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Bibliometric study of distribution system state estimation: advances and challenges

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Abstract
An active distribution network with a large amount of distributed energy resources (DER) requires knowledge of the operational status of the network. In this sense, state estimation is one of the most widely used techniques and a well-developed concept in transmission systems. DERs have some monitoring, protection, and control devices. But due to the large size of the network and the number of users, the massive installation of meters is not yet economically feasible. Therefore, it is necessary to generate artificial measurements to perform all stages of distribution system state estimation (DSSE). DSSE is currently the subject of active research, so this article performs a descriptive bibliometric study, which qualitatively and quantitatively analyzes the topics found in the specialized literature in the period from 2000 to 2022 and part of the 2023. It also identifies the advances, challenges, and proposals for future lines of research in DSSE.

Keywords: distribution system state estimation; bibliometrics study; pseudo-measurements; observability analysis; topology analysis; bad data detection.

Estudio bibliométrico de la estimación del estado de los sistemas de distribución: avances y retos

Resumen
Una red de distribución activa con una gran cantidad de recursos energéticos distribuidos (DER) requiere conocer el estado operativo de la red. En este sentido, la estimación del estado es una de las técnicas más utilizadas y un concepto bien desarrollado en los sistemas de transmisión. Los DER disponen de algunos dispositivos de supervisión, protección y control. Pero debido al gran tamaño de la red y al número de usuarios, la instalación masiva de medidores aún no es económicamente viable. Por lo cual, es necesario generar mediciones artificiales para realizar todas las etapas de la estimación del estado del sistema de distribución (DSSE). DSSE es actualmente objeto de investigación activa, por lo que este artículo realiza un estudio bibliométrico descriptivo, que analiza cualitativa y cuantitativamente los temas encontrados en la literatura especializada en el periodo comprendido entre 2000 al 2022 y parte del 2023. Asimismo, se identifican los avances, retos y propuestas para futuras líneas de investigación en DSSE.

Palabras clave: estimación del estado del sistema de distribución; Estudio bibliométrico; pseudomediciones; análisis de observabilidad; análisis de topología; detección de datos erróneos.

1 Introduction

An active distribution network can be defined as a synergy (join development) of the traditional electric network with modern technologies of information, measurement, protection, control, and communication that allow a more efficient, secure, and reliable operation of the network from the technical and economical point of view. In this new paradigm, Distribution System Operators (DSO) must carry out actions or take decisions to maintain the levels of reliability and service quality, so it is necessary first, to have a complete knowledge of the network state. Thus, the state estimation (SE) is one of the methods mostly used, since it uses real-time measures of voltages and bus flow injections, flow and current line measurements that can be obtained from the HV/MV, reconnectors, switchers in MV, Distribution

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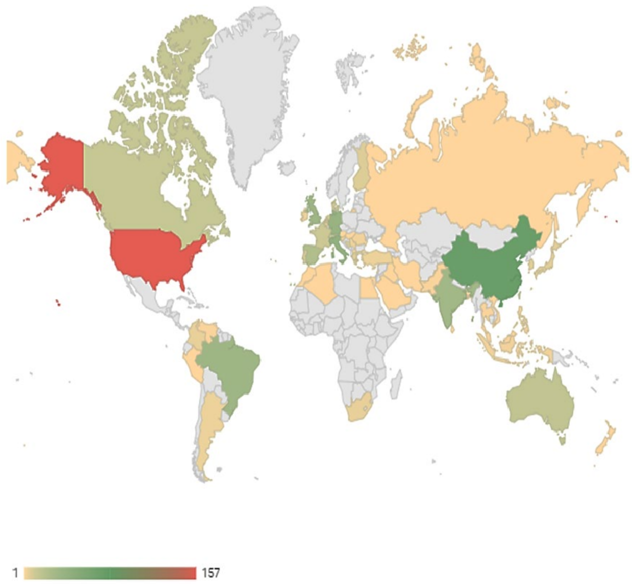

Figure. 1. Density per number of publications in DSSE per country
Source: Own elaboration.

Phasor Measurement Units (D-PMU or μPMU) [1], smart meters [2] and artificial measurements which allow the observability of the system and thus execute the SE algorithm.

