IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 27 November 2023, accepted 6 December 2023, date of publication 18 December 2023, date of current version 27 December 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3344489

TOPICAL REVIEW

Toward Optimal Active Distribution Network Planning: A Critical Review of Conductor Size Selection Methods

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This work was supported by the Centre for Renewable and Sustainable Energy Studies.

ABSTRACT Conductor size selection (CSS) is critical for the optimal design and operation of distribution networks. CSS, like other aspects of network planning, has become increasingly sophisticated as the prevalence of distributed energy resources (DERs) increases. This complexity is linked to DER operational and planning uncertainties, which often exacerbate network issues. Increased uncertainty and uncontrolled DER penetration can result in increased conductor loading and extreme voltage performance concerns (rise, drop, and unbalance) that lower the quality of supply (QoS). Traditional CSS techniques, which were developed for passive systems, do not take DERs into account. Therefore, continued application of these methodologies in CSS for modern networks is untenable. As a result, the shift towards active network design and planning requires new CSS techniques that can enhance the adoption of DERs and facilitate optimal long-term network planning. This paper presents a review of CSS methodologies, focusing on the advances made to accommodate DERs, particularly the adaptation of modeling processes to cater to DER planning and operational uncertainties, and its impacts on other key aspects of CSS. Key CSS processes, including the choice of the CSS objectives, input (loads, generation, and feeder) modeling, load flow assessment, optimization, as well as the incorporation of risk in DER analysis are discussed. Informed by the review, the paper scopes the requirements for a robust CSS methodology for active networks with high DER penetration. The findings of the paper are relevant to future research in the field of active distribution network design with a focus on optimizing the integration and utilization of DERs and the related technical performance of networks.

INDEX TERMS Conductor size selection, distributed energy resources, network planning.

I. INTRODUCTION

The advancement in renewable energy technologies amidst efforts to reduce the global carbon footprint has led to an increased share of distributed energy resources (DERs) on distribution networks. Despite the improved energy security [1], [2] improved system control and observability [3], [4], and decarbonization [1] associated with DERs, their rapid growth is transforming passive networks, traditionally designed for one-directional power flow, into active networks characterized by substantial bidirectional power flows. This transformation introduces various technical challenges, which include excessive voltage deviation (rise and drop), voltage unbalance from single-phase loads, as well as conductor and transformer thermal overloads [5], [6], [7], [8]. These challenges are associated with DER operations and planning uncertainties [9] and ultimately impact the operation of the networks. This limits the network's ability to host DERs while maintaining acceptable technical performance with respect to stipulated quality of supply (QoS) and equipment loading standards. The limit at which further DER capacity violates stipulated technical standards is generally termed the network hosting capacity (HC) [10].

To accommodate higher penetration of DERs beyond the standard HC, distribution network operators (DNOs) need to expand the capacity of the network through various

The associate editor coordinating the review of this manuscript and approving it for publication was Lei Chen.

approaches, including grid reinforcement, which can be classified into soft and hard. Soft approaches are primarily focused on optimizing the utilization of existing grid infrastructure and connected assets rather than upgrading the physical infrastructure. Most soft approaches rely on advanced network control to manage the DER impacts on the distribution network. These approaches include demand response and DER-derived flexibility [11], [12], as well as active network management (ANM) [13], [14]. The use of energy storage [15], electric vehicles [16], and other voltage control strategies aimed at network strengthening have been explored in [17] as part of soft reinforcement strategies.

Studies in [18] and [19] found that soft approaches are likely to become prevalent in active networks, supporting the need for dynamic operation, flexibility, and resilience. However, given that most soft reinforcement options are somewhat temporary (compared to the permanence of hard reinforcement options), they may not fully optimize network utilization, given the embedded infrastructural constraints. As such, soft reinforcement approaches have limited capacity enhancement, beyond which the upgrade of the primary network infrastructure may be inevitable.

Hard reinforcement approaches typically involve the physical or structural modification of the network assets or infrastructure towards a desired HC. These approaches include reconductoring [20], [21], [22], transformer thermal capacity upgrades [23], and the building of new substations [24]. In this regard, proactive planning for future networks will require comprehensive approaches to selecting or replacing the primary network equipment such as conductors and transformers.

Conductor size selection (CSS) is a critical aspect of hard reinforcement approaches as it directly impacts the network's technical performance in terms of voltage, thermal loading, safety, and distribution efficiency. These technical factors define the network loadability, QoS, and reliability. Accordingly, careful consideration of CSS over a defined planning horizon is critical to ensure that the network can meet the current and future system demands while minimizing thermal losses and investment costs [25]. However, integrating a higher share of DERs increases the planning and operational uncertainties in key aspects of CSS modeling such as load magnitude estimation, forecasting, and location, whose characteristics are rapidly changing with the adoption of new technologies. As such, the CSS process must evolve to ensure that the selected conductors are optimal over the planning horizon [26]. Such a process is also central to the development of new electrification projects.

This paper provides a comprehensive overview of existing CSS methodologies in the context of the transformation of distribution networks under the penetration of DERs. It covers conductor selection factors, various methodologies and their limitations, DER modeling and uncertainties, and the selection criteria for optimization methods. The challenges related to active CSS methodologies are also discussed. These insights are crucial for developing a robust CSS framework that can guide the design of future active distribution networks (ADNs).

A. OVERVIEW OF SIMILAR WORKS

One focused literature review on CSS was found in [27]. The review summarized papers from 1955 to 2017 based on feeder type, CSS methodology, objective function, and the inclusion of load growth. However, this study lacks essential details such as input modeling (e.g., loads), uncertainty representation, load flow methods, a detailed discussion of the design objectives, as well as the assumed constraints. Apart from this study, a partial review of CSS is found in several technical articles. However, these articles are less detailed and have the following limitations.

- The reviews in these studies focus on new CSS optimization methods and as such, they only address one component of the CSS as in [28] and [29].
- These reviews compare the convergence of the applied CSS optimization methods [30], and leave out critical components related to CSS evolution.
- In cases where the limited review discusses ADN CSS as in [31], the discussion is inadequate and non-comprehensive.

While there is some value in these partial reviews, the limitations are notable, even on the specific subjects they address-Due to the inexhaustive nature of the reviews, a focused and exhaustive review of the CSS literature is needed, encompassing all critical aspects of the CSS problem, and addressing the evolution of network design amid increasing DER penetrations.

B. PAPER CONTRIBUTIONS AND STRUCTURE

This paper provides several contributions:

- The study provides a consolidated Input-Process-Output (IPO) CSS framework outlining the key inputs, the underlying computational processes, and the required output analysis for a CSS exercise.
- Based on the IPO framework, the study highlights the changing scope of CSS as a higher share of DERs are integrated into the network, detailing the expanded set of inputs, their representation, and limitations associated with present modeling.
- The study reviews over 84 CSS papers from 1955 to 2022 and discusses them according to the CSS and optimization methodologies, uncertainty representation, and the associated limitations.
- The study highlights future research opportunities within the ADN CSS context.

The rest of the paper is as follows: section II scopes the general CSS problem, defining in detail the components of the CSS IPO framework. It further lays out the structure of the subsequent sections III, IV, and V. Section III conducts a review of CSS literature in line with the established framework, detailing the modeling of inputs in passive and active CSS, and the subsequent modeling of the computation

