

# Application-Driven Dynamic Power Management for Self-Powered Vigilant Monitoring

Dawei Fan, Luis Lopez Ruiz, and John Lach, *Senior Member, IEEE*

**Abstract**— While body sensor networks (BSNs) have proven to be a feasible solution for long-term vigilant health monitoring, limited battery life remains one of the main factors that has impeded their widespread adoption. Energy harvesting technologies bring an opportunity to address this issue by enabling the development of self-powered BSNs. However, the dynamic nature of energy harvesting sources poses a challenge to self-powered vigilance. In this paper, an application-driven dynamic power management (DPM) method for self-powered BSNs is presented that optimally adapts system operation to energy availability while meeting application requirements for vigilant monitoring. Vigilant Atrial Fibrillation (AF) monitoring is investigated as an example case study, and a simulation using real-world energy harvesting profiles is executed to validate the model and the optimal solution.

## I. INTRODUCTION

Many body sensor network (BSN) applications require *continuous* data collection over an extended period of time to monitor trends, classify events, assess performance, etc. However, applications that require critical event detection must provide *vigilant* operation – i.e., the BSN cannot miss a critical event and, therefore, must remain active and provide sufficient data quality during times an event might occur. Continuous operation is not necessarily vigilant, as the data quality (sampling frequency, bit depth resolution, sensing modalities, etc.) might not be sufficient to reliably detect a critical event. A representative example is vigilant ECG monitoring, in which the BSN must operate not only continuously but do so with sufficient data quality such that transient abnormal cardiac events, such as atrial fibrillation (AF), can be detected [1]. Other applications requiring vigilant monitoring include agitation detection [2], personal environmental exposure tracking, and physiology monitoring for asthma mitigation [3].

Self-powered BSNs using energy harvesting have grown into an attractive option to sustain long-term operation with no battery-related user compliance issues. Harvesting energy from the human body and ambient environment, such as solar, thermal, and mechanical, provides the potential for quasi-perpetual sensor node operation, but the variable energy supply inherent with harvesting poses challenges for sustaining vigilance. Dynamic power management (DPM) techniques have been developed to the adjust system operating mode based on fluctuations in available energy and workflow requirements [4]–[7], but DPM for vigilant BSNs requires an application-driven approach to determine the relationship between power consumption and the ability to detect critical

events. Previous works discuss signal quality versus power consumption, but many of these approaches come from a data perspective using digital signal metrics, such as Signal-to-Noise Ratio (SNR) and Mean Squared Error (MSE), which may or may not be tied to application-level information metrics, such as event detection vigilance. For example, the time interval between successive heart beats – R-R interval – is frequently used in cardiac monitoring applications [8], including AF detection, and it is typically extracted from digital ECG signals. Fig. 1 shows a 10 second window of ECG waveform from the MIT-BIH AF [9] database at a sampling rate of 250Hz, and three downsampled versions. Along the downsampling, the signal quality of ECG signal degrades, but the QRS complex detection [8] can still be performed properly down to 20Hz.

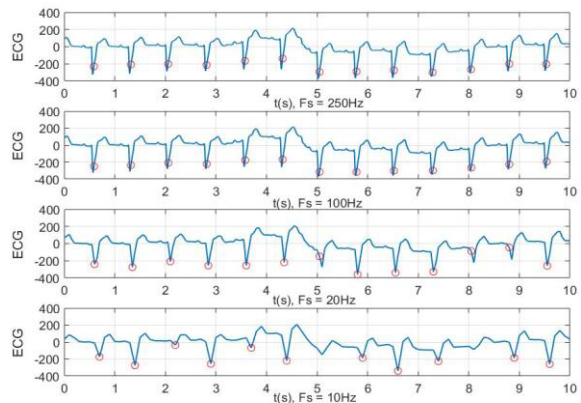


Fig. 1. ECG waveforms and detected QRS complexes in red circles with different sampling rates. With the decrease in sampling rate, the ECG signal becomes distorted, but the QRS complex detection works well until a minimum sampling rate of 20Hz.

