EHDC: An Energy Harvesting Modeling and Profiling Platform for Body Sensor Networks

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

***Abstract*—Energy harvesting is a promising solution to the limited battery lifetimes of body sensor nodes. Self-powered sensor systems capable of quasi-perpetual operation enable the possibility of truly continuous monitoring of patients beyond the clinic. However, the discontinuous and dynamic characteristics of harvesting in real-world scenarios—and their implications for the design and operation of self-powered systems—are not yet well understood. This paper presents a mobile energy harvesting and data collection (EHDC) platform designed to provide a deeper understanding of energy harvesting dynamics. The EHDC platform monitors and records the instantaneous usable power generated by body-worn harvesters, while also collecting human activity and environmental data to provide a comprehensive real-world evaluation of two energy harvesting modalities common to body sensor networks: solar and thermoelectric. The platform was initially validated with benchtop tests and later with real-world deployments on two subjects. 7-h-long multimodal energy harvesting profiles were generated, and the environmental and behavioral data were used to expand upon previously developed Kalman filter based mathematical models for energy harvesting prediction. Results confirm the validity of the EHDC platform and harvesting models, establishing the potential for longer term monitoring of energy harvesting characteristics; thus, informing the design and operation of self-powered body sensor networks.**

***Index Terms*—Body sensor networks, data modeling, energy harvesting, solar energy, thermoelectricity.**

I. Introduction

BODY sensor networks (BSNs) have shown significant promise in the healthcare domain by allowing physicians, scientists, caregivers, and patients themselves to draw specific correlations between data collected with mobile sensor nodes and human health. These established associations have been demonstrated to be useful for the diagnosis, tracking, and treatment of chronic diseases and other health conditions [1]. Thus the advance of BSNs enabling continuous, long-term monitoring and logging of patient data is of great significance for improving healthcare and quality of life while reducing medical costs.

Even though this potential has been identified, many challenges in BSN design and operation have impeded their widespread adoption, including node lifetime, small wearable form factor, and affordable cost. For many applications such as long-term monitoring of chronic diseases [2]–[6], the required node lifetime is effectively indefinite to provide continuous monitoring and ideally infinite to minimize user burden and maximize compliance. BSN researchers and designers have begun to address this challenge by leveraging advances in energy harvesting technology to develop self-powered sensor systems [4].

Being able to utilize internal and ambient energy sources such as thermal gradients, motion or light to power body-worn sensor nodes creates new challenges to their design and operation. Given the nature of the power source, a node must not only consume less energy on average than the amount being harvested but also manage the time-varying profiles characteristic of these energy sources. In the case of the former challenge, extensive research has been done with the primary focus of redesigning the individual components of BSN nodes along with the optimization of algorithms for computation and communication [7]. Even though the latter challenge has attracted positive attention, the work done to address it has been limited and not extended to real-world scenarios.

When designing self-powered sensor systems, sources such as solar (indoor/outdoor), thermoelectric, piezoelectric, RF, wind, etc. have been explored. Regarding self-powered BSNs, availability is a major factor, but also wearability has a high impact when defining the source to be used. Based on these considerations for self-powered BSNs, solar, thermoelectric and piezoelectric energy harvesting are commonly chosen as the power source options [8]. In this paper, we examine the first two types of power source under indoor and outdoor conditions.

Considering the principles of operation of solar and thermoelectric harvesters and the nature of their corresponding energy sources, the amount of energy that can be harvested must have a particular correlation with human activity and ambient conditions [8]. For instance, in the case of solar cells, it is clear that the ambient illumination level defines the maximum amount

Manuscript received December 22, 2016; revised June 16, 2017; accepted July 20, 2017. Date of publication July 31, 2017; date of current version January 3, 2018. This work was supported by the U.S. National Science Foundation under Grant IIS-1231712 and Grant EEC-1160483. *(Corresponding author: Jiaqi Gong.)*

D. Fan is with the Charles L. Brown Department of Electrical and Computer Engineering and Department of Computer Science, UVA Center for Wireless Health, University of Virginia, Charlottesville, VA 22911 USA (e-mail: df5ah@virginia.edu).

L. Lopez Ruiz and J. Lach are with the Charles L. Brown Department of Electrical and Computer Engineering, UVA Center for Wireless Health, University of Virginia, Charlottesville, VA 22911 USA (e-mail: ljl2wf@virginia.edu; jlach@virginia.edu).

J. Gong is with the Department of Information Systems, University of Maryland, Baltimore County, Baltimore, MD 21250 USA (e-mail: jgong@umbc.edu).

