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# 1 Practical PV energy harvesting under real indoor 2 lighting conditions

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## 8 ABSTRACT

9 Indoor light can be used as a new energy source to power  $\mu\text{W}$  low consumption wireless sensor  
10 networks (WSNs), but for wireless electronic devices consuming tens of mW, it is still challenging.  
11 The challenge comes from the low level of irradiance and from the several kinds of source  
12 combinations varying in time (multi-spectral direct, reflective, and scattered mix of artificial and  
13 natural light). This article describes a simple and reliable method that provides a model-based  
14 evaluation of the harvestable energy from any real indoor light environment. This method uses ‘real  
15 condition’ indoor light spectral measurements with a spectrometer as well as ‘controlled condition’  
16 optoelectrical characteristics of the photovoltaic solar cells. The model-based evaluation of the  
17 harvestable energy has been compared with real microsource prototypes based on commercial  
18 photovoltaic cells powering commercial wireless e-ink display (more than 10 mW consumption  
19 averaged on a day). In this article, we show that it is possible to evaluate the harvestable energy, for  
20 several days of indoor light exposure, with an error lower than 6 %. Our method, with such an  
21 accuracy range, will be a helpful tool to assist engineers and researchers in designing light energy  
22 harvesting systems and more generally could find wide application in the growing IoT ecosystem.

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## 24 ARTICLE INFO

25 *Keywords:* Energy Harvesting; Calculation Model; Indoor Light; Indoor PV; Mixed Light; Real Life Conditions.

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## 26 1. Introduction

27 The number of low-power wireless devices is increasing significantly, and as a result, there is more  
28 and more research focusing on new ways to supply energy to these devices (Mathúna et al., 2008).  
29 Indeed, the growth in energy demand induced by this new field of application poses unprecedented  
30 challenges to provide the energy needed to operate these devices (Mathews et al., 2019). It also  
31 requires a review of how this energy is supplied and produced while minimizing its economic and  
32 environmental impact. One practical approach investigated for this purpose is harvesting light energy  
33 from the surroundings of the device. Past research has proven the viability of this approach in outdoor  
34 environments (Shaikh and Zeadally, 2016). In an indoor environment, where radiated levels are low,

35 light energy harvesting has been identified as an effective method to provide enough power to low-  
 36 power electronic systems such  
 37 as wireless sensor networks (Matiko et al., 2014). Moreover, harvesting energy from light has  
 38 demonstrated its capability as a means to achieve battery-free applications (Brunelli et al., 2009; Wang  
 39 et al., 2016).

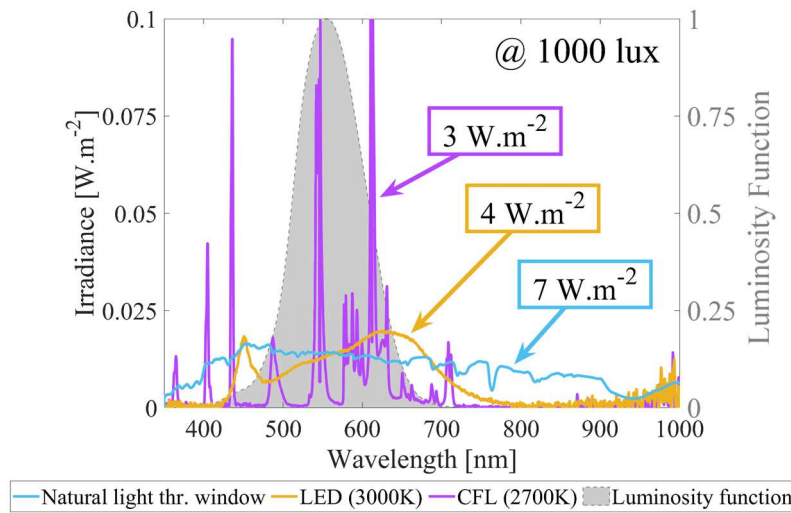
40  
 41 However, when it comes to considering energy harvesting for indoor applications, the difficulty in  
 42 characterizing the harvestable power becomes substantial. Even though Standard Test Conditions  
 43 (STC) from IEC 60904-3 are not entirely representative of the behavior of photovoltaic (PV)  
 44 converters in real-life conditions, it is still a practical way to compare them. As for indoor conditions,  
 45 the situation is somewhat different. The existing standards ISO 8995:2002 and CIE S 008/E define the  
 46 level of luminosity required depending on the task associated with a workplace. The unit of this  
 47 appropriate luminosity level is given in a semi-empirical unit of measure called lux. The lux (or lumen  
 48 per m<sup>2</sup>) value  $E_v$  is given by the following equation:

<b>Nomenclature</b>			
a-Si:H	hydrogenated amorphous silicon	LED	Light-Emitting Diode
CFL	compact fluorescent light	Li-Po	Lithium-Polymer
$\eta^{SQ}$	theoretical SQ solar cell efficiency	MAPE	mean absolute percentage error
$\eta^{meas}$	measured solar cell efficiency	MPPT	maximum power point tracking
$E_g$	bandgap energy	$n$	diode's ideality factor
$EQE$	external quantum efficiency	pc-Si	polycrystalline silicon
$E_v$	illuminance	PCE	power conversion efficiency (PCE)
$FF^{SQ}$	theoretical fill factor from SQ model	$P_{in}$	incident power
$FF^{meas}$	measured fill factor	$\Phi_{p,\lambda}$	incident photon flow
FOCV	fractional open-circuit voltage	$P^{meas}(V)$	measured power -voltage
GaAs	gallium arsenide	$P_{max}^{meas}$	measured maximum power
$h$	Planck's constant	$P^{mod}(V)$	calculated power -voltage
$I_\lambda$	irradiance	$P_{max}^{mod}$	calculated maximum power
$J_{SC}^{SQ}$	short circuit SQ current density	PMIC	power management integrated circuit
$J_{SC}^{QE}$	calculated short circuit current density	$R_s$	parasitic series resistance
J-V	current density-voltage	$R_{sh}$	parasitic shunt resistance
$J_0^{SQ}$	theoretical SQ saturation current density	SMU	Source Meter Unit
$J_{dark}^{meas}(V)$	Measured dark current density- voltage	SQ	related to Shockley-Quiesser model
$J_{ph}$	photocurrent density	STC	Standard Test Conditions
$J_{SC}$	short-circuit current density	$T$	photovoltaic cell temperature
$J^{mod}(V)$	estimated current density-voltage (model)	$V_{OC}^{SQ}$	theoretical SQ open-circuit voltage
$J^{meas}(V)$	measured current density-voltage	WSN	wireless sensor network
$k$	Boltzmann's constant	$Y_\lambda$	photopic luminosity function
$K_{cd}$	maximum spectral efficiency coefficient		

