult problem [56]. Furthermore, the nonlinearity that appears in the upper-level objective function (24) complicates the resolution. Also the fact that each lower problem constraint region is dependent on the outer decision variables amplifies the complexity of the overall solution process.

Several approaches are proposed in the literature to solve a linear bilevel programming problem [50], [57]. However, for a nonlinear, inherently NP-hard problem, like the one at hand, advanced algorithms are necessary. Dempe and Richter [58] and Fanghänel and Dempe [59] develop necessary and sufficient conditions for the existence of optimal solutions to a limited class of problems with continuous upper- and discrete lower-level variables. This means that a global solution of (24) and (32) does not necessarily exist. In fact, the solution set mapping $\Psi^{(p)}$ ($\forall p = 1, \dots, P$) is not upper semicontinuous in general [54], which implies that objective function in (24) is not always lower semicontinuous. Since the lower semicontinuity of the upper-level objective function is a condition for the existence of a global solution of the bilevel programming problem, it follows that the solvability of (24) and (32) is not guaranteed.

## IV. Distributed Solution Algorithm

A solution of (24) and (32) can be determined in a centralized way, using, for instance, the global optimization method described in [55]. This technique consists in reformulating the mixed-integer bilevel programming problem as a single-level mixed integer NLP problem. A drawback of this approach relies on the centralized resolution scheme, because a unique decision maker (i.e., the energy manager) should have full control not only over the CDU actions but also over the decision-making processes of all the LDPs. Unfortunately, in practice, the CDU does not have any direct control over the LDPs' decisions, as these are taken by each urban sector manager, and detailed actions, such as the actual values of $\mathbf{x}^{(p)}$ ($\forall p = 1, \dots, P$), could even be unknown to the CDU. Besides, a centralized approach is not scalable and cannot account for an unpredictably increasing number of LDPs. Therefore, a distributed control mechanism is required for the LDPs to decide in (24) the optimal retrofit action plans whose implementation ensures the CDU to realize the optimization in (32). To successfully capture the interactions between the CDU and the LDPs and the resolution of the entire decision-making process, we propose a distributed algorithm that uses game theory and is detailed in the sequel. Differently from the related literature, the main advantage of the proposed approach is then the absence of a centralized decision maker that should have access to all the information defining the problem and detain adequate computational resources to solve it. Moreover, we also demonstrate that the proposed approach constitutes an exact method for determining a solution to the presented bilevel programming problem.

### A. Game Model

The game theory approach is remarkably suitable to address the optimization problem defined in Section III. In particular, we formulate a noncooperative Stackelberg game to capture the interactions between the CDU (leader) and the LDPs (followers) [60]. A Stackelberg game consists in the multilevel decision-making processes of a number of independent players, i.e., followers, in response to the decision(s) made by the leader(s) of the game. The proposed game is a noncooperative game, since the followers do not communicate with each other, but they may only interact with the leader. Remarkably, the decision-making process of a panel does not depend on the strategy of other city panels.

The proposed noncooperative game is formally defined by its strategic form as follows [60].

*Game 1:*

- The players are the CDU and the LDPs.
- $\mathbf{Y} = [Y^{(1)}, \dots, Y^{(p)}, \dots, Y^{(P)}]$ is the CDU's strategy chosen in its own strategy set $\mathcal{Y}$.
- $\mathbf{x}^{(p)}$ is the $p$th LDP's strategy chosen in its own finite strategy set $\mathcal{U}^{(p)}$ ($\forall p = 1, \dots, P$); let $\mathbf{x} = \{\mathbf{x}^{(1)}, \dots, \mathbf{x}^{(p)}, \dots, \mathbf{x}^{(P)}\}$ denote the composition of all the LDPs' strategies and $\mathcal{U} = \mathcal{U}^{(1)} \times \dots \times \mathcal{U}^{(p)} \times \dots \times \mathcal{U}^{(P)}$ the composition of all the LDPs' strategies sets, respectively.
- $J_l$ is the CDU's cost function, defined as follows:

$$\begin{aligned} J_l(\mathbf{Y}, \mathbf{x}) &= J_l(\mathbf{Y}, \mathbf{x}^{(1)}, \dots, \mathbf{x}^{(p)}, \dots, \mathbf{x}^{(P)}) \\ &= F(\mathbf{Y}, \mathbf{x}^{(1)}, \dots, \mathbf{x}^{(\mathrm{p})}, \dots, \mathbf{x}^{(\mathrm{P})}). \end{aligned} \tag{33}$$

- $J_f^{(p)}$ is the $p$th LDP's cost function ($\forall p = 1, \dots, P$), defined as follows:

$$J_f^{(p)}(Y^{(p)}, \mathbf{x}^{(p)}) = \{-f^{(p)}(\mathbf{x}^{(p)}) : \mathbf{x}^{(p)} \in \mathcal{X}^{(p)}(Y^{(p)})\}. \tag{34}$$

In the proposed game, the CDU acts as the leader and the LDPs are the followers who act in response to the action taken by the game leader. This is a special case of the general Stackelberg game with one leader and multiple followers, because the $p$th follower's payoff function in (33) takes the simpler form $J_f^{(p)}(Y^{(p)}, \mathbf{x}^{(p)})$ instead of $J_f^{(p)}(\mathbf{Y}, \mathbf{x}^{(1)}, \dots, \mathbf{x}^{(p)}, \dots, \mathbf{x}^{(P)})$. This implies that each follower just selects its own best strategies to maximize its objective function, i.e., followers do not concur into forming a Nash equilibrium in order to define the followers' reaction to the leader's adopted strategy.

The suitable solution of the game corresponds to the well-known concept of Stackelberg equilibrium, defined as follows in case of single-leader multiple-followers game [61].

*Definition 1:* The $p$th follower reaction to the leader's adopted strategy is defined as follows:

$$\Psi^{(p)}(Y_*^{(p)}) = \underset{\mathbf{x}^{(p)}}{\operatorname{argmin}}\{J_f^{(p)}(Y_*^{(p)}, \mathbf{x}^{(p)}) : \mathbf{x}^{(p)} \in \mathcal{X}^{(p)}(Y_*^{(p)})\}. \tag{35}$$

Moreover, we denote the followers' reaction to the leader's adopted strategy as:

$$\Psi(\mathbf{Y}_*) = \Psi^{(1)}(Y_*^{(1)}) \times \cdots \times \Psi^{(P)}(Y_*^{(P)}). \tag{36}$$

*Definition 2:* Given the noncooperative Stackelberg game defined in Game 1, a set of strategies $(\mathbf{Y}_*, \mathbf{x}_*)$ with $\mathbf{x}_* = \{\mathbf{x}_*^{(1)}, \ldots, \mathbf{x}_*^{(p)}, \ldots, \mathbf{x}_*^{(P)}\}$ and with $\mathbf{Y}_* = [Y_*^{(1)}, \ldots, Y_*^{(p)}, \ldots, Y_*^{(P)}]$ constitutes a Stackelberg equilibrium of the game if and only if the following inequalities are simultaneously satisfied:

$$\min_{\mathbf{x}\in\Psi\ (\mathbf{Y}_*)} J_l(\mathbf{Y}_*, \mathbf{x}) \leq \min_{\mathbf{x}\in\Psi\ (\mathbf{Y})} J_l(\mathbf{Y}, \mathbf{x}), \quad \forall \mathbf{Y} \in \mathcal{Y} \tag{37}$$

$$\mathbf{x}_* \in \Psi\ (\mathbf{Y}_*). \tag{38}$$

The meaning of the Stackelberg equilibrium represented by (37) and (38) is that neither the CDU nor any LDP in the players' set could benefit—i.e., improve its utility in terms of its corresponding objective function—from a unilateral change in its strategy once all the other game players reach their equilibrium strategy [60].

We now assess the relationship between Game 1 and the solution of the global optimization problem, providing the following proposition whose proof is based on the relationship between bilevel programming and Stackelberg games [60].

