On intelligent energy harvesting

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We probe the potential for intelligent intervention to enhance the power output of energy harvesters. We investigate general principles and a case study: a bi-resonant piezoelectric harvester. We consider intelligent interventions via pre-programmed reversible energy-conserving operations. We find that in important parameter regimes these can outperform diode-based intervention, which in contrast has a fundamental minimum power dissipation bound.

Introduction—Energy harvesting, exploiting ambient energy for our purposes, play a crucial role in human technological development [1]. Currently, an important focal area is micro energy harvesters (with output power 10-100µW). These convert, through various transduction methods, ambient thermal and kinetic energy from the environment to electrical energy. They provide an in-situ power source for remote electronic devices, typically for powering sensor nodes of the Internet of Things. This avoids the problems associated with batteries and/or wiring [2, 3, 6].

A key challenge for micro harvesters is that ambient energy sources are very often random. For instance, the amplitude and the frequency of a vibrational energy source can be highly variable. This makes it difficult to rectify the generated voltage/current and store the energy in an efficient manner [2, 3, 6].

Interventions by an intelligent agent aids energy harvesting from variable sources in certain contexts, as exemplified by the interventions of a sailor, or a windvane turning a generator into the wind. Such examples serve to remind us that the 2nd law of thermodynamics, as used to prove that a Maxwell’s demon cannot work [7], concerns maximum entropy single heat baths, whereas often forces in nature are not maximally random.

Highly sophisticated intelligent interventions in energy harvesting are now practicable, owing to advances in: (i) artificial intelligence software and hardware [8, 9], (ii) electronic interfacing circuitry [10, 11], and (iii) experimental and theoretical understanding of the relation between information and energy, such as the fact that reversible computation has no fundamental energy cost [15, 17]. Taken together, this gives significant hope that intelligent intervention may be a powerful tool in mitigating the randomness faced by micro-harvesters.

We therefore here aim to identify intelligent interventions that allow micro harvesters to extract more rectified power from variable sources than current state-of-the art methods.

A key paradigm we adapt is to use interventions that are reversible and energy conserving. Moreover, for practical and fundamental thermodynamical reasons, these interventions are pre-programmed, chosen by systematic machine learning methods applied to past data from the harvester, as in Fig. 1. We consider general principles and for concreteness also a case study of a piezo-electric harvester which converts motion to electricity [18]. In this case study we consider idealised, pre-programmed, bias-flips and phase-shifts on the electrical outputs. We find these can indeed replace and outperform the current state-of-the art: the diode bridge. We moreover note that the diode bridge has a thermodynamically fundamental lower bound on power dissipation, whereas the methods use here do not.

We proceed as follows. We briefly describe the harvester being used as a case study. We describe the interventions, and how they can be intelligently chosen. We then give the results, followed by a discussion and conclusion.

Harvester and its output—The harvester we use in this paper as a case study is a dual resonant structure energy harvester [18], which can harvest energy from random fluctuation sources at low frequencies (typically less than 100Hz), consistent with motion of everyday objects such as human beings. It consists of two piezoelectric devices, each outputting its own voltage time-series, with
the voltages finally combined to give one voltage time-series. The device is shown in FIG. 2.

FIG. 2. The bi-resonant harvester, originally designed in [13]. Two piezo-covered cantilevers with masses on their free ends are driven by the same vibrational motion source on the right axis. We consider how much bias flips and phase shifts on the outputs can enhance the power output.

The output can be used to charge a capacitor, which is used to power a sensor and wireless transmission of the sensor signal when required. The capacitor, and normally the sensor and transmission components, needs a DC ($V \geq 0$) source with a sufficiently high root mean square voltage $V_{\text{RMS}}$. However the raw voltage from the device is AC. The current state-of-the-art solution for converting it to DC is the diode bridge.

Diode bridge and its power consumption—A diode bridge, as in Fig. 3 will take any voltage polarity on the inputs to a positive polarity on the output, but at a loss in power. The loss in power is necessary given that each diode has a voltage drop. For practical device power dissipation calculations a pn-junction diode’s current vs voltage curve can be approximated as $V = V_0 + IR$ for the regime $V > 0$ [19]. The instantaneous power dissipated by a single diode when $V > 0$ is then $P = IV_0 + I^2R$. (The average and rms power dissipations follow immediately.) The diode bridge has two diodes in each path and thus twice that dissipation.

Note also that in the case of two sub-harvesters the diode bridge can be applied on each before combining the voltages in order to avoid destructive interference, but again at a power loss.

2nd law mandates diode bridge power consumption—If it were possible to reduce the above power dissipation to 0, a diode bridge could be used to violate the second law of thermodynamics, by turning thermal current fluctuations into rectified current at no work cost. Kelvin’s version of the 2nd law states that no work can be extracted from a single heat bath in a closed cycle. Thermal voltage fluctuations depend on materials and it is beyond the scope of this paper to investigate their values for diode bridges used here, but e.g. the thermal voltage $V_{th} = kT/e$ is approx 0.03V at room temperature. (The argument can be modified to other fluctuation sizes).

