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(REVIEW ARTICLE)

OUTAGE SITUATIONAL AWARENESS FOR TRANSMISSION STORM RESTORATION: A REVIEW OF DATA SOURCES, INTEROPERABILITY STANDARDS, AND OPEN GAPS

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ABSTRACT

Restoring the transmission system after severe weather depends on an accurate and current picture of what is out of service, what has lost its source of supply, and how restoration is progressing. That picture is assembled from data built for other purposes: outage-management records, real-time telemetry and topology processing, asset records, network models, and a growing set of public datasets. This narrative review examines 58 sources, including peer-reviewed studies, standards, and federal technical reports published between 1987 and 2026, on the data, standards, and analytics that support outage situational awareness for transmission storm restoration. The literature is organized into four areas: the data sources and their known limitations, interoperability through the Common Information Model, analytics for resilience assessment, outage prediction, restoration, and reporting through business intelligence dashboards, and public data for reproducible research. Five open gaps emerge. Outage records describe operations on equipment rather than the resulting de-energization of the network. Reconciling identifiers across utility systems is costly and rarely documented. Operators without dedicated analytics teams have few accessible tools for integrated reporting. Historical outage data used to train prediction models are incomplete in ways that are seldom measured. Finally, open benchmarks for comparing methods are scarce. The review closes with a research agenda for each gap.

Keywords: Common Information Model; Data Quality; Outage Management; Power System Resilience; Situational Awareness

1 INTRODUCTION

Weather now drives most large power outages in the United States. An analysis of utility reports filed with the U.S. Department of Energy found that 80 percent of major outages reported between 2000 and 2023 were weather-related, and that the country saw roughly twice as many weather-related major outages in 2014–2023 as in 2000–2009 [1]. Federal assessments estimated the cost of weather-related outages in the tens of billions of dollars per year a decade earlier [2,3], and broader estimates of interruption costs to U.S. electricity consumers are of similar magnitude [4]. Studies of long-run reliability trends show that outage duration has been rising, particularly once major events are

included [5]. A National Academies committee has examined how the nation's electricity system can better withstand and recover from such events [6].

Recovery speed depends on what operators and restoration managers know during the event. Situation awareness, in the sense developed in human factors research, means perceiving the relevant elements of an environment, understanding what they mean, and projecting how they will change [7]. In power systems, gaps in operator awareness have contributed to major disturbances [8]; the investigation of the August 2003 blackout in North America identified inadequate situational awareness as one of its principal causes [9]. During a storm, awareness for a transmission operator means knowing which lines and stations are out, which have lost their source of supply as the network breaks apart, what damage exists, and how restoration is proceeding.

Several reviews already cover adjacent ground. Reviews of power system resilience survey definitions, metrics, and enhancement measures [10,11,12]. A recent review covers machine learning for hurricane outage prediction [13], and another spans outage analysis, monitoring, mitigation, and restoration [14]. Less attention has gone to the data layer underneath these methods: where outage information comes from, how the sources fit together, and where they fall short. This gap matters most in the reporting layer that sits between the control room and the rest of the organization, where storm status reports, leadership briefings, regulatory submissions, and after-action reviews are produced.

This review addresses that layer. Its contributions are (i) a structured account of the data sources behind transmission outage situational awareness and their documented limitations, (ii) a summary of how the Common Information Model (CIM) supports, and does not yet fully solve, the integration of those sources, (iii) a synthesis of analytics that consume these data, with attention to what each assumes about its inputs, and (iv) five open gaps with a corresponding research agenda.

The review is organized around four research questions. RQ1: Which data sources describe the state of the transmission network during a storm, and what are their documented limitations? RQ2: To what extent does the CIM allow these sources to be integrated, and what work does it leave to utilities? RQ3: What do analytics for resilience assessment, outage prediction, fault location, and restoration assume about their input data? RQ4: Which gaps remain, and what research would close them? Sections 4, V, VI, and VII answer RQ1 to RQ3, and Sections 8 and IX answer RQ4.

Section 2 describes the review method. Section 3 sets out the situational awareness and resilience concepts used throughout. Section 4 covers data sources, Section 5 interoperability, Section 6 analytics, and Section 7 public data for reproducible research. Section 8 identifies open gaps, Section 9 proposes a research agenda, and Section 10 concludes.