Having into account that the SE is a well-developed concept and widely used in transmission systems (TS), its use at the distribution level still has problems of implementation due to the low amount of measurements available since the massive installment is not economically viable up to now, apart from the unbalance of phases, network size, inaccurate network models due to lack of updating or previous validation, design form, and construction, where the line lengths are shorter and have higher R/X relations. So, countries like the United States, China, Germany, Italy, Brazil, United Kingdom, India, and the rest of the world consider distribution system state estimator (DSSE) an object of active research as it is observed in Fig. 1.

The DSSE is an important tool for distribution network monitoring, as it allows estimating the behavior of the network in a short time. This is useful for distribution system management, as it allows operators to optimize network configuration and detect potential problems before they occur. In addition, DSSE are used to monitor network performance, detect not only the presence of faults on distribution lines but also of unwanted loads, estimate the status of distribution network equipment, find out changes in network behavior, and adjust power supply to meet demand. However, DSSE faces challenges due to errors in the network topology data, the need for a large number of measurements with little error at the time of data acquisition and the subsequent communication with the control center.

Despite the challenges and complexity of the problem, in the state-of-the-art review, it was identified that the most used method for the DSSE is Weighted Least Squares (WLS). The first proposals in this sense were developed in the '90s [2]. After those proposals, there were incorporated Automated Meter Reading (AMR), intelligent meters with architecture Advanced Metering Infrastructure (AMI), and renewable and non-renewable Distributed Energy Resources (DERs). Later, it was included and analyzed the impact and implementation of synchronized or non-synchronized D-PMU. These advances and developments can be found in several state-of-the-art reviews [2-7]. In [2,4] technologies, obstacles, challenges, and components of a DSSE are presented and analyzed. Related works on SE in transmission and distribution systems and critical issues of DSSE concerning the mathematical formulation and other components for estimating the state of DS are analyzed in Dehghanpour´s paper [8]. In [5] highlights the importance of using Machine and Deep Learning to address DSSE. The advantages, disadvantages and applications and a summary of different DSSE methods is presented in [6,7].

The aim of this work, in addition to complementing the aforementioned reviews of the state-of-the-art, is to make a descriptive bibliometric study, in which the topics found in the specialized literature of the last two decades are analyzed not only qualitatively but also quantitatively. The topics found are classified into the three areas that make up a DSSE: input data, functions, and applications, which in turn are divided into sub-areas that have a description of the proposals in the period 2018-2022. This is to identify the advances, challenges, and proposals for future lines of research in DSSE.

The content of this paper is organized as follows: the search procedure and literature review with the classification of topics and subtopics of aspects that make up a DSSE are detailed in Section 2, followed by a description of each. Proposals for future research with the problems that the authors considered relevant to DSSE are included in Section 3. Final conclusions are developed in Section 4.

2 Searching procedure and bibliographic analysis

In the literature review, each paper is analyzed and classified according to the areas described in the Section, so that it can be a quantitative and qualitative distribution to evidence the most investigated areas as well as those relegated ones. All this is done to identify trends and suggest future lines of research. The procedure is established in the following way:

1. Selection of a database: the database covers a complete review of papers or chapters using IEEE Xplore, Google Scholar, ISI Web of Knowledge, and Scopus searching motors.
2. Selection of papers from the database: the compilation covers the main themes of the field of DSSE; each paper is analyzed to verify its relation with the theme and to consider to which classification area or subarea (detailed in Section 3) it belongs.
3. Gathering information: All selected attributions of predefined classifying levels are searched and extracted from each paper.
4. Relational database: a relational database is created and completed since the same paper can provide contributions to different areas of Section 3.
5. Identification of main trends: Based on data stored in

step 4, the papers are grouped obtaining quantitative data and percentages. These are visually grouped to identify trends according to the year of publication.

6. Deep analysis of each trend: based on the main trends identified in step (5) and the knowledge of the authors, the research lines are proposed.

2.1 Analysis and bibliographic classification per research areas

In order, to obtain a solution with the DSSE algorithm it is necessary to count with minimum information of the system which depends on the number of state variables to be calculated and the number of existent measurements. These data are for the electrical modeling of the network as well as other additional information which are used to obtain a solution. Data related to the local characteristics of the electric network must be previously analyzed and if it is necessary these must be completed artificially, only then the algorithm of DSSE can be run. The result of the algorithm must overcome a stage of detection and identification of bad data to be ready to be used in a Distribution Management System (DMS). All this process described before is classified into data, functions, and applications together with the number of papers per area (Fig. 2).

