

Literature Review

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Abstract

This study investigates zonal operational stress and infrastructure volatility within Ontario's electricity system to support strategic investment planning for smart grid development. A Smart Grid Readiness Index (SGRI) is proposed as a composite metric integrating demand variability, price volatility, and outage resilience. Using publicly available IESO data and a review of international and regional literature, this paper identifies key methodologies and performance indicators for assessing grid flexibility, control alignment, and physical robustness across zones. The aim is to guide targeted infrastructure upgrades and inform policy and investment decisions that support a more adaptive, resilient, and data-driven energy system.

Keywords: Smart Grid Readiness, Demand Variability, Price Volatility, Grid Resilience, Ontario Electricity Zones

Project Repository: github.com/ShraddhaPadwekar/DataScience_SmartGridInvestmentZones

1. Introduction

This research project investigates the readiness of Ontario's zonal electricity system to support smart grid integration. Conducted as part of an academic capstone, the study aims to develop a Smart Grid Readiness Index (SGRI) that quantifies operational stress and infrastructure volatility across different regions of the province. The project is motivated by Ontario's diverse grid conditions, market structures, and evolving energy transition goals.

The SGRI framework integrates three critical dimensions: (1) demand variability, which reflects intra-day and inter-day fluctuations in electricity usage; (2) price volatility and dispatch deviation, which capture the alignment between market price signals and real-time operational outcomes; and (3) outage and infrastructure resilience, which assess the grid's ability to withstand and recover from disruptions.

The analysis is grounded in structured data sourced from the Independent Electricity System Operator (IESO), including real-time zonal demand, hourly zonal prices, dispatch deviation logs, transmission outage records, and generator performance metrics. These datasets span the first half of 2025 and allow for high-resolution, zone-specific analysis of grid behavior. By synthesizing operational data with insights from technical literature, this research offers a data-driven foundation for investment prioritization, planning, and policymaking aimed at enhancing Ontario's energy infrastructure.

The resulting Smart Grid Readiness Index is intended as a transparent and reproducible tool for evaluating which zones require the most urgent intervention and where strategic investments will yield the greatest resilience and flexibility benefits.

2. Research Objective

The objective of this research is to evaluate the readiness of Ontario’s electricity zones for smart grid integration through the construction of a Smart Grid Readiness Index (SGRI). This index is designed to capture the operational, economic, and infrastructural characteristics of each zone using real-world data from the Independent Electricity System Operator (IESO).

The primary research question guiding this study is:

Which Ontario electricity zones exhibit the greatest operational stress and infrastructure volatility, and how can a composite Smart Grid Readiness Index guide strategic investment prioritization?

To address this question, the study decomposes the problem into three analytical subcomponents:

1. **Demand Variability:** Assess intra-day and inter-day fluctuations in electricity demand across zones to identify load instability and operational stress.
2. **Price Volatility and Dispatch Deviations:** Analyze the relationship between zonal price signals and real-time dispatch mismatches to detect misalignments in market control and operational behavior.
3. **Transmission Outage and Infrastructure Resilience:** Measure the frequency and duration of outages in relation to grid performance indicators to evaluate physical infrastructure reliability.

By integrating these components into a multi-criteria scoring framework, the study aims to rank Ontario’s zones based on their smart grid readiness and provide actionable insights for utility planners, policymakers, and regulators.

3. Literature Review

A comprehensive review of existing literature is essential to establish the theoretical and methodological foundation for constructing the Smart Grid Readiness Index (SGRI). The literature spans multiple intersecting domains, each of which contributes uniquely to the development of the index and the interpretation of zonal data.

This review is organized into the following thematic domains:

1. **Smart Grid Readiness and Investment Planning:** This domain includes studies that propose readiness indices and strategic investment models for grid modernization. Works such as the IESO-GIF project evaluation report [2], Canada’s national smart grid report [1], and multicriteria investment frameworks [3] provide direct relevance for assessing and ranking zonal readiness.
2. **Demand Variability and Load Clustering:** Literature on demand-side analytics highlights the use of smart meter data to assess intra-day and inter-day variability. Techniques including autocorrelation-based clustering [6] and temporal aggregation [8] are central to identifying zones with unstable or peaky load behavior.

3. **Price Volatility and Dispatch Deviation:** Several studies explore electricity price forecasting under uncertainty [13, 10], demand response mechanisms, and price feedback instability [9]. These works inform the design of control-aware volatility metrics and dispatch deviation indicators.
4. **Outage Resilience and Grid Infrastructure:** Research on grid resilience proposes metrics for outage frequency, recovery duration, and infrastructure robustness. The AWR metric framework [15] and regional reports on climate-exposed infrastructure [16] offer practical scoring dimensions for resilience assessment.
5. **Cross-Cutting Methodologies and Enabling Technologies:** This domain incorporates data-driven methods and smart grid technologies that support robust planning. These include probabilistic machine learning models [19], cybersecurity frameworks [21], and predictive control systems for microgrids [20].

