Overview of Loss Sensitivity Analysis in Modern Distribution Systems

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ABSTRACT

Distribution system planning and operation has seen many structural changes due to the increased participation of consumers in the energy market and the adaptation of new technologies such as distributed energy resources (DERs), electric vehicles (EV) and local energy storage systems (ESSs). Despite the convenience of such technologies and the gradual drop in their prices, new technical challenges (e.g., excessive power losses) have emerged at the system level. Over the past few decades, power loss minimization in distribution systems has gained popularity and the need for loss sensitivity analysis (LSA) frameworks has become a necessity for its successful implementation. Existing work on LSA mostly focuses on system planning aspects through DER optimal placement and sizing. However, enabling LSA-based system operational applications is a vital step toward the successful transition to modern distribution systems (MDSs). Therefore, this paper presents a comprehensive overview on the state of the art in LSA for MDSs. First, the theoretical formulations of existing LSA methods are summarized. Then, the applications of LSA in distribution systems are highlighted. Finally, based on the analysis of literature, open research gaps and future research pathways are discussed.

INDEX TERMS

Modern distribution systems, power loss minimization, DER integration, EV management, sensitivity analysis.

ACRONYMS

ADMS Advanced distribution management system
ANN Artificial neural network
CLF Classical load flow
DER Distributed energy resources
DFIG Doubly-fed induction generator
DSSE Distribution system state estimation
ELF Exact loss formula
ESS Energy storage system
EV Electric vehicle
G2V Grid-to-vehicle
GA Genetic algorithm
HC Hosting capacity
HEMS Home energy management system
IA Incremental allocation
LSA Loss sensitivity analysis
LSM Loss sensitivity matrix
MDS Modern distribution system
MILP Mixed integer linear program
MPPT Maximum power point tracking
NAF Nodal allocation factor
NSF Nodal sensitivity factor
NTL Non-technical losses
OMS Outage management system
OTI Optimal topology identification
PV Photovoltaic
SC Shunt capacitor
SDMS Sensor data management system
STS Standard test system
TL Technical losses
V2G Vehicle-to-grid

I. INTRODUCTION

Modern distribution systems (MDSs) are facing major challenges due to the rapid growth in energy demand and the engagement of consumers in energy markets. Consumers can participate in the energy market through local energy management, home automation, energy storage and usage,
electric vehicle (EV) charging, distributed energy resources (DER) integration, and many other ancillary services [1]. Through this participation, consumers can also schedule their loads based on dynamic electricity prices [2]. The motives for consumers to engage in such activities include: (1) reducing carbon footprint, (2) economic profitability; and/or (3) raising living standards through seeking comfort [3]. However, the increased engagement of consumers in such activities may impose new challenges to the operation of the system. If such consumer activities are not properly accounted for, technical challenges like increased power losses [4], nodal under-voltages [5], and reverse power flow [6] will arise. High levels of power losses in the distribution system results in economic losses and degradation of overall system efficiency. It is estimated that the average power loss across the globe is approximately 8% of the total produced electricity [7], which is a non-negligible amount of economic loss that utilities strive to minimize. Therefore, real-time loss monitoring through loss sensitivity analysis (LSA) will become a necessary tool to determine the impact of these technologies on system losses [8]. In fact, using these sensitivity tools together with efficient communication infrastructure, distribution system operators can optimally control system operations to maximize efficiency [9]. For example, there might be locations in the system where losses can be high during peak demand hours. In this regard, LSA-based real-time optimal EV charging can be used to improve system efficiency and provide economic savings to utilities and consumers. Thus, the adaptation of LSA framework is essential for successful transition to MDSs.

A. RELATED WORK

Power loss minimization in distribution systems has garnered significant attention in the last few decades. In this view, LSA is an impact-assessment tool has attracted many researchers in the field. It has been shown using LSA that DERs such as photovoltaic systems (PV) play a vital role in alleviating excessive power losses. For example, [10] proposes a Monte-Carlo method for optimal placement and sizing of DERs and shunt capacitor (SCs) to reduce active power losses in distribution systems via incremental PV size changes. The study uses LSA to determine optimal locations of DERs and SCs. Similarly, authors in [11] propose a mixed integer linear programming (MILP) approach to determine the optimal size of DERs that minimizes system losses given DER placement criterion using LSA. Typically, in planning studies, the nodes are ranked according to their impact scores on system losses and nodes with the highest scores are chosen as suitable candidates for DER placement [12]–[14]. LSA can also be used in operational applications such as EV charging management [15], [16] or optimal system reconfiguration in the presence of DERs and SCs [17], for maintaining minimum system losses. Due to the extensive literature works on distribution system optimization with LSA, several efforts have also tried to review the state of DER optimal placement and sizing using LSA. For example, [7] proposes a comprehensive study for optimal DER placement techniques for loss minimization and voltage profile enhancement. The study summarizes the optimization techniques into three main categories: (1) classical optimization such as MILP and Monte Carlo method; (2) nature-inspired optimization algorithms such as genetic algorithm (GA) and artificial neural networks (ANN), and (3) hybrid approaches that typically combine different nature inspired optimization algorithms to reduce computational burden or achieve higher optimality. Similarly, [18] reviews state of the art on DER optimal placement and sizing but with more focus on the advantages and disadvantages of optimization algorithms. In addition [19], [20] review definitions, system constraints and type of DERs used for optimal placement and sizing studies. Alternatively, authors in [21]–[23] only focus on nodal voltage profile enhancement whereas references [24]–[26] focus on power loss minimization using optimal DER optimal placement and sizing. While these LSA methods hold promise in system planning, the need for new LSA approaches that enable real-time system monitoring and optimal operation is growing, as we see more active consumers engage in energy markets through DER and EV integration. For instance, it can be easily seen that most of the prior work focuses on the area of DER planning and the corresponding optimization algorithms for finding optimal location or size [10]. However, the structure MDS requires the development of efficient operational applications that will require dynamic and computationally efficient sensitivity frameworks. In this regard, none of the related literature work provides a comprehensive analysis on the fundamental LSA methods that enable efficient operation of modern applications such as system reconfiguration and EV charging management. Therefore, the main aim of this paper is to address this research gap and help direct the focus of future research efforts in this important domain.

