A Bayesian Game of Multisource Energy Harvesting for Batteryless IoT Devices

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***Abstract*—In this paper, we use game theory to analyze the operations of energy harvesting in the context of multiple sources powering an IoT device. Such terminals are often heavily constrained in terms of energy provision, and they solely rely on harvesting procedures, which do not guarantee reliability at all times. We specifically consider a batteryless device that is requested to send periodic updates and, for increased dependability, exploits two different energy sources. The controllers of these sources employ a game theoretic distributed management that is simpler, and also more energy efficient, since no energy is wasted for coordination. To evaluate the performance, we frame the resulting interaction as a Bayesian game, for which we derive the Nash equilibria and the Price of Anarchy. These insights are discussed from a quantitative standpoint, giving numerical assessments of the resulting system efficiency.**

***Keywords*—IoT, energy harvesting, batteryless devices, game theory, Bayesian game, Price of Anarchy**

I. Introduction

In the Internet of things (IoT), thousands of devices are expected to sense the environment and provide services, in the contexts of smart home and factory automation, health-care, cities, and agriculture networks [1], [2].

IoT devices are constrained in terms of performance (memory, computational resources, and so on) but also available energy, since they are often deployed in remote/rural areas or with just wireless connectivity, and it is not feasible or simply inconvenient to provide them with wireline power supply. Thus, it is sought to limit the power consumption to what locally available at the IoT device, and to make it self-sustainable in terms of energy [3], [4].

There are two general trends in research about energetic management of IoT devices. The former is related to the use of low-power consumption protocols, which is beneficial to reduce the overall network consumptions from a general standpoint [5]. For what concerns the energy generation instead, the most adopted proposition is to take advantage of harvesting renewable energy sources from the environment [6]. Both points go in the direction of reducing the direct operational costs of an IoT networks and improve the environmental sustainability [7], i.e., they ultimately decrease the electrical bills as well as the carbon footprint.

Unfortunately, when harvesting techniques are employed, the availability of the device cannot be guaranteed due to irregular and bursty energy arrivals [8], [9]. Some forms of intelligent control becomes required to make the IoT device to operate seamlessly as much as possible. One practical solution would be to provide a rechargeable battery to the IoT devices, so as to implement a *Harvest-Store-Use* architecture [10]. We argue that this just mitigates the issue of dependability of IoT devices without really addressing the main problem that the energy arrivals are erratic. Adding a battery can indeed provide an increased margin against outages but not avoiding them entirely. Also, when introducing these architectures, batteries are always thought of as ideal buffers, while in reality they have several imperfections in their operation [11].

For this reason, we concentrate our analysis on *batteryless* IoT devices, i.e., following a simpler *Harvest-Use* architecture, where the harvested energy cannot be stored and it is therefore either immediately used or wasted [12]. We do not advocate that such operation framework is necessarily better than using some form of energetic buffering, even though it is certainly less expensive for widespread IoT deployments. Still, every analytical insight that we gain in the context of batteryless IoT devices through our analysis can in principle be extended, with proper modifications, to a Harvest-Store-Use setup as well.

Beyond energy buffering, also multiple energy sources to increase reliability of the end device. In particular, we consider an IoT device that can be powered by two different energy harvesting technologies [13], and evaluate whether this increases its reliability. The two sources harvest energy from different ambient effects (e.g., solar and wind). While the maximum benefit would be theoretically achieved whenever the associated natural phenomena are complementary to each other (i.e., one produces energy whenever the other does not), this does not sound very realistic, and therefore we focus on two phenomena that are independent of each other.

We assume that both energy sources are managed by a smart controller. Also, the energy harvesting operation has a cost, although lower than the benefit of having operation from the IoT device. Thus, on the one hand, the controllers of each source would like to limit their activations if they can estimate the other source is already powering the IoT device. On the other hand, there is a risk that one source, despite being able to provide energy, is kept inactive, just to avoid the activation cost, but ultimately resulting in the IoT device being in outage, which is generally to be avoided [14], [15].

Even though some signaling exchanges among the controllers would avoid inefficiency, we argue that this would also consume energy and therefore is not generally convenient [16]. Thus, we would like to see if it is possible to design the interaction of multiple sources in a completely distributed way, so as to reduce overall complexity in terms of management. In particular, we make use of an approach rooted in game theory; specifically, we frame the interaction between the source controllers as a Bayesian game [17].

