

Self-Sensing Closed-Loop Control of Dielectric Elastomer Generators

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Abstract—Dielectric elastomer generators (DEGs) are electrostatic devices that convert mechanical work into electrical energy leveraging cyclic stretching and electrical loading of polymeric variable capacitors. Existing implementations of DEG harvesting cycles either rely on a priori knowledge of the deformation profile, limiting real-world applicability, or require external mechanical sensors, increasing system complexity. This work presents a closed-loop control architecture for DEGs that does not require external sensors. By injecting a high-frequency voltage signal and measuring the corresponding electrical current, we infer the DEG capacitance in real time and use it as a feedback for real-time control of the harvesting cycle. While similar self-sensing (SS) architectures have been explored for actuators, where energy efficiency is not a primary concern, their application to generator systems must explicitly account for the electrical losses introduced by the injected sensing signal. Using state-of-the-art SS algorithms, we systematically investigate the tradeoff between conversion efficiency and sensing accuracy, to maximize the energy yield. We then introduce a new SS method specifically tailored to DEG applications, which uses a modified high-frequency injection to further reduce dissipation. Experimental validation, conducted under sinusoidal and polychromatic deformation profiles, shows that SS control strategies allow converting 85%–95% of the energy achievable with ideal open-loop cycles.

Index Terms—Broadband excitation, closed-loop (CL) control, dielectric elastomer generators (DEGs), energy harvesting, self-sensing (SS).

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I. INTRODUCTION

DIELECTRIC elastomers (DEs) are soft capacitors made of thin dielectric layers coated with compliant electrodes. When a DE membrane is stretched its area increases while its thickness decreases, both contributing to an increase in capacitance. Applying high voltage generates electrostatic forces that produce strain and stress changes. These principles enable the use of DEs as actuators, sensors, and generators [1], [2], [3]. Notably, DE generators (DEGs) offer an attractive alternative to traditional electromechanical harvesters due to their broad bandwidth, high experimentally achieved energy densities up to ~ 800 mJ/g, and direct linear drive [4], [5]. DEGs are especially suitable for harvesting mechanical energy from environments that feature irregular, low-frequency excitation profiles, where piezoelectric or electromagnetic generator technologies struggle to operate efficiently. They have been proposed for energy harvesting from different sources, such as sea waves [6], low-velocity rivers [7], wind [8], or human motion [9]. If the DEG is deformed periodically, then charging it at high capacitance and discharging it at low capacitance allows converting mechanical work into electrical energy. The energy yield increases with the capacitance swing between charge and discharge states, as well as applied electric field magnitude [1].

Different approaches have been proposed to implement DEG charging cycles. Simple diode-based [10], [11] and self-priming [12] circuits have been proposed to trigger self-synchronized charging and discharging. However, such harvesting cycles generally lead to suboptimal charge management, and consequently lower energy yield [1]. Alternatively, more advanced circuits can be used to modulate the applied voltage and, in turn, significantly increase the harvested energy. Optimal constant-field (CF) harvesting cycles are enabled by power converters [13], while tight approximations of those cycles can be achieved using switching schemes [4], [5]. Suboptimal approaches relying on constant-voltage (CV) cycles result in less energy yield, but demand simpler hardware [14]. Although these strategies outperform simple self-synchronizing circuits, practical limitations hinder their implementation. On the one hand, active voltage switching requires knowledge of the time at which maximum and minimum capacitance states are reached. Current implementations of DEG harvesting cycles remain largely at the laboratory stage [1], where the deformation profile is either predefined [4], [15] or measured via external sensors [16]. On the other hand, optimal CF cycles require

continuous knowledge of the DEG capacitance throughout operation. This must be either known in advance or inferred from the DEG deformation using model-based estimation [4], [5], [13]. Transferring those approaches to unpredictable real-world scenarios requires additional sensors, which increase system complexity and introduce an additional point of failure. Moreover, external sensors can be impractical in many applications, e.g., small-scale systems, such as wearable harvesters, where space is limited, or harsh and unstructured environments, where the inclusion of mechanical sensors may reduce the system reliability.

DEs can work as multifunctional transducers, combining many operating modes at the same time. For instance, one can measure DE electrical signals while driving the membrane with high voltage, and use them to infer the material deformation in real time via capacitance estimation [17], [18], [19]. This dual mode is referred to as self-sensing (SS). Several authors have shown the effectiveness of SS in DE actuators, demonstrating sensorless closed-loop (CL) control of position [20], [21], [22] and compliance [23]. To achieve SS, a high-frequency, low-voltage signal is generally superimposed to the driving voltage [23], [24]. This results in a large, measurable current that enables the continuous estimation, but introduces resistive losses. While those losses are generally of little to no concern for DE actuators, they can compromise the capability of a DEG to positively generate energy. A fundamental tradeoff thus emerges between SS accuracy (demanding high current) and energy dissipation (demanding low current). Systematic investigation of such tradeoff for DEGs, and demonstration of energy harvesting feasibility under SS losses, remains to date unexplored. Although potential benefits of SS for DEG applications have been acknowledged in the literature [1], [4], this concept has not yet been demonstrated experimentally. To the best of authors' knowledge, the only work investigating SS in a DEG setting is a simulation-only study by Zanini et al. [25]. In that work, a baseline SS algorithm for DE actuators is used to estimate the DEG capacitance. The capacitance maxima and minima are found with a peak detection algorithm based on a sliding mode differentiator, indicating that this method can be used to synchronize harvesting cycles. However, quantitative investigations on energy performance tradeoffs and SS losses are not performed, and the study remains at the level of conceptual perspective, rather than addressing practical implementation in real-time.

In this work, we present and validate for the first time CL control strategies for DEGs solely based on SS feedback. The main contributions are as follows:

- 1) We introduce new SS architectures to achieve both CV and CF control of a DEG in CL, without any a priori knowledge of the DEG kinematics, via a direct capacitance feedback.
- 2) We implement and experimentally validate both CV and CF harvesting cycles based on real-time capacitive SS, considering both mono-chromatic deformation and poly-chromatic deformation profiles.
- 3) We systematically benchmark the performance of SS energy harvesting with an ideal control scheme.

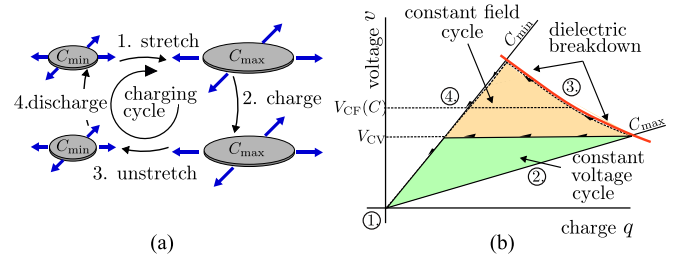


Fig. 1. DEG working principle. (a) Basic generation cycle. (b) Generation cycle on a voltage-charge diagram.

- 4) We systematically quantify the resistive losses occurring with baseline SS algorithms, demonstrating that an optimal tradeoff between accuracy and dissipation exists, and derive design rules to achieve maximal energy extraction under SS control.
- 5) We propose a new, DEG-tailored SS strategy to further reduce the resistive losses.

Ultimately, this article demonstrates for the first time the feasibility of SS DEG control for scenarios in which the deformation profile is not known in advance, paving the way for future autonomous applications.

