Adaptive Maximization of Harvested Kinetic Energy for Small Wearable Medical Sensors

Hamid Mahboubi
Concordia University
Montreal, Canada
mahboubi@ece.concordia.ca

Kamran Sayrafian
National Institute of Standards and Technology
Gaithersburg, USA
kamran.sayrafian@nist.gov

Amir G. Aghdam
Concordia University
Montreal, Canada
aghdam@ece.concordia.ca

***Abstract*—Energy harvesting (EH) is the process of capturing and storing energy from external sources or the ambient environment. The EH devices have found various emerging applications, particularly, in healthcare sector. Kinetic-based micro energy-harvesting is a promising technology that could prolong the lifetime of batteries in small wearable or implantable devices. In this paper, using a mathematical model of a Coulomb-force parametric generator, we analyze the dependency of the output power on the electrostatic force in this micro-harvester. We propose a very low complexity strategy to adaptively change the electrostatic force in order to maximize the harvested power. Simulation results using the human acceleration measurements confirm the effectiveness of the proposed strategy.**

***Index Terms*—Micro energy-harvester, wearable sensors, optimization, Coulomb-Force Parametric Generator**

I. Introduction

WEARABLE and implantable medical sensors (and actuators) have become a promising interdisciplinary research area in the Internet-of-Things technology for healthcare [1]–[5]. With wireless communication capability, these devices will enable an attractive set of applications for remote monitoring of physiological signals such as temperature, respiration, heart rate, glucose, and blood pressure [6], [7]. Increasing functionality and complexity along with the desired miniaturization have drawn the attention of researchers to the limited source of power in these devices [8]. Frequent recharge or battery replacement is simply not feasible in many applications and could negatively impact their market adoption. As such, any technology that can prolong the operational lifetime of these devices will undoubtedly contribute toward their commercial success.

The process of capturing and storing energy from external sources or the ambient environment is referred to as energy harvesting (EH). There are a few sources from which we can harvest energy for wearable or implantable medical sensors. Examples of these sources are ambient light, body heat, and the general movement of the human body [3], [9]–[11]. Kinetic energy harvested from the human body motion is the most convenient solution for wearable devices [12]–[14]. Miniaturized energy-harvesting devices, also known as micro-generators, typically consist of a mass-spring-damper (MSD), transducer, and a power-processing circuit. Movements of the human body are captured by the MSD module and converted into mechanical power. The transducer converts this mechanical power into electrical energy. The power-processing circuitry matches the electrical power generated by the transducer with the load [15], [16].

Kinetic-based microgenerators either utilize the direct application of force on the device or make use of the inertial ambient forces acting on a proof mass. The MSD designs that employ a spring (or a spring-like feature) are mostly suitable for applications where the environment causes the system to constantly vibrate [17]. However, the human body motion is typically not a vibrating source of motion. As a result, a microgenerator that can efficiently capture energy from human motion should have a non-resonating design. One such non-resonating microgenerator architecture is the Coulomb-force parametric generator (CFPG) [18], [19], [20]. The MSD component in this architecture is nonlinear in nature. The proof mass does not vibrate up and down as if anchored on a spring-like structure. Instead, the transducer's damping force, a constant Coulombic electrostatic holding force, keeps the proof mass to an end-stop limit. The proof mass is held against one end-stop until the external acceleration exceeds the holding force threshold [21]. No power is generated while the proof mass is stuck on either end; instead, power is generated when the proof mass makes a full flight from one end-stop to the other. Another advantage of the CFPG design is its transduction method. It utilizes electrostatic force rather than making use of electromagnetic or piezoelectric forces. Any of these forces can be used to generate electrical power by converting mechanical energy into an electrical form. However, on the micro-scale, the electrostatic force becomes more significant and suitable for electric power generation [19]. This means that the transduction method in CFPG allows for further miniaturization of the micro-harvester which is a highly desirable feature for wearable or implantable sensors.

The authors in [22] highlighted the significant impact of the electrostatic force on the magnitude of the harvested power for various human activities. In [23], an adaptive maximization problem was formulated to exploit the dependency of the optimal holding force on the input acceleration waveform in order to achieve a gain in the micro-generator output power.

This research has been supported by the National Institute of Standards and Technology (NIST) under Grant 70NANB8H8146. The extended version of this paper has been submitted to the IEEE Access.