Digital Object Identifier 10.1109/JBHI.2017.2733549

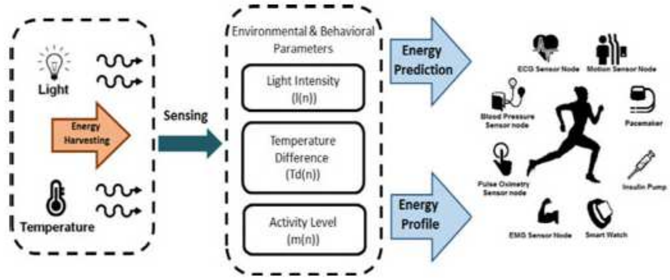

Fig. 1. Profiling and correlating environmental and behavioral parameters with usable harvested energy to model and predict available energy for self-powered body sensor nodes.

of harvested energy, but it also has been studied how the angle of incidence of light impacts the efficiency [9]. In a BSN application where the cell is attached to the body in some manner, both the illumination and the angle of incidence changes as the person moves around during a typical day. Similarly, for a thermoelectric generator (TEG), the temperature difference across the device determines the available power. For a BSN system powered by TEGs, this delta in temperature relates to the difference between the skin temperature and the ambient temperature, most specifically the microclimate surrounding the device. Air flow is a factor that influences this microclimate, and that is also highly dependent on human activity. If the wearer is relatively static, the airflow is practically zero, but while the person is active, the airflow can be high enough to increase the amount of harvested energy considerably. Even though certain information can be retrieved from the datasheets of these devices, the data presented corresponds to static, controlled conditions in a laboratory setting. Accordingly, having a mechanism to understand the relation of human behavior, environmental parameters and energy harvesting can bring valuable insights to help researchers and designers solve key issues for the development of self-powered sensor systems.

Motivated by the challenges above, this research explores the feasibility and dynamics of energy harvesting for self-powered sensors and its correlation with context information in real-world scenarios. Fig. 1 illustrates this concept. The ultimate goal of this work is to provide a framework that gives BSN researchers and designers insights into the design of energy harvesters, low-power electronics, and dynamic power management strategies so that self-powered BSNs can be realized in real-world scenarios.

As part of this exploration, preliminary work was presented in [10] and is expanded here with the following contributions:

1) An energy harvesting and data collection (EHDC) platform – with advances in system integration, flexibility, and wearability – capable of gathering information about human behavioral and environmental parameters along with usable energy harvesting levels from solar and thermoelectric harvesters.
2) Long-term and more naturalistic energy profiles enabled by platform advances that show the interaction among the parameters of interest.
3) Development and validation of a mathematical model that accurately estimates – and makes short-term predictions of – the amount of usable harvested energy based on environmental conditions and activity level.

II. Related Work

This paper focuses on two types of energy harvesting techniques: solar and thermoelectric. Data collections are done in both indoor and outdoor conditions. The EHDC platform is designed to characterize the relationship between environmental and human behavioral conditions and real-world energy harvesting dynamics. Therefore, we review related work in profiling, modeling and predicting energy harvesting instead of a general review on body-worn energy harvesting, which is detailed in [11].

A. Profiling Energy Harvesting

Human behavior profoundly impacts energy harvesting performance in body sensor networks. Therefore, having a better understanding of how such behavior correlates with energy harvesting is fundamental to achieve self-powered sensor platforms. One way to develop this understanding is by defining energy profiles for various energy sources available in the environments where self-powered sensors are deployed.

In [12], power profiles for indoor solar energy harvesting are presented. The profiles were elaborated with data collected over one year, and a simulation for a particular load is designed to show the application of these profiles. The limitation of this work relies on the fact that the energy transducer was fixed next to a window, and as mentioned before, the interest for BSNs is to have profiles that consider human activity. There is even less work on on-body thermoelectric energy harvesting profiling, with one of the few studies presented in [13]. This work shows the correlation of the power generated for one activity (cycling) over one hour and mentions the average amount of energy harvested while working in the office, but it does not present a full profile for different activities over long periods of time. One of the aims of this paper is to present an energy profile over several hours for various typical daily activities, both at work and at home.

B. Solar Energy Harvesting and Modeling

BSN applications must consider both indoor and outdoor use. Most previous research in solar energy harvesting techniques is focused on outdoor applications [14]–[16]. Exponential Weighted Moving Average (EWMA) is a theoretical model issued by Kansal *et al.* [14] to predict harvested solar energy by applying an exponentially weighted moving-average filter on historical data to adapt both diurnal and seasonal variations. Weather-conditioned Moving Average (WCMA) is a model issued in [15] based on EWMA that considers weather changes. It performs better when sudden weather changes occur. Some other works are based on EWMA or WCMA models adding more parameters reflecting environmental variations [16].

BSNs are dominated by indoor use most days for most users, and indoor solar energy harvesting conditions are quite different from the outdoor environment. First, indoor light is usually incandescent light, fluorescent light, LED, etc., rather than the sun.

