An Optimization Framework for Energy Topologies in Smart Cities

Elvina Gindullina and Leonardo Badia
University of Padova, Dept. of Information Engineering, via Gradenigo 6B, 35131 Padova, Italy
email: {elvina.gindullina, badia}@dei.unipd.it

***Abstract*—The definition of "energy topologies" based on energetic cooperation (exploitation and exchange) between interconnected objects is an important feature that can be implemented in Smart Cities. Based on the presence of energy harvesting devices, it is aimed at providing system-wide sustainability by allowing exchange of stored and supplied energy in a similar fashion to communication of data. In this paper, we investigate the possibility of integrating energy cooperation within the design of the energy topology, or, in other words, by establishing energy links between objects, in particular wireless smart nodes powered by harvesting renewable energy sources. To do so, we construct an optimization model, where it is guaranteed that wireless nodes during operation will not be depleted and the optimal energy transfer does not exceed the energy demands of other communication nodes. We analyze how the system conditions can affect the energy topology, in particular, energy harvesting capabilities, energy levels, and energy thresholds. We also identify some theoretical limits for the system to guarantee complete sustainability, that is, nodes do not go out of charge. Also we demonstrated the effectiveness of the model comparing it with the system operation without applied optimization.**

***Index Terms*—Wireless networks; energy harvesting; energy cooperation; energy consumption; Smart Cities.**

I. INTRODUCTION

INTERCONNECTED objects such household or office equipments [1], vehicles [2], human wearable sensors [3], and any other devices belonging to the Internet of things (IoT), in a Smart City can be powered by external energy sources, i.e., either the power grid or renewable sources; energy consumption represents a dynamic process that requires real-time energy management. At the same time, paradigm for network intelligence dictates that smart management also involves optimal cooperation schemes among nodes [4], [5]. While this has been mostly applied to data communications, the emergence of converging network schemes likely suggest that information and communication technologies (iCTs) will interlink independent systems at many levels. As a result, "system-to-system" topology creates the possibilities for new Smart Cities' scenarios. Cooperation capabilities in these contexts will help building new business models, as linking smart cities objects in an optimal way will result in the increase of individual and collective profit as well as sustainability.

IoT technologies enable network optimization by introducing a holistic perspective where the network is considered as a multi-agent cooperative system. As a consequence, we can seek to optimize the energy flows between smart city objects or, generally speaking, energy management in a smart city, which can be considered as including both wireless connected nodes and the power grid as an integral part of it, all included in a common distribution space of information and energy. The outlined distributed system can be considered as a system-of-system topology in which both information and energy flows exist, and they mutually aid each other, so that the power connections supports data communication links, and conversely data communication also carries out the task of optimizing the energy topology.

However, energy management in large complex networks such as a smart city requires high computational capabilities for real-time optimization of energy flows, storage, distribution, and consumption [6]. To manage energy flows and cooperation between IoT nodes, an algorithm defining the optimal nodes to cooperate is needed. Usually, this is handled by considering energy-aware clustering algorithms that try optimizing the energy topology or decrease the number of links in the network [7]. This is because one of the issues limiting the overall network performance is the power limitation of a communication node. To avoid a node failure, energy efficient clustering algorithms were expansively studied in the literature, mainly focusing on the energy awareness rather than energy cooperation. As an initial step for designing a clustering algorithm with energy cooperation capabilities or with embedded energy topology, the study of a scenario with a single cluster (one sink node) is needed.

In this paper, we adopt a global optimization perspective. More specifically, we consider a smart city scenario where the IoT network is represented by a set of wireless nodes, with some information sinks collecting data from the other nodes. These sink nodes are supposed to handle all incoming information [8]. We do not only aim at balancing the energy consumption of different nodes, but rather we try performing a global joint optimization of communication and energy management. Another key factor which is exploited in this sense, aimed to provide the overall sustainability of the system, is energy harvesting capabilities of smart city objects. Renewable sources are too fickle to guarantee reliable functioning. For example, objects powered by solar energy are dependent from daytime and the position of the solar panel. Therefore, it is important to take into account the differences in energy arrivals of the nodes. Energy cooperation is one of the techniques that will help to handle the differences in energy

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This work has received funding from the European Union – Horizon 2020 research and innovation program under the Marie Skłodowska-Curie grant agreement No. 675891 (SCAVENGE).