ICC 2023 - IEEE International Conference on Communications | 978-1-5386-7462-8/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICC45041.2023.10279411

Using the same strategy, the authors in [24] investigated several methodologies such as Least Square and Machine Learning to obtain a near-optimal solution to the maximization problem and adapt the electrostatic force based on the acceleration waveform. Despite the achieved gain in the harvested power, the complexity of the methodologies used in solving the optimization problem is a major concern. High complexity algorithms would consume more energy themselves; and therefore, reduce the net overall gain in the generated energy. As such, our objective in this paper is to focus on a low-complexity approach that can be used to adapt the electrostatic force based on the input acceleration. Following an in-depth analysis and observation of the generated power for several artificially generated acceleration waveforms, we propose a computationally simple strategy that can efficiently maximize the output power in a CFPG. The results are also verified with actual acceleration measurements from the human body motion.

The remainder of this paper is organized as follows. In Section II, we propose a low complexity strategy to adaptively change the electrostatic holding force in order to maximize the average generated power. The performance of the proposed strategy is investigated in Section III. Finally, conclusions and future plans are discussed in Section IV.

II. A Low Complexity Adaptive Strategy

The following non-linear differential equation captures the dynamics of the MSD module in a CFPG micro energy harvester [23].

$$m\ddot{y}(t) = -m\ddot{x}(t) - F(t) \times relay\,(x(t)) \qquad (1)$$

In the above equation, m represents the proof mass, $y(t)$ is the motion of the generator frame with respect to the inertial frame, ($\ddot{y}(t)$ is the second derivative of $y(t)$ and indicates the input acceleration), $\ddot{x}(t)$ is the proof mass acceleration, F represents the Coulomb force (also referred to as electrostatic holding force or more generally the MSD's damping force), $x(t)$ is the absolute motion of the proof mass and $relay(.)$ represents a hysteresis function that switches between $+/-1$ values. The mechanical power generated by the MSD component can be computed as follows:

$$P(t) = F(t) \times \dot{x}(t) \qquad (2)$$

where $F(t)$ is the holding force and $\dot{x}(t)$ represents the velocity of the proof mass.

The Simulink implementation of this model has been provided in [23]. The model accurately represents scenarios where the input acceleration does not cause a full end-to-end flight of the proof mass. In those cases, the instantaneous output power will have equal positive and negative components (reactive power); and therefore, a zero average power will be generated. This complies with the stated physical requirements in [20]. On the other hand, if the amplitude of the input acceleration is sufficient enough to move the proof mass to the other endpoint, then positive energy will be generated.

Using the Simulink model of the MSD, we have studied the average generated power for a step function acceleration. We observed that the average generated power monotonically increases by increasing the electrostatic force up to a certain threshold and then drops to zero. This threshold depends on the amplitude of the step function. Assume that the optimal electrostatic force for the step function with amplitude a is denoted by $F_{opt}(au(t))$. This optimal value is a linear function of the amplitude of the step function i.e., $F_{opt}(au(t))$=$G(|a|)u(t)$, where $G(.)$ represents the linear function, and $|.|$ represents the absolute value function.

Using this result, we can propose a low complexity methodology to adaptively adjust the electrostatic force such that the generated power increases. Consider the acceleration waveform $y(t)$ during the time interval $[0, T]$. Divide this time interval into n equal subintervals of length δ, i.e., $[k\delta, (k+1)\delta],\ k \in \mathbf{n} := \{0, 1, \ldots, n-1\}$. We assume that there is the capability to adjust the electrostatic force at the beginning of each subinterval in order to maximize the average output power of the MSD. Let F_k denote the constant value of the electrostatic force during the time interval $[k\delta, (k+1)\delta]$. As indicated in Eq. (2), the output power during this time interval is directly proportional to F_k. Therefore, the power maximization problem can be formulated as follows:

$$\underset{F_0, F_1, \ldots, F_{n-1}, \delta}{\operatorname{argmax}} \left[\frac{1}{T} \sum_{k=0}^{n-1} \int_{k\delta}^{(k+1)\delta} F_k \times \dot{x}(t)dt \right] \qquad (3)$$

where δ and F_k, $k = 0, 1, \ldots, n-1$, are design parameters, and $\dot{x}(t)$ represents the velocity of the proof mass. Aside from an exhaustive search, identifying a methodology that can determine the optimal values δ^* and F_k^* in Eq. (3) is quite challenging. In this paper, we first simplify the problem by assuming that δ is a given constant. Then, using our observations with the simple acceleration waveform discussed in the previous section, we propose a low complexity methodology that can serve as an approximate solution to Eq. (3). To this end, we first approximate the input acceleration $y(t)$ with the waveform $\widetilde{y}$(t) as a summation of weighted and delayed step functions. Define y_k as the input acceleration $y(t)$ at $t = k\delta$. Then, we will have:

$$y(t) \approx \widetilde{y}(t) = \sum_{k=0}^{n-1} y_k[u(t-k\delta) - u(t-(k+1)\delta)] \qquad (4)$$