In this paper, we develop and discuss a novel application-driven DPM for self-powered vigilant BSNs. In section II, a DPM optimization model for general energy harvesting vigilant systems is proposed. In sections III and IV, vigilant AF monitoring is investigated as a case study, and AF classification performance is used as the application performance metric. The ECG signal sampling rate versus AF classification performance is compared, and a simulation of DPM using an energy profile is tested to validate the DPM model. The contributions of this paper include: a) A general DPM scheduling model and algorithm for self-powered vigilant systems from an application perspective, and b) The exploration of vigilant AF detection as a case study to validate the proposed DPM model.

## II. DYNAMIC POWER MANAGEMENT MODEL

DPM is a design and operating methodology for reconfiguring systems dynamically to provide specific services and performance with optimal energy efficiency by

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Dawei Fan, Luis Lopez Ruiz and John Lach are with Charles L. Brown Department of Electrical and Computer Engineering, UVA Center for Wireless Health, University of Virginia, Charlottesville, VA 22911 USA (e-mail: {jl2wf, jlach}@virginia.edu).

shutting down or otherwise reducing the power consumption of some components. DPM has been widely adopted in a variety of areas, including BSNs and general wireless sensor networks [4]–[7]. There are two fundamental assumptions for the applicability of DPM: a) the workload of the system could fluctuate during operation; and b) it is possible to observe and – at times – reasonably predict the workload change. The system, which usually consists of heterogeneous power-manageable components, could then be managed to achieve a better power/quality efficiency with specific DPM policies.

In the area of self-powered BSNs, the fluctuation of available energy is a critical concern in addition to the workload change. Therefore, DPM in self-powered BSNs should consider the dynamics of both energy harvesting and workload during operation time. On the workload side, the power consumption of major power manageable components in different operating modes could be modeled; while on the energy harvesting side, the harvested energy could be predicted using different methodologies as in [10].

Based on the related work, a scheduling model for a general energy harvesting system is proposed from the perspective of the relationship between power consumption and data quality. Starting from a general cost function, the optimization of a specific period is formalized. An offline optimal scheduling algorithm is provided, and online scheduling with energy prediction is discussed, all while preserving vigilant operation whenever possible.

#### A. Scheduling Model for General Energy Harvesting Systems

Consider an energy harvesting sensor system which is required to run from  $l$ th to  $N$ th discrete time units. The harvested energy in each time slot is given as:

$$e = [e_1, e_2, \dots, e_N]^T. \quad (1)$$

The independent variable is the energy consumption during these time slots. Assuming the power management is continuous:

$$x = [x_1, x_2, \dots, x_N]^T. \quad (2)$$

A cost function of data quality during the entire operation time is denoted as  $J(x)$ .

In order to maintain continuous operation, the consumed power in each time slot is no greater than the available energy (remaining energy plus energy harvested during the current time slot). Assuming  $e_i$  is positive, which means that energy could be always harvested in each slot, even though it might be arbitrarily small, the formal optimization model could be written as:

Minimize:  $J(x)$

Subject to:

$$\sum_{i=1}^k x_i \leq \sum_{i=1}^k e_i \quad (k = 1, 2, \dots, N) \quad (3)$$

$$x_i > 0, e_i > 0 \quad (i = 1, 2, \dots, N) \quad (4)$$

#### B. Cost Function

The power consumption usually has a positive relationship with data quality service. Intuitively, the power consumption increases with the increase of the sampling rate, operating

speed, or transmission rate, but the relationship isn't necessarily linear. For a vigilant application's cost function, when the system is down the penalty should be high. At the other extreme, data quality can be high enough where increasing the data quality should not reduce the cost function significantly, if at all. Without losing generality, the cost function could be selected as follows to model the relationship between power consumption and data quality.

$$J = \sum_{i=1}^N \frac{1}{x_i} \quad (5)$$

#### C. Optimal Solution

Suppose all the information of harvested energy during each time slot (i.e.,  $e$ ) is known.