From the classification of Fig. 2. 795 papers published between 2000 and 2023 were analyzed, where 48,19%, 37,73%, and 14,08% consider the analysis of data, functions, and applications respectively (Fig. 3).

It must be noted that 42,96% of the total amount of publications are from the period 2018-2022, where it maintained the trend of the areas of study (see Fig. 4a). Nevertheless, it is evident that 60,05% of the contributions are centered in four areas (see Fig. 4b). First, the static DSSE algorithms with 25%, second the solution and temporal synchronization with 11,78%, third the location and distribution of different types of measurements with 12,64% and at last, the analysis and algorithms of data generation for pseudo measurements with the 10,63%.

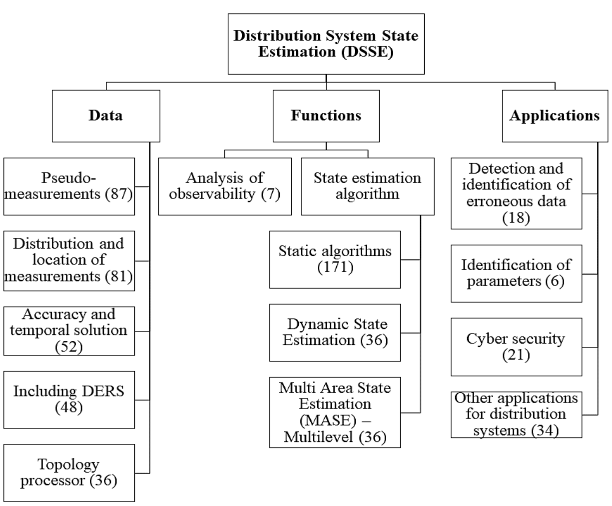

Figure. 2. Classification per areas of research in DSSE
Source: Own elaboration.

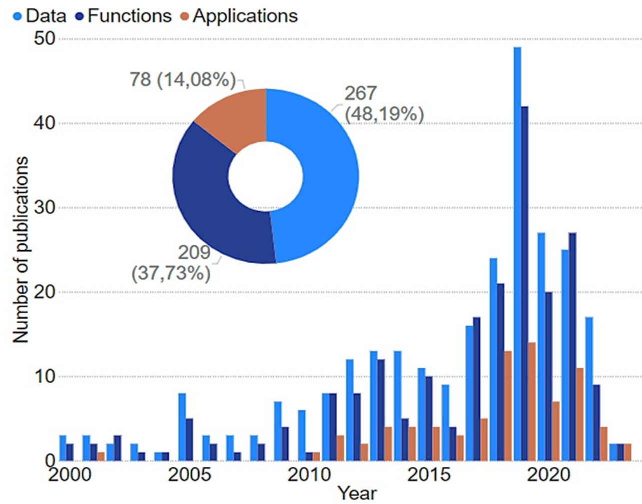

Figure. 3. Percentage and distribution of papers according to data, functions, and applications
Source: Own elaboration.

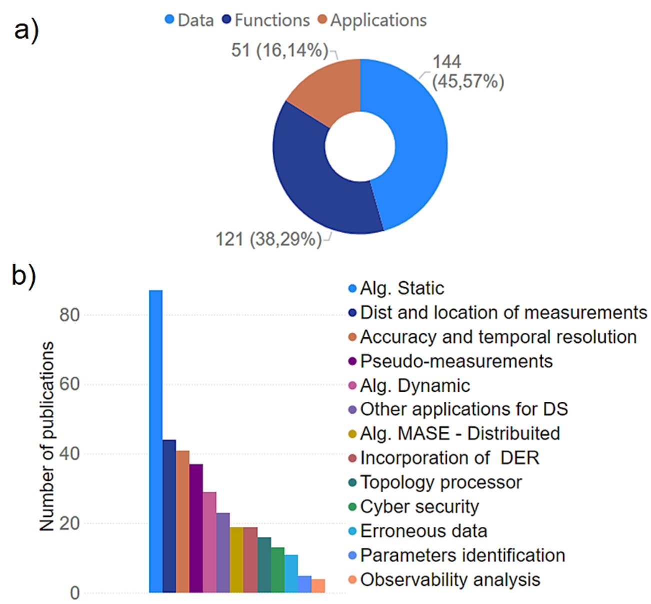

Figure 4. a) Distribution per component b) Number of papers per area of research in the period 2018 – 2023.
Source: Own elaboration.