$$E_v = K_{cd} \int_0^{\infty} I_{\lambda} Y_{\lambda} d\lambda, \quad (1)$$

49 where  $Y_{\lambda}$  is a function related to the human eye's cones sensitivity to light (shown in Fig. 1) also called  
 50 the photopic luminosity function,  $I_{\lambda}$  is the irradiance and  $K_{cd}$  is a coefficient called maximum spectral  
 51 efficiency, defined as  $686 \text{ lux}\cdot\text{W}^{-1}\cdot\text{m}^{-2}$  in such a way that irradiance of  $1000 \text{ W}\cdot\text{m}^{-2}$  in standard  
 52 condition (AM 1.5G) corresponds to 100 klux.

53 Nevertheless, when considering how much energy could be harvested from PV converters, the first  
 54 issue arises: the luminosity in lux is not a reliable quantification of the incident harvestable power  
 55 (Wang et al., 2010). Indeed, as an example, Fig. 1 presents the emission spectra from 3 different light  
 56 sources: i) the natural light through a window, ii) a compact fluorescent light (CFL), and iii) a light-  
 57 emitting diode (LED). The three spectra have been measured with a commercial calibrated  
 58 spectroradiometer, the StellarRAD from StellarNet Inc., equipped with a CR2 cosine receptor with a  
 59 wavelength range from 350 nm to 1100 nm, adapted to indoor environments. Spectra are set to obtain  
 60 a 1000 lux illuminance level, giving three different levels of irradiance for each light source:  $7 \text{ W}\cdot\text{m}^{-2}$   
 61 for natural light through the window,  $3 \text{ W}\cdot\text{m}^{-2}$  for the CFL source, and  $4 \text{ W}\cdot\text{m}^{-2}$  for the LED source.



62  
 63 **Fig. 1.** Typical 1000 lux single source indoor environment light spectra: a 3000K LED bulb (in blue), a 2700K  
 64 CFL bulb (in yellow), and natural light through a window (in red). In green, the luminosity function  $Y_{\lambda}$  used to  
 65 establish the illuminance level (lux).

66 In addition, there is a second problem. In the case of real indoor lighting, the incident radiation is a  
 67 time-varying mixture of multiple natural and artificial direct, reflective, and scattered sources: it has to  
 68 be taken into account to have a reliable estimation of the photovoltaic cell performance based on real  
 69 indoor light illumination (Li et al., 2015; Ma et al., 2017; Minnaert and Veelaert, 2014a; Sacco et al.,  
 70 2013). Finally, the third issue is technological. Indeed, the PV converters are non-ideal devices  
 71 connected to a non-ideal electrical storage device via a non-ideal power management integrated circuit  
 72 (PMIC) devices. It means that the electrical energy received by the final consumer device is  
 73 technology dependent and should be far from the standard theoretical Shockley-Queisser (SQ) limit

74 model predictions (Shockley and Queisser, 1961), whatever the relaxing assumption of the SQ model  
 75 taken into account (Guillemoles et al., 2019). In the last few years, many researchers have been  
 76 focused on overcoming these challenges to reach a reliable valuation of the harvestable surrounding  
 77 low light energy, for example by optimizing the one diode photovoltaic model parameter or new  
 78 experimental methods for indoor applications (Bader et al., 2019; Fajardo Jaimes and Rangel de  
 79 Sousa, 2017; Ma et al., 2020; Masoudinejad et al., 2016). But in each of these studies, only the case of  
 80 controlled mono artificial sources is considered.

81 In this article, we present a methodology that allows estimating the harvestable energy from any  
 82 real indoor varying light environment. The first part will present a standard model based on SQ and  
 83 compare it to some usual real-life PV converters. The second part will present a calculation model  
 84 based on experimental data focusing mainly on a commercial flexible thin-film Gallium-Arsenide  
 85 (GaAs) PV solar cell from *Alta Devices Inc.* (Kayes et al., 2011) under several controlled single  
 86 sources of light. Finally, the third part will present an energy harvesting system prototype based on the  
 87 GaAs solar cell, working for several days in real varying indoor environments. It is to be noted that  
 88 this prototype is the micro source of a classic wireless e-ink wifi connected device, with an average  
 89 power consumption of around 10 mW.