Define  $g(x)$  and the Lagrange function as:

$$g(x) = \sum_{i=1}^k x_i - \sum_{i=1}^k e_i \quad (k = 1, 2, \dots, N) \quad (6)$$

$$L(x, \lambda) = f(x) + \lambda g(x), \quad \lambda_i \geq 0, \text{ for } i = 1, 2, \dots, N \quad (7)$$

To find the minimum of  $f(x)$ , the Karush–Kuhn–Tucker (KKT) conditions are:

$$\frac{\partial}{\partial x} L(x, \lambda) = 0 \quad (8)$$

$$\lambda g(x) = 0 \quad (9)$$

That is:

$$\frac{1}{x_i^2} = \sum_{k=i}^N \lambda_k \quad (10)$$

$$\lambda_i (\sum_{i=1}^k x_i - \sum_{i=1}^k e_i) = 0 \quad (11)$$

Note that:

$$\lambda_i = \frac{1}{x_i^2} - \frac{1}{x_{i+1}^2} \quad (i = 1, 2, \dots, N-1) \quad (12)$$

$$\lambda_N = \frac{1}{x_N^2} \quad (i = N) \quad (13)$$

Which indicates:

$$x_i \leq x_{i+1} \quad (14)$$

$$\sum_{i=1}^N x_i = \sum_{i=1}^N e_i \quad (15)$$

There are two trivial solutions. If  $e$  is non-decreasing, then  $x_i = e_i$ . If  $e$  is non-increasing, then  $x_i = \text{average}(e)$ . For a general  $e$  sequence, first we find the  $k$ th equation which is active for  $x_1$ . Find  $k$  ( $1 \leq k \leq N$ ) that minimizes  $\frac{\sum_{i=1}^k e_i}{k}$ , and assign:

$$x_1 = \frac{\sum_{i=1}^k e_i}{k} \quad (i = 1, 2, \dots, N) \quad (16)$$

In this scenario,  $x_1$  is optimal since it cannot be larger to hold the  $k$ th inequalities. If  $x_1$  is smaller, the target function will be larger even though other  $x_i$  gets larger.

Suppose  $\{x_1, x_2, \dots, x_n\}$  is calculated, then for  $x_{n+1}$ :

$$\sum_{i=n+1}^N x_i \leq \sum_{i=1}^N e_i - \sum_{i=1}^n x_i \quad (17)$$

Similar to the way to find  $x_1$ :

$$x_{n+1} = \text{argmin}_k \frac{\sum_{i=1}^k e_i - \sum_{i=1}^n x_i}{k-n}, \quad (n+1 \leq k \leq N) \quad (18)$$

The end case is:

$$x_N = \sum_{i=1}^N e_i - \sum_{i=1}^{N-1} x_i \quad (19)$$

The algorithm is shown below and the complexity is  $O(N^2)$ . The conclusion will still hold if the cost function is extended to  $J = \sum_{i=1}^N \frac{c}{x_i^\alpha}$ ,  $\alpha \geq 1, c > 0$ .

In practice, future energy harvesting information is unknown, but energy harvesting prediction could be employed for online scheduling. In our previous work, we explored energy profiling and leveraged a Kalman Filter (KF) based algorithm for energy prediction[10][11]. Similar to the offline algorithm, the online version could instead use the predicted value  $\hat{e}_i$  in future.

**ALGORITHM:** optimal offline scheduling  
**1: Input:**  $e = [e_1, e_2, \dots, e_N]^T$  for harvested energy in each time slot, and  $N$  for the number time slots  
**2:**  $J = \sum_{i=1}^N \frac{1}{x_i}$  as the cost function of data quality  
**3: Output:**  $x$ , power consumption in each time slot to maximize overall data quality  
**4:**  $x = []$   
**5:** for each  $i$  in  $\{1, 2, \dots, N\}$  do  
**6:**  $min = \text{infinity}$   
**7:** for each  $j$  in  $\{i, i+1, \dots, N\}$  do  
**8:**  $min = \text{Min}(min, \frac{\sum_{k=1}^j e_k - \sum_{k=1}^{i-1} x_k}{j-i+1})$   
**9:** end for  
**10:** assign  $x_i = min$   
**11:** end for  
**12:** return  $x = [x_1, x_2, \dots, x_N]^T$

