Towards Human-powered IoT: Optimizing Harvested Power from Human Daily Motion

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***Abstract*—Human kinetic energy is considered to be a promising green energy source to enable human-powered Internet of Things (IoT), as constrained lifetime has become a bottleneck problem for IoT devices. However, the scarce energy collected by human motion severely restricts the operation of human-powered IoT and stresses the need for an optimized inertial harvester to provide more energy from human daily activities. In this paper, we investigate the feasibility and efficiency of using a single frequency inertial energy harvester, which is optimized based on a typical one-day motion of a human subject, to harvest kinetic energy from multiple-day activities of the same human subject. To facilitate this investigation, we propose a novel optimization framework to maximize the harvested power from human daily motion using a single-frequency energy harvester. By analyzing the frequency characteristics of human daily motion and the inertial harvester model, the optimal inertial harvester parameters are determined to maximize power generation from a typical one-day motion, and are used to harvest power from the same human subject's motion of other days. The real world human motion dataset is used for evaluation. The results demonstrate that the propose method can maximize power generated from one-day motion. Furthermore, the optimal harvester parameters determined by one-day trace can also achieve near-optimal harvested power from other days.**

***Index Terms*—IoT, power management, human kinetic energy.**

I. Introduction

The past decade has witnessed revolutionary changes brought by Internet of Things (IoT) [1] and IoT-supported services. It is estimated that the overall IoT devices will exceed 50 billion in 2020. With such a large number of IoT devices, energy supply becomes a critical issue that restrains the lifetime of IoT. In order to enable sustainable and cost-efficient operation, energy harvesting technologies are widely explored to provide renewable energy for IoT [2]. Extensive research has been conducted to utilize various kinds of ambient energy, such as solar [3], human kinetic [4], and Radio Frequency signal [5]. With renewable energy, IoT devices can provide long-term maintenance-free service [6] for a plethora of applications (e.g., environmental monitoring [7], body sensor networks [8] and etc.).

Recently, human kinetic energy [9], [10] is receiving increased research attention. Our daily activities, such as walking, cycling and climbing stairs, can generate electrical power to support low-power IoT devices. There are several publications focusing on collecting human motion data and analyzing kinetic energy harvesting. Gorlatova *et al.* [11] collects motion acceleration traces and studies energy generation process from short-term activity traces and long-term daily traces. Zhang and Seyedi [12] investigate the statistical properties of human kinetic energy. By studying the real world human motion data, the existing literatures show that the power harvested from human daily motion is scarce[1]. Thus, it is desired to investigate optimal harvester design to provide higher level of energy harvested from human daily motion.

For human daily motion, it is non-trivial to determine the optimal design of a single-frequency inertial harvester since human daily motion combines various activities such as walking, relaxing and running, and each activity has its own frequency that varies with each individual. The existing literatures [4], [11] use a heuristic algorithm to optimize kinetic power by matching the harvester resonant frequency to the dominant motion frequency. This method is valid for short-term motion traces with relatively singular frequency patterns. However, for day-long motion traces that may present diversified frequency features, it requires a thorough study of the frequency pattern to determine the optimal resonant frequency for the harvester. In addition, another challenging problem is the applicability of the optimized harvester design. Due to the causal restriction, we can only derive the optimal inertial harvester design based on the history human motion trace. It remains unclear whether the optimal harvester derived from history data can achieve good energy harvesting performance for the future motion traces.

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[1]According to [4], [11], the average harvested power from human daily motion is around several micro-watts.

TABLE I: Notations in the VDRG model

Parameters	Description
m	proof mass $[kg]$
r_L	proof mass displacement limit $[m]$
k	spring constant [kg$\cdot s^2$]
b	damping factor $[kg/s]$
$a(t)$	acceleration $[m/s^2]$
f_r	resonant frequency $[Hz]$
η	energy conversion efficiency
$r(t)$	proof mass displacement $[m]$
$P(t)$	harvested power $[W]$
$u(t)$	absolution position of the external frame $[m]$

In this paper, we explore the feasibility and applicability of using a single-frequency inertial harvester, which is optimized based on a typical one-day motion of a human, to harvester kinetic energy from multiple-day activities of the same human. For low-power IoT devices with constrained physical size and manufacturing cost, a single-frequency energy harvester is preferred than a multi-frequency energy harvester due to its simple design and small form factor [13]. A novel optimization framework is proposed to calculate the optimal harvester design parameters to maximize the harvested power from human daily motion. The optimal inertial harvester parameters are derived based on an in-depth study of both the inertial harvester model and the human daily motion. Real world human motion traces are used to evaluate the effectiveness of the proposed method.