*Proposition 2:* A Stackelberg equilibrium of Game 1 is equivalent to an optimal solution of bilevel programming problems (24) and (32).

The existence of a solution of the proposed Stackelberg game needs to be evaluated, because this is not always guaranteed in noncooperative games [60].

*Definition 3:* The leader's Stackelberg cost is defined as follows:

$$J_l^* = \inf_{\mathbf{Y}\in\mathcal{Y}} \min_{\mathbf{x}\in\Psi(\mathbf{Y})} J_l(\mathbf{Y}, \mathbf{x}). \tag{39}$$

If there does not exist any Stackelberg equilibrium, there will always exist a leader strategy $\mathbf{Y}_* \in \mathcal{Y}$, which will ensure a solution function value arbitrarily close to $J_l^*$. This observation brings to the definition of $\varepsilon$-optimal solution.

*Definition 4:* Given the noncooperative Stackelberg game defined in Game 1, a set of strategies $(\mathbf{Y}_*, \mathbf{x}_*)$ with $\mathbf{Y}_* = [Y_*^{(1)}, \ldots, Y_*^{(p)}, \ldots, Y_*^{(P)}]$ and $\{\mathbf{x}_*^{(1)}, \ldots, \mathbf{x}_*^{(p)}, \ldots, \mathbf{x}_*^{(P)}\}$ constitutes an $\varepsilon$ Stackelberg equilibrium of the game if the following conditions are verified:

$$\min_{\mathbf{x}\in\Psi\ (\mathbf{Y}_*)} J_l(\mathbf{Y}_*, \mathbf{x}_*) \leq J_l^* + \varepsilon \tag{40}$$

$$\mathbf{x}_* \in \Psi\ (\mathbf{Y}_*). \tag{41}$$

As defined in Definition 4, the following property holds [60].

*Property 1:* Let $J_l^*$ be a finite number; then, given $\varepsilon > 0$, an $\varepsilon$ Stackelberg equilibrium necessarily exists.

## *B. Distributed Algorithm*

Having defined Game 1 and highlighted its relationship with the bilevel programming problems (24) and (32), we now focus on using game properties for characterizing the solutions of the presented global optimization problem and for determining at least a nearly optimal solution.

As a precondition, we report the following result.

*Proposition 3:* For any set of followers' strategies, the leader strategy is unique.

*Proof:* Let $\tilde{\mathbf{x}} = \{\widetilde{\mathbf{x}^{(1)}}, \ldots, \widetilde{\mathbf{x}^{(p)}}, \ldots, \widetilde{\mathbf{x}^{(P)}}\} \in \mathcal{U}$ be a given set of followers' strategies, where the tilde sign indicates a specific set of strategies.

According to (33), the leader determines his strategy solving the following optimization problem:

$$\widetilde{J_l^*} = \min_{\mathbf{Y}\in\mathcal{Y}} \sum_{p=1}^{P-1} \sum_{q=p+1}^{P} \left( \frac{f^{(q)}(\widetilde{\mathbf{x}^{(q)}})}{Y^{(\mathrm{q})}} - \frac{f^{(p)}(\widetilde{\mathbf{x}^{(p)}})}{Y^{(p)}} \right)^2 \tag{42}$$

where the minimum argument function is the function $F$ as defined in (20). This function is a summation of quadratic terms; thus it is nonnegative and is lower bounded by zero value.

Hence, the proof consists in demonstrating that there exist a unique point $\widetilde{\mathbf{Y}} \in \mathcal{Y}$ where the argument function in the right-hand side of (42) equals zero.

Let us define $\tilde{\mathbf{Y}} = [\widetilde{Y^{(1)}}, \ldots, \widetilde{Y^{(p)}}, \ldots, \widetilde{Y^{(P)}}]$ as follows:

$$\widetilde{Y^{(p)}} = \frac{f^{(p)}(\widetilde{\mathbf{x}^{(p)}})}{\sum_{p=1}^{P} f^{(p)}(\widetilde{\mathbf{x}^{(p)}})} \cdot E_T, \quad \forall p = 1, \ldots, P. \tag{43}$$

Based on the definition in (43), it is evident that $\widetilde{\mathbf{Y}} \in \mathcal{Y}$. Furthermore, replacing (43) in (20), we also get

$$F(\tilde{\mathbf{Y}}, \widetilde{\mathbf{x}^{(1)}}, \ldots, \widetilde{\mathbf{x}^{(p)}}, \ldots, \widetilde{\mathbf{x}^{(P)}}) = 0. \tag{44}$$

We conclude that the minimum $\widetilde{J_l^*}$ is uniquely attained and equals zero. Thus, Proposition 3 is proved.

Now, we first assess the existence of a lower bound of the leader's Stackelberg cost, and consequently of the solution to the bilevel programming problem. To this aim, the following two propositions hold.

*Proposition 4:* A lower bound for the leader's Stackelberg cost is equal to the minimum cost attained by the leader in case he has decision control over both his own strategies and followers' strategies.

*Proof:* Let $\overline{J_l^*}$ be the minimum cost attained by the leader in case he has decision control over both his own strategies and followers' strategies. Then, $\overline{J_l^*}$ is computed as follows:

$$\overline{J_l^*} = \min_{\mathbf{Y}\in\mathcal{Y}, \mathbf{x}\in\mathcal{U}} J_l(\mathbf{Y}, \mathbf{x}^{(1)}, \ldots, \mathbf{x}^{(\mathrm{p})}, \ldots, \mathbf{x}^{(P)}). \tag{45}$$

Using the properties of parametric optimization [62], (45) may be reformulated as

$$\overline{J_l^*} = \min_{\mathbf{Y}\in\mathcal{Y}} \min_{\mathbf{x}\in\mathcal{U}} J_l(\mathbf{Y}, \mathbf{x}^{(1)}, \ldots, \mathbf{x}^{(p)}, \ldots, \mathbf{x}^{(P)}). \tag{46}$$

**Algorithm 1** : Inner-Outer Iteration Algorithm

1 The CDU initializes $\mathbf{Y}_{(0)} = [Y_{(0)}^{(1)}, \ldots, Y_{(0)}^{(p)}, \ldots, Y_{(0)}^{(P)}]$
2 Set $r \leftarrow 0$
3 **repeat**
4 The CDU sends $Y_{(r)}^{(p)}$ to the $p$th LDP, $\forall p = 1, \ldots, P$
5 In parallel, $\forall p = 1, \ldots, P$:
6 The $p$th LDP determines $\mathbf{x}_{(r)}^{(p)}$ solving local problem (24) with $Y_{(r)}^{(p)}$
7 The $p$th LDP sends $f^{(p)}(\mathbf{x}_{(r)}^{(p)})$ back to the CDU
8 The CDU updates $\mathbf{Y}_{(r+1)}$ solving central problem (32) using $f^{(p)}(\mathbf{x}_{(r)}^{(p)}) \forall p = 1, \ldots, P$
9 Set $r \leftarrow r + 1$
10 **until** the value of $\mathbf{Y}_{(r)}$ satisfies the termination criterion (50)

Observing that $\Psi\ (\mathbf{Y}) \subseteq \mathcal{U}$, we get

$$\min_{\mathbf{x}\in\mathcal{U}} J_l(\mathbf{Y}, \mathbf{x}^{(1)}, \ldots, \mathbf{x}^{(p)}, \ldots, \mathbf{x}^{(P)}) \leq \min_{\mathbf{x}\in\Psi\ (\mathbf{Y})} J_l(\mathbf{Y}, \mathbf{x}^{(1)}, \ldots, \mathbf{x}^{(p)}, \ldots, \mathbf{x}^{(P)}). \quad (47)$$

Combining (46) and (39) into (47), we conclude that $\overline{J_l^*} \leq J_l^*$. Thus, Proposition 4 is proved. □

*Proposition 5:* The lower bound $\overline{J_l^*}$ of the solution to the bilevel programming problem is zero valued.