As such, we discuss the resulting Bayesian Nash equilibrium (NE) and the Price of anarchy (PoA), arguing whether the introduction of multiple sources can be beneficial to avoid outages, and a distributed management is really efficient. The results imply that, whenever one of the multiple sources is clearly better, e.g., in terms of suitability (lower cost, higher availability), a rational decision making process would lead to always use that source, and smart controllers can consider any less efficient source to be strictly dominated. This result is in line with the finding of [14], showing that multiple sources of different effectiveness have little use as the best one will be used for most of the operation, if not always.

Conversely, multiple source diversity might be useful when the sources have similar characteristics. However, also in this case, inefficiencies may arise from a distributed management, especially since the lack of coordination may lead to unnecessary activations. In short, multisource energy diversity may not be beneficial if not properly controlled.

In the following, after introducing some game theory principles in Section II, we develop in Section III a mathematical model of the interaction between two sources of energy that attempt providing energy to an IoT node. Section IV computes the NEs. We provide quantitative results in V and finally we conclude the paper in Section VI.

II. Game Theory Fundamentals

Making predictions about the conduct of multiple concurring agents is the main application of Game Theory which is, in recent times, increasingly being used for information and communication technology (ICT) [18], [19], as well as energy management [6], [20], [21].

Agents interacting within a game are called *players*. Each of them aims to achieve an individual objective, described as the maximization of the *utility* of that player. In particular, we consider a game involving a set of players $\mathcal{N}$, choosing their pure strategies (in our case, to be active or not) in a set $\mathcal{S}$, and $\mathcal{U}$ is the set of utilities that result from the joint selection by all the players.

An important concept is the Nash equilibrium, defined as a joint strategy profile that leads to locally maximize the individual utilities of all the players. In other words, at an NE each agent is playing a *best response* to what are the predicted strategies of all the others [22], i.e., the so called *beliefs*. Thus, a NE is a strategy profile for which no player has an incentive to unilaterally deviate. Also, we remark that we can consider *pure strategies* (i.e., elements of sets $\mathcal{S}$) or extend the discussion to *mixed strategies*, i.e., probability distributions over the set of pure strategies. This latter extension is relevant because a game with finite strategy set is guaranteed to have a NE only in the sense of mixed strategies, in general.

For the present case, we consider a *Bayesian game*, i.e., a scenario of *incomplete information* in which beliefs over the characteristics and behaviors of other players are also captured by *types* [17]. In essence, depending on the type, a player can have a different utility function. Each player has only knowledge about its own type, while it is unaware of the types of the opponents and only knows the probability distribution over them. More precisely, the probability distribution over the types of the players is common knowledge among the players.

III. System model

We focus on a system consisting of two energy harvesting sources `S1` and `S2` and an IoT device that is the only user of the produced energy. We suppose that the IoT device has some data to send, but it can do that only if at least one of the sources is providing energy. A source can provide energy if it is able to harvest it from the environment in that specific slot, and this happens with a certain probability. If this condition does not hold (i.e., no energy is received by the device) the sender is not able to complete its job, failing its task [12]. To be more precise, if a source collect energy but it does not send it until the end of the same slot, the energy will be lost, so it cannot be stored to be sent in subsequent slots. In our specific model, the end device is treated as a completely passive object since its only role is to send data whenever it has available energy; for this reason, it is not a player of the game.

A. Players characterization

Sources `S1` and `S2` are not always able to power the device with sufficient energy for its operation. We assume that this relates to some random ambient condition, on which the energy harvest is based, so that each source has a different probability of being able to produce electrical energy in a given slot [8]. The harvesting conditions are i.i.d for each slot and also the two sources are mutually independent. This is the proper description, for example, if the two sources generate energy from different natural phenomena (e.g., solar or wind energy); and, of course, having the energy arrivals to each source being independent from one another appears justified as it increases the diversity.

So, denote with λ_1 and λ_2, the probability that sources `S1` and `S2`, respectively, have available energy on that time slot. Each source is characterized by an action set that provides two different options:

idle (I): if a source decided to stay *idle* it means that independently from the fact that there is or not energy availability, it will not provide any energy to the target device;

send energy (E): if a source decided to be active it means that it will try anyway to provide power to the target device anyways, and therefore, possibly failing if the energy is not available in actuality. To send energy, it must activate paying an activation cost in term of used power.