## 90 2. The Shockley-Queisser limit theoretical model adapted to indoor light energy harvesting

91 During the last decade, several studies have been conducted to compare the performance of different  
 92 PV technologies under controlled artificial indoor light single sources (Apostolou et al., 2016;  
 93 Carvalho and Paulino, 2014; De Rossi et al., 2015; Kasemann et al., 2014; Li et al., 2015; Minnaert  
 94 and Veelaert, 2014b; Müller et al., 2009). Trying to face the complex task of choosing the best  
 95 technology to use when dealing with indoor light-harvesting, there is an attractive approach that  
 96 consists in applying the SQ limit model. This model gives the theoretical maximum conversion  
 97 efficiency  $\eta^{SQ}$  for an ideal semiconductor single-junction solar cell at any theoretical bandgap:

$$\eta^{SQ}(E_g) = \frac{V_{OC}^{SQ} J_{SC}^{SQ} FF^{SQ}}{P_{in}}, \quad (2)$$

98 with  $P_{in}$  the incident power depending on the spectrum composition,  $V_{OC}^{SQ}$  the ideal SQ open-circuit  
 99 voltage of the PV converter,  $J_{SC}^{SQ}$  the ideal SQ short circuit current and  $FF^{SQ}$  the ideal SQ fill-factor. In  
 100 the case of an ideal semiconductor, the short-circuit current equals the photocurrent  $J_{ph}^{SQ}$ , which is  
 101 related to the number of incident photons carrying more energy than the bandgap  $E_g$ :

$$J_{SC}^{SQ} = J_{ph}^{SQ} = q \int_0^{\lambda_g} \Phi_{p,\lambda} d\lambda, \quad (3)$$

102 Where  $\Phi_{p,\lambda}$  is the incident photon flow at each optical wavelength  $\lambda$ ,  $q$  the elementary electric  
 103 charge, and  $\lambda_g$  the wavelength corresponding to the considered bandgap  $E_g$ .

104 The ideal SQ fill factor  $FF^{SQ}$  can be found following the semi-empirical model from Green's  
 105 approximation (Green and Hall, 1982):

$$FF^{SQ} = \frac{\left[ \frac{qV_{OC}^{SQ}}{kT} - \ln \left( \frac{qV_{OC}^{SQ}}{kT} + 0.72 \right) \right]}{\left( \frac{qV_{OC}^{SQ}}{kT} + 1 \right)} \quad (4)$$

106 with  $k$  being the Boltzmann's constant and  $T$  the device's temperature. The PV cell open-circuit  
 107 voltage  $V_{OC}$  can be defined by the following equation, in the case of an ideality factor  $n$  equal to 1:

$$V_{OC}^{SQ} = \frac{kT}{q} \times \ln \left( \frac{J_{ph}^{SQ}}{J_0^{SQ}} + 1 \right). \quad (5)$$

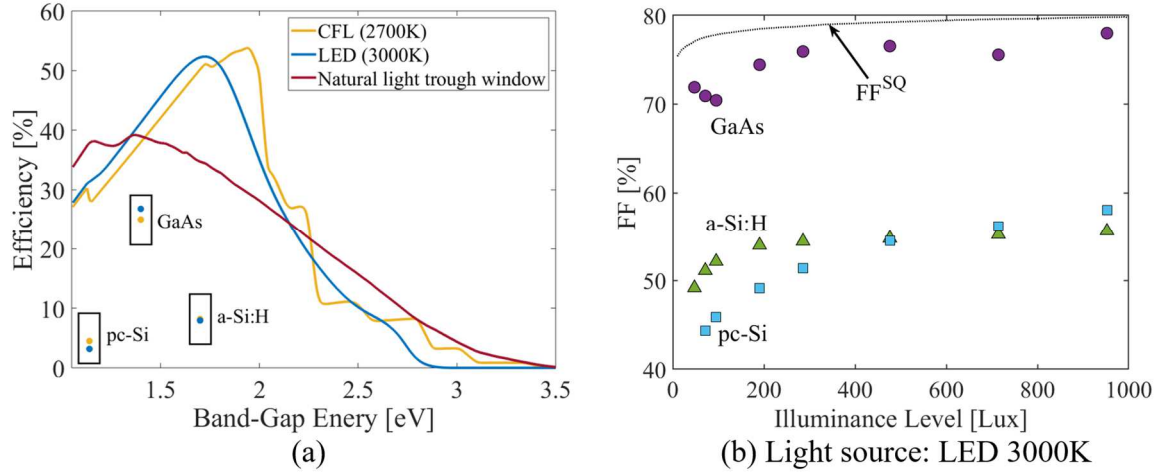
108 Finally, the ideal theoretical dark current density saturation  $J_0^{SQ}$  in a single junction is given by  
 109 (Shockley and Queisser, 1961) and (Müller et al., 2013):

$$J_0^{SQ} = qA \frac{2\pi kT}{h^3 c^2} (E_g + kT)^2 e^{-\frac{E_g}{kT}} \quad (6)$$

110 with  $A$  the active surface area of the PV converter,  $h$  the Planck's constant, and  $c$  the speed of light in  
 111 vacuum.

112 This SQ model is mostly known for having predicted the famous limit efficiency of 33 % for an  
 113 ideal bandgap around 1.14 eV under the standard (AM 1.5G) sun radiation (Shockley and Queisser,  
 114 1961). However, it can also be applied to any kind of spectra like one of the indoor light  
 115 environments (Müller et al., 2013). For example, Fig. 2(a) shows the result of the SQ model when  
 116 applied to typical indoor environments, identical to those in Fig. 1, each with an illuminance of 1000  
 117 lux. As expected, theoretical efficiencies depend on the spectrum composition and on the fact that the  
 118 ideal bandgap changes from one single source to another. As a result of this application of the SQ  
 119 model, for any indoor light, the model gives theoretical efficiency much higher than the solar STC  
 120 AM1.5G spectrum. In the case of a CFL source, with a theoretical semiconductor with a bandgap  
 121 around  $E_g = 1.95$  eV, an efficiency as high as  $\eta^{SQ}(E_g) = 54$  % is predicted.

122 To compare the SQ limit theory to experimental measurement, a commercial source-meter unit  
 123 (SMU), 2450 from Keithley, has been used to measure  $J^{meas}(V)$ : the current density-voltage  
 124 characteristics of different PV converters made of different technologies: hydrogenated amorphous  
 125 silicon (a-Si:H) solar cell (panel) from *Xiamen Mars Rock Science Technology Co.*, a gallium-arsenide  
 126 (GaAs) mono-junction flexible PV solar cell from *Alta Devices Inc.* (Kayes et al., 2011), and a  
 127 polycrystalline silicon (pc-Si) solar cell from *SEEDSTUDIO*, in controlled indoor single source  
 128 environments, with different levels of irradiance. The results of the measured fill-factor  $FF^{meas}$   
 129 extracted from the  $J^{meas}(V)$  curves, as well as the  $FF^{SQ}$  are plotted in Fig. 2(b).



