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Using Ambient Light Sensors in Smartphones for Evaluating Indoor Lighting Conditions

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***Abstract* – This paper discusses opportunities for collecting data on lighting conditions in indoor environments with the help of ambient light sensors in smartphones. Environmental data is needed to allocate the most beneficial location for solar energy harvesters on the one hand and provide energy predictions for their users on the other. Here, we focus on the illumination of surfaces and the use of ambient light sensors to measure the amount of light intensity. A comparison of sensors in different smartphones such as entry-level devices, mid-range and flagship phones is presented and the obtained results are verified against a luxmeter and commercial available ambient light sensors. Furthermore, the impact of the measured light intensity on energy predictions is discussed.**

I. INTRODUCTION

No matter how powerful portable or wearable devices such as smartphones, smartwatches and activity trackers are, they are rendered unusable if the battery runs out. The battery capacities are stagnant with the increased energy demand of all the embedded functionalities and, therefore, devices run out of power during the day. This scenario is commonplace and very frustrating for users [1]. We aim to prolong standby and operating times with the help of solar energy harvesting, both under indoor and outdoor environmental conditions [2].

Nowadays, energy harvesting is popular for many different types of applications, for example wireless sensor network (WSN) nodes. In general, the target is to overcome the disadvantages of batteries [3]. Considering future applications, such as embedded sensors in smart homes, energy harvesting will become more and more important. In the case of smartphones, sensors can be helpful to localise beneficial locations for solar energy harvesters [4–6]. In particular in indoor environments, the amount of available light is significantly lower than outdoors and depending on the location, for example on the distance from the light source [5–7].

Thus, it is crucial to position solar energy harvesters in a favourable location in which a high amount of light intensity is present [2], [5]. Fig. 1 illustrates different light conditions in an indoor environment, for example a library. It is worth noting that the output power of solar panels (P_{solar}) is directly proportional to the illumination (E_v) of the solar panel. Simplified, the factors influencing P_{solar} can be summarised as follows [6]:

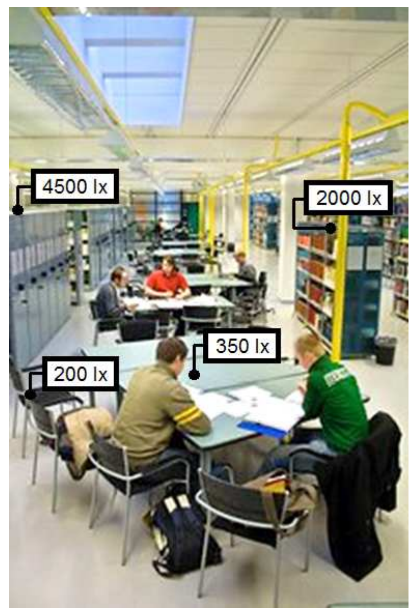

Fig. 1. Example for indoor environmental conditions.

$$P_{solar} = k_{solar} \times E_v \times A_{solar} \tag{1}$$

where and k_{solar} is a factor for considering the material of the solar panel and type of light source, and A_{solar} is the size of the solar panel. In order to provide an understanding of the available power from solar panels indoors, we determined the performance of two different materials for solar panels, polycrystalline silicon (poly-Si) and amorphous silicon (a-Si), respectively. As discussed in [6], the available power of solar panels also depends on the spectrum of the light source, more precisely on the wavelength of the light source.

II. OPPORTUNITIES FOR SOLAR ENERGY HARVESTING INDOORS

A. Influences of the Material and Type of Light Source

k_{solar} can be verified with the help of experiments. Table 1 presents the factor k_{solar} in respect to the material of the solar panel and type of light source. As seen in Table 1, solar panels made out of poly-Si and halogen lamps as light source provided the highest value and, thus, provide the most beneficial circumstances for solar energy harvesting.

Table 1. Experimental verification of k_{solar} [$\frac{\mu W}{lx \times cm^2}$]

	halogen lamp	LED lamp
poly-Si	0.305	0.032
a-Si	0.022	0.021

B. Energy Predictions

If users of smartphones are aware about the power consumption of different applications on their phone, they consider the impact of the usage of certain applications on the battery life. Moreover, users are able to react and change their behaviour in order to prolong standby and operating times of their devices [8]. The power consumption of different types of applications and functionalities can be verified and, thus, the impact on the battery duration can be estimated [9].

