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Review

A Systematic Review of Uncertainty Handling Approaches for Electric Grids Considering Electrical Vehicles

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Abstract: This paper systematically reviews the techniques and dynamics to study uncertainty modelling in the electric grids considering electric vehicles with vehicle-to-grid integration. Uncertainty types and the most frequent uncertainty modelling approaches for electric vehicles are outlined. The modelling approaches discussed in this paper are Monte Carlo, probabilistic scenarios, stochastic, point estimate method and robust optimisation. Then, *Scopus* is used to search for articles, and according to these categories, data from articles are extracted. The findings suggest that the probabilistic techniques are the most widely applied, with Monte Carlo and scenario analysis leading. In particular, 19% of the cases benefit from Monte Carlo, 15% from scenario analysis, and 10% each from robust optimisation and the stochastic approach, respectively. Early articles consider robust optimisation relatively more frequent, possibly due to the lack of historical data, while more recent articles adopt the Monte Carlo simulation approach. The uncertainty handling techniques depend on the uncertainty type and human resource availability in aggregate but are unrelated to the generation type. Finally, future directions are given.

Keywords: uncertainty; uncertainty analysis; electric vehicle; smart grids; demand response; vehicle to grid

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1. Introduction

With more accelerated integration of RE feed-in, as renewables become the default option for capacity additions in almost all countries [1], the electrical grid becomes even more volatile. However, DSM and V2G integration strategies can smooth residual loads [2]. In particular, V2G integration allows EV batteries to be discharged when grid load is low, and the price is therefore relatively high. However, flexible EV integration is currently not on track to achieve smoothing on a large scale [3].

Given this importance for V2G in the future to curb volatility in electricity loads on an aggregate level, it is important to study uncertainties related to the EVs in V2G integration. Uncertainty can be understood as a state of doubt which requires to be addressed [4]. Uncertainty handling approaches refer to dealing with (characterising and managing) uncertainties, whether by incorporating them into the model or quantifying and performing sensitivity analysis of the proposed model.

Although uncertainty handling methods for power systems [5–7] and recent techniques to model for uncertainty [8] have been reviewed thoroughly and specific reviews on probabilistic stability analysis [9] have been developed so far, no reviews specific to uncertainties related to V2G integrated EVs are available yet.

Moreover, specific methods have been reviewed to guide researchers in the choice of appropriate method, but fewer systematic reviews on method selection have been undertaken (the exception is [10] on optimisation models under uncertainty). The authors, therefore, attempt to question the dynamics of the application of the uncertainty handling methods and relate them to economic aggregates to inquire about the following specific RQs:

RQ1: What is the geographical distribution of research?

RQ2: What techniques are applied to uncertainty handling for uncertainties related to EVs in smart grids with V2G?

RQ3: What are the dynamics of the application?

RQ4: How does the method relate to the country's aggregate data? How does it relate to generation source? How does it relate to uncertainty considered?

To answer research questions, a search on the *Scopus* website (Amsterdam, Netherlands) is made, and articles not related to V2G in the text and articles not considering EV-related uncertainties are excluded. In total, 87 articles are considered and 30 articles are discussed in-depth due to their high impact (citations).

After addressing these questions, it was found that probabilistic methods are the most popular, with MC and scenario approaches leading (the exception was the early years of modelling with robust optimisation when sufficient historical data was unavailable). Uncertainty handling methods show differences when it comes to the accumulation of EVs and researcher share in the population (PEM is significantly different). There seems to be no significant correlation with generation source, but there are differences in uncertainty handling methods regarding the uncertainty object.

The paper is organised as follows: Section 2 provides the background on the most common uncertainties and uncertainty handling methods, Section 3 describes the search design and methodology overall, and Section 4 systematically describes the dynamics of uncertainty handling methods. Section 5 overviews the most cited works, and Section 6 discusses the results. Finally, Section 7 concludes and suggests future directions.

2. Background

This section will discuss the Monte Carlo, probabilistic scenarios, stochastic, PEM and robust optimisation methods as well as possible uncertainties.

Uncertainties can arise from basic random variables, the most considered type of uncertainty in uncertainty-handling approaches [7]. To provide an overview of uncertainties in DSM, the possible sources of uncertainty, along with examples, are listed in Table 1.

Table 1. Sources of uncertainty in DSM.

Source of Uncertainty		Type of Uncertainty	Examples	Description
Uncertainty in model inputs	Basic random variables	General uncertainty	Load values	Electricity consumption of consumers may vary, or the measurement of it may be imprecise.
			Wind speed	Wind speed may vary across different periods (hours, seasons).
			Solar irradiance	Solar irradiance may vary across different periods (hours, seasons).
			Power price	Power price may be market-determined in real-time, or fixed by the government (in which case, uncertainty is related to policy uncertainty).

Table 1. *Cont.*

Source of Uncertainty		Type of Uncertainty	Examples	Description
			Feed-in tariff	Feed-in tariffs may be market-determined in real-time, or fixed by the government (in which case, uncertainty is related to policy uncertainty).
	Initial conditions		State of charge	The initial state of charge for the battery may not be known with high precision and is subject to change.
	Boundary conditions		Solar radiation intensity	The intensity may vary depending on the season and cloud cover.
	Forcings		Solar radiation intensity	Radiation intensity due to changes in climate is uncertain.
Model discrepancy or inadequacy	Form of probabilistic sub-model	Uncertain model error		The model may not consider non-linearities or dependencies.
	Selection of the physical sub-models	Uncertain modelling error		The model may exclude relevant variables.
	Estimation of parameters of physical sub-models	Statistical uncertainty		The model may exclude relevant variables and/or may be incorrectly specified.
	Estimation of parameters of probabilistic sub-models	Statistical uncertainty		The model may exclude relevant variables and/or may be incorrectly specified.
	Measurement of observations	Uncertain errors		Measurements of observations may have an uncertain error.
Computational costs, solution and coding errors	Correspondence between random modelling variables and derived variables	Uncertain errors		There may be computational errors, numerical approximations or truncations when deriving the variables using computational methods.

Source: based on categorisation by [2,3].

As can be seen from Table 1, uncertainties have different types depending on the source. Of the three uncertainty source groups, the least uncertain component is the numerical errors [7].

The three settings in which validation of physical models takes place are testing of theory, analysing data obtained from experiments, and making predictions [11]. Corresponding to this setting, the classical setting of uncertainty handling in power systems involves identifying sources of uncertainty, quantifying uncertainty, propagating it through the model, and mitigating or addressing it. However, in severe uncertainty, when the model is unknown, events are transitive, among other cases of uncertainty, alternative approaches are better suited.

The uncertainty handling methods, as commonly segregated, are described in Figure 1.

Further, approaches for handling uncertainties, as defined in the meta-analysis, are discussed.