130

131 **Fig. 2.** (a) Theoretical maximum conversion efficiency  $\eta^{SQ}(E_g)$  of a single ideal p-n junction based on the SQ  
 132 model for different single sources: CFL, LED, and natural light through a window. Dots are the measured  
 133 efficiency of different PV converters technology under CFL and LED at around 500 lux. (b) Experimentally  
 134 measured Fill-factor  $FF^{meas}$  of commercial solar cells (GaAs, a-S:H and pc-Si) and their evolution versus  
 135 LED light intensity. As a comparison, an ideal solar cell  $FF^{SQ}$  based on the SQ model is shown in plain black.

136 The efficiency conversion of the different commercial PV converters technologies is, as expected,  
 137 different in real conditions from what has been theoretically predicted by the SQ model. It is mostly  
 138 attributed to several losses, such as shadowing, series and shunt resistance, ideality factor, optical  
 139 absorption, semiconductor quality, low mobility, small minority carrier lifetime, and the PV  
 140 converters' fill-factors and thus efficiencies decreasing at low light intensity (Randall and Jacot, 2003).  
 141 Indeed,  $J_{ph}^{SQ}$  varies linearly with the light intensity (3),  $V_{OC}^{SQ}$  depends on  $J_{ph}^{SQ}$  (5) and  $FF^{SQ}$  depends on  
 142  $V_{OC}^{SQ}$  (4). As an example, the theoretical fill-factor based on the SQ model is shown in Fig. 2(b) for a  
 143 theoretical bandgap corresponding to the standard technologies for indoor application (a-Si:H, pc-Si,  
 144 and GaAs) and illuminance (from 100 to 1000 lux) with a LED single source. When comparing the  
 145 experimental results of three commercial PV converters while varying the light intensity of a LED  
 146 bulb, it can be seen that the fill-factor decreases with lower light intensity, as it is forecast by the  
 147 theoretical  $FF$  equation, but with a more dramatic decrease. Indeed, the experimental  $FF^{meas}$  of the  
 148 pc-Si cell strongly decreases when reducing the light intensity, mainly due to their too low shunt  
 149 resistance (Reich et al., 2009). Thus, as reported previously and exposed in Fig. 2(b), the c-Si  
 150 technology is not the most suitable technology for indoor applications, and therefore not a good  
 151 candidate for developing a model based on a one-diode photovoltaic model where the  $FF$  needs to  
 152 vary as little as possible. The a-Si:H and GaAs technologies have a more stable  $FF$  from 100 to 1000  
 153 lux, which seems ideal for the simple model presented. Nevertheless, the  $FF$  of the a-Si:H PV  
 154 converter is lower than the GaAs cell, and thus its power conversion efficiency (PCE)  $\eta^{meas}$  tends to  
 155 indicate less promising model performance. For indoor applications, especially when dealing with

156 consumer devices with an average consumption of 10 mW, a technology that does not suffer from a  
157 low level of light, but also that has a  $FF$  and a PCE close their ideal value is needed. As seen in Fig.  
158 2(b), only the GaAs cells have demonstrated such good performances, with a measured  $FF$  closer to  
159 the  $FF$  of the Shockley-Queisser model of an ideal solar cell than other considered cells: this is not  
160 surprising since III-V solar cells are known to be among the most efficient cells, even under low  
161 indoor light conditions (Mathews et al., 2016). This difference in performance is mainly due to the  
162 known fact that the carrier mobility is high and the lifetime long in GaAs devices (Kayes et al., 2011),  
163 that the series resistance is low enough, and the shunt resistance high enough to avoid deviation of the  
164  $FF$ , even in a low light environment. In conclusion, the fact that the experimental  $FF^{meas}$  is almost  
165 constant under an illuminance ranging from 100 to 1000 lux considerably simplifies the theoretical  
166 calculation of the output power of a GaAs PV cell from any spectrum, by safely applying the  
167 superposition model, even at a low light intensity.

168 The next paragraph will describe a methodology based on the superposition model to predict the  
169 extractable energy from the GaAs thin-film solar cell, whatever the real indoor light source  
170 environment.

### 171 3. A calculation model of indoor light energy harvesting based on a one-diode photovoltaic model

172 The method is based on the combination of the results from three measurements: i) the light  
173 environment spectrum (which is fluctuating in time), ii) the external quantum efficiency ( $EQE$ ) of the  
174 PV cell (unchanging intrinsic values) and iii) the measurement of the current density-voltage  $J_{dark}^{meas}(V)$   
175 characteristic in the dark (unchanging intrinsic values). This simple methodology allows us to consider  
176 the primary deviations from the SQ model: a real  $EQE$  instead of an ideal one over the whole range of  
177 the spectra, and a real  $J_{dark}^{meas}(V)$  curve, which takes into account the real “shape”( $FF$ ) of the current  
178 density -voltage  $J(V)$  characteristic, including the parasitic series  $R_s$  and shunt  $R_{sh}$  resistances as well  
179 as the ideality factor  $n$ , which can vary from 1 to 2. The spectral response was measured with a  
180 custom-built setup composed of a Xenon lamp, a monochromator equipped with two diffraction  
181 gratings, a filter wheel to remove the higher diffraction orders of radiation, and a lock-in amplifier. The  
182 measurements were calibrated with Si and Ge photodiodes (Thorlabs FDS100-CAL and FDG03-CAL,  
183 respectively) to cover the whole wavelength range of interest. This characterization does not consider  
184 the impact of the solid angle of the radiation. It studies the characteristics of the PV converter with a  
185 photon flow that is normal to its surface. For each wavelength band produced by the source, the current  
186 generated by the characterized PV cell is measured. A known cell is used as a current-generation  
187 reference to establish the  $EQE$  of the characterized PV cell by comparison.