Fig. 1 demonstrates a sample acceleration waveform and its approximation according to Eq. (4) with $\delta = 0.02$ s.

With $\widetilde{y}(t)$ expressed as a sequence of weighted step functions, we can estimate the optimal value for the electrostatic force as follows:

$$F_{opt}(\widetilde{y}(t)) = F_{opt}(\sum_{k=0}^{n-1} y_k[u(t-k\delta) - u(t-(k+1)\delta)] \qquad (5)$$

Eq. (5) can be further simplified to:

$$F_{opt}(\widetilde{y}(t)) \approx \sum_{k=0}^{n-1} G(|y_k|)[u(t-k\delta) - u(t-(k+1)\delta)] \qquad (6)$$

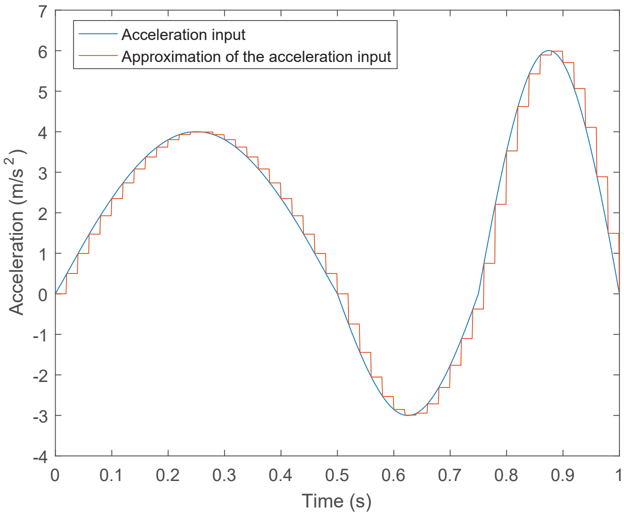

Fig. 1: Acceleration waveform and its approximation

Note that the results for a single step function assumed that the proof mass is initially resting at an end-stop. Here, we propose to use Eq. (6) as an approximate solution to the maximization problem expressed by Eq. (3). In other words, if F_k^{adp} denotes an adaptive strategy to update the value of F_k at each time instant $k\delta,\ k \in \mathbf{n}$, then we claim that the following equation:

$$F_k^{adp} = G(|y_k|) \tag{7}$$

provides a low complexity scheme to adjust the electrostatic force for input acceleration waveform $y(t)$ at each time instant $k\delta,\ k \in \mathbf{n}$. Fig. 2 demonstrates the adaptive electrostatic force based on Eq. (7) corresponding to the input waveform shown in Fig. 1.

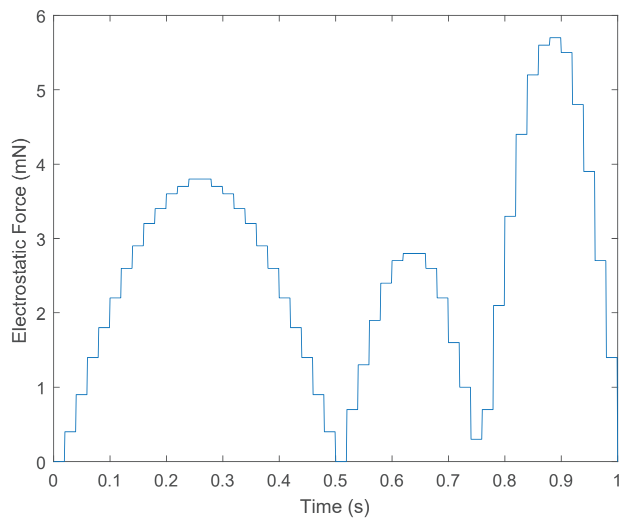

Fig. 2: Adaptive electrostatic force corresponding to acceleration input $y(t)$ given in Fig. 1