The rest of this article is organized as follows. Section II introduces the main SS control architecture. Section III performs a parametric study to quantify the effects of the SS signal on the converted energy. Section IV presents experimental validation of the proposed CL harvesting cycle. Finally, Section V concludes this article.

II. SS ENERGY HARVESTING ARCHITECTURE

Here, we introduce the DEG SS control scheme.

A. Harvesting Cycles

Fig. 1(a) shows the typical harvesting cycle of a DEG, which are as follows.

- 1) An external mechanical force stretches the DEG, bringing it to a maximum capacitance configuration $C_{\max}$.
- 2) The DEG is electrically charged.
- 3) The mechanical force is removed and the DEG capacitance is brought back to the initial value $C_{\min}$.
- 4) The DEG is electrically discharged and the cycle can restart.

Since the DEG charge q , voltage v , and capacitance C are related by $q = Cv$, the change in C occurring at step 3) causes variations in q and/or v , which can be exploited for energy harvesting.

In the sequel, two popular strategies to implement phase 3) are described, namely, CV and CF [1]. In CV cycles, a constant harvesting voltage $v_h = v_{CV}$ is applied during the transition from $C_{\max}$ to $C_{\min}$, as shown in the voltage-charge diagram in Fig. 1(b). Here, the enclosed green area represents the energy harvested in a cycle. Voltage V_{CV} must be limited to keep the electric field $E = v/d$, where d is the DEG thickness, below the DE breakdown strength E_b . Instead, in CF cycles, the voltage v_h is continuously changed to keep the electric field E constant (with $E \leq E_b$), when transitioning from $C_{\max}$ to $C_{\min}$. This

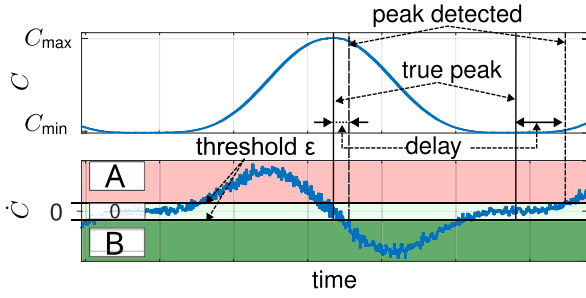


Fig. 2. Qualitative depiction of capacitance peak detection.

strategy allows converting the additional orange area, shown in Fig. 1(b), and maximizes the converted energy for a given range of deformations [13]. Existing CF cycle implementations [26] rely on kinematic models of the DEG to adapt the voltage in real time, making them sensitive to errors. DE incompressibility and homogeneous deformations imply $C = C_{\min}(d_{\min}/d)^2$, where $d_{\min}$ is the DEG thickness corresponding to $C_{\min}$. Combined with $E = v/d$, this enables constant E control by adapting the voltage in real time using only C as feedback, independently of the DEG kinematics

$$v_h = V_{CV} \sqrt{\frac{C_{\max}}{C}}. \quad (1)$$

Equation (1) ensures that $v = V_{CV}$ as in a CV cycle when $C = C_{\max}$, and then increases as C transitions to $C_{\min}$ due to a decreasing d . While a CV cycle only requires detection of the capacitance extrema to trigger charging/discharging, a CF cycle requires continuous measurement of C [cf., (1)].

B. Capacitance Peak Detection

The harvesting cycles described in Section II-A rely on applying a given voltage profile at specific points of the deformation profile. If the DEG capacitance is known, identifying peaks and valleys in its profile enables accurate timing of the voltage signal. The simplest way to detect maxima and minima in C is based on computing zero-crossing of its derivative $\dot{C}$. To mitigate measurement noise in practical implementations, we assume that $\dot{C}$ is approximated by processing C with a first order high-pass filter (i.e., an ideal derivative cascaded with a first order low-pass filter). Fig. 2 shows a qualitative example of estimated capacitance signal with realistic measurement noise, alongside its filtered derivative. Peaks are identified whenever $\dot{C}$ crosses from the positive region A to the negative region B and vice versa. To further make this process robust against noise, a threshold region O of width $\pm\epsilon$ around zero is introduced, where transitions are ignored. Using this method, peaks are only detected after the signal has decreased/risen by a sufficient amount below/above the given value, as in Fig. 2.

The introduction of both high-pass filter and threshold cause a delay in the detected extrema (see Fig. 2). This delay leads to a suboptimal harvesting cycle, as the DE is no longer charged/discharged exactly at $C_{\max}/C_{\min}$, thus reducing the generated energy. In practice, filter bandwidth and threshold must be tuned based on the signal-to-noise ratio (SNR), to avoid false triggers while minimizing the introduced delay.

C. Standard SS Method for Capacitance Estimation

This section reviews the baseline SS method for DE actuators from [23]. For SS purposes, the DEG electrical impedance can be modeled as a series RC circuit

$$v = R(t)i + \frac{1}{C(t)} \int_0^t i(\tau) d\tau \quad (2)$$

where v and i are DEG voltage and current, while R and C represent the deformation-dependent electrode resistance and DE capacitance. This model accurately describes the DEG electrical dynamics over timescales much shorter than the dielectric relaxation time constant of the DE material [21], [23], i.e., when the DEG leakage current is negligible [27]. Equation (2) is discretized using the prewarped Tustin rule

$$v[t_k] - v[t_{k-1}] = R(i[t_k] - i[t_{k-1}]) + \frac{K_T}{C}(i[t_k] + i[t_{k-1}]) \quad (3)$$

where $K_T = \frac{\tan(\pi f_p T_s)}{2\pi f_p}$, with warping frequency f_p and sampling time T_s . Equation (3) can be used to reconstruct R and C in real time based on measurements of v and i , using an iterative recursive least squares (RLS) algorithm with forgetting factor μ [23]. Since v and i change much faster than C and R , the RLS treats the latter as slow-varying parameters whose variation is accounted for by choosing $\mu < 1$.

Note that (2) describes a high-pass map from v to i . To provide a sufficiently large current signal for the RLS estimation, the DEG driving voltage v is set as follows:

$$v = v_h + v_{ss}. \quad (4)$$

In (4), v_h is a slowly varying high voltage component responsible for generation, while v_{ss} is a low-voltage, high-frequency signal, which is purposely added for SS. The latter is chosen as a sinusoid with amplitude V_{ss} and frequency f_{ss}

$$v_{ss} = V_{ss} \cos(2\pi f_{ss} t). \quad (5)$$

The current i resulting from the application of (4) is

$$i = i_h + i_{ss} \quad (6)$$

where i_h is the charging current caused by v_h , which is the driver for power generation, and i_{ss} is a high-frequency component of the current due to v_{ss} . The DEG capacitive nature implies $|i_{ss}| \gg |i_h|$ for typical SS frequencies, therefore $i \simeq i_{ss}$. For slow-varying R and C , we have

$$i \simeq i_{ss} = \frac{2\pi f_{ss} C V_{ss}}{\sqrt{1 + (2\pi f_{ss} R C)^2}} \cos(2\pi f_{ss} t + \phi_{ss}) \quad (7)$$

$$\phi_{ss} = 0.5\pi - \arctan(2\pi f_{ss} R C). \quad (8)$$

If the SS-frequency f_{ss} is chosen much smaller than the RC cutoff frequency, as common in applications [23], then $2\pi f_{ss} R C \ll 1$ and the current can be further approximated as

$$i_{ss} \simeq 2\pi f_{ss} C V_{ss} \cos(2\pi f_{ss} t + 0.5\pi). \quad (9)$$

In practice, V_{ss} and f_{ss} are chosen large enough to let i_{ss} dominate i_h , and $f_p = f_{ss}$ for optimal discretization accuracy.