B. CONTRIBUTIONS

This paper presents a comprehensive analysis of existing literature that uses LSA for MDS planning and optimal operation. The major contributions of this work are listed below.

1) This work, for the first time, summarizes and categorizes existing LSA approaches including load-flow methods, nodal sensitivity factors, and analytical approximations based on different metrics.
2) The work highlights the advantages and disadvantages of LSA methods and further includes a comparative analysis between selected classical load flow and analytical sensitivity methods.
3) Based on a comprehensive analysis of the literature, this paper discusses in details existing research gaps and presents possible future research directions related to LSA-based planning and operational applications.

The rest of the paper is organized as follows. Section II includes a brief background on LSA and summarizes existing loss sensitivity methods. Section III provides a short comparative analysis between the most widely used sensitivity methods and discusses the opportunities for utilizing
analytical sensitivity frameworks to accommodate DER uncertainty. Section IV summarizes existing applications of LSA including optimal topology identification, DER planning, SC allocation and EV management. Section V analyzes the existing literature work and lists the research gaps and future directions. Finally, section VI concludes the paper.

II. POWER LOSS SENSITIVITY ANALYSIS

Power in distribution systems is transferred either via overhead lines or underground cables. In both types, the system is susceptible to power losses due to the increased heat in conductors [27]. Power loss can be categorized into either technical (TL) or non-technical losses (NTL) [28]. The first category includes losses due to resistance of system lines and the relative amount of current flow, leakage and transformer losses and corona losses [29]. NTLs in the system can be caused by several factors such as inaccurate meter readings, device malfunctioning, and billing cycle errors. In other words, NTLs occur when energy is efficiently delivered but not accurately measured at the consumer end due to device errors, fraud or theft [30]. TLs contribute the highest to total system losses as they are related to system mode of operation. Therefore, this section thoroughly explains existing methods for technical LSA in distribution systems.

A. SYSTEM DESCRIPTION

TLs in distribution systems can either be active or reactive power losses. Active power loss is mainly due to the resistance of lines in the system whereas reactive power loss depends on the reactance of lines. Active power, i.e., power transferred to consumers, is the main focus of utilities because increased active power loss in the system can result in significant amounts of economic losses [31]. However, this does not mean that reactive power loss is insignificant. Reactive power provides support to system operation in many aspects [32]. For instance, reactive power is essential for maintaining system voltage while delivering active power to consumers. Reactive power can also be used by DERs, such as doubly-fed induction generator (DFIG)-based wind turbines, in order to generate active power. Both active and reactive power losses can be computed in order to analyze system performance. To start with, consider a radial distribution system with \( L \) lines \( N \) nodes. Assume the line \( l \in L \) connects nodes \( m, n \in N \) with impedance of \( Z_{mn} = R_{mn} + jX_{mn} \) as illustrated in Fig.1. Here, node \( m \) denotes the origin node and \( n \) represents the destination, where power flows from the origin to the destination node. Then, the complex power loss (\( L_{mn} \)) on line \( l \) can be computed as, [32],

\[
L_{mn} = |I_{mn}|^2Z_{mn} = I_{mn,P} + jI_{mn,Q} = \left[|I_{mn}|^2R_{mn} + j|I_{mn}|^2X_{mn}\right]
\]

where \( L_{mn,P} \) and \( L_{mn,Q} \) are the active and reactive power losses on line \( l \). Eq. 1 can also be used to compute the overall power loss in the system (\( L_s \)) as,

\[
L_s = \sum_{l \in L} |I_l|^2Z_l = \sum_{l \in L} L_{l,P} + j\sum_{l \in L} L_{l,Q} = \sum_{l \in L} |I_l|^2R_l + j\sum_{l \in L} |I_l|^2X_l.
\]

There is ample work in the literature that analyzes the impact of consumer resources on system losses. In this regard, LSA can be defined as the sensitivity of system losses to changes in complex power at any node in the system. The following subsections thoroughly investigate existing loss sensitivity methods and highlights their major advantages and disadvantages. Fig. 2 summarizes the steps of each LSA method as discussed in the following subsections.

B. CLASSICAL LOAD FLOW SENSITIVITY

Classical load flow (CLF) sensitivity exploits the inverse of system Jacobian to compute the change in losses on individual distribution lines, and thereby, overall system losses. Line loss sensitivity is related to voltage sensitivity given a particular change in power consumption or injection at different locations in the system (\( \Delta y \)). The Newton-Raphson method is first used to compute the change in voltage magnitude (\( \Delta V_k \)) and angle (\( \Delta \delta_k \)) of node \( k \in N \). In this case, the known system parameters are the real and reactive power and the unknown parameters are the voltage magnitude and angle. Using system Jacobian matrix (\( J \)), one can calculate the unknown voltage magnitude and angles for all nodes as,

\[
\Delta x = J^{-1}\Delta y.
\]

where, \( \Delta x = [\Delta V_k, \delta_k]^T \) and \( \Delta y = [\Delta p, \Delta q]^T \). The change in line current flows (\( \Delta I \)) can be computed based on the admittance matrix \( Y \) as,

\[
\Delta I = Y \cdot \Delta x.
\]

The change in current flow from origin to destination node allows computing the change in complex power loss through that line (\( \Delta L_{mn} \)) as,

\[
\Delta L_{mn} = |\Delta I_{mn}|^2Z_{mn}.
\]

Based on (2), (5) can also be used to determine the change in total system complex power losses (\( \Delta L_s \)) as

\[
\Delta L_s = \sum_{m,n \in N} |\Delta I_{mn}|^2Z_{mn}.
\]
CLF-based sensitivity serves as the groundtruth and is typically used as a benchmark to validate analytical approaches for voltage and loss sensitivity. The dependence of this method on the Jacobian matrix calculation limits its applicability in MDSs due to the relative computational complexity compared to analytical methods [33]. Further, the accuracy of load flow sensitivity methods relies on simulating large number of scenarios to capture the uncertainties with DERs.