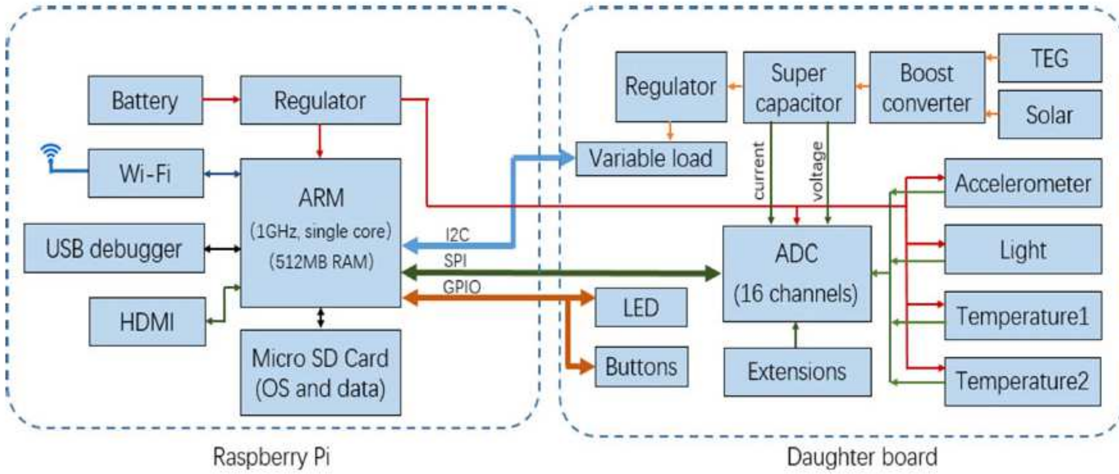

Fig. 2. Block diagram of the EHDC platform and the interface with the Raspberry Pi computer.

The radiant spectra of these light sources differ and therefore affect the efficiency of solar cells. Second, the indoor light has lower illumination level, usually less than 1000 lux, compared to outdoor sunlight, which is 10000–200000 lux. The power density of indoor solar is around $1\,\mu\text{W/mm}^2$ [17]. Third, the indoor light is more controlled by people and has less dependence on weather or seasonal changes.

C. Thermoelectric Energy Harvesting and Modeling

Since human beings are warm-blooded, they can be used as a heat source for TEGs attached to the skin. With consideration of the comfort level for people to wear these devices, it is common to attach TEGs on the wrist or arm. A prototype is proposed and implemented in [18] to demonstrate that TEGs are comparable and even better than solar energy harvesting. They can harvest 250 μW in daytime corresponding to $20\,\mu\text{W/cm}^2$. The TEG harvested energy could be used to extend sensor node lifetime in medical systems, as shown in [19] which presented a fall detection system powered by thermal energy harvested from human warmth with the highest power of 520 μW. A hybrid of indoor ambient light and thermal energy scheme is presented in [8], and the result shows that they can harvest an average of 621 μW with an average indoor irradiance of 1010lux and thermal gradient of 10 K. However, there is still little research on modeling TEG harvesting performance in a variety of real-world environments and human behaviors.

D. Hybrid Modeling

Most previous modeling techniques have limitations on time resolution and robustness to dramatic dynamics of energy harvesting, which is not suitable for self-powered sensors. In real-time embedded systems, an accurate short-term prediction model is required to achieve higher energy efficiency with optimization techniques like dynamic voltage and frequency scaling (DVFS) [13]. In [17], three different prediction methods are tested, and it is concluded that regression analysis works better for a short-time prediction on simulation data. In [18], six empirical statistical models including uniform distribution, geometric distribution, transformed geometric distribution, Poisson distribution, transformed Poisson distribution and a Markovian model are tested for both outdoor and indoor environments, and results show that no single model fits all the data sets. In [20], a hybrid profile energy model (Pro-Energy) of solar and wind was proposed to predict the harvested energy. The model can provide accurate predictions for short and medium term forecasting horizons, but it is not designed for BSN applications and the associated behavior and environmental dynamics.

III. Platform

The EHDC platform incorporates thermoelectric and solar energy harvesting capabilities. It is entirely based on commercial-off-the-shelf (COTS) components, and it interfaces with a Raspberry Pi computer, which serves as a data logger and as a mean to validate the developed models. The architecture of the system is comprised of three main blocks: energy harvesting and power management, sensing and monitoring, and data logging. A block diagram of the full EHDC platform is presented in Fig. 2.

A. Energy Harvesting and Power Management

The main component of the energy harvesting and power management block is the harvester since it transforms a form of harvestable energy into electrical energy. However the output voltage level of the harvester – commonly in the order of mV for BSN applications – often is not adequate to power electronics. Also, if the irregularity of energy available is accounted for, the need for other elements arises. To address the former, a boost converter is a good solution since it not only increases the voltage that is received at the input but it also has the capability of extracting the maximum power from the harvester through an additional circuit that has been designed for this task. In the case of the latter challenge, once the voltage is at the right level, the harvested energy is stored in a supercapacitor that feeds a voltage regulator to provide the load with a constant voltage as it is usually required. As more components are added to the system, it starts to become apparent that certain power is lost during the conversion on each stage. This topology is common to energy harvesting systems, and the relationship between each component can be modeled as depicted in Fig. 3.