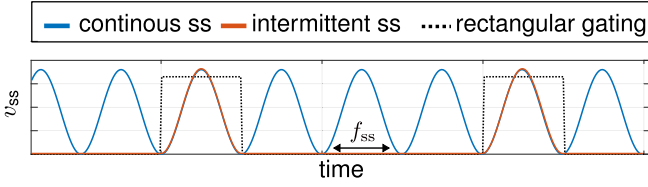


Fig. 3. Working principle of intermittent SS, in which $N_{IM} = 3$ periods are suppressed for each SS period.

D. Advanced SS Method for Capacitance Estimation

To mitigate resistive losses introduced by the SS current i_{ss} , we propose a modification of the baseline method from Section II-C based on a combination of two strategies.

The first strategy consists of replacing the sinusoidal voltage v_{ss} in (5) with an intermittent signal, as shown in Fig. 3. Here, instead of having a continuous sinusoidal signal (blue line), we apply v_{ss} for one period and then suppress it for N_{IM} periods using a rectangular gating (red line). This approach leads to smaller resistive losses and avoids discontinuities in the voltage signal (which, in turn, ensure bounded current). However, the temporal resolution of the capacitance estimation is reduced, as the RLS algorithm stops updating the parameter estimation during the time window in which v_{ss} is zero, and requires time to converge when parameter update is resumed. To mitigate this effect and reduce convergence time, the RLS parameters are initialized at the start of each active window using a linear extrapolation of the previous parameter trend.

The second strategy exploits the fact that i_{ss} is approximately proportional to the factor CV_{ss} , cf., (9). In the standard method, this implies that i_{ss} increases in amplitude as C becomes larger. To keep the amplitude of i_{ss} approximately constant throughout the DEG cycle, we modify the SS signal in (5) by replacing the constant V_{ss} with a time-varying amplitude $V_{ss,mod}(t)$, determined based on the instantaneous value of C by imposing $C(t)V_{ss,mod}(t) = C_{min}V_{ss}$. When implementing this strategy together with the pulsed activation described above, we keep $V_{ss,mod}$ constant throughout a single pulse, and change it only between activations based on the last measured value of C . This minimizes harmonic distortions.

E. Complete CL Generation Architecture

The overall SS CL architecture is schematized in Fig. 4. The DEG (green box) is cyclically by an external mechanical source, causing variations in both capacitance and resistance. The current and voltage signals are measured (yellow box) and used to estimate the instantaneous values of C and R . The corresponding generation voltage v_h is computed based on C according to the desired control strategy (gray box). Only detected peaks and valleys of C are used for the CV cycle, while the whole continuous signal C is used to implement (1) in the CF cycle. The combined voltage $v = v_h + v_{ss}$ is then applied to the DEG (blue box).

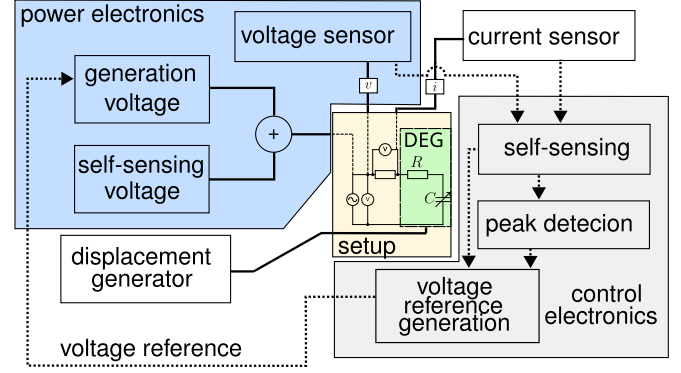


Fig. 4. Overview of the CL harvesting architecture.

III. PARAMETRIC ANALYSIS

This section investigates energy tradeoffs and tuning rules for SS DEGs. In the following, $\tilde{x}$ is used to denote a generic variable x normalized to a theoretical maximum value.

A. Energy Performance Calculation

According to [1], the maximum energies harvestable with the two cycles described in Section II-A can be expressed as

$$\mathcal{E}_{CV} = \frac{1}{2} C_{\max} V_{CV}^2 \left(1 - \frac{C_{\min}}{C_{\max}} \right) \quad (10)$$

$$\mathcal{E}_{CF} = \frac{1}{2} C_{\max} V_{CV}^2 \log \left(\frac{C_{\max}}{C_{\min}} \right) \quad (11)$$

where $\mathcal{E}_{CV}$ and $\mathcal{E}_{CF}$ are the corresponding energies for the CV and CF cases, respectively, and V_{CV} is the voltage applied when $C = C_{\max}$. The energies in (10) and (11) are equivalent to the shaded areas in Fig. 1(b), with $\mathcal{E}_{CF} > \mathcal{E}_{CV}$, and correspond to maximal theoretical values in the absence of resistive losses.

The energy dissipated on the DEG resistance R over a generation cycle of duration T_c is computed as follows:

$$\mathcal{E}_{diss} = \int_0^{T_c} R(t) i^2(t) dt. \quad (12)$$

Based on (12), we can characterize the energy dissipation for the two SS strategies described above. To simplify the analytic calculation, we make the following assumptions. 1) $T_c f_{ss} \gg 1$, i.e., the generation cycle contains a large number of SS signal periods. 2) $i \simeq i_{ss}$, i.e., resistive losses are dominated by the high-frequency SS current. 3) $2\pi f_{ss} RC \ll 1$, which implies that (9) holds true. 4) The resistance $R(t)$ does not exhibit large variations from its average value, and can be approximated with a constant value R . Based on those assumptions, we use (12) to compute the energy $\mathcal{E}_{diss1}$ dissipated by the standard SS method as

$$\mathcal{E}_{diss1} = 2\pi^2 f_{ss}^2 C_{rms}^2 V_{ss}^2 R T_c \quad (13)$$

where the rms capacitance C_{rms} over a cycle is defined as

$$C_{rms} = \sqrt{\frac{1}{T_c} \int_0^{T_c} C^2(t) dt}. \quad (14)$$

Next, by considering the voltage waveform in Fig. 3 and recalling that in this case $C(t)V_{ss,mod}(t) = C_{min}V_{ss}$, we can estimate the advanced SS dissipation $\mathcal{E}_{diss2}$ as

$$\mathcal{E}_{diss2} = \frac{2\pi^2 f_{ss}^2 C_{min}^2 V_{ss}^2 R T_c}{N_{IM} + 1}. \quad (15)$$

Equations (13) and (15) reveal that, for both methods, the losses per cycle increase linearly with the series resistance R and cycle period T_c , and quadratically with the SS amplitude V_{ss} and frequency f_{ss} . The harvestable energies over a cycle (10) and (11), on the other hand, are independent of T_c and scale only with the applicable voltage (usually constrained by the electronics or breakdown conditions) and the ratio C_{max}/C_{min} . By comparing (13) and (15), we obtain

$$\frac{\mathcal{E}_{diss2}}{\mathcal{E}_{diss1}} = \frac{1}{N_{IM} + 1} \left(\frac{C_{min}}{C_{RMS}} \right)^2 \leq 1. \quad (16)$$

This ratio can be further reduced by increasing N_{IM} , although this reduces the temporal resolution of C . If, on the other hand, a fixed energy budget is allocated for SS, then (16) implies that either V_{ss} or f_{ss} can be increased by a factor $\sqrt{N_{IM} + 1}$ in pulsed SS, without affecting the total dissipation. Implications of this fact for the overall SS accuracy are discussed in a simulation study reported in the Supplementary Material. The introduction of variable $V_{ss,mod}$ results in the factor $\frac{C_{min}}{C_{RMS}} \leq 1$ in (16), which always reduces dissipation without compromising SS accuracy.