C. EXACT LOSS FORMULA (ELF)

The ELF is based on system topology and the change in system states such as nodal voltages, line impedance, and the change in complex power [34]. According to the ELF, the total real power loss in the system can be computed as [35],

$$ L_s = \sum_{m \in N} \sum_{n \in N} \left[ \alpha_{mn}(P_mP_n + Q_mQ_n) + \beta_{mn}(Q_mP_n - P_mQ_n) \right], $$

(7)

where $\alpha_{mn} = \frac{R_{mn}}{V_mV_n} \cos(\delta_m - \delta_n)$, $\beta_{mn} = \frac{X_{mn}}{V_mV_n} \sin(\delta_m - \delta_n)$.

Here, $V_m$ and $V_n$ are the voltage magnitudes whereas $\delta_m$ and $\delta_n$ are the voltage angles of nodes $m$ and $n$, respectively. When complex power at node $m$ changes from $S_m = P_m + jQ_m$ to $S_m' = P_m' + jQ_m'$ with $\Delta S_m = S_m' - S_m = \Delta P_m + j\Delta Q_m$, the ELF can be rewritten as,

$$ L_s = \sum_{m \in N} \sum_{n \in N} \left[ \alpha_{mn}(\Delta P_mP_n + \Delta Q_mQ_n) + \beta_{mn}(\Delta Q_mP_n - \Delta P_mQ_n) \right]. $$

(8)

D. NODAL SENSITIVITY FACTORS (NSFs)

NSFs relate the sensitivity of system losses to individual nodes given a particular static complex power change profile.

This method is used as a way of reducing the search space when selecting candidate nodes for DER placement algorithms (with lower complexity and execution time) [37]. For instance, nodes with high NSFs are selected as candidate nodes for optimal placement of DERs and SCs [38], [39]. NSFs are computed using partial derivatives of system line losses. Consider again nodes $m$ and $n$ that are shown in Fig. 1 connected by line impedance $Z_{mn}$. The active and reactive power losses on this line can be written as [36], [40] [37],

$$ L_{mn,p} = \frac{(P_m^2 + Q_m^2)R_{mn}}{(V_n)^2} $$

(9)

$$ L_{mn,q} = \frac{(P_m^2 + Q_m^2)X_{mn}}{(V_n)^2}. $$

(10)
Using (9) and (10), one can compute NSFs based on partial derivatives [36], [38] of system losses with respect to active power consumption at the destination \( n \) node as follows,

\[
NSF_p = \frac{\partial L_{mn,p}}{\partial Q_n} = \frac{2Q_nR_{mn}}{(V_n)^2}
\]

(11)

\[
NSF_q = \frac{\partial L_{mn,q}}{\partial Q_n} = \frac{2Q_nX_{mn}}{(V_n)^2}.
\]

(12)

Other NSF approaches are used in literature [41]–[43] where the partial derivatives are taken with respect to the active power at node \( n \). In this way, the active power NSF can be formulated as,

\[
NSF_p = \frac{\partial L_{mn,p}}{\partial P_n} = \frac{2P_nR_{mn}}{(V_n)^2}.
\]

(13)

Further studies propose the concept of combined-NSFs [45]–[47], which takes into account both real and reactive power changes into the sensitivity criteria, which results in the following loss sensitivity matrix (LSM),

\[
LSM = \begin{bmatrix}
\frac{\partial L_{mn,p}}{\partial P_n} & \frac{\partial L_{mn,q}}{\partial P_n} \\
\frac{\partial L_{mn,p}}{\partial Q_n} & \frac{\partial L_{mn,q}}{\partial Q_n}
\end{bmatrix}.
\]

(14)

The control variables in this case are both active and reactive power change. In [45]–[48], NSFs are computed considering peak demand at a particular node. This can also be extended to accommodate time-series analysis with a given consumption profile [49]. Finally, NSFs can be computed in the presence of DERs where the analysis is based on the change in system loss before and after DER integration. In this case, NSF is the ratio of power loss change to the change in active power injection at that particular node [44]. Accordingly, NSF can be formulated as,

\[
NSF_p = \frac{\Delta L_s}{\Delta P_n}
\]

(15)

where \( \Delta L_s \) is the change in system active power losses after DER placement and \( \Delta P_n \) is the increase in DER capacity at node \( n \).

NSFs provide useful insights on critical locations in the system and therefore help enhance its performance. NSFs depend on power flow solution to obtain the base nodal voltages. Therefore, these factors are generally used in planning applications as prior information for various control purposes. It can also be noticed that, NSFs do not account for any uncertainty associated with the knowledge of system states or DER power outputs, which is why these factors are typically used at the planning stage. The literature on NSFs is briefly summarized in Table 1 based on the control variable, test system used, and load model.

### E. NODAL ALLOCATION FACTORS (NAFs)

Along with NSFs, there have been few studies that propose the concept of NAFs to study the impact of nodal power changes on losses in the system including incremental allocation method, proportional sharing method and Z-bus allocation. This subsection briefly describes each of these methods.

1) **INCREMENTAL ALLOCATION METHOD**

The main goal of this method is to identify the contribution of node power changes to total system losses. First appearing in [50], this method is based on determining three components given a certain scenario of power change:

- **Generator domain**: for a generating node \( k \in N \), the domain is the set of nodes that are supplied by power injections at \( k \).
- **Commons**: represents the set of nodes supplied by the same generating node.
- **State graph**: Line flows are determined to form a directed state graph.

Using the domains and commons in a given state graph, it is possible to determine the contribution of each generator to line flows, which helps to determine its contribution to line losses as described in Fig. 2. Some nodes may contribute low power to loads but high contribution in line losses [50]. This method has been shown to be effective in determining the contribution of nodes (either negative or positive) to system losses. Yet, computing the domains and commons, highlighted by \( * \) in Fig. 2, is complex for large systems. Moreover, MDSs typically experience stochastic complex power changes at different locations as well as variable system configurations, which may lead to topology changes of the state graph.