B. Payoffs description

We consider that the only goal of the two sources is to guarantee that the IoT device has the necessary energy to transmit data. For this reason, it is not important whence the required power comes from; consequently, if in a given time instant the transmission succeeded, both the players will receive an identical reward, set to an arbitrary value of 1. Given that the utilities only have ordinal meaning, these values can be rescaled if needed [23]. Following the same reasoning, if neither `S1` nor `S2` provide energy to the target device in a given time slot, both of them will get utility 0.

Each source has to pay a cost to *send* energy to the IoT device. Independently from the fact that a given player has available energy or not in the considered time slot, if it decides to *send* power, it will pay the corresponding cost. Since we are considering two different types of sources, each one of them has a different cost value $k_i \in (0,\ 1)\ \forall i = 1, 2$.

The overall expected payoff obtained by each player depends on the action chosen by the other one, but also its own cost of sending power, and the probabilities that `S1` and `S2` are able to collect energy, i.e., λ_1 and λ_2, respectively. Consequently, as described above, we assume that if the IoT device will be able to transmit its packet, both sources get a profit equal to 1. The utility is equal to the profit minus the player's own cost of sending power to the user. Furthermore, if both players decide to send energy simultaneously, there is no added benefit, since they will both pay the sending cost and the profit will still be 1, without any advantage from the extra energy sent, which is wasted.

C. Game model

This problem can be modeled as a Bayesian static game with two players [17], `S1` and `S2`. Each of them can be of two types according to $\lambda_i,\ \forall i = 1, 2$. The set of actions that players can take is {E, I}, independent of their type.

In more detail, the two sources (or better, their controllers) are rational selfish players that can decide whether to be active or not. In the former case, the IoT device is powered: it is enough that just one source is active, but of course both sources being active is also a valid option to power the device. On the other hand, the controllers incur a cost in being active, which implies that both of them choosing the same course of action is inefficient: if they are both active, some unnecessary cost is incurred, while if they are both inactive, the IoT device is in outage. Finally, we consider the option of the environmental sources to be harvested by each of the controllers to be available with given independent probabilities, which are common priors for the players. In game theoretic jargon, this corresponds to introducing a *Bayesian type* of the players, describing their actual ability of choosing to be active.

According to the choices of the players, we have 16 possible outcomes, as we can see in the *Normal form* representation of Fig. 2, derived from the *Extensive form* of Fig. 1.

IV. Nash Equilibria computation

Starting from the game representation, we compute all the payoffs as functions of parameters k_i and λ_i. It can be shown that four situations occur, depending on the numerical values of the parameters. According to the region where their values fall, the set of NEs changes, and consequently the preferred strategies of each player. Actually, this count can be increased by considering threshold cases where border values are taken. We can write strategies as pairs XY of actions, meaning that a player plays X or Y depending on whether it has energy available or not, respectively.

We can distinguish the following cases:

(A) $\lambda_1 < 1 - k_2$, $\lambda_2 < 1 - k_1$: the only NE is (EI, EI)

(B) $\lambda_1 < 1 - k_2$, $\lambda_2 > 1 - k_1$: the only NE is (II, EI)

(C) $\lambda_1 > 1 - k_2$, $\lambda_2 < 1 - k_1$: the only NE is (EI, II)

(D) $\lambda_1 > 1 - k_2$, $\lambda_2 > 1 - k_1$: there are three NEs, that is, both (II, EI), (EI, II) and one in mixed strategies: (αEI + $(1-\alpha)$II, $(1-\beta)$EI + βII), with parameters $\alpha, \beta \in [0, 1]$.

These situations also become blended along the borders, i.e., whenever one of the conditions holds with equality. In the followings we will discuss each region of interest separately.

A. Analysis of region A

In this case, the two λ_is are similarly valued and on the lower side of their range, and this is known to both controllers. Hence, from a game theoretic perspective, the two sources decide to play conservatively. In other words, they always send energy if they have some, in order to ensure the maximal power availability to the target node. In this way, the drawback of those strategies is that there is a real chance that both sources decide to transmit together, which leads to a waste of energy. Anyway, our model does not explicitly penalize wasting energy if power delivery is successful. For this reason, given the low probabilities involved, they prefer to always transmit if they can.