2 REVIEW METHOD

This is a narrative review rather than a systematic review. Sources were identified through keyword searches of IEEE Xplore, Google Scholar, and ScienceDirect, and through the publication pages of federal agencies and national laboratories. Search terms combined "outage management," "outage data," "situational awareness," "topology processing," "Common Information Model," "outage prediction," "power system resilience," "synthetic grid," "dashboard," and "business intelligence." Reference lists of relevant papers were then followed to locate further sources. Peer-reviewed journal and conference papers, books, standards, federal technical reports, and vendor documentation for widely used reporting platforms were included when they described outage data sources, their quality, their integration, or analytics that consume them. Studies focused solely on generation adequacy, market operations, or cyber security were excluded. Each candidate source was screened against the four research questions, and a source was retained only if it contributed evidence to at least one of them. The final set contains 58 sources published between 1987 and 2026.

Two limitations follow from this approach. A narrative review does not guarantee complete coverage, so the absence of a topic from the cited literature should be read as limited visibility rather than proof that no work exists. In addition, practices inside utilities are often documented in vendor material, internal reports, or industry presentations that are not indexed by academic databases; the review relies on published sources and may therefore understate current industry practice.

3 SITUATIONAL AWARENESS AND RESILIENCE CONCEPTS

Endsley's model describes situation awareness at three levels: perception of elements in the environment, comprehension of their meaning, and projection of their future status [7]. Mapped to storm operations, perception corresponds to knowing which equipment is out of service, comprehension to understanding which parts of the network have lost supply as a result and why, and projection to anticipating how the outage will evolve and how quickly

restoration will proceed. Panteli and Kirschen apply this model to power system operation and propose a procedure for designing information systems that accounts for both the technology and the people who use it [8].

Resilience frameworks describe a system's performance over the course of an extreme event. Panteli and Mancarella present resilience as the ability to withstand, adapt to, and recover from high-impact, low-probability events [15]. Panteli et al. extend the familiar resilience triangle to a trapezoid with distinct phases of disturbance, degraded operation, and restoration, and propose time-dependent metrics for each [16]. Ouyang and Dueñas-Osorio assess hurricane resilience along several dimensions, including the speed of recovery [17]. All of these metrics are computed from a time series of system state, usually the amount of load, customers, or equipment out of service at each moment. Their accuracy is bounded by the accuracy of that time series, which links resilience assessment directly to the data sources discussed next.

4 DATA SOURCES FOR OUTAGE SITUATIONAL AWARENESS

4.1 Utility Outage Records

Outage-management systems record equipment that is removed from service and later returned, with times, causes, and often damage information. At the distribution level, interruption records feed the standard reliability indices defined in IEEE Std 1366, which also defines major event days so that extreme events can be separated from routine performance [18]. At the transmission level in North America, the North American Electric Reliability Corporation collects outage data from transmission owners through its Transmission Availability Data System (TADS) [19].

These records are the usual basis for storm reports, regulatory submissions, and historical reliability analysis. Their structure carries an important limitation: they record operations on equipment and the immediate cause of each outage, not the full set of consequences for the network. When several line outages together separate part of the system from every source, the stranded stations and lines lose supply without any operation being recorded against them. Whether such loss-of-source effects appear in the records depends on local practice. Section 8 returns to this point.

4.2 Telemetry and Topology Processing

In real-time operations, energy management systems (EMS) determine network configuration from telemetered breaker and switch status. Topology processing converts that status and the detailed network model into the bus-level model used by state estimation and other applications [20,21,22]. Synchronized phasor measurements add high-resolution observations of system state [23], and fault location methods use these and other measurements to identify where faults occurred [24]. This telemetry-based picture is the authoritative real-time view of energization. It is, however, generally confined to control-room systems. It is not built to reconstruct the history of a storm after the fact, and it is not always accessible to the staff who prepare reports for leadership, regulators, and after-action reviews.