*Proof:* According to (20) and (45), $\overline{J_l^*}$ is expressed as follows:

$$\overline{J_l^*} = \min_{\mathbf{Y}\in\mathcal{Y}, \mathbf{x}\in\mathcal{U}} \sum_{p=1}^{P-1} \sum_{q=p+1}^{P} \left( \frac{f^{(q)}(\mathbf{x}^{(q)})}{Y^{(q)}} - \frac{f^{(p)}(\mathbf{x}^{(p)})}{Y^{(p)}} \right)^2. \quad (48)$$

The proof consists in demonstrating that there exist a point ($\bar{\mathbf{x}} \in \mathcal{U}$ and $\bar{\mathbf{Y}} \in \mathcal{Y}$) where the function $F$ attains the zero value. First, let us choose $\bar{\mathbf{x}} = [\bar{\mathbf{x}}^{(1)}, \ldots, \bar{\mathbf{x}}^{(p)}, \ldots, \bar{\mathbf{x}}^{(P)}] \in \mathcal{U}$ arbitrarialy different from zero values, where the bar indicates a specific set of strategies. Then, applying Proposition 3, there exists $\bar{\mathbf{Y}}$, such that

$$F(\overline{\mathbf{Y}}, \overline{\mathbf{x}^{(1)}}, \ldots, \overline{\mathbf{x}^{(p)}}, \ldots, \overline{\mathbf{x}^{(P)}}) = 0. \quad (49)$$

Thus, Proposition 5 is proved. □

We now complete the characterization of the presented global optimization problem, defining a method to provide an upper bound to the solutions. Subsequently, we propose Algorithm 1 as the resolution technique that allows the CDU and LDPs to reach the Stackelberg equilibrium of Game 1 and consequently the global solution to the presented bilevel programming problem.

The algorithm is based on the so-called inner–outer method [63], in which the leader's problem and the set of followers' problems are solved iteratively based on the most recently computed strategies of the complementary player. Next, we explain how Algorithm 1 works. As initialization phase, the CDU initializes his own strategies (i.e., the budget allocation) and the iteration step counter (lines 1 and 2). First, the CDU sends the budget allocation to all the LDPs (line 4). Accordingly, in parallel, all LDPs compute their own strategy (i.e., the retrofit action plans that maximize their payoffs) and send the achieved payoff information back to the CDU (lines 5–7). Based on the information, received last the CDU updates the budget allocation and the step counter (lines 8 and 9). The described steps are repeated until the CDU realizes that there are no significant value changes in two consecutive budget allocation updates (line 10). The termination criterion is defined as follows:

$$\|\mathbf{Y}_{(r)} - \mathbf{Y}_{(r-1)}\| < \varepsilon \quad (50)$$

where $\varepsilon > 0$ is the required algorithm convergence tolerance. When (50) holds, the algorithm has reached its fixed point. The nearly optimal budget allocation $\overline{\overline{\mathbf{Y}}}$ and local panel optimal action strategies $\overline{\overline{\mathbf{x}^{(p)}}}$ ($\forall p = 1, \ldots, P$) are then computed.

In the following propositions, we assess the convergence and optimality properties of Algorithm 1.

*Proposition 6:* Starting from any randomly selected initial condition, Algorithm 1 converges finitely to its fixed point.

*Proof:* We have to prove that the algorithm stops after a finite number of iterations. Assume that this is not true. Then, for any selected initial conditions, sequences $\{\mathbf{Y}_{(r)}\}_{r=1}^{\infty} \subseteq \mathcal{Y}$ and $\{\mathbf{x}_{(r)}\}_{r=1}^{\infty} \subseteq \mathcal{U}$ are computed with

$$\|\mathbf{Y}_{(r)} - \mathbf{Y}_{(r+1)}\| \geqslant \varepsilon, \quad \forall r = 1, \ldots, \infty. \quad (51)$$

Since card($\mathcal{U}$) $< \infty$ by definition, there exists an index $r$ with $\mathbf{x}_{(r)} = \mathbf{x}_{(r-1)}$. In accordance with Proposition 3, the CDU is able to find a unique strategy vector in response to the LDPs' strategy vectors; consequently, we obtain $\mathbf{Y}_{(r)} = \mathbf{Y}_{(r+1)}$. But, this is in contradiction with (51). Thus, Algorithm 1 stops after a finite number of iterations and Proposition 6 is proved. □

*Definition 5:* Let us denote by $(\overline{\overline{\mathbf{Y}}}, \overline{\overline{\mathbf{x}}})$ a fixed point of Algorithm 1. Let $\overline{\overline{J_l^*}}$ denote the corresponding cost attained by the CDU, that is

$$\overline{\overline{J_l^*}} = J_l(\overline{\overline{\mathbf{Y}}}, \overline{\overline{\mathbf{x}}}). \quad (52)$$

*Proposition 7:* The solution to the bilevel programming problems (24) and (32) is upper bounded by the value of $\overline{\overline{J_l^*}}$ as computed by Algorithm 1.

*Proof:* The proof is based on noting that the proposed inner–outer approach in Algorithm 1 corresponds to determining a Nash equilibrium of Game 1 using the Gauss–Seidel decomposition method [64]. Subsequently, recalling that the leader in a Stackelberg strategy achieves at least as good (possibly better) a cost function value (i.e., $J_l^*$) as the cost function value in the corresponding Nash solution (i.e., $\overline{\overline{J_l^*}}$) [60], Proposition 7 is proved.

*Proposition 8:* The upper bound $\overline{\overline{J_l^*}}$ of the solution to the bilevel programming problem is zero valued.

*Proof:* Assume that $\overline{\overline{J_l^*}}$ is attained in correspondence of Algorithm 1 fixed point $(\overline{\overline{\mathbf{Y}}}, \overline{\overline{\mathbf{x}}})$. Based on Algorithm 1, $\overline{\overline{\mathbf{Y}}}$ is the solution of the central problem (32) in case $\mathbf{x} = \overline{\overline{\mathbf{x}}}$, that is

$$\overline{\overline{\mathbf{Y}}} = \underset{\mathbf{Y}}{\operatorname{argmin}} \{F(\mathbf{Y}, \overline{\overline{\mathbf{x}^{(1)}}}, \ldots, \overline{\overline{\mathbf{x}^{(p)}}}, \ldots, \overline{\overline{\mathbf{x}^{(P)}}}) : \mathbf{Y} \in \mathcal{Y}\}. \tag{53}$$

Based on Proposition 3, it is evident that it holds

$$F(\overline{\overline{\mathbf{Y}}}, \overline{\overline{\mathbf{x}^{(1)}}}, \ldots, \overline{\overline{\mathbf{x}^{(p)}}}, \ldots, \overline{\overline{\mathbf{x}^{(P)}}}) = 0. \tag{54}$$

We conclude that $\overline{\overline{J_l^*}} = 0$. Thus, Proposition 8 is proved.

Finally, the cornerstone of our investigation is Theorem 1.

*Theorem 1:* Algorithm 1 converges to the Stackelberg equilibrium of Game 1.

*Proof:* The proof is based on the results given by Propositions 5 and 8. Combining (49) and (54), we obtain

$$0 = \overline{J_l^*} \leq J_l^* \leq \overline{\overline{J_l^*}} = 0 \tag{55}$$

which implies that the leader's Stackelberg cost is $J_l^* = 0$. Consequently, Algorithm 1 converges to the Stackelberg equilibrium of Game 1, and thus, Theorem 1 is proved.

Summing up, combining the results of Theorem 1 and Proposition 2, we conclude that Algorithm 1 is an exact method for determining a solution to the presented bilevel programming problem.

## V. Case Study

We apply the developed smart city energy management strategy to the case of the municipality of Bari, the capital city of the Apulia region, in southern Italy. Bari is currently engaged in a series of smart city initiatives promoted by the European Union (EU) and mainly dedicated to reducing $CO_2$ emissions and increasing the quality of life [11]. These initiatives include energy efficiency projects, urban planning, renovation of heating and lighting infrastructure and networks, intelligent buildings, introducing renewable energy sources, and carrying out education campaigns. In particular, a specific initiative within the Bari smart city program focuses on the design, development, and testing of a new tool supporting the PA in the city energy management, namely the so-called UCC.