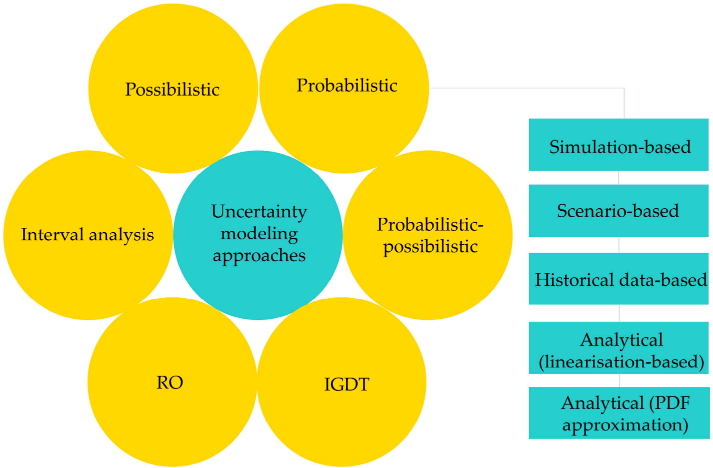

Figure 1. Uncertainty handling approaches. Source: based on [5,7]. Notes: this partitioning of uncertainty handling methods is debated. One may add historical data-based (probability fitting) to probabilistic methods. Stochastic optimisation is also distinguished in the subsequent meta-analysis. The probabilistic methods can also be distinguished as methods dealing with objective (Objective probabilities, or the classical aleatory [12] frequentist approach, has a long research tradition and is based on historical data. This probability is a feature of the world, independent of beliefs about it.) and subjective (Subjective, or the belief-based, epistemic, probabilities emerged later and are now applied widely in social sciences whereby person's degree of confidence about the event's likelihood to occur describe it.) probabilities.

2.1. Monte Carlo Simulation

The general process of standard Monte Carlo simulation involves the static model generation, input distribution identification, random sample generation, evaluation of a predictive model for the current set of inputs, and after repetitions of the previous steps, the analysis of output distribution and computation of variance and statistical confidence intervals [13]. The classical Monte Carlo method relies on simple random sampling, in which the samples are generated as independent and identically distributed realisations on sample space are then applied to the model, and statistically evaluated. The steps of the standard Monte Carlo are introduced in [14], and the recent advances in Monte Carlo techniques are reviewed by [15]; these will not be discussed here.

2.2. Probabilistic Scenarios

In scenario design, whereby scenarios refer to any instance of the uncertainty parameter, a finite number of constructed scenarios representing the future possible states are optimised. To generate the scenarios and every scenario's weight, scenario simulation may be performed, and to select the scenarios, scenario reduction can be applied. Overall, this method, compared to probabilistic Monte Carlo, is more robust to distributional assumptions and has reduced computational complexity. Therefore, it can be applied better to real-time problems.

2.3. Stochastic Optimisation Approach

When uncertainty is too difficult to model deterministically, a stochastic approach may be applied, whereupon the uncertainty is considered as a random variable following probability distribution. To carry out stochastic optimisation, a model with random variables or stochastic processes is built, which is then used to generate random samples in order to estimate the objective function and update the solution iteratively to find an optimal solution. Alternatively, a deterministic model can be solved by replacing stochastic constraints by deterministic ones that should be satisfied with a predetermined probability. This approach, compared to Monte Carlo, is more suitable for less complex problems.

2.4. PEM

Point estimation methods use the probability density function to solve for the uncertainty of output random variables. With n uncertain parameters, $2n$ calculations are performed, obtaining expected values, and the point estimation method replaces the probabilistic distribution with discrete points, matching the distributions until the third statistical moment and providing the information on central moments (concentrations). When point and model information is used in conjunction, uncertainty about outputs can be obtained. See [16] (p. 17) for a more detailed process description.

2.5. Other Methods

Possibilistic (fuzzy) methods, joint probabilistic—possibilistic, interval analysis and IGDT are the other methods used in uncertainty handling.

2.5.1. Robust Optimisation

Robust optimisation is applicable to mathematical programming problems. Here, the uncertainty model is deterministic and set-based and contrary to previous methods, the decision-maker optimises to find a solution that is immune to any realisation of uncertainty in the set [17]. In other words, the unknown is represented by its expected profile and associated confidence intervals as an interval number [18]. Then, the generic uncertain w can be represented as in ibid:

$$w_{mn} \in [\mathrm{E}\,(w_{mn}) - \Delta w_{mn},\, \mathrm{E}\,(w_{mn}) + \Delta w_{mn}];\ \forall m,n \in J_m \tag{1}$$

Various settings can be adopted—worst-case hedge, interval uncertainty, min-max regret, or uncertainty sets. For a detailed setting overview, see [19]. Robust optimisation drawback lies in being a bi-level problem, and is thus difficult to solve. Moreover, it makes no distinction concerning how likely the different uncertainty realisations are.

2.5.2. Possibilistic Approaches

For the scope of this review, quantitative possibility theory in the sense of physical possibility, as introduced by [20], will be discussed. Fuzzy sets, viewed as possibility distributions, allow one to flexibly constrain variables in natural language sentences [21]. The *possibility* measure estimates the consistency of information with the statement that x is in subset A. The duality referring to complement events (when "not A" is impossible, "A" is thus certain) is used to define the degree of *necessity* of A. The duality relation describing how A becomes more certain as a possibility of "not A" is less consistent with the available logic, which allows one to estimate to what extent the complement of A has a low degree of possibility with a property that an event is completely possible before being somewhat certain, and "A and B" are all the more certain as each A and B are certain [21]. Other set functions, as a measure of *guaranteed possibility* and *potential certainty*, affords intuition between consistency–certainty and feasibility–possibility relations. Further consideration of the quantitative possibility theory, including the assumption of possibility distribution to range in the unit interval, must be introduced.

A similar question to one used for the probability approach is asked: if membership functions of input variables are known, what is the membership function of output? To use the possibilistic approach, a membership function is assigned to each uncertain parameter (for example, fuzzy trapezoidal number function), and distribution of output variable can be obtained using the α-cut method. Alternatively, defuzzification can be applied via the centroid method (but also max-min, centre of gravity and other methods), converting fuzzy number to crisp one. We now give a short description of the two methods.

For a given input variable, the α-cut of epistemic uncertain input variables X is defined as

$$A^{\alpha} = \{x \in \mathrm{U} \mid \pi_X\,(x) \geq \alpha,\ 0 \leq \alpha \leq 1\} \tag{2}$$

where U denotes universe of possible values of X and π_X is a possibility distribution on U.

$$A^{\alpha} = \{\underline{A}^{\alpha}, \overline{A}^{\alpha}\} \tag{3}$$

where $\underline{A}^{\alpha}$ is the lower limit and $\overline{A}^{\alpha}$ the upper limit of A^{α}. When the α-cut is obtained for each input variable, then the α-cut of the output variable's Y upper and lower bounds are calculated as:

$$Y^{\alpha} = \{\underline{Y}^{\alpha}, \overline{Y}^{\alpha}\} \tag{4}$$

$$\underline{Y}^{\alpha} = \min f\ (X^{\alpha}) \tag{5}$$

$$\overline{Y}^{\alpha} = \max f\ (X^{\alpha}) \tag{6}$$

Defuzzification allows to obtain a crisp number form the fuzzy number obtained in Equation (4). This can be performed by the centroid method as in:

$$Y^{*} = \frac{\int_{\mathrm{X(x)xdx}}}{\int \pi_{\mathrm{X(x)dx}}} \tag{7}$$

2.5.3. Probabilistic-Possibilistic Approaches

Fuzzy scenario combines possibilistic and probabilistic approaches, and some parameters are handled by fuzzy arithmetic, and others by scenario-based approach, or unscented transformation method and fuzzy arithmetic, both with α-cut methods (as reviewed by [7]).