4.3 Asset Records and Network Models

Asset management systems hold equipment attributes, locations, ratings, and line lengths. They are needed to turn outages into reportable quantities such as miles of line affected or the number of structures damaged. Network models describe how equipment is connected and are maintained for planning and operations. The network model is the only source that can show how individual outages combine to separate the system into islands. Asset systems, outage systems, and network models are usually maintained by different groups and use different identifiers for the same equipment, which makes joining them a recurring effort [25].

4.4 Public and Federal Outage Data

Several public datasets now support outage research at national scale. Utilities report qualifying incidents and disturbances to the Department of Energy on Form OE-417 [26]; the Climate Central analysis cited above is built on these reports [1]. The Energy Information Administration collects distribution reliability indices through Form EIA-861 [27]. The EAGLE-I historical dataset, released by Oak Ridge National Laboratory, provides county-level customer outage counts at 15-minute intervals from 2014 onward and represented about 92 percent of U.S. utility customers by 2022 [28]. Commercial aggregations of utility outage maps have also been used in research [29]. The Storm Events Database of the National Oceanic and Atmospheric Administration (NOAA) records the timing, location, and characteristics of severe weather [30], which allows outage records to be linked to the hazards that caused them.

Each of these sources has documented limitations. Ankit et al., working with OE-417 reports from 2002 to 2019, had to correct or remove records with negative elapsed times, negative customer counts, or missing customer counts, and consolidated dozens of reported causes into a few categories [31]. They also note that, as of 2017, only about a third of utilities reported the standard duration and frequency indices [31]. OE-417 itself covers only incidents that meet federal reporting criteria [26]. The EAGLE-I documentation states that the data miss outages shorter than 15 minutes, capture

small, rural, and independent utilities less reliably than large ones, and are affected over long periods by changes in the reporting utility population [28]. Li et al. note that utility customer counts cannot be translated directly to population, because utilities define a customer as a meter, a building, or a facility [32]. Table 1 summarizes the sources and their main limitations for storm situational awareness.

Table 1: Data Sources for Transmission Outage Situational Awareness

Source	What it describes	Resolution	Main limitation for storm awareness
Utility outage records [18], [19]	Equipment removed from and returned to service; causes; damage	Equipment, event time	Record operations, not network consequences; practice varies by utility
EMS telemetry and topology [20], [22]	Real-time switching status and energization	Device, seconds	Confined to control room; not built for historical replay
Asset records [25]	Equipment attributes, location, length	Equipment	Identifiers differ from other systems
Network model [33], [34]	Equipment connectivity	Equipment	Static; must be combined with event data to show islands
Form OE-417 [26], [31]	Major incidents and disturbances	Event	Major events only; records need correction
Form EIA-861 [27], [31]	Annual distribution reliability indices	Utility, year	Annual aggregates; incomplete reporting
EAGLE-I [28]	Customers without power	County, 15 min	Misses short outages; weaker coverage of small utilities; distribution-dominated
NOAA Storm Events [30]	Severe weather occurrence	County or zone, event	Describes hazards, not grid impact

4.5 What Large Outage Datasets Have Shown

Studies that combine these sources have produced findings that bear directly on situational awareness. Ji et al. analyzed failure and recovery data from four utility service regions in New York, including Superstorm Sandy. They found that a small share of failures caused most customer interruptions, with the top 20 percent of failures accounting for 84 percent of interrupted service, and concluded that extreme weather exposes weaknesses that remain hidden in routine operation [35]. Do et al. used outage records for 2,447 U.S. counties covering about 74 percent of the population from 2018 to 2020. They identified 231,174 outages lasting at least one hour and 17,484 lasting at least eight hours, and found that about 62 percent of the eight-hour outages coincided with extreme weather or climate events [29]. Using EAGLE-I data from late 2014 to 2023, Li et al. report that outages became more frequent, longer, and more intense over the decade, and that counties with higher social vulnerability experienced more severe and more frequent outages [32]. Larsen et al. related 13 years of utility reliability data to weather and system characteristics and found that outage duration was associated with wind, precipitation, and the share of underground lines [5]. Mukherjee et al. combined major-outage records with climate, land-use, and socioeconomic data and found that risk depended on hazard type, the extent of overhead lines, and the rural or urban character of each state [36].