Remark 1. When $\delta = T$, solving the maximization problem in Eq. (3) results in the optimal constant value for the electrostatic force, hereafter denoted by F_{opt}^c. It is to be noted that finding F_{opt}^c is not realistic, as in most practical situations, knowledge of the entire waveform is not available or predictable beforehand. In the next section, we compare the harvested power under our proposed adaptive scheme with several constant values of the electrostatic force F^c. We have also considered F_{opt}^c for performance evaluation purposes although obtaining its value is not practically feasible. In general, the gain of any adaptive scheme should be measured against a constant electrostatic force which may not necessarily be optimal.

III. Simulation Results

In this section, the effectiveness of the proposed adaptive strategy is investigated using acceleration data measured from several human activities[1]. The data is obtained by using an X16-mini USB triaxial accelerometer[2]. With a small dimension of 51×25×13 mm, this accelerometer can be easily placed on different parts of the body to perform various measurements. The measurement samples are time-stamped and stored in a CSV file in an onboard memory for later retrieval. The accelerometer has adjustable sampling rates from 12 Hz to 800 Hz. A sampling rate of 100 Hz has been used in our measurements. The results in this paper have been obtained assuming a MSD with the following specifications: proof mass = 0.965 g, and the distance between the two end-stops = 5 mm. We conjecture that the general conclusions expressed here are independent of the MSD specifications.

Extensive experiments using this accelerometer have been done to generate a dataset of various acceleration waveforms corresponding to several human activities at various intensity levels and different placements of the accelerometer. Figs. 3 and 4 show the acceleration waveforms for random body movements when the accelerometer is placed on the chest and wrist, respectively. The optimal constant electrostatic force for these waveforms are $F_{opt}^c = 1$ mN and $F_{opt}^c = 2.9$ mN, respectively. Considering an adaptation interval of $\delta = 0.02$, Figs. 5 and 6 display the harvested energy under the adaptive holding force strategy, the optimal constant force, and constant forces $F^c = 0.5$ mN and $F^c = 1.5$ mN. As observed, the harvested energy with the acceleration data from the chest is 652.0 μJ, 263.7 μJ, 211.8 μJ and 141.2 μJ under the adaptive strategy, optimal constant holding force, and constant forces $F^c = 0.5$ mN and $F^c = 1.5$ mN respectively. This indicates 147%, 207%, and 362% increases in the harvested energy using the proposed adaptive strategy compared to the harvested energy using optimal constant force, constant forces $F^c = 0.5$ mN and $F^c = 1.5$ mN, respectively. Similarly, with the acceleration data obtained from the wrist motion, the

[1]The experiments were conducted according to the research ethics regulations under the approval number 30013664 at Concordia University and ITL-2021-0273 at NIST.

[2]X16 mini accelerometer is a product of Gulf Coast Data Concepts, LLC. Commercial products mentioned in this paper are merely intended to foster research and understanding. Such identification does not imply recommendation or endorsement by the National Institute of Standards and Technology.

harvested energy under the adaptive strategy is 790.9 μJ, 24%, 212%, and 65% more than the 635.5 μJ, 253.3 μJ, and 480.5 μJ harvested under the optimal constant electrostatic forces $F^c = 0.5$ mN and $F^c = 1.5$ mN, respectively. These results indicate noticeable gain of our proposed adaptive strategy in harvesting energy from kinetic motion of the human body.

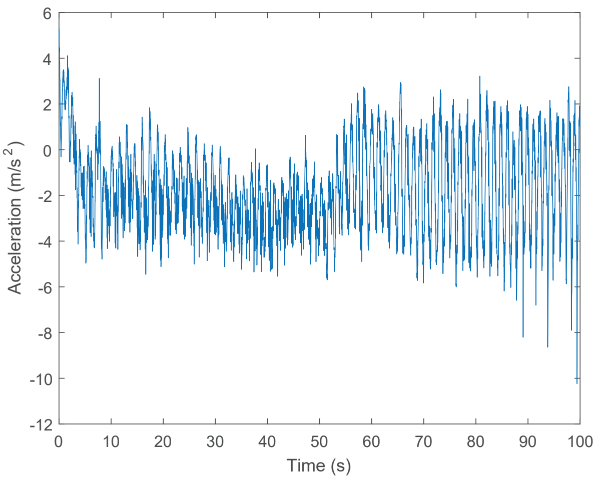

Fig. 3: Acceleration waveform corresponding to random body movements with the accelerometer placed on the chest