2) **Z-BUS ALLOCATION METHOD**

This method is based on the Z-bus matrix of the system, which is the inverse of the Y-bus (admittance matrix). The main idea of the Z-bus method is to determine whether a node receives incentives or penalties for load increments based on loss contribution to the system. The active power loss in the system can be expressed as,

\[
L_s = \sum_{k=1}^{N} L_k,
\]

(16)

where \( L_k \) stands for the loss contribution due to current injections at node \( k \). This can be expressed in terms of \( Y \) and \( V \) or \( Z \) and \( I \) through,

\[
L_s = \sum_{k=1}^{N} V_k \sum_{j=1}^{N} Y_{kj} V_j^* \quad \text{(17)}
\]

\[
L_s = \sum_{k=1}^{N} I_k \sum_{j=1}^{N} Z_{kj} I_j \quad \text{(18)}
\]

where, \( Y_{kj} \) and \( Z_{kj} \) correspond to the \( kj \)th element of the Y-bus and Z-bus matrices, respectively. This method uses the Newton-Raphson power flow solution to determine current flows. The Z-bus allocation method can provide insights on node contributions to system losses similar to IA method. For instance, in [51], the method is used to determine the loss sensitivity using the IEEE 14 node and the IEEE 118 node transmission test systems. For the first system, only one scenario is considered where a 100 MW generator is added, and the loss is monitored. Another alternative to this method is discussed in the following subsection where the proportion...
of nodal power injections with respect to neighboring lines is considered.

3) PROPORTIONAL SHARING METHOD
Unlike the previous NAFs, this proportional sharing method is based on determining the proportion of node generation to line flows [52]. This can be computed using the proportional sharing matrix that helps determine contribution of nodes to line losses. To demonstrate the underlying principle, consider the nodal illustration in Fig. 3. The proportional method says that the 70 MW on \( i - m = \frac{40}{100}70 + \frac{60}{100}70 \), which means, 28 MW from line \( j - i \) and 42 MW from \( k - i \). Similarly, the 30 MW on \( i - l = \frac{40}{100}30 + \frac{60}{100}30 \). In other words, 12 MW from line \( j - i \) and 18 MW from \( k - i \). Fig. 2 illustrates the steps toward computing the NAF using the proportional sharing method. In [52], the method is implemented on an arbitrary 4 node test system to demonstrate its effectiveness. Nevertheless, this method requires details derivation for systems greater than 4 nodes, which increases the complexity of this method. It is important to mention that this method works very well with transmission systems due to the existence of multiple generating nodes.

F. ANALYTICAL SOLUTIONS TO LOSS SENSITIVITY
Analytical solutions typically involve Optimization-based loss estimation, approximation of annual losses, or deterministic/probabilistic approximations based on system topology and nodal power dynamics. Optimization-based methods can be applied to NTL sensitivity at the consumer end in order to detect malfunctioning devices or energy fraud activities [53]. For example, [30] proposes a new data-driven weighted least square method to estimate NTLs and identify vulnerable NTL nodes in unbalanced distribution systems. The study concludes that nodes without power flow measurements tend to be more difficult for NTL identification. Alternatively, annual loss approximation depends on readily available historical data of system states. For example, [28] compares different approximation algorithms that exploit the relationships between load and loss factors in distribution systems. The most commonly used analytical relationship between loss \( (F_s) \) and load factor \( (F_d) \) is given by [54],

\[
F_s = 0.3F_d + 0.7F_d^2.
\]

Different versions of this approximation were proposed in [55], [56]. While such relationships are useful for planning purposes, where rough estimates are sufficient for system design [57], the dynamic nature of loads in MDSs requires more accurate loss monitoring schemes to enable proactive asset management in the system [58]. Additionally, the uncertainty with DERs makes it nearly impossible to approximate losses in real-time using classical methods. Therefore, new research [58] attempts to solve this problem by introducing analytical approximation of change in losses at different lines in the system. The change in active losses at the monitored line \( (\Delta L_{mn}) \) can be approximated as a function of the aggregate impact of complex power change at multiple nodes \( (A \in \mathcal{A}) \) [58],

\[
\Delta L_{mn} \approx \left| \sum_{A \in \mathcal{A}} \frac{\Delta S_{A}^* \Psi_{MA}}{V_A^2} \right| Z_{mn},
\]

where, \( Z_{mn} = R_{mn} + jX_{mn} \) is the impedance of the monitored line \( mn \) as shown in Fig. 1, \( \Delta S_A^* \) is the complex conjugate of power change at node \( A \), \( V_A^2 \) is the complex conjugate of base voltage of node \( A \) and \( \Psi_{MA} \) represents the influence indicator. \( \Psi_{MA} \) can be set to 1 when node \( A \) is a child node of line \( M \) in radial distribution systems [58]. The linearity of this approximation makes it very suitable for assessing the impact of random power changes on line losses, which is mainly caused by DERs and abrupt load increments. If we assume \( \Delta S \sim N(0, \Sigma_{\Delta A}) \), where \( \Sigma_{\Delta A} \) is the covariance structure of complex power changes at all nodes due to load as well as DERs, it can be shown that the underlying distribution of active power losses at \( M \) converges to a Gamma distribution [58],

\[
\Delta L_M' \sim \Gamma(k, R_{mn}\theta)
\]

with scale and shape parameters \( k = \frac{(\sigma_r^2+\sigma_i^2)}{\theta} \) and \( \theta = \frac{2(\sigma_r^2+\sigma_i^2+2k\gamma)}{\sigma_r^2+\sigma_i^2} \), respectively. Here, \( \sigma_r^2 \triangleq k_r^T \Sigma_{\Delta A} k_r \) and \( \sigma_i^2 \triangleq k_i^T \Sigma_{\Delta A} k_i \), and the vectors \( k_r \) and \( k_i \) are fixed and related to system topology. See [58] for proof and more details.