These studies are not directly comparable, because each defines an outage differently. OE-417 captures only events that meet federal reporting criteria [26], EAGLE-I counts customers out of service in 15-minute snapshots [28], and Do et al. count outages that exceed fixed duration thresholds [29]. Apparent differences in frequency or duration across studies therefore reflect differences in definition and coverage as well as differences in the grid. Comparisons across datasets need to align the definition of an outage, the minimum duration, and the population covered before drawing conclusions. Two observations follow. First, nearly all of these studies work at the level of customers and counties, which reflects distribution impacts; transmission-level outage dynamics are much less visible in public data. Second, every study depends on the completeness and consistency of outage records, and some had to correct or remove records before analysis [31].

5 INTEROPERABILITY THROUGH THE COMMON INFORMATION MODEL

The Common Information Model is a vendor-neutral information model for electric utility data. Its base classes for transmission and generation are defined in International Electrotechnical Commission (IEC) standard 61970-301 [33], with distribution extensions in IEC 61968-11 [37]. Profiles such as IEC 61970-452 define which classes are exchanged for static transmission network models [34], and IEC 61970-552 defines the XML format used to exchange them [38]. The National Institute of Standards and Technology (NIST) framework for smart grid interoperability lists the CIM among the standards that support information exchange across utility systems [39]. Introductory treatments describe the model's structure, its use of unique resource identifiers (mRIDs) for each object, and its representation of connectivity through terminals and connectivity nodes [40,25].

For outage situational awareness, the CIM offers two things. Its persistent identifiers can serve as a common key for joining outage records, asset data, and the network model. Its explicit representation of connectivity allows energization to be computed from the model rather than inferred from records alone. Translating CIM models into the formats required by analysis tools is an established practice [41].

The CIM does not by itself reconcile identifiers across systems. Outage-management and asset systems frequently use their own equipment keys, and mapping them to CIM identifiers relies on crosswalk tables that must be built and maintained. Practitioner literature acknowledges that adopting the CIM involves substantial mapping and organizational work [25], but published, quantitative accounts of this effort, of the share of records that fail to map, and of practices that keep crosswalks current are scarce in the sources reviewed.

6 ANALYTICS FOR SITUATIONAL AWARENESS AND OUTAGE PREDICTION

6.1 Resilience Assessment

Resilience assessment methods quantify performance over an event and compare enhancement options. Wang et al. review resilience research for natural disasters, including definitions, evaluation methods, and enhancement measures [10]. Bie et al. propose a quantitative assessment framework and examine smart-grid measures such as microgrids and topology reconfiguration [11]. Panteli et al. apply time-dependent operational and infrastructure metrics to a reduced model of the Great Britain transmission system under windstorms [16], and Bhusal et al. survey current practice and open challenges [12]. These methods generally take the time series of the system state as given. When they are applied to historical events, that time series comes from outage records, so any incompleteness in the records carries into the computed metrics.

6.2 Outage Prediction

A large body of work predicts weather-driven outages before or during events. Guikema et al. estimated hurricane damage to distribution systems ahead of landfall [42] and later described a model used to support storm response planning [43]. Nateghi et al. found that simpler statistical models can match or outperform more complex ones for tropical cyclone outage estimation [44] and developed methods to forecast outage durations [45]. Wanik et al. built storm outage models for a distribution network in the northeastern United States using weather, vegetation, and infrastructure data [46]. Cerrai et al. extended that work with a storm classifier and new representations of weather and vegetation, reducing the median absolute percentage error of service-territory predictions from about 130 percent to 59 percent across 120 held-out storms [47]. Fatima et al. review machine learning methods for hurricane outage prediction and identify integration with existing utility systems as a remaining challenge [13].

Most of these models predict distribution outages or customer counts and are trained on historical outage records. Their accuracy is limited by the quality of those labels. If records omit consequences such as loss of supply due to network separation, the models learn from an incomplete picture of past storms. The literature reviewed here rarely measures label completeness directly.

6.3 Outage Detection and Fault Location

Fault location methods use substation and wide-area measurements to identify where faults occurred on transmission lines [24,23]. These methods identify where an outage originated. They are complementary to, rather than a substitute for, an account of which parts of the network lost supply as a consequence.

