VALIDATION METHODS FOR CAPACITY EXPANSION PLANNING MODELS: A REVIEW

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Abstract

This paper reviews different methods used to validate that variable renewable energy (VRE) is accurately represented in capacity expansion planning models. A method of categorising the various validation methods found in the literature is proposed. Both the validation methods and their possible uses are discussed for each of the proposed categories. The purpose of the categorisation is to assist firstly researchers investigating the impact of VRE on the accuracy of capacity expansion planning (CEP) models, and secondly planners in selecting appropriate validation methods when incorporating VRE into their CEP models.

Keywords: Validation Methods, VRE, CEP Models.

1. Introduction

When planning electricity systems different approaches and modelling tools are used depending on the planning window and the size of the system that is being planned [1]. Various names are used in the literature, but for clarity the term capacity expansion planning (CEP) models will be used in this study when referring to the optimisation models that are used to plan the expansion of electricity generation capacity in a system over long planning windows of anything between 20 and 100+ years. These models make use of low temporal resolution and minimal technical detail in order to ensure that solving them doesn't become prohibitively computationally expensive [1, 2].

The increased uptake in variable renewable energy (VRE) has resulted in CEP models needing to account for additional complexity in various ways which both complicates the modelling process [3] and results in additional need for validation of the models [4]. While the landscape of tools and methods for dealing with the complexities caused by the addition of VRE to the pool of generating technologies when doing CEP modelling is often reviewed [5 - 12] the methods for validating CEP models has not enjoyed the same level of attention. In part this is due to the fact that given the time horizons covered by the models no form of validation could ever be proved to be 100% accurate. Furthermore, in the case of VRE uptake there are not a sufficient number of large systems in the world with very high levels of renewable uptake in order to facilitate validation against reality [13].

This paper reviews and classifies the various validation methods found in literature and identifies where these validation methods would be applicable. Section 2 of the paper details some of the challenges that the inclusion of VRE introduces into CEP modelling, Section 3 classifies the various validation methods and some conclusions are discussed in Section 4.

2. VRE related modelling challenges

It is commonly acknowledged that the introduction of VRE sources into electricity systems result in certain additional costs to the system. Hirth *et al*. [14] find that these additional costs are related to the fact that VRE does not follow load, the fact that production uncertainty can result from forecasting errors and the fact that VRE locations can be far from load centres resulting in the need for additional transmission infrastructure.

In order to incorporate VRE accurately into long-term models these cost factors need to be accounted for. Reducing the variability of wind and solar represented in CEP models tends to lead to the optimal uptake in these technologies being overstated [15] unless this reduction in variability also obscures temporal matching between generation and demand, in which case the optimal uptake can be underestimated [16]. Unfortunately, accounting for these costs directly by using hourly or sub- hourly timeseries data to represent variable output curves from different technologies and the interaction of these outputs with demand would result in insurmountable computational cost in a CEP model. Thus, ways must be found to either account for the characteristics of VRE within reduced input datasets or by adding constraints to CEP models to account for the additional costs without unduly restricting the deployment of VRE. Various ways of validating that this has been done successfully within the models have been created and is discussed in the next section.

3. Classification of Validation Methods

The five validation methods that will be discussed in this section and the parts of the CEP modelling method that they relate to are depicted in figure 1.

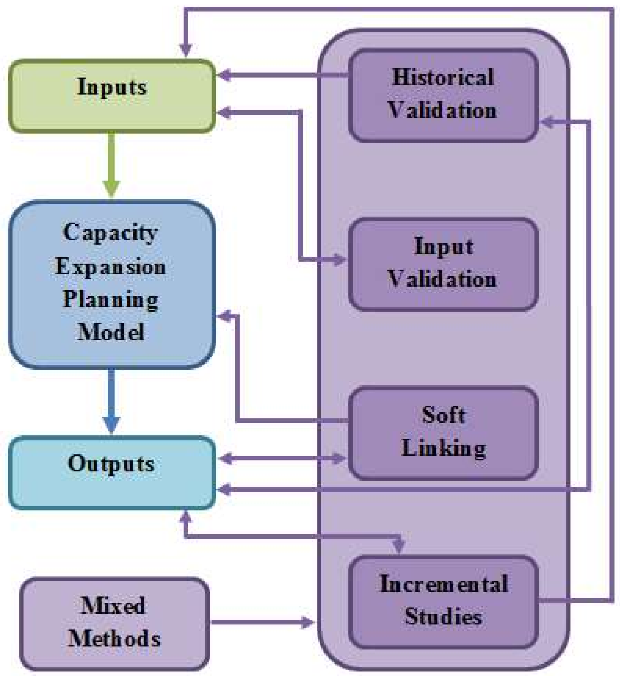

Fig. 1. CEP Model Validation Methods

3.1. Historical Validation

Historical validation refers to the practice where the modellers start the CEP model a few years in the past and then use the outputs for the first few years to validate the model against the historical record.