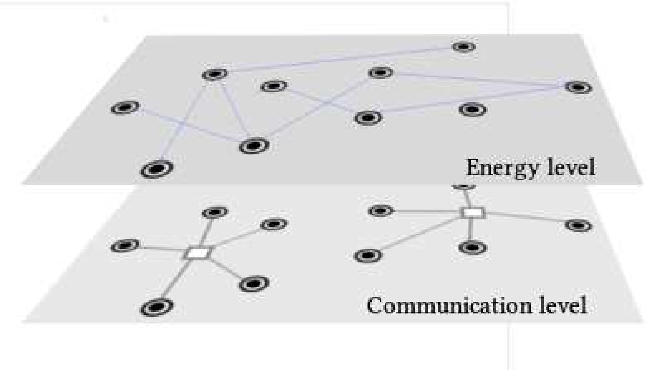

Fig. 1 – Topology scheme

arrivals of different nodes. In this case, objects that are not advantageously located will have possibility to be powered by a node with higher energy arrival capabilities.

The rest of this paper is organized as follows. In Section II we discuss models proposed in the literature for energy cooperation features among communication nodes. In Section III we outline our proposed optimization model for a WSN scenario with a single sink node. The numerical results are discussed in Section IV that shows the effectiveness of the proposed model and the behavior dependency from different parameters . Finally, we draw the conclusions in Section V.

II. BACKGROUND

Our representation of a smart city involves a network of nodes in which each element is capable of energy transmission to another node in need, meaning that each node has a possibility to manage the energy flows.

Designing the energy topology of connected IoT devices means establishment of energy links (edges) in an optimal way on top of the communication topology (Figure 1). The system represents a biplex network, in which the two layer are the communication and energy networks. The number of optimal connected neighboring nodes defines the energy topology of the system. The advantages of multiplex systems in Smart City, that includes the energy cooperation between objects was shown in [9]. Authors claim that considering a single type of static links is an oversimplification which can lead to inability to solve certain problems.

The power imbalance could be reduced when the effective interaction between the power supply and the demand is established. This was argued, for example, in [10], where an energy demand management solution was proposed to mitigate the imbalances between buildings. Authors proposed a scheme to analyze the energy potential of buildings and possibilities for cooperation, taking into account charging/discharging rate of buildings.

Lots of researches have been performed in investigating the energy cooperation capabilities in Smart Grids, in particular including: optimal scheduling among smart objects, optimizing both power expenditure and operation time [11]; optimal selection and sizing of a smart building system [12]; scheduling for optimal energy consumption to balance the load among residential subscribers [13]; analysis of the optimal power flow for distributed systems, in particular for the electrical network [14]; cooperative architecture for optimal voltage regulation [15]; optimal control of power exchange in a network of microgrid based on the energy consumption information [16].

These papers are aimed to study the Smart Grid without considering the communication topology and energy consumption of a system. Conversely, we consider the power consumption of a communication node to be also dependent on communication parameters, such as the distance from a sink node and the size of the transmitted data packets.

The efficient energy cooperation schemes that include both communication and energy cooperation usually are considered in wireless power transfer scenarios. In particular, in [17] authors introduced three techniques for multi-hop wireless energy transfer: store and forward, direct flow and hybrid technique. In [18], the authors consider a non-cooperative scheme, where information/energy are transported via direct links, then an optimization problem is formulated to minimize the transmitted power under outage probability and harvesting constraints.

In contrast with these outlined techniques, we focus on the energy links designing, which can be established not only with the near located nodes, but with any node of a network. It caused by possibilities to have cooperation between any IoT device that can belongs to different smart city objects. Moreover, while in wireless power transfer scenarios the communication links and energy links are simultaneous, in our analysis, the energy and communication links are separated and not simultaneous.