A Fuzzy Monte Carlo of a system with possibilistic and probabilistic uncertainties and variables are categorised into probabilistic and possibilistic (sets X and Z), where these are then solved based on two loops. On the first outer loop, the Monte Carlo simulation is applied for the probabilistic variable based on its probability density function Z^e. On the second inner loop, the fuzzy α-cut method is applied, and uncertainty diagnosis for possibilistic variables is made, calculating minimum and maximum values:

$$\underline{Y}^{\alpha} = \min f\ (X^{\alpha},\ Z^{e}) \tag{8}$$

$$\overline{Y}^{\alpha} = \max f\ (X^{\alpha},\ Z^{e}) \tag{9}$$

2.5.4. Interval Analysis

Interval analysis can only be applied when the upper and lower bounds of the uncertain input parameters are known, yielding the result of upper and lower bounds for the output. Specifically, following [22], if f: $D \subseteq \mathbf{R} \rightarrow \mathbf{R}$, given by model *f(x)* composed of operations and functions $\varphi \in F$. Replacing variable x by interval $[x] \subseteq D$, and evaluating the expression according to basic operations (addition, subtraction, multiplication, and division rules, assuming 0 is not included in the denominator set for division) and standard interval functions ($\varphi \in F$ = {sin; cos; tan; arctan; exp; ln; abs; sqr; sqrt}, which are defined via their range) then interval is again obtained, denoted by f ([x]).

2.5.5. IGDT

When there is severe uncertainty due to insufficient information to select probability distribution, or even when information is plentiful but the past is a weak indication of a future under structural changes, IGDT can be applied, as it has no measure functions and concentrates on disparity between what is known and what could be known, placing little emphasis on the structure of the uncertainty, and organising the uncertainty by clustering events of two consequences: failure (robustness immunity function) and success (opportuneness immunity function), rather than in probability distributions [23].

The IGDT consists of decision space Q, uncertainty space S including all uncertain elements, a reward function R measuring how successful the decision is, and a non-probabilistic model U for the uncertain quantities in the reward function, parametrised by uncertainty measuring parameter [24]. Robustness and opportunity provide the basis for making decisions. Robustness refers to the decision to be the maximum amount of uncertainty for the minimum reward associated with the decision to be greater than the critical reward, while opportunity refers to the minimum amount of uncertainty enabling the possibility of outcomes to exceed the critical reward [24].

To apply IGDT, first, the system model, which indicates the input-output structure, must be identified. Next, the uncertainty of parameters must be stated. Multiple types of models exist for uncertain parameters, including energy-bound models, envelope-bound models, Minkowski norm models, and others. The structure of an info-gap model is chosen to "define the smallest and strictest family of sets whose elements are consistent with prior information" [23]. Next, the desired strategy (robustness or opportuneness) must be defined, and the extent to which uncertain parameters can deviate from their forecasted amounts according to the objective function can be analysed [25].

For a comparison of the methods with their advantages and disadvantages, see Table 2.

Table 2. Uncertainty handling method comparison.

Uncertainty Handling Method	Advantages	Disadvantages	Applications
Probabilistic	Ease of implementation, and accuracy for complex and non-linear problems.	Extensive historical data is needed, computationally expensive.	EV parking pattern, load pattern.
Possibilistic	Ability to model uncertainty with missing or imprecise historical data, extract numerical values from language.	Complex and time-expensive implementation, cannot model dependency.	
Probabilistic-possibilistic	Model both types of uncertainty.	Computationally and time-expensive.	Battery state of charge, parking pattern.
Interval analysis	Can obtain output bounds from input bounds.	Intra-interval correlation cannot be modelled.	Electricity price, state of charge.
RO	Optimisation with uncertainty.	Complex use for non-linear models, do not consider intra-uncertainty set correlations.	Solar generation, wind generation, line outage.
IGDT	Useful for severe uncertainties.	Highly complex.	Line outage.

Source: based on [7].

3. Methodology

To answer the research questions presented in the Introduction, a search on the *Scopus* website was conducted, including the keywords *uncertainty*, *electric vehicles*, *demand side*, or *PHEV* or *EV*. The search was limited to articles in the English language, and exact keywords: *Electric Vehicles*, *Uncertainty Analysis*, *Electric Vehicle*, or *Uncertainty*. The search yielded 406 articles (see Figure 2). Because of the interest in the V2G technology, 255 articles were excluded after a search in the article text and references for the term *V2G*, and if positive, search for *discharg*–, if these two subsequent searches yielded no result. As the next step, the articles to which the authors did not have access (n = 4), and which did not handle uncertainty explicitly (n = 12) were excluded, as well as articles which were not primary research (n = 2). These exclusion criteria yielded 133 articles, and after excluding articles which did not consider uncertainty in EV, the final set of 87 articles was obtained. Inclusion and exclusion criteria of search-returned articles are summarised in Table 3.

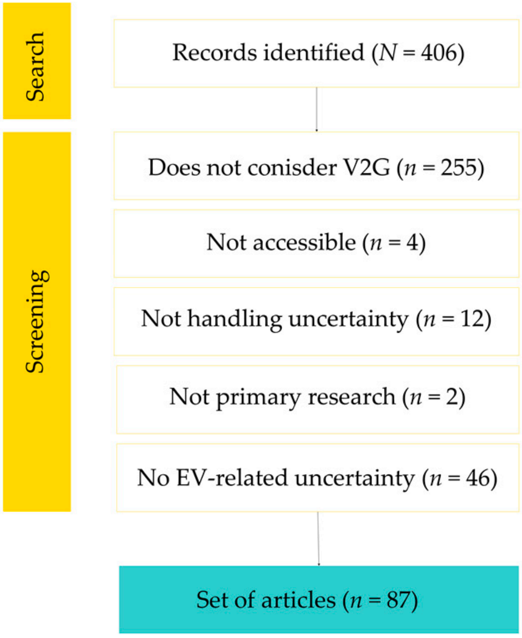

Figure 2. Search strategy and selection process.

Table 3. Exclusion and inclusion criteria of the studies returned by the search.

Criteria	Inclusion/Exclusion
Includes "V2G" in text or references	✓
Access to full text not available to authors	✕
Uncertainty not handled explicitly	✕
Secondary research article	✕
Does not concern uncertainty in EV	✕

Note: hereafter, ✓ denotes inclusion and ✕ denotes exclusion.

Of these articles, the articles which exceed the 90th percentile *CiteScore* citations in *Scopus* (*n* = 29, see Table A1), were analysed and discussed in detail in a semi-narrative way, systematised by the uncertainty handling items considered and uncertainty handling methods of the respective items. Articles which had made less impact (*n* = 36: [26–61]) or for which the *CiteScore* was unavailable (*n* = 22: [62–82]), were not discussed in-depth, but summarised instead (see Table A2 in Appendix A). The type of electricity market covered and the type of DSR equipment targeted are also covered (categorisation of the studies is proposed by [80]).

To answer the research questions, the visual approach was primarily used (see Table 4):

Table 4. Research questions and related figures and tables in the article.

RQ	Figure	Figure Title
1	2	Leading countries in research
1	3	Publication citation distribution by country
2	4a	The proportion of uncertainty handling methods used in studies
3	4b	Five most popular method distribution methods over the years
3	4c	Five most popular uncertainty handling method ranking through the years
4	5	Five most frequent uncertainty handling methods for each of the four most common uncertainty groups
4	6	Heat plot with the generation source and uncertainty handling techniques

4. Dynamics of Uncertainties in EVs

The considered temporal period is not constrained, and the included article set concerns the years 2014–2023. As for the origins of the research, the first authors are most frequently affiliated with Chinese (22%), Iranian (18%) and Indian (13%) institutions. Published articles in proportion to the average populations of these countries in the middle of the considered period (in 2018) Qatar, Iran and Canada are leading (see Figure 3). In proportion to these countries' average GDP per capita, China, the United Kingdom and the United States lead the research. Yet, when evaluated by the population share (Data for population working in R&D (per million people) is not available for Brazil, Australia, Switzerland, Pakistan and Iran. Therefore, these countries are excluded from the Figure 3c) working in R&D, India, China, and Egypt are the leaders in research output. (There are no data available for Turkey and Taiwan from the cited source (see Figure 3). Therefore, these countries are excluded from Figure 2).