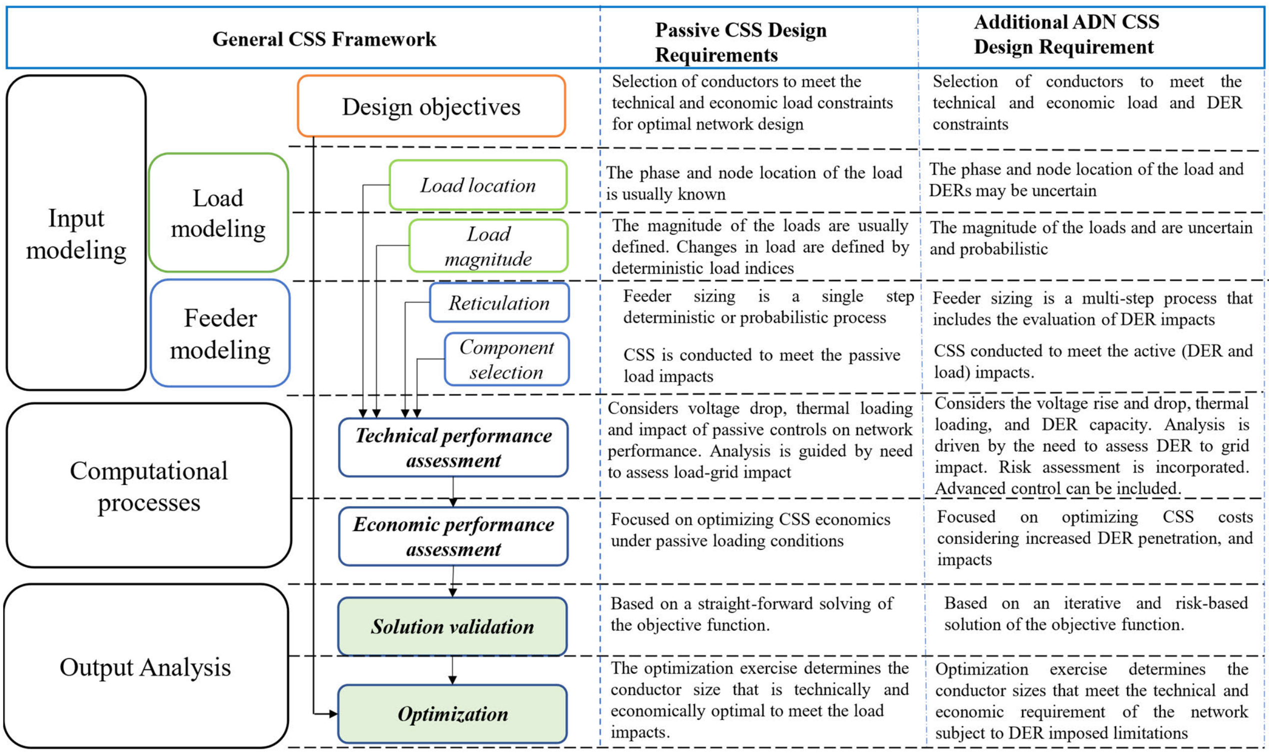

FIGURE 1. Outlining the requirements for active distribution network (ADN) CSS formulation.

processes, including load flow analysis, optimization, and the limitations of the various computational elements. Informed by the findings from section III, section IV scopes the requirements for a robust ADN CSS, and the implication to distribution network planning and operation procedures. Section V concludes the paper, highlighting the opportunities for future research.

II. SCOPING THE CSS PROBLEM

Network design processes are informed by several system performance indicators including thermal loading, voltage quality, and power supply reliability. The objective of the CSS component in distribution network design is to size network conductors that service the total power flows while meeting the selected design constraints, including cost and quality of supply (QoS) standards. Under ADN design, the total power flows comprise the balance of the power drawn from, and the power injected into the network by the loads and generators that include DERs. Fig. 1 provides an overview of the general CSS framework. It outlines the generally accepted requirements at each stage of the process and compares the traditional passive approach to the new requirements imposed by the introduction of DERs.

The CSS framework can be broken into three major components using an IPO approach. These components include (i) input modeling (ii) computational processing, and (iii) output analysis. Each of these components comprises sub-processes as illustrated in the figure.

Input modeling is divided into two large subprocesses: load and feeder modeling. The load, i.e., consumer power consumption, is the primary focus of input modeling in passive CSS. The placement and magnitude of the load are critical considerations in load depiction and ultimately influence the selection of conductors. These factors were considerably fixed and sufficiently modeled by deterministic means [18]. For modern ADN CSS, modeling loads extend to DERs. This change significantly alters the modeling requirements due to two uncertainty elements, namely DER allocation and operational uncertainties, which affect feeder performance [31]. Operational uncertainties affect the load magnitude, i.e., the magnitude of power flows (between the DER and the network) and the DER time-of-use (ToU) characteristics. Then, the allocation uncertainties, which can be classified as planning uncertainties, highly influence the modeling of the load location. To avoid increasing technical challenges, and possible future failures on the network, CSS methodologies must carefully characterize and model these uncertainties in the inputs [26].

The next step in the CSS process involves reticulation, which can be described as the design of the network route and the specification of cables and other supporting infrastructure (e.g., breakers and fuses) necessary to efficiently deliver power to customers. Additionally, the sizing and placement of other key equipment such as voltage regulators, capacitors, and energy storage, is usually carried out at this stage [32].

The computation module assesses the technical and economic performance of the CSS process. Key technical considerations in passive CSS design include voltage drop, conductor loading, and power losses on the network [36]. On the other hand, active networks have a wider range of challenges, that require additional assessments including the analysis of voltage rise conditions, and network HC [33], [34].

The economic and technical analyses are closely tied as the validity of the economic assessment may depend on the results of the technical analysis. In general, economic analysis for passive CSS computes the investment (typically capex and opex) needed for the conductors and other support infrastructure. In ADNs, extended investments in support infrastructure, e.g., towards the modernization of line protection equipment for effectively managing the dynamic power flow within the network, may affect the scope of CSS economic assessments. Incorporation of advanced monitoring and control equipment may be inevitable in most modern power systems.

CSS output analysis comprises the validation and optimization processes, whose function is to direct the finalization of equipment selection guided by the planner's objectives and techno-economic performance metrics. In general, passive CSS validation is relatively simple and is typically aimed at obtaining a deterministic solution to the CSS problem. Even though this simplicity reduces the computational challenges associated with ADN processes, it can result in a suboptimal solution. The lack of consideration for load and DER uncertainties makes deterministic approaches unsuitable for representing the changing network operational dynamics and is thus inapplicable in active CSS design. Given the input uncertainties, some form of risk assessment is required in the validation process. DER planning uncertainties, which tend to be epistemic, will extend the scope and form of this risk assessment. Even though these considerations increase the complexity of the ADN-based validation, they improve the accuracy of the process.

CSS optimization aims to select ideal conductors for optimal network performance while adhering to the techno-economic objectives and constraints. The passive CSS process is relatively simple in dimension and is primarily focused on achieving the optimal cost or minimizing technical losses under a set of techno-economic constraints. On the other hand, CSS objectives in the ADN scenario can include the capacity optimization of multiple DERs and unique economic objectives. The resulting optimization process is thus geared at meeting the requirements associated with both the load and DERs, which can lead to multi-layered, multi-objective optimization problems.

From the preceding discussion, there are differences between the traditional passive CSS methodologies and the active-based CSS methodologies. Based on these, the next section explores the formulation and representation of these key CSS aspects in the published literature. A detailed comparison between active and passive CSS is provided in Table 1.

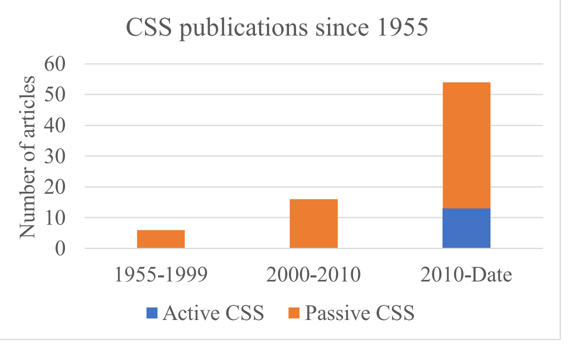

FIGURE 2. Number of CSS publications (1955-2022).

III. A REVIEW OF CSS—TOWARD ACTIVE NETWORK PLANNING

This section reviews how CSS has been conducted in literature. It considers papers that are published in the English language. Even though this work is focused on CSS, for completeness, papers that examine CSS in the context of distribution network planning (DNP) are also reviewed and discussed. In total, 84 papers were reviewed, with 76 falling into the CSS-focused category. A further classification of the CSS-focused methodologies is performed, resulting in two separate classes focused on active and passive CSS. Passive CSS is discussed in [27], [28], [29], [30], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66], [67], [68], [69], [70], [71], [72], [73], [74], [75], [76], [77], [78], [79], [80], [81], [82], [83], [84], [85], [86], [87], [88], [89], [90], [91], [93], [94], and [95] while active CSS formulation is outlined in [20], [21], [26], [31], [32], [96], [97], [98], [99], [100], [101], and [102]. Additional studies in [24], [99], [100], [103], [104], [105], [106], and [107] highlight more works that have a CSS component in DNP formulation. Details on how each of the papers formulated the CSS problem are provided in Table 2 and focused discussion is provided in subsequent subsections.

Fig.2 shows the number of publications between 1955 and 2022, based on whether the formulation was passive or active. About 15% of the publications have active formulation. These are covered in the DER modeling section. Further analysis reveals that more than half of the CSS literature was published between 2010 and to date, indicating the subject's importance as network planning shifts from passive to active.

Given the centrality of CSS in distribution engineering, and the costs associated with the process, CSS is formulated as an optimization process under a set of constraints prescribed by network planners. The following subsections discuss the progression of CSS formulation as planning and operation shift from passive to active. The discussion dissects the existing

TABLE 1. A comparison of passive and active CSS methodologies in Literature: Summary 1.