### A. Urban Control Center

The UCC is an innovative ICT platform for monitoring and managing urban energy dynamics: it is designed by IBM and Politecnico di Bari and developed by IBM. The UCC provides city managers with accessible operational and progress metrics and statuses. It integrates different and older ICT systems into one engine that can simplify inputs, providing a complete overview of the city energetic status and ensuring that the municipal staff is alerted if anything out of the ordinary (extreme or important) occurs. It can kick off workflows and situation management, and it provides real-time situational analysis, and tracks daily issues. The core of the UCC is the Intelligent Operations Center IBM solution [65], which obtains data from the various urban subsystems (electricity, water, buildings, etc.). The UCC has two main functionalities. First, the UCC is equipped with performance evaluation tools: data are automatically collected, aggregated, and elaborated from a variety of sources. Hence, data are aggregated into a KPI dashboard and can be navigated on different space and time spans and on a map paradigm. Several map boards are available, each addressing specific energy and environmental aspects of the city. Second, the UCC is provided with business intelligence tools for strategic decision making and planning for the city energy management. In particular, the presented hierarchical decision-making model is already integrated as a decision support module into the UCC recently developed prototype in the framework of RES NOVAE, an energy governance research project developed in Bari (Italy) and funded by the Italian Ministry of Research and University [8].

TABLE I
Results of Diagnosis in the PuBLDP

| | | Indicators | | |
|---|---|---|---|---|
| | | $I_1$ [KWh/year] | $I_2$ [m$^3$/year] | $I_3$ [m$^3$/year] |
| **Buildings** | $B_1^{(1)}$ | 25290 | 50652 | 1950 |
| | $B_2^{(1)}$ | 39500 | 84275 | 2700 |
| | $B_3^{(1)}$ | 41026 | 36080 | 2250 |
| | $B_4^{(1)}$ | 43851 | 86732 | 2500 |
| | $B_5^{(1)}$ | 44582 | 33713 | 2400 |

In the current UCC version, the prototyped decision-making module was built using MATLAB as a computation engine. This means that the front end (user interface) was actually coded in application server languages while the back end (algorithmic content) was programmed in MATLAB. Indeed, MATLAB provides a library of functions (MATLAB engine) that allows external application to start and end the MATLAB process, send data to and from MATLAB, and send commands to be processed in MATLAB [66]. Since the presented decision-making concerns off-line optimization, the actual software implementation is not a real issue in the evaluation of computing efficiency.

### B. Scenarios Definition

We now present the application of the proposed bilevel programming model in supporting the Bari city managers to solve the following decision problem: optimally dividing a predefined budget $E_T = €600\,000.00$ between the public building panel, the private building panel, and the street lighting building panel, for implementing energy retrofitting actions planning in a given urban area.

Within the given urban area, a stock of $K^{(1)} = 5$ public buildings (namely, five school buildings identified as $B_1^{(1)}$ to $B_5^{(1)}$) and a stock of $K^{(2)} = 10$ private buildings (namely, commercial buildings identified as $B_1^{(2)}$ to $B_{10}^{(2)}$) are examined. After a joint analysis and walk-through surveys conducted with technical experts, the following set of $H = 3$ performance indicators to minimize are considered as set of decision criteria both in case of PuBLDP and PrBLDP (i.e., $\mathcal{H}^{(2)} = \mathcal{H}^{(1)}$): electrical energy consumption due to lighting and water heating ($I_1$), methane consumption due to heating ($I_2$), and water consumption ($I_3$). Tables I and II report the outcomes of the diagnosis phase performed for each building of the stock of PuBLDP and PrBLDP, respectively.

TABLE II
RESULTS OF DIAGNOSIS IN THE PrBLDP

| | | Indicators | | |
|---|---|---|---|---|
| | | $I_1$ [KWh/year] | $I_2$ [m$^3$/year] | $I_3$ [m$^3$/year] |
| Buildings | $B_1^{(2)}$ | 5058 | 10130 | 390 |
| | $B_2^{(2)}$ | 8295 | 17698 | 567 |
| | $B_3^{(2)}$ | 9026 | 7938 | 495 |
| | $B_4^{(2)}$ | 8770 | 17346 | 500 |
| | $B_5^{(2)}$ | 11146 | 8428 | 600 |
| | $B_6^{(2)}$ | 5817 | 11650 | 449 |
| | $B_7^{(2)}$ | 9480 | 20226 | 648 |
| | $B_8^{(2)}$ | 10667 | 9381 | 585 |
| | $B_9^{(2)}$ | 9209 | 18214 | 525 |
| | $B_{10}^{(2)}$ | 9808 | 7417 | 528 |

TABLE III
LIST OF THE ACTIONS CONSIDERED IN THE PuBLDP AND PrBLDP

| Code | Description | Building element |
|---|---|---|
| $A_1$ | external walls thermal insulation | Envelope |
| $A_2$ | roof thermal insulation | |
| $A_3$ | windows replacement | |
| $A_4$ | external walls thermal insulation + roof thermal insulation | |
| $A_5$ | external walls thermal insulation + windows replacement | |
| $A_6$ | roof thermal insulation + windows replacement | |
| $A_7$ | external walls thermal insulation + roof thermal insulation + windows replacement | |
| $A_8$ | boiler replacement | HVAC |
| $A_9$ | thermostatic radiator valves installation | |
| $A_{10}$ | boiler replacement + thermostatic radiator valves installation | |
| $A_{11}$ | water tap aerators installation | Water equipment |
| $A_{12}$ | electric water heater replacement | |
| $A_{13}$ | water tap aerators installation + electric water heater replacement | |
| $A_{14}$ | electric lighting replacement | Lighting equipment |

Table III collects the findings of a feasibility study on the set of retrofitting actions that are applicable to the portfolio both in case of PuBLDP and PrBLDP (i.e., $\mathcal{J}^{(2)} = \mathcal{J}^{(1)}$). Tables IV and V and Tables VI and VII contain the results of the evaluation of retrofit measures in case of PuBLDP and PrBLDP, respectively: Tables IV and V report the unitary cost of each action, while the latter contain the payoff matrix for each building with respect to each criterion.

In the same given urban area, the lighting system is composed by $S = 10$ zone lighting subsystems that make use of $N = 316$ lighting units of $T = 2$ types: Table VIII enumerates the lighting units for each type in each subsystem (i.e., $N_{st}$). Table IX reports the outcomes of the diagnosis phase performed for each lighting unit type and accordingly reports the ex-ante values of each indicator (i.e., $\gamma_t$, $\varphi_t$, and $\rho_t$). In addition, Table IX collects the ex-post value of lighting unit indicator resulting by luminaire replacement (i.e., $\gamma_t'$, $\varphi_t'$, and $\rho_t'$) and associated unit cost ($c^{u,t}$). Finally, Tables X and XI report the costs and payoffs referred to the remaining retrofitting actions ($c^v$ and $\Omega$ for the energy harvesting module and $c^w$ and $\alpha_s$ for the dimming installation, respectively).

### *C. Results and Discussion*

All the following results are obtained using the current UCC prototype that calls for Algorithm 1 implemented in MATLAB R2013b running on a PC with Intel Core i5–3317 CPU at 2.40 GHz, 8-GB RAM memory, and 64-b Windows 7 OS. The run time equals less than 100 ms. We use the Solving Constraint Integer Programs solver [67], supplied with the OPTI Toolbox for MATLAB [68], to solve the KP problems (8), the BKP problem in (17), and the NLP problem (21) under consideration.