In addition, the data analysis concluded that 1 out of 6 articles studied the DSSE problem in balanced or single-phase networks the rest corresponds to multiphase and unbalanced systems. In the following sections, the description of each area and the different methodologies proposed in the literature are presented in detail, together with the percentages per number of papers per area in the period 2000-2023. Due to space reasons, only those papers which the authors considered more relevant from 2018-2022 are referenced; several from 2023 are included.

2.2 *Input Data*

DSSE inputs include every knowledge of the system which could affect the result, as well as the physical characteristics of the network. These data include the information technology and the physical attributes gathered at the control center and visualized through a Supervisory Control and Data Acquisition (SCADA) system and which provide measurements such as:

SCADA Measurements: They generally provide data at the substation level, including the active and reactive power, the current magnitude at each distribution feeder, and the voltage magnitude in the bus of the substation. Besides, metering installed along the feeder, which is also included.

1. Smart meters: These meters are installed at the customer's side, connected through bidirectional networks of communication with the system of data management located at the electric company. These devices can provide measurements of active and reactive power, voltage and current and medium power.
2. PMU o D-PMU: The main output is the phasor measurement of voltage waveforms and sampled currents, magnitude, and angle, with which other measurements can be derived and calculated.
3. Pseudo-measurements: To compensate for the lack of data, the set of input data must be increased artificially and/or corrected to compensate for erroneous data. This can be done using "pseudo-measurements", which are generated artificially, for example, active/reactive power, voltage, current, etc.
4. Virtual measurements: these are voltage falls to a cero in closed commutation devices, cero power flows in open commutation devices, and cero bus injections passive in nodes, as a commutation station.

Other important aspects to be considered are data or network parameters, i.e., all permanent features of the electric system which do not change in the daily operation. In particular, those network parameters include network connectivity, line parameters (line and mutual impedance, phase configuration, etc.) bus parameters (connected customers, network equipment, derivation elements, etc.), and equipment parameters (transformers, switchers, protection elements, etc.).

2.2.1 Pseudo-measurements

The existent measurements are stored to be used later on to generate the missing data required for the DSSE, which are used as pseudo-measurements. This represents the 13,88% where it can be found the analysis of uncertainties and correlations detailed in [9]. As well as load forecasting proposals with methods of load estimation [10] and allocating profiles [11], Markov model [9]. Finally, it must be mentioned criteria based on learning such as Artificial Neural Networks [12–14], Relevance Vector Machine (RVM) [15], and clustering techniques [16].

2.2.2 Distribution and location of measurements

This area deals with the 12,92% of the papers which have the aim of determining the location of PMUs, smart meters, pseudo-measurements, and line flow meters among others, through optimization functions with constraints that consider costs, yield indexes, number of measurements, measurement redundancy and the error in the DSSE. An analysis of the state-of-the-art in this field is presented in [17].

In addition, there are proposals related with noise of non-Gaussian measurements [18], chaos simulation and/or Monte Carlo [10,19], Genetics Algorithm [20], Heuristic Methods, Combined or Hybrid [9,21] Integer Linear Programming (ILP) [22], Mixed Integer Semi-Definite Programming (MISDP) [23], Information Entropy Evaluation and multi-objective optimization [24].

2.2.3 Accuracy *and temporal solution*

Another field is the analysis of the accuracy and temporal solution, which includes 8,29% of the works, where it is considered that the distribution system is commonly comprised of a wide variety of measurement equipment, located at different voltage levels and with different time resolutions and measurement errors, Table 1.

Thus, these data considered have a wide range of temporal resolution and different measurement errors. In this sense, two fields of study are identified. The first one is related to the analysis of measurements, i.e., correlations, accuracy, and uncertainties that can appear considering measurements with or without synchronism. The second one is related to the effects that the different types of measurements have on the result of the DSSE, here, the different types of measurements and communication techniques, times of acquisition, non-synchronic and lacking measurements are included. The different areas of research identified are detailed in Table 2.

Table 1.
Type of measurement, location, and temporal resolution

Type	**Error**	**Location**		**Temporal resolution**			
		MV	**LV**	**msec**	**sec**	**min**	**hours**
D-PMU	1%	X		X	X		
SCADA	3% to 5%	X			X	X	
AMI	10%		X			X	X

Source: Own elaboration

Table 2.
Areas of research referred to measurements and their effect on the DSSE.