III. COMPARATIVE ANALYSIS
This section provides a short comparative analysis of selected loss sensitivity methods presented earlier. The methods are evaluated using the IEEE 69 node test system. The base voltage of this test system is 12.66 kV and the standard base loads are used for the analysis [59]. The first scenario includes computing NSF based on active and reactive power base loading of all nodes using equations (11) and (12), respectively. Normalized NSFs are computed and ranked for the top 10 nodes and tabulated in Table 2. It can be seen from the table that both NSFp and NSFq are similar and that is due to the base loading of the IEEE 69 node test system in which node 61 has the highest loading for both active and reactive power. Therefore, node 61 is suitable for PV integration as it will result in significant loss reduction compared to other nodes. The second scenario focuses on the change in line losses due to complex power changes at different active consumer sites according to a hypothetical
wind, PV, and ESS profile as shown in Fig. 4. Power change profile is injected at a randomly selected set of nodes \( A \in [5, 15, 20, 25, 30, 40, 55, 67] \). The magnitude of change in current flow as well as active power loss sensitivity across the entire time horizon are computed using actual load flow, z-bus allocation, and analytical sensitivity-based methods. Fig. 5 shows the mean and variance of the change in line current magnitude whereas Fig. 6 shows loss sensitivity at all lines. As can be seen from the figure, the analytical approach is quite accurate in approximating the changes in line losses.

The derivation of exact loss change expression for three-phase system topology will be pursued as part of our future work.

IV. DISTRIBUTION SYSTEM MANAGEMENT WITH LSA

One of the goals of MDS is to integrate consumer level activities with core distribution planning and optimal operation tools [61]. This integration results in various advantages, one of which is consumer flexibility. In the modern framework, consumers are more engaged in the energy market by exchanging information over the communication infrastructure [1]. Other benefits include improving system situational awareness and providing accurate measures regarding the impact of consumer activities on system operation [33]. Fig. 7 illustrates an MDS architecture, where utilities leverage the capabilities of the communication infrastructure to transfer information from consumer level to a sensor data management system (SDMS) [62]. The main goal of SDMS is to filter incoming data from consumer resources [61]. This information can then be transferred to distribution system state estimation (DSSE). DSSE provides the asset management center with the required information about nodal voltages, power measurements and line current flows [63]–[65]. Such information can be used as the input to outage management systems (OMS) [66]. Functionalities of OMS include managing planned/unplanned outages, outage call reports, field maintenance crews and reliability index

1) EXTENSION TO PRACTICAL DISTRIBUTION SYSTEMS

Prior to considering practical distribution systems, we need to extend the proposed novel analytical LSA technique to three-phase unbalanced systems. The first step toward extending the LSA framework to three-phase distribution systems is to consider the coupling terms in the impedance matrix. In particular, the line impedance within a single phase system is captured by a single value. However, for three phase distribution systems, the impedance of any line includes additional coupling terms. For example, the impedance matrix \( Z_{mn} \) of line \( mn \) in a three phase setup can be written as,

\[
Z_{mn} = \begin{bmatrix}
Z_{a,a}^m & Z_{a,b}^m & Z_{a,c}^m \\
Z_{b,a}^m & Z_{b,b}^m & Z_{b,c}^m \\
Z_{c,a}^m & Z_{c,b}^m & Z_{c,c}^m
\end{bmatrix}
\]  

(22)

where, the superscripts \( a, b \) and \( c \) represent different phases. Now, given any complex power changes at any node in the system, the change in line current flow and the corresponding change in losses at any monitored line \( mn \) can be written (at the three phases) as,

\[
\Delta I_{mn} = \begin{bmatrix}
\Delta I_{a,mn}^a \\
\Delta I_{b,mn}^b \\
\Delta I_{c,mn}^c
\end{bmatrix}, \quad \Delta L_{mn} = \begin{bmatrix}
\Delta L_{a,mn}^a \\
\Delta L_{b,mn}^b \\
\Delta L_{c,mn}^c
\end{bmatrix}
\]

(23)

The derivation of exact loss change expression for three-phase system topology will be pursued as part of our future work.

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TABLE 3. Comparison of various LSA methods.

| Method   | Application       | Strength                                      | Weakness                                                                 |
|----------|-------------------|-----------------------------------------------|--------------------------------------------------------------------------|
| CLF      | Planning and monitoring | Ground truth sensitivity                      | Computationally complex when considering DER uncertainty               |
| NSF      | Planning          | Accurate ranking of nodes                    | Requires recomputing system states with the introduction of DERs          |
| NAF      | Planning and monitoring | Simple                                        | Requires algorithmic extension for large systems                        |
| Analytical methods | Planning and monitoring | Simple accurate, considers DER uncertainty and computationally efficient | Requires extension to 3-phase systems (currently under progress) |

FIGURE 6. Mean and variance of change in line losses.

analysis [67]–[69]. Additionally, secondary-level DSSE information enable home energy management systems (HEMS) [70], which can include applications like demand side management [71] and load shifting [72], [73]. Home automation features can also be embedded into HEMS, in which consumers can remotely control household appliances [74]. Finally, customer-level information can be fed to the advanced distribution management system (ADMS). ADMS include the distribution system optimal planning, operational applications, and sensitivity analysis that optimize system operation and study system dynamics in the presence of consumer-level resources [60], [75], [76]. In the light of LSA, ADMS accommodates different types of applications such as optimal system reconfiguration, DER planning, SC allocation and EV charging station management [77], [78]. The following subsections summarize state of the art and provides a glimpse at future pathways. Table 4 includes a summary of LSA applications on IEEE standard test systems (STS).

A. SYSTEM RECONFIGURATION

System reconfiguration - also known as optimal topology identification (OTI) - can be defined as the process of changing the status (open or close) of system switches in order to find the optimal topology that keeps power losses minimum and voltage profiles within permissible limits [79]. Many research efforts in literature have proposed algorithms to solve this reconfiguration problem based on different sensitivity metrics [80]. One of the early attempts appeared in [81] where authors focused on loss minimization by searching for the optimal spanning tree configuration. Later on, different optimization techniques have been developed based on leveraging various loss sensitivity techniques. For example, [82]–[87] use CLF-based sensitivity analysis (II-B) to find the optimal configuration of the system. [12], [17], [79], [88], [89] use NSF-based sensitivity analysis (II-D). Most of LSA-based system reconfiguration studies rely on base load analysis [84], [88], [89]. In the last decade, however, researchers have started incorporating the impact of system assets on optimal reconfiguration. [79], [85], for example, consider the impact of DERs on system losses and propose new heuristic optimization algorithms to solve the reconfiguration problem. In addition to DERs, [17] takes into account the impact of SCs on system reconfiguration. Except [17], most of the prior work on LSA-based system reconfiguration studies are based on static load models. However, it is desired to address the reconfiguration problem from an operational point of view because static analysis may not fully capture actual MDS dynamics.