6.4 Restoration Planning

Restoration methods determine the sequence of repairs, switching, and load pickup. Adibi's collection documents established methodologies and implementation strategies for bulk system restoration [48]. Optimization approaches co-optimize repair crew routing with network reconfiguration and distributed generation dispatch [49] or treat the

dispatch of repair crews as a vehicle routing problem coupled to the power network [50]. These methods assume an accurate starting state: which equipment is damaged and which parts of the network are de-energized. Errors in that state propagate into the restoration plan.

Table 2 compares these method families against four criteria: the inputs each requires, what it assumes about the outage state, its spatial resolution, and its sensitivity to incomplete outage records. The first three criteria are taken from the cited studies. The sensitivity column is this review's assessment, based on whether the method uses outage records directly as inputs or training labels. The comparison shows that the methods most often applied after the fact, namely resilience assessment, outage prediction, and restoration planning, are also the ones most exposed to gaps in the records.

Table 2: Comparison of Analytic Method Families by Data Requirements

Method family	Main inputs	Assumption about outage state	Resolution	Sensitivity to incomplete records
Topology processing and state estimation [20], [22]	Telemetered breaker status; network model	Telemetry is complete and current	Device, real time	Low; uses telemetry, not records
Resilience assessment [16], [11], [17]	Time series of load, customers, or equipment out	State series is complete over the event	System or region, event duration	High; missing outages understate degradation
Outage prediction [42], [46], [47]	Historical outages; weather; vegetation; infrastructure	Historical labels are complete	Grid cell or service territory	High; models learn from incomplete labels
Fault location [24], [23]	Substation and wide-area measurements	Measurements available at fault time	Line, fault point	Low; finds origin, not consequences
Restoration planning [48], [49], [50]	Damaged components; network model; crews	Starting state is accurate	Component	High; errors propagate into the plan

6.5 Reporting and Visualization

Situation awareness research emphasizes that the presentation of information shapes what operators understand [7,8]. In the sources reviewed, however, peer-reviewed work on the reporting layer used outside the control room, including storm dashboards, leadership briefings, and the integration of outage, asset, and network data for those purposes, is limited. Much of this practice appears to be documented in industry material rather than in the research literature.

Outside the control room, storm reporting is commonly delivered through general-purpose business intelligence (BI) platforms, of which Microsoft Power BI is a widely used example. These platforms combine data from several systems into one semantic model and publish interactive dashboards for incident command staff, leadership, and regulators. How close to real time such a dashboard can be depends on how its data are connected. Imported models are refreshed on a schedule. Reports connected through DirectQuery can use automatic page refresh, which re-queries the source at a fixed interval or when a monitored measure changes; the minimum interval is 30 minutes in shared capacity and, subject to administrator settings, as short as one second in dedicated capacity [51]. Push and streaming datasets, previously used for live dashboard tiles, are being retired in favor of the Real-Time Intelligence workload in Microsoft Fabric [52]. The latency of a storm dashboard is therefore a design choice set by licensing, connection mode, and the load the source systems can bear, rather than a property of the tool.

Two limits of dashboard-based reporting follow from the rest of this review. First, a dashboard can display only what its sources record. A dashboard built on outage records alone inherits the gap between recorded operations and network de-energization described in Section 4.1, and faster refresh shows that incomplete picture sooner rather than correcting it. Second, BI platforms model tables and relationships, not network connectivity, so topology-dependent measures such as loss of supply must be computed upstream and loaded as data. Visualization research on outage management has found that operators benefit from views that link network topology with geography [53], and control-room studies have proposed display types organized around situational awareness [54]. Peer-reviewed evaluations of BI dashboards for storm restoration outside the control room, covering their refresh latency, data completeness, or effect on decisions, were not found in the sources reviewed.