		Passive CSS methodologies	Active CSS methodologies
CSS Component	*Sub-component methods*	*Details and selected references*	*Details and selected references*
Input modeling	Modeling of the Loads and DERs	• A diverse set of LV load models is used in passive CSS. Deterministic loads [20] and time-varying loads [57] are modeled. • Load growth factor is applied in passive CSS to represent the varying loads across the planning period [50], [143]. • Load growth factors are premised on forecasted historical data and used to determine the conductor losses over the planning period [56], [60]. • The prevalence of deterministic LV models arises from their simplicity and the low level of uncertainty.	• LV Probabilistic load models [21], [31] and LV deterministic load models [96]. • The application of load growth factors based on historical data is inadequate because of the changing load patterns. • DERs can be DGs modeled as negative loads [31] or DLs which are modeled as loads according to their time of use. • DER capacity and output can be deterministic [96]. • DER output is mostly modeled using probabilistic approaches [32].
	Representation of uncertainty	• Most passive CSS studies have limited load uncertainty representation.	• Emphasis on uncertainty modeling is made. Probabilistic loads are common [31]. • In active CSS, DER output uncertainty has been modeled using PDFs [21], [102], and interval analysis [32] among others. • DER planning uncertainty is also modeled but to a lesser extent using MCS [31].
	Time-dependence of the input data	• Some passive models have considered dynamic loads [42]. • Most of the studies consider fixed loading conditions [57] in which the worst-case conditions are defined by the peak load.	• Most active CSS methods have considered the single interval with worst-case conditions for the loads and DERs [26]. • The interval is selected such that the worst network conditions arise from the combination of loads and DERs. • Few studies have integrated time-series data in the formulation of active CSS problems.
Computational process	Load flow methods	• Load analysis determines the performance of the network. As such load flow analysis output is the driving engine in determining compliance. • The backward forward sweep and AC-PF are prevalent [28], [42]	• The output of different forms of HC analysis, in which load flow analysis is integrated determines the compliance of the selected conductors [31].
Output analysis	Scope of optimization methods	• Different classes of optimization methods have been developed and used in passive CSS. There is comprehensive testing and use of heuristics [87], [88], [144] and mathematical methods [39], [147]. • The most prevalent heuristics methods include search optimization [88], and genetic algorithms [72]. • Prevalent mathematical methods include linear programming approaches [145] • Most of the developed optimization methods have been tested under the passive CSS conditions.	• The incorporation of optimization methods in active CSS is not fully developed. A few studies have incorporated heuristic methods into active CSS where DERs with fixed location and capacity are known [96], [102]. • Integrating the heuristic optimization method adds a computational layer to the active CSS problem that is already computationally extensive. • Integrating mathematical optimization methods into the active CSS increases the complexity of the active CSS process.
	Scope of optimization objectives	• Objectives comprise the minimization of CAPEX and OPEX associated with conductors and the reactive and active energy losses associated with the conductors [79]. • Other objectives can include maintaining acceptable voltage drops [73], and reduction of harmonics [51].	• In addition to the CAPEX and OPEX minimization [96], active CSS seeks to optimize the capacity of DERs on the network [21]. • Technical objectives for active CSS may comprise maintaining optimal voltage rise [32] and drop [21] on the line as well.
	Computational efficiency	• The methodology has lesser computational requirements due to less uncertainty modeling requirements. • The computation efficiency of the passive CSS is most constrained by the efficiency of the optimization method applied.	• Multiple layers of computational requirements arise to meet the modeling requirements associated with DER planning and operations. • Given this, the efficiency is constrained by the need for uncertainty representation as well as the need to integrate extensive optimization models.

literature based on the components described in the general CSS framework in Fig. 1.

A. MODELING CSS INPUTS

Several inputs are critical in CSS modeling. These depend on the implemented CSS type. In passive CSS, customer loads are the most critical input. However, in active CSS, DERs are considered, given their impact on network planning and operations. This section scopes the extent to which loads and DERs have been modeled in the CSS literature.

1) MODELLING OF LOADS IN CSS

A comprehensive review of load models is presented in [108]. These are classified into static and dynamic load models. Static load models depict power at any instant of time as a function of the bus voltage, and frequency while dynamic load models express power as a function of both voltage and time [108]. The other classes include the composite load models, and the low voltage (LV) load models, also known as the lumped models.

Static load models are the most widely applied models in CSS. They are classified into deterministic and probabilistic load representations. A sample of studies that applied the static load model is found in [41], [45], [46], and [47]. Static load models have also been used in active DNP studies as reported in [32] and [97]. The prevalence of static models can be attributed to their simplicity, and thus their ease of implementation.

Several studies used probabilistic load models (PLMs) in CSS formulation. PLMs allow the consideration of load uncertainty in CSS problems. These models are applied in [21], [26], and [31]. In these studies, beta PDFs are used to model the diversity of the load at a five-minute interval. While the application of PLMs enhances model accuracy, the integration of PLF approaches makes them computationally intensive. However, these models are critical in representing the changing network load dynamics.

The resolution at which the load is modeled is critical and this can be done in two dimensions. These include the inter-interval cadence, depicting the interval between the sample of data, and a second dimension relating to the horizon of the data. This can be worst-case [21], annual [24], or multi-year [28]. Other studies that considered annual resolution include [40], [93], and [94].

Limitations of the Existing Load Models Used in CSS

In general, static models are prevalent in application. Static load models are characterized by high computational requirements given the iterations linked with the modeling of

TABLE 2. Comprehensive comparison of the reviewed CSS literature: summary 2.

	Class of CSS			Stated elements of the objective function					Stated optimization constraints						
Ref	*Active*	*Passive*	*DER type*	*Volt. Reg*	*Min. CAPEX*	*Min. OPEX*	*Min. Losses*	*DER enha.*	*Voltage deviation*	*Thermal loading*	*Energy loss*	*other*	***Load model****	*Opti. method*	*Power flow method*
[20]	✓		PV		✓	✓			✓	✓		FRI	Static DLM-STS	SSO	Deterministic – FBS
[21]	✓		EVs					✓	✓	✓			Static PLM -STS	Exact	Probabilistic - HBE
[26]	✓		PV					✓	✓	✓			Static PLM -STS	Exact	Probabilistic - HBE
[27]		✓			✓	✓	✓		✓	✓			Static DLM-STS	GO	Deterministic - FS
[30]		✓			✓	✓			✓	✓	✓		Static DLM-STS-SY	Exact-MINLP	Deterministic - FBS
[42]		✓			✓				✓	✓				Exact-MINLP	Deterministic – ACPF
[29]		✓			✓	✓			✓	✓			Static DLM-STS-SY	TLBO	Deterministic
[31]			PV					✓	✓	✓			Static PLM -STS	Exact	Probabilistic - HBE
[28]		✓			✓	✓			✓	✓			Static DLM-STS-SY	WO	Deterministic - FBS
[32]	✓		PV, wind		✓	✓		✓	✓	✓			Static DLM-STS-SY	GA	Probabilistic - SUT
[35]		✓			✓	✓			✓	✓			Static DLM-STS	DPSO	Deterministic
[36]		✓		✓	✓	✓			✓	✓		Isc.	Static DLM-STS	Exact	Deterministic
[37]		✓			✓				✓			RC	Static DLM-STS-SY	Exact	Deterministic-ECD
[38]		✓			✓	✓			✓	✓			Static DLM-STS	DE	Deterministic
[39]		✓			✓	✓			✓	✓	✓		Static DLM-STS	Exact-MILP	Deterministic
[40]		✓			✓	✓			✓	✓			Static DLM-STS	Exact	Deterministic
[41]		✓			✓				✓	✓			Static DLM-STS	ES	Deterministic - FBS
[43]		✓			✓		✓		✓	✓		THD	Static DLM-STS	GA	Deterministic- NR
[44]		✓			✓	✓			✓	✓			Static DLM-STS	Exact	Deterministic
[45]		✓			✓				✓	✓			Static DLM-STS	CSA	Deterministic -FBS
[46]		✓			✓	✓			✓	✓			Static DLM-STS	GA	Deterministic -GS
[47]		✓			✓	✓			✓	✓			Static DLM-STS	SPSO	Deterministic
[48]		✓			✓	✓			✓	✓		RC	Static DLM-STS-SY	Exact	Deterministic -ECD
[49]		✓			✓	✓			✓	✓			Static-DLM-STS	Exact	Deterministic
[50]		✓		✓	✓	✓	✓		✓	✓			Static DLM-STS-SY	Exact	Deterministic
[51]		✓					✓		✓	✓		THD	Static DLM-MTS	GA	Deterministic -DigS
[52]		✓		✓	✓	✓			✓	✓			Static DLM-STS	Exact	Deterministic
[53]		✓			✓	✓			✓				Static DLM-STS	Exact	Deterministic
[54]		✓		✓	✓				✓				Static DLM-STS	GA	Deterministic -FBS
[55]		✓				✓	✓					RC	Static DLM-STS	Exact	Deterministic - FBS
[56]		✓		✓			✓		✓	✓			Static DLM-STS-SY	MDE	Deterministic- DLF
[57]		✓		✓	✓	✓	✓		✓	✓			Static DLM-STS	HSA	Deterministic
[58]		✓				✓	✓		✓	✓			Static DLM-STS	DPSO	Deterministic
[59]		✓			✓	✓			✓	✓			Static DLM-STS-SY	Exact	Deterministic
[60]		✓			✓	✓			✓	✓			Static DLM-STS	EP	Deterministic
[61]		✓			✓	✓	✓		✓	✓			Static DLM-STS-SY	BWMT	Deterministic
[62]		✓			✓	✓			✓	✓			Static DLM-STS	ER-WCA	Deterministic- FBS
[63]		✓				✓			✓	✓			Static DLM-STS	GA	Deterministic -FBS
[64]		✓			✓	✓	✓		✓	✓			Static DLM-STS-SY	Exact	Deterministic
[65]		✓		✓	✓	✓			✓	✓			Static DLM-STS	CSA	Deterministic -FBS
[66]		✓			✓	✓			✓	✓			Static DLM-STS	Exact	Deterministic
[67]		✓			✓	✓			✓	✓			Static DLM-STS-SY	Exact	Deterministic
[68]		✓				✓			✓	✓			Static DLM-STS-SY	ICA	Deterministic -FBS
[69]		✓			✓	✓			✓	✓			Static DLM-STS-SY	Exact	Deterministic
[70]		✓			✓	✓			✓	✓			Static DLM-STS-SY	PGS	Deterministic
[71]		✓			✓	✓	✓		✓	✓			Static DLM-STS	Exact	Deterministic
[72]		✓		✓	✓		✓		✓	✓			Static DLM-STS-SY	GA	Deterministic
[73]		✓			✓	✓			✓	✓			Static DLM-STS-SY	Exact	Deterministic-ETAP
[74]		✓			✓	✓	✓		✓		✓	RC	Static -DLM-STS	Exact	Deterministic
[75]		✓							✓				Static DLM-STS	Exact	Deterministic
[76]		✓		✓	✓	✓	✓						Static DLM-STS	Exact	Deterministic
[77]		✓					✓		✓	✓			Static DLM-STS	DE	Deterministic
[79]		✓			✓				✓	✓	✓		Static DLM-STS	ES	Deterministic
[80]		✓			✓	✓			✓	✓			Static DLM-STS-SY	MINLP	Deterministic -FBS
[81]		✓			✓	✓			✓	✓			Static DLM-STS-SY	DP	Deterministic
[82]		✓			✓				✓	✓			Static DLM-STS-SY	PSO	Deterministic -FBS
[83]		✓				✓				✓	✓		Static DLM-STS	Exact	Deterministic
[84]		✓		✓		✓			✓	✓	✓		Static DLM-STS-SY	GA	Deterministic
[85]		✓				✓			✓	✓			Static DLM-STS-SY	ICA	Deterministic -FBS
[86]		✓			✓	✓			✓	✓			Static DLM-STS-SY	Exact	Deterministic
[87]		✓		✓	✓	✓			✓	✓			Static DLM-STS	SPSO	Deterministic
[88]		✓				✓			✓	✓			Static DLM-STS-SY	PSO	Deterministic
[89]		✓			✓	✓			✓	✓			Static PLM-MTS	MCS	Probabilistic
[90]		✓			✓				✓	✓	✓		Static DLM-STS	Exact	Deterministic

