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Multiyear calibration of simulations of energy systems

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ABSTRACT

Energy system simulation tools are important to assess and plan the energy transition to future power systems with large integration of renewables. The calibration of power balance models, to assure that they accurately reproduce the energy system, is usually made by the reproduction of a single year past time series. This makes the calibration sensitive to that year's particular conditions, such as water availability to generate hydropower, which may jeopardise the adequacy of simulations of scenarios with different environmental conditions. This paper proposes a multiyear calibration method using linear regressions to obtain the relevant calibration parameters. To validate the method, calibrated EnergyPLAN simulations of two heterogeneous historical years in Portugal are used to compare the standard and the multiyear calibrations. Results show that the multiyear calibration allowed significant improvement in the model accuracy, showing up to 3.8 times lower errors and up to 11.2 times lower standard deviation, enhancing the confidence on the simulation of future scenarios.

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1. Introduction

Electric system operation relies on the instantaneous balance between supply and demand, which makes it highly vulnerable to their variability. Planning is a crucial phase in the system operation to guarantee its reliability, thus it should carefully consider the variability of supply sources. Large-scale renewables' integration into the electric system can be a major challenge due to variability and uncertainty in the resource [1]. Hence, the projection of future power systems with high share of renewables and its resilience should account for variations in the energy resource, which may be intensified by climate change [2].

Planning and testing possible changes on the system can be done modelling electric system scenarios. A variety of methods and simulation tools are available, which recently have been reviewed. Debnath and Mourshed [3] summarises the methods used in energy planning tools. Collins et al. [4] reviewed different methodologies, using energy models, and analysed their capability of considering short-term variations on the power system. Connolly et al. [5] reviewed modelling tools, presenting a thorough description of the characteristics of each one. A more recent review of energy models was made by Liu et al. [6], focusing the challenges of modelling isolated regions.

RETScreen [7], HOMER [8], LEAP [9], MARKAL/TIMES [10] and EnergyPLAN [11] are some of the most commonly used tools to model energy systems, differing in the approach, e.g. bottom-up or top-down, and features and scope, e.g. timestep resolution and horizon and geographic scope. Table 1 presents some examples of energy modelling tools and some of their most relevant features.

A scenario simulation should be preceded by a calibration of the model, to make sure it works accurately. "*Calibration is the estimation and adjustment of model parameters and constants to improve the agreement between model output and a data set*" [16]. It is performed by adjusting a set of not perfectly defined parameters to fit the simulation outputs to the historical data [16]. The standard calibration of electric systems' simulation considers a single year of historical data, regardless of the focus of the study or tool used, as some examples are hereafter mentioned. Cleary et al. [17] studied the wind energy integration in Ireland and in the United Kingdom, using Balmorel and PLEXOS. Zhao et al. [18] worked on low carbon scenarios for Beijing, using EnergyPLAN. Hast et al. [19] combined several energy modelling tools (energyPRO, WILMAR and BALMOREL) to study the impact of the electricity price fluctuation due to high renewable penetration on a district heating system in a Finnish city.

Usually, the calibration parameters are kept constant in the simulation of new scenarios. In systems highly based on renewables, the choice of a meteorological year (usually the most recent or the typical one) to make the calibration can result in inaccuracies when simulating a dissimilar year, e.g. simulating a scenario where

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Table 1
Examples and features of energy models.

	Geographic scope	Timestep	Time horizon
BALMOREL [12]	International	Hourly	Max. of 50 years
EnergyPLAN [11]	National/regional	Hourly	1 year
energyPRO [13]	Regional/Several locations	Minute	Max. of 40 years
HOMER [8]	Local	Minute	1 year
LEAP [9]	Global/National/Regional/Local	Yearly	No limit
MARKAL/TIMES [10]	National/regional	User defined	Max. 50 years
PLEXOS [14]	International	Hourly to minute	Max. of 10 years
RETScreen [7]	User defined	Monthly	Max. 50 years
WILMAR [15]	International	Hourly	1 year