B. DER MANAGEMENT

DER integration into distribution systems is complex and requires in-depth assessment and efficient operational and planning tools. This is mainly because DERs are not dispatchable by distribution system operators and can have a large impact on losses, power flow, voltage stability and power quality [90], [91]. Numerous algorithms have been employed for DER optimal allocation, resulting in the best location and size of DERs considering loss reduction [92]. These algorithms are broadly based on analytical techniques, optimization algorithms, or heuristics [35], [93]. Additionally, the existing work on DER allocation considers either single [25] or multiple allocation [11], [26]. For computing loss sensitivity, the vast majority of existing work uses PQ-based NSFs where the factors are computed based on active and reactive power injections (or withdrawal) by the DER unit [10], [94] [13], [14] [95]–[97] [98]. Few works [25], [26], [99] use the ELF whereas others determine the loss sensitivity using CLF method [90], [100]–[102] [103]. Despite the efficacy of existing methods for DER planning based on loss sensitivity, MDSs require system performance analysis with different penetration levels of DERs. In this regard, DER hosting capacity (HC) attracts the attention of MDS practitioners. HC can be defined as the maximum amount of DERs (such as PV or wind) that MDS can accommodate without the need for
 infrastructure upgrades while keeping system performance indicators within safe limits [104]. A comprehensive HC analysis framework must incorporate different system performance indicators such as power losses, line thermal loading or nodal voltage stability [105]. The adoption of different DER resources, ESSs and EVs motivates hybrid HC analysis due to the differential impact of these technologies [92]. For example, while rooftop PV systems inject power, EVs form additional loading at different locations in the system. This introduces spatio-temporal randomness in power injections (or withdrawals) that classical sensitivity methods failed to address.

C. SHUNT CAPACITOR ALLOCATION

SC placement in distribution systems can significantly help reduce system losses and stabilize voltage by improving the power factor of the system [106]. SCs can be connected to primary or lateral feeders and/or secondary level loads depending on system topology. The installation of SC at secondary feeder indeed provides enhanced system efficiency in terms of voltage support and loss minimization. However, in some cases, the resources can be limited and the installation of additional SCs can be an expensive alternative to minimize losses (or provide voltage support) [39]. Therefore, it is possible in such scenarios to integrate SCs at the primary feeder. In this scheme, losses at the secondary level can be minimized through controllable DER assets. This scheme may also have adverse impacts on different locations in the system since some nodes can be very sensitive to complex power changes at other nodes [38]. For this reason, several research efforts in literature propose optimal placement and sizing algorithms for loss minimization [107]–[109]. To determine the loss sensitivity, ELF [110], PQ-based NSF [14], [17], [94], [111], [112], or CLF method [106], [113], [114] can be used. Few studies focus on loss minimization by optimal placement and sizing of SCs with the presence of DERs [14], [94], [106] or system optimal reconfiguration [113]. The effectiveness of SCs (as well as other regulatory devices such as tap changers [115] and static var compensators [116]) is limited by their maximum allowable limits in the system. In addition, the installation of such devices might be very expensive, especially for large systems. Recent research utilizes PQ-based DERs instead of complete reliance on the deployment of regulatory devices [117]. Utilities can adjust the PQ setpoints of inverters in order to maintain system indicators within safe operational limits. In cases where DERs operate at maximum power point tracking (MPPT) mode, i.e., PQ setpoints are not controllable by utilities, assistive SCs can be installed with DERs and operated as needed.

D. EV COORDINATION

The decay in natural fuel reserves, increase in gasoline prices and the stringent governmental regulations on adopting greener technologies have spanned the growth of EVs [131]. Compared to classical fuel-based vehicles, EVs are fuel efficient and environmental friendly [132]. Yet, the integration of EVs into distribution systems brings new challenges to utilities in order to maintain system efficiency. A typical, yet detrimental scenario of EV operation occurs when consumers charge their EVs during peak-load hours such as early morning and after work hours. Such uncontrolled grid-to-vehicle (G2V) charging patterns increase the stress on nodal power withdrawal and has been linked to voltage violations [133], active power losses [134] and increased likelihood of blackouts due to system overloading [135]. EVs can also be operated in vehicle-to-grid (V2G) mode in which the EV is regarded as a controllable resource that provides ancillary services to system operation such as active loss reduction [136], [137], voltage control [138], peak shaving [129], [139] or demand response programs [140].

With the technological advancements in communication infrastructures and computational resources, efficient G2V or V2G coordination algorithms are currently being developed to limit EV impacts on distribution systems. Many EV coordination studies consider active loss reduction in distribution systems. For instance, [121]–[125] propose optimal planning strategies of G2V-based EV planning for improving system indicators including loss reduction. The planning problem can be formulated as optimal placement and sizing of charging stations across the system [126], [141]. For loss sensitivity calculations in G2V planning, few studies use linear approximation of annual losses [122], [127], [129] whereas others use CLF analysis [123], [125] or NSFs [124]. In addition to planning, the system optimal operation is widely studied in the literature. Typically, the interaction between EVs and system is modeled with a temporal profile of complex power dynamics. For example, [15] shows that system losses can be minimized by integrating ESSs with different levels of EV penetration. The study uses NSFs for computing the sensitivity. Similarly, [16] shows that optimal control of EV charging locations can significantly reduce system losses using classical load flow loss sensitivity. In addition to G2V scheme, research has shown with LSA that it is possible to reduce power losses in V2G scheme [142], [143] [144]. For example, authors in [128] propose a new placement and