188 In the developed model, the measured  $EQE$  is added in (3) to consider the deviation from the SQ  
189 model due to the real external quantum efficiency of the PV cell. The resulting short-circuit current

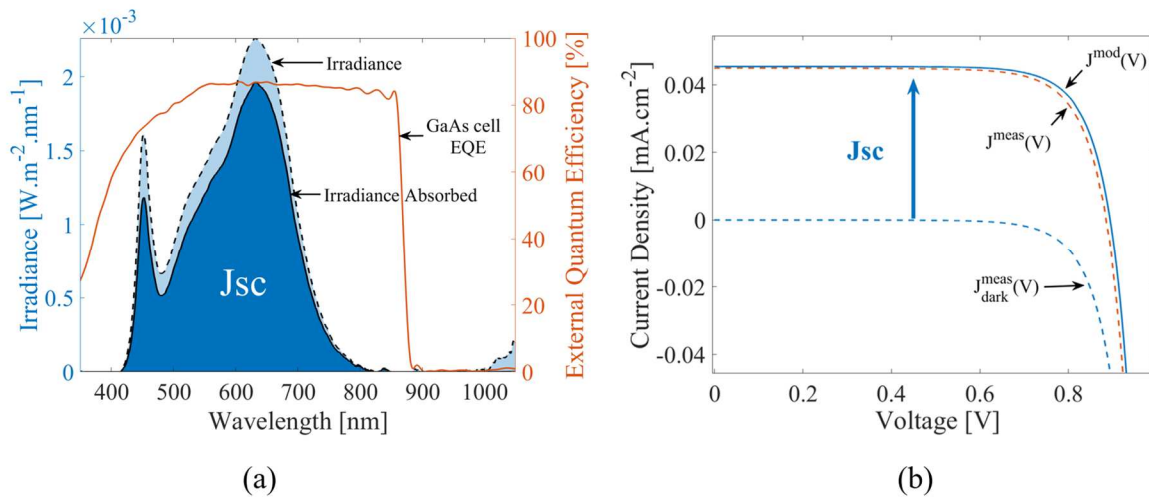
190 density  $J_{SC}^{QE}$  is thus an estimation based on two measurements: the  $EQE$  which is fixed for each PV  
 191 converter and the spectra  $\Phi_{p,\lambda}$  fluctuating in time:

$$J_{SC}^{QE} = q \int_0^{\lambda_g} \Phi_{p,\lambda} \times EQE \, d\lambda \quad (7)$$

192 Now that the spectral response  $EQE$  is not ideal anymore but is measured from a real solar cell, the  
 193 equation (7) gives an estimated value of the short circuit density current  $J_{SC}^{QE}$  lower than in the ideal  
 194 case based on the SQ model ( $J_{SC}^{SQ}$ ). This value depends on the real measured spectra at any given time.  
 195 Then, the measured dark current density-voltage curves  $J_{dark}^{meas}(V)$  of the PV converters can be  
 196 collected by the SMU 2450 from Keithley, and using the superposition principle (Lindholm et al.,  
 197 1979; Tarr and Pulfrey, 1980) or more commonly known as the one-diode photovoltaic model, it is  
 198 possible to deduce the estimated current density-voltage  $J^{mod}(V)$  model at any given time of the  
 199 fluctuating spectra:

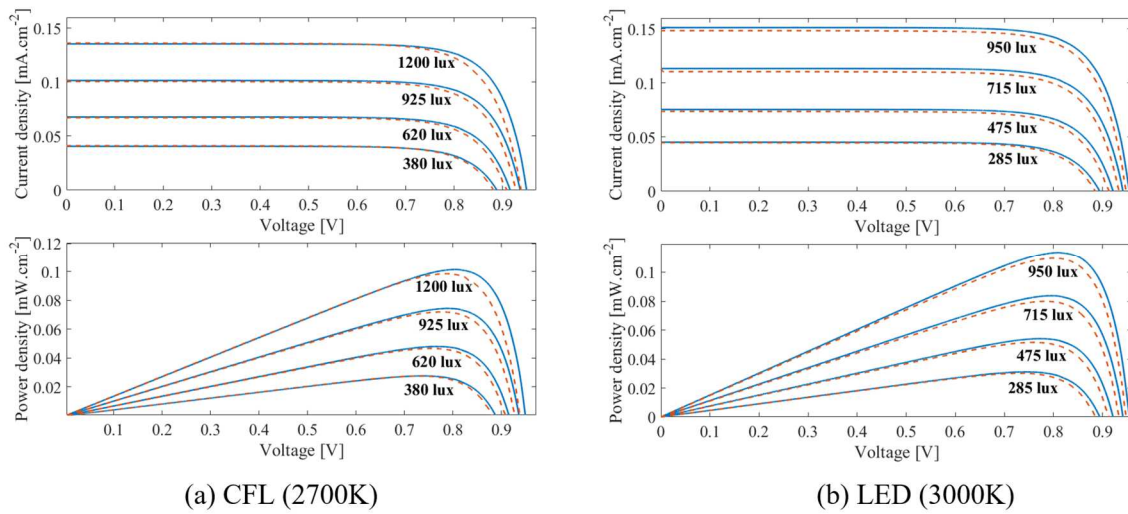
$$J^{mod}(V) = J_{dark}^{meas}(V) + J_{SC}^{QE} \quad (8)$$

200 As an example, Fig. 3(a) shows the LED spectra of a 300 lux LED 3000K bulb as well as the  
 201 measured  $EQE$  curve of a GaAs solar cell and the current generation of this cell resulting from its  
 202 absorption of the photon flux. In Fig. 3(b), based on the previous  $EQE$  curve and the LED spectra and  
 203 the  $J_{dark}^{meas}(V)$  curve, the estimated  $J^{mod}(V)$  is shown as well as the measured  $J^{meas}(V)$ . In this first  
 204 example, the current density curve  $J^{mod}(V)$ , estimated from the developed model, is in good  
 205 agreement with the experimentally measured  $J^{meas}(V)$ . In this example, the extracted maximal power  
 206 values  $P_{max}^{mod}$  and  $P_{max}^{meas}$  from the model  $J^{mod}(V)$  and measured  $J^{meas}(V)$ , are  $30 \mu\text{W}/\text{cm}^2$  and  
 207  $31 \mu\text{W}/\text{cm}^2$ , respectively, with a difference of about 3 %.