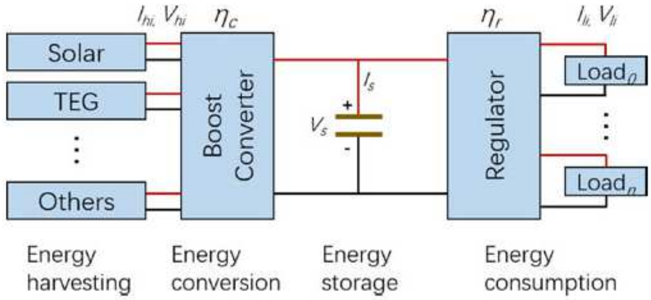

Fig. 3. Diagram of a typical energy harvesting system which consists of four modules: energy harvesting, energy conversion, energy storage, and energy consumption.

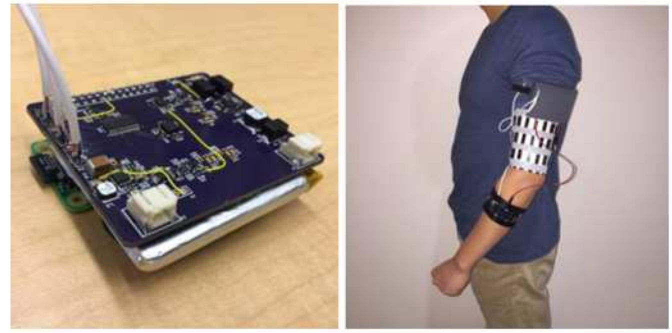

Fig. 4. From left to right, the full EHDC platform for multi-source energy harvesting and the platform deployed for data collection.

The input electrical power from the harvester (I_{hi}, V_{hi}) is reduced by a factor η_c intrinsic to the boost converter, then the resultant power is delivered to the supercapacitor and the regulator. If we consider the supercapacitor as our source at this point, we can assume that the input power to the regulator (I_s, V_s) will be reduced again by a factor η_r defined by the regulator. Finally, the power delivered to the load will be defined by I_l and V_l.

Following the described topology, for the particular case of solar energy harvesting in our platform, we selected an amorphous solar cell from Sanyo. The AM-1417CA cell responds to light sources whose wavelengths are within the 400 nm to 700 nm spectrum range, which makes it ideal for indoor conditions. As a boost converter, the BQ25504 chip from Texas Instruments was considered. The converter incorporates a configurable circuit for maximum power point tracking (MPPT) that senses the input voltage and adjusts the operating frequency of the device to extract the maximum power available. To store the harvested energy, the supercapacitor AVX BZ155B823ZNB was added. It has a capacitance of 82 mF and an equivalent series resistance (ESR) of 125 mΩ. A low-power, low-dropout regulator (LDO) from Linear Technologies was incorporated to implement this block of the system. Most of the current low-voltage devices operate at voltages around 1.8 V, and therefore the output of the LDO was set at that value.

Regarding thermoelectric energy, the SP5424-04AC thermoelectric generators (TEGs) from Marlow were selected. These TEGs have a minimal form factor, which made them ideal for creating an armband for our application. A heatsink was attached to the cold side of each TEG using small carbon conductive tabs to maximize the temperature difference across the TEGs,. Commonly TEGs have lower voltage outputs than solar cells and attending to this need; a different boost converter was dedicated for this case. The LTC3108 from Linear Technologies is a boost converter that can operate from inputs as low as 20 mV by using a small step-up transformer at the input to achieve this functionality. For energy storage and voltage regulation, the same supercapacitor and regulator were used as in the solar case.

B. Sensing and Monitoring

Several sensors were incorporated to monitor the variables relevant to the selected energy sources with the goal of correlating environmental and human behavioral parameters with energy harvesting.

To determine the illumination levels at which the solar cells were exposed, the NOA1212 light sensor from On Semiconductor was attached very close to the cells. Its spectral response is very close to the human eye and within the range of the solar cells of our platform. For temperature measurements, two MAX6605 sensors from Maxim Integrated were used. This device has an accuracy of 0.75 °C at 25 °C and a linear output voltage. One of the MAX6605 was attached to the inner side of the TEG armband for skin temperature measurements while the other one was left exposed close to the heatsinks to monitor the ambient temperature. As a tracker of the activity level, we included the ADXL326 accelerometer from Analog Devices to the platform. This sensor has a minimal form factor, and the external components required for its operation are minimal. To determine the instantaneous usable power, we monitored the current delivered by the boost converter and its output voltage. In the first case, we used the current shunt monitor INA285 from Texas Instruments with a shunt resistor of 20 Ω. This setup allows us to monitor current in high-resolution while also minimizing losses. For the latter, we used a 16-channel analog to digital converter (ADC) from Analog Devices. By having the AD7490 in our platform, we were not only able to monitor the voltage at the output of the boost converter but also digitize the readings from the other analog sensors used for later processing and logging. It is worth to remind the reader that one of the goals of this work is to determine the usable power and not to characterize the harvesters. Thus our setup just described. Fig. 4 presents the full EHDC platform and a subject wearing it during one of the data collection sessions.