### III. VIGILANT ATRIAL FIBRILLATION MONITORING

To demonstrate the proposed application-driven DPM model analysis, vigilant AF detection is investigated as a case study. AF is an abnormal heart rhythm, which usually is associated with heart diseases like cardiac failure. Studies show that AF is related to stroke and occurs frequently in elderly persons[1]. The early detection and diagnose of AF could help to prevent heart failure and stroke, but vigilant monitoring is necessary to capture transient periods of AF.

There are two main classes of AF detection approaches: using R-R intervals or QRS waveforms. In a comparative study of AF detection [12], algorithm performances were compared, and the R-R interval-based approach provided better performance. In addition, the QRS waveform could be distorted when the sampling rate is low; therefore, we focus on the R-R interval based AF detection in this work.

The R-R interval variations are used in different ways for AF detection. In [13], a normalized R-R interval variation threshold is set to classify AF events. Some use both the R-R interval and its change for detection[14]. In [15], the Kolmogorov-Smirnov test is used to detect AF episodes. In this paper, we use the method in [13] for its simplicity and high performance.

For R-R interval calculation, we use the curve length transform in [8] and additional methods such as a wavelet transform [16]. The curve length transform algorithm could deal with baseline changes using dynamic threshold.

### IV. EXPERIMENTS AND RESULTS

In this section, ECG signals are resampled at different frequencies to test the AF detection performance to determine the impact of the signal quality in the application performance. A simulation is designed using a real-world energy profile to validate the proposed DPM algorithm.

The ECG data was retrieved from the MIT-BIH AF database[9], number 05121. The recording total length is 10.23 hours, which contains 26 AF and junctional premature episodes that comprise 6.51 hours out of the total length. The WFDB MATLAB Toolbox [17] [18] was used for reading the ECG signal and annotations. The R-R interval calculation algorithm was reimplemented from [8] to tune the parameters for dealing with low sampling frequency scenarios.

#### A. AF Detection Performance vs. Sampling Rate

In the experiment, the raw ECG signal, which was collected at 250Hz originally, is downsampled to simulate low sampling rate scenarios. Then the AF detection with R-R interval calculation algorithm is executed using the downsampled ECG signals. The ROC curves of AF detection under 9 sampling rates from 250Hz to 10Hz are illustrated in Fig. 2. In general, the curve is moving inward as the sampling rate decreases.

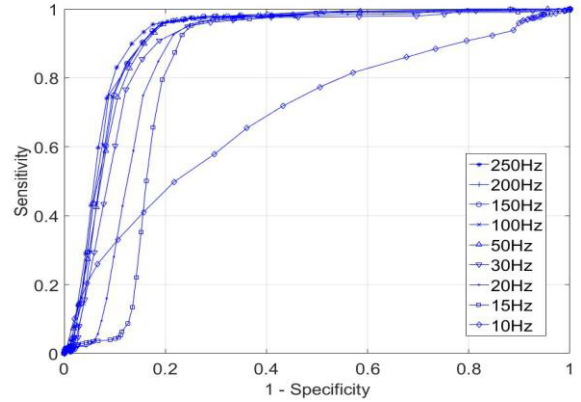


Fig. 2. The receiver operating characteristic (ROC) curve of AF detection under 9 sampling rates. The curve is moving inward as the sampling rate decreases.