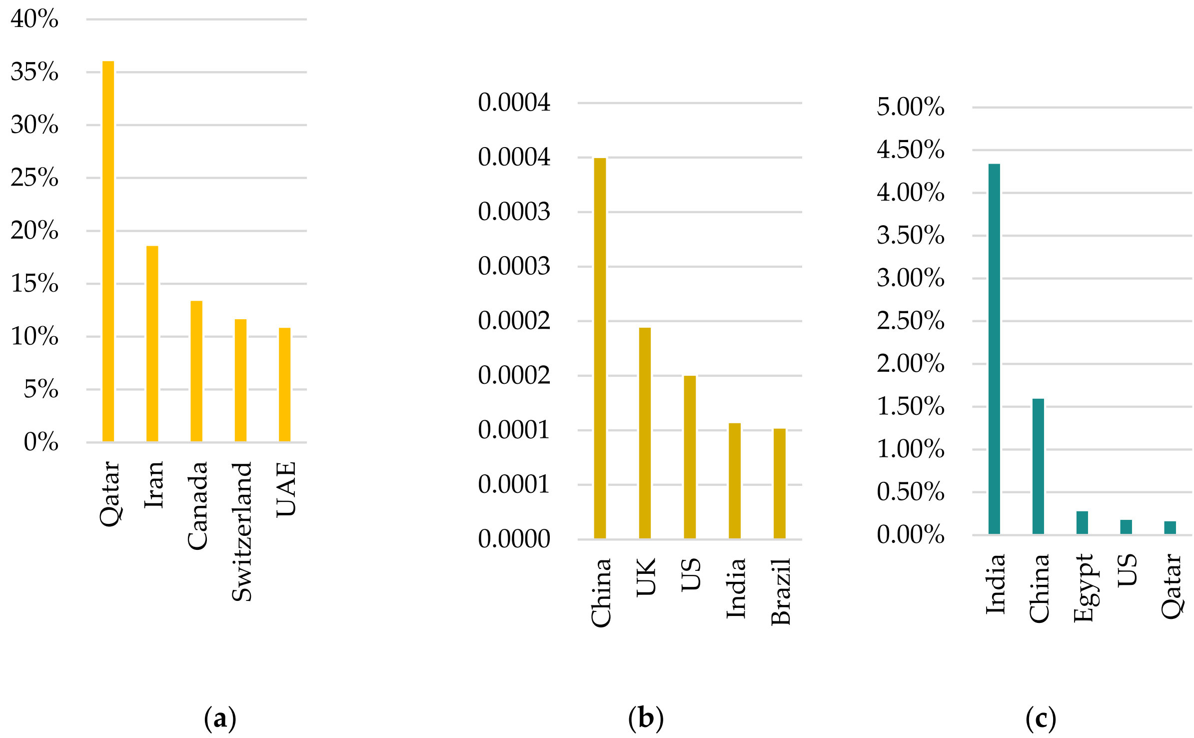

Figure 3. Leading countries in research in proportion to the total population (**a**), GDP per capita in current local currency units (**b**), and per researchers in R&D (per million people) (**c**). Note: For representation purposes, data in (**a**) are multiplied by 1,000,000. Data for the population working in R&D is per million people. All calculations were made with data for 2018 (the middle of the study period). Data source: [83].

As for the influential articles (see Table A1 in Appendix A), the most highly cited (per *Scopus CiteScore*) article-producing countries (mainly the US, Iran, but also Italy, and Belgium) are not necessarily the largest ones (as in the case with US, Italy and Belgium), but are among the most prosperous (US) and with a productive workforce in the R&D (US) (see Figures 3 and 4).

As seen from Figure 3, most of the considered articles lie within the first quartile of citation score on Scopus. This shows the importance of the topic under review. As for the countries contributing the most research within the first quartile of articles, the US, Iran, China and India are leading. South Korea, Egypt and the UK are lagging in their published article citation scores.

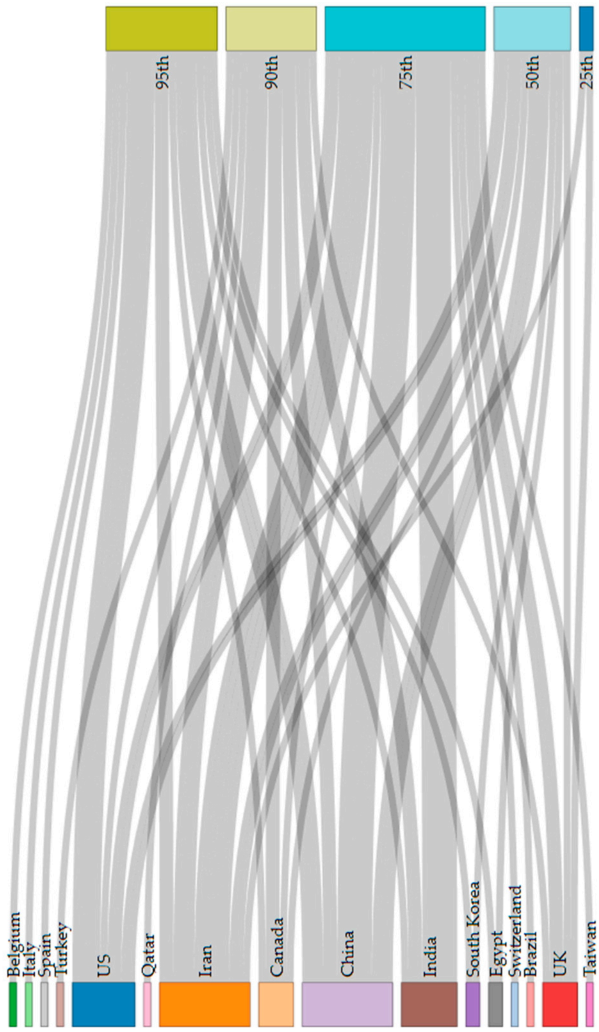

Figure 4. Publication citation distribution by the country of the lead author's institution. *Notes:* 95th corresponds to articles within the range 95th–100th percentiles, 90th corresponds to 90th–94th percentile, 75th corresponds to 75th–89th percentile, 50th corresponds to 50th–74th percentile, 25th corresponds to 25th–49th percentile. No articles represent lower percentiles of *CiteScore*.

5. Meta-Analysis of Uncertainty Handling Method Selection

The most frequently used uncertainty handling methods are MC simulation (n = 19), scenario analysis (n = 15), robust optimisation (n = 10), stochastic optimisation (n = 10), PEM (n = 6; see Figure 5a). Thus, one can conclude that probabilistic methods (such as MC, scenario-based analysis, and PEM) are more popular than possibilistic or hybrid approaches.

The MC simulation, scenario analysis and robust optimisation have been used most frequently throughout the years, but the MC has been ranking first more recently (see Figure 5b,c).