For the device to be called a diode the current $I \approx 0$ for negative voltages beyond the thermal fluctuation range of $-V_{th}$ (up to some breakdown voltage which is outside of the range currently considered). Then for voltages in the positive thermal fluctuation range we must also have $I \approx 0$, or else the diode would generate a current in a circuit embedded in the heat bath, a circuit which could include a load driven by that current, violating the 2nd law. Thus, according to the above argument, there is an inescapable voltage drop of $V_{th}$ in a diode, and associated power loss. We now turn to the competing approach to turn the AC into DC and to remove destructive interference between voltages.

Two examples of intelligent interventions: sign flip and phase shift—The sign flip, which can also be called voltage inversion, can be written as $V \rightarrow -V$ where $V$ is the instantaneous voltage. This can switch between being on and off with period $\tau$. $\tau$ is a priori a free parameter and will later be set according to optimising based on past data.

The phase shift is simply a delay of the voltage time series by some amount $\phi$ (so strictly speaking it is a delay rather than a phase shift which should only be between 0 and $2\pi$ times some period). It can be written as $V(t) \rightarrow V(t + \phi) \forall t$ where $t$ is time.

Interventions are orthogonal matrices—It is convenient to use bra-ket vector notation here such that a voltage time series $V_i(t_0),...V_i(t_f)$ is a vector $|V_i\rangle$ with the first entry $V_i(t_0)$. (The time series is discrete as it is sampled experimentally at a finite rate). The transpose of the vector is denoted $\langle V_i |$, such that the dot product of two vectors $|V_i\rangle, |V_j\rangle$ is written as $\langle V_i | V_j \rangle = \langle V_i | V_j \rangle$. In this notation

$$V_{\text{RMS}} = \sqrt{\frac{1}{d} \langle V_i | V_i \rangle},$$

where $d$ is the dimension of $|V_i\rangle$. Moreover let $|V'_i\rangle$ denote the transformed $|V_i\rangle$.

In an idealised case the intelligent transformations preserve $V_{\text{RMS}}$ such that

$$\langle V_i | V'_i \rangle = \langle V_i | V_i \rangle \forall i. \quad (1)$$

Then, if we also assume the interventions can be represented as matrices, the interventions correspond to orthogonal matrices $O$, meaning $O^T O = I$ where $I$ is the identity and $T$ the transpose. The idealised interven-
tions we consider are indeed orthogonal matrices: phase shifting can be represented as a cyclic permutation of elements, a particular permutation matrix, and voltage inversion as a diagonal matrix with diagonal entries all 1 or -1. More generally the interventions \( \mathcal{S} \) are naturally represented as matrices, since they should respect probabilistic mixtures of different voltages: 
\[
\mathcal{S}(\sum_i p_i |V_i\rangle) = \sum_i p_i \mathcal{S}(|V_i\rangle)
\]
This together with Eq.1 implies the idealised interventions, beyond the examples of bias flips and phase shifts, should indeed be represented as orthogonal matrices acting on the voltage vectors.

**Optimal interventions when combining two voltages**— Now we can compare the \( \text{V}_{\text{RMS}} \) before and after interventions. For example phase shifts can be used to reduce destructive interference, due to individual sub-generators producing voltages out of phase. Given two or more voltage time series, how high can the \( \text{V}_{\text{RMS}} \) of the combined outputs be, if we are allowed to do intelligent interventions on each time series before combining them? For notational convenience let us consider maximising the combined outputs be, if we are allowed to do intelligent interventions on each time series before combining them? For notational convenience let us consider maximising the combined outputs be, if we are allowed to do intelligent interventions on each time series before combining them? For notational convenience let us consider maximising it over permutation matrices and sign flips. Note that

\[
\langle V \rangle_{\text{RMS}}^2 = \sum_i |V_i|^2
\]

Thus maximising the \( \text{V}_{\text{RMS}} \) improvement for a given \( |V_1\rangle, |V_2\rangle \) means maximising \( \langle V_1' V_2' \rangle \). Can we find a closed form expression for how high this can be? Let us consider maximising it over permutation matrices and sign flips. Note firstly that making the signs the same for all entries, e.g. plus, cannot decrease \( \langle V_1' V_2' \rangle \). We can assume that in the optimal case the signs are the same, say all positive. Now it is known that the dot product is maximised by ordering the entries of each in descending order: \( |V_1'\rangle \uparrow |V_2'\rangle \downarrow \). This follows from the rearrangement inequality. Thus the maximum \( \text{dV}_{\text{RMS}}^2 \) one can obtain by signflips and permutations is

\[
\max \text{sgnflip+perm} \ (V_1' + V_2')(V_1' + V_2) = 2 \langle V_1' V_2' \rangle - \langle V_1 V_2 \rangle
\]

An important case here is where the phase shift is done before combining the two voltages, followed by a joint inversion. In this case, in line with Eq.2 we use the cost function

\[
C(\tau, \phi) = C_{\text{V RMS}} + C_{\text{POS}}
\]

where \( |V'\rangle \) is the sum of the two voltages after the first phase shift and \( |V''\rangle = |V'\rangle + |V''\rangle \).

