Joint Energy Management for Distributed Energy Harvesting Systems

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ABSTRACT

Employing energy harvesting to power the Internet of Things supports their long-term, self-sustainable, and maintenance-free operation. These energy harvesting systems have an energy management subsystem to orchestrate the flow of energy and optimize their achievable system performance. Numerous such algorithms for a single harvesting-based system have been proposed. When envisioning the joint use of multiple distributed energy harvesting nodes in a single application, the performance and behavior of the distributed system depends on the mutual energy availability and therefore energy management of all nodes. We propose to perform the energy management of multiple distributed energy harvesting nodes jointly and thus, optimize the distributed system's performance as opposed to the performance of each energy harvesting node individually. We demonstrate the novel joint optimization in a scenario with multiple energy harvesting nodes and observe that the distributed system's performance improves by 28 % compared to when each node's energy is managed individually.

CCS CONCEPTS

• **Computer systems organization** → **Sensor networks; Sensors and actuators**; • **Hardware** → **Sensor applications and deployments**.

KEYWORDS

Distributed Systems, Energy Harvesting, Energy Management, Internet of Things, Joint Optimization, Scheduling

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1 INTRODUCTION

Distributed embedded systems such as Wireless Sensor Networks or the Internet of Things are found in a broad range of applications, including precision agriculture and smart buildings [8]. Although these ubiquitous systems can be powered with batteries, this approach does not scale well and incurs a significant maintenance effort. Introducing energy harvesting addresses these disadvantages but is accompanied by other challenges.

In particular, an energy harvesting system has limited resources, such as the harvested energy and energy storage capacity, that need to be utilized efficiently. Numerous schedulers [9] have been proposed to manage the resources of a single energy harvesting system and determine the flow of energy within the system. These schedulers adjust the energy consumer's behavior and can make use of predictions of the future harvested energy to optimize the individual system's long-term performance.

In a distributed system there are multiple energy harvesting systems exposed to various environments working together for a single application. We consider scenarios where the energy harvesting nodes are wirelessly connected to a central host where the data is collected and utilized. This aligns with numerous control applications where nodes sense the control plant state and the host performs automatic control based on the sensed data. For example, in a smart building application, energy harvesting nodes measuring temperature and humidity are distributed outside and throughout a building as, in [11] and [1]. Sensed data from all nodes is necessary for the host to control the rooms for thermal comfort and save energy required for heating or cooling. This scenario is also found in monitoring applications where sensed data from the energy harvesting nodes is collected and further processed at the host. If the host requires sensed data from all energy harvesting nodes, then when and how often sensed data is available is dictated by the mutual energy availability and usage of all nodes. The distributed system cannot benefit from only a few nodes sensing more frequently or various nodes sensing more frequently at different times. In such scenarios the distributed system's performance is dictated by the common energy usage all nodes can support at the same time.

We propose for distributed energy harvesting systems to manage their nodes's energy jointly. When nodes manage their energy separately, they optimize their own performance but not that of the distributed system. A joint optimization improves and optimizes the performance of the distributed system. This moves towards

enabling the efficient use of energy harvesting in distributed embedded systems thus facilitating novel applications. We present the joint optimization for their energy management and demonstrate its improvements over separate energy management.

2 SCENARIO AND SYSTEM MODEL

We consider a scenario with N energy harvesting systems, each equipped with a harvester, energy storage, energy management, as well as a sensor, processing and wireless communication unit. Each application execution, i.e. a node sensing and communicating data, requires the same and constant energy from each node. The nodes are wirelessly connected to a central host without resource constraints that utilizes the sensed data and requires sensed information from all N nodes. When and how much sensed data is available at the host is thus directly related to the common energy consumption supported by all nodes.

The joint energy management's goal is to adjust the used energy of all harvesting-based systems such that they provide a maximized minimal sensed data rate and optimize a concave-shaped distributed system utility. In control applications, this relates to providing a minimal sensing rate such that the resulting control is stable [5]. The concave utility implies that with additional energy it is better to increase the sensing rate when it is low rather than to increase it further when it is already high. This relationship of diminishing returns is also observable in many other application domains. We now formalize a system model and specify this objective.