For the five most popular uncertainties considered in the studies (solar generation, electricity price, EV arrival, EV demand and EV departure), the same MC technique is again leading, followed by scenarios, RO and stochastic techniques and PEM.

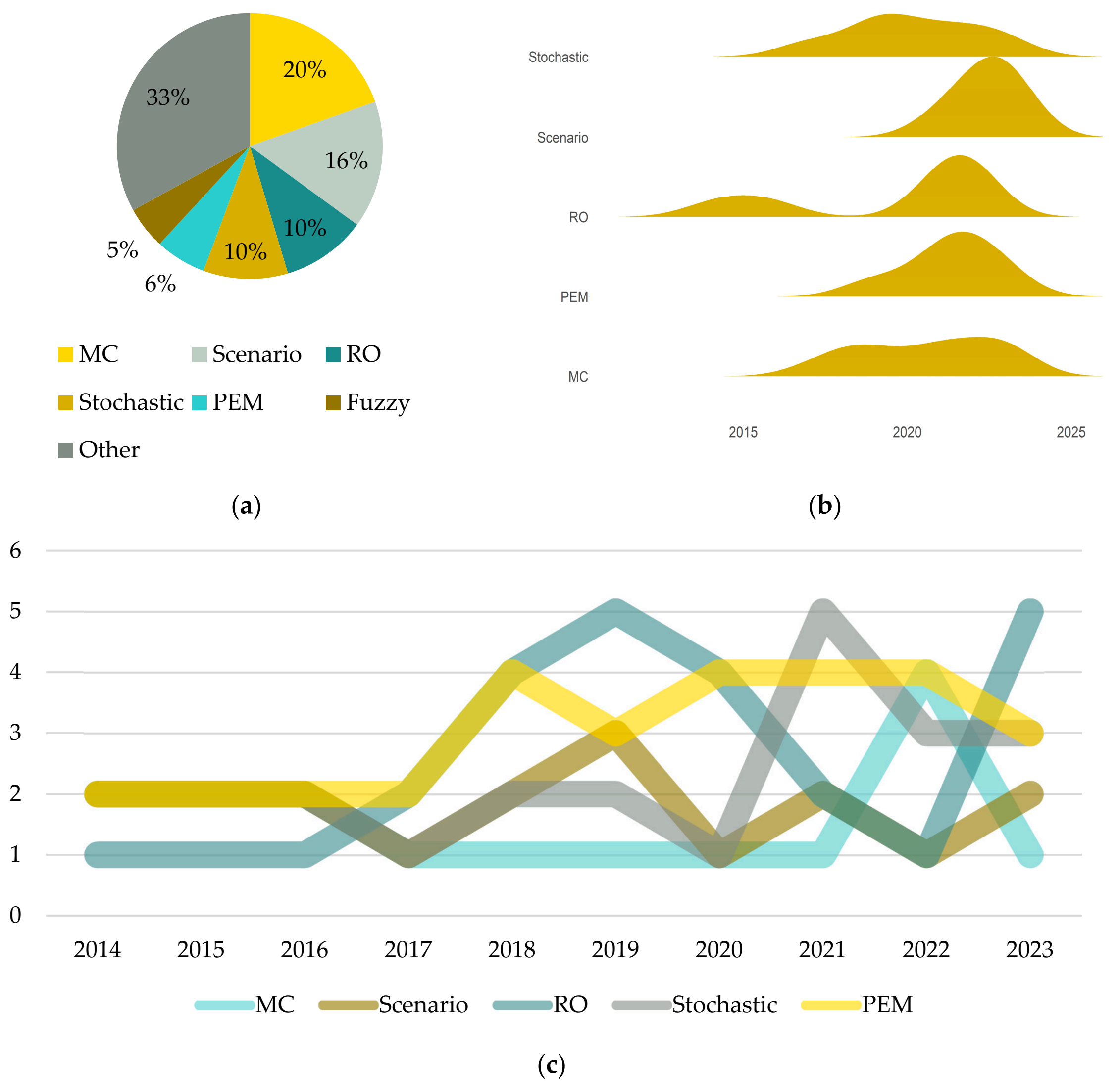

Figure 5. The proportion of studies using uncertainty handling methods (**a**), the five most popular method distribution of the methods over the years (**b**), and their ranking throughout the years (**c**).

5.1. Uncertainty Handling Techniques by Uncertainty Considered

Regarding specific uncertainties, studies considering V2G load flows, that is, EV battery discharge into the grid (V2G), home or building (V2H, V2B) [31,34,48,54,60,84–87] or to another vehicle (V2V) [31,66,88], considered different uncertainty handling methods. RE generation was most frequently handled by MC simulation techniques, followed by PEM and scenario approach (see Figure 6).

Electricity price is also handled most commonly by using MC simulation, but it is also distinctively common to use a robust optimisation framework. Robust optimisation has also found its way in EV demand uncertainty handling, for which the PEM is more frequent than other uncertainty items.

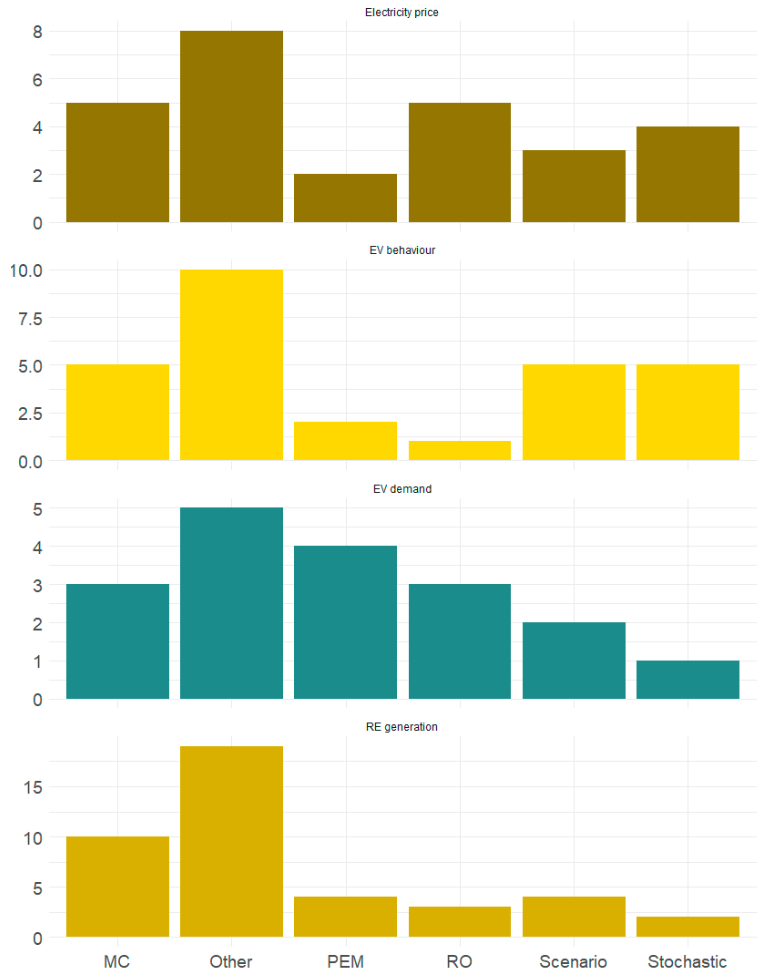

Figure 6. Five most frequent uncertainty handling methods for the four most common uncertainty groups.

