A New Model Approach for the Prediction of the Incoming Energy for Solar Based Wireless Sensor Nodes

Christian Viehweger and Olfa Kanoun
Chair for Measurement and Sensor Technology, Technische Universität Chemnitz
Chemnitz, GERMANY
Email: christian.viehweger@etit.tu-chemnitz.de

***Abstract*—Wireless sensor networks can be used to monitor environmental conditions over a large area. The use of solar cells for their power supply makes them independent from stationary power sources and batteries. Photovoltaik powering of sensor nodes requires new strategies for the usage of energy. As, due to clouds and other shadowing effects, the source is not constantly available, an intelligent management is required. The energy management must have a more complex functionality than common ones that use only DC/DC and storage strategies or MPP tracking as optimization. The energy management needs to have the functionality of predicting the incoming power to decide about the state of function of the autonomous system. This paper presents an approach for the modeling of the incoming energy as basis for the prediction.**

***Index Terms*—Wireless Sensor Network, Solar Cell, Energy Prediction, Energy Management**

I. Introduction

Wireless sensor networks (WSN) offer a possibility to monitor and surveil environmental conditions for a variety of applications. The use of a solar based supply makes individual nodes autonomous and enables a maintenance free operation. The powering of sensor nodes with solar cells reveals new challenges for soft- and hardware. The incoming energy for such a case is not constant but varies during one day, according to the environmental conditions. Also, energy is only available during daytime and none in the night.

To encounter these difficulties, an efficient energy management (EM) has to be developed. The EM is a combination of hardware and software, as efficiency and power savings can be realized with both. In the current state of research different proceedings for the implementation of an energy management can be found. Most of the researchers consider an adapted DC/DC converter, sometimes with impedance matching, or a MPP tracking functionality as energy management [1]–[4]. Only a few continue with the treatment of the storage part or different operating modes. Nevertheless, this is necessary to reach the state of 'energy neutrality', as described in [5]. This means that, considering a defined period of time, the consumed energy must not exceed the transduced. Otherwise there will be a lack of energy which has to be compensated by any kind of storage element. If this battery or capacitor got no charge left, the system will fail.

To prevent the system from breakdown and bridge smaller energy gaps efficiently, an intelligent management system has to be developed. An important part of this system is the prediction of the incoming energy. The knowledge of the energy income, enables the EM to decide where to direct the current flow. Depending on the current status the energy can be directed to a long or short term storage element or it can be used to boost the current functionality, like decreasing the measurement or transmission intervals for instance.

This paper describes the modeling of the behavior of the energy income, which can be used as basis for the prediction.

II. Common Methods for Solar Energy Prediction

The typical method to determine the power output of a solar cell in outdoor applications is the AM 1.5 test using standard test conditions. The AM spectrum describes the wavelength-dependent illumination under clear sky conditions on ground level, with an angle of 48° between solar cell and sun. Using this spectrum (see fig. 1) the behavior of the cell, depending on the position and the inclination angle, can be characterized.

As for the energy output of a solar cell in outdoor conditions more effects than just the theoretical illumination have an influence, this simple consideration is not enough. Therefor clear sky models are available, that take other aspects into consideration. For example air pollution or the humidity are reducing the intensity of the incoming light, due to absorption and scattering effects. An overview about different parameters used for those models is given in table I. It is obvious that there are various factors that can't be obtained easily. Temperature and humidity are real-time parameters for example. Other variables like the amount of ozone or the visibility are difficult to measure. Overall, these parameters are not suitable to be used for a model running on a wireless sensor node.

A wireless sensor node contains a microcontroller with a reduced functionality. This makes the system low-cost, but also inflexible. Low production costs are necessary for a network with a high number of nodes. Reduced functionality means that the controller has only a few amount of memory and a computation speed that is just sufficient to fulfil the tasks.