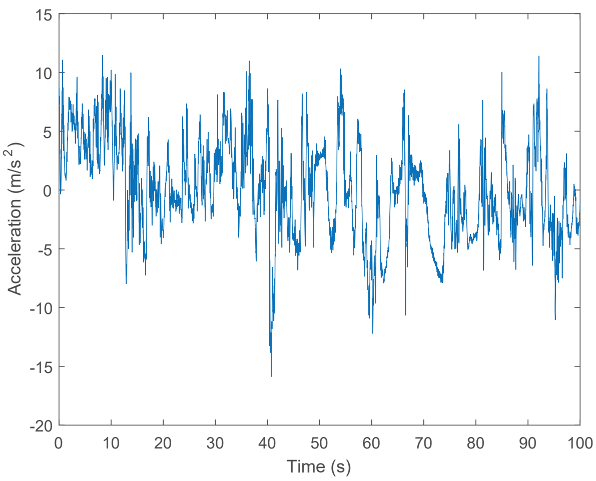

Fig. 4: Acceleration waveform corresponding to random body movements with the accelerometer placed on the wrist

Figs. 7 and 8 display the instantaneous power generated under the adaptive strategy and optimal constant holding force for the chest acceleration data. Similar to the results for the light jogging motion, there are fewer instances of zero instantaneous power with the adaptive strategy. In addition, the generated instantaneous power with the adaptive strategy is visibly higher compared to case when constant holding force is used. As a result, higher average power under the adaptive strategy is obtained.

IV. Conclusions and Future Work

Limited source of power is one of the major challenges in developing miniaturized medical wearable or implantable sen-

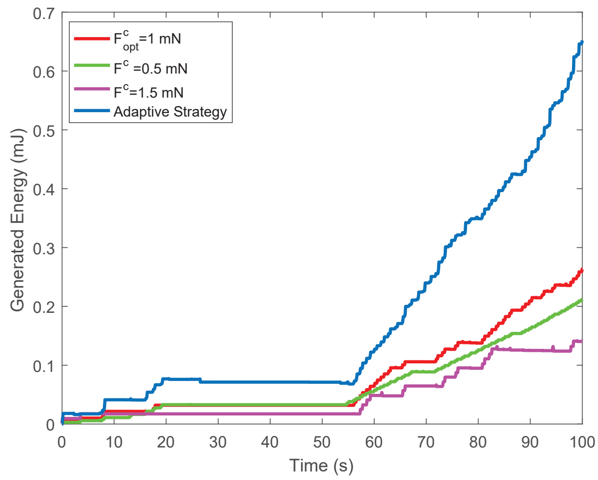

Fig. 5: Harvested energy under the adaptive holding force strategy, optimal constant electrostatic force, $F^c = 0.5$ mN and $F^c = 1.5$ mN with the acceleration data from the chest

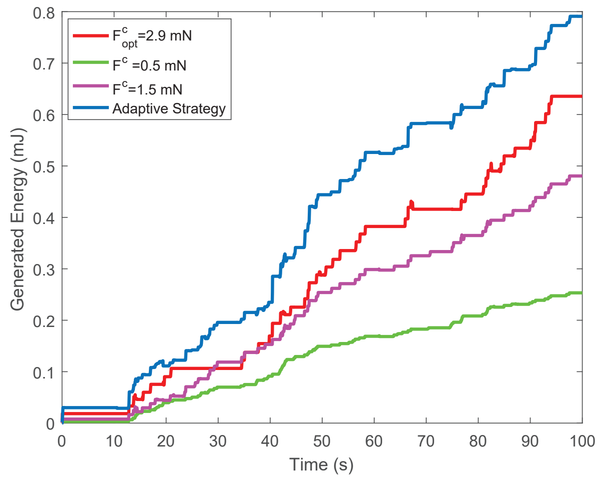

Fig. 6: Harvested energy under the adaptive holding force strategy, optimal constant electrostatic force, $F^c = 0.5$ mN and $F^c = 1.5$ mN with the acceleration data from the wrist