III. MODEL

We consider a system consisting of N communication nodes and a sink node, whose energy levels are denoted as $e_i, \quad i \in \{1...N\}$. V:=1,..,N is a vertex set of a complete graph $G = (V, A)$, where A is a set of edges (i, j) that represent the bidirectional energy link between communication nodes i and j. Node i can receive energy from other nodes as well as forward energy.

To provide a mathematical model to the problem, for each arc $a \in A$ we introduce a boolean variable:

$$l_a := \begin{cases} 1 & \text{if and only if the energy link between nodes} \\ & i \text{ and } j \text{ is established,} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

The total number of possible bidirectional energy links varies in the following limits:

$$0 \leqslant L \leqslant \frac{(N-1)N}{2} \tag{2}$$

where $L = \sum_{i,j=1}^{N} l_{ij}$ is total number of links, $l_{ij} = \{0, 1\}$ is a link between nodes i and j, equals to 1 if the link is set.

Here is considered and applied the energy consumption of a communication node caused by communication exchanges between nodes. As done by [19], [20], we take into account that energy consumption of a connection between a transmitter and receiver depends on the distance between them. Increasing the distance from a sink node will cause a higher energy consumption E for communication, according to the following relationship:

$$E = a \cdot k + b \cdot k \cdot d^n \tag{3}$$

where k is the information unit size (packet) expressed in bits, and d is the distance between sink node and communication node. Parameters a and b are energy consumption parameters of the transmitter electronics and transmitter amplifier, respectively. In [21], the following parameters are suggested: $a = 50$, $b = 0.1$ and $n = 2$. We do not consider the energy consumption of a sink node, as the aim of this work to investigate the energy cooperation between communication nodes only.

The aim is to calculate the amount of energy links needed to provide sustainability taking into account the energy consumption, energy arrival profile and a current energy level of each object. In relevance with it, the optimization problem can be formulated as follows:

$$\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij} l_{ij} \rightarrow min \tag{4}$$

such that

$$l_{ii} = 0 \quad \text{for} \quad i = 1, .., N \tag{5}$$

$$l_{ij} = l_{ij} \quad \text{for} \quad i, j = 1, .., N \tag{6}$$

$$\begin{gathered} e_i - (a \cdot k + b \cdot k \cdot d_i^n) + f_i + \sum_{j=1}^{N} l_{ij} \cdot e_{tr}^{ij} > 0 \\ \text{for} \quad i, j = 1, .., N \end{gathered} \tag{7}$$

$$\begin{gathered} e_i - (a \cdot k + b \cdot k \cdot d_i^) + f_i + \sum_{j=1}^{N} l_{ij} \cdot e_{tr}^{ij} \leqslant c \\ \text{for} \quad i, j = 1, .., N \end{gathered} \tag{8}$$

$$\sum_{i=1}^{N} l_{i,j} \leqslant \alpha \leqslant N - 1 \quad \text{for} \quad j = 1, .., N \tag{9}$$

$$\sum_{j=1}^{N} l_{i,j} \leqslant \alpha \leqslant N - 1 \quad \text{for} \quad i = 1, .., N \tag{10}$$

where $w_i j$ is a weight of an energy link. A larger distance between energy arrival profiles and the communication consumptions results in a larger value w_{ij}. Value of w_{ij} is normalized:

$$w_{ij} = \left| \frac{e_n^{ij} + f_n^{ij} - (a \cdot k + b \cdot k \cdot d_{ij}^n)}{(e_n^{ij} + f_n^{ij} - (a \cdot k + b \cdot k \cdot d_{ij}^n))_{\max}} \right| \tag{11}$$

where f_n^{ij} and d_n^{ij} are differences in energy arrival profiles and distances to the sink node between communication nodes i and j:

$$e_n^{ij} = e_i - e_j \tag{12}$$

$$f_n^{ij} = f_i - f_j \tag{13}$$

$$d_n^{ij} = d_i - d_j \tag{14}$$

Constraints (5) and (6) are imposed to respect the requirements of the absence of energy links of a node with itself and symmetry of energy links: if energy can flow from object i to j, then automatically the energy can flow in opposite direction from j to i and the bidirectional link is established.