FIGURE 7. Architecture of MDS.
TABLE 4. Application summary. †: system reconfiguration, ‡: DER management, ⊙: SC allocation, ⊗: EV coordination, *: applicable to transmission system.

| Category | Ref. | LSA | Test system Type | Scale | Load model | Brief description | Hybrid |
|----------|------|-----|-----------------|-------|------------|-----------------|--------|
| [79]     | NSF  | IEEE STS | ✓ | ✓ | ✓ | ✓ | OTI with DERs | † |
| [17]     | NSF  | IEEE STS* | × | ✓ | ✓ | ✓ | OTI with DERs and SCs | ⊙ |
| [82]     | CLF  | IEEE STS | ✓ | ✓ | ✓ | ✓ | OTI | X |
| [83]     | CLF  | IEEE STS* | ✓ | × | × | × | Tier-based OTI | X |
| [88]     | NSF  | IEEE STS | ✓ | ✓ | ✓ | ✓ | OTI | X |
| [84]     | CLF  | IEEE STS | ✓ | ✓ | ✓ | ✓ | OTI with DERs | ⊙ |
| [85]     | CLF  | Non IEEE | ✓ | ✓ | ✓ | ✓ | Path-based system modelling | ⊗ |
| [12]     | NSF  | IEEE STS* | ✓ | × | ✓ | ✓ | OTI with and without line faults | ⊙ |
| [87]     | CLF  | IEEE STS | ✓ | ✓ | ✓ | ✓ | OTI with probabilistic reliability measures | X |
| [10]     | NSF  | IEEE STS | ✓ | × | ✓ | ✓ | DER and SC allocation | ⊙ |
| [94]     | NSF  | IEEE STS* | ✓ | ✓ | ✓ | ✓ | DER and SC allocation | ⊙ |
| [13]     | NSF  | IEEE STS* | ✓ | ✓ | ✓ | ✓ | DER allocation | X |
| [14]     | NSF  | IEEE STS* | ✓ | ✓ | ✓ | ✓ | DER and SC allocation | ⊙ |
| [100]    | CLF  | IEEE STS | ✓ | × | ✓ | ✓ | DER allocation and OTI | ⊙ |
| [118]    | NSF  | IEEE STS | ✓ | × | ✓ | ✓ | DER allocation | ⊙ |
| [101]    | CLF  | IEEE STS | ✓ | × | ✓ | ✓ | DER allocation | X |
| [97]     | NSF  | IEEE STS | ✓ | × | ✓ | ✓ | DER allocation considering load growth | X |
| [26]     | ELF  | IEEE STS | ✓ | × | ✓ | ✓ | DER allocation | X |
| [95]     | NSF  | IEEE STS | ✓ | × | ✓ | ✓ | DER allocation | X |
| [96]     | NSF  | IEEE STS | ✓ | × | ✓ | ✓ | DER allocation | ⊙ |
| [102]    | CLF  | IEEE STS | ✓ | × | ✓ | ✓ | DER allocation | X |
| [103]    | CLF  | IEEE STS | ✓ | × | ✓ | ✓ | DER allocation | X |
| [45]     | ELF  | IEEE STS | ✓ | × | ✓ | ✓ | DER allocation - different types of DER | X |
| [98]     | NSF  | IEEE STS | ✓ | × | ✓ | ✓ | DER allocation and OTI | ⊙ |
| [99]     | ELF  | IEEE STS | ✓ | × | ✓ | ✓ | DER allocation with seasonal generation | X |
| [94]     | NSF  | IEEE STS | ✓ | × | ✓ | ✓ | SC optimal placement | ⊙ |
| [110]    | ELF  | IEEE STS | ✓ | × | ✓ | ✓ | SC optimal placement | X |
| [14]     | NSF  | IEEE STS* | ✓ | ✓ | × | ✓ | SC optimal placement | ⊙ |
| [106]    | CLF  | IEEE STS | ✓ | × | ✓ | ✓ | SC optimal placement | ⊙ |
| [113]    | CLF  | IEEE STS | ✓ | × | ✓ | ✓ | SC optimal placement | ⊙ |
| [14]     | NSF  | IEEE STS | ✓ | × | ✓ | ✓ | SC optimal placement | ⊙ |
| [17]     | NSF  | IEEE STS* | ✓ | ✓ | ✓ | ✓ | SC optimal placement | ⊙ |
| [111]    | NSF  | IEEE STS | ✓ | × | ✓ | ✓ | SC optimal placement | ⊙ |
| [112]    | NSF  | IEEE STS* | ✓ | × | ✓ | ✓ | SC optimal placement | ⊙ |
| [119]    | NSF  | IEEE STS | ✓ | × | ✓ | ✓ | G2V charging planning with DERs | ⊙ |
| [114]    | CLF  | IEEE STS | ✓ | × | ✓ | ✓ | G2V charging planning with SC | ⊙ |
| [120]    | CLF  | IEEE STS | ✓ | × | ✓ | ✓ | G2V charging planning | ⊙ |
| [121]    | CLF  | IEEE STS | ✓ | × | ✓ | ✓ | G2V charging seasonal planning | ⊙ |
| [122]    | CLF  | IEEE STS | ✓ | × | ✓ | ✓ | G2V charging planning | X |
| [123]    | CLF  | IEEE STS | ✓ | × | ✓ | ✓ | G2V charging planning | X |
| [124]    | NSF  | IEEE STS | ✓ | × | ✓ | ✓ | G2V optimal operation | X |
| [125]    | CLF  | IEEE STS | ✓ | × | ✓ | ✓ | G2V charging planning | X |
| [126]    | CLF  | IEEE STS | ✓ | × | ✓ | ✓ | G2V optimal operation | ⊙ |
| [127]    | CLF  | IEEE STS | ✓ | × | ✓ | ✓ | G2V charging planning (annual) | X |
| [16]     | NSF  | IEEE STS | ✓ | × | ✓ | ✓ | G2V Coordinated optimal operation | X |
| [15]     | NSF  | IEEE STS | ✓ | × | ✓ | ✓ | G2V optimal operation with ESSs | X |
| [128]    | CLF  | IEEE STS | ✓ | × | ✓ | ✓ | V2G optimal placement and sizing | X |
| [129]    | CLF  | Non IEEE | ✓ | × | ✓ | ✓ | V2G coordination with DERs | ⊙ |
| [130]    | NSF  | IEEE STS | × | ✓ | ✓ | ✓ | Reliability-oriented V2G OTI | ⊙ |

sizing approach of V2G facilities using CLF-based LSA. Similarly, [129] studies V2G coordination via optimal placement and sizing but with integrated DERs across the system. In [130], system optimal reconfiguration is considered with V2G coordination, where the objective is to minimize losses and ensure system reliability. The last block of Table 4 summarizes the EV management studies based on loss sensitivity.