TABLE 2. ***(Continued.)*** **Comprehensive comparison of the reviewed CSS literature: summary 2.**

[91]		✓		✓	✓			✓	✓	✓		Static DLM-STS	Exact	Deterministic
[92]		✓		✓	✓			✓	✓			Static DLM-STS	ICA	Deterministic -FBS
[93]		✓		✓	✓			✓	✓	✓		Static DLM-STS	HSA	Deterministic
[94]		✓		✓	✓			✓	✓	✓		Static DLM-STS	ICA	Deterministic -FBS
[95]		✓		✓	✓			✓	✓			Static DLM-STS-SY	ICSA	Deterministic -FBS
[96]	✓		wind	✓	✓		✓	✓	✓	✓		Static DLM-STS-SY	AGA	Deterministic-AC OPF
[97]	✓		wind	✓	✓		✓	✓	✓			Static PLM-MTS	GA	Deterministic - FBS
[98]	✓		BESS	✓	✓		✓	✓	✓			Static DLM-STS-SY	MINLP	Deterministic-DC OPF
[100]	✓		ESS	✓	✓		✓	✓	✓			Static DLM-STS	Exact	Deterministic
[101]	✓		EVs	✓	✓	✓	✓	✓	✓			Static DLM-STS	FPA	Deterministic
[102]	✓		PV	✓	✓	✓	✓	✓	✓			Static DLM-STS	FPA	Probabilistic -
[24]	✓		*Wind, PV*	✓	✓	✓	✓	✓	✓			Static DLM-MTS	GA	
[103]		✓			✓							Static DLM-STS	Exact	Deterministic
[104]	✓		*DGs*	✓	✓		✓	✓	✓			Static PLM-MTS	PSO	Deterministic - FBS
[105]	✓		*ESS*	✓	✓		✓	✓	✓			Static PLM-MTS	MILP	Deterministic AC OPF
[140]		✓		✓	✓			✓	✓		RC	Static DLM-STS	PSO	Deterministic -FBS
[106]		✓		✓	✓			✓	✓			Static DLM-STS	DP	Deterministic - FBS
[107]	✓		DG	✓	✓			✓	✓			Static PLM-MTS	MOPSO	Probabilistic

[*] In this work, the load model is described in 4 parts: The type (static/dynamic), load representation (deterministic load model (DLM) or Probabilistic load model (PLM)), the resolution (single time step (STS)) or multiple time step (MTS)). This results in the nomenclature used as show in the table.

uncertainties. In addition, such a modeling approach requires extensive data to sufficiently characterize the loads. Even though static and deterministic methods may be simpler in implementation, they may lead to inaccuracies in the assessment.

2) LOAD GROWTH MODELLING IN CSS

Load growth is an essential component of load modeling in the CSS problem. Essentially, selected conductors must meet load scenarios in a defined planning horizon. A predetermined annual growth index, g_{index}, is applied in most of the studies as depicted in [27], [64], and [86]. The load in the planning period N, is thus a factor of the current load and is based on the equation below.

$$Load_{yearN} = Load_{year=1} \times (1 + g_{index})^N \tag{1}$$

The index is generally derived through forecasts that are based on historical loads.

Limitations of the Current Load Growth Models:

The use of load growth indices can be limited where active CSS is concerned. This arises from various factors discussed below.

- The use of historical data to compute load growth indices is inaccurate given the emerging load patterns. As such, the projection of future load scenarios must include forecasts of technology adoption such as EVs, BESS, and PV systems to adequately represent the changing load dynamics.
- Current load growth models do not incorporate the extensive spatial-temporal DER characteristics necessary to address the planning uncertainties that may occur in future loads.
- The use of deterministic load growth indices may be inapplicable to modern CSS due to the DER uncertainties.

3) MODELLING DER UNCERTAINTIES IN CSS

Generally, DERs can be charging/discharging loads or distributed generation (DGs). Charging/discharging loads have a dual mode of operation and can draw or inject power into the network. They consist of electric mobility and energy storage systems. On the other hand, DGs generally inject power into the network. Their operation (output and use) depends on stochastic factors such as uncertain wind speed for wind DGs [97] to unknown ToU for EVs [21]. These uncertainties can affect distribution network operations.

The representation of DER planning and operational uncertainty in the CSS literature are explored in the following paragraphs.

a: MODELING DER PLANNING UNCERTAINTIES IN CSS FORMULATIONS

Aspects of DER planning, including the type, the sitting, and the capacity of DERs connected to the node and phase of the distribution network are critical in the CSS process. These aspects, also referred to as DER allocation properties, often determine the severity and magnitude of DER impact, particularly at the LV distribution level, where they are random and unknown to the utility operator. Therefore, it is important to formulate appropriate models that can represent the randomness in DER planning [26]. To establish the limitations that must be addressed, this section examines DER planning uncertainty and how DER placement has been modeled in literature.

Most literature points to two kinds of DER placement. These consist of fixed and random placements. In the fixed placement approach, the type, and the capacity of DERs connected to the network are predetermined. For example, in [96] and [97], the authors model the fixed placement of wind turbines. In [100] and [105] a fixed battery storage system is modeled. Even though the selection of the type of DERs depends on several factors including resource availability and suitability of the technology, the selection of the capacity must follow a detailed study that determines the network HC. Studies reported in [21], [26], and [31] incorporated random placement of DERs in the CSS process. In these, random placement is implemented using the Monte Carlo simulation (MCS) approach.