B. Analysis of region B

If the combination of costs and probabilities falls in B, we can conclude that `S1` decides to never send energy regardless its probability and cost, while `S2` decides to send energy only if it has enough energy available in that specific time slot. If this is not the case, also `S2` chooses to stay idle. This happens because, with this parameters, the payoff of `S2` playing this strategy is always greater or equal than the ones obtained by playing others strategies. The situation is analogous for `S1`.

In practice, inside region B, both players know that source 2 is the more adequate to provide energy ($\lambda_2 > \lambda_1$). So, `S1` has an incentive in staying idle in any case.

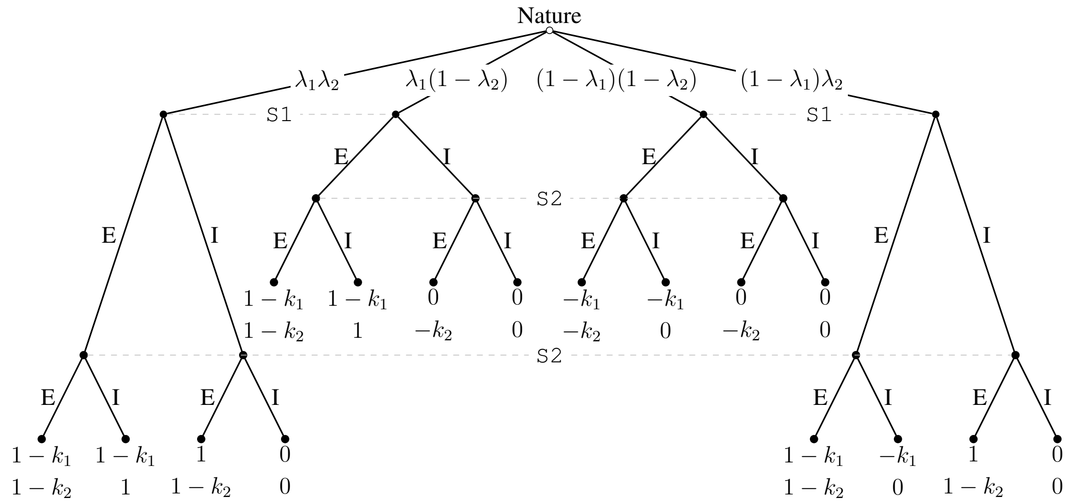


Fig. 1. Extensive form representation.

S1 \ S2	EE	EI	IE	II
EE	$\lambda_1+\lambda_2-\lambda_1\lambda_2-k_1$ $\lambda_1+\lambda_2-\lambda_1\lambda_2-k_2$	$\lambda_1+\lambda_2-\lambda_1\lambda_2-k_1$ $\lambda_1+\lambda_2-\lambda_1\lambda_2-\lambda_2k_2$	λ_1-k_1 $\lambda_1+\lambda_2k_2-k_2$	λ_1-k_1 λ_1
EI	$\lambda_1+\lambda_2-\lambda_1\lambda_2-\lambda_1k_1$ $\lambda_1+\lambda_2-\lambda_1\lambda_2-k_2$	$\lambda_1+\lambda_2-\lambda_1\lambda_2-\lambda_1k_1$ $\lambda_1+\lambda_2-\lambda_1\lambda_2-\lambda_2k_2$	$\lambda_1(1-k_1)$ $\lambda_1+\lambda_2k_2-k_2$	$\lambda_1(1-k_1)$ λ_1
IE	$\lambda_1k_1+\lambda_2-k_1$ $-\lambda_2-k_2$	$\lambda_1k_1+\lambda_2-k_1$ $\lambda_2-\lambda_2k_2$	$\lambda_1k_1-k_1$ $\lambda_2k_2-k_2$	$\lambda_1k_1-k_1$ 0
II	λ_2 λ_2-k_2	λ_2 $\lambda_2-\lambda_2k_2$	0 $\lambda_2k_2-k_2$	0 0

Fig. 2. Normal form of the game.

C. Analysis of region C

In area C, what happens is somehow symmetrical to what described in area B. `S2` decides to never send energy regardless its probability and cost, while `S1` decides to send energy only if it has enough in that specific moment. If it is not so, also `S1` chooses to stay idle. For both players, these actions are always the best response to the other player's choice and hence they describe dominant strategies.