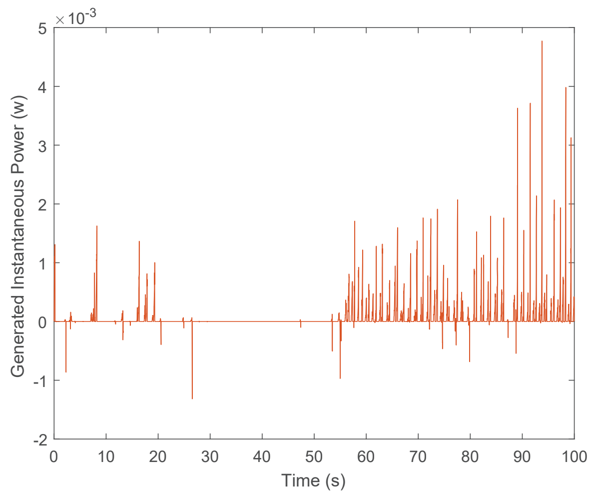

Fig. 7: Instantaneous output power under the adaptive holding force strategy with acceleration waveform from the chest

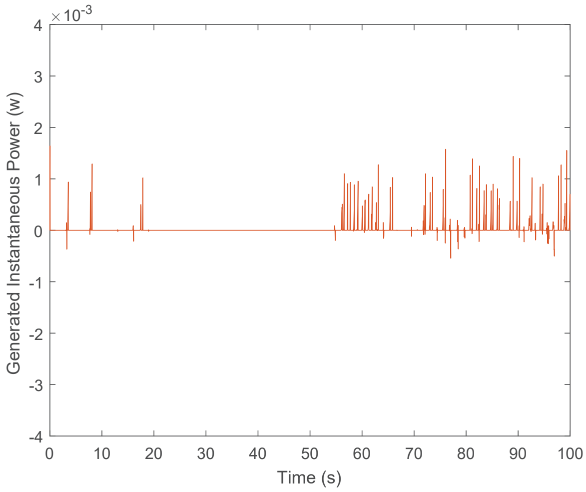

Fig. 8: Instantaneous output power under the optimal constant electrostatic force with acceleration waveform from the chest

sors with more functionality. This power is typically provided by small batteries. Integration of micro energy-harvesters with these sensors could be a promising approach in prolonging their battery lifetime. Considering the significant impact of the electrostatic force on the harvested power in a CFPG, we have proposed a simple methodology to adapt the holding force based on the input acceleration waveform. Simulation results for various human activities confirm the noticeable increase in the harvested power that can be achieved using this strategy. Other sophisticated adaptive schemes that may lead to higher output power have also been proposed for this purpose [24]. However, the complexity of such adaptive schemes is extremely important as this additional module in the CFPG architecture would itself require power to operate. This required power reduces the overall achievable gain in the harvested power compared to the case with a constant electrostatic force.

Although the computational complexity of the adaptive holding force strategy developed in this work is relatively low, further research to estimate its required power for a given adaptation interval (δ) is needed. In this paper, a fixed adaptation interval has been assumed to simplify the general optimization problem stated in Eq. (3). It is conceivable that joint holding force-adaptation interval optimization could results in higher gains. The authors plan to investigate these issues in the future.

References

[1] G. E. Santagati, N. Dave, and T. Melodia, "Design and performance evaluation of an implantable ultrasonic networking platform for the internet of medical things," *IEEE/ACM Transactions on Networking*, vol. 28, no. 1, pp. 29–42, 2020.

[2] Z. Xu, C. Xu, W. Liang, J. Xu, and H. Chen, "A lightweight mutual authentication and key agreement scheme for medical internet of things," *IEEE Access*, vol. 7, pp. 53 922–53 931, 2019.

[3] T. Wu, J.-M. Redouté, and M. R. Yuce, "A wireless implantable sensor design with subcutaneous energy harvesting for long-term iot healthcare applications," *IEEE Access*, vol. 6, pp. 35 801–35 808, 2018.

[4] C. Beach, S. Krachunov, J. Pope, X. Fafoutis, R. J. Piechocki, I. Craddock, and A. J. Casson, "An ultra low power personalizable wrist worn ecg monitor integrated with iot infrastructure," *IEEE Access*, vol. 6, pp. 44 010–44 021, 2018.

[5] M. A. Sayeed, S. P. Mohanty, E. Kougianos, and H. P. Zaveri, "eseiz: An edge-device for accurate seizure detection for smart healthcare," *IEEE Transactions on Consumer Electronics*, vol. 65, no. 3, pp. 379–387, 2019.