It is further expected that future networks will have multiple DER technologies such as EVs, ESS, and DGs that include solar PV and wind turbines. These technologies have different operational characteristics and may require different modeling approaches. However, from the literature, CSS studies consider at most, two DERs, and in most cases, where there are two DER types, fixed DER placement is used. In [32], both wind turbines and solar PV, with fixed placement, are considered and a combination of PV and ESS is studied in [20], [98]. Some active CSS studies consider multiple DERs in the formulation of the CSS framework. Compounding the need to model multiple DERs with the lack of knowledge about DER placement further complicates the modeling problem.

Allocation modeling has been carried out in various power system planning studies. Studies reported in [99] and [105] investigated wind DG allocation in multi-stage and joint DNP problems respectively. Similarly, energy storage systems' (ESS) allocation is considered in the expansion planning problem to offer voltage support [107]. Additionally, ESS and DG allocation are reported in [109], [110], and [111]. Similarly, the study in [112] explored the allocation of fast charging stations to enhance EV utilization. In [113], the authors model random DG placement using MCS. Similar work is conducted in [114]. In addition to these, optimal allocation of critical network equipment such as capacitors, and voltage regulators is reported in [32]. Understanding the underlying allocation procedures may provide a guideline on how to model DER placement in CSS-related studies.

b: MODELING OF DER GROWTH IN CSS FORMULATION

Modeling of DER growth is a key aspect of long-term network planning, which usually spans up to about 30 years. As such, DER growth can significantly impact conductor sizes. To meet the likely challenges associated with the increasing penetration of DERs, DER growth must be incorporated into CSS models. Growth modeling is also critical in the effective management of DERs, which depends on the planning as well as the DER rate of adoption [115]. Growth models can also identify the spatial-temporal points at which the network becomes constrained [116].

Several studies related to DER growth planning have been published. Some focus on DG growth planning [102], [117], electric vehicle growth modeling [118], [119], [120], growth of storage [121], and solar PV diffusion modeling [122]. However, the integration of these models into CSS has not been carried out.

c: MODELING DER OPERATIONAL UNCERTAINTIES IN CSS FORMULATIONS

DER output modeling is important in understanding the temporal output characteristics of DERs, and their potential effects [123]. Further, understanding the ToU patterns is critical as it can influence key decisions such as the choice of reinforcement approach. From the literature, several DER output models have been applied in CSS. This study classifies them into probabilistic and deterministic models.

Probabilistic output models usually incorporate uncertainty modeling. These models characterize the DER output using PDFs or through an alternative uncertainty-based approach. In describing the expected output, such methods must incorporate risk. In [26] and [31], the output of solar PV is computed based on a solar irradiance proxy, modeled using a peaky beta PDF, typical of a summer season's irradiance for a small geographic area.

A similar method is used in [21] to characterize the loading characteristics of EVs connected to an LV network. In addition to the use of PDFs, interval analysis is used in [32] to model the output of solar PV and wind generation. The wind output is characterized based on the wind speed intervals, ranging from zero to the cut-off wind speeds. Similarly, the output of solar PV is defined in a piecewise manner based on interval segments, as a function of the range of irradiance. A similar approach is used in [97]. Finally, in [98], the authors provided a generalized output of PV and ESS ToU characteristics and used them in CSS for reconductoring.

Deterministic modeling of DER output is explored in [96]. The output of wind generators is modeled based on the maximum possible output. A similar modeling approach is used in [20].

d: LIMITATIONS OF THE CURRENT DER UNCERTAINTY MODELS

Some of the limitations associated with the current DER planning uncertainty models are explored below.

- Fixed placement modeling of DERs simplifies the computational problem but does not represent DER adoption in practice. Even if such modeling is useful in circumstances where rigorous laws govern growth plans, it is still impossible to regulate the capacity, loading, and output of other types of DERs, particularly ESS and EVs, whose installation and use are more random and complex.
- MCS probabilistic modeling allows for extensive planning of allocation possibilities. While these planning models can accurately analyze the locational implications of high DER penetration, they have higher processing requirements.

- CSS is a long-term planning endeavor that must take DER growth into account. However, this is not well covered in the current CSS formulations.

Appropriate growth models are therefore required.

On the other hand, while there is progression relating to the modeling of operational uncertainties in CSS, various limitations exist, and some are highlighted below.

- The application of deterministic approaches can lead to inaccurate estimation of DER impacts, and the selection of suboptimal conductors.
- More work is needed to model several types of DERs on the network to fully capture future operational scenarios.

Accurate modeling of inputs is key in ensuring that the subsequent CSS computational processes obtain the correct inputs. The following sections discuss how key aspects of the CSS computation and analysis have been conducted in the literature.

B. LOAD FLOW COMPUTATION

Load flow computation is key in determining the magnitude of the line power flows, the levels of voltage, and the unbalance in the network, among other critical parameters. These parameters determine the compliance of the network performance to the set-out QoS standards under various loading and DER allocation scenarios. In general, load flow computation is a standard component of the CSS problem. The selection of the approach is dictated by the desired accuracy and sometimes the need to reduce the computation burden. There are two main classifications of load flow approaches reported in the literature. These consist of deterministic and probabilistic approaches [124].

Deterministic load flow approaches use average values to represent the magnitude of the loads [125]. They are implemented using various methods highlighted in [126]. In [42], [96], and [105], the alternating current optimal power flow (AC-OPF) method is used. The linear load flow method has been used in power flow studies related to CSS in radial networks [39], [40]. Compared to the other methods, the linear load flow approach is simple to implement. The node power balance method, which is a direct deterministic load flow (DLF) method is reported in [48] and [91]. The method is also applied in [35], [36], and [44]. Most direct methods are approximate and relatively easy to implement given the less computational requirement associated with them.

Forward-backward sweep (FBS) propagation is an iterative DLF method implemented by considering the deviation of parameters, particularly voltage levels from a reference node. The use of iterations makes the process time-consuming. The method has been widely applied in CSS and capacitor allocation [84], [95], CSS for SWER lines [80], [82], and in solving the most general CSS problems, highlighted by representative studies in [41], [50], and [94]. The Gauss-Seidel method has been used in [46] and [84]. The Gauss-Seidel method is simple but is usually restricted to small networks since it is iterative and can be time-consuming when used to solve power flows on larger networks. The other reported DLF method is the unbalanced three-phase load flow method [77]. In general, the use of DLF methods does not sufficiently capture the inherent uncertainties associated with the load and as such may result in poor load estimation, leading to suboptimal conductor choice.

Probabilistic load flow (PLF) methods are built to sufficiently represent the uncertainties of the inputs to the power flow computation exercise [126]. As such, these inputs are represented as PDFs or use an alternative probabilistic representation [127]. Various PLF methods have been used in CSS in the recent past. Analytical PLF is applied in [21], [26], and [31]. In these studies, the loads and DER inputs are defined using beta distribution for each period, and the worst-case interval used in the computation process.

Power flow input uncertainties can also be represented using an interval-based approach as detailed in [128]. This method is applied in [32] and [97]. Given the computational requirement of this process, the authors in [32] used the spherical unscented transform (SUT) to represent the interval parameters.

PLF methods are likely to record higher accuracies due to the repeated simulations, and the incorporation of all the temporal loading conditions. As such, they are more suitable in the context of high uncertainty prevalent in ADN planning. Caution must be taken in the selection of the specific PLF method, considering the representativity of numerical simulation methods, the extent of simplifications in analytical methods, and the trade-off between computational speed and accuracy.

C. OPTIMIZATION METHODS IN CSS

Optimization is the process of finding the minimum or maximum value of a function [129]. The process comprises three elements: (a) the objective function – which defines the goal of the optimization process, (b) the constraints – which impose limitations on the optimization objective, by defining the bounds of a feasible design and (c) the decision variables, which are the variables that the objective function can modify to come up with the optimal values [130]. It is important to carefully select the decision variables, the constraints, and the objective function. A generic optimization equation takes a form that combines all these elements as in equations (2) to (4).

$$\min_{x} C(x) \tag{2}$$
$$\text{s.t} \quad f(x) = \emptyset \tag{3}$$

and

$$g(x) \leq \theta \tag{4}$$

The functions C(x), g(x), and f(x) represent the objective function, the inequality constraints, and the equality constraints respectively. The variable x represents the selected decision variable.

This section provides a comprehensive analysis of the optimization methods found and used in CSS problems. It discusses the optimization methods, the objective functions, and the scope of constraints used in these studies.