Historical validation can typically be used to determine if the model is behaving in a reasonable manner for the base case scenario, as is done by Ludig *et al.* [17] where the authors compare power production for different technology types in the model against the real-world production given a five-year validation period.

It should be noted that the model outputs need not match the actual reality exactly, but discrepancies must be adequately explained. A good example of this is the validation of a TIMES model developed by Pina *et al.* [18]. Data for Sao Miguel covering the time span from 2006 to 2009 is used to validate the model. Given that this time frame includes the 2007 financial crisis and its economic aftermath there are significant differences between the modeled results and reality that have to be considered carefully when determining whether the model is sufficiently accurate.

3.2 Input Validation

Complicated time series inputs, such as the expected hourly demand in the system that is being modelled or the expected hourly power production from wind farms, have to be compressed into much smaller data sets in order to make CEP models solvable [2]. Typically, a small data set is created where each data point will represent a large number of data points in the original times series [19 - 21]. Input validation refers to the methods that are used to verify how well the input data represents the characteristics of the original time series. It is often used when comparing different methods for selecting an input dataset [22]. Poncelet *et al.* [23] define the different temporal aspects that should be captured in the input data and for which validation is required as:

- Average value of the time series and distribution of individual values over a year.
- Short- and medium-term fluctuation behavior
- Correlation between different time series

Different methods are employed to verify the accuracy with which each of the above aspects of the original time series is captured in the representative input dataset. While not all of the studies surveyed will necessarily validate all three of the identified factors, the more recent ones tend to.

3.2.1. Average value and value distribution

In order to compare the original times series with the representative data, a representative time series has to be created. This is done by reproducing each input value for the number of data points that it represents. Thus, a representative time series that has the same number of data points as the original, but only contains the data from the input dataset, is created [22, 24]. By arranging the datasets from largest to smallest value, load duration curves (demand), residual load duration curves (demand - renewable production), and renewable production curves can be generated. Comparing the curves generated by the original and representative timeseries can be used to illustrate whether the input dataset accurately presents the average distribution of values over a year. This can be done either visually [25, 26] or by applying methods such as a root means square error comparison [22, 24]. Comparing the area underneath the graphs also indicates whether the average value of the original timeseries is being accurately captured [23].

Figure 2 shows the residual load duration curve (RLDC) for an hourly dataset and two representative datasets, one based on hourly data from four days and the other based on six hourly averaged data from four days. In this example it can clearly be seen that the two representative datasets do not accurately capture periods with very high or very low renewable production.

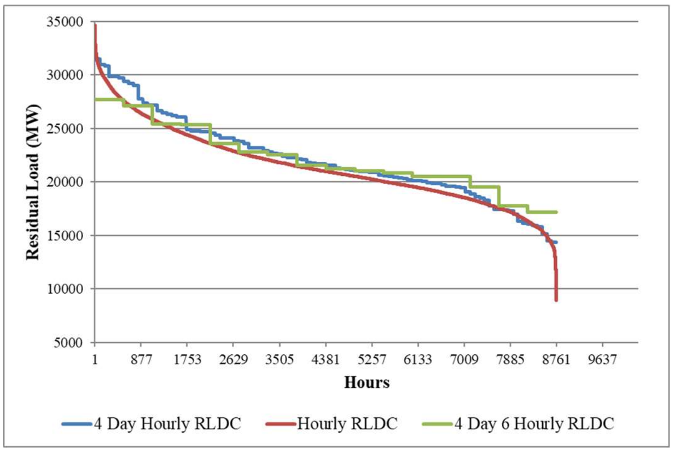

Fig. 2. RLDC comparison

3.2.2. Fluctuation behaviour

It is important to represent fluctuation behaviour because fluctuation results in cost and thus the fluctuation needs to either be covered by the representative data or accounted for in the CEP model in some other manner. Fluctuation needs to be checked, both across the entire data set length and for the smaller length of time that are being specifically represented [23]. In either case, the method of validation remains the same. The level of fluctuation in the representative data is calculated and then divided by the level of fluctuation in the original dataset. This then gives the percentage of fluctuation behaviour that is covered by the representative data [17].