B. SS Tradeoff Evaluation

Equations (13) and (15) suggest that SS parameters V_{ss} and f_{ss} must be chosen as small as possible to minimize resistive losses. In practice, both voltage and current measurements are affected by noise. If the SNR in v and i is not sufficiently large, then the estimated capacitance is also noisy, hindering the implementation of SS control strategies. Errors in C affect implementation of (1) for CF cycles, and noise is especially critical for peak detection needed in both CF and CV cycles as it involves differentiation. Although Section II-B proposed strategies to mitigate resistive losses, those induce a delay in the peak detection, which can reduce the energy yield. This creates a tradeoff: large SS voltage/frequency result in an accurate harvesting cycle synchronization, but produce high resistive losses; small voltage/frequency values reduce losses, but lead to poorly synchronized harvesting cycles. This tradeoff exists regardless of the adopted harvesting cycle or SS strategy.

To illustrate this effect and derive tuning guidelines, a simulation study is conducted considering standard SS harvesting cycles. In the study, we implemented the RC circuit model (2) in MATLAB using a stationary resistance R and a capacitance profile $C(t) = C_0(1 - 0.3 \cos(2\pi f_c t))$, with $f_c = \frac{1}{T_c}$, and used it to simulate CV and CF cycles. A Gaussian bandwidth-limited noise with standard deviation σ_i and σ_v is applied to the simulated voltage and current, respectively. We chose simulation parameters in line with the experimental tests (cf., Section IV): $C_0 = 600$ pF, $R = 300$ k Ω , $\sigma_v = 100$ μ V, $\sigma_i = 3$ μ A, $\mu = 0.99$, $T_c \in [1, 2, 5]$ s, $V_{CV} = 2000$ V. Since the weight of V_{ss} and f_{ss} on the dissipated power is virtually identical [cf., (13) and (15)], we fix $f_{ss} = 400$ Hz and iterate over V_{ss} . For

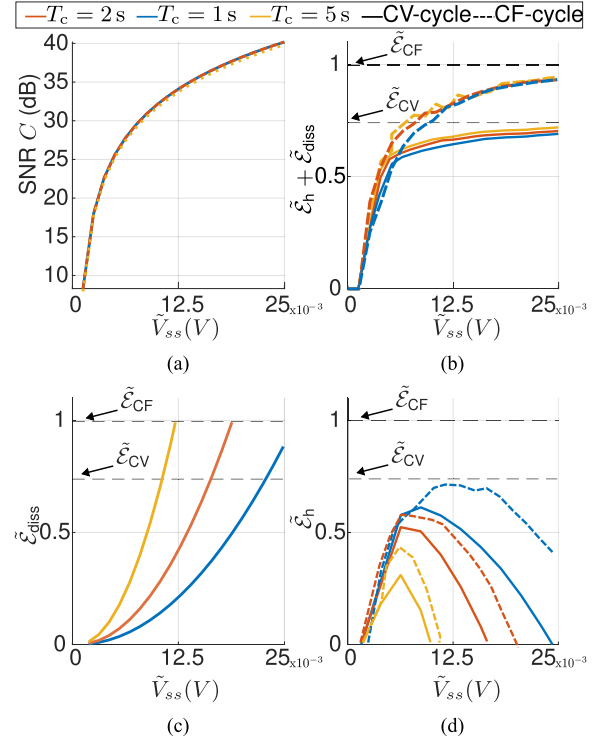


Fig. 5. Simulation study highlighting the tradeoff between accuracy and losses for the CV and CF cycles. (a) Estimated capacitance SNR. (b) Generated energy without SS losses. (c) SS losses. (d) Net generated energy.

each V_{ss} , the peak detection parameters (high-pass filter critical frequency and threshold ε) are tuned using numerical optimization to maximize the harvested energy averaging all three T_c . The harvested energy over a generation cycle $\mathcal{E}_h$ is computed as

$$\mathcal{E}_h = - \int_0^{T_c} v(t) i(t) dt \quad (17)$$

where the minus sign reflects the adopted power convention. Fig. 5(a) shows the SNR of the reconstructed capacitance, Fig. 5(b) shows the harvested energy without SS losses, Fig. 5(c) shows the energy losses caused by SS, and Fig. 5(d) shows the harvested energy, including the SS losses. All energy values reported in Fig. 5 are normalized with respect to the theoretical maximum energy $\mathcal{E}_{CF}$ computed following (11), while the SS voltage V_{ss} is normalized with respect to the harvesting voltage V_{CV} . The capacitance SNR in Fig. 5(a), and thus the estimation accuracy, increases monotonically with $\tilde{V}_{ss}$. For low $\tilde{V}_{ss}$, the optimal peak detection parameters consist of a small critical frequency and large threshold, which are robust to the noisy estimate but introduce delay in the synchronization, thus reducing the energy yield. This can be seen in Fig. 5(b), where the total generated energy (harvested energy plus SS losses) asymptotically approaches the theoretical maximum as $\tilde{V}_{ss}$ increases. This also indicates that well timed peak detection is possible beyond a certain SNR threshold value, and further improvements of the SNR yield incremental gain in energy. The resistive losses in Fig. 5(c) coincide for both CV and CF cycles, and increase quadratically with $\tilde{V}_{ss}$ while strongly

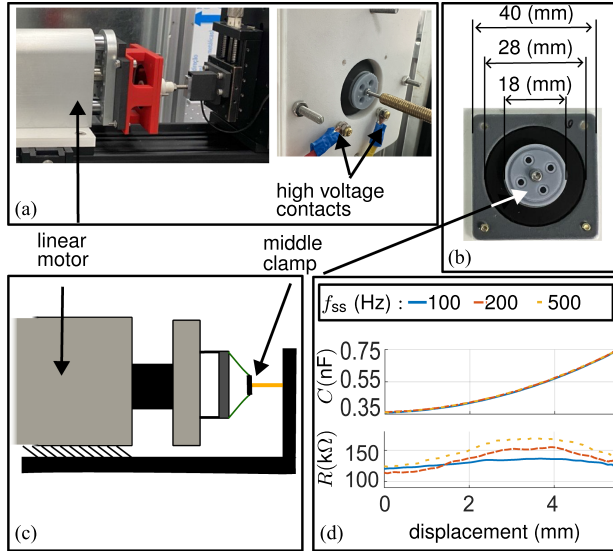


Fig. 6. Experimental setup. (a) picture and (b) sketch of the test bench, (c) front view of unmounted DE and (d) estimated DEG capacitance and series resistance over out-of-plane displacement for several SS frequencies.

depending on T_c , in agreement with (13). When T_c is large enough, $\tilde{\mathcal{E}}_{diss} > 1$ and the harvested energy $\tilde{\mathcal{E}}_h$ becomes negative. The combined tradeoff between accuracy and dissipation can be clearly seen in Fig. 5(d), where for each T_c there exists a value of $\tilde{V}_{ss}$ maximizing $\tilde{\mathcal{E}}_h$. Simulations reveal that the optimal value $\tilde{V}_{ss}$ depends on several factors, including sensors measurement noise, excitation frequency and waveform, available harvestable energy, and DEG resistance.