Table XII reports some parameters necessary for running Algorithm 1, namely, the weights indicating the importance of each objective chosen by each local decision maker (i.e., $[\pi_1^{(p)}, \pi_2^{(p)}, \pi_3^{(p)}], \forall p = 1, 2, 3$), the algorithm convergence tolerance (i.e., $\varepsilon$), and the algorithm initialization parameters (i.e., the CDU initial budget allocation $[Y_{(0)}^{(1)}, Y_{(0)}^{(2)}, Y_{(0)}^{(3)}]$). The results of Algorithm 1 are reported in Tables XIII–XV, which represent the three optimal action plans, respectively, for the public buildings ($Y^{(1)} =$ €202 463.45), private buildings ($Y^{(2)} =$ €211 157.27), and street lighting ($Y^{(3)} =$ €186 379.26). In particular, Tables XIII and XIV represent, respectively, the values assumed by the PuBLDP and PrBLDP decision variables (i.e., $\mathbf{x}^{(1)}$ and $\mathbf{x}^{(2)}$) when Algorithm 1 converges. The $j$-row $k$-column cell of Tables XIII and XIV contains information on whether the $j$th action has to be applied to the $k$th building (1 value) or not (0 value). Similarly, Table XV represents the values assumed by the StLLDP decision variables when Algorithm 1 reaches the convergence. The top subtable in Table XV contains information about the quantities of luminaries of types 1 and 2 to be replaced in each lighting subsystem ($u_{st}$). The center subtable contains information about the quantities of energy harvesting modules to be installed ($v_s$). The bottom subtable contains information whether the zonal dimming device has to be applied to the $s$th subsystem (1 value) or not (0 value) ($w_s$). Counting the occurrence of planned actions (i.e., when decision variables referred to each action take 1 value) in Tables XIII and XIV, we note that both in the PuBLDP and PrBLDP, the most occurring planned actions imply the boiler replacement and thermostatic radiator valves installation ($A_{10}$), the water tap aerators installation with the electric water heater replacement ($A_{13}$), and finally the electric lighting replacement ($A_{14}$). In the StLLDP, instead, the most occurring optimal action plan concerns the luminaire replacement and and the dimming installation. In fact, counting the quantities of luminaries of types 1 and 2 to be replaced in each lighting subsystem ($u_{st}$) in the top subtable in Table XV, we infer that around half the lamps are planned to be replaced. Similarly, we note that $v_s = 0$, $\forall s = 1, \ldots, 10$ (no energy harvesting module is planned to be installed in any subsystem) and $w_s = 1$, $\forall s = 1, \ldots, 10$ (i.e., all the subsystems are planned to be dimmed) in center and bottom part of Table XV.

TABLE IV
ACTION PAYOFFS IN THE PuBLDP

| **Buildings** | | $B_1^{(1)}$ | | | $B_2^{(1)}$ | | | $B_3^{(1)}$ | | | $B_4^{(1)}$ | | | $B_5^{(1)}$ | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Payoffs** | | $P_{1j1}^{(1)}$ [kWh/yr.] | $P_{2j1}^{(1)}$ [m$^3$/yr.] | $P_{3j1}^{(1)}$ [m$^3$/yr.] | $P_{1j2}^{(1)}$ [kWh/yr.] | $P_{2j2}^{(1)}$ [m$^3$/yr.] | $P_{3j2}^{(1)}$ [m$^3$/yr.] | $P_{1j3}^{(1)}$ [kWh/yr.] | $P_{2j3}^{(1)}$ [m$^3$/yr.] | $P_{3j3}^{(1)}$ [m$^3$/yr.] | $P_{1j4}^{(1)}$ [kWh/yr.] | $P_{2j4}^{(1)}$ [m$^3$/yr.] | $P_{3j4}^{(1)}$ [m$^3$/yr.] | $P_{1j5}^{(1)}$ [kWh/yr.] | $P_{2j5}^{(1)}$ [m$^3$/yr.] | $P_{3j5}^{(1)}$ [m$^3$/yr.] |
| **Actions** | $A_1$ | - | 1463 | - | - | 8404 | - | - | 2142 | - | - | 7783 | - | - | 2022 | - |
| | $A_2$ | - | 1989 | - | - | 3364 | - | - | 1799 | - | - | 5201 | - | - | 1010 | - |
| | $A_3$ | - | 1490 | - | - | 5055 | - | - | 1081 | - | - | 2603 | - | - | 1347 | - |
| | $A_4$ | - | 4052 | - | - | 11799 | - | - | 3247 | - | - | 11275 | - | - | 2023 | - |
| | $A_5$ | - | 2026 | - | - | 10956 | - | - | 2886 | - | - | 10408 | - | - | 3034 | - |
| | $A_6$ | - | 4052 | - | - | 6742 | - | - | 2526 | - | - | 6071 | - | - | 3034 | - |
| | $A_7$ | - | 4559 | - | - | 16012 | - | - | 4690 | - | - | 13010 | - | - | 3034 | - |
| | $A_8$ | - | 7454 | - | - | 17698 | - | - | 3607 | - | - | 13876 | - | - | 6740 | - |
| | $A_9$ | - | 1491 | - | - | 2528 | - | - | 901 | - | - | 1300 | - | - | 842 | - |
| | $A_{10}$ | - | 8104 | - | - | 21069 | - | - | 5051 | - | - | 15612 | - | - | 7754 | - |
| | $A_{11}$ | 113 | - | 390 | 178 | - | 594 | 213 | - | 453 | 211 | - | 475 | 200 | - | 456 |
| | $A_{12}$ | 757 | - | - | 1184 | - | - | 2135 | - | - | 1643 | - | - | 1067 | - | - |
| | $A_{13}$ | 794 | - | 390 | 1302 | - | 594 | 2277 | - | 453 | 1708 | - | 475 | 1335 | - | 456 |
| | $A_{14}$ | 506 | - | - | 790 | - | - | 1228 | - | - | 1312 | - | - | 1335 | - | - |

