Do Energy-Harvesting Pixels Reduce Carbon Cost of Visual Computing Systems?

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***Abstract*—Energy harvesting is a common solution to reduce carbon emissions from system design, usually with external solar panels. However, visual computing systems offer a unique opportunity: beyond the solar panel, pixels can inherently convert light energy into electrical energy, functioning as both imagers and harvesters. Intuitively, energy-harvesting pixels could partially or fully satisfy system's energy needs, reduce the required solar panel size and thus embodied carbon emissions. In practice, their impact is complicated by energy-autonomy constraints and the tight coupling between image quality, energy consumption, and harvested energy. These factors make carbon cost difficult to assess without system-level analysis.**

In this paper, we present a framework to quantify the carbon emissions of visual computing systems under energy-autonomy constraints, while accounting for image quality. The framework models energy harvesting, energy consumption, and carbon emissions, based on image quality metrics and hardware parameters. We show that energy-harvesting pixels provide limited carbon emission reduction, primarily due to the high embodied carbon intensity of IC fabrication.

I. INTRODUCTION

Reducing carbon emissions has become a critical challenge in system design as the number of deployed devices continues to grow [7]. In long-term deployments, operational carbon emissions can account for a substantial fraction of a system's total carbon emissions [2]. Energy harvesting (EH) is therefore a promising approach to eliminate these emissions, with solar panels (SPs) as the common energy harvester.

Visual computing platforms present unique opportunities: image sensors can inherently convert optical energy to electrical energy. This enables the image sensor itself to function as an energy harvester, supplementing or even replacing the external solar panel [12], and potentially reducing the embodied carbon emissions from hardware manufacture. Motivated by this, prior work has explored EH pixels (EHPs) that switch between imaging and EH modes to enable self-powered visual computing systems [1], [6], [10]–[12].

While EHPs have been shown to enable self-powered operation, their impact on system's carbon cost — reducing required solar panel size and thus embodied carbon emissions from hardware manufacture — has never been discussed.

Assessing the carbon cost of self-powered visual computing systems depends on two factors. First, self-powered systems are constrained by energy autonomy: harvested energy must be sufficient to sustain system operation. Second, both harvested energy and energy consumption are coupled with image quality. As a result, the carbon cost and potential benefit may vary across different image quality requirements. For example,

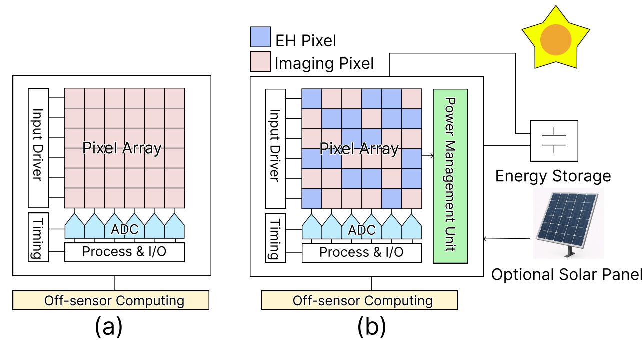

Fig. 1: (a) Conventional CIS structure; (b) Self-Powered CIS with both a solar panel and EH pixels.

higher frame-per-second (FPS) reduces harvesting time and thus limits the carbon cost reduction.

Can EHPs reduce system's carbon emissions in practice? If so, by how much? And how does this potential reduction vary across different image quality requirements? These questions remain unclear, yet are critical for system designers when deciding whether to equip image sensors with EHPs.

In this paper, we present a system-level analysis framework for self-powered visual computing systems with EHPs. Our framework jointly models energy harvesting, energy consumption, image quality, and carbon emissions, enabling quantitative evaluation of how incorporating EHPs reduces system-level carbon emissions under energy-autonomy constraints.

II. ENERGY AND CARBON MODELING

To model the carbon emissions of this energy-autonomous system, we first model the system's harvested energy and energy consumption to determine the required SP size, which is then used to evaluate system carbon emissions. The energy and carbon models take image quality specifications (e.g., resolution, frame rate, and sampling rate) as inputs to analyze carbon emissions across operating conditions.

Basic Hardware System. We distill a common hardware template from prior work [4], [5], [10], [12], [14], [15] for further modeling and discussing, shown in Fig. 1 (b).

As shown in Fig. 1 (a), the conventional CMOS image sensor (CIS) consists of a pixel array, an analog-to-digital converter (ADC) and an on-sensor image signal processing circuit. It is optionally integrated with an off-sensor computing unit to reduce data bandwidth.

Self-powered CIS differs from it in two ways. First, energy can be harvested from both EHPs and an external SP, with pixels dynamically configured for harvesting or imaging across frames. Second, the additional hardware component to support the energy harvesting, including a power management unit (PMU) and energy storage (supercapacitors).

Modeling Harvested Energy. During each frame, the energy harvested by EHPs and SP can be modeled as the harvesting power times the harvesting time:

$$Q_{\text{EH\_CIS}} = \left(\frac{R}{\text{FPS}} - k \cdot T_{\text{exp}}\right) \cdot P_{\text{EH,CIS}}, \quad (1)$$

$$Q_{EH\_SP} = \frac{P_{EH,SP}}{\text{FPS}}. \quad (2)$$

In our model, a pixel is harvesting energy when it is not exposed for imaging, which applies to common shutter modes such as global and rolling shutter. Thus, the effective EH time in CIS depends on resolution R, frame rate FPS, exposure time T_{exp}, and the number of imaging pixels k. In contrast, SP can harvest energy continuously over the entire frame.