D. Analysis of region D

In region D, three NEs are found: two in pure strategies and one in mixed strategies, mixing the same strategies already involved in the pure NEs. This situation can be interpreted considering that both players have high probabilities of having energy to send. So, what happens in the pure NEs is that one of the players takes action, at which point the other has no incentive to intervene. Indeed, the latter always stay idle, assuming that the high probability of the other source to have energy is a good assurance about the successful delivery.

In the mixed case, both the sources play both strategies according to a certain probability. In particular, the presence of the mixed strategies NE is justified by the fact that a player may not want to always play the same strategy, but it may prefer to play sometimes "EI" and others "II". Accordingly to the probabilities of the mixed strategies, it is possible that the alternation of strategies will lead to a lower number of times in which both stay idle, alternatively transmit or both transmit.

E. Analysis of the borders

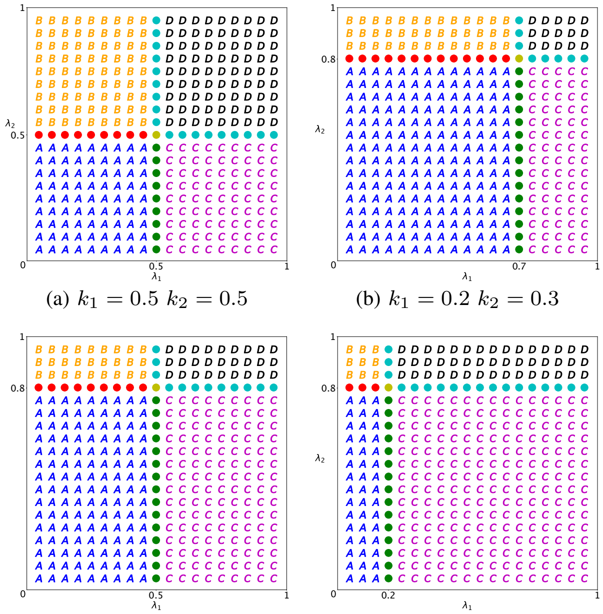
In the situations where $\lambda_1 = 1-k_2$ and/or $\lambda_2 = 1-k_1$, that is, values along the borders between the main regions, we fall in some sort of hybrid operating points. Indeed, in those cases the resulting NEs are the combinations of the equilibria of the involved areas.

Without giving a specific analysis of every combination, we can connect the outcomes over each border region with the surrounding areas. It is important to point out that, somehow analogous to region D, in the border points also multiple equilibria are present. On the one hand, this leads to multiple options for the two players. On the other hand, this means that the system behavior is difficult to predict and a distributed strategic choice by individual selfish players may not be the best course of action, as this can lead to lack of coordination, opposed to the cases where a single NE is present.

F. Remarks

When the parameters falls in region A, both sources contribute to the overall system availability. In regions B and C, one of the sources always remains idle. Thus, if $\lambda_1 \in (0,\ 1-k_2) \wedge \lambda_2 \in (1-k_1,\ 1)$ there is no point in having `S1` as just `S2` is possibly used. If $\lambda_1 \in (1-k_2,\ 1) \wedge \lambda_2 \in (0,\ 1-k_1)$, the situation is reversed and the only used source is `S1`. This has to be taken into account while dimensioning the system, deciding to implement two sources only if it is worth the effort.