208 (a)  
 209 **Fig.3.** (a) spectra of a 300 lux LED 3000K bulb and the same spectra modulated by the measured external  
 210 quantum efficiency of a GaAs solar cell. (b) the  $J_{dark}^{meas}(V)$  curve of the GaAs solar cell in blue dash used to  
 211 calculate the expected  $J^{mod}(V)$  based on (8) in orange dash, compared to the experimentally measured  $J^{meas}(V)$ .

212 We have used this method with the same GaAs solar cell under single controlled sources light  
 213 environments, for different sources (CFL and LED) at many different levels of indoor irradiance (from  
 214 200 lux up to 1000 lux), to verify the reliability of the one-diode photovoltaic model. The  
 215 characteristics resulting from the model,  $J^{mod}(V)$  and the  $P^{mod}(V)$ , are shown in Fig. 4 and compared  
 216 to their experimental equivalents,  $J^{meas}(V)$  and the  $P^{meas}(V)$ . The deviation between model results  
 217 and the experimental measurements is noticeable but minor. With an average error of less than 3 %  
 218 and never exceeding 5 %, considering the numerous experimental bias possible, these results seem  
 219 sufficiently accurate to be useful for the calculation of a harvestable power approximation in various  
 220 low irradiance indoor environments.



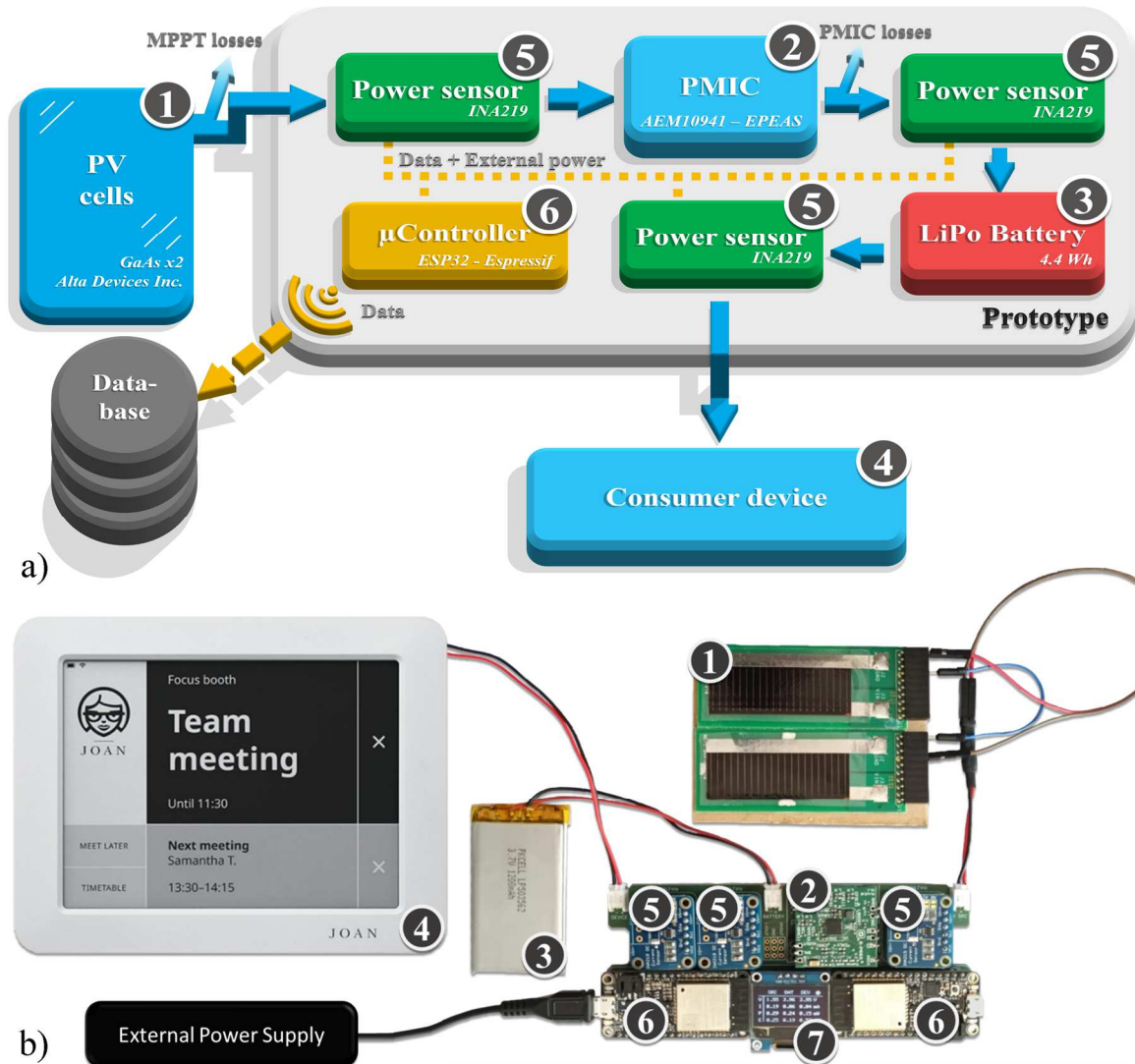
221 (a) CFL (2700K) (b) LED (3000K)  
 222 **Fig. 4** Comparison between the calculated  $J^{mod}$ -V and the  $P^{mod}$ -V (plain blue lines) from the one-diode  
 223 photovoltaic model and the corresponding experimental characteristics  $J^{meas}$ -V and the  $P^{meas}$ -V (dotted orange  
 224 lines) of a GaAs solar cell for different illuminance under (a) a CFL light source and (b) a LED light source.

