ABSTRACT
Accurate simulations of building thermal dynamics are crucial to the validation of load management algorithms involving the control of heating, ventilation, and air conditioning (HVAC), as many control strategies make use of them to estimate the internal state of the controlled system. The recent diffusion of inexpensive smart meters and environmental sensors makes data available for an inexpensive system identification of building thermal dynamics models. In this study we explore the possibility to identify building thermal dynamics based on electrical power and temperature measurements only. A number of thermal-electrical equivalent models of increasing complexity are proposed and their parameters estimated based on real data acquired from a test building located in Lugano, Switzerland. The possibility to use photovoltaic electrical power production as an indicator of solar irradiance is explored in detail.

INTRODUCTION
The ongoing change in the electric energy sector is driven by the strong increase in renewable energy sources (RES), in particular photovoltaics (PV). The lack of controllability and the stochastic nature of RES will increase the stress on the distribution grid and could lead to voltage instabilities. Demand side management (DSM) can help mitigating these problems, by actively controlling the dispatchable loads in the grid, for the purpose of reducing power peaks. Such smart grid approach could represent a cheaper alternative to grid refurbishment (Martínez Ceseña et al., 2015). Space heating and cooling of buildings using electric power is particularly interesting in the DSM context. It requires a substantial amount of energy, which can be easily shifted in time thanks to the high thermal inertia of buildings. With an almost negligible loss of comfort for the residents, heat pumps and heating control systems in combination with thermal storages can help solving the grid balancing problem (Mendoza-Serrano and Chmielewski, 2014). Coordinated load shifting is a complex problem, and multiple aspects must be taken into account in order to solve it. Many recent studies use model predictive control (MPC) combined with mixed-integer linear programming (MILP) to achieve this goal (Kriett and Salani, 2012) (Prodan and Zio, 2014) (Di Giorgio et al., 2014). MPC is a control method that computes an optimal control action based on a model of a dynamical system and its predicted future evolution on a finite time-horizon. One of the main obstacles towards the standardization and commercialization of MPC control for HVAC resides in the identification of a suitable model for the heat dynamics of the building (Sturzenegger et al., 2013). Setting up a physic-based (white-box) model for a particular building requires detailed information on the building’s structure and heating system, which are always difficult to obtain. Although white-box models can provide highly accurate results for energy consumption and internal states of the building, creating these physics-based models normally requires extended work of an engineer or a researcher, which is clearly a barrier to the diffusion of this kind of application. Moreover, white-box models rely on detailed dynamic equations, resulting in a model which is both time consuming to develop and to solve (Li and Wen, 2014). For these reasons, highly sophisticated white-box simulation softwares are not the best choice for the building’s temperature prediction for an MPC implementation. A different approach is to adapt a rather simple model to different buildings, using sensor’s data. This model has to be as general as possible, in order to be applied to a wide variety of building topologies, but complex enough to be able to predict the temperature of the building over the receding horizon. To estimate the building thermal dynamics, several model typologies have been explored, among which linear regression, ARMAX models, linear and non-linear state space models, impulse response and transfer function models, and neural networks (Jiménez and Madsen, 2008) (Li and Wen, 2014). We identify the thermal dynamics of a test building in the form of a grey-box model. Grey-box models are suited when the physics underlying the identified system is known. One of the main benefits is that the identified parameters have a physical meaning. Furthermore, their state space formulation can be easily used in a MPC algorithm. The first step of the grey-box identification process consists in choosing an a-priori representation of the system. Most studies on parameter estimation for
building thermal models focus on a single a-priori representation (Wang and Xu, 2006) (Neill et al., 2010). In (Bacher and Madsen, 2011) several grey-box models for a building have been identified and their performance compared. However, the proposed models lack of insight into building physics. In the present work, different models are derived from an analysis of the main heat transfer mechanisms inside a building. A particular focus is laid on solar gains. Three possible inputs are compared: global horizontal irradiance (GHI) measured with a pyranometer, the solar irradiance projected on each façade and the electrical power of the rooftop PV plant. We show that in our test case PV power can be used as a solar gain estimator, eliminating the need for an additional irradiance sensor.

Another problem is represented by the cost of the monitoring equipment that is required to obtain the data onto which to perform system identification. In this study, we investigate the possibility to use only electrical power and temperature measurements as input data, by using the output of the PV plant as a substitute for an irradiance sensor.