V. RESEARCH GAPS AND FUTURE TRENDS

This section discusses the major shortcomings of existing loss sensitivity methods from the perspective of MDSs and provides future recommendations to direct the focus of new research efforts in this domain.

1) ENABLING REAL-TIME MONITORING

Classical loss sensitivity methods have shown value at system planning stage for various applications such as DER and SC placement. For example, it can be seen from Tables 1 and 4 that the most commonly used load model is the static model. This implies the that loss sensitivity has been widely used in distribution system planning. The diverse structure of MDS in terms of end-user technologies motivates the need for
real-time monitoring tools that are able to quantify the impact of consumer level activities on system losses. This is mainly due to the difference in the impact that different technologies may have on the system. For instance, PV units supply active power to local loads and thereby, reduce system losses since less power is withdrawn from the source. EVs, on the other hand, increase local loading and therefore, may lead to excess losses during existing peak demand hours. Therefore, real-time monitoring of loss is important to ensure system efficiency.

2) INCORPORATING UNCERTAINTY
The variable nature of DER power outputs and load profiles in MDSs can cause adverse impacts on system operation and reliability. This uncertainty can result from changing weather conditions, partial shading over PV panels, or sudden peak in local loads. All of the aforementioned factors can contribute to excessive amounts of power losses. This obligates the inclusion of uncertainty analysis to loss sensitivity methods. Uncertainty analysis with real-time monitoring enables system operators to apply optimal consumer asset management, e.g., G2V charging scheduling or real-time allocation, to maintain minimum losses during peak hours. Unfortunately, based on the review in this paper, uncertainty analysis is still a knowledge gap that must be addressed by exploring new methods of loss sensitivity or by innovating existing frameworks in an accurate and a computationally efficient manner.

3) ALLEVIATING COMPUTATIONAL BURDEN
MDS optimal operation with minimum losses entails a wide range of time-sensitive and data-intensive tools for sensitivity analysis. Based on the review in this paper, there are two major areas where computational complexity requires further attention: (1) the requirement for algorithmic extensions, and (2) complexity of scenario based sensitivity analysis for realistic systems, especially at system operation stage. For instance, the set of domains and commons in II-E1 requires significant algorithmic extensions for systems larger than 4 nodes. In addition, although a majority of the reviewed methods consider large IEEE STSs in the analysis, the results must be validated against realistic unbalanced distribution systems along with the secondary feeder level to efficiently capture the impacts of active consumers on losses. This inevitably increases the computational complexity, especially when uncertainty is incorporated in the analysis because it requires running multiple scenarios to obtain the desired accuracy as can be seen from Fig. 2 for CLF-based sensitivity.

4) STATE ESTIMATION AND MEASUREMENT DEVICES
System states are obtained via measurement devices at the main feeder side such as the SCADA system that provide nodal active/reactive power and real/imaginary voltage readings, through which loss sensitivity can be computed. Yet, distribution systems are mostly constrained with few measurement devices at select locations, rendering the system unobservable. One solution to this can be the installation of additional measurement devices at every location in the system. However, this approach is not cost-effective. In this regard, state estimation of low observable distribution systems is an attractive alternative. Based on the literature analysis in this paper, the majority of works consider full availability of system states for computing the sensitivity. Breaking the barriers between state estimation and sensitivity analysis is a key element in MDSs that can result in efficient planning, monitoring and optimal asset control.

5) OTHER RESEARCH PATHWAYS
Legacy distribution systems were designed in a top-down structure with limited coordination between management systems. Such coordination is important for impact assessment of consumer resources on both device and system level. Therefore, the dynamic nature of MDSs calls for advanced frameworks to collaboratively foresee the evolving needs of the system. In this regard, loss sensitivity can be integrated with other frameworks (e.g., voltage sensitivity analysis) to predict system response and guide optimal management strategies. As far as asset management is concerned, fairness to consumers participating in the management program is another aspect that will draw the attention of system operators. Finally, cybersecurity and data privacy will also be relevant areas with sensitivity analysis, especially during the process of communicating control commands from system operators to the consumer level.

VI. CONCLUSION
The increased penetration levels of consumer resources in MDSs necessitates the development of accurate tools that examine their impact on system losses. In this regard, LSA as an impact-assessment tool, has garnered huge interest because it enables efficient system planning while keeping losses in the system minimal. Despite the proliferation of LSA-based distribution system planning applications, the need for LSA-based real-time loss monitoring is an essential step that helps enable efficient system operation in MDSs. Therefore, this paper proposes a comprehensive analysis on existing literature work and reviews the state of the art to identify future research directions. Theoretical formulations of LSA are initially summarized with a brief comparative analysis that highlights the possibility of accounting for DER uncertainty. Then, the applications of LSA are thoroughly discussed and categorized based on the LSA framework used. After extensive analysis on literature, this paper presents existing research gaps and provides a vision for future research directions. It is found that the development of computationally efficient sensitivity frameworks is essential to achieve real-time monitoring and enable optimal asset management at the ADMSs. Moreover, DER uncertainty and lack of measurement devices are two important aspects that can help provide realistic results for system planning and operations using LSA. Future work includes extending the probabilistic sensitivity framework in equation (21) to the case of 3-phase unbalanced distribution systems.
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