For practical real-world implementation, rather than resorting to a full numerical optimization, SS parameters can be identified using simplified procedures, e.g., starting from large initial values of V_{ss} and f_{ss} and iteratively reducing them until a stationary value of the harvested energy is reached. A formalized algorithmic procedure to tune the SS parameters is reported in the Supplementary Material.

IV. EXPERIMENTAL RESULTS

This section validates the proposed closed-loop self-sensing (CL-SS) harvesting strategies via an extensive experimental campaign.

A. Experimental Setup

All tests are performed with the setup shown in Fig. 6. A circular out-of-plane silicone DE is mounted to the sled of a linear motor (LinMot DM01-37x120F-HP-R-95 with embedded CL position control), clamped to its center part. Inputs are applied via a high-voltage amplifier (HiVolt HA3B3-S, ± 3 kV, ± 5 mA, 1 kHz full range bandwidth, 20 kHz small signal bandwidth). Voltage is acquired with the amplifier's built-in monitor, while current is measured on a 2 kΩ shunt resistor via an isolation amplifier (Broadcom HCPL-7800 A, max. voltage input 200 mV). For the tested signal with the highest dynamical range (i.e., $f_{ss} = 400$ Hz and $V_{ss} = 60$ V), we verified that the

measured voltage exhibits a total harmonic distortion of 0.19%. Data acquisition and algorithm execution are performed on a real-time target machine (Speedgoat Performance) equipped with a high-speed analog/digital I/O module (Speedgoat IO133), at a sampling rate of 20 kHz.

B. DE Characterization

The considered DE, manufactured by Parker Hannifin, consists of two stacked ring-shaped silicone membranes coated by compliant carbon-based electrodes [23]. Its outer diameter, inner diameter, and thickness of each layer in the flat configuration are 28 mm, 18 mm, and 46 μm, respectively. The DE can be deformed out-of-plane, as shown in Fig. 6(b). The circular out-of-plane configuration, combined with a high aspect ratio leads to an almost pure shear deformation [28], making this architecture a popular choice for DEG [1]. The total volume of the DE membrane is 0.034 cm³. Fig. 6(d) shows the capacitance and series resistance of the DEG measured at different SS-frequencies $f_{ss} \in [100, 200, 500]$ Hz and out-of-plane displacements. The corresponding SS voltage amplitudes are chosen as $V_{ss} \in [500, 200, 100]$ V, scaled with f_{ss} to provide comparable current amplitude [see (9)].

The capacitance estimate is nearly identical for all considered f_{ss} , while a mild increase in resistance occurs at higher frequencies. The minimum capacitance in flat configuration is $C_{min} = 390$ pF, while a maximum capacitance $C_{max} = 750$ pF is reached for an out-of-plane displacement of 5.5 mm. We choose $V_{CV} = 2050$ V for both CV and CF cycles, so that the two harvesting voltages v_h coincide when $C = C_{max}$, while $v_h \approx 2900$ V for the CF cycle only when $C = C_{min}$ [cf., (1)].

C. Benchmark Harvesting Scenario

The benchmark harvesting performance is evaluated by displacing the DE out-of-plane with the motor with a sinusoidal profile ranging from 0 to 5.5 mm, considering three different periods $T_c = [5, 2, 1]$ s.

1) **Benchmark Open-Loop (OL) Experiments:** Initial harvesting experiments are performed to obtain benchmark performance metrics. First, CV and CF tests are conducted by applying a SS voltage v_{ss} with $V_{ss} = 100$ V and $f_{ss} = 500$ Hz (leading to accurate estimates of the capacitance and its peaks) to identify a target harvesting voltage profile v_h . Then, the CV and CF tests are repeated in OL by considering the same v_h computed previously, this time without introducing the SS signal and relative losses. The applied voltages are shown in the center row of Fig. 7(a) for both CV and CF cycles, considering different T_c , while the corresponding capacitance profiles are shown in upper top row of Fig. 7(a). To limit current peaks, the voltage is applied as a ramp with a duration of 50 ms. The capacitance estimations are slightly perturbed due to the current spikes occurring during charging periods.

2) **Energy Calculation:** The generated and dissipated energies can be computed from (17) and (12), respectively, using measured v and i and estimated R . However, integration drift due to unavoidable measurement bias in the current makes this approach unreliable. To improve accuracy, energy computations

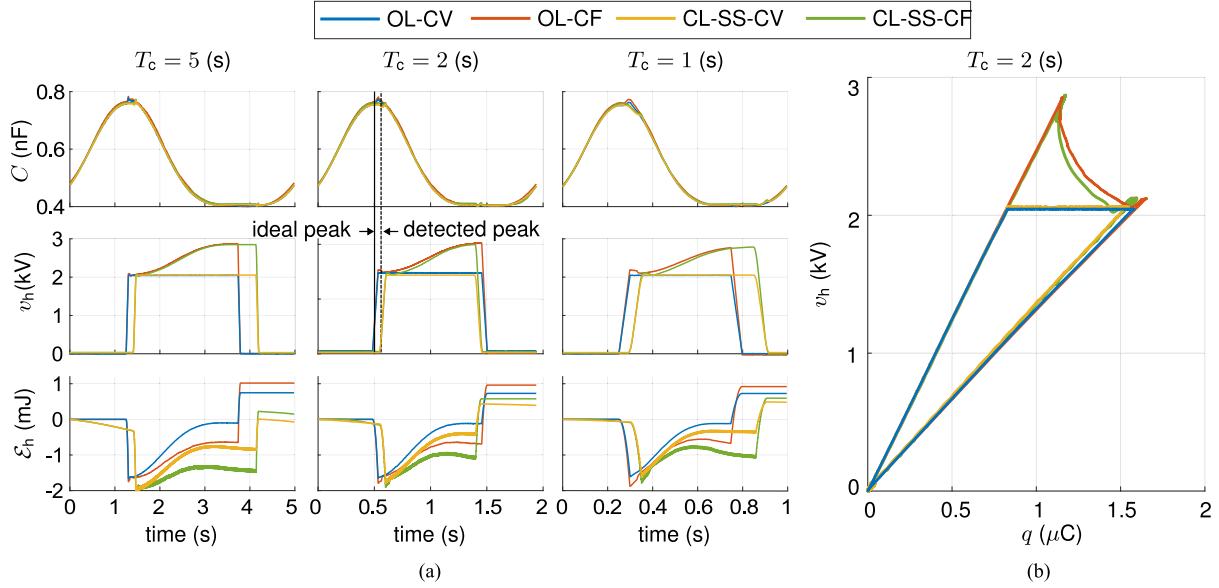


Fig. 7. OL and CL harvesting cycles for $T_c \in [5, 2, 1]$ s with unoptimized SS signal (400 Hz, 30 V). (a) estimated capacitance, harvesting voltage, and harvested energy; (b) voltage–charge diagram for $T_c = 2$ s.

are updated using a simulation model based on (2), driven by experimental measurements and estimated R and C . This approach is shown to provide reliable and repeatable energy computation (see the Supplementary Material for details). Based on (10) and (11), the theoretical upper bounds for the energy per cycle are computed as $\mathcal{E}_{CV} = 0.75$ mJ and $\mathcal{E}_{CF} = 1.03$ mJ, respectively, the latter corresponding to an energy density of ~ 30 mJ/cm³. Experimentally measured energies per cycle are obtained by running each experiment for 20 s and computing the average over all cycles. The resulting energies for the OL CV and CF cycles are listed in Table I for three different deformation periods, including both average value and standard deviation, alongside the theoretical maxima obtained with (10) and (11). A noticeable drop in energy generation occurs for T_c of 2 s and 1 s, especially for the CF case, likely due to the delay in voltage application caused by the adopted ramp profile. These experiments therefore provide an upper bound for the achievable energy and isolate the losses introduced by finite time charging/discharging (voltage ramp), and other setup losses. The fraction of harvested energy ranges between 87% (OL CF, $T_c = 1$ s) and 98% (OL CV, $T_c = 5$ s) of the theoretical maxima. Fig. 7(b) shows the voltage–charge diagram of the OL CV and OL CF cycles for $T_c = 2$ s, where charge q is plotted against v_h . The cycles follow typical shapes discussed in Section II-A. These results serve as a realistic upper bound on the harvesting performance with ideal peak detection and without SS losses.