TABLE V
ACTION PAYOFFS IN THE PrBLDP

| **Buildings** | | $B_1^{(2)}$ | | | $B_2^{(2)}$ | | | $B_3^{(2)}$ | | | $B_4^{(2)}$ | | | $B_5^{(2)}$ | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Payoffs** | | $P_{1j1}^{(2)}$ [kWh/yr.] | $P_{2j1}^{(2)}$ [m$^3$/yr.] | $P_{3j1}^{(2)}$ [m$^3$/yr.] | $P_{1j2}^{(2)}$ [kWh/yr.] | $P_{2j2}^{(2)}$ [m$^3$/yr.] | $P_{3j2}^{(2)}$ [m$^3$/yr.] | $P_{1j3}^{(2)}$ [kWh/yr.] | $P_{2j3}^{(2)}$ [m$^3$/yr.] | $P_{3j3}^{(2)}$ [m$^3$/yr.] | $P_{1j4}^{(2)}$ [kWh/yr.] | $P_{2j4}^{(2)}$ [m$^3$/yr.] | $P_{3j4}^{(2)}$ [m$^3$/yr.] | $P_{1j5}^{(2)}$ [kWh/yr.] | $P_{2j5}^{(2)}$ [m$^3$/yr.] | $P_{3j5}^{(2)}$ [m$^3$/yr.] |
| **Actions** | $A_1$ | - | 293 | - | - | 1765 | - | - | 471 | - | - | 1557 | - | - | 506 | - |
| | $A_2$ | - | 398 | - | - | 706 | - | - | 396 | - | - | 1040 | - | - | 253 | - |
| | $A_3$ | - | 298 | - | - | 1062 | - | - | 238 | - | - | 521 | - | - | 337 | - |
| | $A_4$ | - | 810 | - | - | 2478 | - | - | 714 | - | - | 2255 | - | - | 506 | - |
| | $A_5$ | - | 405 | - | - | 2301 | - | - | 635 | - | - | 2082 | - | - | 759 | - |
| | $A_6$ | - | 810 | - | - | 1416 | - | - | 556 | - | - | 1214 | - | - | 759 | - |
| | $A_7$ | - | 912 | - | - | 3363 | - | - | 1032 | - | - | 2602 | - | - | 759 | - |
| | $A_8$ | - | 1491 | - | - | 3717 | - | - | 794 | - | - | 2775 | - | - | 1685 | - |
| | $A_9$ | - | 298 | - | - | 531 | - | - | 198 | - | - | 260 | - | - | 211 | - |
| | $A_{10}$ | - | 1621 | - | - | 1765 | - | - | 1111 | - | - | 3122 | - | - | 1939 | - |
| | $A_{11}$ | 23 | - | 78 | 37 | - | 125 | 47 | - | 100 | 42 | - | 95 | 50 | - | 114 |
| | $A_{12}$ | 151 | - | - | 249 | - | - | 470 | - | - | 329 | - | - | 267 | - | - |
| | $A_{13}$ | 159 | - | 78 | 273 | - | 125 | 501 | - | 100 | 342 | - | 95 | 334 | - | 114 |
| | $A_{14}$ | 101 | - | - | 166 | - | - | 270 | - | - | 262 | - | - | 334 | - | - |
| **Buildings** | | $B_6^{(2)}$ | | | $B_7^{(2)}$ | | | $B_8^{(2)}$ | | | $B_9^{(2)}$ | | | $B_{10}^{(2)}$ | | |
| **Payoffs** | | $P_{1j6}^{(2)}$ [kWh/yr.] | $P_{2j6}^{(2)}$ [m$^3$/yr.] | $P_{3j6}^{(2)}$ [m$^3$/yr.] | $P_{1j7}^{(2)}$ [kWh/yr.] | $P_{2j7}^{(2)}$ [m$^3$/yr.] | $P_{3j7}^{(2)}$ [m$^3$/yr.] | $P_{1j8}^{(2)}$ [kWh/yr.] | $P_{2j8}^{(2)}$ [m$^3$/yr.] | $P_{3j8}^{(2)}$ [m$^3$/yr.] | $P_{1j9}^{(2)}$ [kWh/yr.] | $P_{2j9}^{(2)}$ [m$^3$/yr.] | $P_{3j9}^{(2)}$ [m$^3$/yr.] | $P_{1j10}^{(2)}$ [kWh/yr.] | $P_{2j10}^{(2)}$ [m$^3$/yr.] | $P_{3j10}^{(2)}$ [m$^3$/yr.] |
| **Actions** | $A_1$ | - | 67 | - | - | 424 | - | - | 123 | - | - | 327 | - | - | 111 | - |
| | $A_2$ | - | 91 | - | - | 170 | - | - | 103 | - | - | 218 | - | - | 56 | - |
| | $A_3$ | - | 69 | - | - | 255 | - | - | 62 | - | - | 109 | - | - | 74 | - |
| | $A_4$ | - | 186 | - | - | 595 | - | - | 186 | - | - | 474 | - | - | 111 | - |
| | $A_5$ | - | 93 | - | - | 552 | - | - | 165 | - | - | 437 | - | - | 167 | - |
| | $A_6$ | - | 186 | - | - | 340 | - | - | 144 | - | - | 255 | - | - | 167 | - |
| | $A_7$ | - | 210 | - | - | 807 | - | - | 268 | - | - | 546 | - | - | 167 | - |
| | $A_8$ | - | 343 | - | - | 892 | - | - | 206 | - | - | 583 | - | - | 371 | - |
| | $A_9$ | - | 69 | - | - | 127 | - | - | 52 | - | - | 55 | - | - | 46 | - |
| | $A_{10}$ | - | 373 | - | - | 1062 | - | - | 289 | - | - | 656 | - | - | 426 | - |
| | $A_{11}$ | 5 | - | 18 | 9 | - | 30 | 12 | - | 26 | 9 | - | 20 | 11 | 111 | 25 |
| | $A_{12}$ | 35 | - | - | 60 | - | - | 122 | - | - | 69 | - | - | 59 | - | - |
| | $A_{13}$ | 37 | - | 18 | 66 | - | 30 | 130 | - | 26 | 72 | - | 20 | 73 | - | 25 |
| | $A_{14}$ | 23 | - | - | 40 | - | - | 70 | - | - | 55 | - | - | 73 | - | - |

Summing up, the proposed bilevel programming method allows the energy manager distributing resources among divisions in the city, while simultaneously maximizing the global achievements of the urban energy system, the contribution of individual panels to global targets, and the share of each panel to the allocated resources. We remark that the final budget allocation between panels obtained in a distributed way by Algorithm 1 is identical to the minimum value that may be obtained solving the bilevel programming problems (24) and (32) in a centralized fashion, e.g., using

TABLE VI

ACTION COSTS IN THE PuBLDP

| | Buildings | | | | |
|---|---|---|---|---|---|
| | $B_1^{(1)}$ | $B_2^{(1)}$ | $B_3^{(1)}$ | $B_4^{(1)}$ | $B_5^{(1)}$ |
| $A_1$ | 165063.86 | 183599.20 | 164424.93 | 129561.72 | 88004.76 |
| $A_2$ | 79541.40 | 102111.24 | 51858.00 | 126579.96 | 86869.12 |
| $A_3$ | 176727.52 | 87366.68 | 137018.56 | 101974.28 | 37453.32 |
| $A_4$ | 244605.26 | 285710.44 | 216282.93 | 256141.68 | 174873.88 |
| $A_5$ | 341791.37 | 270965.88 | 301443.50 | 231536.00 | 125458.08 |
| $A_6$ | 256268.92 | 189477.92 | 188876.56 | 228554.24 | 124322.44 |
| $A_7$ | 421332.77 | 373077.12 | 353301.50 | 358115.96 | 212327.20 |
| $A_8$ | 19500.00 | 9750.00 | 9750.00 | 9750.00 | 39000.00 |
| $A_9$ | 5031.40 | 3201.80 | 3201.80 | 2744.40 | 2744.40 |
| $A_{10}$ | 24531.40 | 12951.80 | 12951.80 | 12494.40 | 41744.40 |
| $A_{11}$ | 1286.00 | 1286.00 | 1028.80 | 1028.80 | 771.60 |
| $A_{12}$ | 210.00 | 280.00 | 280.00 | 280.00 | 210.00 |
| $A_{13}$ | 1496.00 | 1566.00 | 1308.80 | 1308.80 | 981.60 |
| $A_{14}$ | 25435.80 | 25827.12 | 23479.20 | 23805.30 | 22761.78 |

TABLE VII

ACTION COSTS IN THE PrBLDP

| | Buildings | | | | |
|---|---|---|---|---|---|
| | $B_1^{(2)}$ | $B_2^{(2)}$ | $B_3^{(2)}$ | $B_4^{(2)}$ | $B_5^{(2)}$ |
| $A_1$ | 49519.16 | 45899.80 | 32884.99 | 38868.52 | 22001.19 |
| $A_2$ | 23862.42 | 25527.81 | 10371.60 | 37973.99 | 21717.28 |
| $A_3$ | 53018.26 | 21841.67 | 27403.71 | 30592.28 | 9363.33 |
| $A_4$ | 73381.58 | 71427.61 | 43256.59 | 76842.50 | 43718.47 |
| $A_5$ | 102537.41 | 67741.47 | 60288.70 | 69460.80 | 31364.52 |
| $A_6$ | 76880.68 | 47369.48 | 37775.31 | 68566.27 | 31080.61 |
| $A_7$ | 126399.83 | 93269.28 | 70660.30 | 107434.79 | 53081.80 |
| $A_8$ | 5850.00 | 2437.50 | 1950.00 | 2925.00 | 9750.00 |
| $A_9$ | 1509.42 | 800.45 | 640.36 | 823.32 | 686.10 |
| $A_{10}$ | 7359.42 | 3237.95 | 2590.36 | 3748.32 | 10436.10 |
| $A_{11}$ | 385.80 | 321.50 | 205.76 | 308.64 | 192.90 |
| $A_{12}$ | 63.00 | 70.00 | 56.00 | 84.00 | 52.50 |
| $A_{13}$ | 448.80 | 391.50 | 261.76 | 392.64 | 245.40 |
| $A_{14}$ | 7630.74 | 6456.78 | 4695.84 | 7141.59 | 5690.45 |
| | Buildings | | | | |
| | $B_6^{(2)}$ | $B_7^{(2)}$ | $B_8^{(2)}$ | $B_9^{(2)}$ | $B_{10}^{(2)}$ |
| $A_1$ | 33012.77 | 55079.76 | 41106.23 | 25912.34 | 26401.43 |
| $A_2$ | 15908.28 | 30633.37 | 12964.50 | 25315.99 | 26060.74 |
| $A_3$ | 35345.50 | 26210.00 | 34254.64 | 20394.86 | 11236.00 |
| $A_4$ | 48921.05 | 85713.13 | 54070.73 | 51228.34 | 52462.16 |
| $A_5$ | 68358.27 | 81289.76 | 75360.88 | 46307.20 | 37637.42 |
| $A_6$ | 51253.78 | 56843.38 | 47219.14 | 45710.85 | 37296.73 |
| $A_7$ | 84266.55 | 111923.14 | 88325.38 | 71623.19 | 63698.16 |
| $A_8$ | 3900.00 | 2925.00 | 2437.50 | 1950.00 | 11700.00 |
| $A_9$ | 1006.28 | 960.54 | 800.45 | 548.88 | 823.32 |
| $A_{10}$ | 4906.28 | 3885.54 | 3237.95 | 2498.88 | 12523.32 |
| $A_{11}$ | 257.20 | 385.80 | 257.20 | 205.76 | 231.48 |
| $A_{12}$ | 42.00 | 84.00 | 70.00 | 56.00 | 63.00 |
| $A_{13}$ | 299.20 | 469.80 | 327.20 | 261.76 | 294.48 |
| $A_{14}$ | 5087.16 | 7748.14 | 5869.80 | 4761.06 | 6828.53 |