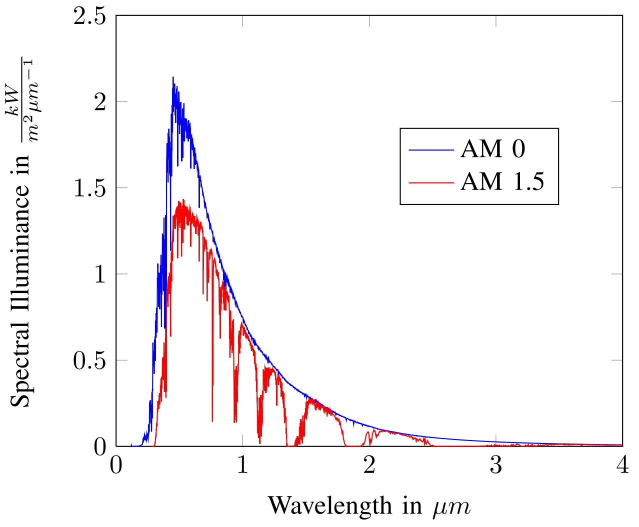

Fig. 1. Air mass spectrum used for the characterization of solar cells.

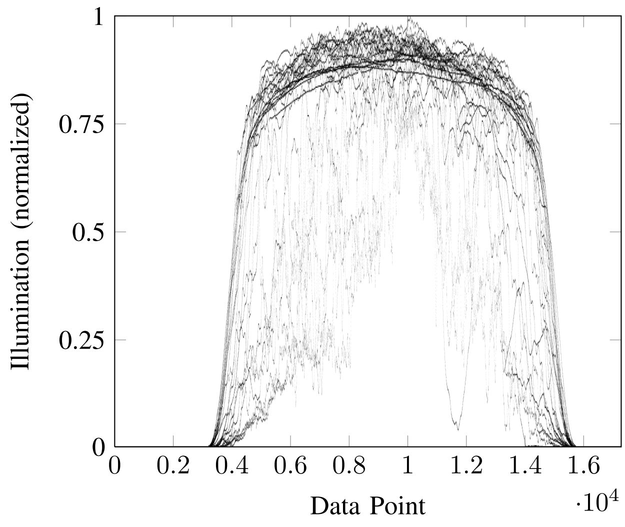

Fig. 2. Density of the datasets in June.

Symbol	Meaning
z	Zenith angle (deg)
m	Air mass
ρ_g	Ground albedo
p	Air pressure (hPa)
T	Air temperature (°C)
U	Humidity (%)
W	Wind speed (m/s)
vis	Visibility (km)
w	Precipitable water (cm)
u_o	ozone vertical pathlength
u_n	NO_2 vertical pathlength
α	Angstrom wavelength exponent
β	Angstrom turbidity
τ_a	Unsworth–Monteith turbidity coefficient
T_L	Linke turbidity
ω	Aerosol single-scattering

TABLE I
OVERVIEW OF PARAMETERS USED FOR CLEAR SKY MODELS [6].

This limitations prevent the microcontroller from the usage of complex algorithms that require more memory than just a few KBytes. Another obstacle for the use of those complex clear sky models is that the parameters need to be updated. It would be against the intention of reduced functionality if the node itself has the ability to measure them. Also, this would generate a higher energy demand. Another approach would be to update them via the network. This requires a bidirectional communication, which is often not the case. Also, it causes new challenges for the routing of the wireless network, especially for collision detection. As the intention is to have a prediction functionality without negative influences on the function of the system and without increasing the hardware requirements, those common model approaches are not sufficient.

III. RECORDING OF ILLUMINANCE PROFILES

A parameter that can be obtained by a sensor node easily is the qualitative curve of the illuminance. It requires only one A/D port of the microcontroller and a photodiode for example. It also has no influence on the energy supply part, as a repeated measurement of the solar cell power itself would have. The hereby measured current illuminance can be compared to a reference illuminance given by a model. The result of this comparison is the basis for the decision making of the EM.

The reference illumination for a given position among clear sky conditions can be pre-estimated using date, daytime and lookup tables. In real environments this consideration is not sufficient, as clear sky conditions are rare. To find out how the photodiode-measured illuminance proceeds among real conditions a database of profiles has been recorded. These curves correspond qualitatively to the incoming power. An example for the density of the datasets in June can be seen in figure 2. It is obvious that the density of the curves shows a main trend, but fluctuations have a high influence and can cause variations of more than 50 %. Fig. 2 also shows that it is possible to find a smooth envelope function that describes the ideal peak trend of the dataset.