225 As stated previously in this paper, the lack of standards to rely on makes studying in the field of  
 226 indoor PV more complex. Consequently, it is necessary to find a method to evaluate the produced  
 227 energy based on the analysis of a fluctuating mix of natural and artificial light environments. The next  
 228 paragraph will demonstrate the reliability of the simple one-diode photovoltaic model described  
 229 beforehand to calculate the harvestable energy in real-life indoor conditions, even for several days.

#### 230 4. The model applied in real conditions for several days

231 The ultimate purpose of this study is to establish a model to calculate, as precisely as possible, the  
 232 level of harvestable energy in a real indoor environment for an extended period. Therefore, it is  
 233 necessary to test the model under real-life conditions, observing the light environment over time to  
 234 know the variations in its composition and to compare the calculated results to experimental results. A  
 235 complete energy harvesting prototype, shown in Fig. 5, has been developed to validate the developed  
 236 model experimentally in real-life environments. This prototype is based on two GaAs thin-film solar  
 237 cells providing electrical energy to the energy storage device (here a Lithium-Polymer battery) of a

238 consumer device like an e-ink connected device. To extract the maximum power from the solar cells, a  
 239 very low consumption commercial power management integrated circuit (PMIC) from *e-PEAS* has  
 240 been placed between the PV cells and the LiPo battery.



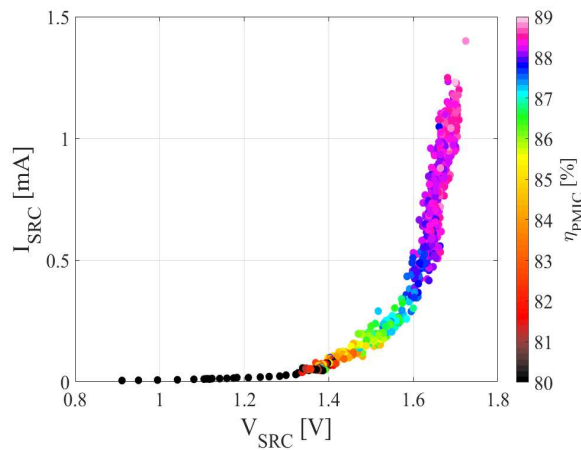
241  
 242 **Fig. 5. a)** Schematic of the energy harvesting prototype (PV cells + PMIC + LiPo battery) that has been  
 243 instrumented by three INA 219 electrical power sensors and two ESP32 microchips to collect the data and send  
 244 them to a database. Let's note there is a specific external power source that allows the acquisition and  
 245 transmission of data without affecting the performance of the energy harvester. b) a picture of the described  
 246 prototype integrating GaAs solar cells (1), a PMIC : an *e-peas* 'EVK10941M' Mini Evaluation Board based on  
 247 the 'AEM10941' Solar Energy Harvesting IC (2); a LiPo electrical storage device (3), the e-ink communicating  
 248 device to power (4), the INA219 power sensors (5), the ESP32 low cost low power microcontroller chips (6) and  
 249 an OLED screen (7).

250 The used PMIC is based on a max power point tracking (MPPT) algorithm called fractional open-  
 251 circuit voltage (FOCV). This method relies on getting a sample of the  $V_{oc}$  and then applies and holds a  
 252 fraction of its value to the PV cells or module (Motahhir et al., 2020). Besides not being the most  
 253 performant in casual energy harvesting situations, such an MPPT algorithm has demonstrated its use of  
 254 relevance in low light environments (Weddell et al., 2012). Even though this PMIC is adapted for low

255 energy harvesting applications, the losses are not negligible. To include these losses in our model, and  
 256 to be able to measure the “real” power harvested by the prototype at any time into the LiPo battery,  
 257 two voltage and current sensing chips INA219 from *Texas Instrument* have been inserted between the  
 258 PV cells and the PMIC and between the PMIC and the LiPo. Regarding the classical Lithium Polymer  
 259 (LiPo) battery whom internal resistance is usually less than  $100\text{m}\Omega$ , it has no impact in term of losses  
 260 when considering the low current level in our application. In addition, a third INA219 has been  
 261 inserted between the LiPo battery and the consumer device to monitor its consumption. A set of two  
 262 microcontrollers associated with these power sensors allows the acquisition of the power  
 263 generation/consumption data from the three INA 219, and their recording on a database in the cloud.  
 264 An external power source is used to power the sensors and the microcontrollers.

265

266 The e-peas PMIC Mini Evaluation Board EVK10941M chosen for the prototype uses the fractional  
 267 open-circuit voltage (FOCV) algorithm. To extract the maximum power from the PV cells, this PMIC  
 268 algorithm can be configured to apply 70%, 75%, 85%, or 90% of their  $V_{oc}$ . In our application, by  
 269 choosing the fraction of 85%, the MPPT losses due to the optimal fraction of  $V_{oc}$  not being exactly  
 270 equal to 85%, are evaluated to be lower than 1% over the whole range of illumination. Regarding the  
 271 PMIC losses induced by the classical losses of a buck-boost converter, they can vary from 10% to 20%  
 272 depending on the level of illumination. As can be seen in Fig.6, at low light (and low  $V_{SRC}$  et low  $I_{SRC}$ ),  
 273 the efficiency of the PMIC is only 80 % while at moderate to high illumination the efficiency is about  
 274 90%. From the plot of Fig.6, a regressive equation has been added to our model to include the PMIC  
 275 efficiency  $\eta^{PMIC}$ .