Constraints (7) and (8) provide the sustainability of a system after optimization, in particular, desirable energy levels range for each node. The first three terms represent the initial energy level of a node corrected by transmitting energy consumption and energy arrived to a node (f_i - energy arrival profile). The last term represents the energy transferred to the node i from all nodes j. The energy level has to be larger than 0 and do not exceed the battery capacity c, by this we guarantee that battery will not be out of charge and the transferring energy will not exceed demand of the node.

The transferred energy from node j to node i depend to conditions:

- the node j has enough energy to transmit;
- the node j has to have more energy than node i:
- the energy level of node j has to be higher than a threshold.

$$\begin{cases} e_{tr} = e_{th} - e_i \quad \text{if} \quad e_j > e_i \quad \text{and} \quad e_{th} < e_j \\ e_{tr} = 0 \quad \text{otherwise} \end{cases} \tag{15}$$

Objective function enforces to create energy links between nodes that have bigger energy potential differences. If nodes have similar energy arrival profile and consumption, then the cost of established energy link will not be justified as not much energy cooperation will be performed.

Another possible constraint arise if a node has to have a limited amount of energy links. In this case, the number of links are limited by constraints (9) and (10), where α is a maximum amount of allowed links, should not exceed $N - 1$. Nevertheless, in this paper we do not investigate the situation in which a communication object has such a limitation.

IV. NUMERICAL RESULTS

Numerical results were conducted with the aim to investigate the behavior of an optimization model solution for different types of systems: different distance distribution, non-homogeneity in energy arrivals and in energy levels. As the second part of results we show the effectiveness of the optimization in comparison if no optimization is applied to the system.

Optimization is performed using the CPLEX solver ver. 12.6.1. We assume that all communication nodes have similar battery capacities.

As the first step, the matrices are defined: $(d_i) \in \mathbb{R}^{1xn}$, $(f_i) \in \mathbb{R}^{1xn}$, $(d_n^{ij}) \in \mathbb{R}^{nxn}$, $(f_n^{ij}) \in \mathbb{R}^{1xn}$, $(w_{ij}) \in \mathbb{R}^{nxn}$, $(e_{tr}^{ij}) \in \mathbb{R}^{nxn}$, $(e_i) \in \mathbb{R}^{1xn}$, $e_{th} = conts$, $c = conts$ and $k = conts$.

TABLE I – Parameters

Parameters	**Values**
Number of communication nodes (N)	50
Number of transmitted bits (k)	1
Communication parameter a	50
Communication parameter b	0.1
Communication parameter n	2
Battery capacity (c)	200

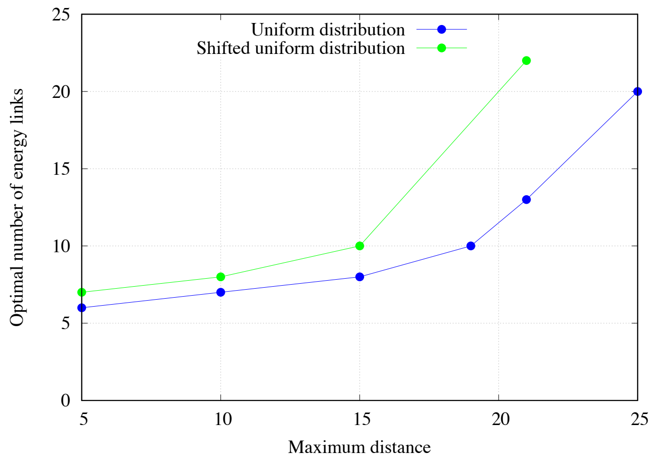

Fig. 2 – Distance distribution vs. optimal amount energy links

Matrices (d_i), (f_i) and (e_i) are random in ranges $(0, 15)$, $(0, 20)$ and $(0, 200)$ respectively, unless we vary their meanings in order to investigate these properties.

