



Development and experimental validation of a comprehensive thermoelectric dynamic model of photovoltaic modules



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ABSTRACT

In order to increase PV penetration and guarantee the grid stability, it is fundamental to accurately predict the power produced from PV plants. This work discusses a comprehensive thermo-electric model accounting for PV module dynamic behavior. Specifically, the thermal part considers five different sections featuring the five layers of the PV module. The electrical behavior of the PV module is described by the five parameters electric equivalent circuit where the operating temperature is calculated within the thermal model. The accuracy of the model is evaluated against the power produced by two monocrystalline silicon modules at the SolarTech^{Lab} of Politecnico di Milano using both actual weather information and the weather forecast. Results highlight that dynamic models adequately characterize the behavior of the modules when actual weather measurements are available; the resulting error indexes WMAE and RMSE for the dynamic model are reduced with respect to steady-state and conventional approaches based on NOCT by 50%. Indeed, the WMAE is approximately 1%, which is comparable to the uncertainty related to measuring instrumentations, whereas the RMSE is included between 3 W and 4 W. When using the long term weather forecast, no advantages in the development of dynamic models can be noted.

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1. Introduction

The electricity produced by renewable energy sources (RES) has been increasing world-wide thanks to technological advancements, cost reduction and government policies. For example, the total installed capacity of RES in the world has doubled since 2006 (1036 GW in 2006 vs. 1985 GW in 2015) ([Renewable Capacity Statistics 2016](#), n.d.). Most of this growth is related to the increased capacity of photovoltaic (6 GW vs. 222 GW) and wind energy (73 GW vs. 440 GW). As consequence, the higher share of variable RES in the power generation sector leads to significant challenges in the control and reliability of the power transmission system: grid operators have to control a variable power supply together with a variable demand. Two options can be used to control the grid while using most of the renewable energy produced: the first one requires the installation of storage systems (which can be batteries, pump-hydro, etc.) and the second one is the development of accurate models for power generation prediction starting from the weather forecast/conditions. This work fits in

the second group, focusing on Photovoltaic (PV) technology: therefore, only PV forecasting models will be discussed from now on.

The existing approaches of forecasting models can be classified into these three categories: physical, statistical and hybrid ([Ruscas et al., 2014](#); [Ulbricht et al., 2013](#)).

Physical models predict the power generated by PV modules describing the conversion processes from the solar energy to electricity. Being physical models the core of this work, more details will be discussed later. Statistical methods are based on the concept of persistence, or stochastic time series, and are typically based on machine learning methods. Reviewed literature shows that artificial neural networks (ANN) have been successfully applied for forecasts of fluctuating energy supply ([Hocaoglu et al., 2008](#); [Izgi et al., 2012](#); [Mellit and Massi Pavan, 2010](#)). These methods learn to recognize patterns in data using training data sets which is the main disadvantage of this approach.

Any combination of two or more of the previously described methods leads to a hybrid model. The idea is to combine different models with unique features to overcome the single negative performance and finally improve the forecast ([Chopde et al., 2016](#); [Ogliari et al., 2013](#)).

Focusing only on physical models, two different approaches can be found in the scientific literature:

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Nomenclature

A	area (m^2)	β	tilt angle ($^\circ$)
C	electric or thermal capacitance (F or J K^{-1})	ε	emissivity (–)
c	specific heat ($\text{J kg}^{-1} \text{K}^{-1}$)	θ	incident angle ($^\circ$)
D	diameter (m)	ν	kinematic viscosity ($\text{m}^2 \text{s}^{-1}$)
E_G	bandgap energy of the silicon (eV)	ρ	density (kg m^{-3}) or reflectance (–)
e	error (W)	σ	stefan-Boltzmann constant (W K^{-4})
h	convective heat transfer coefficient ($\text{W m}^{-2} \text{K}^{-1}$)	τ	transmittance (–)
k	thermal conductivity ($\text{W m}^{-1} \text{K}^{-1}$) or Boltzmann constant (eV)	ϕ	heat flux (W m^{-2})
G	solar radiation (W m^{-2})	Subscript	
g	gravity acceleration (m s^{-2})	A	ambient
I	current (A)	B	back layer or Beam component
l	length (m)	C	single PV cell
N	number of PV cells connected in series (–)	D	diffuse component or diode
$NOCT$	nominal operating cell temperature (K)	E	EVA (Ethylene Vinyl Acetate) layer
Nu	Nusselt number (–)	G	glass layer
n	diode ideality factor (n)	$GLOB$	global
P	electric power (W)	H	horizontal
Pr	Prandtl number (–)	HYD	hydraulic
R	electric or thermal resistance (Ω or K W^{-1})	M	overall PV module or measured
$RMSE$	root mean square error (W)	MPP	maximum power point
Ra	Rayleigh number (–)	OC	open circuit
Re	Reynolds number (–)	P	predicted
s	thickness (m)	R	roof or reflected component
T	temperature (K)	REF	reference
t	time (s)	PV	photovoltaic cell layer or module
V	voltage (V)	S	sky or surface or cell series
v	velocity (m s^{-1})	SC	short circuit
$WMAE$	weighted mean absolute error (–)	SH	shunt
w	width (m)	T	thermal
z	height from the ground (m)	W	wind
		Z	zenith
Greek symbols			
α	absorbance (–)		
α_{ISC}	temperature coefficient for short circuit current (–)		

1. Models aiming to the characterization of the cell temperature through detailed description of the thermal phenomena. The electric conversion is described by explicit formulas (Notton et al., 2005; Tina et al., 2011);
2. Models concentrating on the electric conversion mechanisms within the module for the prediction of the I-V characteristic curve (Barth et al., 2016; Celik and Acikgoz, 2007; Ciulla et al., 2014; de Blas et al., 2002; Lineykin et al., 2014; Lo Brano et al., 2010; Ma et al., 2013, 2014; Shongwe and Hanif, 2015; Siddiqui et al., 2013; Tossa et al., 2014). In this case the cell temperature used in the model is generally calculated with the NOCT approach. In few cases, the temperature is calculated through more complex thermal models (Bizzarri et al., 2012; Dolara et al., 2015; King et al., 2004).

This paper proposes an integration between these two approaches to accurately describe all the phenomena occurring within a PV module. The proposed models are developed under steady-state and dynamic conditions aiming to determine the importance of the dynamic behavior using both actual weather conditions and weather forecasts.

Various studies regarding the implementation of dynamic models for the calculation of PV cell temperature are available in literature. Generally, in those cases, the electric power produced is calculated with simple and explicit relations, considering for example NOCT model or the fill factor.

Jones and Underwood (2001), Torres Lobera and Valkealahti (2013) proposed a simple thermal model, characterized by a global energy balance on the module with one equivalent thermal capacity. In both studies, only the cell absorbance has been included in the optical model, which is considered independent from the incidence angle. Results showed that the standard error is between 1.2 °C and 3.0 °C (Jones and Underwood, 2001) or that the RMSE varies between 1.18 °C and 4.76 °C, furtherly reduced below 2 °C after performing a sensitivity analysis (Torres Lobera and Valkealahti, 2013).

On the other hand, Tsai and Tsai (2012) developed a single-capacity thermal model coupled with a five parameters electric equivalent circuit that was able to achieve a normalized RMSE of 1.98 % after performing a parameters optimization through a sensitivity analysis.

Three thermal capacities for the PV module are considered in other studies (Notton et al., 2005; Tina et al., 2011), increasing the accuracy of the thermal mechanisms within the panel together with the complexity of the model. In both studies, the incident irradiance is split into two fractions: the first one absorbed by the glass and the remaining by the PV cells; the optical parameters are assumed to be independent from the incidence angle. The model proposed by Notton et al. (2005) has a RMSE of 1.30 °C for the cell temperature and 1.52 °C for the back temperature. On the other side, in (Tina et al., 2011) the irradiance absorbed by cells includes multiple reflections mechanisms between layers and the electric power is calculated considering the module efficiency, which is a

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