In this way, energy predictions can be helpful for users to optimise the use of their devices. The performance of the solar energy harvester can be described with the help of the following equation:

$$P_{harvester} = P_{solar} \times \eta_{harvester} \tag{2}$$

where $P_{harvester}$ is the output power of the solar energy harvester which can be used for charging devices such as smartphones, and $\eta_{harvester}$ is the degree of efficiency of the solar energy harvester. If $\eta_{harvester}$ is assumed to be constant, the charging power directly depends on the available power of the solar panel (P_{solar}). Commonly, under indoor environmental conditions, the illumination and temperature are constant which affect the output performance of solar panels.

As mentioned before, the amount of power from solar panels (P_{solar}) depends on several factors such as the size of the solar panel (A_{solar}), in other words, the area dedicated for solar energy production, and the illumination of the solar panel (E_v). In general, a possible area for the solar panel can be the back of a smartphone. In this way, the solar panel could be either integrated into the device or used as an add-on for the phone. The solar panel can also be foldable, in such a way that the size of the solar panel doubles in the case the solar panel is unfold.

If ambient conditions are constant, it is possible in an easy way to estimate the amount of energy which can be harvested over a certain period of time and provide this valuable information to the user. In a possible use case scenario, smartphone users evaluate their surroundings with the help of sensors which are integrated into their devices in order to allocate most beneficial position for solar energy harvesters [5], [6]. Here, the information of the illumination (E_v) is crucial for the energy prediction.

For example, the use of poly-Si under halogen lamps provides a factor k_{solar} = 0.305. In Fig. 2, two different sizes of solar panels are compared with each other, one with a diagonal of 5 inch, and another one with 10 inch for a solar energy harvester with an efficiency $\eta_{harvester}$ = 0.7. As seen in Fig. 2, the higher the illumination, the higher the available power from the energy harvester. It can be seen that the power of the solar energy harvester increases linearly with the light intensity.

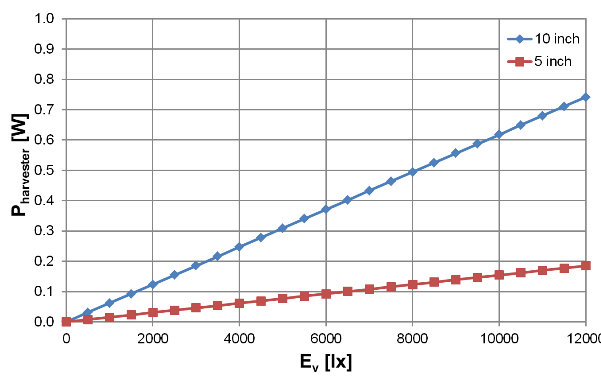

Fig. 2. Power of harvester depending on the illumination.

If the illumination (E_v) is known, P_{solar} can be estimated and, thus, the energy from the harvester ($E_{harvester}$) can be predicted. For example, at E_v = 6,000 lx, a power of about 90 mW can be obtained with a solar panel of a diagonal of 5 inch, while about 370 mW can be obtained with a solar panel of a diagonal of 10 inch. Using the 10 inch solar panel, in one hour, about 370 mWh can harvested, while about 740 mWh can be harvested in two hours, and so on.

As in previous research, the ambient light sensor (ALS) of a smartphone can be used to measure the light intensity (E_v) [5], [6]. With the help of this information collected, the energy can be estimated which can be harvested after a certain period of time (t), obtained as follows:

$$E_{harvester} = P_{harvester} \times t \tag{3}$$

As a result, it is possible estimating the percentage of battery capacity ($Q_{battery}$) which can be charged with the harvested solar energy, calculated as follows:

$$SOC_{charge} = \frac{E_{harvester}}{\frac{Q_{battery} \times V_{battery}}{100}} \times \eta_{charge} \tag{4}$$

Table 2. Comparison of measurement results (sensors in smartphones and lux sensors)