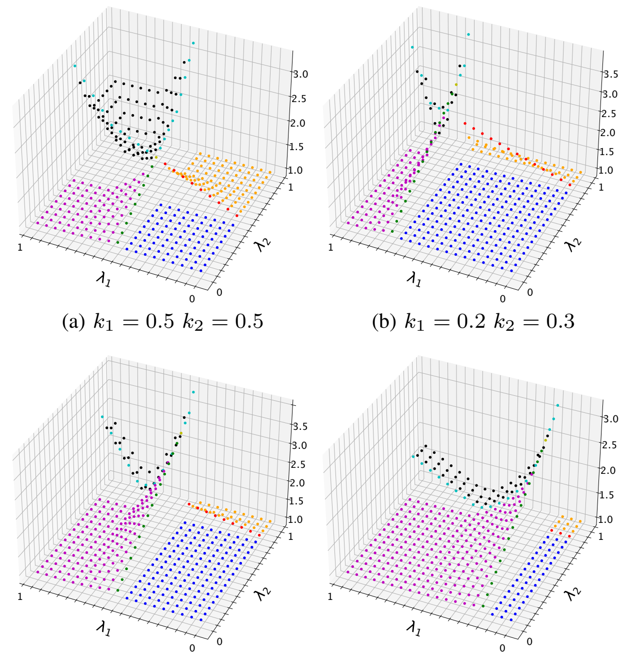
Finally, in region D, the mixed NE makes the outcome more difficult to predict. Also, when the mixed equilibrium is chosen, with non-zero probability both source are inactive. Overall, this may lead to inefficiencies, especially if the availability of energy is quite high for both sources. In this case, a selfish behavior by a source can be to stay inactive and avoid paying the cost; however, if they both act this way, the outcome is in the end that the IoT device is not powered. Surprisingly, this might be worse than what happens in strongly unbalanced scenarios, i.e., when only one source has high energy availability, since the NE will be unequivocally determined as that source being the energy provider.



(a) $k_1 = 0.5$ $k_2 = 0.5$ (b) $k_1 = 0.2$ $k_2 = 0.3$

(c) $k_1 = 0.2$ $k_2 = 0.5$ (d) $k_1 = 0.2$ $k_2 = 0.8$

Fig. 3. Numerical instances.



(a) $k_1 = 0.5$ $k_2 = 0.5$ (b) $k_1 = 0.2$ $k_2 = 0.3$

(c) $k_1 = 0.2$ $k_2 = 0.5$ (d) $k_1 = 0.2$ $k_2 = 0.8$

Fig. 4. Graphs of PoA for the four different situations.

V. Numerical results

We consider a game theoretic management of a two source energy harvesting system as described in the previous section, and we consider specific choices of the numerical parameters, in particular for what concerns their operating costs, discussing the resulting NEs and operating regions. We consider four situations, represented in Fig. 3:

(a) both sources have equal intermediate costs k_1=k_2=0.5
(b) both costs are low, but different, $k_1 = 0.2$, $k_2 = 0.3$
(c) the costs of the sources are low and intermediate, respectively, i.e., $k_1 = 0.2$, $k_2 = 0.5$
(d) the costs of the sources are low and high, respectively, i.e., $k_1 = 0.2$, $k_2 = 0.8$.

We see that whenever k_1 is close to k_2, we have a similar role played by both sources, which leads region B and C to be small. The width of regions A and D depends instead on the magnitude of k_1 and k_2. Notably, when these costs are average to large, as in Fig. 3a, the area of D may be quite large and, as we will discuss next, we expect that in this case the outcome can be extremely variable. On average, in region D, the presence of two sources that act egoistically tends to be even worse than a single source.

Thus, it would be more convenient to operate in situations such as the one in Fig. 3b, where both sources are analogous and their cost is low. In this case, we obtain that the largest region is A, where the only NE is also the most efficient, as we will discuss later. Hence, the presence of multiple affordable sources boosts the efficiency of the system.

To quantify the efficiency of the outcomes for each scenario and in each region, we discuss the PoA of the resulting system. This is a game theoretic concept often used to describe the impact of players' egoistic behaviors on the system performance. We compute the PoA based on the *total system utility* by taking the ratio between its maximum possible value and its value at the NE; in the case of multiple NEs, we take the worst one. The idea is that if the PoA is close to 1, then the NE obtain close-to-optimal performance. Otherwise, the PoA quantifies the extra cost paid by the system due to inefficiency in coordination [24]. The graphs of the PoA are shown in Fig. 4, where the colors match those used in Fig. 3.

It is immediate to see that the PoA in region A is very close to 1. This means that the situation with one single NE equal to (EI, EI) achieves the best possible outcome for the system. This is of course more likely to happen when the costs are low, in which case region A is bigger. In such a region, both sources are aware that the cost of sending energy is low and the likelihood that the other source is active is high. So, in this case, even an egoistic choice of strategy makes the interest of the whole system as well. Therefore, the use of a distributed management in such a scenario is well justified. Seen the other way around, this scenario implies that the extension to multiple sources is sensible only if both are sufficiently reliable and cheap, in which case the system performance is increased by means of added source diversity. Conversely, there is almost no point in adding a significantly worse source to a system, as any benefit is nullified by the added burden for managing it, as will be shown next.