Table II gives an overview about the curves recorded over one year. It shows the qualitative empirical classification of the curves. More than 50 % of the 280 profiles show strong variations or a flat slope. 16.5 % of the profiles show a smooth behavior, either shadowed or not. 30 % of the curves show only small deviations or a 50:50 behavior, where half of the curve behaves smooth and the other half shows small deviations.

Figure 3 shows the peak values of the functions over the season of the year. It can be seen that the variation of the peaks in winter is distinctly higher than in summer. This corresponds to the varying and harsh weather conditionssuring this season.

The width of the recorded profiles over one year is shown in fig. 4. As expected, there is a harmonic transition over

	Strong Variations	Slight Variations	50:50	Flat Slope	Ideal	Shadow	Others
Quantity	112	49	37	33	31	15	3
%	40	17,5	13,2	11,8	11,1	5,4	1

TABLE II
EMPIRICAL CLASSIFICATION OF THE DATASETS OF ONE YEAR ACCORDING TO THEIR VARIATIONS.

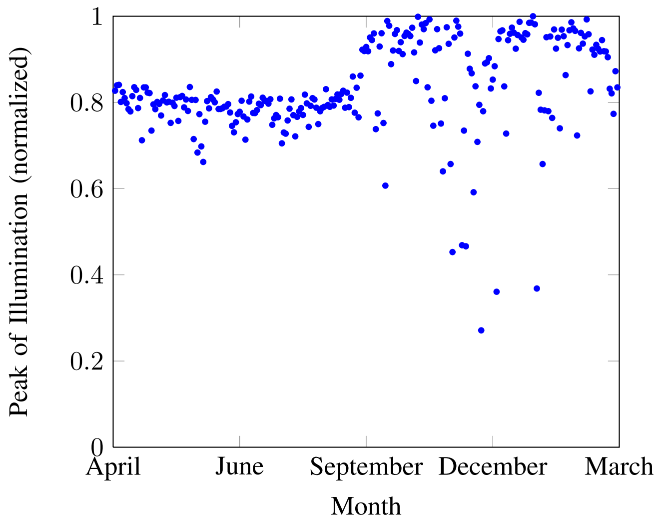

Fig. 3. Curve of the peak values over one year.

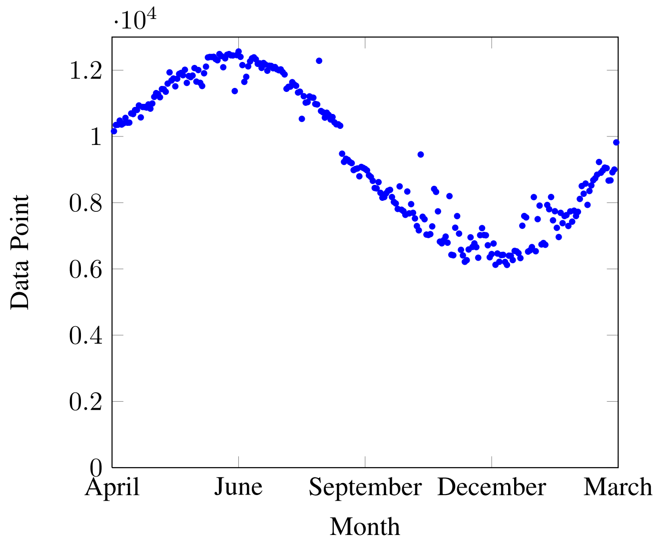

Fig. 4. Number of Datapoints at which the solar cell transduces energy per day. Overview about one year.

time according to the daytime. It can be seen that also for the time of illuminance per day the curves measured in winter show more deviations than in summer. Again this represents the weather conditions and influences therefor the generated power.

Considering table II and the figures 3 and 4, it is obvious that the common AM models and clear sky approaches cannot be used for an application in a wireless sensor network. With the use of those models the direct progress of the curves is, according to the fluctuations, only inaccurately describable. Especially for the cloud skies in winter the prediction functionality is important, as there is a higher number of energy gaps to bridge. For those situations the deviations between model and reality can go above 50 % [7], which is why the use of the high number of clear sky parameters is unjustifiable.