**Systematic training methods exist**— To have a systematic and scalable approach we consider the well-proven machine learning/optimisation technique of gradient descent on a suitably defined cost function. The
FIG. 4. Intelligently chosen periodic voltage inversion gives better $V_{RMS}$ performance than diode bridge for the same input. The diode bridge data is fully experimental. The intelligent intervention data is from applying the corresponding orthogonal matrix on the raw data experimental data before the diode bridge. $V_{IF}$ is the voltage after the intelligently chosen flip (experiment+simulated intervention). $V_{RAW}$ (experimental) is the direct output from the harvester, and $V_{DB}$ is that after the diode bridge. $V_{IF}$ is the voltage after the intelligently chosen flip (experiment+simulated intervention), $V_{RAW}$ (experimental) is the direct output from the harvester, and $V_{DB}$ is that after the diode bridge. $V_{IF}$ is the voltage after the intelligently chosen flip (experiment+simulated intervention), $V_{RAW}$ (experimental) is the direct output from the harvester, and $V_{DB}$ is that after the diode bridge. Gradient descent rule as applied here is that

$$\left(\tau, \theta\right) \rightarrow \left(\tau, \theta\right) - \eta \left(\frac{C(\theta, \tau + \delta) - C(\theta, \tau)}{\delta} \right),$$

where $\delta$ and $\eta$ are numerical parameters chosen according to what works.

Moreover, when faced with local minima in the cost function landscape, we employ the genetic algorithm, a type of evolutionary algorithm commonly used to find global minima when there are many local minima. In the genetic algorithm, the global minimum (highest fitness generation) can often be found, after operations like mutation, crossover and selection [22].

We use some of the time-series data (80%) for determining the optimal interventions, and then test those interventions on the remaining data (20%).

The training used here can be classified as reinforcement learning, as the performance is evaluated (rather than the output being compared to a known correct answer as in supervised learning).

Simulated intelligent intervention beats diode bridge— Our simulation shows that a combination of periodic voltage inversion and phase shift provides DC voltage that is higher than that after the diode bridge. The diode bridge penalty of about 0.2V is significant in regimes where $V_{RMS}$ is of the order of 0.2 or less. It is in these regimes it makes sense to consider replacing the diode bridge.

Fig.4 shows how the $V_{RMS}$ is left essentially undiminished and approximately non-negative by an intelligently chosen periodic voltage inversion, whereas the diode bridge loses about half of the $V_{RMS}$. In regimes of even lower $V_{RMS}$ this advantage will be even greater of course.

In the case of two sub-generators we find that the simulated intelligently chosen delay plus intelligently chosen periodic inversion can also in principle significantly outperform the diode bridge, as shown in Fig.5. An example of the cost function landscape for real experimental data combined with simulated intervention is in Fig.6, showing local minima, which is why we employed the genetic algorithm for the training. The $V_{RMS}$ improvement here is given in Table I.

Signal-to-noise ratio important— We consider adjusting the power of additive Gaussian white noise to see the change of $V_{RMS}$ and $C$ of the intelligent interventions and diode bridge respectively.

We find that whilst the $V_{RMS}$ of the intelligent inter-
**Table I.** Improvement of $V_{\text{RMS}}$ ($C_{\text{POS}}$ of Eq.3). Three cases: (i) raw data without intelligent intervention or diode bridge, (ii) data after diode bridge, (iii) data for intelligent intervention replacing diode bridge. For the case of 1 voltage only being used the bias flip is employed. For the case of both voltages being used, there is a phase shift applied, followed by combining the voltages, followed by a bias flip.

| $V_{\text{RMS}}$ ($C_{\text{POS}}$) | 1 voltage | 2 voltages |
|----------------------------------|----------|-----------|
| raw data                         | 0.89(1.6) | 0.59(0.7) |
| DB                               | 0.37(0.5) | 0.22(0.2) |
| IEH                              | 0.89(0.01) | 0.59(0.47) |

**Fig. 7.** Comparison of diode bridge and intelligent intervention under noise with three cases illustrating the corresponding parameter regime: (a) SNR(signal-to-noise ratio) is greater than 5, in which the intelligent harvesting (IEH) has a better cost function performance, (b) SNR is close to 5, wherein the cost of IEH and the diode bridge (DB) are similar, and (c) SNR is less than 5, wherein the cost of the diode bridge is lower.

**Conclusion**—We conclude from this study that in the case of small voltages and multiple sub-generators, intelligent intervention can significantly outperform the diode bridge. This suggest it may be strikingly useful to divide existing harvesters into independently moving sub-components together with intelligent interventions on the outputs. Such a harvester with multiple (in the case here 2) sub-harvesters could have a much wider operating range than a single large harvester which may not move at all when exposed to small and/or in different locations opposing forces.

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