Regions B and C are characterized by symmetric NEs and as such, their PoA trends are analogous. The symmetry is evident especially in Fig. 4a, where the costs are equal. What happens is that when the probability for a source of having energy is much bigger than the other, the PoA is close to 1, i.e., very low. However, this does not necessarily comment on the resulting efficiency, but rather implies that the distributed choices of the players lead to a very predictable outcome. Specifically, in this case one source has little availability on average, so the other source would be better off by being always active. As a result, the PoA is low as there is no doubt on the outcome, but it is hardly an increase in efficiency from the system management point of view, it simply means that the less efficient source is never used, and its presence may even be questioned.

When the probabilities become similar, the PoA of regions B and C increases. This is because the NEs in these regions are (II, EI) and (EI, II), respectively, i.e., there is only one active source, and the efficiency of choosing it depends on whether this is actually significantly better than the other. If they are comparable, instead, it is inefficient to use the better of them but not exploiting the other, that is just slightly worse. Also, as the values approach region D, there is a steep increase of the PoA due to the sources possibly changing roles.

Indeed, in region D, the PoA is generally quite high in all situations. This is especially due to the presence of multiple NEs, which can lead to lack of coordination. In fact, while game theory postulates that selfish rational users will operate at an NE, in the presence of multiple equilibria they can end up in choosing different uncoordinated policies, unlike the situation where the equilibrium is unique and there is no doubt on the choice. As a side comment, the PoA also happens to be high on the borders, for the very same reason, i.e., the presence of multiple equilibria, as discussed in the previous section. This result comments on the insertion of multiple sources in an energy harvesting platform not being always beneficial if the sources are not sufficiently reliable. While the case with one weak source is just pointless, the scenario where all the sources are weak can even lead to harmful outcomes if the controllers are not properly coordinated, which jeopardizes the possibility of a distributed management. We believe that this stands out as a particularly useful guideline for system implementation.

VI. Conclusions

We presented a game theoretic analysis of an energy harvesting system with two renewable sources powering an IoT target node with distributed management. We considered the key parameters of the activation cost and the probability of being capable to deliver energy, which is framed as the Bayesian type of the players.

We showed the impact of both parameters on the choices of the players and the resulting system equilibrium. Our analysis shows that the availability/cost tradeoff of both sources is actually key in determining whether the use of multiple sources is beneficial. The introduction of multiple sources with uneven properties (i.e., one is much more often available and less expensive than the others) is basically useless, since the worse source will never be used anyways [17]. When both sources have analogous properties, they better have good availability and/or low cost, in which case their distributed management will be efficient and with low PoA. Conversely, the introduction of multiple sources with bad properties might even make the distributed management inefficient [14].

References

[1] J. Holm, F. Chiariotti, M. Nielsen, and P. Popovski, "Lifetime maximization of an Internet of things (IoT) network based on graph signal processing," vol. 25, no. 8, pp. 2763–2767, 2021.

[2] G. Cisotto and S. Pupolin, "Evolution of ICT for the improvement of quality of life," *IEEE Aerosp. Electron. Syst. Mag.*, vol. 33, no. 5-6, pp. 6–12, 2018.

[3] S. Sudevalayam and P. Kulkarni, "Energy harvesting sensor nodes: Survey and implications," *IEEE Commun. Surveys Tuts.*, vol. 13, no. 3, pp. 443–461, 2010.

[4] E. Gindullina, L. Badia, and D. Gündüz, "Average age-of-information with a backup information source," in *Proc. IEEE PIMRC*, 2019, pp. 1–6.

[5] S. Martiradonna, G. Cisotto, G. Boggia, G. Piro, L. Vangelista, and S. Tomasin, "Cascaded WLAN-FWA networking and computing architecture for pervasive in-home healthcare," *IEEE Wireless Commun.*, vol. 28, no. 3, pp. 92–99, 2021.

[6] J. Zheng, Y. Cai, X. Shen, Z. Zheng, and W. Yang, "Green energy optimization in energy harvesting wireless sensor networks," *IEEE Commun. Mag.*, vol. 53, no. 11, pp. 150–157, 2015.