The paper is structured as follows. We first present the test setup and the data acquisition process. Then, the mathematical base of the applied grey-box identification methods is briefly described. Next, the models used for the estimation process and the underlying building physics are explained. Finally, the models are compared by means of statistical tests and qualitative comparisons.

TEST SETUP

Test building

The test building is a lightweight wooden lodge located on the roof of the ISAAC institute, in Lugano, Switzerland. The building is currently used as smart grid test facility accommodating three battery to grid systems, an electric vehicle charger, a 2.5 kW controllable synthetic load and a 2.5 kW air conditioner. The azimuth angle of the southern facade is 176°. The roof is equipped with 1.5 kWp PV plant, mounted with a tilt angle of 14°.

Monitoring

The electric equipment is monitored using Class 0.5 smart meters (PM-3133, ICP DAS, Hukuo, Taiwan). The outdoor temperature is monitored at 2m from the ground using a weather station (WXT520, Vaisala, Helsinki, Finland). The indoor temperature is monitored at 1m from the ground using a thermometer (TH2E, Papouch, Prague, Czech Republic), which has been shielded from long wave radiation. Global horizontal irradiation is monitored using a pyranometer (CMP21 Kipp & Zonen, Delft, The Netherlands) installed approximately 10m north of the building.

System excitation

In order to thermally excite the system, an electric heater with a nominal power of 700W was installed in the building and controlled using a pseudo random binary sequence (PRBS). The PRBS has some advantageous properties, e.g. the signal is deterministic and uncorrelated with meteorological data (Madsen and Schultz, 1993) and its spectrum is a good approximation to band-limited white noise (Fairweather et al., 2010). The PRBS is obtained with a linear feedback shift register of order $n = 7$ and time period of $\Delta t = 10$ minutes. This results in a PRBS with a periodicity of $\Delta t(2^n - 1) = 21$ hours. $T$ and $n$ are determined by the expected time constant of the system. The lower bound of the sampling frequency is fixed by the Nyquist-Shannon sampling theorem to:

$$f_s \geq 2f_{max}$$

where $f_s$ is the sampling frequency and $f_{max}$ is the maximum characteristic frequency of the system. In practice, to compensate measurement errors, an even smaller sampling time is advised (Verhelst, 2012). In our case, a sampling period of 2.5 minutes is used.

![Figure 1: Data example. Top: Internal (black) and external (red) temperatures. Center: Electric power of the heater (black) and the rest of the electronic devices (red). Bottom: Global horizontal irradiation (black), rescaled power output of the PV plant (red), solar radiation projected on the external walls of the test building (green).](image-url)

Data collection and analysis

The system was uninterruptedly monitored for 92 hours, which we estimated to be abundantly above its largest time constant (Verhelst, 2012). The sampling frequency was 1Hz for the electrical quantities and 1/60Hz for irradiance and temperatures. As a first step, the data were filtered in order to properly handle missing observations and measurement outliers. During the data acquisition period, batteries were idle, the air conditioner was turned off and the door and the windows were closed all the time. The most relevant monitored values used in the identification process are shown in figure 1.
SYSTEM IDENTIFICATION

Maximum likelihood estimator

Generally speaking, a model of a given system should provide a prediction of the system’s observables at time $k$, given all the observations up to time $k-1$, which is:

$$y_k = f(\theta, \gamma_{k-1})$$  \hspace{1cm} (2)

where $\theta$ is the vector of the parameters of the system, which one wants to identify. This is accomplished by an estimator:

$$\hat{\theta}(\gamma_{k-1})$$  \hspace{1cm} (3)

We used the maximum likelihood estimator (MLE) implemented in the CTSMr R library (Kristensen and Madsen, 2003). Maximum likelihood estimation consists in finding the values of $\theta$ that maximizes the likelihood of the observations $\gamma_{k-1}$. The likelihood function is the joint probability of the observations:

$$L(\theta; \gamma_N) = p_0(y_0|\theta) \prod_{k=1}^{N} p(y_k|\gamma_{k-1}, \theta)$$  \hspace{1cm} (4)