5.2. Uncertainty Handling, Data Availability and Human Resource

To analyse the variances between the uncertainty handling method groups in relation to aggregate data, such as the aggregate income of the country of the lead author's institution and HR in R&D (for data used, see Table A3 in Appendix A), ANOVA can be applied (for tests on ANOVA assumptions for accumulation of (sales of) EVs and researchers in R&D, see Tables A4 and A5, respectively). These are proxies for data availability to researchers and research human resources.

Although test results are not uniform, as the Shapiro-Wilk test [89] reports non-normality in EV sales data, the Kolmogorov-Smirnov test [90] allows us to conclude that the EV sales distribution against Student's t 5-degree distribution cannot be distinguished.

As for the assumption of homogeneity of variance, Bartlett's test [91] does not generally allow to reject the assumption that the variances are homogeneous in relation to accumulated EV sales or researchers in R&D (except for the stochastic method).

As for the correlations between the uncertainty handling techniques and external data, ANOVA results (see Table 5) show that concerning the EV accumulation, differences between group means are only statistically significant for PEM. Additionally, when researchers working in R&D are compared between the groups of uncertainty handling techniques, the model appears to be statistically significant overall, with the PEM uncertainty handling technique differing in their means from the sample.

Table 5. ANOVA for EV sales per capita, researchers in R&D, by groups of uncertainty handling techniques used.

Source	EV Accumulated		Researchers in R&D	
	df	F	df	F
Model	5	1.14	5	1.51
RO	1	1.99	1	0.30
Stochastic	1	2.12	1	1.49
MC	1	0.61	1	0.02
PEM	1	2.79 *	1	4.42 **
Scenario	1	0.00	1	0.61
Residual	61		69	

Note: ** and * denotes 5% and 10% significance levels. The last available datapoint was used for the subsequent years. EV accumulation was obtained from data starting in 2010 and is not available entirely for Iran, Turkey, Taiwan, Qatar, Egypt, Thailand and United Arab Emirates. Source: [83,92].

5.3. Uncertainty Handling and Energy Generation

Regarding the generation source and uncertainty handling methods, there is no explicit relation between these two variables (see Figure 7). However, one can deduce that when EVs are integrated into distributed generation systems with PV (more common than WT), it is less likely to apply stochastic methods. Moreover, when integrated with distributed generation, the EV is more likely to have PV and WT simultaneously than power it with another generation source (such as a diesel engine or hydrogen).

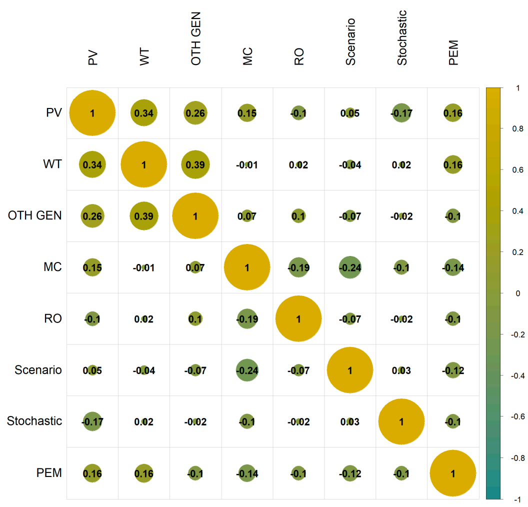

Figure 7. Heat plot with the generation source and uncertainty handling technique.

6. A Narrative Review of Uncertainty Handling Methods

In the following subsection, uncertainty handling methods of the most influential articles will be discussed in relation to the type of electricity market covered and the type of uncertainties considered.

Uncertainty Handling Techniques

The early influential works [88,93] consider the optimal scheduling and operation and problems, modelling for price uncertainty with the robust optimisation approach. More recently, hybrid robust–stochastic approaches have been applied in order to model EV behaviour, electricity price, electrical demand, and WT output [94].

Later on, probabilistic approaches emerge, notably in the work of [95], where the authors use a scenario reduction approach to address uncertainties of different charging policies, parking availability, renewable energy generation, and load patterns. In addition, [85] in a highly cited work model for uncertainties in PV and WT generation and EV availability via scenario reduction, and [96] model for aggregate EV arrival, EV departure and SoC with scenario reduction as well. The probabilistic scenario approach has been used by [97] to model for uncertainties in EV arrival, EV departure, parking pattern and electricity price. Load, electricity price, PV and WT generation are considered uncertainties in [98] using the scenario approach.

The deterministic scenario approach is also used in case of lack of historical data and due to the reduction in run-time of live optimisation for frequency among other parameters, EV frequency load [99], which by authors is deemed feasible when small aggregations of EV fleets are present, more likely in the near term.

Probabilistic MC simulation is applied in a highly influential work by [84], where the uncertainties in PV generation and EV driving schedule are considered. Additionally, [100] model uncertainties in the presence of EVs in the parking lot, SoC of EVs, and PV and WT generation. MC is used to model load and PV generation in [101].

The probabilistic PEM has been applied by [102] to address the uncertainties in EV arrival, EV demand and SoC. Ref. [103] fit the historical data to probability distribution functions to model for PV generation, EV arrival and departure, and EV distance uncertainties. This method has been deemed as one of the most accurate and efficient methods [9] and one that requires less historical data compared to other probabilistic techniques, such as MC.

As a less popular approach, [104] uses the fuzzy approach to model for uncertainties in RGV and RVG; [105] also use a fuzzy approach to model for power availability, parking pattern, and SoC of the battery. To model for PV, WT generations and load demand, the fuzzy approach is applied [106].

Ref. [107] use MDP to address the randomness of electricity price and commuting behaviour, and [108] use the Markov game to address uncertainties in electricity price, load consumption and EV demand.

Ref. [109] models PV and WT generation, as well as EV battery charge/discharge status by using simulation. The driver's experience, charging preference and charging location is considered uncertain in [110] where the simulation is applied as well as EV battery charge/discharge status

The interval technique, another less used uncertainty modelling approach, is applied in [111] to model demand and electricity price. Ref. [112] uses a hybrid interval and stochastic approach to model demand, PV generation, electricity price, and EV departure.

Yet another way to handle uncertainty is to model via dynamic optimisation [113] when considering EV load. Relatively newer techniques, such as DQN and MARL, are considered in the works of [114] and [115]. These works handle uncertainties in electricity price and V2G power, as well as travel pattern [114], PV and WT generation, demand SoC and EV departure [115].

Overall, it can be concluded that various methods are applied, but in the most cited works, the probabilistic scenarios are the most common, followed by the probabilistic MC simulation and general simulation (see Figure 8). This aligns with findings from the overall set of articles, which also consider probabilistic MC and scenario methods with the highest frequency, followed by simulation (see Figure 5a).

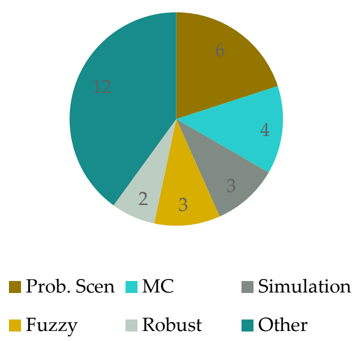

Figure 8. Most frequently used uncertainty handling approaches in most cited articles.