The remaining part of the paper is organized as follows: Section II illustrates the inertial harvester model; Section III details the proposed optimization framework; Section IV presents simulation results for evaluation; and Section V concludes the paper.

II. Inertial harvester Model

In this paper, we consider a Velocity Damped Resonant Generator (VDRG) as the inertial harvester to convert the mechanical energy into electrical energy. Fig. 1 shows the VDRG model [12]. The magnetic proof mass m is connected to the frame with a spring and is damped by the damping factor b. The harvested power is generated from the movement of the proof mass m. With the VDRG model, we can estimate the kinetic energy that can be harvested from a human acceleration trace. Table. I lists the notation of the VDRG model.

According to [12], the relationship between the acceleration $a(t)$ and mass displacement $r(t)$ is given by Equation (1), where k is the spring constant. The resonant frequency f_r is determined by the spring constant k and proof mass m, as shown in Equation (2). When the dominant frequency of the motion matches the resonant frequency f_r, the VDRG harvester generates maximized power.

$$m \cdot \ddot{r} = -k \cdot r(t) - b \cdot \dot{r} - m \cdot a(t) \tag{1}$$

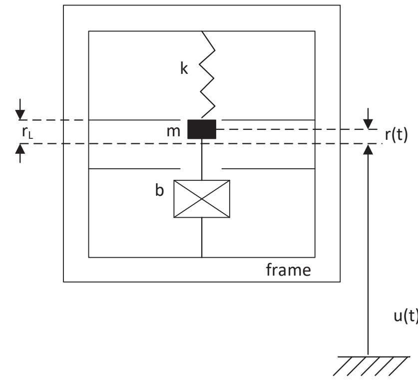

Fig. 1: Model of inertial harvester VDRG [12]

$$f_r = \frac{\sqrt{\frac{k}{m}}}{2\pi} \tag{2}$$

Through Laplace transform, the corresponding transfer function $G(s)$ between the Laplace transforms of the mass displacement position $R(s)$ and the acceleration $A(s)$ is derived in Equation (3).

$$G(s) = \frac{R(s)}{A(s)} = -\frac{1}{s^2 + \frac{b}{m} \cdot s + \frac{k}{m}} \tag{3}$$

Due to the size limitation of VDRG, the mass displacement $r(t)$ should be limited within the mass displacement constraint r_L. Thus, we have $|r(t)| \leq r_L$. According to previous literature [4], the power generated by the mass movement is shown in Equation (4), where η is the energy conversion efficiency. In this paper, we use $\eta = 20\%$ based on the previous literatures [4], [11].

$$P(t) = \eta \cdot b \cdot \dot{r}^2(t) \tag{4}$$

III. Optimization of human kinetic energy

A. Problem Formulation

From the previous discussion, we can see that the harvested human kinetic power is affected by the proof mass m, spring constant k, damping factor b and mass displacement limit r_L of a VDRG. m and r_L are limited by the harvester weight and dimension consideration, which is dependent on application requirements. We consider m and r_L are given conditions, which is a common approach in the existing human kinetic research works [4], [11], [12]. For a VDRG inertial harvester with given proof mass m and mass displacement limit r_L, it is desired to optimize the VDRG parameters to generate optimal kinetic power from a given long-term human motion trace. Therefore, we formulate the optimal human kinetic energy harvesting problem as Equation (5), where T is the total length of the motion trace. $\bar{P}$ is the average harvested power generated by the motion trace.

$$
\begin{aligned}
max \quad & \bar{P} = \frac{1}{T}\int_0^T P(t)dt \\
s.t. \quad & k,\ b > 0
\end{aligned}
\tag{5}
$$

The formulated optimization problem has a large searching space due to the open range of the spring constant k and damping factor b. Therefore, we need to look into the human motion trace and the VDRG model to find a reasonable range for the spring constant k and damping factor b.