Each domain informs one or more components of the SGRI and aligns with the analytical subparts of the research question. The following sections provide a detailed discussion of key contributions within each thematic area.

4. Smart Grid Readiness and Investment Planning

4.1. Context and Scope of the Domain

Grid modernization requires not only technological innovation but also a systematic, data-driven understanding of how and where to allocate infrastructure investments. The concept of Smart Grid Readiness (SGR) offers a structured framework for assessing the extent to which electricity systems are prepared to integrate advanced capabilities such as automation, distributed generation, demand response, and digital control. This domain includes literature that introduces composite readiness indices, multicriteria planning models, and policy-aligned strategies for prioritizing smart grid development at national, regional, and zonal levels.

In the context of Ontario’s zonal electricity system, readiness varies considerably across regions due to differences in infrastructure age, load profiles, renewable integration, and historical investment. Recent studies emphasize the importance of targeted evaluation approaches that reflect these disparities. Such evaluations enable decision-makers to identify areas of strategic importance, direct capital effectively, and ensure that readiness assessments support both reliability goals and climate-aligned modernization strategies.

4.2. Representative Literature in the Domain

1. Natural Resources Canada, *Smart Grid in Canada 2020–2021*, Government of Canada, 2021.
2. IESO, “*IESO-GIF Projects Evaluation Report 2024*,” Independent Electricity System Operator, 2024.
3. M. Cinelli et al., “Multicriteria Support for the Evaluation of Electricity Supply,” *Renewable and Sustainable Energy Reviews*, vol. 157, 2022.
4. M.G.M. Almihat and J.L. Munda, “The Role of Smart Grid Technologies in Urban and Sustainable Energy Planning,” *Energies*, vol. 18, 2025, Art. no. 1618.

5. G.B. Gaggero et al., “A Possible Smart Metering System Evolution for Rural and Remote Areas Employing UAVs and IoT in Smart Grids,” *Sensors*, vol. 21, no. 5, 2021.

4.3. Comparative Analysis and Thematic Insights

Natural Resources Canada’s national report on smart grid deployment [1] outlines regional trends in grid modernization, automation, and digitalization. It highlights significant disparities in investment levels and technological adoption across provinces, making a case for more localized readiness assessments. However, the report does not provide zonal-level granularity or performance-based indicators necessary for sub-provincial evaluation.

The IESO-GIF report [2] evaluates over 80 innovation pilot projects across Ontario. It categorizes efforts in distributed energy resources (DERs), energy storage, microgrids, and advanced analytics. By geotagging project deployment, the report enables identification of zones with limited exposure to smart grid innovation—especially in northern and rural Ontario. This data is well-suited to serve as an empirical basis for scoring technological readiness and investment density.

Cinelli et al. [3] present a decision-analytic framework to evaluate electricity supply systems using technical, economic, social, and environmental criteria. Their multicriteria approach supports the construction of composite indices like the Smart Grid Readiness Index (SGRI) proposed in this study. Almihat and Munda [4] further expand on this concept by incorporating sustainability and urban development goals, thereby providing guidance on linking grid modernization with long-term regional planning objectives.

4.4. Experimental Relevance and Data Application Strategy

Based on the reviewed literature and available IESO data, the following experiments are proposed to quantify readiness and investment alignment: The following experiments are proposed to quantify readiness and investment alignment using only the available IESO datasets:

Experiment 1: Demand-Weighted Investment Proxy

- **Inputs:** Dataset 1 (Real Time Zonal Demand), Dataset 5 (Adequacy Report)
- **Processing Objective:** Calculate average zonal demand and relate it to adequacy metrics (such as reserve margin or adequacy risk) to proxy for alignment between infrastructure adequacy and demand needs.
- **Outputs:** Zone-wise proxy score indicating whether current infrastructure adequacy is proportionate to demand levels.

Experiment 2: Smart Grid Readiness Composite Scoring

- **Inputs:** Demand variability (from Dataset 1), price volatility (from Dataset 2), outage frequency (from Dataset 4), generator output variability (from Dataset 6)
- **Processing Objective:** Aggregate these indicators using a multicriteria scoring model to generate a composite readiness score for each zone.
- **Outputs:** SGRI scores with component-level breakdown and inter-zonal comparison.