3.2.3. Correlation

Given that electricity needs to be used as it is generated in the system, or stored at a cost, electricity production that corresponds to peak demand is more valuable than the electricity that is generated at times when demand is low [14]. When doing long-term modelling this aspect is generally not important for technologies that are considered to be dispatchable as it is assumed that their output will be optimised to optimise economic outcomes. This is not necessarily the case when it comes to VRE and thus it becomes important to account for the correlation between various input datasets and to ensure that these correlations are representative of the correlations present in the original data [21]. This is illustrated in figure 3 and figure 4. Figure 3 shows a case where production from PV is highly correlated with peak demand resulting in a flattening of the residual demand curve. Conversely, in figure 4 a case is shown where PV poorly correlates with peak demand and in fact causes a sharpening of peaks in the residual demand curve. Comparing these two cases it can be seen that the inclusion of PV in the first case holds more economic benefit than it does in the second case.

As suggested by Poncelet *et al*. [23] and implemented by P. Nahmmacher *et al.* [22] the correlation error can be calculated by calculating the absolute difference between the correlation between two timeseries in the original dataset and the correlation between the two representative timeseries. Blanford *et al*. [21] take a slightly different approach in that they simply calculate correlation factors for the original and all the representative input datasets that they are comparing and present these factors visually.

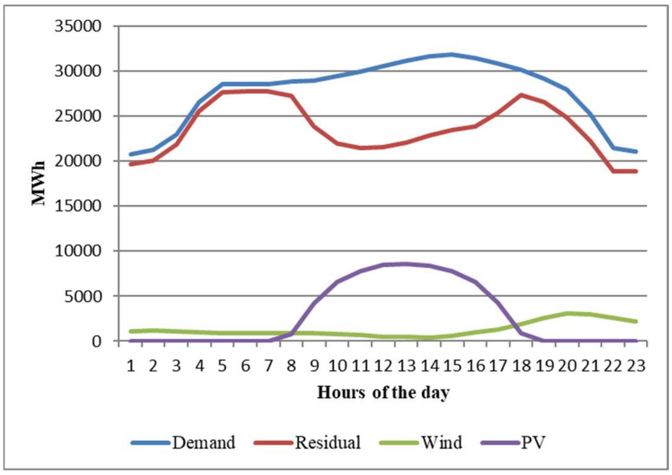

Fig. 3. High correlation between PV and peak demand

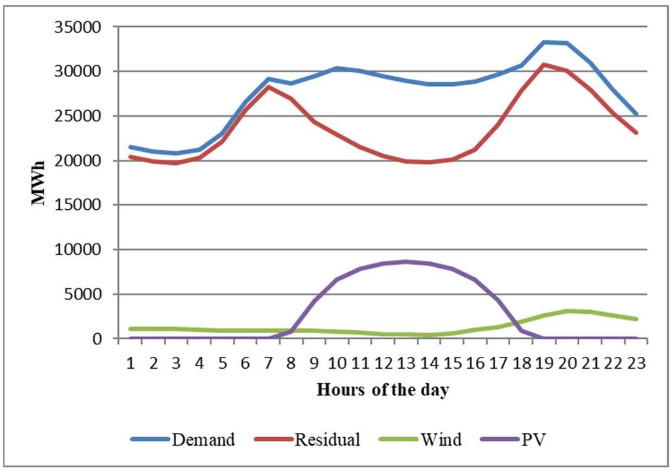

Fig. 4. Low correlation between PV and peak demand

3.3. Soft Linking

Soft linking refers to the practice of using a short-term more detailed model to model the system designed by a CEP model in order to compare outcomes. Collins et al. [5] identifies soft linking as one of two main types of modelling approaches that can be used when incorporating VRE into long-term models. The authors go on to identify two types of soft linking: bidirectional [27 - 29] and unidirectional [20, 30 - 35] soft linking. Figure 5 shows a flow diagram that gives a general process flow for unidirectional soft linking. The system design recommended by a CEP model is fed into a more detailed model and then aspects of the more detailed model's outputs and the outputs from the CEP model are compared. This can be contrasted with the process flow of a bidirectional soft linked model as shown in figure 6, where there is a feedback loop from the outputs of the more detailed model back into the CEP model.