D. Unoptimized CL Tests, Standard SS

As discussed in Section III-B, the choice of sensingSS parameters must account for the tradeoff between estimation accuracy and resistive losses. To highlight the importance of this tradeoff, the first iteration of CL harvesting tests is performed using the standard sensingSS algorithm from Section II-C, choosing the parameters in an unoptimized way. Specifically, we set $f_{ss} =$

TABLE I
GENERATED ENERGY $\mathcal{E}_H$ AND SS DISSIPATION $\mathcal{E}_{DISS}$ (MEAN VALUE $\pm$ STANDARD DEVIATION) PER CYCLE FOR OL AND CL SS HARVESTING STRATEGIES, CONSIDERING BOTH CV (ROWS 1-5) AND CF (ROWS 6-10) CYCLES

	$T_c = 5$ s		$T_c = 2$ s		$T_c = 1$ s	
	$\mathcal{E}_h$ (mJ)	$\mathcal{E}_{diss}$ (mJ)	$\mathcal{E}_h$ (mJ)	$\mathcal{E}_{diss}$ (mJ)	$\mathcal{E}_h$ (mJ)	$\mathcal{E}_{diss}$ (mJ)
Theoretical max. CV	0.75	-	0.75	-	0.75	-
OL-CV	0.740 ± 0.002	-	0.733 ± 0.002	-	0.725 ± 0.001	-
CL-SS-CV	-0.029 ± 0.031	0.726 ± 0.002	0.383 ± 0.009	0.300 $\pm \approx 0$	0.481 ± 0.006	0.178 $\pm \approx 0$
CL-SS-CV, opt.	0.671 ± 0.006	0.05 ± 0.002	0.693 ± 0.017	0.020 $\pm \approx 0$	0.627 ± 0.032	0.009 $\pm \approx 0$
CL-AD-SS-CV	0.67 ± 0.009	0.004 ± 0.001	0.61 ± 0.024	0.0017 $\pm \approx 0$	0.55 ± 0.057	0.001 $\pm \approx 0$
Theoretical max. CF	1.03	-	1.03	-	1.03	-
OL-CF	0.991 ± 0.002	-	0.945 ± 0.001	-	0.893 ± 0.001	-
CL-SS-CF	0.204 ± 0.033	0.725 ± 0.002	0.543 ± 0.014	0.302 $\pm \approx 0$	0.601 ± 0.008	0.17 $\pm \approx 0$
CL-SS-CF, opt.	0.91 ± 0.007	0.052 ± 0.002	0.86 ± 0.031	0.025 $\pm \approx 0$	0.76 ± 0.006	0.012 $\pm \approx 0$
CL-AD-SS-CF	0.90 ± 0.011	0.004 ± 0.001	0.79 ± 0.062	0.0017 $\pm \approx 0$	0.64 ± 0.078	0.001 $\pm \approx 0$

For both strategies, the rows represent: Theoretical maximum, energy harvested in OL, basic self-sensing with unoptimized parameters ($f_{ss} = 400$ Hz, $V_{ss} = 30$ V), basic self-sensing with optimized parameters ($f_{ss} = 100$ Hz, $V_{ss} = 30$ V), and advanced self-sensing ($f_{ss} = 400$ Hz, $V_{ss} = 15$ V, $NIM = 10$).

400 Hz and $V_{ss} = 30$ V, corresponding to a capacitance SNR value of 45.9 dB. Note that these values are already quite low compared to typical actuator applications [23], [24]. The peak detection parameters, i.e., the high-pass filter critical frequency and threshold ε , are also tuned heuristically (see Algorithm 2 in the Supplementary Material).

The corresponding v_h is generated based on the estimated C as described in Section II-A–B and is shown in the center row of Fig. 7(a), resulting in the harvested energies shown in the bottom row. It can be seen that the harvested energy is

smaller than in the OL scenario for all strategies and cycle periods. This reduction in energy is due to different factors. First, the application of v_{ss} leads to resistive losses, which cause a constant-rate decrease in harvested energy even when no harvesting voltage is applied. Second, the timing of the harvesting voltage application is delayed compared to the OL scenario. This delay has a sensible impact on the harvesting performance, as discussed in the following.

To quantify the loss in performance, Table I reports $\mathcal{E}_h$ and $\mathcal{E}_{diss}$ for both CV and CF CL sensingSS cycles (rows 3 and 8, respectively). For $T_c = 5$ s, the harvesting yield is small and almost all energy is dissipated as sensingSS resistive losses. Faster cycles lead to meaningful energy generation, since the losses accumulate over a shorter time and thus their relative impact is reduced. In the best CL scenario (CV, $T_c = 1$ s), $\mathcal{E}_h$ is $\sim 67\%$ of the OL counterpart. Fig. 7(b) also reports the voltage-charge diagram for the CL-SS cycles. Although the energy dissipated by resistive losses is not visible here, the reduction in converted energy (i.e., the inscribed area) can be seen clearly and attributed to the slight delay in voltage application caused by the nonideal peak detection. To estimate the energy penalty caused by this delay in the CV case, we use the measured capacitance at the actual charging/discharging instants (rather than C_{max} and C_{min}) in (10) to compute the energy convertible in this restricted range. The difference between this value and the theoretical energy convertible over the full capacitance range defines the delay loss. For CV and $T_c = 1$, this delay loss equals 0.126 mJ; summing this value with the SS losses $\mathcal{E}_{diss} = 0.178$ mJ and the harvested energy $\mathcal{E}_h = 0.481$ mJ (see Table I) yields 0.722 mJ, which compared to the 0.725 mJ harvested in OL explains 99% of the accumulated losses. This suggests that the delay loss and SS losses together account for nearly all the energy reduction relative to the OL case. The same result can be verified to hold true for all experiments shown in the rest of this section, provided that the energy is computed within the bounds of its standard deviations, as shown in Table I (detailed calculations are omitted for conciseness). In the CF case, in addition to the delay, small deviations in v_h can be observed due to the reduced accuracy of the capacitance estimate, cf., (1). The mean absolute error in voltage trajectory between SS and ideal scenario is 29 V for the three considered cycles, i.e., approximately 1% of the total magnitude. Therefore, also in this case the additional reduction in harvested energy on top of resistive dissipation can be mostly attributed to the delay in voltage application. These results show that simple use of SS methods developed for DE actuators may lead to limited or no energy generation, if the dissipation-accuracy tradeoff is not accounted for.