In our case, we considered only linear time-invariant models. Thus, the general formulation shown in equation (2) can be written as a stochastic state space model in continuous time (Kristensen and Madsen, 2003):

$$\dot{x}_t = [A(\theta)x_t + B(\theta)u_t]dt + \epsilon(\theta)\omega$$

$$y_t = [C(\theta)x_t + D(\theta)u_t]dt + \epsilon_k$$  \hspace{1cm} (5)

where $t \in \mathbb{R}$ is time, $x \in \mathbb{R}^n$ represents the state of the system, $u \in \mathbb{R}^m$ is the input vector, $y \in \mathbb{R}^d$ is the output vector. The system noise is represented by the n-dimensional standard Wiener process $\omega$ with associated incremental variance $\sigma^2$, while the measurement noise $\epsilon$ is assumed to be Gaussian white noise. In this case, the conditional density in equation (4) can be written as:

$$p(y_k|\gamma_{k-1}) = \frac{\exp(-\frac{1}{2}\epsilon^T R^{-1}\epsilon_k)}{\sqrt{\det(R_k)|\sigma^2|2\pi}}$$  \hspace{1cm} (6)

where $\epsilon$ is the model error between the predicted observation at time $k$, given the previous $k-1$ observations, and the observed value at time $k$:

$$\epsilon_k = y_k - \hat{y}_{k|k-1}$$  \hspace{1cm} (7)

and $R$ is the covariance of the observation. The value of $\hat{y}_{k|k-1}$, also known as conditional mean, is defined as:

$$\hat{y}_{k|k-1} = E[y_k|y_{k-1}, \theta]$$  \hspace{1cm} (8)

The values of the conditional mean, $\epsilon$ and $R$ can be estimated with a Kalman filter. Using equations (4) and (6), the vector $\theta$ can be estimated by solving the following optimization problem (Madsen, H., Holst, 1995):

$$\hat{\theta} = \arg\min_{\theta} -ln(L(\theta; \gamma_n|y_0))$$

$$= \arg\min_{\theta} -\frac{1}{2} \sum_{k=1}^{N} \ln(det(R_{k|k-1})) + \epsilon^T R_{k|k-1}^{-1} \epsilon_k + \text{const}$$  \hspace{1cm} (9)

One of the advantages of the maximum likelihood estimation, compared for example to the output error method, is the possibility to estimate the noise and the standard deviations of the estimated parameters (Palmkvist, 2014). Furthermore, the estimator $\hat{\theta}$ is guaranteed to be unbiased as the number of observations tends to infinity (Ljung, 1999).

GREY-BOX MODELLING

RC network models

Seven RC networks of increasing complexity are proposed (Figure 2). As the complexity increases, subtler thermal phenomena are taken into account. All the RC networks can be written as state space models in the form of equation 5, where $x_t$ is the vector of the model’s states, and $y_t$ is the observed internal temperature. The matrix $C$ has only a non-zero element, equal to one, on its diagonal and the matrix $D$ is a null matrix. All the states of the system are temperatures. The models proposed in this study consist of two states at most.

The state space model can be written as:

$$dT_t = AT_t dt + Bu_t dt + \sigma d\omega$$

$$y_t = CT_t dt + \epsilon_k$$  \hspace{1cm} (10)

The simplest model is the standard 1R1C model (Figure 2A). The dynamic equation of the system can be written as:

$$C_i dT_i = \frac{1}{R_e} (T_a - T_i) + P_h + P_e + A_w G + \sigma d\omega$$  \hspace{1cm} (11)

where $C_i$ is the building heat capacity, $T_i$ is the observed temperature inside the building, $R_e$ is the overall resistance between the internal part of the building and the external air $T_a$, $P_h$ is the power from the electric heater, $P_e$ is the power from the electronic devices inside the building, $A_w$ is the equivalent window area and $G$ is the solar irradiance.