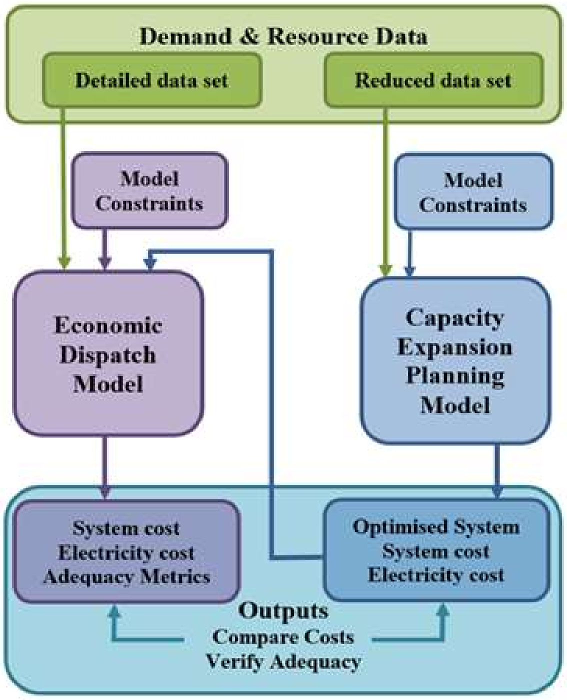

Fig. 5. Unidirectional Soft-linked Model

Considering these two diagrams it is easy to understand why the unidirectional approach in particular can also be seen as a form validation even though it is commonly classified as a modelling approach. While the bidirectional model is still used to verify if the CEP model is fulfilling certain requirements, it is clearly used more as part of the model than as a separate validation method.

Pina *et al.* [27] makes use of bidirectional soft linking. An EnergyPLAN model is linked with a TIMES model of the Portuguese electricity system and analysed over five-year intervals of the TIMES model to see whether the optimized system meets the renewable energy deployment targets that were set. When this is not the case the outputs of the EnergyPLAN model are used to recalibrate the TIMES model and the five-year section is rerun until the target is met. Tigas et al. [28] also makes use of a bidirectional soft linking approach when modeling widescale renewable uptake in the Greek electricity system. They run the long term and detailed models iteratively until the detail model indicates that all ancillary service requirements (balancing units, storage etc.) for a given timestep is being met. It is clear from these examples that in the case of bidirectional soft linking the more detailed model is not necessarily strictly used for validation. This is however not typically the case when it comes to unidirectional soft linking.

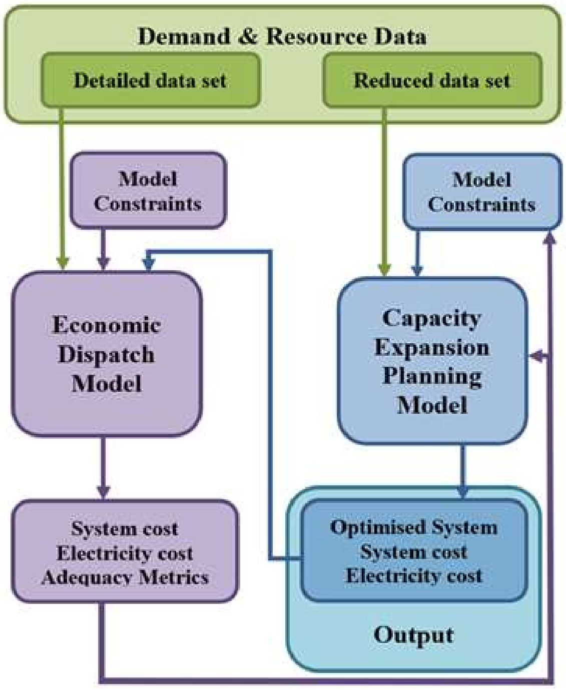

Fig. 6. Bidirectional Soft-linked Model

Deane *et al.* [30] use a half hourly PLEXOS model to evaluate the outputs of a TIMES model of the Irish power system for 2020. Aspects such as system reliability, unit commitment and dispatch, flexibility and CO2 emissions were investigated using the PLEXOS model. In this case the system designed by the TIMES model was shown to be adequate, but differences in the expected technology capacity factors and the levels of wind curtailment between the two models were highlighted.