E. Optimized CL Tests, Standard SS

In the experiments provided in the previous section, the resistive dissipation represents the largest share of loss with respect to the benchmark. To demonstrate the feasibility of efficient energy harvesting via SS, we co-optimize the SS-parameters and the peak detection parameters following the strategy outlined in Section III-B and formalized in the Supplementary Material.

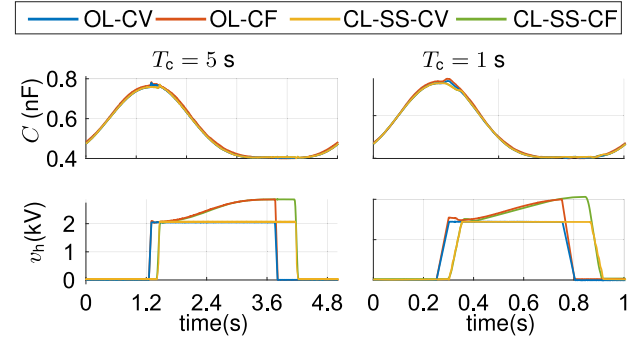


Fig. 8. OL and CL harvesting for $T_c = 5$ s and $T_c = 1$ with optimized SS ($f_{ss} = 100$ Hz, $V_{ss} = 30$ V), estimated capacitance and DEG voltage.

We keep $V_{ss} = 30$ V, and obtain an optimal SS frequency of 100 Hz, which leads to a capacitance SNR value of 35.6 dB. Fig. 8 shows the OL and CL application of v_h as well as the estimated capacitance profiles C . The voltage application occurs with minimal delay in both the 5 and 1 s cycles. The 2 s cycle shows qualitatively similar results, so it is omitted for conciseness. The harvested energy in the CL-SS CV and CF cycles is close to the values obtained in OL conditions, as reported in rows 4 and 9 of Table I. Especially for the slower cycles, the delay in the peak detection has a small impact on harvesting. In the CF case, the error in voltage trajectory does not exceed 1%. The resulting $\mathcal{E}_{diss}$ never exceeds 7% of $\mathcal{E}_h$ in all scenarios, leading to a harvesting performance ranging from 85% (CL-SS-CF, 1 s) to 95% (CL-SS-CV, 2 s) of the OL counterpart. The CF cycles consistently outperform CV ones by a factor between 22% ($T_c = 1$ s) and 36% ($T_c = 5$ s).

F. Advanced SS Strategy

The heuristic optimization proved effective during CL validation of the harvesting cycles, as it allows harvesting most of the available energy while strongly reducing resistive losses, even in situations in which the sensor noise or the boundary conditions do not allow adopting very low SS voltage amplitude and frequency. The advanced SS strategy discussed in Section II-D offers a means to further reduce the SS losses. The modulation of V_{ss} can be applied straightforwardly, and without any reduction of the worst-case SS accuracy. This is illustrated on the right-hand side of Fig. 9, where i_{ss} is shown using the advanced strategies and compared with the current envelope for the baseline SS signal.

The intermittent application of the SS signal tradesoff temporal resolution with reduced resistive losses, and the optimal N_{IM} depends on the scenario under consideration. The left-hand side of Fig. 9 shows the capacitance profiles estimated using a continuous SS signal, as well as various parameterizations of the advanced-strategy for $T_c = 1$ s, with $v_h = 0$. In all cases, the product $f_{ss}V_{ss}$ is kept constant to ensure a comparable SS current amplitude. For $N_{IM} = 2$, $f_{ss} = 200$ Hz, the temporal quantization is small relative to T_c , and the estimated capacitance follows the continuous SS profile well. For $N_{IM} = 5$, $f_{ss} = 400$ Hz the RLS is updated at the same time as the previous case but each pulse is half the duration. The capacitance estimation accuracy

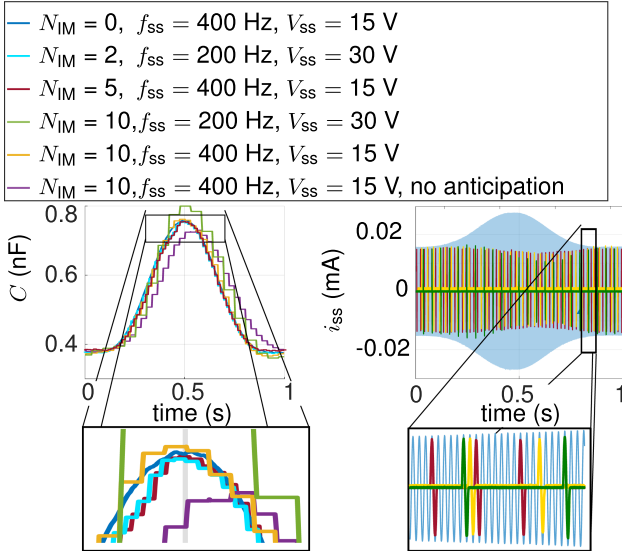


Fig. 9. Effects of advanced SS on estimated capacitance and injected current, compared to baseline SS. The blue shaded area in the top right plot represents the envelope of the current for the baseline SS.

is overall similar to the previous case, although a noticeable estimation delay occurs due to the reduction in convergence period. This suggests that a higher frequency, i.e., a more frequent update, is beneficial for the considered scenario. The result can be further confirmed by comparing $N_{IM} = 10$ and $f_{ss} = 200$ Hz with $N_{IM} = 10$ and $f_{ss} = 400$ Hz, where the latter tracks the reference profile more accurately despite causing comparable SS-losses. Finally, we show the effect of the capacitance trend extrapolation and RLS reinitialization previously discussed in Section II-D. The importance of this extrapolation can be seen comparing $N_{IM} = 10$ and $f_{ss} = 400$ Hz with and without anticipation (i.e., extrapolation). In the latter case, the estimated capacitance exhibits a noticeable lag. On the other hand, $N_{IM} = 10$ and $f_{ss} = 200$ Hz visibly overshoots the reference due to the anticipatory extrapolation.

For the CL implementation of the advanced SS strategy, we select $f_{ss} = 400$ Hz, given its performance in the initial investigation. The other SS parameters are set to $N_{IM} = 10$ and $V_{ss} = 15$ V. These parameters are selected by decreasing V_{ss} and increasing N_{IM} up to a point in which accurate peak detection could no longer be obtained (even upon retuning of the high-pass filter and ε parameters).

The CL performance of advanced SS can be seen in Fig. 10, where the upper plot compares the capacitance for the OL tests (see Section IV-C) and the closed-loop-advanced self-sensing (CL-AD-SS) strategy. For the deformation cycle at $T_c = 5$ s the difference in capacitance is barely distinguishable, while for $T_c = 1$ s the temporal quantization becomes significant, while the corresponding delay in peak detection is small in both cases. In the lower row of Fig. 10, it can be observed that the voltage trajectory for the CF cycles follows well the OL case, again with an error lower than 1% over all cycles. The resulting values of $\mathcal{E}_h$ are listed in Table I for both CV and CF cycles (rows 5 and 10, respectively). The harvested energy for $T_c = 5$ s is practically identical to that for the strategy discussed in Section IV-E and close to the ideal OL one, see Table I.