1) CLASSIFYING OPTIMIZATION METHODS

There are different classes of optimization algorithms in the literature. These are classified into mathematical, stochastic, statistical, and non-traditional optimization techniques [129]. The non-traditional class of optimization algorithms mimics natural processes such as genetic mutation processes, and the behavior of insects among others. These are also known as modern heuristic algorithms. Studies in [130] and [131], classified these techniques into mathematical (exact) and heuristic algorithms. In general, exact algorithms perform better than heuristic approaches in finding optimal solutions. This review uses the classification in [130] and [131].

a: MATHEMATICAL ALGORITHMS IN CSS

Mathematical or exact optimization algorithms are based on mathematical relations. They are usually well-defined and follow the characteristics of the underlying equations (2) to (4) and as such their formulation and solutions are based on the relationship between the function variables or constraints. For instance, where C(x) or g(x) and/or f(x) are nonlinear, a non-linear solution is applied. Equally, if C(x), g(x), and/or f(x) are linear, a linear approach is used. Similarly, integer programming can be applied in problems where all decision variables are integers. In cases where the variables are mixed, the problem is referred to as mixed-integer programming (MIP). Further, the formulation of optimization problems can take the form of mixed-integer linear or non-linear programming [130].

Different forms of mathematical optimization have been applied in CSS. Notably, mixed integer linear programming (MILP) and modified chance-constrained MILP version are used in optimizing the cost of conductors in [39], and in optimizing the total investment costs for a DNP process in [105] respectively. The chance-constrained MILP achieves better results. Mixed Integer Non-linear Programming (MINLP) is applied to minimize the cost of losses through CSS and capacitor placement [42] and in optimizing CSS costs for a SWER line [80].

Dynamic programming (DP) is applied in CSS and other DNP problems, mainly in multi-stage decision problems where optimal solutions are required over multiple intervals [130]. Studies in [81] and [132] applied DP in CSS and reconductoring problems respectively. DP is also applied in [106]. Other passive CSS studies that used exact optimization are outlined in [40] and [55]. Exact methods in active CSS studies are also explored in [21], [26], and [31].

In [37] and [48], the authors used an integrated approach combining the economic current density (ECD) and heuristic-based methods to conduct optimal CSS. ECD method is also adopted for transmission line CSS [90]. Evidently, by utilizing the mathematical relations between the function variables, and exploiting the nature of variables, mathematical optimizations can be formulated. In general, mathematical algorithms are complex in implementation [130].

b: MODERN HEURISTICS ALGORITHMS IN CSS

Modern heuristic algorithms apply problem-independent frameworks using concepts, and operators that follow principles of analogy, and induction to solve a problem [131]. These ideas are generally derived from natural or biological processes [130]. Reported heuristic algorithms include genetic algorithms (GA), evolutionary strategies (ES), and various forms of particle swarm optimization (PSO) algorithms, among others. The following paragraphs provide a high-level discussion of their application in CSS.

GA has been extensively applied in CSS. In [54], the authors used GA to select optimal conductor sizes. Similarly, in [97] the method is used in optimizing conductor sizes for a system with wind generation. In [32], [46], and [84], the optimization of conductor and capacitor sizes was implemented using GA. This method was applied to the maximum loss reduction problem through CSS and capacitor placement [43]. Its modified version, adaptive GA is used in [96] to select conductors for a network with DGs. Other works in which GA has been applied include the selection of conductors in a multi-stage DNP problem [24], and in solving combined CSS and capacitor allocation problems as reported in representative studies in [46] and [51]. The wide application of GA in optimization and search problems can be attributed to its high probability of finding the global optimum [129].

ES optimization methods have been used in [41] to solve a CSS problem. Similarly, in [68], [85], and [92], the imperialistic competitive ES is also used in CSS optimization. ES approaches are relevant in providing approximate solutions, in cases where other approaches cannot be applied. The studies in [38], [56], and [77] applied differential evolution (DE) in CSS optimization.

PSO methods have also been used in CSS problems [82]. Further CSS optimization has been done using selective PSO in [47] and [87], and discrete PSO in [35]. PSO has been similarly proposed in [104] for optimization in DNP problems. The prevalent use of PSO is linked to its relative simplicity when compared to other heuristic algorithms as well as its better convergence speed.

Search algorithms have been used in CSS optimization. Notable ones include the crow-search algorithm in [45] and the harmony search algorithm in [57]. Other algorithms used in CSS optimization include fuzzy methods [60], sine cosine algorithm [133], tree generation [44], and grasshopper optimization [27].

In general, the choice of the optimization algorithm adopted is guided by several factors including its convergence speed, and the ability of the approach to attain a global optimum [131]. Other additional factors that influence the choice of the optimization method are discussed below.

- *The complexity and type of the optimization problem:* The complexity of an optimization problem is influenced by the type of the problem, the number of decision variables, objectives, and intervals. For instance, non-convex CSS formulations (as is in most cases [134], [135]) with a higher order affine function, are more complex and require methods with better convergence compared to single-objective convex problems.
- *Computational efficiency:* Computational efficiency is a key aspect of optimization. For instance, while heuristic-based methods are suitable for searching large solution spaces, they are iterative, and this limits the computational time.
- *Number and type of decision variables:* The formulation of optimization problems depends on the type of decision variables, and as such, the choice of the optimization method must consider this and subsequently, the type of variables that determine the selection of the method.
- *Required accuracy:* The level of accuracy may determine the optimization method used. Mathematical methods may be preferred over heuristic methods when strict adherence to accuracy is required, even though they are complex.

A selected comparison of the different optimization methods is provided in Table 3, based on their prevalence in the literature.

2) CSS OPTIMIZATION OBJECTIVES

Optimal network performance and the choice of distribution network components depend on multiple objectives that influence the selection of conductors in distribution networks. These objectives can be broadly classified into technical and economic. Technical objectives relate to the desired technical performance characteristics and capabilities of the network. These objectives focus on ensuring the network's reliability and efficiency. Economic objectives, on the other hand, focus on optimizing the system's cost-effectiveness, considering both capital investments and operations costs. Fig.3 illustrates the major types of technical and economic objectives considered in the CSS literature.

a: TECHNICAL OBJECTIVES

Technical objectives focus on the optimal technical performance of the network. The reported objectives in traditional CSS include the reduction of energy losses and voltage drop. In addition, the reduction of thermal losses is a key consideration in passive and active technical design [72], [82]. Loss reduction enhances the overall QoS and minimizes conductor degradation [59]. Loss reduction with time-varying loads is explored in [50] while in [28], this is coupled with voltage regulation. This is also reported in [52] and [57].

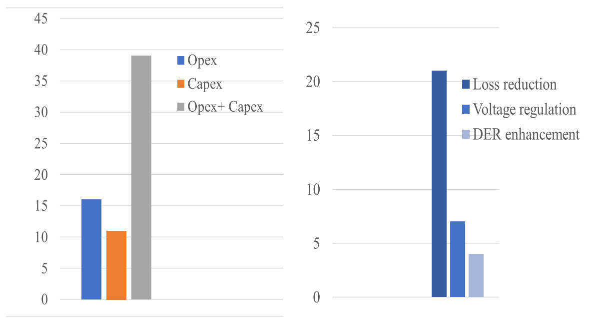

FIGURE 3. **Number of papers with the technical and economic objectives.**

Related studies in [29] and [81] investigated the minimization of energy losses in CSS while in [47], [42], [50], and [59] this objective is addressed through reconductoring and capacitor allocation. Similar objectives have been carried out in the CSS for SWER lines [80], [82]. Other studies considering power losses are reported in [43], [46], [64], and [73].

In DER-related studies, loss minimization is linked to managing reverse-power flow, which when unmitigated can lead to increased thermal losses in the system. As such, some active CSS methodologies have focused on reducing the losses that may arise due to increased DERs on the network [20]. Studies in [20] and [31], explored CSS as a way of increasing the network loading capacity, thus directly reducing the expected network losses. In [32], a stochastic approach to computing power and energy losses is formulated and used.

Voltage management is vital for optimal network performance. In various CSS studies, voltage deviation is a critical parameter often treated as an inequality constraint, bounded by specific limits to uphold system performance. Keeping operations within acceptable bounds is essential for maintaining QoS.

A few passive CSS studies have considered voltage regulation as an objective. In [40], optimal CSS addresses voltage constraint violations, while [43] and [73] focus on reducing active power losses and improving the voltage profile. Other studies like [42] and [47] implement piecewise CSS and capacitor allocation to meet thermal and bus voltage constraints. These studies emphasize optimal capacitor placement to enhance the voltage profile. Furthermore, [51] investigates optimal CSS and capacitor placement to rectify voltage deviation and manage harmonics.

Similar objectives are pursued in DER studies such as [32] and [102] where capacitor placement mitigates power and energy losses while aiding in voltage management. Additionally, [20], [26], and [31] employed CSS to limit voltage deviation within acceptable margins, facilitating increased DER penetration while applying loading constraints. In [136], the authors explore different approaches to selecting the neutral conductor. Proactive planning requires the formulation of CSS under a varying mix of DER technologies, as a possible reflection of future networks.

TABLE 3. A non-exhaustive comparison of the characteristics of optimization methods used in literature: Summary 3.