By profiling the common activities in human daily life, we can get a frequency range of human motion. f_{min} and f_{max} are defined to be the minimum and maximum motion frequency, respectively. In previous literature [4], it has shown than the human motion is low frequency vibration which is within $10\,\mathrm{Hz}$. Thus, we have $f_{min} = 0\,\mathrm{Hz}$ and $f_{max} = 10\,\mathrm{Hz}$. To achieve the optimal kinetic energy from the motion trace, the resonant frequency f_r should also be in the range $[f_{min}, f_{max}]$. According to Equation (2), we can derive the range for the spring constant k, as shown in Equation (6).

$$
m \cdot (2\pi \cdot f_{min})^2 \le k \le m \cdot (2\pi \cdot f_{max})^2 \tag{6}
$$

Then we study the inherent feature of the VDRG model to derive a reasonable range for the spring constant b. According to [14], there are three damping cases for a VDRG depending on the poles of the transfer function $G(s)$, as shown in Definition 1.

Definition 1. For a second-order mass-spring damping system whose system function is shown as Equation (1): (1) If $b^2 < 4m \cdot k$, the system is *under damping*; (2) If $b^2 = 4m \cdot k$, the system is *critical damping*; and (3) If $b^2 > 4m \cdot k$, the system is *over damping*.

Proposition 1. To achieve optimal harvested power, a VDRG should be designed to be under damping.

We analyze the temporal response $h(t)$ of the VDRG harvester to explain Proposition 1. Fig. 2 demonstrate the temporal response $h(t)$ for different damping cases[2]. For the critical damping and over damping cases, the VDRG system does not vibrate so that the mass movement is low. As we discussed before, the harvested kinetic energy comes from the mass movement. A VDRG designed to be under damping will enable a higher energy generation due to its relatively larger mass movement compared with the critical damping and over damping cases. Proposition 1 sets a restrain for the spring factor b, as shown in Equation (7). Therefore, the overall equivalent searching space is refined.

$$
0 < b < \sqrt{4m \cdot k} \tag{7}
$$

[2]We use $m = 0.001\,\mathrm{kg}$ and $k = 0.1\,\mathrm{kg \cdot s^2}$ for all three damping cases. For the under damping case, $b = 0.005\,\mathrm{kg/s}$. For the critical damping case, $b = 0.02\,\mathrm{kg/s}$. And for the over damping case, $b = 0.035\,\mathrm{kg/s}$.

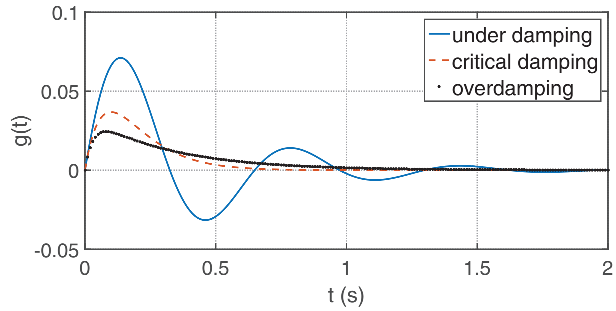

Fig. 2: Temporal response $h(t)$ for different damping cases

Combining Equations (6) and (7), we can rewrite the problem formulation into:

$$
\begin{aligned}
max \quad & \bar{P} = \frac{1}{T}\int_0^T P(t)dt \\
s.t. \quad & m \cdot (2\pi \cdot f_{min})^2 \le k \le m \cdot (2\pi \cdot f_{max})^2 \\
& 0 < b < \sqrt{4m \cdot k}
\end{aligned}
\tag{8}
$$

B. Optimal design for a VDRG harvester

Algorithm 1: VDRG parameters optimization

Input : $\{a(t)\},\ t \in [0, T]$;
$m,\ \eta,\ r_L$;
Output: $\bar{P}^*$;
$k^*,\ b^*$;
Init : $k_{min} \leftarrow m \cdot (2\pi \cdot f_{min})^2$;
$k_{max} \leftarrow m \cdot (2\pi \cdot f_{max})^2$;
for $k = k_{min}$; $k \le k_{max}$; $k = k + \delta_k$ **do**
  for $b = \sqrt{4\pi \cdot k}$; $b > 0$; $b = b - \delta_b$ **do**
    $\bar{P}_{k,b} = power\_gen(k,\ b,\ r_L,\ \{a(t)\})$;
  end
  $b_k \leftarrow \arg\max_{0<b\le\sqrt{4\pi\cdot k}} \{\bar{P}_{k,b}\}$;
  $\bar{P}_k \leftarrow \max_{0<b\le\sqrt{4\pi\cdot k}} \{\bar{P}_{k,b}\}$;
end
$k^* \leftarrow \arg\max_{k_{min}\le k\le k_{max}} \{\bar{P}_k\}$;
$b^* \leftarrow b_{k^*}$;
$\bar{P}^* \leftarrow \max_{k_{min}\le k\le k_{max}} \{\bar{P}_k\}$;
Function *power_gen*($k,\ b,\ r_L,\ \{a(t)\}$):
  $r(t) = a(t) * g(t)$;
  if $|r(t)| \ge r_L$ **then**
    $r(t) = \frac{r(t)}{|r(t)|} \cdot r_L$;
  end
  $P(t) = \eta \cdot b \cdot \dot{r}^2(t)$;
  $\bar{P} = \frac{1}{T}\int_0^T P(t)dt$;
  return $\bar{P}$;