We assume a discrete-time model, where the time horizon $[0, T)$ is discretized into intervals $t \in \mathbb{Z}_{\geq 0}$. The harvester of node i harvests $E_{\text{harv},i}(t)$ during $[t, t + 1)$. The harvested energy of node i during the next time horizon is predicted to be $E_{\text{pred},i}(t)$. The harvested energy is stored in a rechargeable energy storage, such as a super-capacitor. The energy storage of node i has a capacity of B_i and its state of charge at time t is denoted as $b_i(t)$. It evolves according to $b_i(t + 1) = b_i(t) + E_{\text{harv},i}(t) - a_i(t)$ where $a_i(t) \geq 0$ is the energy consumed by node i during $[t, t + 1)$. This model has been shown to be realistic and system inefficiencies, for example, related to charging the energy storage can be incorporated by adapting model parameters [3]. Because the harvesting-based system has to operate in energy neutrality and the energy storage state of charge must remain $b_i(t + 1) \in [0, B_i]$, the energy $a_i(t) \geq 0$ that is available to be used is bounded. Since the host requires sensed data from all nodes, all nodes must support a common consumed energy that can be utilized towards the distributed system functionality. We specify this mutual used energy during the time interval $[t, t + 1)$ as $u(t)$. This energy has to be available at all nodes and hence it must hold that $\forall 1 \leq i \leq N; \forall 0 \leq t < T : 0 \leq u(t) \leq a_i(t)$. The common used energy dictates with what frequency sensed data from all nodes is available to the host. Therefore, the objective of the joint energy management is to maximize the minimal common consumed energy, $\min_t u(t)$ maximizing the minimal sensing rate. Additionally, it maximizes a distributed system utility with diminishing returns, i.e. $\sum_t \mu(u(t))$ with a concave function μ .

3 JOINT ENERGY MANAGEMENT

We build our energy management on the work presented in [2]. The energy management of each node is initially performed separately

using [2] without considering the necessity for common energy availability. We propose to subsequently jointly optimize the mutual used energy of all nodes.

Separate Optimization Initially, the resources of each energy harvesting node are optimized separately using the scheduler in [2]. This work assumes the same model as described in Section 2 and has the same optimization objective. The scheduler determines how much energy should be used in subsequent time intervals. The provably optimal energies are found through an iterative algorithm [2]. This scheduler is employed for each node i to determine its optimized used energy for the time horizon, denoted as $a_i^*(t)$. The scheduler's properties guarantee that the energies $a_i^*(t)$ for $t \in [0, T]$ maximize the minimal used energy and utility of node i . From these separate optimizations, the common energy useable for the distributed system is dictated by the smallest available energy and is $u_{\text{sep}}(t) = \min_i a_i^*(t)$. By construction, this mutual consumed energy is feasible for all nodes i .

We postulate that for the specified assumptions, the minimal mutual used energy determined by the separate optimizations, $\min_{0 \leq t < T} u_{\text{sep}}(t)$ cannot be improved, i.e. for any other feasible mutual used energy $u'(t)$ it holds that $\min_t u'(t) \leq \min_t u_{\text{sep}}(t)$. This holds because in [2] it was proven that for node i the energies $a_i^*(t)$ maximize the minimal used energy. Suppose there is a mutual energy usage $u'(t)$ that has a larger minimum, then there would need to be at least one node that can support a higher minimal used energy than what was determined by the scheduler. However, this directly contradicts this scheduler's proven optimality [2].

Joint Optimization Although the minimum mutual used energy cannot be improved, the utility and thus distributed system's performance can be by considering all nodes in a joint optimization. For the joint optimization, the concave utility function μ is approximated with a piecewise linear function. This approximation has L linear pieces with coefficients $c_{0,j}, c_{1,j}$ for $1 \leq j \leq L$. For a specified number of pieces, the approximation can be determined with a global optimization, as implemented in [6]. The proposed joint optimization is

$$\underset{v, a_i}{\text{maximize}} \sum_{0 \leq t < T} v(t) \quad (1)$$

$$\forall 1 \leq i \leq N, 0 \leq t < T : b_i(t + 1) = b_i(t) + E_{\text{pred},i}(t) - a_i(t) \quad (2)$$

$$\forall 1 \leq i \leq N, 0 \leq t < T : u_{\text{sep}}(t) \leq a_i(t) \quad (3)$$

$$\forall 1 \leq i \leq N : b_i(0) = B_i^{\text{init}}; b_i(T) = b_i(0) \quad (4)$$

$$\forall 1 \leq i \leq N, 0 \leq t < T : 0 \leq b_i(t) \leq B_i; 0 \leq a_i(t) \quad (5)$$

$$\forall 1 \leq i \leq N, 0 \leq t < T, 1 \leq j \leq L : v(t) \leq c_{0,j} + c_{1,j} \cdot a_i(t) \quad (6)$$

where $v(t)$ is an auxiliary variable. (2) is the evolution of the energy storage state of charge, (4) initializes the state of charge and ensures the final level is the same as the initial. This is also enforced in [2]. (3) guarantees that the minimal consumed energy is no smaller than that obtained by the separate optimization. (1) and (6) together incorporate the linear approximation of the utility function and maximize the sum of the concave function. The resulting mutual used energy for the distributed system is obtained as

$$\forall 0 \leq t < T : u(t) = \min_{1 \leq i \leq N} a_i^*(t) \quad (7)$$

where $a_i^*(t)$ are the solutions from the optimization (1).