TABLE VIII

ENUMERATION OF LIGHTING UNITS IN THE StLLDP

| Parameter | | $N_{st}$ | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| ***Subsystem*** | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| ***Type*** | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 5 | 52 | 5 | 27 |
| | 2 | 44 | 33 | 29 | 26 | 30 | 3 | 23 | 54 | 29 | 45 |

TABLE IX

COSTS AND PAYOFFS OF LUMINAIRE REPLACEMENT IN THE StLLDP

| Parameter | | $\gamma_t$ | $\varphi_t$ | $\rho_t$ | $c^{u,t}$ | $\gamma_t{}'$ | $\varphi_t{}'$ | $\rho_t{}'$ |
|---|---|---|---|---|---|---|---|---|
| Unit | | kWh/yr | lm | - | €/pc. | kWh/yr | lm | - |
| ***Type*** | 1 | 660 | 10 | 35 | 1300.00 | 400 | 5 | 60 |
| | 2 | 1100 | 10 | 40 | 1500.00 | 720 | 5 | 60 |

TABLE X

PAYOFF OF DIMMER INSTALLATION IN THE StLLDP

| Parameter | $\alpha_s$ | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| ***Subsystem*** | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 |

TABLE XI

OTHER COST AND PAYOFF PARAMETERS IN THE StLLDP

| Parameter | $c^v$ | $\Omega$ | $c^w$ |
|---|---|---|---|
| Unit | €/pc. | kWh/yr | €/pc. |
| | 500.00 | 240 | 800.00 |

TABLE XII

PARAMETERS OF ALGORITHM 1

| Parameter | Value | Unit |
|---|---|---|
| $[\pi_1^{(1)},\ \pi_2^{(1)},\ \pi_3^{(1)}]$ | [1/3 1/3 1/3] | - |
| $[\pi_1^{(2)},\ \pi_2^{(2)},\ \pi_3^{(2)}]$ | [1/3 1/3 1/3] | - |
| $[\pi_1^{(3)},\ \pi_2^{(3)},\ \pi_3^{(3)}]$ | [1/3 1/3 1/3] | - |
| $\varepsilon$ | $10^{-3}$ | € |
| $[Y_{(0)}^{(1)}, Y_{(0)}^{(2)}, Y_{(0)}^{(3)}]$ | $[0.40\ 0.30\ 0.30] \cdot E_T$ in case (a)<br>$[0.90\ 0.05\ 0.05] \cdot E_T$ in case (b) | € |

TABLE XIII

OPTIMAL ACTION PLAN IN THE PuBLDP

| $X_{\mathrm{jk}}^{(1)}$ | Buildings | | | | |
|---|---|---|---|---|---|
| | $B_1^{(1)}$ | $B_2^{(1)}$ | $B_3^{(1)}$ | $B_4^{(1)}$ | $B_5^{(1)}$ |
| $A_1$ | 0 | 0 | 0 | 0 | 0 |
| $A_2$ | 0 | 0 | 0 | 0 | 0 |
| $A_3$ | 0 | 0 | 0 | 0 | 0 |
| $A_4$ | 0 | 0 | 0 | 0 | 0 |
| $A_5$ | 0 | 0 | 0 | 0 | 0 |
| $A_6$ | 0 | 0 | 0 | 0 | 0 |
| $A_7$ | 0 | 0 | 0 | 0 | 0 |
| $A_8$ | 1 | 0 | 0 | 0 | 1 |
| $A_9$ | 0 | 0 | 0 | 0 | 0 |
| $A_{10}$ | 0 | 1 | 1 | 1 | 0 |
| $A_{11}$ | 0 | 0 | 0 | 0 | 0 |
| $A_{12}$ | 0 | 0 | 0 | 0 | 0 |
| $A_{13}$ | 1 | 1 | 1 | 1 | 1 |
| $A_{14}$ | 0 | 1 | 1 | 1 | 1 |

the global optimization method described in [55]. Conversely, the proposed multilevel computational technique solves an optimization problem of lower dimension than the original global problem. The approach deals with subproblems that can be solved in parallel speeding up the computational process. Furthermore, dealing with a lower order problem is advantageous for the overall optimization process and allows over-

TABLE XIV

OPTIMAL ACTION PLAN IN THE PrBLDP

| $X_{jk}^{(2)}$ | Buildings $B_1^{(2)}$ | $B_2^{(2)}$ | $B_3^{(2)}$ | $B_4^{(2)}$ | $B_5^{(2)}$ |
|---|---|---|---|---|---|
| $A_1$ | 0 | 0 | 0 | 0 | 0 |
| $A_2$ | 0 | 0 | 0 | 0 | 0 |
| $A_3$ | 0 | 0 | 0 | 0 | 0 |
| $A_4$ | 1 | 0 | 0 | 0 | 0 |
| $A_5$ | 0 | 0 | 0 | 0 | 0 |
| $A_6$ | 0 | 0 | 0 | 0 | 1 |
| $A_7$ | 0 | 1 | 1 | 1 | 0 |
| $A_8$ | 0 | 0 | 0 | 0 | 0 |
| $A_9$ | 0 | 0 | 0 | 0 | 0 |
| $A_{10}$ | 1 | 1 | 1 | 1 | 1 |
| $A_{11}$ | 0 | 0 | 0 | 0 | 0 |
| $A_{12}$ | 0 | 0 | 0 | 0 | 0 |
| $A_{13}$ | 1 | 1 | 1 | 1 | 1 |
| $A_{14}$ | 1 | 1 | 1 | 1 | 1 |
| $X_{jk}^{(2)}$ | Buildings $B_6^{(2)}$ | $B_7^{(2)}$ | $B_8^{(2)}$ | $B_9^{(2)}$ | $B_{10}^{(2)}$ |
| $A_1$ | 0 | 0 | 0 | 0 | 0 |
| $A_2$ | 1 | 0 | 1 | 0 | 0 |
| $A_3$ | 0 | 0 | 0 | 0 | 1 |
| $A_4$ | 0 | 0 | 0 | 1 | 0 |
| $A_5$ | 0 | 0 | 0 | 0 | 0 |
| $A_6$ | 0 | 0 | 0 | 0 | 0 |
| $A_7$ | 0 | 1 | 0 | 0 | 0 |
| $A_8$ | 0 | 0 | 0 | 0 | 0 |
| $A_9$ | 0 | 0 | 0 | 0 | 0 |
| $A_{10}$ | 1 | 1 | 1 | 1 | 1 |
| $A_{11}$ | 0 | 0 | 0 | 0 | 0 |
| $A_{12}$ | 0 | 0 | 0 | 0 | 0 |
| $A_{13}$ | 1 | 1 | 1 | 1 | 1 |
| $A_{14}$ | 1 | 1 | 1 | 1 | 1 |

TABLE XV

OPTIMAL ACTION PLAN IN THE StLLDP

| **Parameter** | | $u_{st}$ | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| ***Subsystem*** | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| ***Type*** | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 5 | 52 | 5 | 27 |
| | 2 | 27 | 0 | 0 | 0 | 0 | 2 | 18 | 2 | 24 | 18 |
| **Parameter** | | $v_s$ | | | | | | | | | |
| ***Subsystem*** | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| | | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **Parameter** | | $w_s$ | | | | | | | | | |
| ***Subsystem*** | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| | | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |

coming scalability issue in case the method is applied to the case of a larger number of decision panels.