Optimization method	Objective	Mathematical formulation of the objective function	Prevalent constraints	Power flow method	DER uncertainty modeling	Merits	Limitations
Genetic algorithm (GA)	Minimize cost of conductors (CC), minimize cost energy losses (EC), minimize demand costs [97]	$\min(C_{inv} + C_{E.losses} + C_{demand})$	Voltage deviation (upper, and lower limits), Conductor thermal loading,	Forward Backward Sweep (BFS)	DER output modeled using interval analysis	GA can find solutions for non-convex problems, including those presented in CSS. GA can perform parallel comparisons of the solutions in the search space improving the likelihood of convergence. GA can search a large enough solution space and therefore more likelihood of getting a global optimum.	GA, like most heuristic methods, has high computational requirements. It also has slow convergence in its search for a global optimum.
	Minimize the investment costs, power loss costs ($C_{P.losses}$), the total energy procurement costs C_{EP} for the period of procurement, and the maintenance costs C_{mc}. [96]	$\min(C_{inv} + C_{P.losses} + C_{mc} + C_{Ep})$	Voltage limits, conductor thermal limits, power balance	AC OPF	No DER uncertainty is modeled.		
	Minimize the conductor investment costs, the cost of power and energy losses over t=8760 hours [32]	$\min(C_{inv} + C_{E.losses})$	Voltage limits (voltage rise, drop), Conductor thermal loading. Side constraint: Conductor search space, $\emptyset_{con}$	Spherical Unscented Transform (SUT)	Solar PV and wind are modeled.		
Particle Swarm optimization methods	Minimize the total costs of conductors and power losses [82]	$\min(C_{P\ losses} + C_{inv}$	Voltage limits, conductor thermal loading	FBS	No DERs	PSO has a relatively faster convergence speed compared to GA. It also has easier implementation and usually has fewer parameters to tune.	PSO may select a suboptimal solution compared to GA and may not have an effective convergence where there is a large search space.
	Minimize the cost of energy losses and the cost of depreciation on the cost of capital investments, C_{dep} [88]	$\min(C_{E.losses} + C_{dep})$	Voltage limit, conductor thermal limits	Direct DLF	No DERs		
Exact method-Mixed integer nonlinear programming (MINLP)	Minimize the investment cost of the conductors the cost of annual energy losses and the cost of penalties (C_{pen}) for a balanced three-phase distribution network for 1 year [30].	$\min(C_{E.losses} + C_{inv} + C_{pen})$	Active (P) and reactive (Q) power balance, voltage deviation, and thermal loading. Side constraint: The search space	FBS	No DERs	MINLP has the advantage of optimizing real-life decision variables, that are non-linear, and sometimes binary.	Such approaches are usually mathematically complex.
	Minimize the investment costs of conductors and capacitors as well as the cost of energy losses [42].	$\min(C_{inv} + C_{cap} + C_{loss})$	Conductor thermal limits, voltage limit constraints	AC OPF	No DERs.		
Exact methods - Numerical	Minimize the conductor investment costs, the cost of power and energy losses over t=8760 hours [37]	$\min(C_{inv} + C_{E.losses})$	Voltage limits (voltage rise, drop), Conductor thermal loading. Radiality constraints	Economic current density (ECD)	No DERs	Exact methods are generally accurate and robust when applied to a	Exact methods cannot guarantee an optimal choice of conductors,
	Minimize the power loss cost and cost of depreciation on capital investments [55]	$\min(C_{P.loss} + C_{dep})$	Voltage limits, thermal loading.	FBS	No DERs	suitable class of problems.	especially in non-convex problems. Exact methods cannot easily represent discrete variables. Exact methods are also not well suited to solving multi-objective optimization problems

b: ECONOMIC OBJECTIVES

Extensive distribution changes require significant capital (Capex) and operational expenditures (Opex) [137]. Capex covers initial conductor investment, while Opex includes operation, maintenance, and reconductoring costs, as well as energy/power losses in CSS. Energy losses impact the cost of energy, the frequency of reconductoring, and the overall efficiency of the system. Therefore, CSS's economic objectives aim to minimize some of these costs. This review groups these into Opex minimization, Capex minimization, and Simultaneous Opex and Capex minimization, focusing on reducing costs associated with these categories [25], [138].

Minimizing Opex is key in managing energy losses as evidenced in heuristic-based studies reported in [27], [65], [68], [70], and [95], and in mathematical optimizations such as [76]. This extends to minimizing conductor depreciation costs, highlighted in [35], [40], and [63]. Opex also encompasses interruption costs, emphasized in [106], and depreciation on capital, as seen in [58]. Additional costs including installation and maintenance are also included in the Opex [96]. Effective capacitor placement, which aids in loss reduction, is highlighted in various papers such as [42], [46], and [84]. Some studies have also focused on cost minimization for transmission lines, illustrated in [89], and enhancing reliability by reducing losses, as seen in [139]. Additional research on minimizing energy loss costs can be found in [71] and [73]. Opex minimization is extended to active CSS with wind DGs in [97].

Studies reported in [41], [79], and [82] aim to only minimize the capex in CSS. Additional research includes topology considerations [140], and the minimization of reconductoring and capacitor allocation costs [141]. In [99], the authors integrate DG cost in capex minimization for CSS, while [105] incorporates energy storage and conductor costs in multi-stage planning for active networks. In [86], the emphasis is on reducing the cost of losses at a substation.

Several studies attempt to simultaneously minimize the cost of capex and opex by deploying varied methods.

Different combinations of search algorithms are used to achieve this result [30], [45], [57]. Sample works that deploy exact approaches to optimize for both Capex and Opex are studied in [29], [39], and [60]. In [44], the minimization is carried out for a radial network problem while in [67] and [69], the reticulation costs, and the annualized cost of feeder losses are minimized.

Similar studies are carried out using different forms of heuristic methods including evaporating rate water cycle algorithm (ERWCA) [62], PSO [88], and ICSA [94], [95]. Furthermore in [28] and [56], the capex and opex costs are minimized considering load growth.

Initial costs for capacitor placement, losses as well as the cost of conductors are considered in [42], [43], and [93]. Similar work is carried out in [48] to improve the reactive power planning capacity. On the other hand, in [76], the focus is on the total life cycle costs, and it incorporates the cost of energy and the wholesale power cost escalation. Total life cycle costs have also been computed in [96], considering DGs and [90] in optimizing the cost of transmission lines.

Capex and Opex minimization have also been carried out in active CSS [20] to manage the planned DG capacity. Similar work is carried out in [32] and it includes the simultaneous placement of capacitors on networks with solar and wind DGs. In [98], cost minimization for active DC networks is conducted. Additionally, the study in [104] explored cost minimization in a DNP problem with DGs. The study in [97] emphasizes conductor and maintenance cost minimization to enhance the CSS process while [50] tackles capex and opex minimization for time-varying loads. In [59], optimization methods for capital and energy loss cost reduction are explored while [61] incorporates weather-sensitive load flow to minimize the fixed and variable costs. In [64], the cost minimization aims to enhance network loadability, and [80] seeks the simultaneous minimization of fixed and variable costs. Lastly, [81] focuses on minimizing capex and opex in a multi-stage CSS problem.

The extent to which the objectives affect CSS depends on factors such as the length of the feeder, the type, capacity, and location of the loads and DERs on the feeder among others. Optimizing capex and opex is key in techno-economic optimization. It is critical to consider all factors and the associated trade-offs in this process.

3) SCOPE OF OPTIMIZATION CONSTRAINTS

Optimal CSS depends on the outcomes of load flow computation. Optimality is defined by a set of common technical and economic constraints. The technical constraints include line voltage deviation, power equality balance, and thermal loading as shown in Table 2. On the other hand, the economic constraints are associated with the cost implications of the technical choices. As such, technical constraints such as voltage deviation, and thermal loading constraints usually form a set of binding constraints beyond which technical optimality is not achievable. Other binding constraints that have been applied in CSS studies include power equality constraints [96], harmonic distortion [51], and temperature [75]. In most CSS problems, the binding constraints $f(x)$ and $g(x)$ are constants, defined by regulatory limits. With the shift towards ADNs, other emerging constraints include the capacity of DERs, the acceptable risk, and the level of planned curtailment, among others. Other aspects that need consideration include load and DER growth. Load and DER growth indices are key in projecting the expected DER and load capacity [28]. In addition to these, some studies have applied radiality constraints [142].

4) APPLICATION OF RISK IN CSS

Due to the DER uncertainties, probabilistic multi-scenario analysis is usually applied in ADN CSS. For this reason, risk-based interpretation is required in CSS. Therefore, instead of using central tendencies, such as the mean, or standard deviation, risk analysis is preferred in evaluating acceptable performance. By quantifying the level of risk, the planner can consider alternative means of mitigating the low-likelihood, high-impact events on the system.