7 PUBLIC DATA AND SYNTHETIC NETWORKS FOR REPRODUCIBLE RESEARCH

Real transmission network data are confidential, which limits reproducibility in outage research. Synthetic networks address this by providing realistic, publicly available test cases. Birchfield et al. established structural characteristics that synthetic networks should match to be considered realistic [55]. The Texas A&M University Electric Grid Test Case Repository provides test cases from 9 to 82,000 buses, with fictitious geographic coordinates for the substations of its large synthetic cases and a 2,000-bus case on the footprint of Texas, distributed in PowerWorld, MATPOWER, PSS/E, and PSLF formats [56]. Open tools such as MATPOWER [57] and the NetworkX graph library [58] make it straightforward to load these cases and analyze their connectivity.

Combining geographically sited synthetic networks with public hazard data from the NOAA Storm Events Database [30] and public outage data from EAGLE-I [28] makes it possible to construct storm scenarios that are realistic in footprint and severity without exposing confidential infrastructure. The repository description does not list CIM among its formats [56], so research on CIM-based methods using these cases requires a conversion step.

8 OPEN GAPS

Gap 1: Recorded outages are not the same as de-energization. Storm reporting outside the control room is typically built from outage records, which describe operations on equipment (Section 4.1). When outages separate the network into islands, stations and lines lose supply without a corresponding record. The authoritative real-time picture from telemetry and topology processing (Section 4.2) is often unavailable to reporting staff and is not designed for historical replay. None of the sources reviewed measures how large the resulting gap is across storm types or network structures.

Gap 2: Identifier reconciliation is costly and poorly documented. The CIM provides a common identifier space (Section 5), but joining outage and asset records to it relies on manually maintained crosswalks. Quantitative accounts of the effort involved, the share of records that fail to map, and the effect of mapping failures on reporting accuracy are largely absent from the literature.

Gap 3: Few accessible tools for operators without dedicated analytics teams. Integrated, topology-aware reporting requires combining several data sources and maintaining the network model, which is easier for large organizations. Public outage data show that small and rural utilities are already less visible in national datasets [28], and outage burdens fall disproportionately on socially vulnerable counties [29,32]. Open, documented tools suited to smaller transmission operators, municipal systems, and cooperatives are scarce in the published record. General-purpose BI platforms lower the cost of building dashboards, but they do not supply the network model or topology processing that integrated reporting requires (Section 6.5).

Gap 4: Incomplete labels in historical outage data. Prediction models and resilience metrics inherit the completeness of the records they are built on (Section 6). Studies using national datasets have had to correct or remove records [31], but label completeness with respect to network consequences such as loss of supply is rarely assessed.

Gap 5: Few open benchmarks. Public synthetic networks [55,56] and public hazard and outage data [30,28] now exist, but shared storm scenarios, agreed metrics, and reference implementations for comparing situational awareness methods are not yet established.

9 RESEARCH AGENDA

Quantify the gap between recorded outages and topology-implied de-energization across storm types and network structures, using synthetic networks and public storm data, and define a standard measure of record completeness.

Develop methods that infer network-wide de-energization from outage records and a CIM network model without requiring real-time telemetry, so that reporting staff and historical analyses can use them.

Publish reusable practices and measurements for CIM-anchored identifier reconciliation, including the share of unmapped records and its effect on reporting.

Release open, documented tools that let smaller operators produce topology-aware storm reports from data they already hold, with outputs that load directly into common BI dashboards for near-real-time visibility, and evaluate how dashboard refresh latency and data completeness affect restoration decisions.

Use topology-aware reconstruction of historical storms to produce more complete training labels and test whether they improve outage prediction.

Establish public benchmark scenarios that combine synthetic networks with NOAA and EAGLE-I data, with agreed metrics and reference implementations.

10 CONCLUSION

Situational awareness during transmission storm restoration rests on data that were not designed to work together. Outage records, real-time telemetry, asset records, network models, and public datasets each describe part of the picture, and each has documented limitations. The Common Information Model provides a common vocabulary but leaves the work of reconciling identifiers to individual utilities. Analytics for resilience assessment, outage prediction, and restoration planning all assume an accurate account of what was out and what lost supply, yet the completeness of that account is rarely measured. The most consequential of the five gaps identified here is the difference between what outage records show and what is actually de-energized when the network separates. Closing it, together with the other four gaps, would improve the accuracy of storm reporting, the quality of historical outage data, and the reliability of the analytics built on both.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

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