precipitation is above average, leading to underestimation of the hydro resource. Thus, single year calibrations will depend on the specific meteorological characteristics of that year. A well-calibrated model should be accurate within all the spectrum of conditions. This issue is particularly important in renewables-based systems with high inter-annual variabilities such as hydro [20] and wind power [21,22]. In addition to inter-annual changes, climate change also has a significant impact on energy systems' modelling. For instance: Teotónio et al. [23] uses the tool TIMES (a cost-optimisation model) to simulate the Portuguese electric system in 2050, assuming that hydropower generation is the most affected renewable supply source, declining up to 41% due to precipitation decrease. Mendes et al. [24] studies the impact of climate change on revenues from hydropower plants in the Amazon, concluding that changes on river flows will result on less revenues in 2050, continuing to decline until 2100.

This work proposes a new calibration method using a multiyear approach, based on linear regressions of weather indicators to determine the calibration parameters. It allows building a flexible simulation model, adjustable to different environmental conditions since the calibration period covers a wide spectrum of system operating conditions. The accuracy of single and multiyear calibrations, using as reference the Portuguese power system during the period 2011–2015, is assessed modelling two very different years as far as weather was concerned, 2000 and 2005, and comparing the results.

The article follows detailing the methods (Section 2); the case study, the Portuguese electric system, is described in Section 3; the results are shown in Section 4; finally, Section 5 presents the conclusions.

2. Methods

A period of n years of historical data is used to calibrate the model, by determining different calibration parameters Y_i^j , where $i = 1 \ldots m$ refers to the parameter (m parameters, such as power plants efficiency or run-of-river hydro generation, etc.) and $j = 1 \ldots n$ refers to the year. Linear regressions are applied to each calibration parameter using a wide range of weather and energy variables. The regression that best fits each calibration parameter is selected, defining $\widehat{Y}_i$, the calibrated parameter to be used in simulations.

The method is assessed by running energy system simulations for two past years, with very different weather conditions. For each, two approaches are used for the simulations:

(1) n single year calibrations using parameters Y_i^j, denoted *model year j*; and
(2) one linear regression, multiyear (*MY*) *model*, using $\widehat{Y}_i$.

Fig. 1 shows a summarised scheme of the proposed methods.

2.1. Standard calibrations

A calibration using a historical period should be performed before applying the model to other scenarios. A single year calibration – henceforth denoted *standard calibration*– begins with input of all the historical data required by the energy system model. Then, it is performed a comparison between selected indicators, such as renewable energy share or annual CO_2 emissions, from historical data and simulation outputs. The calibration is done iteratively, changing model inputs not properly described in the historical data, the *calibration parameters*. It should be noticed that the number m of parameters will vary with the case study and/or simulation tool. In electric system simulations, the calibration parameters are normally related to the performance of power plants and the available energy resources; these parameters may not be accurately described by the available data and/or may depend on the power plant fleet operating conditions and weather conditions. When an acceptable pre-established maximum difference between the historical and the simulation outputs is achieved, the calibration parameters are finally defined.

2.2. Multiyear calibration

The linear regression of standard calibrations results, Y_i^j, to meteorological and energy indicators for the n years are used to determine the multiyear calibration parameters. In general, a multivariable linear regression enables the prediction of a dependent variable Y, i.e., the calibration parameters Y_i^j, from independent variables X_k, their estimated coefficients $\widehat{\beta}_k$, and error ε, as shown in Eq. (1).

$$Y = \widehat{\beta}_0 + \widehat{\beta}_1 X_1 + \ldots + \widehat{\beta}_k X_k + \varepsilon \quad (1)$$

When there is only one independent variable, the linear regression is called simple linear regression. The prediction of the dependent variable lies on testing its relationship with different independent variables. Since calibration parameters can depend on the system operation and weather conditions, weather and energy variables were chosen to be tested for each regression, as listed in Table 2.

The number n of reference years is limited to five because structural changes in energy systems are occurring so fast that using longer periods for calibration would certainly lead to incoherent results. A restrictive set of reference years allows only simple and two independent variable regression models to be tested.

A preliminary analysis using the determination coefficient (R^2) to understand the relationship of the different independent variables with each dependent variable is performed. Independent variables showing an R^2 less than 30% or without an explainable causal relationship with the dependent variable were discarded.

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