Risk has been incorporated in [21], [26], and [31] for CSS. Similarly, risk is used in [102] to assess the impact of PV on the network. Other forms of risk interpretation have been explored in [97], where a probability index is used to represent the likelihood of a state related to wind output. This index is integrated into the calculation of associated power losses. A similar approach is used in [32] to provide indices for different wind and solar output states. The risk-based analysis provides a planner with a wide range of design possibilities and influences the mitigating options to unexpected system events. Such interpretation provides an avenue for exploring and quantifying alternative non-infrastructural solutions, such as curtailment, energy storage, and demand response in network design problems.

IV. DISCUSSION

A. OVERVIEW

It is crucial to examine how the emerging complexities associated with ADN planning can be incorporated into the CSS process, given its centrality in distribution engineering. This is important in enhancing the accuracy and cost-effective mitigation of DER impacts. This section outlines the limitations associated with the present CSS methodologies and discusses the relevance of integrating these missing aspects into the formulation of CSS. It explores two critical aspects, namely, the requirements for a robust CSS process, and the implication of these requirements on ADN planning and operations.

B. REQUIREMENTS OF A ROBUST ADN CSS

1) CSS FORMULATIONS MUST INTEGRATE DER UNCERTAINTY MODELING

Literature shows that about 15% of the CSS studies incorporated DERs. This indicates that planners are aware of the changing planning and operational requirements linked to active distribution networks. Transition to grids with a higher share of DERs requires accurate modeling of the planning and operational uncertainties. New CSS models must extensively incorporate uncertainty modeling to cater to the complexities associated with DER operations and planning.

2) CSS FORMULATIONS MUST INCORPORATE HC ANALYSIS

Traditional CSS methodologies adopted different versions of load flow computation methods. However, given the multiplicity of objectives in active CSS that include enhancement of DER capacity, HC tools must be integrated into active CSS. Accurate formulation of HC analysis tools is thus a necessity as operations shift from passive to active.

3) RISK MUST BE INCLUDED AS A CSS OPTIMIZATION VARIABLE

The prevalent application of deterministic tools in passive CSS often ignores the uncertainty in the load given the predictability of traditional loads and load profiles. However, DERs introduce extensive uncertainty that requires probabilistic analysis. Interpretation of the probabilistic analysis requires an application of risk. While this has been included in several ADN CSS methodologies, it needs to be integrated as a variable in CSS optimization. This is central to getting viable tradeoffs for a cost-effective CSS process.

4) CSS FORMULATION MUST CONSIDER MULTIPLE DERs

Most of the proposed active CSS methodologies focused on one type of DER, like solar PV or BESS [3], [146], [147], [148], [149]. This limits the analysis of the possible future scenarios. It is also necessary to include complementarity analysis in network HC optimization is a crucial part of the multi-DER analysis.

5) CSS FORMULATIONS MUST ADOPT THE EXTENSIVE USE OF UPDATED LOAD DATA AND CONTROL METHODS

Traditional planning and design use a fit-and-forget strategy with yearly load growth indices approximating worst-case loads [150]. However, these models are presently unsuitable due to the changing dynamics of the load. The use of indices obtained from historical data is unreliable given the widespread adoption of dynamic loads and DGs that subsequently alter the traditional load profile. Given this, extensive data collection and management are required to understand the DER diffusion and impact on the load profile and the network. Further, the use of real-time data integration is pivotal in implementing risk-management solutions for active systems. Presently, CSS methodologies do not encompass such factors, which often results in system oversizing.

6) ACTIVE CSS OPTIMIZATION METHODS MUST INCREASINGLY BECOME MULTI-SCENARIO AND MULTI-OBJECTIVE

The number of decision variables has increased in active CSS. New variables include the capacity of different types of DERs, the capacity of complementary DERs, allowable voltage rise, the level of reverse power flow, and the risk that needs to be optimized during the CSS process. With such an increasing set of variables, associated tradeoffs arise, leading to a broad spectrum of optimization objectives that can extend beyond network cost implications. These may include the cost of optimal complementarity—using battery storage to enhance solar PV capacity— among others. In addition, the influence of emerging technologies like storage, active management tactics such as DSM, and the effects of curtailment on CSS costs should be accounted for.

C. IMPLICATION ON NETWORK PLANNING

The requirements associated with ADN CSS affect multiple aspects of network planning. Firstly, the increased need for modeling and processing uncertainty-based outputs has implication on the current design standards. Guidelines such as the NRS-048 in South Africa [151] and EN 50106 [152] widely used in Europe may require revision to consider the changing load dynamics. Planners shall likely be required to modify the existing compatibility standards to accommodate the changes in the load profiles. Persistent loading arising from dynamic loads such as BESS and EV charging may be inconsistent with the standard loading duration, and the frequency of voltage rise may increase.

Secondly, the revision of planning procedures cannot rely on the worst-case scenario without a simultaneous consideration of loading impact severity and duration. To this end, new guidelines on the acceptable severity levels, linked to their duration are necessary. This is critical in the economic optimization of the distribution engineering processes such as CSS.

The integration of risk in the design process is necessary in the planning and operation of ADNs. This is because the formulation and the level of acceptable risk can determine critical factors such as the acceptable duration of violation and subsequent level of soft mitigation needed. Studies linked to the standardization of the ADN risk models, the risk level, and the associated mitigations in distribution engineering are necessary. Additionally, the development and subsequent inclusion of new models in the distribution engineering process, including ADN CSS, requires the retraining of distribution operators to enhance the utilization of the tools.

From the preceding discussion, the transition toward active distribution engineering has implications for distribution planning and operations. Careful integration is thus needed to provide accurate planning and operation models.

V. CONCLUSION

The study analyzed 84 CSS articles from 1955 to 2022, focusing on CSS modeling to monitor progress as power systems shift to active operations. It identified limitations and proposed solutions for emerging challenges in ADN CSS. The study provided an active CSS framework, outlining the key areas that require modification. The study further discussed progressive modeling in three key aspects of active CSS:

TABLE 4. List of abbreviations.

Abbreviation	
AC OPF	*Alternating current optimal power flow*
AC_l	*Accessories purchasing costs of the conductors*
AGA	*Adaptive genetic algorithm*
AP_l	*Asset purchasing costs of conductors*
BFS	*Backward forward sweep*
BWMT	*Branch-wise minimization technique*
CSA	*Crow search algorithm*
DC*	*Demand costs*
DC OPF	*Direct current optimal power flow*
DE	*Dynamic evolution*
DigS	*Dig Silent*
DLF	*Distribution load flow*
DP	*Dynamic programming*
DPSO	*Discrete particle swarm optimization*
EC	*Energy costs*
ECD	*Economic current density*
EP	*Evolutionary programming*
EP_l	*Energy procurement costs*
ER-WCA	*Evaporation rate water cycle algorithm*
ES	*Evolutionary strategy*
FBS	*Forward-backward sweep*
FDLF	*Fast deterministic load flow*
FPA	*Flower pollination algorithm*
FRI	*Feeder reinforcement index*
GA	*Genetic algorithm*
GO	*Grasshopper optimization*
GS	*Gauss-Seidel*
HBE	*Herman beta extended*
HSA	*Harmony search algorithm*
ICA	*Imperialist competitive algorithm*
ICSA	*Improved cuckoo search algorithm*
IN_l	*Installation costs of the conductors*
Isc	*Short-circuit currents*
ISP	*Inspection costs*
IST	*Inspection times per year*
MCS	*Monte Carlo Simulation*
MDE	*Modified differential evolution*
MILP	*Mixed integer linear programming*
MINLP	*Mixed integer non-linear programming*
MOPSO	*Multi-objective particle swarm optimization*
NR	*Newton Raphson*
OC	*Operations costs*
PGS	*Plant growth simulation*
PL_l	*Power loss associated with the conductors*
PSO	*Particle swarm optimization*
RC	*Radiality constraint*
REC	*Recondition costs of the conductors*
RET	*Reconditions times per year*
SPSO	*Selective particle swarm optimization*
SSO	*Salp Swarm Optimization*
SUT	*Spherical unscented transform*
TC	*Total costs*
THD	*Total harmonic distortion*
TL	*Thermal life*
TLBO	*Teaching learning-based optimization*
WO	*Whale optimization*

(1) loads and DERs, (2) load flow computation methods, and (3) optimization methods stressing the need to integrate uncertainty modeling and HC analysis into CSS formulation. It further highlighted the complexity of active CSS due to multiple objectives and scenarios, necessitating consideration of various variables for accurate analysis, including incorporating risk in optimization models. The study emphasized the importance of data collection and utilization to grasp evolving dynamics in DERs and loads for effective decision-making in active CSS. Findings from this study offer general guiding principles for the selection of power system equipment in active networks.

APPENDIX: LIST OF ABBREVIATIONS

See Table 4.

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