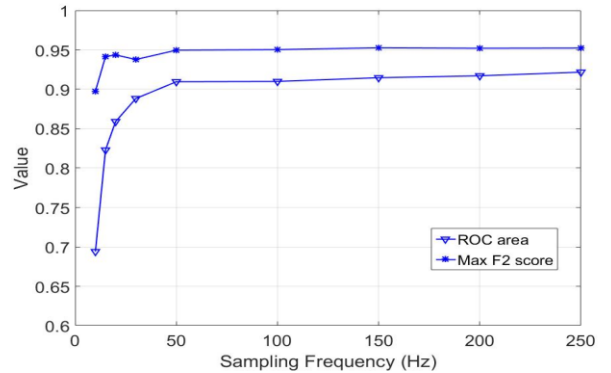


Fig. 3. The ROC area and maximum F2 score over sampling rates.

To compare the AF detection performance numerically under different sampling rates, the ROC area and the maximum F2 score are illustrated in Fig. 3. The ROC area is the area under the ROC curve as shown in Fig 2. The F2 score

considers both classification recall/sensitivity and precision and weights recall higher to reduce the false negative rate (failed to detect AF). For each sampling rate, the maximum F2 score is calculated over the threshold set. For both curves, the value generally increases with sampling rate. For ROC area, the performance increases fast when the sampling rate is low, and slowly when the sampling rate is higher. In addition, the performance almost saturates after 50Hz.

### B. DPM Simulation

A 6-hour duration energy harvesting profile previously collected on body in the real-world is used for simulation. The energy sources include solar and thermoelectric, and the description of the energy profile is in [10].

The profile is used for comparing power management strategies including the proposed algorithm, stoplight without energy harvesting prediction, and a greedy algorithm. The proposed algorithm includes an offline oracle solution and an online algorithm with prediction. For energy harvesting prediction, we assume there is 25% fluctuation for the future 10 minutes, and 60% for the longer timescale. For the stoplight strategy, three power consumption levels are used, and the power manager adjusts power consumption based on current stored energy. For the greedy strategy, all the harvested energy is consumed in each time slot.

For the cost function, 1-ROC could be used as an example in this application. The cost function is adjusted to  $J = \sum_{i=1}^N \frac{a}{x_i + a}$  where  $a=0.17$  according to the curve fitting of the experimental result.

The result of each algorithm is illustrated in Fig. 4. The cost of offline, online, greedy, and stoplight algorithms are 130.99, 131.06, 140.20, and 144.75 respectively. The oracle offline DPM algorithm naturally performs the best, but the proposed online DPM algorithm nearly matches it, performing significantly better than the other two analyzed algorithms.

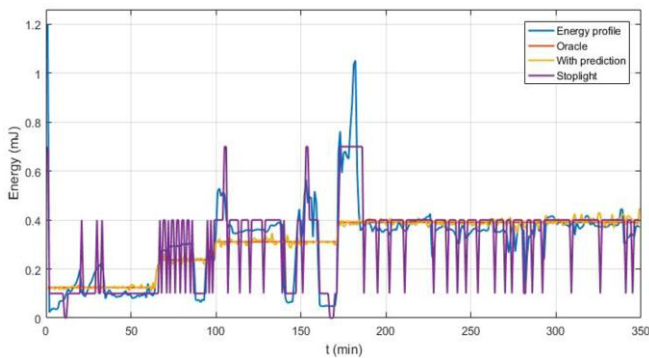


Fig. 4. Simulation of DPM strategies on an energy profile. The cost of offline, online, greedy, and stoplight algorithm is 130.99, 131.06, 140.20, and 144.75 respectively.

## V. CONCLUSION

This paper presents a novel technique for DPM in self-powered BSNs using an application-driven approach that considers the fluctuations in energy available and workload. The DPM scheduling model is proposed and the optimal solution is derived. The vigilant Atrial Fibrillation (AF) monitoring is investigated as a typical case study. The relationship between ECG signal sampling rate and the AF

detection performance is analyzed. A simulation using the real-world energy profile was executed to validate the DPM model, and the optimal solution and results show the high performance of the model against other techniques. In the future, other vigilant monitoring applications will be studied to generalize the DPM idea. Other factors that affect the scheduling model like the capacity of batteries and saturated power consumption will be studied.

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