Optimal component sizing in a two-reservoir passive energy harvesting system

E. Munsing, M. Cowell, S. Moura and P. Wright

1 Energy Controls and Applications Laboratory, University of California, Berkeley CA 94720
2 Advanced Manufacturing for Energy, University of California, Berkeley CA 94720, USA

E-mail: e.munsing@berkeley.edu

Abstract. We utilize particle swarm optimization to reduce the size of the energy management components in an energy harvesting system, allowing us to eliminate the need for voltage regulators or DC-DC converters without affecting system performance. Prior literature on optimal power management in microelectronics [1, 2] has relied on engineering estimates or exhaustive parameter searches to optimize system design. No prior literature has considered the optimal design of a device with only passive components [3]. By using particle swarm optimization, we demonstrate a 55% reduction in device size relative to conventional engineering calculations of an optimal device design.

1. Introduction

Energy management systems for wireless sensor nodes must deliver reliable power and voltage while being small and low-cost. In prior literature, power reliability is maintained by using active energy management components (voltage regulators, DC/DC converters), but these impose efficiency losses [4] while increasing device cost and size [1, 2]. While the use of an active energy management system allows for a convex formulation of the optimal sizing problem in a two-reservoir battery/capacitor system [5], the passive energy management problem is nonconvex and has not been explored in prior literature.

Building on previous work developing flexible printed batteries [6], capacitors [7], and generators [8, 9] we propose a design which eliminates the need for active power management, and instead passively maintains device performance through optimal sizing of generators, batteries, and supercapacitors. To overcome the nonconvexity in this problem, we employ a Particle Swarm Optimization (PSO) algorithm to identify an optimal design [10], and are able to demonstrate a significant reduction in system size while meeting all payload power requirements.

1.1. Novel Contributions

This work extends prior literature on energy management in energy harvesting systems in the following ways:

- Demonstrates a method for designing a passive energy management system without the use of voltage regulators or DC/DC converters, and
- Applies particle swarm optimization to microelectronic energy management system design.
2. System Model

We consider a circuit model shown in figure 1 in which power is harvested through strings of thermoelectric generator cells (TEGs) in series; the approach we consider can also accommodate photovoltaics or other energy harvesting modes [9]. Charge is stored in parallel banks of supercapacitors and batteries; the components are linked by a main bus at voltage $V$. A wireless sensor node (WSN) is attached to the bus, and is modeled as a current sink with 15-second cycles with a deterministic current profile. The radio current draw $I_R$ is shown in figure 2: a 15-second inactive period is followed by a 50-millisecond data acquisition and transmission load. We seek to design an energy management system which can repeat this load cycle indefinitely.

The system designer chooses the number of TEG elements in series $s$, number of TEG strings in parallel $p$, number of batteries $b$, and number of capacitors $c$. As the batteries have a low current capacity and supercapacitors have low energy capacity, we expect that an optimal design may include both storage reservoirs. We assume that each component has a constant per-unit cost, captured in the TEG unit cost $\alpha$, battery unit cost $\beta$, and supercapacitor unit cost $\gamma$; the net system cost is thus $\alpha ps + \beta b + \gamma c$.

The system dynamics can be derived through the application of Kirchoff’s Current and Voltage Laws (KCL and KVL) and a simple battery model where open circuit voltage $OCV$ is linearized within the acceptable ranges of State Of Charge $SOC_{\text{min}}$ and $SOC_{\text{max}}$. These governing equations and limits on variables are captured below, where italic fonts are used to denote optimization variables:

\[
\begin{align*}
\text{Subject to:} & & \\
\text{KCL for circuit:} & & pI_T + cI_C + bI_B = I_R \quad (2) \\
\text{TEG dynamics:} & & I_T + \frac{1}{s}V_\zeta = T_0 \Delta K \quad (3) \\
\text{KVL in Capacitor:} & & V + I_C R_{C1} - V_C = 0 \quad (4) \\
\text{KCL in Capacitor:} & & \dot{V}_C + \frac{1}{C_C} I_C + \frac{1}{C_C R_{C2}} V_C = 0 \quad (5) \\
\text{KVL in Battery:} & & V + I_B R_{B1} - V_B - OCV = 0 \quad (6)
\end{align*}
\]
3. System Design

3.1. Conventional Engineering Calculations

We expand on the methods in [1, 2, 3, 11] to provide a baseline estimate of system design using conventional engineering calculations.