The results of the detailed model developed by Deane *et al.* [30] was later used by Welsch *et al.* [31] to validate an OSeMOSYS model adapted to take constraints such as system flexibility into account. Mallapragada *et al.* [20] also makes use of a more detailed hourly production cost model as a validation tool. A detailed model is used to compare the results of CEP models that were run with input datasets where the representative datasets were selected using various selection methods.

While most examples of soft linking mentioned here investigate aspects of the electricity system related to generating capacity, the approach can also be applied when investigating the impact that incorporating VRE has on the transmission grid, as was done by Hess *et al.* [32]. The practice of using a copperplate approach with a single node to represent the transmission network in capacity expansion planning models was investigated by using the more detailed 491 node model of the area under investigation to validate projected transmission costs.

The line drawn here between bidirectional soft linking that can be considered a modelling approach and unidirectional soft linking that is used mostly for validation can become somewhat blurred. This is the case with Vithayasrichareon *et al.* [33] where a PLEXOS model with half hourly time steps was originally used to validate a range of system compositions produced by a CEP model. The results of this validation process were then used to incorporate operational constraints into the CEP model.

3.4. Incremental Studies

Incremental studies refer to an exploratory method used to determine the level of sensitivity a model has to variation in certain input parameters or aspects of the modelling method. The method entails varying the level of detail for a certain parameter in an incremental fashion to check the impact on the model outputs. This method has been applied to investigate amongst other things the impact of temporal detail [36, 37], different levels of technical detail [30] and varying levels of VRE integration [37, 38]. Each of these are explored further in the sections below

3.4.1. Temporal Detail

A number of studies vary the number of time slices used in representative input datasets in order to investigate the value of increased temporal resolution [18, 36, 39]. In some cases, the impact of different methods for selecting input data sets given various levels of temporal detail is investigated in the same way [21, 22]. These studies compare outcomes such as systems cost and VRE uptake or contribution and technology capacity factors to compare the outcomes of models with various levels of temporal detail. Deane et al. [40] take things in a slightly different direction by investigating the impact of sub hourly modelling in a more isolated system.

3.4.2. Technical Detail

Some studies approach investigating the impact of including technical detail into CEP models by modelling various levels of technical detail in short term unit commitment models. Poncelet *et al.* [41] make use of this approach to compare the impact of the level of technical detail with the impact of the level of temporal detail in a CEP model. Deane et al. [30] do the same when using a soft linked unit commitment model with various levels of technical detail to validate a CEP model.

There are also cases where the impact of increased technical detail is modeled within CEP models and the results are analyzed. Schwele *et al.* [42] propose a method for incorporating unit commitment constraints into CEP models and then investigates the impact of various constraints such as hourly ramp rate, minimum production levels and start-up and shutdown costs. In contrast van Stiphout *et al.* [43] focus on a single constraint, investigating the impact of including operational reserves in CEP models and the impact that methods for optimising operational reserves has on VRE integration costs.

3.4.3. VRE Integration Levels

The levels of VRE uptake is often varied in conjunction with varying levels of temporal resolution or technical detail in order to investigate the impact of these changes to the model under different VRE uptake scenarios.

Nicolosi [37] incrementally increases the number of representative time slices in a model for a scenario where wind has a low uptake and a scenario where wind has a high uptake. By doing this he shows that as temporal resolution increases in the high uptake scenario it is clearly shown that baseload is overrepresented in the low temporal resolution model and more flexible technologies are underrepresented. Ludig *et al.* [17] also employs this method when testing methods for selecting input datasets.

Haydt et al. [39] make use of scenarios with different levels of renewable uptake when testing different methodologies for balancing supply and demand incorporated within different models.

3.5. Mixed Methods

It is quite common to see more than one of the previously mentioned validation methods used in conjunction with each other. For the purpose of this analysis that practice is referred to as mixed methods. Depending on what is being investigated anything from two to all four of the previously described methods may be used.

Examples of this is particularly prevalent when it comes to including aspects of incremental studies when applying other validation methods. Such instances include gradually increasing the number of time slices when doing input validation [17, 21, 22] and using a soft linked model to compare outcomes where technical details and constraints are being added to a CEP model [30].

4. Conclusion

The appropriate validation of new approaches for incorporating VRE into CEP models is of great importance to ensure accurate long-term electricity system planning. This paper proposed a categorisation method for the various approaches to validating the impact of adding VRE to CEP models. Given that not all validation methods are necessarily applicable depending on the research question, the classification and review provided should assist researchers and system planners in determining what methods they need to apply in order to ensure adequate validation of the CEP models they use.

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