Luxmeter (reference)	500 lx	1,000 lx	1,500 lx	2,000 lx
Nokia Lumia 520 (1)	2,077.3 lx	4,084.5 lx	6,959.4 lx	8,916.4 lx
Nokia Lumia 520 (2)	371.7 lx	692.1 lx	1,115.7 lx	1,490.5 lx
Nokia Lumia 920 (1)	719.4 lx	1,614.4 lx	2,450.9 lx	3,026.3 lx
Nokia Lumia 920 (2)	914.6 lx	2,096.3 lx	3,396.4 lx	4,070.5 lx
Samsung Galaxy S2 Plus (1)	580.0 lx	1,075.0 lx	1,745.0 lx	2,470.0 lx
Samsung Galaxy S2 Plus (2)	355.0 lx	685.0 lx	1,090.0 lx	1,470.0 lx
Samsung Galaxy S3 (1)	808.0 lx	1,522.0 lx	2,455.0 lx	3,140.0 lx
Samsung Galaxy S3 (2)	672.0 lx	1,278.0 lx	1,971.0 lx	2,790.0 lx
Lux sensor (1)	522.5 lx	1,015.7 lx	1,492.5 lx	2,152.2 lx
Lux sensor (2)	522.0 lx	1,014.8 lx	1,491.3 lx	2,156.6 lx
Lux sensor (3)	519.2 lx	1,014.3 lx	1,491.7 lx	4,229.2 lx
Lux sensor (4)	524.8 lx	1,016.9 lx	1,495.3 lx	4,229.2 lx
Lux sensor (5)	523.4 lx	1,012.5 lx	1,495.5 lx	4,229.2 lx
Lux sensor (6)	549.8 lx	1,038.5 lx	1,490.4 lx	2,206.5 lx

where SOC_{charge} is the state of charge (SOC) of the smartphones' battery which can be charged with the help of the solar harvester, $V_{battery}$ is the smartphones' battery voltage level, and η_{charge} is the efficiency of charging smartphones with the solar harvester.

For example, the Nokia Lumia 520 has a battery capacity ($Q_{battery}$) of 1,430 mAh and a battery voltage ($V_{battery}$) of 3.7 V. Thus, SOC_{charge} can be estimated which can be achieved with a solar harvester in one hour and using, for example, a 10 inch poly-Si solar panel under halogen lamps at a light intensity (E_v) of 6,000 lx, calculated as follows:

$$\begin{aligned} SOC_{charge} &= \frac{P_{harvester} \times t}{\frac{Q_{battery} \times V_{battery}}{100}} \times \eta_{charge} \\ &= \frac{370mW \times 1h}{\frac{1430mAh \times 3.7V}{100}} \times 0.8 = 5.59\% \end{aligned}$$

III. ERROR OF AMBIENT LIGHT SENSORS

A. *Types of Ambient Light Sensors in Smartphones*

As in previous research, we used the luxmeter from Voltcraft type BL-10 as reference to verify the performance of ambient light sensors in smartphones. In previous research, we have noticed significant variations in the measurement results between the ALS in smartphones and conventional measurement equipment [5], [6].

Commonly, small ALS are embedded in smartphones. For example, the CM3663 from Capella Inc. is installed in the Samsung Galaxy S2 Plus, while the CM36651 (a colour-ALS) from the same company is installed in the Samsung Galaxy S3. According to the datasheet of the CM3663, the tolerance limit on the readings of the sensor is $\pm$ 15 %. However, in previous research measurement results exceeded these tolerance limits.

It can be said that the primary purpose of the ALS in smartphones is to control the background light of the display based on light conditions of the surroundings. For example, under outdoor environmental condition, if sun light shines on the display of a smartphone, the information on the display should be still readable for the user. On smartphones, applications are available in order to use the phone as luxmeter for measuring light intensities, for example in indoor environments.

B. *Measurement setup and results*

In a typical use case scenario, users measure the light intensity under a light source when searching for a beneficial location for solar harvesting, as illustrated in Fig. 3. Here, the smartphone with the ambient light sensor is placed at a distance (d) and an angle (α) under the light source, for example a fluorescent lamp. In this paper, we investigate if the small size and type of ambient light sensor is the reason for the different readings in light intensities which we have observed in previous research [5], [6].

Table 2 presents the measurement results at certain light intensities: 500 lx, 1000 lx, 1500 lx, and 2000 lx, respectively. The light source was a fluorescent lamp (General Electric Starcoat T5, F35W/830), as shown in Fig. 3. In the comparison, we used each time two devices of the same type of phone. Each time we made sure that the two phones are identical in terms of hardware and installed software. No screen protection was present which could have influenced measurement results.

We compare the results with the TSL2561 from TAOS (Texas Advanced Optoelectronics Solutions). The TSL2561 is a light-to-digital converter and approximates the human eye response in a similar way as the CM3663 from Capella Inc. installed in the Samsung Galaxy S2 Plus. Data from the TSL2561 can be read by smartphones, for example through NFC or Bluetooth [5].