Optimization parameters are presented in Table I. Parameters a, b and n are chosen similarly with [21]. We consider the simple case transmission of 1 bit ($k = 1$).

In the first optimization setup, we check the dependence of optimal amount energy links and distance distribution (Figure 2). First, we set up an uniform distribution in the range from $(0, 5)$ till $(0, 20)$. In this case, the distance range increasing leads to increase of the energy consumption, therefore, a larger number of energy links is needed to provide sustainability of the system.

In the second experiment, we shifted the distance distribution from $(2, 5)$ to $(10, 20)$. By this, we guarantee that all communication nodes have a higher energy consumption, therefore the optimal amount of energy links is higher than in the first case. The optimal solution will not be obtained in case of distance increasing to $d_{ij} > 20$. Even with strengthen of the energy topology some communication nodes will be depleted. In particular, for range $[0, 21]$ the solution is $13 \quad links$ obtained by feasible relaxed sum of infeasibilities.

Furthermore, we examined the dependency of the energy levels of the communication nodes and the optimal energy topology design (Figure 3). The energy level is varied in range from $(0, 70)$ till $(0, 200)$, where the highest value is the maximum capacity of the battery. The increase in the energy levels of the communication nodes tends to decrease the demand of energy links. If the energy level range is less than an energy threshold, then no optimization is performed as no energy transmission is done, according to (15).

Then the energy distribution was shifted from $(35, 70)$ to $(100, 200)$. This provides on average a higher initial charge of the system and higher energy independence of communication nodes. Due to it, in comparison with the first case, the optimal amount of required energy links is halved; for $e_i > 120$ no energy topology is required.