C. Data Logging

To log the sensor data that was being collected for later analysis, the Raspberry Pi microcomputer was designated for this task given its flexibility and easiness of use. Linux was used as the operating system (OS) for the Raspberry Pi, and the software for logging the data from the EHDC platform was programmed in Java. The collected sensor data was stored in a micro SD card and to reduce the power expended with each logging; the data was compressed into binary files. Additional software was developed to enable uploading the sensor data to a custom cloud server for data visualization and storage in real time.

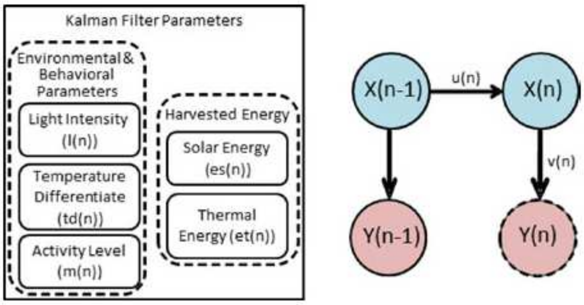

Fig. 5. Illustration of the prediction model, which is consisted of state process and measurement; the state process is defined by the environmental and human behavioral parameters, particularly the sensor values regarding of light intensity, temperature difference, and human activity level, while the measurement is the data from sensors.

IV. Energy Prediction Model

In this section, we propose a Kalman Filter (KF) based model to predict the harvested energy based on environmental and human behavioral parameters. KF is an estimation model that combines several previous observations to produce an estimate for the desired unknown as it is presented in [21]. The proposed model was adapted from this work and consists of state process and measurements by sensors; the state process is defined by the environmental and human behavioral parameters since they represent the physical principle of self-powered energy harvesting while the measurement values are acquired from sensors. Fig. 5 demonstrates the prediction model.

A discrete time-slotted system is assumed to facilitate the processing. The time slot is selected considering sensor sensitivity, human motion features, and the desired time scale to predict. Here the time slot is selected as 10 seconds. Then the model could be defined as:

$$\begin{aligned} x(n) &= Ax(n-1) + u(n) \\ y(n) &= Hx(n) + v(n) \end{aligned} \tag{1}$$

in which $x(n)$ is the state vector, $y(n)$ is the measurement vector, $u(n)$ is the process noise, and $v(n)$ is the measurement noise. For simplicity, it is assumed that $u(n)$ and $v(n)$ are independent and both Gaussian distributed with zero mean and variance of σ_u^2 and σ_v^2, respectively.

A. Adaptation of Kalman Filtering for Harvesting Prediction

Kalman Filtering is used to estimate the observation and to predict the harvested energy in the near future. The observation measurement $y(n)$ includes harvested energy from solar, thermoelectric source, and also the parameters of light intensity, temperature difference, and human motion. The latter is assumed to be related to the change of harvested energy since it directly affects the energy received by the transducer. For instance, the amount of incident light to the indoor solar cell will vary if the person moves closer or further from the light sources while walking to another room. Similarly, thermoelectric energy will fluctuate according to the airflow across the heat sink due to slow or fast movements. Therefore, the state vector is chosen as:

$$x(n) = [e_s(n),\ e_t(n),\ l(n),\ t_d(n),\ m(n)] \tag{2}$$

where $e_s(n)$ and $e_t(n)$ are harvested solar and thermoelectric energy in the time-slot, $l(n)$ is light intensity sampled by the light sensor and t_d is the temperature difference. $m(n)$ is a function of human motion; in this paper, we use the Teager energy calculator.

The measurement vector is the same as the state vector. Note that the harvested energy is calculated using measured voltage and current.

$$y(n) = [e_s(n),\ e_t(n),\ l(n),\ t_d(n),\ m(n)] \tag{3}$$

The transition matrix can be modeled as

$$A = \begin{bmatrix} 0 & 0 & a & 0 & b \\ 0 & 0 & 0 & c & d \\ 0 & 0 & 1 & 0 & e \\ 0 & 0 & 0 & 1 & f \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{4}$$

Since the measurement data is simply from sensors (or with simple calculation), the measurement matrix is an identity matrix.