[6] A. Rezvanitabar, G. Jung, Y. S. Yaras, F. L. Degertekin, and M. Ghovanloo, "A power-efficient bridge readout circuit for implantable, wearable, and iot applications," *IEEE Sensors Journal*, vol. 20, no. 17, pp. 9955–9962, 2020.

[7] G.-Z. Yang, *Body Sensor Networks*. Springer-Verlag London, 2006.

[8] Y.-W. Chong, W. Ismail, K. Ko, and C.-Y. Lee, "Energy harvesting for wearable devices: A review," *IEEE Sensors Journal*, vol. 19, no. 20, pp. 9047–9062, 2019.

[9] A. Cadei, A. Dionisi, E. Sardini, and M. Serpelloni, "Kinetic and thermal energy harvesters for implantable medical devices and biomedical autonomous sensors," *Measurement Science and Technology*, vol. 25, no. 1, pp. 1–14, 2013.

[10] K. Li, Q. He, and J. Wang, "Wearable energy harvesters generating electricity from low-frequency human limb movement," *Microsyst Nanoeng*, vol. 25, no. 4, pp. 1–3, 2018.

[11] M. M. Sandhu, S. Khalifa, R. Jurdak, and M. Portmann, "Task scheduling for energy-harvesting-based iot: A survey and critical analysis," *IEEE Internet of Things Journal*, vol. 8, no. 18, pp. 13 825–13 848, 2021.

[12] C. Beach and A. J. Casson, "Inertial kinetic energy harvesters for wearables: The benefits of energy harvesting at the foot," *IEEE Access*, vol. 8, pp. 208 136–208 148, 2020.

[13] P. Mayer, M. Magno, and L. Benini, "Energy-positive activity recognition - from kinetic energy harvesting to smart self-sustainable wearable devices," *IEEE Transactions on Biomedical Circuits and Systems*, vol. 15, no. 5, pp. 926–937, 2021.

[14] M. Hassan, W. Hu, G. Lan, A. Seneviratne, S. Khalifa, and S. K. Das, "Kinetic-powered health wearables: Challenges and opportunities," *Computer*, vol. 51, no. 9, pp. 64–74, 2018.

[15] K. Gandu, "Power processing for electrostatic microgenerators," in *PhD dissertation, Imperial College*, 2011.

[16] C. Cepnik, R. Lausecker, and U. Wallrabe, "Review on electrodynamic energy harvesters — a classification approach," *Micromachines*, vol. 4, no. 2, pp. 168–196, 2013.

[17] T. J. Kazmierski and S. Beeby, *Energy Harvesting Systems*. Springer-Verlag New York, 2011.

[18] P. D. Mitcheson, E. M. Yeatman, G. K. Rao, A. S. Holmes, and T. C. Green, "Energy harvesting from human and machine motion for wireless electronic devices," *Proceedings of the IEEE*, vol. 96, no. 9, pp. 1457–1486, 2008.

[19] P. Mitcheson, T. Green, E. Yeatman, and A. Holmes, "Architectures for vibration-driven micropower generators," *Journal of Microelectromechanical Systems*, vol. 13, no. 3, pp. 429–440, 2004.

[20] P. D. Mitcheson, "Analysis and optimisation of energy-harvesting micro-generator systems," in *PhD dissertation, Imperial College*, 2005.

[21] T. von Buren, P. Mitcheson, T. Green, E. Yeatman, A. Holmes, and G. Troster, "Optimization of inertial micropower generators for human walking motion," *IEEE Sensors Journal*, vol. 6, no. 1, pp. 28–38, 2006.

[22] D. Budić, D. Šimunić, and K. Sayrafian, "Kinetic-based micro energy-harvesting for wearable sensors," in *proceeding of the 6th IEEE International Conference on Cognitive Infocommunications (CogInfoCom)*, 2015, pp. 505–509.

[23] M. Dadfarnia, K. Sayrafian, P. Mitcheson, and J. S. Baras, "Maximizing output power of a cfpg micro energy-harvester for wearable medical sensors," in *proceeding of the 4th International Conference on Wireless Mobile Communication and Healthcare (MOBIHEALTH)*, 2014, pp. 218–221.

[24] M. Roudneshin, K. Sayrafian, and A. G. Aghdam, "Maximizing harvested energy in coulomb force parametric generators," in *proceeding of the American Control Conference*, 2022.