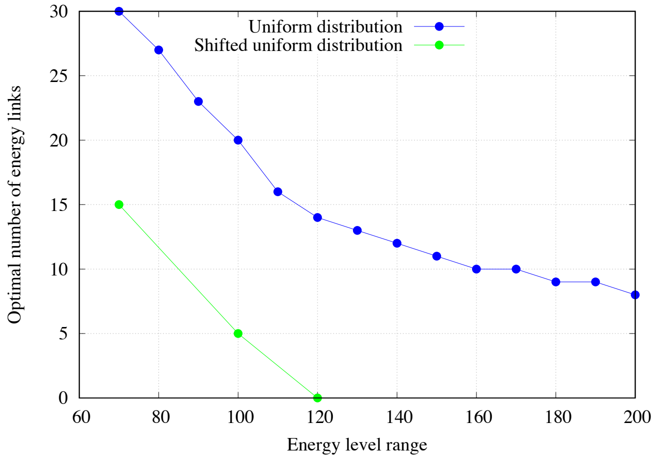

Fig. 3 – Optimal amount energy links vs. energy level distribution

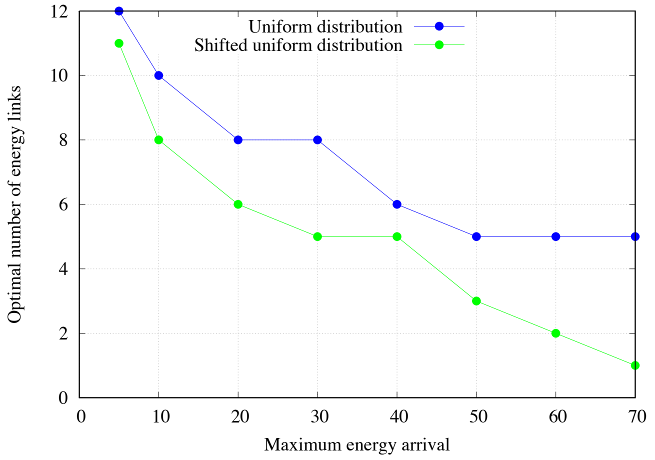

Fig. 4 – Optimal amount energy links vs. energy arrival profile

Energy harvesting capabilities of communication nodes in the model are defined by an energy arrival profile. It is an important feature of a communication node that defines the sustainability of a node. To examine this feature, we varied the energy profile of each node in range from $(0, 5)$ till $(0, 70)$, as is shown in Figure 4. Notably, increasing the average energy harvesting capability of a system will decrease the need for providing additional energy topology links. In case $f_i \geqslant 70$, a near-optimal solution is obtained, in which the transmitted energy from one communication node to another is higher than a real demand of a node, i.e., the capacity constraints (8) are violated.

Shifted distribution from $(2, 5)$ till $(35, 70)$ provides a higher energy capabilities of a system in general and lower optimal amount of energy links. In both cases, for $f_i = 70$ the solution is near-optimal in the plot.

Finally, the dependency of optimal energy topology and energy threshold was studied. Here, a simple case is con-

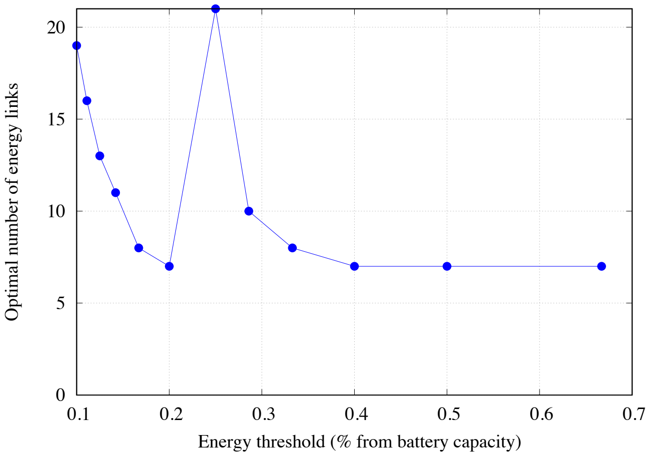

Fig. 5 – Optimal amount energy links vs. energy threshold

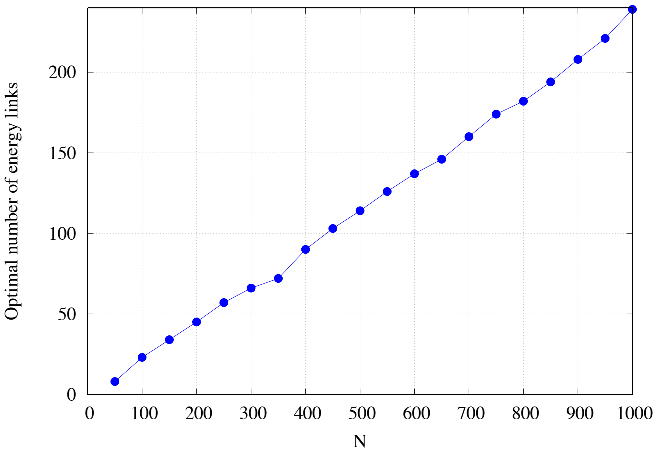

Fig. 6 – Optimal amount energy links vs. amount of communication nodes in WSN

sidered in which all batteries have similar capacity and, therefore, similar energy threshold, defined as a ratio from the battery capacity. For threshold in range from $e_{th} = c/10$ till $e_{th} = c/5$, the increase of ratio leads in decreasing the optimal amount of energy links. However, the solution is always near optimal, low values of energy threshold are accompanied by violation of outage constraints (7).

The same tendency is observed for $e_th > c/10$, but in this case the optimal solution is obtained and after optimization no communication nodes is completely depleted.

The optimization model was tested on systems of different size, i.e., the number of communication nodes was changed ($N \leqslant 1000$). From Figure 6 we can see that the optimal amount of energy links and the system size has a linear behavior. In case of big size systems with high value of N, a clustering algorithm would need to be applied, to obtain a nearly-optimizal solution restricted to a cluster with tractable size.