The second model (Figure 2B) is derived from the linearization of the main mechanisms of heat transfer. The heat balance on the exterior surface can be written as:

$$\dot{Q}_d + \dot{Q}_v + \dot{Q}_{lw} + \dot{Q}_{sw} = 0$$  \hspace{1cm} (12)

where $\dot{Q}_d$ is the conductive heat flow through the wall, $\dot{Q}_v$ is the convective heat flow, $\dot{Q}_{lw}$ is the long-wave radiation and $\dot{Q}_{sw}$ is the shortwave radiation.
They can respectively be written as:

\[
\dot{Q}_d = \frac{1}{R_{\text{cond}}}(T_1 - T_w)
\]
\[
\dot{Q}_v = \frac{1}{R_{\text{conv}}}(T_a - T_w)
\]
\[
\dot{Q}_{\text{ext}} = \sigma \epsilon A_{\text{ext}} [F_a(T_a^4 - T_w^4) + F_s(T_s^4 - T_w^4)]
\]
\[
\dot{Q}_{\text{ext}} = \epsilon G A_{\text{ext}}
\]

(13)

where \(R_{\text{conv}}\) and \(R_{\text{cond}}\) are the convective and conductive resistances, \(T_a\), \(T_i\), \(T_e\), and \(T_w\) are respectively the external, internal, sky and wall external temperature, \(\sigma\) is the Stefan-Boltzmann constant, \(\epsilon\) is the emissivity of the wall, \(F_a\) and \(F_s\) are the view factor between the wall and the ambient and between the wall and the sky. Note that \(R_{\text{conv}}\) is in general dependent on wind speed (Defraeye, 2011), but can be considered constant as a first approximation. We can use the following normalization condition for the view factors:

\[
F_a + F_s = 1
\]

(14)

Again, as first approximation, we can consider the sky temperature to be proportional to \(T_a\) (Adelard, 1998):

\[
T_s = k_s T_a
\]

(15)

We can then linearize the radiation term using the following relation (Amir Faghri, Yuwen Zhang, 2010):

\[
T_1^4 - T_2^4 \approx 4T^3(1 - T)
\]

(16)

where \(T\) is the mean temperature between \(T_1\) and \(T_2\). Under these assumptions, the model can be reduced to the one shown in figure 2B. In the most complex configurations D-G, an additional capacity \(C_e\) takes into account the mass of the walls. In models C, F and G the additional resistance \(R_{\text{inf}}\) is introduced to consider the direct heat transfer between \(T_a\) and \(T_i\) due to air infiltration.

**Radiation models for the computation of solar gains**

Three different signals for the assessment of solar gains have been considered (Figure 1). The first one is the GHI measured by the pyranometer. The second one is the AC power output of the PV plant, \(P_{\text{pv}}\). The third one is the projection of the diffuse and direct components of the solar radiation on the external walls of the house, \(P_{\text{sol}}\). Both \(P_{\text{pv}}\) and \(P_{\text{sol}}\) are then normalized by the 90% quantile of the GHI signal. The normalization allows a direct comparison of the weighting coefficients of the solar radiation (\(A_w\) in equation (11)) among the three different solar gain models.

The projected solar radiation is modelled as follows. Solar radiation on a flat surface can be computed as:

\[
I = I_b + I_d + I_g
\]

(17)

where \(I\), \(I_b\), \(I_d\) and \(I_g\) are respectively the total, direct beam, diffuse and ground reflected irradiance. The ground reflected component can be computed as:

\[
I_g = \frac{1}{2} a G HI (1 - \cos(\theta_T))
\]

(18)

where \(a\) is the albedo coefficient and \(\theta_T\) is the tilt angle of the surface on which the projection is computed. The direct component \(I_b\) is given by:

\[
I_b = DNI \cos(\text{AOI})
\]

(19)

where \(\text{AOI}\) is the angle of incidence and \(DNI\) is the direct normal irradiance. \(DNI\) can be found using the
DISC model (Maxwell, 1987). Then we can use the following relation:

\[ GHI = DHI + \cos(\theta_Z)DNI \]  

(20)

where \( \theta_Z \) is the zenith angle for the sun, from which we obtain the diffuse horizontal irradiance (DHI), and use it to compute the \( I_d \) term with the Perez model (Perez, 1992). The PVLIB toolbox from Sandia National Laboratories (Andrews et al., 2012) has been used to compute both the DISC and the Perez model. The value of \( P_{sol} \) is then calculated as:

\[ P_{sol} = \sum_{i=1}^{6} A_i I_i \]  