Area	**Analysis**	**Ref.**
Analysis of measurements	Correlations	[25]
	Accuracy and uncertainties	[26,27]
	Optimal management of the information	[28]
	Synchronic	[29,30]
	Non-synchronic	[31,32]
Effects in the DSSE	Including measurements	[33]
	System of communication	[34,35]
	Times of acquisition	[36,37]
	Non-synchronic measurements	[29,38]
	Lacking measurements	[39]

Source: Own elaboration

2.2.4 Including DERS in the DSSE

Publications related to the inclusion of the renewable and non-renewable DERs in the DSSE correspond to 7,66%. They include the analysis of the correlation between the DERs and the result of the DSSE in [11] and how it affects the result is developed in [40]. To deal with this theme the injection curves and DERs measurements are used as well as the result of the DSSE in [41], then mathematic models according to the type of generator [42] or models which consider environmental variables [43], and others with probabilistic points of view [44] and learning ones [45].

2.2.5 Topology processor

Its function is to verify that the parameters and network model are the correct ones before running the algorithm of the DSSE. This represents 4,78% of the works and they include proposals where the basic topology will suffer changes over time due to local events such as faults, line disconnections, commutation events, etc. Therefore, various proposals have been done which include the analysis of uncertainties in the network topologies [46], in which variables related to the commutation devices and/or measurements are used [47,48]. As well as methods based on decision trees [49], or learning [50,51], verifying signs of temporal series [52], and an approach based on tracking data [53,54].

2.3 Functions

2.3.1 Analysis of observability

The aim is to determine if the number of available measurements as well as their geographical distribution allows estimating all the states of the system. It must be taken into account that, if the measurements are wrongly distributed, this can be over-determined in one zone and even though be unobservable. Proposals in this area correspond to 1,12%, these are focused on knowing if the system is or not observable. Thus, redundant and critical measurements were identified, detecting observable isles. Therefore, various methodologies have been introduced based on: numerical approaches [55,56], learning, heuristic, topological, algebraic, null space, probabilistic, and graphs theory [57] just to mention the most important ones.

2.3.2 State estimation algorithm

As it was mentioned the most widely used method in the DSSE is WLS. Greater details of the mathematical formulation of this method can be found in [4,58].

Nevertheless, depending on the state variables calculated, these can be Node Voltage (NV) or Branch Current (BC). In the literature, these two formulations are compared as regards their implementation, inclusion of PMU, computing time, numerical stability, convergence, sensitivity, and other aspects in [4]. The BC offers better advantages than the NV in the DSSE. A similar comparison was done in [59] with PMU synchronized and non-synchronized measurements from the SCADA.

Table 3.
Proposals for static algorithms of DSSE

Methodology		Ref.
Weighted Least Squares (WLS)	Linear approach	[22,60]
	Modifications to WLS	[61,62]
	Load flow	[63]
Alternative ones	Alternative WLS	[64,65]
	Admittance Matrix Based (AMB)	[66]
	Accelerated Probabilistic State Estimator (APSE)	[67]
Robust	Hybrids	[49,68]
	Interval Arithmetic (IA)	[27,69]
	Block tensor completion	[70]
Heuristic and computational intelligence techniques	Neural networks	[71,72]
	Semi-definite programming (SDP)	[73]
	Particle Swarm Optimization (PSO)	[68]
	Another heuristic algorithm	[74]

Source: Own elaboration

Table 4.
Proposals for dynamic algorithms and MASE – Multilevel

Methodologies		Ref.
Kalman filter (KF)	KF	[75]
	Ensemble KF (EnKF)	[76]
	IEKF	[42,77]
	Unscented KF (UKF)	[78]
	Augmented Complex KF (ACKF)	[79]
Alternative to KF	*First-Order Prediction-Correction* (FOPC)	[80]
	Alternating Direction Method of Multipliers (ADMM)	[81]
	FASE - Recursive	[82,83]
	Hybrids	[84]
Hybrid AC/DC		[85]
MASE – Multilevel – Distributed		[19,86]

Source: Own elaboration

Nevertheless, no matter the type of state variable calculated, they are classified in statics with 27,27%, dynamics known as Dynamic State Estimation (DSE) or Forecasting-Aided State Estimation (FASE) with 5,74% and Multi Area State Estimation (MASE) – Multilevel approach with 5,74%. Static algorithms are divided into methodologies based on WLS, alternatives to WLS, robust approaches, and those based on computational intelligence and heuristic methods. Dynamic algorithms are based on the Kalman filter and other alternative methods. Proposals of static, dynamic, and MASE-Multilevel algorithms are detailed in Tables 3 and 4, respectively.