[7] S. Guruacharya and E. Hossain, "Self-sustainability of energy harvesting systems: concept, analysis, and design," *IEEE Trans. Green Commun. Netw.*, vol. 2, no. 1, pp. 175–192, 2017.

[8] E. Gindullina, L. Badia, and X. Vilajosana, "Energy modeling and adaptive sampling algorithms for energy-harvesting powered nodes with sampling rate limitations," *Trans. Emerg. Telecommun. Tech.*, vol. 31, no. 3, p. e3754, 2020.

[9] L. Badia, "On the impact of correlated arrivals and errors on ARQ delay terms," *IEEE Trans. Commun.*, vol. 57, no. 2, Feb. 2009.

[10] N. Michelusi, K. Stamatiou, L. Badia, and M. Zorzi, "Operation policies for energy harvesting devices with imperfect state-of-charge knowledge," in *Proc. IEEE ICC*, 2012, pp. 5782–5787.

[11] L. Badia, E. Feltre, and E. Gindullina, "A Markov model accounting for charge recovery in energy harvesting devices," in *Proc. IEEE WCNC Wkshps*, 2017, pp. 1–6.

[12] M. Capuzzo, C. Delgado, A. K. Sultania, J. Famaey, and A. Zanella, "Enabling green IoT: Energy-aware communication protocols for batteryless LoRaWAN devices," in *Proc. ACM MSWiM*, 2021, pp. 95–98.

[13] A. S. Weddell, M. Magno, G. V. Merrett, D. Brunelli, B. M. Al-Hashimi, and L. Benini, "A survey of multi-source energy harvesting systems," in *Proc. IEEE DATE*, 2013, pp. 905–908.

[14] E. Gindullina, L. Badia, and D. Gündüz, "Age-of-information with information source diversity in an energy harvesting system," *IEEE Trans. Green Commun. Netw.*, vol. 5, no. 3, pp. 1529–1540, 2021.

[15] A. Arafa, J. Yang, S. Ulukus, and H. V. Poor, "Timely status updating over erasure channels using an energy harvesting sensor: Single and multiple sources," *IEEE Trans. Green Commun. Netw.*, vol. 6, no. 1, pp. 6–19, 2021.

[16] N. Michelusi, L. Badia, R. Carli, K. Stamatiou, and M. Zorzi, "Correlated energy generation and imperfect state-of-charge knowledge in energy harvesting devices," in *Proc. IEEE IWCMC*, 2012, pp. 401–406.

[17] E. Gindullina and L. Badia, "Asymmetry in energy-harvesting wireless sensor network operation modeled via Bayesian games," in *Proc. IEEE WoWMoM*, 2017, pp. 1–3.

[18] S. Kim, "Adaptive data center management algorithm based on the cooperative game approach," *IEEE Access*, vol. 9, pp. 3461–3470, 2020.

[19] L. Pasini, A. Policante, D. Rusmini, G. Cisotto, E. Gindullina, and L. Badia, "On the choice of utility functions for multi-agent area survey by unmanned explorers," in *Proc. IEEE IWCMC*, 2022, pp. 1136–1141.

[20] M. Cappelletti, N. Cibin, and L. Badia, "Game-theoretic economic models of duopolies applied to green ICT design," in *Proc. IEEE EPEC*, 2021, pp. 267–272.

[21] N. Reyhanian, B. Maham, V. Shah-Mansouri, W. Tushar, and C. Yuen, "Game-theoretic approaches for energy cooperation in energy harvesting small cell networks," *IEEE Trans. Veh. Technol.*, vol. 66, no. 8, pp. 7178–7194, 2017.

[22] M. Scalabrin, V. Vadori, A. V. Guglielmi, and L. Badia, "A zero-sum jamming game with incomplete position information in wireless scenarios," in *Proc. Eur. Wirel.*, 2015, pp. 1–6.

[23] L. Badia and M. Zorzi, "On utility-based radio resource management with and without service guarantees," in *Proc. ACM MSWiM*, 2004, pp. 244–251.

[24] L. Prospero, R. Costa, and L. Badia, "Resource sharing in the Internet of Things and selfish behaviors of the agents," *IEEE Trans. Circuits Syst. II*, vol. 68, no. 12, pp. 3488–3492, 2021.