The harvesting power of each EHP and SP is given by:

$$P_{\text{EH},x} = \eta_x \cdot E_{\text{light}} \cdot \text{Area}_x, \quad x \in \{\text{CIS}, \text{SP}\}, \quad (3)$$

where η_x is the light-to-electricity conversion efficiency of each device, E_{light} is the incident light irradiance, and $Area_x$ is the light-sensitive area.

Modeling Energy Consumption. The energy consumption of system consists of the energy used by the pixel array (PA), data transmission, memory accesses, and computation:

$$Q_{cons} = Q_{PA} + Q_{transmission} + Q_{memory} + Q_{compute}. \quad (4)$$

Modeling Carbon Emissions. We model the total embodied carbon emissions (CE) as the sum of individual hardware components, including CIS, computing unit, memory, supercapacitors, SP, and circuit board (PCB):

$$CE = CE_{\text{CIS}} + CE_{\text{comp}} + CE_{\text{mem}} + CE_{\text{cap}} + CE_{\text{SP}} + CE_{\text{PCB}}. \quad (5)$$

For each component, CE is computed from its hardware parameters (e.g., area, memory size, or capacitance) using device-level carbon emission factors derived from published life cycle assessment (LCA) studies. Specifically, we use carbon-per-area (CPA), carbon-per-size (CPS) [7], and carbon-per-capacitance (CPC) [3]:

$$CE = \sum_{\text{item} \in \{\text{CIS, comp, SP, PCB}\}} \text{Area}_{\text{item}} \cdot \text{CPA}_{\text{item}} + S_{\text{mem}} \cdot \text{CPS}_{\text{mem}} + C_{\text{cap}} \cdot \text{CPC}_{\text{cap}}. \quad (6)$$

III. Results and Analysis

In this section, we evaluate the carbon emissions of all feasible design points that meet the requirement of energy-autonomy $Q_{EH} \geq Q_{cons}$. We quantify the carbon benefit of incorporating EHPs across a global design space parameterized by imaging quality specifications, and determine when, and by how much, EHPs reduce system's carbon emissions.

We define the design space using key image quality parameters, including resolution R, frame-per-second FPS and sampling rate SR. With the model in Sec. II, these parameters determine the feasibility of energy-autonomous operation. We independently perform design space exploration for two system classes — SP-only systems (conventional CIS powered by SPs), and SP+EHP systems (CIS with EHPs and optional SPs). Under identical imaging configurations, we compute their embodied carbon emissions, denoted as $CE_{\text{SP-only}}$ and $CE_{\text{SP+EHP}}$, respectively.

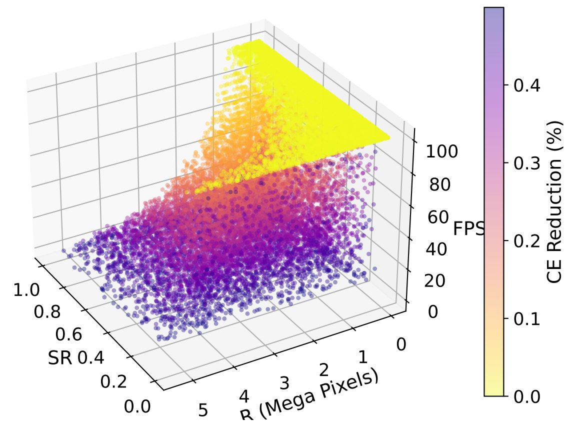

Fig. 2: Relative reduction in carbon emissions

Fig. 2 visualizes the reduction in embodied carbon emissions from the SP-only system to the SP+EHP system, defined as $\frac{CE_{\text{SP-only}} - CE_{\text{SP+EHP}}}{CE_{\text{SP-only}}}$, as the three imaging quality metrics (FPS, R, and SR) vary.

From Fig. 2, we can conclude that augmenting the system with EHPs reduces the embodied carbon emission. **However, the reduction is very marginal across the entire design space** — at most 0.5%. The reason is three-fold:

- The energy harvesting efficiency of common CISs is lower than that of SPs (e.g., 3% vs. 20%, estimated based on the optical structure of SPs and CISs).
- CISs has higher weight density (e.g., 33 kg/m^2 vs. 10 kg/m^2 [9]).
- The embodied carbon intensity of CISs is much higher than that of SPs (15,000 kg/m^2 vs. 242 kg/m^2) [8], [13].

Therefore, the main bottleneck of carbon reduction is the much higher carbon intensity of image-sensor (IC) fabrication compared with SPs, rather than harvesting efficiency. We can thus infer that even with improved pixel structures or power management, carbon gains remain limited.

Finding: *EH pixels yield negligible embodied-carbon benefits due to the high carbon intensity of IC fabrication.*

IV. Conclusion

In this paper, we quantify the carbon emission benefit of EHPs in self-powered visual computing systems. We find that EHPs provide only marginal carbon reductions, primarily because of high carbon intensity of CIS manufacturing. Therefore, adopting EHPs solely for carbon reduction is not worthwhile. EHPs may still be attractive for objectives beyond carbon reduction, which we leave for future work.

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