B. State Prediction Using Kalman Filtering

There are two steps in Kalman Filtering: a prediction step and an update step. In prediction step, the current state is estimated using previous data, and this is also called *a priori* estimate.

$$\hat{x}(n|n-1) = A\hat{x}(n-1|n-1) \tag{5}$$

$$P(n|n-1) = AP(n|n-1)A' + {\sigma_u}^2 \tag{6}$$

where $\hat{x}(n|n-1)$ is the predicted current state according to previous results and $P(n|n-1)$ is the covariance matrix. With the current measurement, the residual, variance, and the optimal KF gain is

$$\tilde{y}(n) = y(n) - Hx(n|n-1) \tag{7}$$

$$S(n) = HP(n|n-1)H' + {\sigma_v}^2 \tag{8}$$

$$K(n) = P(n|n-1)H'S(n)^{-1} \tag{9}$$

In the update step, the updated estimation is

$$\hat{x}(n|n) = \hat{x}(n-1|n-1) + K(n)(y(n) - H\hat{x}(n|n-1)) \tag{10}$$

$$P(n|n) = (I - K(n)H)P(n|n-1) \tag{11}$$

This is also called the *a posteriori* estimate. To predict future state, (5) could be used one or more times.

V. Experimental Results

This section presents the profile of energy harvesting in the real world and the performance of the proposed prediction model.

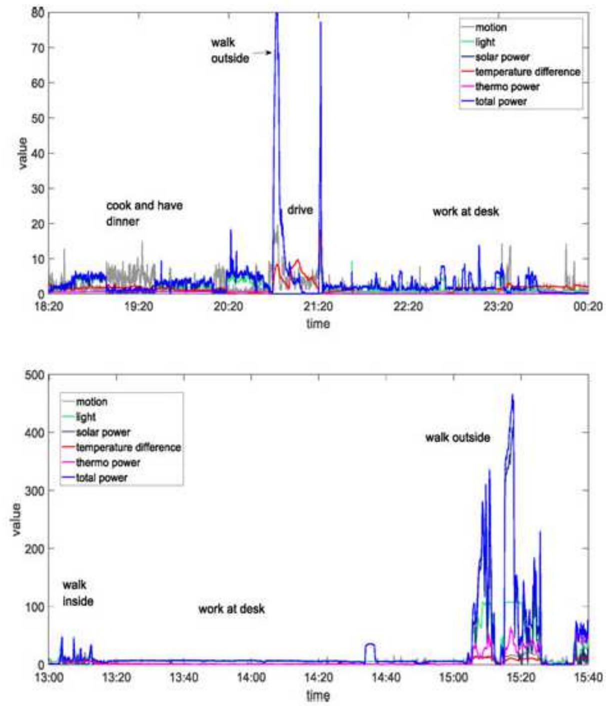

Fig. 6. Energy harvesting profile at home (top) and office (bottom). The profile includes motion (scaled Teager energy), light intensity (100 lux), averaged solar power (μW), the temperature difference between skin and ambient air (°C), averaged thermoelectric power (μW), and total power (μW). Activities are marked in the figures.

A. Energy Harvesting Profile

We created four profiles from two male subjects who worn the platform across multiple days to collect data in mainly indoor environments (e.g., office and at home). More than 80% of the activities occurred indoor, but some outdoor activities are also included. The energy profile display motion (scaled Teager energy), light intensity (unit: 100 lux), averaged solar power (μW), the temperature difference between skin and ambient air (°C), averaged thermoelectric power (μW), total power (μW). Due to the limited space, only two of the profiles are shown in Fig. 6.

The energy harvesting profile data displayed in Fig. 6 (top) is collected mainly at home. The activities include indoor activities like cooking, working at a desk, and walking around, and a short period of outdoor activities, such as walking outside and driving. The average indoor light intensity is 209 lux, and around 0 lux outdoor since it is at night. The average temperature difference indoor is 1.1 °C, and 6.1 °C when walking outdoor. The average indoor power is 3.6 μW, and average outdoor power is 41.7 μW which is almost all thermal energy.

Fig. 6 (bottom) displays a profile created in and around the office. The activities include indoor walking, working at a desk, and outdoor walking. The average light intensity in the office room is 537.1 lux and more than 10000 lux outdoor. The average temperature difference is 5.0 °C when the subject is walking indoor, and only 0.9 °C when sitting at desk. When walking outdoor, the average temperature difference is 9.7 °C. The average indoor power is 7.1 μW, and average outdoor power is 171.4 μW.

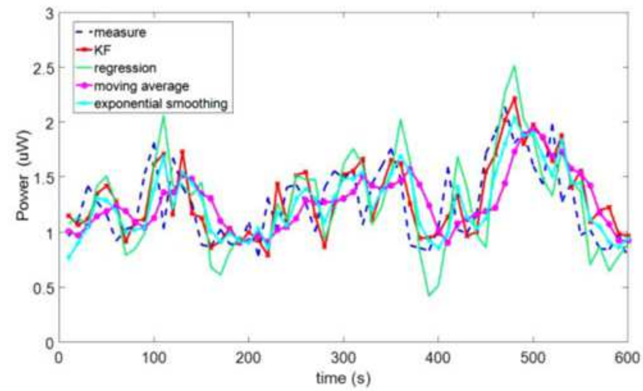

Fig. 7. Comparison results (a duration of 10 min) of the energy prediction using proposed KF model and model of regression (n = 4), exponential smoothing (a = 0.3), moving average (n = 4). MAPE values are 19.8% from the proposed model, and 26.2%, 22.0%, 20.6% from the regression, moving average, and exponential smoothing model, respectively.