2.4 Applications of the estimated state

2.4.1 Detection and identification of bad data

Erroneous measurements are processed, identified, and eliminated here, those which are erroneous due to faults in the communication or to the package of false metrics/data [64] from the calculated state. This area belongs to the 2,87% of the works, where the methodologies are based on statistical analysis, such as the chi-square test, normalized residual test [45,87], and orthogonal formulation [88]. Besides, techniques with approaches to neural networks and geometrics are also included.

2.4.2 Identification of parameters

Only in 0,96% of them are analyzed how the line impedances and network equipment affect the quality result of the state estimation. Proposals are related to the connectivity of the network/mapping of incidence [89] and line parameters [90].

2.4.3 Cyber security

This topic represents the 3,35%, where it is analyzed how the malicious alteration of data from certain measurement devices [91], the injection of false data [92], and topological data affect the knowledge of the real state of the system and the risk in the privacy and confidentiality of users. A review of the state-of-the-art in this area can be seen in [93].

2.4.4 Other applications for distribution systems

The aim of using the DSSE in real time operation is to provide a higher level of confidence of the network state to support decision making or to find an optimal solution. These proposals correspond to 5,42%, as the ones included in [94] , where the results indicate that the identification of non-technical losses from the erroneous data detection approach is promising. While a sensitivity analysis of the DSSE with respect to phase mislabeling of single-phase service transformers is presented in Trevizan et al [95]. In Bindu et al. [96] a methodology for using DSSE in DG interconnected distribution network is proposed which, in turn, depends on the minimization of system losses. In [97], a centralized self-healing scheme employing a three-phase state estimator with a short-term load forecasting method and a fault location algorithm for service restoration is designed and simulated. Another use for running DSSE with topology detection is to locate faults and isolated components [60,98] [66,104]. In demand response schemes, DSSE improves the basis for sending load disturbance signals to dynamic consumers [99]. Finally, in transmission and distribution operator coordination, DSSE improves load forecasting techniques and current state accuracy integrating into the transmission model [100]. In addition, it can be included in applications or algorithms that contribute to data cleansing, network optimization and topology, system reliability, dynamic energy pricing, monitoring, and operation control.

3 Proposals of Future Research

After analyzing the literature, proposals have focused on improving the quality of the information and completing the observability of the distribution system before running the DSSE algorithm. However, unlike TS, there are various factors that make distribution system (DS) very diverse in terms of construction, load, topology, investments in technologies or network reinforcements, insufficient metering, adoption of DERs, communication systems, etc. Therefore, DSSE still faces the challenges of estimating non-measurable variables in non-linear DS. Thus, the authors propose the following lines of future research to help achieving the effective adoption of DSSE in the face of ADNs challenges.

3.1 Pseudo-measurements

Accuracy of pseudo-measurements can be improved through the use of a scheme of the close circuit in which the output of DSSE feedback the load models [101], or in turn using data mining techniques [102].

In fact, in case of smart meters, they can have two metering schemes Net Billing or Net Metering. In the case of Net Billing, the pseudo-algorithms could use data from users and injection power to model the load behavior in the DSSE. But in the case of Net Metering, more parameters, models, environmental, social variables, uncertainties, etc. must be selected which allows the recognition of the difference between consumption and generation.

3.2 System operation

At an active distribution network (ADN), being operated dynamically, with constant changes in generation, load, and network topology, among others, the static algorithms of DSSE are not able to capture these changes easily, since they consider that the state of the system does not change much between two consecutive updates of the state estimator. While the DSE or FASE techniques, consider the state temporal evolution over time and they can track the system changes during normal performance [4], requiring only the reduction of the computational load and times of convergence of the DSSE [103]. These are the proposals that take advantage of the MASE executing various estimators in sequence or parallel.

3.3 DERs progressive insertion

The impact of the presence of DERs analyzed from the point of view of the DSSE will depend on the percentage of insertion and the type of installed technology, a low percentage of power injection to the system does not affect the calculus of state variables, but as this percentage increases, the DSO must differentiate between load and generation. In addition, it becomes necessary to consider the uncertainties related to the type of generation due to the dependence on intermittent natural resource and their storage. Thus, approaches, techniques, and the most advanced challenges regarding the modeling of uncertainties of DERs in the electric system are briefly presented in [104].