Simulations were conducted without any optimization on top as comparison terms, in order to analyze the effectiveness of proposed model. For each amount of communication nodes we simulated 100 instances, in which distances are in range $(0, 15)$, initial energy level is in range $(0, 200)$ and energy arrival profile is in range $(0, 20)$. The distribution of depleted communication nodes are shown in Fig. 7. With increase of system size the amount of depleted objects and variance is increasing. For $N = 100$ the amount of depleted nodes is around $10 - 30\%$ of total object's amount.

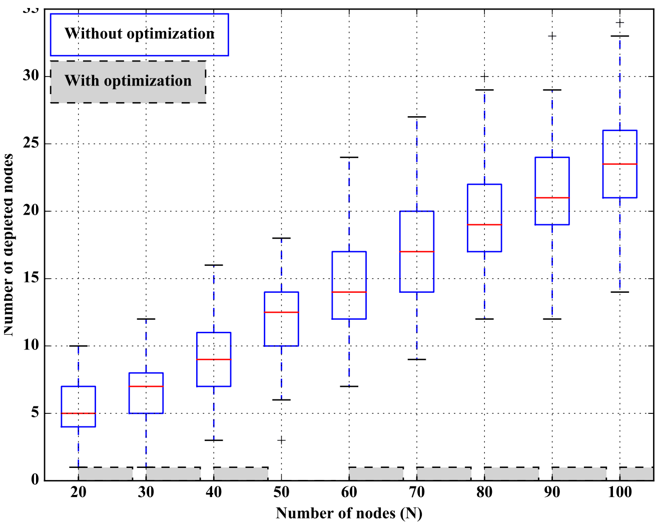

Fig. 7 – Amount of depleted communication nodes with/without optimization

The optimization model was applied to the same simulated instances. In this case, the number of depleted nodes did not increase of more than 1 node per instance. In particular, for $N = 20, 30, 40, 100$ only in one instance out of 100 one node was depleted. For $N = 60, 70, 90$ in two instances one communication node was depleted. For $N = 80$ in three instances one communication node was out of charge; here, due to the absence of an optimal solution, the near-optimal one was proposed. Applying optimization framework to the system significantly increase the sustainability of the system.

V. CONCLUSIONS AND FUTURE WORK

We proposed the energy cooperation scheme in a smart cities, in which the energy flows from nodes with higher energy level, less energy consumption and with more energy harvesting capabilities to the nodes that have lower energy arrival profile, more distant from a sink node and more exploited. For this purpose, an energy topology is designed, in which energy links are established among communication nodes. The priority is given to nodes with higher energy potential differences. As every link establishment is associated with costs, the energy topology has to be optimized such that no communication node is depleted, and energy transmission does not exceed the demand of the interacting node.

Based on the proposed optimization model, we analyzed the dependency of optimal energy topology of a system from such factors as distance distribution of communication nodes, energy harvesting capabilities of the nodes, and distribution of energy arrival profiles of each node, selected energy threshold and energy level distributions. All these factors define the optimal amount of energy links. We demonstrated that in the generated scenarios, the system will have up to 30% of depleted nodes and embedded optimization scenario helps to decrease the amount to almost 0.

To extend the present results to more general cases, we remark that we focused on a single cluster case, with just one cluster head/sink. As future work, clustering schemes could be considered with embedded energy cooperation capabilities of energy harvesting multi-hop wireless networks. The assumption about homogeneity of a system has to be relaxed, therefore in the clustering scheme batteries capacities and energy thresholds have to be individual for each node.

Also, the energy arrival profile was formed for each communication node randomly, with independent and identical distribution for all the nodes. The realistic energy arrival profiles have to be integrated based on the chosen source of renewable energy, possibly including some correlation. Another possibility is to consider alternative energy exchange models, based not only on the energy thresholds but on more diverse parameters of each communication nodes. In relevance with energy consumption model, more diverse data size has to be considered and other energy consumption models should be applied and compared.

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