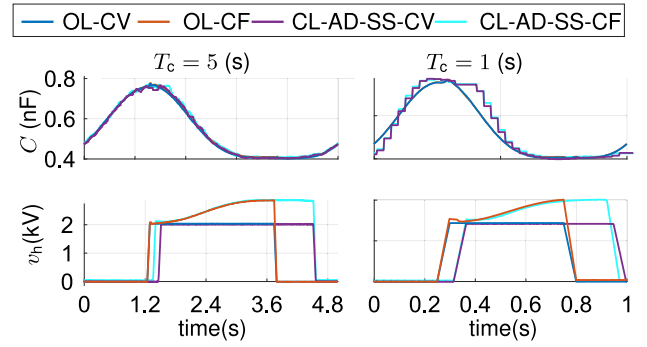


Fig. 10. OL and CL harvesting performance for $T_c = 5$ s and $T_c = 1$ s with the advanced SS strategy (400 Hz, 15 V, $N_{IM} = 10$), estimated capacitance and DEG voltage.

In addition, the dissipated energy is approximately one order of magnitude smaller than $\mathcal{E}_{diss}$ of the optimized baseline SS, i.e., in this case, the differences between CL and OL harvesting are mainly due to delays in peak detection, rather than the SS dissipation. For $T_c = 1$ s, the harvested energy is reduced by 18% and 29% for the CV and CF cycles, respectively. This is because time quantization induces a larger relative delay on peak detection for fast deformations, whose associated loss explains most of the difference with respect to the OL cycle. This result suggests that the advanced SS provides advantage in scenarios with slower mechanical deformations, where SS resistive losses accumulate over a longer time. In this case, mitigation strategies, such as the proposed advanced SS are key to retain positive energy generation.

G. Polychromatic Excitation

The previous tests showed that the proposed CL-SS method allows harvesting a meaningful fraction of the theoretical available energy for a broad range of sinusoidal deformations. In practice, however, ambient mechanical excitations rarely follow sinusoidal waveforms [14]. To evaluate the performance of the proposed method in the presence of more realistic excitations, new tests are conducted using a polychromatic position profile as the reference trajectory for the linear motor. The deformation profile power spectral density follows an inverse Weibull distribution with shape parameter $k = 2.5$ and scale parameter $\lambda = 0.4$ Hz, properly rescaled in such a way that the capacitance value C_{max} (c.f., Section IV-B) is not exceeded at maximum displacement. This deformation profile allows us reproducing a harvesting scenario in which no a priori knowledge of the excitation profile is embedded into the control logic. After generating the deformation profile, a 100 s experiment is performed in which the proposed CL strategies are tested against the OL performance. All SS parameters are the same as in the monochromatic experiments. A 15 s cut of the experiment is shown in Fig. 11, where the upper plot shows the capacitance profile resulting from the polychromatic deformation, the central row presents the applied voltages for the CF generation cycles, and the row illustrates the cumulated generated energy. It can be observed that the peaks are consistently detected with minimal delay. One noticeable exception occurs around plateaus in the capacitance profile, as indicated in the figure. Here, significant

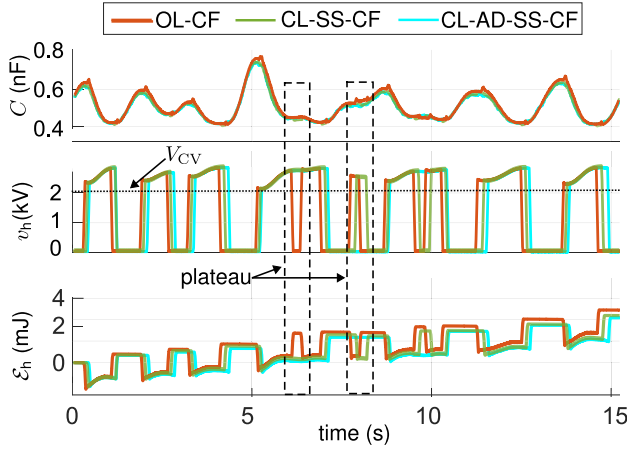


Fig. 11. Harvesting performance for a polychromatic deformation profile, estimated capacitance, applied CF voltage, and cumulated harvested energy for OL SS, CL-SS, and CL-AD-SS strategies.

TABLE II

HARVESTED ENERGY AND SS LOSSES FOR A 100 s POLYCHROMATIC EXPERIMENT, CV (ROWS 1–3) AND CF (ROWS 4–6)

	$\mathcal{E}_h$ (mJ)	$\mathcal{E}_{diss}$ (mJ)
OL-CV	17.18	-
CL-SS-CV	13.80	1.40
CL-AD-SS-CV	13.26	0.10
OL-CF	21.89	-
CL-SS-CF	17.80	1.40
CL-AD-SS-CF	16.60	0.10

For both strategies, the different rows represent: OL; CL-SS with $f_{ss} = 100$ Hz, $V_{ss} = 30$ V; CL-AD-SS with $f_{ss} = 400$ Hz, $V_{ss} = 15$ V, NIM = 10.

deviations (missed charging/discharging) from the OL control occur. Since no significant capacitance change occurs during those brief periods, little to no harvestable energy is lost, rendering the missed charging/discharging insignificant. From Table II and the lower row of Fig. 11, it can be seen that the generated energies are very similar for all three CL methods, and range within 76%–82% of the OL energy [note that no theoretical maxima are reported in this case, since different cycles feature different values of the maximum/minimum capacitance, thus rendering the application of (10) and (11) unpractical]. Although the global performance is slightly lower, these values show that the parameters tuned for the sinusoidal profiles generalize well to the polychromatic setting. Since the capacitance profile is no longer consistently varying between C_{min} and C_{max} , the voltage applied immediately after charging in CF cycles is now larger than V_{CV} , as visible in the center row of Fig. 11. This leads to an increase in harvested energy of about 25%–29% compared to CV cycles, cf., Table II.

V. CONCLUSION

In this work, we implemented and experimentally validated for the first time SS-based CL control of dielectric elastomer generators. We tested our method with both CV and CF harvesting cycles, considering simple sinusoidal deformation cycles at various frequencies, as well as general polychromatic excitations. We systematically quantified the additional resistive losses induced by the injected SS voltage signal, and studied

the tradeoff between losses and peak detection accuracy. Experimental validation showed that SS-based CL cycles harvested between 85% and 95% of the energy obtained in idealized OL experiments, corresponding to 74% and 92% of the theoretical maximal energy, respectively. To further reduce the impact of SS on harvesting performance, we introduced modifications in the baseline SS methods. Using this tailored SS approach, resistive losses are reduced by one order of magnitude without significantly degrading the overall accuracy. This strategy is shown to be effective in scenarios, where long cycles make continuous SS lossy, since it reduces resistive losses by sacrificing temporal accuracy. Short period cycles may not benefit from this strategy, as the reduced temporal resolution can lead to suboptimal charge/discharge timing and thus reduce the overall generated energy. Even when the SS losses represent a very small fraction of the generated energy, the maximal energy harvested in CL is at best 89% of the theoretical maximum, mainly due to delays introduced by peak detection. Therefore, in the case of well-tuned SS, the main source of inefficiency is the delay introduced by peak detection rather than the resistive losses.

Our study demonstrates the feasibility of controlling a DEG via SS with high energy yield, allowing them to convert unpredictable energy sources without the need for extra electro-mechanical sensors. Future research will focus on investigating new SS harvesting cycles with improved energy yield and better robustness to peak detection delay (e.g., smooth voltage control and energy-optimal model predictive control), as well as integrating the proposed SS strategies in other types of electrostatic harvesters.

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