TABLE II: Simulation Parameters

Parameters	Description
proof mass m	$0.001\,\mathrm{kg}$
mass displacement limit r_L	$0.01\,\mathrm{m}$
maximum human motion frequency f_{max}	$10\,\mathrm{Hz}$
minimum human motion frequency f_{min}	$0\,\mathrm{Hz}$
sampling frequency f_s	$100\,\mathrm{Hz}$
energy conversion efficiency η	20%
step size δ_k	$0.05\,\mathrm{kg}\cdot\mathrm{s}^2$
step size δ_b	$0.005\,\mathrm{kg/s}$

Algorithm 1 details the overall process of the VDRG parameter optimization process. Based on Equation (6), k_{min} and k_{max} refer to the maximum and minimum spring constant values, respectively. k^* and b^* are the optimal spring constant and damping factor for VDRG, respectively. $\bar{P}^*$ is the optimal average kinetic power. Algorithm 1 derives the optimal spring constant k^* and damping factor b^* by traversing the solution space of both k and b, as shown from line 7 to line 16. δ_k and δ_b are step sizes for adjusting k and b, respectively.

Lines 17 to 24 in Algorithm 1 are used to calculate the human kinetic energy that is generated from the motion traces[3]. This method is widely used in the existing literatures [4], [11], [12] to estimate the kinetic power from the human acceleration measurements.

For each k value, Algorithm 1 searches the solution space of b. Thus, for each k, the maximum computation steps it takes to find an optimal b is $O(\frac{\sqrt{4\pi\cdot k_{max}}}{\delta_b}\cdot conv(n))$, where $conv(n)$ is the complexity of convolution[4] of two sequence with length of n. For a motion trace with T as the total time length and f_s as the sampling frequency, we have $n=\frac{T}{f_s}$. Thus, the overall complexity of Algorithm 1 is $O(\frac{k_{max}-k_{min}}{\delta_k}\cdot\frac{\sqrt{4\pi\cdot k_{max}}}{\delta_b}\cdot conv(\frac{T}{f_s}))$.

IV. Evaluation

A. Simulation Setup

In this section, we perform a series of simulations to evaluate the effectiveness of the proposed optimization framework. Real world human motion traces [11] are used to derive the human kinetic energy. This dataset contains unscripted human daily acceleration measurement with 5 participants over 25 days. The participants are indexed by M1, M2, M3, M4 and M5. The acceleration data is measured with a sampling frequency of $100\,\mathrm{Hz}$. In order to filter the earth gravity of $9.8\,\mathrm{m/s^2}$, we apply a third-order Butterworth high-pass filter with a cutoff frequency of $0.1\,\mathrm{Hz}$. Table. II details the parameter values used in the simulation.

[3]The operator "*" in line 18 refers to convolution.

[4]For a naive implementation, the complexity of convolution of two sequence with the size of n is $O(n^2)$. With fast convolution algorithms such as circular convolution theorem [15], the computational cost of the convolution is reduced to $O(N\cdot logN)$.