In the indoor environment, most of the time solar power dominates the total power profile. In certain situations, such as walking, the thermoelectric power dominates due to the arm movement. In the outdoor environment, since the ambient air temperature is low, there is much more thermal energy harvested than indoor.

From the figures, it is possible to see that the light intensity and harvesting power have a good linear relationship. On the other hand, the temperature difference and harvested thermoelectric power are not linearly related. Instead, thermoelectric power is related with motion for some time. This indicates that human activity level – which relates to airflow – has a significant influence on thermoelectric energy harvesting. Also, it is noteworthy that solar cells are more efficient than TEGs by providing approximately 27.4 $\mathrm{uW/cm^2}$ compared to 4.45 $\mathrm{uW/cm^2}$ of the latter, both under good harvesting conditions.

Even though the usable power coming from energy harvesting is very limited here, it is important to note that this work focuses on the feasibility and dynamics of energy harvesting for self-powered BSNs in the real world and is not intended to characterize or optimize the harvesters themselves. If higher power is needed for a particular application, the area of the harvester(s) could be increased. However, the state-of-the-art of ultra-low power electronics has presented solutions for self-powered BSNs at even these low harvesting levels. For instance, in [22] a 6.45 uW system-on-chip (SoC) for biomedical applications was presented and a 23 nW temperature sensor was introduced in [23]. Similarly, leading edge COTS technology has available devices for self-powered BSNs such as the ADXL362 accelerometer from Analog Devices that consumes 3.6 uW or the Bluetooth SoC DA14580 from dialog semiconductor, which can operate with 1.2 uW when setting into the deep-sleep mode.

B. Performance of the Prediction Model

The performance of the proposed short time energy prediction model is shown in Fig. 7, which compares predictions using the proposed KF model with environmental and behavioral parameters and other models including regression, moving average, and exponential smoothing, which is compared in [17]. It is shown in the figure that the prediction from proposed model accords better with the measured values than the other models.

The mean absolute percentage error (MAPE), which is the computed average of percentage errors between predicted values and measured values, is used to compare the prediction performance. MAPE values are 19.8% from the proposed model, and 26.2%, 22.0%, 20.6% from the regression, moving average, and exponential smoothing model, respectively.

According to the performance comparison, the proposed model with environmental and human behavioral parameters performed better than the others. The improvement in performance comes from the information integration of dynamic environmental and human behavioral parameters. Besides, the results reveal the relationship between environmental and human behavioral parameters and energy harvesting.

VI. Conclusion

This paper was motivated by the demands of balancing energy harvesting and energy consumption in BSNs and inspired by the relationship between environmental and human behavioral parameters and energy harvesting. We designed, implemented, and validated a wearable platform – EHDC – for collecting simultaneous data on environmental and human behavioral parameters and on solar and TEG harvested energy to generate time-domain profiles of energy harvesting under real-world BSN scenarios. Also, this paper proposed a KF based model to predict the harvested energy, which can then be used to manage both harvesters and energy consuming electronics dynamically. The main contributions come from the hardware platform, time-domain profiling of energy harvesting and the prediction model, which together provide a new view into self-powered wearable sensor design. Experimental results demonstrate that human behaviors profoundly impact energy harvesting and that the prediction model is efficient to calculate and predict harvested energy in real time.

Future work focuses on more experiments for collection and analysis of new data to extend and develop more complex, nonlinear models that lead to improvements on accuracy for short and long term harvesting prediction.

References

[1] M. A. Hanson *et al.*, "Body area sensor networks: Challenges and opportunities," *Computers*, vol. 42, no. 1, pp. 58–65, Jan. 2009.

[2] T. Falck, J. Espina, J. Ebert, and D. Dietterle, "BASUMA—The sixth sense for chronically ill patients," in *Proc. Int. Workshop Wearable Implantable Body Sensor Netw.*, 2006, pp. 57–60.

[3] A. Maciuca, M. Strutu, D. Popescu, and G. Stamatescu, "Cell-based sensor network for complex monitoring at home of patients with chronic diseases," *4th Int. Symp. Elect. Electron. Eng.*, 2013, pp. 1–6.

[4] J. Dieffenderfer *et al.*, "Low-power wearable systems for continuous monitoring of environment and health for chronic respiratory disease," *IEEE J. Biomed. Health Informat.*, vol. 20, no. 5, pp. 1251–1264, Sep. 2016.

[5] M. Gors, M. Albert, K. Schwedhelm, C. Herrmann, and K. Schilling, "Design of an advanced telemedicine system for remote supervision," *IEEE Syst. J.*, vol. 10, no. 3, pp. 1089–1097, Sep. 2016.