(21)

where \( A_i \) is the surface area of the \( i \)th external wall of the building. The absorption coefficient is not taken into account, since it is considered to be a constant property of the external walls, independent from AOI. As such, its value is estimated during the identification process as a part of the solar weighting coefficients. The Perez model uses 48 coefficients in order to find the diffuse irradiance from the sky on a tilted surface. These coefficients are location-dependent and are derived via least-squares fitting of a large experimental database (Perez, 1992). Since the PVLIB Toolbox does not include a set of coefficients for Switzerland, we estimated them using one year of irradiation data, collected by three pyranometers with a sampling time of 1 minute. The first pyranometer measures GHI, the second DHI, while the third one is mounted on a surface with a tilt angle \( \theta_T = 45^\circ \) and an azimuth angle of \( \theta_A = 178^\circ \). As an example, a 4 days period of the data used to estimate the parameters of the Perez model, is shown in figure 3.

\[ P_{sol} = \sum_{i=1}^{6} A_i I_i \]  

Figure 3: Example of data used for the fit of the Perez coefficients. In blue: GHI, in green: DHI, in red: irradiance on the plane of array (POA) with \( \theta_T = 45^\circ \) and \( \theta_A = 178^\circ \). The parameters are found by minimizing the root mean squared error:

\[
\arg \min_c \sqrt{\frac{1}{n} \sum_{i=1}^{n} (I_s - I_p(c))^2} 
\]  

(22)

where \( I_s \) is the measured irradiance on the surface and \( I_p(c) \) is the irradiance computed by the Perez model, which is function of the parameter vector \( c \). The minimization is performed by means of a genetic algorithm. The RMSE for the optimized set of parameters \( c \) is 20.36 W/m². The optimization leads to a 6.6% improvement of the RMSE function with respect to the default values of \( c \), provided by the PVLIB toolbox. Figure 4 shows a scatter plot between the measured an computed irradiance on the plane of array.

**DATA ANALYSIS**

**Model comparison**

The different models are compared by means of both quantitative and qualitative analysis. A common approach to validate the quality of a model is the analysis of the \( n \) step-ahead predictions. We used one step-ahead predictions for the computation of the likelihood function (equation 4), as they are the optimal choice when estimating the true model of a system (Stoica and Nehorai, 1989). Principally, the assumption that the model error \( \epsilon_k \) is white noise has to be verified. A qualitative way to confirm this assumption is to plot the auto correlation function (ACF) of \( \epsilon_k \). Additionally, likelihood-ratio tests are performed between different models. The likelihood-ratio test is a statistical test for discerning which, between two models of different complexity, is more likely to have generated the observed data (Madsen and Thyregod, 2010). Starting from the simplest model, comparison is carried out in a forward selection strategy, comparing models with an increasing number of unknown parameters.

**Use of different solar inputs**

The RMSE of the one step-ahead predictions for the models is shown in Figure 5. Model G has the lowest RMSE when GHI or PV power are the input of choice. The use of the PV signal, instead of the GHI signal, reduces the RMSE. This can be explained by the fact

\[ GHI = DHI + \cos(\theta_Z)DNI \]  

(20)
that the PV is mounted on the roof of the building, thus its signal is affected by the same shading factor of the building. This is not the case for the GHI sensor, even if it is located within a 10 meters distance from the building. Furthermore, the radiation seen by the PV, which is aligned the with roof, could be more representative of the overall radiation received by the building than the GHI. Figure 6 shows the log-likelihood of the models. The results are in line with of those obtained when comparing the RMSE (Figure 3) and the same conclusions can be drawn.

The likelihood-ratio tests between the models confirm that the best models are model E and model F. The likelihood-ratio test between these two models returns a p-value of 0.066, thus we can conclude that model F is not significantly better than model E. As a consequence, model E is to be preferred over F, since its number of unknowns is lower.

As expected, using $P_{sol}$ instead of GHI decrease the value of the one step-ahead prediction’s RMSE, and increase the log Likelihood. Anyway, the decrement in RMSE is more important for the simplest model and less significant for the last model. This behavior is confirmed also by the ACF of $\epsilon_k$.

**Figure 5:** RMS of $\epsilon_k$ for the different models, using different signals for solar gains.

**Figure 6:** Log Likelihood for the different models, using different signals for solar gains.

**Figure 7:** ACF of $\epsilon_k$ for model A, with 95% confidence band, using different signals for solar gains, on a period of 6 hours. GHI signal (red), Ppv signal (yellow), Psol signal (blue) and confidence band (dashed).

**Figure 8:** ACF of $\epsilon_k$ for model E, with 95% confidence band, using different signals for solar gains, on a period of 6 hours. GHI signal (red), Ppv signal (yellow), Psol signal (blue) and confidence band (dashed).