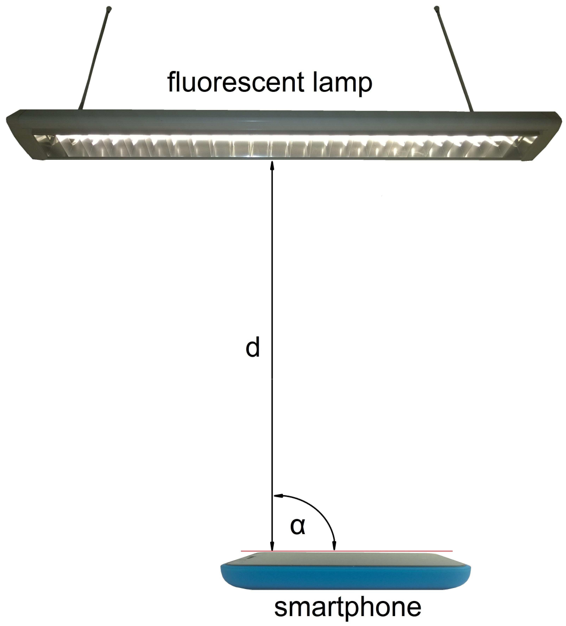

Fig. 3. Measurement of light intensities with a smartphone.

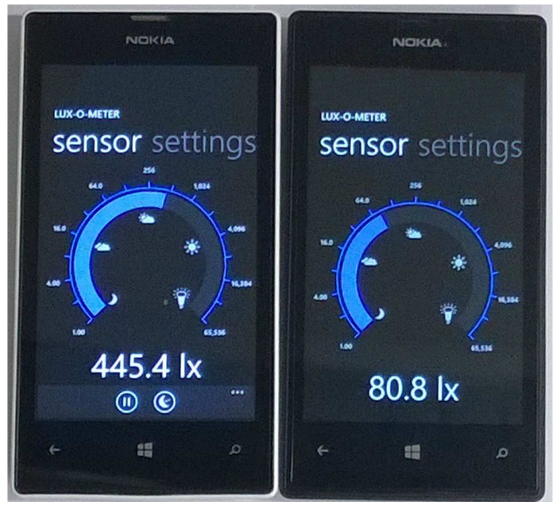

Fig. 4. Two similar phones, two different readings.

Table 3. Error to luxmeter

Device	Error to luxmeter
Nokia Lumia 520 (1)	+ 333.42 % ± 26.03 %
Nokia Lumia 520 (2)	– 26.89 % ± 2.60 %
Nokia Lumia 920 (1)	+ 55.01 % ± 9.11 %
Nokia Lumia 920 (2)	+ 105.63 % ± 17.97 %
Samsung Galaxy S2 Plus (1)	+ 15.83 % ± 6.54 %
Samsung Galaxy S2 Plus (2)	– 28.58 % ± 2.20 %
Samsung Galaxy S3 (1)	+ 58.62 % ± 5.11 %
Samsung Galaxy S3 (2)	+ 33.28 % ± 4.95 %
Lux sensor (1)	+ 3.97 % ± 4.70 %
Lux sensor (2)	+ 3.28 % ± 3.66 %
Lux sensor (3)	+ 3.10 % ± 3.54 %
Lux sensor (4)	+ 3.55 % ± 3.61 %
Lux sensor (5)	+ 3.40 % ± 3.69 %
Lux sensor (6)	+ 5.20 % ± 4.63 %

In Table 2, lux sensor (1) to (5) are samples of the TSL2561 in a chipscale (CS) package, while lux sensor (6) is the same type of sensor in a flat no-leads (FN) package. From Table 3 it can be seen that smartphones measure the illumination either too high or too low. As seen in Fig. 4, there is even a remarkable difference present in measured light intensity in the same type of phone. These circumstances have a significant impact on the value for E_v which is used for estimating the amount of harvested energy.

However, these large variations in readings cannot be seen in the lux sensors from TAOS. The readings are very consistent throughout the measured levels of light intensities. Only a slightly higher error can be seen in the TSL2561 in the FN package. Thus, if the readings of these lux sensors are obtained with the help of NFC or Bluetooth an accurate energy prediction can be made. Alternatively, it is also possible to use the solar panel in the solar energy harvester for reading the light intensity. However, this approach requires more effort in terms of hardware and software compared to the already available sensor inside the smartphone.

In order to verify the impacts of reflections on measurement results, we created a test environment in which we can control lighting conditions and ambient temperature. Fig. 5 shows the test environment (reflective background) which was used for experiments. Different light sources at a constant distance were used to obtain measurement results from the different smartphones and sensors at the same lighting conditions. Halogen lamps (Airam Electric Ab) were used as light source at a constant distance (d) to achieve light intensities of 1,000 and 2,000 lx. Table 4 summarises the measurement results.