3.4 Microgrids and storage systems

In the system operation, there must be coordination between the network and the existent microgrid or microgrids, so that the result of the SE be used as input data for the functions of self-reestablishment of a microgrid, and depending on the result of such functions, they will be used as input in the new calculation of DSSE.

In the case of those storage systems that do not belong to a Microgrid, their state will depend on the control system of the inverter or the present regulation, so the DSO needs to quantify the load level about the maximum nominal load of the battery to be used as measurement or in case to obtain observability as pseudo-measurement. These load and discharge models must be considered within the DSSE, to be able to control temporal variations of state variables [105].

3.5 Efficient metering and data acquisition architectures

It is necessary to develop low-cost smart metering devices that comply with international standards [106] and architectures for data collection from thousands of smart meters in a relatively short period (on the order of minutes) it is not feasible nowadays [107], having into account the diversity of metering technologies installed, the acquisition time and uncertainties associated to each of them [108]. The DSSE must model these uncertainties locally and find ways to take advantage of information from different time scales and combine them with artificial measurements if necessary.

3.6 Relegated research areas

According to Fig. 4b, the contributions to the state-of-the-art during the year 2018-2022 are focused on four areas: static DSSE algorithms, analysis and effects in the DSSE, the resolution and temporal synchronization, location and distribution of different types of measurements, and generation of data to be used as pseudo-measurements.

Nevertheless, according to the proposed classification, the new contributions could focus on areas such as Topological processor which considers the presence of DERs with fast algorithms with a low computational load to detect the constant changes expected in ADN; the detection and identification of bad data using methods based on artificial intelligence; cyber security seen from a point of view of the DSSE. The identification of parameters that use phasor meters at strategic points of the network allows for determining parameters through the measures provided by them. Finally, in the observability analysis and considering the enormous size of distribution networks with few measurements, it was identified that it is still necessary to propose solutions related to the detection of critical measurements that guarantee the observability of the network.

4 Conclusions

From the analysis of the state-of-the-art and the development of ADN, it is understood that in order to improve the real-time operation it is necessary to have an efficient estimation of DSSE. For this reason, this work identified the advances, challenges and proposals for future lines of research in DSSE, after analyzing 795 papers. Thus, a descriptive bibliometric study was carried out, in which the topics that make up a DSSE are qualitative and quantitatively analyzed

Countries such as the United States, China, Germany, Italy, Brazil, the United Kingdom and India have generated around 60% of contributions on the subject and it continues to be an active area of research with new articles being published every year.

Distribution systems are quite diverse in their form of construction, loading, topology, DER adoption, technologies, etc. Consequently, DSSE faces challenges due to errors in the network topology data and the need of a large number of measurements. However, DSSE is necessary for DSO since it helps them to have higher reliability in the short term through the estimated state because it allows the detection of potential problems before they occur. In addition, DSSE can be included in applications or algorithms that contribute to data cleansing, network and topology optimization, system reliability, dynamic energy pricing, operations monitoring, and control.

The contributions of the period 2018-2022 are focused on four areas: static DSSE algorithms, analysis and algorithms of data generation for pseudo-measurements, location and distribution of different types of measurements, and the resolution and temporal synchronization.

Due to the dynamics and uncertainties expected in the ADN, state estimation conventional techniques proposed for transmission systems cannot be applied to distribution systems. Therefore, future research should focus on DSSE algorithms or FASE and MASE ones with less convergence time and low computational load thinking on a real-time operation.

Barriers to the development of DSSE are mostly related to the availability of communications and the effective use of the information generated by the AMI, as well as the low PMU installed and SCADA distributed measurements.

There are still some pending challenges as regards the DSSE in such areas as pseudo-measurements, system operation, DERs progressive insertion, microgrids and storage systems, efficient metering and data acquisition architectures, and research areas detailed in Section 3. So, it is expected that this paper contributes to developing the research on those themes that may achieve the effective adoption of DSSE by electric service companies.

This work allows an evaluation of the different advances in the areas of knowledge concerning DSSE and can be a guide to propose new lines of research or as a decision-making process for the allocation of resources for research and development in the case that an electric company plans to implement a DSSE in the short term.

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