7. Discussion and Future Directions

The main findings of the current work will be presented by the research question addressed. That is, this paper attempted to address four research questions: what is the geographical distribution of research? What techniques are applied to uncertainty handling for uncertainties related to EVs in smart grids with V2G? What are the dynamics of the application? How does the method relate to the country's aggregate data and generation source and uncertainty considered? This was all intending to question the applicability of uncertainty handling methods in the case of EV integration and the capability of V2G discharge, which is considered a future staple addition to demand response.

The main findings are as follows:

- The leading countries in research are not necessarily the ones with the highest potential for EV V2G integration.
- MC simulation, scenario analysis and robust optimisation have been used most frequently throughout the years.
- RO is leading in the early years, outranked by MC later.
- There are differences with respect to the accumulated EVs in the country and a share of the population working in R&D, with PEM differing significantly. As for the generation source, there seems to be no significant correlation. For the uncertainty considered, there are differences in application frequencies: for electricity price, MC and RO are the most applied; for EV behaviour, these are the MC, scenario and stochastic approaches, and for EV demand, the PEM is most applied. The MC and scenario approaches are mainly considered for the most frequently considered uncertainty, that is, uncertainty in RE generation.

These results indicate differences in uncertainty handling methods applied concerning different uncertainties considered. The choice of the method also depends on the human resources available and historical data availability.

Regarding **RQ1**, the leading countries in research are not necessarily the ones with the highest potential for EVs V2G integration, as it has the greatest absolute potential in China, European Union and the United States [3], but the most output per researcher is observable in India and China, and most output relative to income level is observed in China, the UK, and the US. On an absolute level as well, the research output absolute leaders are affiliated with Chinese, Iranian and Indian institutions. We, therefore, expect more research to be conducted in the European Union and the US in the future.

In particular, regarding **RQ2**, MC simulation is accurate but comes at a high computational cost and requires historical data. Probabilistic scenario analysis comes next, and its accuracy depends on the number of selected scenarios but can only give the mean values of output variables [5]. This result is in line with the previous studies, which have similar conclusions, with probabilistic techniques being the ones mainly applied to power system uncertainties [6]. The descriptive simulation approach describes how a power system behaves, while optimisation models prescribe optimal strategies for efficient use of resources (i.e., routing and scheduling to minimise operational cost). Given that most research articles had used optimisation and applied the simulation to handle uncertainty, it can be concluded that optimality is the key concern. Regarding **RQ3**, the result of the robust optimisation being used at the relative start of the time period of review aligns with the rationale that this method does not require large amounts of historical data, and is based on a forecast interval range [116]; however, because the forecasts are often conservative, anti-risk techniques should be used. At least with the most cited articles, this is not the case. This could come as a detriment to the optimal operation planning quantity if too conservative solutions are considered.

As for the **RQ4**, the share of the population working in R&D does differ for applications of PEM, which requires fewer data when compared to MC. The same can be said about the accumulated sales of EVs. This suggests that method selection may differ with respect to available data. More research could be directed towards the explanatory variables of the choice of the uncertainty handling method. This would require a more in-depth categorisation of methods according to data requirements, computing expense, and others.

As for the generation source, there seems to be no significant interlinkage between the type of generation considered and the type of uncertainty handling method applied. This implies that researchers do not, in general, distinguish between uncertainty arising from wind or solar RE sources.

The differences in frequencies of application of uncertainty handling methods for the uncertainty considered are relatively large. Although most studies do not distinguish between the method for different uncertainties, there may be gains in differentiating between the uncertainty handling methods within a study respective to different uncertainties.

In general, the main criticism of moving towards the MC approach lies in its time-consuming implementation. Although many markets only require day optimisation, there are markets which require real-time (that is, optimisation with up to 15 min frequency; many times, as frequent as every 5 min.) This poses a challenge to implementing big and complex problems at which the MC is well suited for [5]. This is concerning, because as multi-objective optimisation of several home units, or several EV charging industrial stations are integrated in the system, the optimisation problem can become complex fairly quickly.

Still, as computers are becoming increasingly capable of undertaking computationally expensive tasks in a short amount of time, and more and more data on EVs with V2G integration is accumulating, it can be expected that probabilistic methods, in particular, straightforward and accurate method as MC, are going to continue to lead. Still, as recognised by [9], the implementation, development, or proposition of accurate and efficient modelling techniques for probabilistic analysis will continue.

As for the secondary research, it is also expected that because of the increasing availability of aggregate data, the macroeconomic view is emerging in both secondary and primary research on, for instance, economic and regulatory uncertainties [117]. What can be expected in the future is a further merging of micro and macro views in secondary research.

8. Conclusions

In this paper, a comprehensive systematic review of uncertainty handling approaches for electric grids considering electric vehicles with V2G technology was carried out, and inquiry was made to research questions: what is the geographical distribution of research? What techniques are applied to uncertainty handling for uncertainties related to EVs in smart grids with V2G? What are the dynamics of the application? How does the method relate to the country's aggregate data and generation source and uncertainty considered?

First, the *Scopus* was searched for applicable terms, and articles were excluded for the final set to address uncertainties in EVs, yielding 87 articles to be reviewed systematically. During the systematic review, applied uncertainty handling methods were classified and ranked according to their frequency of application. Then these methods were correlated with the generation, and method variances were compared for accumulated EV sales and population in R&D data. Finally, a narrative overview of the most influential works was given.

The findings suggest that changes in historical data availability and the computing power of computers may have influenced the choice of the uncertainty handling method. An overwhelming majority of articles apply probabilistic techniques, with MC leading in the recent years. Robust optimisation is common in the first years of the period reviewed. There are differences in PEM application with respect to the share of researchers working in R&D in population and accumulated EV sales (a proxy for data availability).

These results allow one to follow the dynamics of modelling techniques for large and/or complex systems (such as home energy management systems or EV charging station network) which have since the start developed in complexity and data availability. These findings can be informative to researchers, policymakers or other stakeholders when modelling for complex systems with social, economic and technical aspects.

In the future, more integration of machine learning and further development of non-parametric approaches can be expected. Suggested by [118], machine learning techniques have been applied in works by [74,110,118–120], among others.

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Abbreviations

ABM	Agent-based modelling
ANN	Artificial neural network
RNN	Recurrent neural network
DSM	Demand side management
DQN	Deep Q-network
DRLO	Deep reinforcement learning optimisation
EV	Electric vehicle
HR	Human resources
IGDT	Information gap decision theory
LHS	Latin Hypercube Sampling
MARL	Multiagent reinforcement learning
MC	Monte Carlo
MPC	Model predictive control
PDF	Probability density function
PEM	Point estimate method
PV	Photovoltaic
R&D	Research and development
RE	Renewable energy
RGV	Readiness of grid to vehicle
RO	Robust optimisation
RVG	Readiness of vehicle to grid
V2G	Vehicle to grid
WT	Wind turbine

Appendix A

Table A1. The most influential articles.