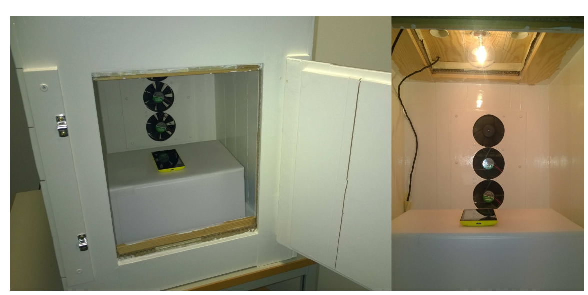

Fig. 5. Controlled test environment for experiments (reflective background).

Fig. 6 shows the same test environment with a non-

Table 4. Comparison of measurement results in test environment (reflective background)

Luxmeter (reference)	1,000 lx	2,000 lx
Nokia Lumia 520 (1)	928.1 lx	1,729.0 lx
Nokia Lumia 520 (2)	735.0 lx	1,468.6 lx
Nokia Lumia 920 (1)	1,559.1 lx	2,084.8 lx
Nokia Lumia 920 (2)	1,513.0 lx	2,266.6 lx
Samsung Galaxy S2 Plus (1)	6,420.0 lx	12,445.0 lx
Samsung Galaxy S2 Plus (2)	2,125.0 lx	4,110.0 lx
Samsung Galaxy S3 (1)	1,504.0 lx	3,482.0 lx
Samsung Galaxy S3 (2)	1,618.0 lx	3,754.0 lx
Lux sensor (1)	429.0 lx	792.2 lx
Lux sensor (2)	440.0 lx	804.0 lx
Lux sensor (3)	438.6 lx	795.1 lx
Lux sensor (4)	424.6 lx	760.8 lx
Lux sensor (5)	418.9 lx	745.3 lx
Lux sensor (6)	605.0 lx	1,127.7 lx

Table 5. Comparison of measurement results in test environment (non-reflective background)

Luxmeter (reference)	1,000 lx	2,000 lx
Nokia Lumia 520 (1)	1,483.2 lx	2,819.4 lx
Nokia Lumia 520 (2)	1,370.2 lx	2,462.2 lx
Nokia Lumia 920 (1)	1,933.7 lx	3,714.0 lx
Nokia Lumia 920 (2)	2,125.3 lx	4,206.1 lx
Samsung Galaxy S2 Plus (1)	10,565.0 lx	20,030.0 lx
Samsung Galaxy S2 Plus (2)	3,460.0 lx	6,575.0 lx
Samsung Galaxy S3 (1)	2,731.0 lx	6,544.0 lx
Samsung Galaxy S3 (2)	3,089.0 lx	7,148.0 lx
Lux sensor (1)	157.4 lx	280.7 lx
Lux sensor (2)	140.5 lx	289.7 lx
Lux sensor (3)	141.3 lx	290.5 lx
Lux sensor (4)	142.3 lx	288.9 lx
Lux sensor (5)	135.6 lx	281.4 lx
Lux sensor (6)	136.8 lx	280.5 lx

reflective, dark background. Again, the same lighting conditions were established and measurements were made which are summarised in Table 5.

Fig. 6. Controlled test environment for experiments (non-reflective background).

C. Measurement analysis

Comparing the experimental results of Table 2, 4, and 5 with each other, it can be noted that also the lux sensors of the type TSL2561 from TAOS show significant errors under the spectrum of halogen lamps. In previous research, it was noted that the spectrum of light sources indeed has an impact on measurement results [6]. However, the variation in obtained light intensities by the same lux sensor is still minor compared with the variations in the readings of the ambient light sensors in similar smartphones.

Furthermore, it can be stated that potential reflections due to the surrounding background have an impact on measurement results as well. These circumstances make it difficult to obtain an accurate value of the light intensity (E_v) with the help of the ambient light sensors in smartphones which is required for the estimation of $E_{harvester}$ and SOC_{charge}.

IV. CONCLUSION

In this paper, we revisited the use of ambient light sensors in smartphones to obtain information on indoor environmental conditions. In addition, we presented the opportunity to estimate the solar energy harvested indoors over a certain period of time. We showed that there are significant errors present in the readings of ambient light sensors in smartphones, even if the same type of phone is used. These errors will have a negative impact on the prediction of harvested solar energy.

Due to the non-linearity of the error and the strong impact of the spectrum of the light source on measurement results, it is difficult to correct the given error in ambient light sensors of smartphones. However, energy predictions are needed in order to provide helpful information to users of smartphones as how much solar energy can be harvested after a certain period of time. Hence, it order to estimate $E_{harvester}$ correctly, it is required to measure P_{solar} with the help of the solar energy harvester.

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