Finally, Fig. 3 reports the budget allocation (as percentage of the total budget) between the three panels (i.e., $100\ Y^{(p)}/E_T, \forall p = 1, 2, 3$) over the algorithm iterations, for the two different initial budget allocations $[Y_{(0)}^{(1)}, Y_{(0)}^{(2)}, Y_{(0)}^{(3)}]$ detailed in Table XII (top and bottom plots refer to Cases a and b, respectively). In particular, the graphs show how, independently from the initial condition (in Case a, 40%, 30%, and 30% for each panel in their order, and in Case b, 90%, 5%, and 5%), the budget allocation converges to the final value: in both the cases, convergence is reached after a few iterations (iteration step $r = 5$ in Algorithm 1).

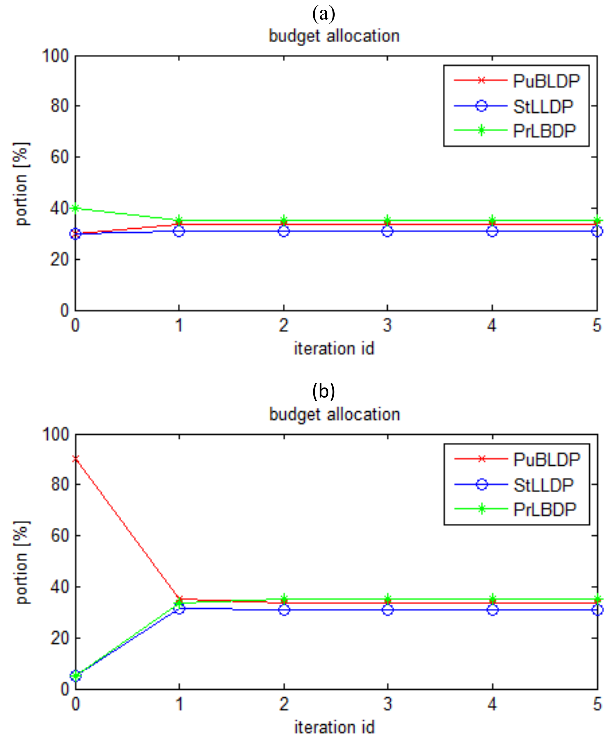


Fig. 3. Algorithm convergence for two different initial budget allocations (cases a and b).

## D. Usability of Results

In this section, we debate the model usability reporting the results of a discussion with the city energy manager, who is involved in the research project RES NOVAE in which this paper has been developed [8]. The achieved results are of practical relevance for the implementation of the energy efficiency initiatives that smart cities are worldwide putting in place. For instance, in Europe, the Covenant of Mayors for Climate and Energy has brought together thousands of municipal authorities voluntarily committed to implementing climate and energy objectives on their territory [69]. Through their participation to the Covenant, signatories profess their intention to meet and exceed the EU target of 20% reduction in $CO_2$ emissions by 2020 and commit to develop a sustainable energy action plan (SEAP). The SEAP is the main policy act that each municipality adopts to reach concerns action at local level within the competence of the local authority. As a consequence, an SEAP is the key document in which the Covenant signatory defines the concrete activities and measures setup to achieve the targets, together with time frames and assigned responsibilities [69]. In most cases, a large number of actions are proposed, ranging from renewable energy production to energy saving [16]. It, therefore, emerges the need of methodologies for guiding the administrators to the selection of the most effective actions for the achievement of the desired emission reduction, compatible with budget and resource availability. The approach usually used is an economic one that privileges actions that, given the same initial investment, generate the greatest energy savings. Alternatively, the local authority may rank the possible measures by importance. These approaches, however, are limited, since they do not consider many aspects, which are important in a complex and multisectorial system. In fact, as it has been widely recognized, in any form of governments, one of the most crucial decisions concerns the allocation of resources to different government sectors [70].

Coherently with the described SEAP policy, the objective of the methodology proposed in this paper and applied to the case study is exactly to serve as a reference method to support PA/local authorities in implementing SEAP in priority urban sectors. Indeed, the proposed decision-making strategy allows planning in detail tangible measures (i.e., the computed actions reported in Tables XIII–XV) and actual budgets (see allocated budgets $Y^{(1)}$, $Y^{(2)}$, $Y^{(3)}$) for the integrated energy management of different urban sectors.

We finally remark that, although the decision model is specifically presented in the domain of the energy efficiency initiatives, it may be straightforwardly extended for application to other urban domains, e.g., water. In fact, since water is becoming a scarce resource in a growing number of countries, several local initiatives are being promoted to improve currently used technologies and to integrate innovative tools for monitoring and managing citizens' water use, water networks, and wastewater treatment. In this framework, the proposed bilevel programming model may be used as a decision support tool to facilitate the selection of combinations of water saving and water efficiency strategies in all the involved urban sectors, such as the upstream distribution network, the public, private, and commercial facilities, and the collection network sewage system.

## VI. Conclusion

This paper describes a hierarchical decision-making strategy for smart city energy management. The proposed decision process enables the energy manager to govern the city energy system as a whole while addressing different urban sectors with an integrated, structured, and transparent planning.

This paper results are of interest to both researchers and practitioners. As a theoretical contribution, we fill the gap in the existing literature that lacks techniques dealing with energy retrofit of urban subsystems in an integrated way rather than on a subsystem by subsystem basis. The result obtained by this innovative holistic approach is an optimal set of action plans in an urban area, which: 1) improves globally the city energy performances, by the given budget constraint and 2) deals with conflicting objectives and requirements, fragmented decision making, and difficult subsystem cross optimization. On the one hand, it provides a set of sectorial decision support tools for specific retrofit interventions on an individual subsystem; on the other hand, it provides a mechanism to design and coordinate all the decisions distributed over multiple urban decision units participating in the energy management optimization. As for the contribution to managerial practice, we provide a tool that supports the energy manager of the PA in defining strategic and multisectorial action plans for the city energy management. It is able to optimize the energy performance of each specific urban subsystem, while considering the higher level CDU and constraints, in terms of performance and budget. This is particularly important in the current era where smart cities are called to develop plans for improving urban performance in terms of energy efficiency and environmental sustainability, as required by the recalled SEAPs committed by several European municipalities.

The main limitation of the presented approach is related to the assessment of model parameters (payoffs and costs of each action). This activity is nonnegligible as well as a source of uncertainty. Future research will, therefore, be devoted to modeling uncertainties that affect the estimation of optimization model parameters. Future research will also address the integration of the decision-making model of other urban energy subsystems (e.g., the urban mobility panel) and the investigation of other models of the CDU, both in terms of objective function and constraints. Other possible improvements are including the definition of the goal programming problem in the decision-making process, i.e., determining the optimal partition of the overall goal among the LDPs; considering benchmarking strategies to identify underperforming subsystems, which may be candidates for major energy efficiency improvements; and integrating simulation in the decision process to perform what-if analyses of the action plans.

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