**Figure 9:** Simulation results for model E. Top: $\epsilon_k$ (black) and 24 hours steps-ahead residuals (green). Center: Observed internal temperature (black), one step ahead predictions (red) and one 24 hours ahead predictions (green) with 95% confidence band (dashed lines). Bottom: Observed (black) and simulated (blue) internal temperature.

Figure 7 shows that the use of $P_{sol}$ instead of GHI increases the whiteness of the residuals. Again, this effect is less evident for the complex model, as shown.
in figure 8. For completeness, in Figure 9 we plot the residuals of the one-step-ahead predictions ($\epsilon_k$) and the residuals of the 24 hours ahead predictions, for a two days period. The second part of the figures shows the simulated internal temperature.

The estimated values for model E are listed in Table 1. $Ti0$ and $Te0$ represent the estimated initial conditions for the internal and wall temperatures. The first column shows the estimated values when the GHI is used. The second column shows the estimated standard deviation for the parameters of column one. The value in the third and fourth columns represent the relative deviation between the parameters of the first column and the one estimated with different solar inputs, calculated as follows:

$$\frac{\theta_{GHI} - \theta}{\theta_{GHI}}$$  \hspace{1cm} (23)

where $\theta$ is relative to Ppv in the third column and to Psol in the fourth column. The greatest deviation is between the GHI and Ppv estimations of Aw, which represents the windows area. This can be explained by the fact that windows are present only on the north facade of the building, and the Ppv panels are facing south.

<table>
<thead>
<tr>
<th></th>
<th>GHI</th>
<th>Std.Error</th>
<th>Ppv</th>
<th>Psol</th>
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<tbody>
<tr>
<td>Ti0</td>
<td>3.0e+2</td>
<td>2.2e-2</td>
<td>1.3e-06</td>
<td>3.9e-06</td>
</tr>
<tr>
<td>Te0</td>
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<td>Aext</td>
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<td>-2.4e-03</td>
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<td>1.0e+00</td>
<td>5.5e-01</td>
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</tr>
<tr>
<td>Rie</td>
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<td>2.1e-04</td>
<td>-7.8e-04</td>
<td>6.5e-03</td>
</tr>
</tbody>
</table>

Table 1: Parameters of model E. The first column shows the identified values when the solar input was GHI. The second column shows the estimated standard error. The third and fourth columns show the relative difference between the parameters identified with Ppv and Psol as solar inputs and the values of the first column.

CONCLUSIONS

In this study, we performed a system identification of the thermal dynamics of a building. The system was excited in open-loop using a heater controlled by a PRBS. Seven grey-box models of increasing complexity were proposed and their performance in predicting the building thermal behavior compared. The system identification successfully converged for all the proposed models and the RMSE prediction of the internal temperature varied from 4.8e-2K to 4.27e-2K for the next-step prediction and from 0.814K to 0.644K for a 24h prediction. The best results were achieved with one of the two-state models (Figure 2E), which has 6 free parameters.

In a normal inhabited building, in which an active control of the internal temperature is operative, the system identification would reveal itself more complex for two main reasons, which will be the object of further studies. First, the closed loop control strategy of the temperature control strategy would also need to be identified. Second, for electric cooling and most of the times also for electric heating, heat pumps (HPs) are used. In HPs, electric energy is not directly converted 1:1 into thermal energy, as it is done by simple electric heaters. In the case of HPs, the coefficient of performance (COP) needs to be identified. The COP could also be directly computed by measuring water flows and temperatures of the HVAC system (Záčeková et al., 2014). However, this approach requires the installation of a number of expensive sensors, therefore reducing the attractiveness for commercial applications.

We explored the possibility to use only temperature and electric power sensors in the identification process. This could represent a cost effective solution, especially because a massive penetration of cheap smart meters, needed by DSM algorithms, has already begun. In particular, for the estimate of solar gains we used the power output of the PV plant. The results are promising. PV output even gave better results than when the GHI signal measured by a professional pyranometer was used. This could be explained by the fact that the PV plant was directly mounted on the roof of the building, while the GHI sensor was not. The use of accurate solar projections for each facade of the building through the Perez model increased the accuracy for the simplest models. However, for the more complex models the benefits of using solar projections are not qualitatively significant.

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