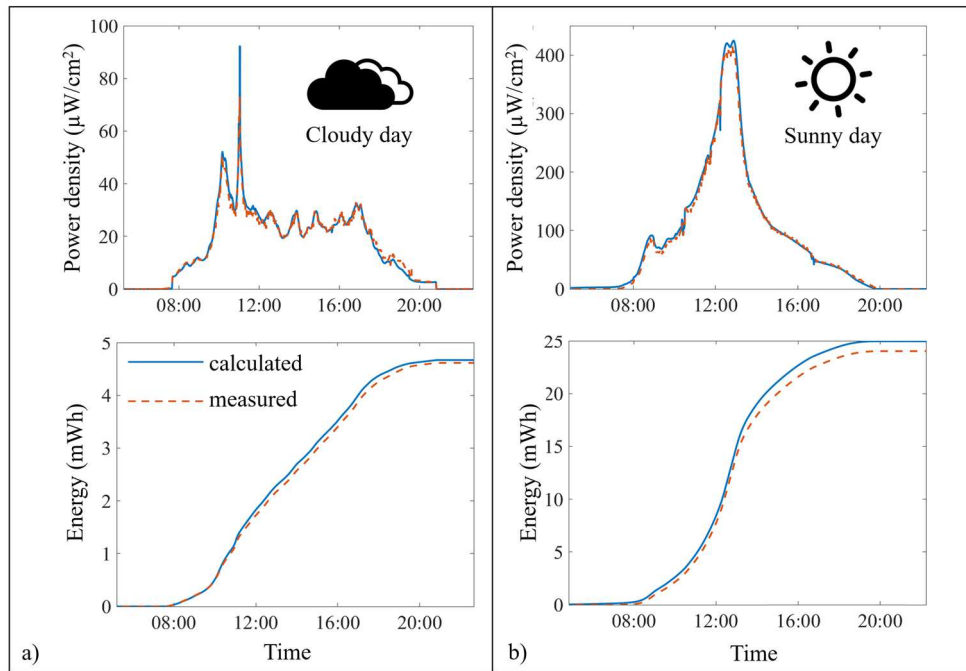


276

277 *Fig. 6. Experimental PMIC efficiency  $\eta^{PMIC}$  depending on light intensity. These curve depends on the*  
 278 *experimental set-up , in our case two GaAs solar cell in series , an epeas based PMIC and a single cell LiPo.*

279 Finally, the purpose of the experiment is to compare the harvestable energy calculated by the model  
 280 and the real harvested energy measured by the power sensor, the power measurements must be carried  
 281 out simultaneously with the spectrometer analysis of the light environment to which the prototype is  
 282 exposed. This experiment has been carried out over 21 days. The results of 2 typical days (sunny and

283 cloudy days) are shown in Fig.7. While the orange dashed line is the experimental harvested power  
 284 stored into the Lithium Polymer battery measured directly by an INA219, the blue line represents the  
 285 model calculation results based on one-minute spectra measurement intervals. A qualitative agreement  
 286 between the model calculation of power and energy harvesting and the real usable power generated  
 287 and energy transferred to the prototype battery can be observed. The mean absolute percentage error  
 288 (MAPE) between the model curve and the experimental power curve of each of the 21 days is lower  
 289 than 6%. These very good results are comforting the fact that our model and methods are reliable  
 290 enough to be an interesting tool for researchers and engineers conceiving indoor micro source elements  
 291 for IoT applications or consumer devices.



292  
 293  
 294 **Fig. 7.** model's power density and energy calculations (plain blue) and experimentally measured power-density  
 295 and energy (dash orange) generated from the GaAs solar cell in a real-life indoor environment harvested into the  
 296 Lithium Polymer storage device for a) a cloudy day and b) a sunny day.

297 The 6% of error are potentially due to several factors: i) the MPPT losses ii) the LiPo battery losses,  
 298 iii) the reliability of the low-cost INA219, iv) the reliability of our model which has been taken as  
 299 simple as possible without taking into account potential variation of  $R_{sh}$  and  $R_s$  with light intensity,  
 300 v) the small effect of temperature in indoor Environment, vi) and of course the experimental setup.

301  
 302 These results obtained after 21 days of observation of the office's real lighting environment show  
 303 that the model makes it possible to determine the level of harvestable energy per surface unit quite  
 304 accurately, even if there is still room for improvement. It is then possible to determine, based on these  
 305 21 days of observation, the harvesting surface area or the number of PV cells required in this  
 306 environment to compensate for the energy needs of an electronic device fully. For example, a classical

307 wireless e-ink dashboard, as the one used in this study, depending on its size and the significance of its  
308 sleeping mode, consumes about 10 mW on average. In such a case, a preliminary extrapolation shows  
309 that 14x14 cm<sup>2</sup> of similar solar cells would be sufficient to supply it enough power to make it  
310 energetically autonomous.

## 311 **5. Conclusion**

312 In summary, the simple model presented applying the superposition principle, based on the  
313 combination of the measured optical EQE and electrical  $J_{dark}^{meas}$ -V of GaAs PV cell in the dark,  
314 combined with the spectral measurements of real-life indoor environments, has demonstrated the  
315 ability to calculate the potentially harvestable energy in the environment that is being studied. Using  
316 an energy-harvesting prototype installed in the environment studied by the spectrometer feeding the  
317 developed model allowed to confront results from the model to actual power and energy harvest. The  
318 confrontation result corroborates the ability of the proposed model to calculate the harvestable energy  
319 with an error lower than 6 % for the 21 days of the test. In a more practical sense, this paper shows  
320 that in real-life indoor environments, a module based on PV cells similar to *Alta Devices Inc.* GaAs  
321 PV solar cells and smaller than a third of a sheet of paper (A4 format) is enough to make devices  
322 consuming about 10 mW.

323 We believe that the method presented in this article will be helpful to engineers and researchers  
324 attempting to overcome the various challenges toward the accurate design of energy harvesting  
325 devices in the future.

## 326 **Declaration of Competing Interest**

327 The authors declare no conflict of interest.

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