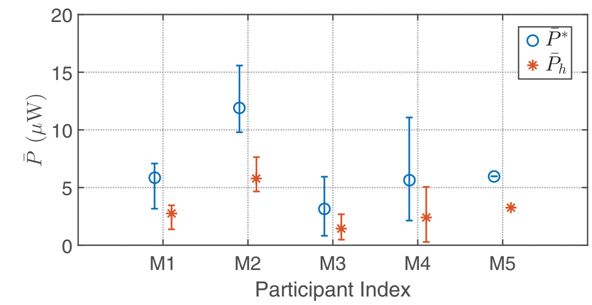

Fig. 3: Optimized kinetic power from the human motion dataset

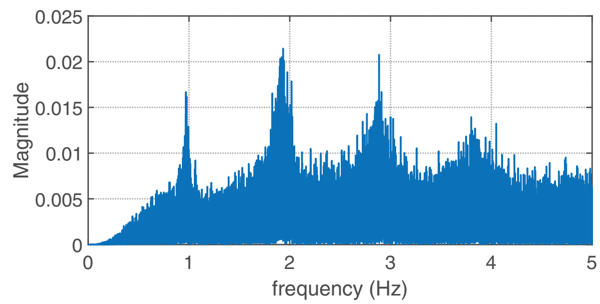

Fig. 4: Frequency feature of the first day trace of the participant M1

B. Evaluation of the proposed optimization framework

To study the effectiveness of the proposed optimization framework, we optimize the VDRG parameters using the proposed Algorithm 1 with the given motion traces. Then we derive the average harvested kinetic power, $\bar{P}^*$, using the optimized VDRG parameters. For comparison, we also refer $\bar{P}_h$ as the average power with the VDRG parameters generated by a heuristic optimization method from the previous literatures [4], [11]. Fig. 3[5] demonstrates the comparison between $\bar{P}^*$ and $\bar{P}_h$.

From Fig. 3, we can see that the by using the proposed optimization framework, a VDRG harvester can generate significantly higher kinetic power than that of the heuristic method for the same motion traces. The average harvested power improvement ranges from 83.31% to 135.69% with different participants.

The heuristic optimization method matches the resonant frequency f_r to the dominant frequency of the given motion traces to derive the spring constant k. Then it searches for a relatively large damping constant b to finalize the optimal value for b. The heuristic method is valid for motion traces with a single dominant frequency. However, day-long traces may have several dominant

[5]Fig. 3 shows the maximum, average and minimum value of the average harvested power, which refers to the upper horizontal line, the marker ("o" and "*") and the lower horizontal line, respectively. Due to the fact that the dataset [11] only collects a one-day trace for the participant M5, M5 has one data point in Fig. 3.

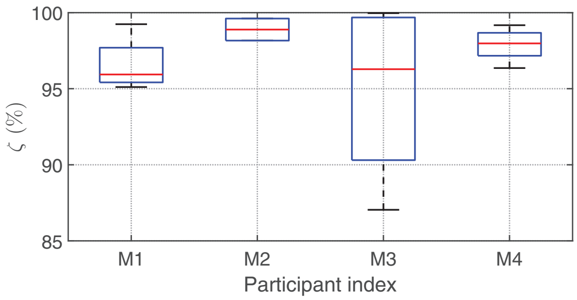

Fig. 5: ζ with different participants

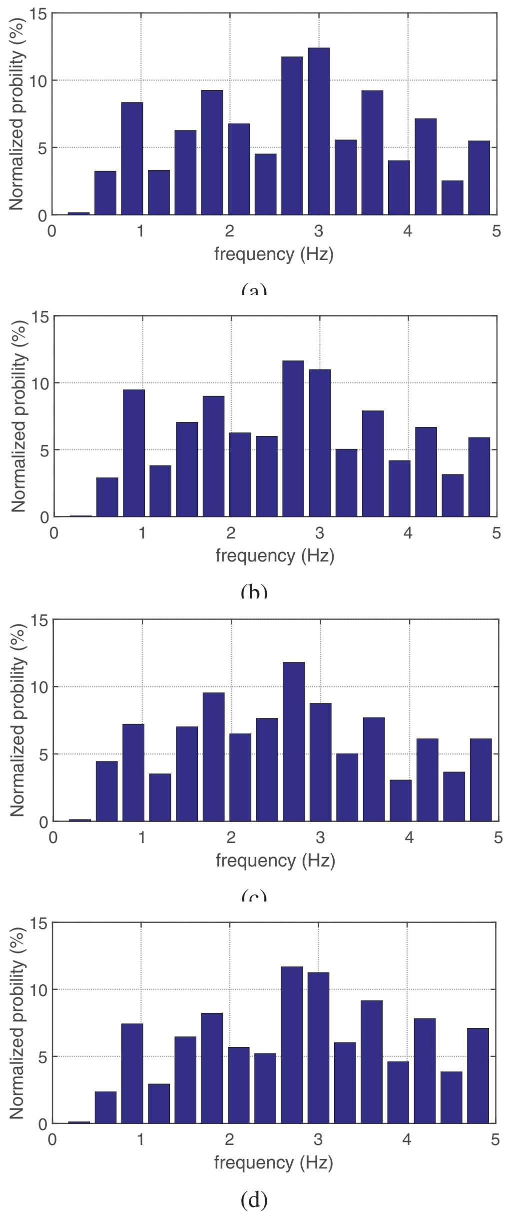

Fig. 6: Dominant frequency analysis for: (a) M1 day 1; (b) M1 day 2 (c) M1 day3; (d) M1 day 4