Figure 1: Separate energy management of the energy harvesting nodes and then taking the minimum. A significant amount of energy is not useful to the distributed system.

The optimization is performed at the central host that does not have resource constraints. At the beginning of each time interval, the energy harvesting nodes also communicate system information with which the host performs the optimizations. The host then communicates the optimized energy thus the sensing rate to the nodes. The overhead is limited as when designed appropriately, only the energy storage state of charge and energy used in the last interval need to be communicated. In addition, this overhead is only incurred once per time interval and a time interval can span a long time such as a week [2].

4 EVALUATION

We demonstrate the proposed joint optimization in a scenario where multiple energy harvesting nodes are distributed in a building which aligns with applications in automatic building control.

Indoor harvesting data [10] from an employee office and a student office in the same building is used. Each node has the same architecture consisting of a solar panel with a size of 50 mm · 33 mm and an energy storage. Due to its location the first node harvests on average roughly 30 % more energy than the second. To account for the differences in harvested energy, the energy storage capacities are 1 J and 4 J, respectively. All energy storages are initially half full. The prediction of the future harvestable energy of each node is generated with the exponentially weighted moving average (EWMA) [7] algorithm with a weighting factor of $\alpha = 0.5$. The time horizon over which the host optimizes is one week discretized into one-hour steps. The optimizations are executed in a finite-horizon approach. As in [2] the function μ has a square-root shape and is approximated with a piecewise linear function with 3 pieces.

We first show the performance achievable with separate optimizations. Figure 1 depicts both the separate energies as determined by each individual scheduler as well as the resulting mutual used energy, which is the minimum of the former two. A significant amount of energy is available at the nodes at different times and therefore not beneficial to the distributed system. The minimal used energy with this approach is 2.1 mJ and the system utility is 61.

The distributed system's performance is improved by applying the proposed joint energy management. Figure 2 depicts the mutual used energy determined by the separate optimizations from above as well as with the proposed method. The minimum energy remains the same, but for numerous other time intervals, the mutual used energy improves. The system utility improves by 28 %.

Figure 2: The joint optimization can improve the overall consumed energy compared to the separate energy management, but it cannot improve the minimal consumed energy.

5 SUMMARY AND FUTURE WORK

We propose a joint energy management optimization for distributed energy harvesting systems that sense and communicate information to a central host. Compared to separate energy management, this approach improves the distributed system's performance. There are further opportunities to improve the distributed system's performance. In some scenarios, it is not necessary to obtain sensed data from all nodes but rather only from a subset of nodes. For such scenarios, the energy management needs to be considered in conjunction with node selection. Furthermore, the energy requirement per application execution does not have to be the same for all nodes. The communication of sensed data to the host can be done with a low-power wireless bus that originally requires all nodes to forward data [4]. But the nodes that forward sensed data can also only be a subset of all nodes, balancing energy availability, communication reliability, and latency. We will address the design and optimization of such scenarios in future work.

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REFERENCES

- [1] Samar Abbas et al. 2018. Inverted HVAC: Greenifying older buildings, one room at a time. *ACM Trans. on Sensor Networks (TOSN)* (2018).
- [2] Bernhard Buchli et al. 2015. Optimal power management with guaranteed minimum energy utilization for solar energy harvesting systems. In *Procs of DCOSS'15*. IEEE.
- [3] Stefan Draskovic et al. 2021. Optimal Power Management for Energy Harvesting Systems with A Backup Power Source. In *Procs of MECO'21*. IEEE.
- [4] Federico Ferrari et al. 2012. Low-power wireless bus. In *Procs of SenSys'12*. ACM.
- [5] Gene F Franklin et al. 1998. *Digital control of dynamic systems*. Vol. 3. Addison-wesley Reading, MA.
- [6] Charles Jekel et al. 2019. *pwlf: A Python Library for Fitting 1D Continuous Piecewise Linear Functions*. https://github.com/cjekel/piecewise_linear_fit_py
- [7] Aman Kansal et al. 2007. Power Management in Energy Harvesting Sensor Networks. *ACM Trans. Embed. Comput. Syst.* (2007).
- [8] SR Jino Ramson et al. 2017. Applications of wireless sensor networks — A survey. In *Procs of IEEE/INT'17*. IEEE.
- [9] Amandeep Sharma et al. 2020. A review on solar forecasting and power management approaches for energy-harvesting wireless sensor networks. *International Journal of Communication Systems* (2020).
- [10] Lukas Sigrist et al. 2019. Dataset: Tracing indoor solar harvesting. In *Procs of DATA'19*. ACM.
- [11] Naomi Stricker et al. [n. d.]. Self-triggered Model Predictive Control with Embedded Energy Harvesting Systems. To be published.