To calculate the number of TEG elements in series within each string, and number of TEG strings in parallel, we use the linear TEG dynamics found in equation (3) and consider a constant temperature difference $\Delta K = 20$. We determine the number of TEGs in series by dividing the nominal bus voltage by the midpoint voltage of the TEG output curve found in [8]. Similarly, we calculate the necessary number of parallel TEG strings by dividing the average WSN current demand by the midpoint current of a single TEG module.

We calculate the number of supercapacitors required to ensure that maximum payload current $I_{C_{\text{max}}}$ can be satisfied without violating $V \geq V_{\text{cutoff}}$. We estimate the minimum number of parallel supercapacitors by dividing $I_{C_{\text{max}}}$ by the maximum current a single supercapacitor is able to deliver, $I_{C_{\text{max}}}$. We then verify that the combination of coulombic voltage drop and ohmic voltage drop at $I_{\text{max}}$ will not depress the bus voltage below $V_{\text{cutoff}}$.

Because the current limit of the batteries is 2.5% that of the supercapacitors, the battery’s contribution to the radio’s current demand during peak discharge is assumed to be negligible. Instead, the battery is sized such that it will be able to provide a nominal baseload power, here considered as 10% of $I_{\text{max}}$, and has sufficient capacity to trickle charge the supercapacitor over the cycle should the TEG power drop.

3.2. Particle Swarm Optimization

Particle Swarm Optimization is a nonlinear optimization method in which a large number of particles explore the parameter space to identify a low-cost solution [10]. We consider an optimization space in the state variables $SOC(0)$, $V_C(0)$, and $V_B(0)$ in addition to the design variables variables $p$, $s$, $b$, and $c$. We provide a brief description of our implementation below; additional details can be found in [10] and associated references.

We assign a set of $n$ particles to random locations and velocities in the optimization space, and use the equations above to simulate the system dynamics at each particle’s coordinates. If constraints are violated a high penalty is assigned, and the total cost (penalty plus the value of the objective function) is saved for that point. After simulating the system at each particle’s location, the location of the lowest-cost point is broadcast to all particles in the swarm. The velocities of all particles are then updated as the weighted sum of the particle’s own velocity and the vector to its own best location and the swarm’s overall best location. The process is repeated until the swarm converges on a low-cost point, though this may not be the global optimum.

4. Results

The results for both design methods are shown in table 1 and the resulting bus voltage during the data transmission period is shown in figure 3. We assume that a constant per-unit cost for each component, $\alpha = \beta = \gamma = 1$. We see that both designs are feasible, though the nonlinear
optimization method converges on a solution which does not use batteries and more closely tracks the system constraints. This contributes to a 55% decrease in the number of components required to power the payload.

A number of other demand profiles were considered, including those in which the TEGs were not able to produce power for a portion of the load cycle. In these scenarios, the nonlinear optimization resulted in a design in which batteries are added to maintain bus voltage through the drop in generation.

We note that the convergence rate of the nonlinear optimization is dependent on the penalty function, and was found to slow significantly for longer study periods.

5. Conclusions
We demonstrate a method for energy management in a wireless sensor node which does not require the use of voltage regulators or DC-DC converters, instead satisfying payload requirements through optimal component sizing. Using particle swarm optimization, we find a design with significant reductions in system cost relative to conventional engineering calculations. While this nonlinear optimization technique does not guarantee a globally optimal design, it can be readily applied to other demand profiles and generation/storage technologies and we expect that similar results may be found in other energy management problems.

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