Ref.	Year	Country	Optimisation Timeframe	Market Operation of the Country	Uncertainty Handling Technique					
					MC	Scen	RO	Stoch	PEM	Other
[93]	2014	US	DA	Mixed			✓			
[88]	2015	US	DA	Mixed			✓			

Table A1. *Cont.*

Ref.	Year	Country	Optimisation Timeframe	Market Operation of the Country	Uncertainty Handling Technique					
					MC	Scen	RO	Stoch	PEM	Other
[95]	2016	US	RT	Mixed		✓				
[121]	2018	Canada	RT	RT						Simulation
[99]	2018	US	DA	Mixed		✓				
[84]	2018	Belgium	DA	DA	✓					
[85]	2018	Italy	NA	DA		✓				
[104]	2018	Canada	NA	RT						Fuzzy
[107]	2018	US	RT	Mixed						MDP
[105]	2019	South Korea	NA	DA						Fuzzy
[109]	2019	Iran	DA	NA						Simulation
[100]	2019	Iran	DA	NA	✓					
[96]	2019	Canada	RT	RT		✓				
[101]	2019	India	RT	DA	✓					
[103]	2020	Iran	NA	NA						Probability fitting
[97]	2020	Turkey	RT	NA				✓		
[94]	2021	China	DA	NA			✓‡	✓‡		
[102]	2021	India	DA	DA					✓	
[86]	2021	Qatar	DA	NA		✓				
[122]	2021	Iran	DA	NA				✓		
[98]	2021	China	DA	NA		✓				
[111]	2021	Iran	DA	NA	✓‡					Interval‡
[110]	2021	China	NA	NA						Simulation
[106]	2022	Egypt	DA	NA						Fuzzy
[112]	2022	Spain	NA	DA				✓‡		Interval‡
[113]	2022	India	RT	DA						Dynamic optimisation
[108]	2022	China	RT	NA						MDP
[114]	2023	China	RT	NA						DQN
[115]	2023	UK	DA	DA						MARL

Source: market operation data obtained from [123], when available. Note: here *Stoch* denotes stochastic, *Scen* denotes scenarios. DA and RT denote day ahead and real-time, respectively, ✓ denotes inclusion, and ‡ denotes a hybrid approach used.

Table A2. The less influential articles and articles without the *CiteScore*.

Ref.	Year	Country	Optimisation Timeframe	Market Operation of the Country	Uncertainty Handling Technique					
					MC	Scen	RO	Stoch	PEM	Other
				Less influential articles						
[26]	2016	Switzerland	DA	DA			✓			
[27]	2017	US	DA	DA				✓		
[28]	2017	Iran	RT	NA	✓					
[29]	2018	US	RT	DA	✓					
[30]	2018	UK	NA	DA	✓‡			✓‡		
[31]	2018	Brazil	DA	NA						Multi-period optimisation
[32]	2019	China	RT	NA	✓‡					Fuzzy‡
[33]	2019	Iran	DA	NA				✓		
[34]	2019	South Korea	DA	DA				✓		
[35]	2019	Iran	DA	NA						IGDT
[36]	2019	China	RT	NA						ABM
[37]	2019	India	DA	DA					✓	
[38]	2020	India	DA	DA	✓					
[39]	2020	Iran	DA	NA		✓				

Table A2. *Cont.*

Ref.	Year	Country	Optimisation Timeframe	Market Operation of the Country	Uncertainty Handling Technique					
					MC	Scen	RO	Stoch	PEM	Other
[40]	2020	China	RT	NA						LHS
[41]	2020	China	RT	NA						Probability fitting, MDP
[42]	2021	China	RT	NA						Probability fitting
[43]	2021	China	RT	NA			✓			
[44]	2021	Taiwan	RT	NA	✓					
[45]	2021	China	RT	NA				✓		
[46]	2021	China	RT	NA	✓					
[47]	2021	Egypt	RT	NA						ANN,MDP
[48]	2021	Iran	DA	NA					✓	
[49]	2021	US	RT	DA	✓					
[50]	2021	Canada	NA	RT		✓‡	✓‡			
[51]	2021	UK	NA	DA						IGDT
[52]	2022	Iran	NA	NA		✓‡		✓‡		
[61]	2022	US	DA	DA		✓				
[53]	2022	UK	RT	DA			✓			
[54]	2022	India	NA	DA					✓	
[55]	2022	Iran	DA	NA					✓	
[56]	2022	India	DA	DA			✓			
[57]	2022	UK	RT	DA	✓					
[58]	2022	Canada	DA	RT			✓			
[59]	2022	Iran	RT	NA		✓				
[60]	2022	India	RT	DA		✓				
Articles without the *CiteScore*										
[62]	2021	Thailand	DA	NA	✓					
[63]	2021	UK	RT	DA						CVaR
[64]	2022	China	DA	NA		✓				
[65]	2022	China	DA	NA	✓					
[66]	2022	Turkey	DA	NA						RNN
[67]	2022	India	NA	DA						Simulation
[68]	2022	Iran	NA	NA					✓	
[69]	2022	Iran	NA	NA			✓			
[70]	2023	India	NA	DA	✓					
[71]	2023	China	NA	NA	✓					
[72]	2023	Italy	Week ahead	DA	✓					
[73]	2023	Brazil	DA	NA				✓		
[74]	2023	China	RT	NA		✓				
[75]	2023	China	RT							DQN
[76]	2023	Australia	RT	RT						Fuzzy
[77]	2023	Iran	NA	NA	✓					
[124]	2023	Spain	DA	DA		✓				
[78]	2023	Thailand	RT	NA		✓‡				DRLO‡
[79]	2023	China	RT	NA		✓				
[80]	2023	Japan	DA	NA	✓					Markov chain
[81]	2023	India	DA	DA					✓	
[82]	2023	UAE	DA, RT	NA		✓				

Source: market operation data obtained from [123], when available. Note: here *Stoch* denotes stochastic, *Scen* denotes scenarios. DA and RT denote day ahead and real-time, respectively, ✓ denotes inclusion, and ‡ denotes a hybrid approach used.

Table A3. Data sources for aggregate data (The most recent datapoints were applied).

Variable	Years	Source
Population, total	2014–2021	[83]
GDP per capita in current LCU	2014–2021	[83]
Researchers in R&D (per million people)	2014–2020	[83]

Table A4. Tests applied for ANOVA assumptions for variable EV.

Assumption	Test	Obs				
Normality	Shapiro-Wilk test	62	*W*	*V*	*z*	*Prob*
			0.7069	16.356	6.035	0.0000
	Kolmogorov-Smirnov test	62	*D*			*Prob*
			0.0000			1.0000
Homogeneity of variance	Analysis of variance					
		RO	*Stochastic*	*MC*	*PEM*	*Scenario*
		0.94	0.2685	0.06	1.85	0.23
	Bartlett's test	*RO*	*Stochastic*	*MC*	*PEM*	*Scenario*
		2.2732	4.2912 **	0.0344	24.0911	0.6326

Note: *Stata* commands *swilk, ksmirnov,* and *oneway* were used. ** denotes 5% significance level. The Kolmogorov-Smirnov test was performed using for comparison the Student's *t* distribution with five degrees of freedom. For variance test, standard deviation 1.96 was tested for.

Table A5. Tests applied for ANOVA assumptions for variable HR.

Assumption	Test	Obs				
Normality	Shapiro-Wilk test		*W*	*V*	*z*	*Prob*
		75	0.8499	9.775	4.977	0.0000
	Kolmogorov-Smirnov test		*D*			*Prob*
			0.0000			1.0000
Homogeneity of variance	Analysis of variance					
		RO	*Stochastic*	*MC*	*PEM*	*Scenario*
		0.75	1.91	0.03	5.07	0.27
	Bartlett's test	*RO*	*Stochastic*	*MC*	*PEM*	*Scenario*
		0.0616	1.4266	0.3548	3.2374	1.5781

Note: *Stata* commands *swilk, ksmirnov,* and *oneway* were used. Note 2: The Kolmogorov-Smirnov test was performed using for comparison the Student's *t* distribution with five degrees of freedom. For variance test, standard deviation 1.96 was tested for.

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