[6] Q. Javaid, N. F. Fesmire, M. A. Weitnauer, and O. T. Inan, "Towards robust estimation of systolic time intervals using head-to-foot and dorso-ventral components of sternal acceleration signals," *IEEE 12th Int. Conf. Wearable Implantable Body Sensor Netw.*, 2015, pp. 1–5.

[7] V. Misra *et al.*, "Flexible technologies for self-powered wearable health and environmental sensing," *Proc. IEEE*, vol. 103, no. 4, pp. 665–681, Apr. 2015.

[8] Y. K. Tan and S. K. Panda, "Energy harvesting from hybrid indoor ambient light and thermal energy sources for enhanced performance of wireless sensor nodes," *IEEE Trans. Ind. Electron.*, vol. 58, no. 9, pp. 4424–4435, Sep. 2011.

[9] C. Seshan, "Cell efficiency dependence on solar incidence angle," in *Proc. 35th IEEE Photovolt. Spec. Conf.*, 2010, pp. 2102–2105.

[10] D. Fan, L. L. Ruiz, J. Gong, and J. Lach, "Profiling, modeling, and predicting energy harvesting for self-powered body sensor platforms," in *Proc. 13th Int. Conf. Wearable Implantable Body Sensor Netw.*, 2016, pp. 402–407.

[11] V. Leonov, "Energy harvesting for self-powered wearable devices," in *Wearable Monitoring Systems*. New York, NY, USA: Springer, 2011, pp. 27–49.

[12] C. Viehweger, M. Baldauf, T. Keutel, and O. Kanoun, "Energy profile analysis by simulation for the design of energy harvesting systems," *Int. Multi-Conf. Syst., Signals Devices*, 2012, pp. 1–3.

[13] V. Leonov, "Thermoelectric energy harvesting of human body heat for wearable sensors," *IEEE Sensors J.*, vol. 13, no. 6, pp. 2284–2291, Jun. 2013.

[14] A. Kansal, J. Hsu, S. Zahedi, and M. B. Srivastava, "Power management in energy harvesting sensor networks," *ACM Trans. Embedded Comput. Syst.*, vol. 6, no. 4, 2007, Art. no. 32.

[15] J. R. Piorno, C. Bergonzini, D. Atienza, and T. S. Rosing, "Prediction and management in energy harvested wireless sensor nodes," in *Proc. 2009 1st Int. Conf. Wireless Commun., Veh. Technol., Inf. Theory Aerosp. Electron. Syst. Technol.*, 2009, pp. 6–10.

[16] M. Hassan and A. Bermak, "Solar harvested energy prediction algorithm for wireless sensors," in *Proc. 4th Asia Symp. Qual. Electron. Des.*, 2012, pp. 178–181.

[17] J. Lu, S. Liu, Q. Wu, and Q. Qiu, "Accurate modeling and prediction of energy availability in energy harvesting real-time embedded systems," in *Proc. 2010 Int. Conf. Green Comput.*, 2010, pp. 469–476.

[18] P. Lee, Z. A. Eu, M. Han, and H.-P. Tan, "Empirical modeling of a solar-powered energy harvesting wireless sensor node for time-slotted operation," in *Proc. 2011 IEEE Wireless Commun. Netw. Conf.*, 2011, pp. 179–184.

[19] S. Bader and B. Oelmann, "Enabling battery-less wireless sensor operation using solar energy harvesting at locations with limited solar radiation," in *Proc. 4th Int. Conf. Sensor Technol. Appl.*, 2010, pp. 602–608.

[20] V. Leonov, T. Torfs, P. Fiorini, and C. Van Hoof, "Thermoelectric converters of human warmth for self-powered wireless sensor nodes," *IEEE Sens. J.*, vol. 7, no. 5, pp. 650–657, May 2007.

[21] D. C. Hoang, Y. K. Tan, H. B. Chng, and S. K. Panda, "Thermal energy harvesting from human warmth for wireless body area network in medical healthcare system," in *Proc. Int. Conf. Power Electron. Drive Syst.*, 2009, pp. 1277–1282.

[22] A. Cammarano, C. Petrioli, and D. Spenza, "Pro-energy: A novel energy prediction model for solar and wind energy harvesting wireless sensor networks," in *Proc. Int. Conf. Mobile Ad-Hoc Sensor Syst.*, 2012, pp. 75–83.

[23] R. E. Kalman and R. S. Bucy, "New results in linear filtering and prediction theory," *J. Basic Eng.*, vol. 83, no. 1, pp. 95–108, 1961.

[24] A. Roy *et al.*, "A 6.45 μW self-powered SoC with integrated energy-harvesting power management and ULP asymmetric radios for portable biomedical systems," *IEEE Trans. Biomed. Circuits Syst.*, vol. 9, no. 6, pp. 862–874, Dec. 2015.

[25] A. Kamakshi, A. Shrivastava, and B. Calhoun, "A 0.2 V, 23 nW CMOS temperature sensor for ultra-low-power IoT applications," *J. Low Power Electron. Appl.*, vol. 6, no. 2, pp. 1–16, 2016.