frequencies. Fig. 4 demonstrates the frequency analysis of the first day motion trace of participant M1. From Fig. 4, we can observe that the trace has three dominant frequencies, roughly around $1\,\mathrm{Hz}$, $2\,\mathrm{Hz}$ and $3\,\mathrm{Hz}$. For the heuristic optimization method, the resonant frequency f_r is set to be $2\,\mathrm{Hz}$ as it has the largest magnitude. By using the proposed Algorithm 1, we find that the optimal resonant frequency f_r should be $2.93\,\mathrm{Hz}$. Therefore, for day-long traces with complicated frequency features, the frequency matching based heuristic method cannot guarantee the optimal VDRG design parameters.

C. Applicability of the optimized energy harvester on future daily motion traces for the same subject

In the previous evaluation, we demonstrate that the proposed optimization framework is capable of providing optimal VDRG parameters to maximize the harvested power. There is still one question remaining. If we use a one-day trace to derive the optimal VDRG parameters, can we use the derived optimal VDRG to generate high kinetic power from the future traces of the same subject?

To investigate this problem, we use the first-day trace of each participant to derive the optimal VDRG parameters. Then the optimal VDRG design is utilized to calculate the average harvested power, $\bar{P}_1$, for the other traces from the same subject. For comparison, we derive the optimal design for each day and the corresponding optimal average harvested power is denoted as $\bar{P}_{max}$. $\bar{P}_{max}$ is the upper bound of the generated kinetic power using a single frequency harvester. In real applications, due to the causal restriction that the future day-long motion trace is a priori unknown, it is difficult for the actual harvested kinetic power to reach the upper bound $\bar{P}_{max}$.

$$\zeta = \frac{\bar{P}_1}{\bar{P}_{max}} \times 100\% \tag{9}$$

We define power generation ratio, ζ, to be the ratio between $\bar{P}_1$ and $\bar{P}_{max}$, as shown in Equation (9). A larger ζ value indicates that the optimal VDRG design derived from the first-day trace achieves high kinetic power from the other trace. The boxplot in Fig. 5 illustrates the distribution of the harvested power ratio ζ for different participants[6]. From Fig. 5, we can see that the power generation ratio ζ is high over all the participants. ζ ranges from 86.7% to 99.1%. The results demonstrate that the optimal VDRG parameters derived from a one-day trace can be applied to the future traces and generate high kinetic power.

To further look into the applicability problem, we conduct statistical analysis on the dominant frequencies of the human motion traces. For each trace, we segment

[6]For the participant M5, the dataset [11] only consists of a one-day motion trace. Thus, M5 is not used in the applicability test shown in Fig. 5.

the day-long trace into small windows. The window size is 5 s. For each window, we use Fast Fourier Transform (FFT) to derive the frequency feature and then record the dominant frequency. Fig. 6 demonstrates the statistical analysis of the dominant frequency distribution for the first 4-day traces of participant M1. We can see that these 4 days share a similar distribution pattern of the dominant frequency. Therefore, the VDRG parameters optimized for the day 1 trace can also generate high kinetic power for the future days (day 2, day 3 and day 4).

V. Conclusion

In this paper, we investigate the problem of human kinetic power generation from day-long motion traces. With in-depth study of the inertial harvester model, we formulate the optimal harvester design problem with a refined searching space for the spring constant and damping factor. A novel optimization framework is proposed to derive the optimal inertial harvester parameters to achieve maximized kinetic power. The real world human motion traces are used for evaluation. Compared with the existing harvester optimization algorithm, the proposed method is capable of generating higher kinetic power from the same motion trace dataset. The simulation results also demonstrate that the harvester parameters optimized by a one-day trace of a human subject can achieve high kinetic power for the other traces of the same human subject.

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