IV. MODEL FOR THE PREDICTION OF ENERGY

The approach in the work presented here is to use a model for the incoming illuminance and compare it to the current illuminance that can easily be measured by the node. If the model represents the ideal curve, it will be the maximum that can be expected. The current value will reach either the value given from the model or be below. The deviation between current value and the value given from the model can be analyzed and predicted and used as input for the decision making of the energy management.

For the modeling of the data shown in figure 2 a harmonical approach has been used. Basis for the model is the hyperbolic cosine:

$$m(t) = \mathrm{e}^t + \mathrm{e}^{-t} \tag{1}$$

which is modified by with the peak values (fig. 3) and the correction factor c_1:

$$m(t) = \hat{h}(t) - c_1 \left(\mathrm{e}^t + \mathrm{e}^{-t}\right). \tag{2}$$

Including the influence of the season s, obtained from figure 4, equation 2 becomes

$$m(t_s) = \hat{h}(t_s) - c_1 \left(\mathrm{e}^{t_s} + \mathrm{e}^{-t_s}\right). \tag{3}$$

The comparison of the model function 3 with a measured curve shows residual deviations at the break points (figure 5).

To improve the model at these points an additional correction needs to be done. Therefor an overlapping sigmoid function with quadratic slope has been used to improve the fit and adapt it to the varying conditions of the different seasons:

$$\begin{aligned} corr\,(t_s) &= c_2 \left(1 + \tanh\left(\frac{t_s}{c_3}\right)\right) \\ &= c_2 \left(1 - \frac{2}{\mathrm{e}^{2\frac{t_s}{c_3}} - 1}\right). \end{aligned} \tag{4}$$

The combination between the base and the correction function

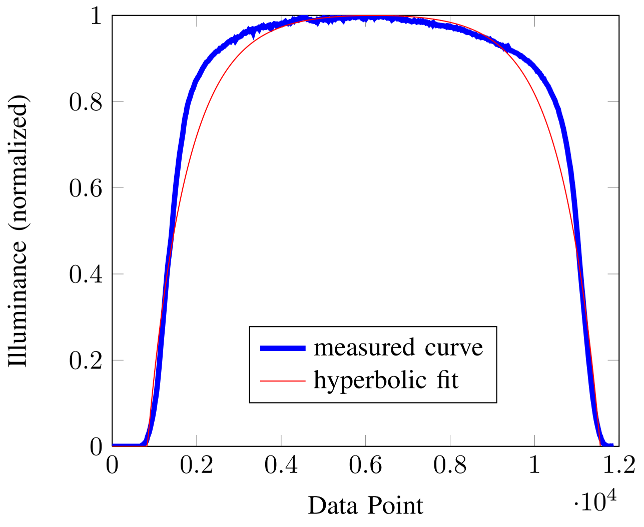

Fig. 5. Number of Datapoints at which the solar cell transduces energy per day. Overview about one year.

$$m_{corr}\left(t_s\right) = corr\left(t_s\right) * m(t_s) \tag{5}$$

represents the model.

The resulting function shows an average error of 21.8 % with a median error of 0.25 %. The 0.75 quantile is at 30.6 %. This includes both clear and cloud sky conditions. Compared to the typical error rate given from the literature [7] this is, especially considering the use of only the illumination as input parameter, still sufficient for the prediction.

V. Conclusion and Outlook

For an optimal control of the states of function due to the fluctuating power source for a solar powered wireless sensor node an energy prediction functionality is required. This functionality enables the node to make the decision between directing the incoming power to a storage element or using it to enhance the systems function. The common AM and clear sky models are not sufficient to be the basis for the prediction. Therefor a model has been developed that uses only the illumination as input parameter and allows the prediction of the incoming power with respect to the reduced functionality of a sensor node.

In future prediction methods will be investigated that require only few computation power and have a minimum memory demand for the microcontroller. The model and the prediction functionality will be integrated into the energy management of the wireless sensor node.

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