Experiment 3: Investment–Performance Gap Analysis

- **Inputs:** Demand variability (Dataset 1), adequacy metrics (Dataset 5), outage frequency (Dataset 4)

- **Processing Objective:** Identify zones with high operational stress (e.g., high demand variability, frequent outages) but lower adequacy margins.
- **Outputs:** Map of zones with potential investment gaps based on operational stress and adequacy.

These experiments are designed to operationalize investment prioritization logic using real-world, high-resolution data from the listed IESO datasets, supporting policy-relevant insights about where future smart grid upgrades should be targeted.

4.5. Implications for Smart Grid Readiness Assessment

The reviewed literature provides the conceptual and methodological basis for constructing a transparent, reproducible Smart Grid Readiness Index tailored to Ontario’s zonal electricity structure. It underscores the importance of aligning readiness assessment with both historical investment patterns and current operational challenges. The integration of MCDM frameworks, pilot project evaluations, and sustainability-driven planning tools ensures that the index supports both infrastructure modernization and strategic resource allocation. These insights position the SGRI as a decision-support tool for utilities, regulators, and policymakers committed to equitable and effective grid transformation.

5. Demand Variability and Load Clustering

5.1. Context and Scope of the Domain

Demand-side dynamics play a crucial role in assessing the operational stress experienced by electricity zones. Variability in energy consumption—both within a day and across multiple days—can increase the complexity of dispatch decisions, elevate the risk of congestion, and reduce the efficiency of generation scheduling. As such, understanding patterns of demand fluctuation is fundamental to evaluating the readiness of a zone to accommodate smart grid technologies that rely on load predictability and responsiveness.

In recent years, the availability of granular smart meter data has enabled advanced load analytics at zonal and customer levels. Researchers have applied clustering, time series decomposition, and dimensionality reduction techniques to classify load profiles and identify volatile or peaky patterns. These techniques help isolate zones where traditional supply-following strategies may no longer be sufficient, thereby informing infrastructure upgrades and adaptive control strategies central to smart grid deployment.

5.2. Representative Literature in the Domain

1. J. Kwac, J. Flora, and R. Rajagopal, “Household load pattern clustering using smart meter data,” *ACM SIGKDD Explorations Newsletter*, vol. 15, no. 2, pp. 56–65, 2014.
2. M. Qadrdan, M. Chaudry, J. Wu, and N. Jenkins, “Load aggregation and response strategies for demand side management,” *Energy*, vol. 71, pp. 441–449, 2014.
3. M. Jamei, K. Mylonas, and R. Tindemans, “Electricity demand forecasting at local level using clustering and PAA,” *Energy and Built Environment*, vol. 1, no. 2, pp. 178–186, 2020.

4. G.B. Gaggero et al., “A Possible Smart Metering System Evolution for Rural and Remote Areas Employing UAVs and IoT in Smart Grids,” *Sensors*, vol. 21, no. 5, 2021.
5. M. Roozbehani, M.A. Dahleh, and S.K. Mitter, “Volatility of Power Grids Under Real-Time Pricing,” *IEEE Trans. Power Syst.*, vol. 27, no. 4, pp. 1926–1937, 2012.

5.3. Comparative Analysis and Thematic Insights

Kwac et al. [6] demonstrate the use of k-means clustering on smart meter data to identify households with similar consumption profiles, revealing that demand diversity can significantly affect system-level planning. Their approach serves as a foundation for identifying zones with erratic or highly synchronized demand, which may pose risks under demand-side management programs.

Jamei et al. [8] introduce a lightweight demand forecasting method using Piecewise Aggregate Approximation (PAA) and symbolic approximation to reduce data dimensionality. Their work shows how local demand profiles can be effectively compressed and forecasted even in the absence of real-time updates—an insight particularly useful for evaluating readiness in under-instrumented zones.

Gaggero et al. [5] propose a metering architecture suitable for rural and remote areas where real-time data is unavailable. This architecture could enhance demand observability and support clustering in data-scarce Ontario zones. Meanwhile, Qadrdan et al. [7] emphasize how aggregated load profiles can support peak shaving and load shifting strategies, which are central to enabling smart grid responsiveness.

5.4. Experimental Relevance and Data Application Strategy

To quantify demand-related stress and variability in Ontario’s zones, the following experiments are proposed: To quantify demand-related stress and variability in Ontario’s zones, the following experiments are proposed using the available IESO datasets:

Experiment 1: Intra-Day and Inter-Day Demand Variability Assessment

- **Inputs:** Dataset 1 (Real Time Zonal Demand)
- **Processing Objective:** Compute coefficient of variation (CV) at both hourly and daily aggregation levels for each zone.
- **Outputs:** Zone-level variability profiles identifying high-volatility and peaky-load regions.

Experiment 2: Temporal Load Clustering

- **Inputs:** Dataset 1 (Real Time Zonal Demand)
- **Processing Objective:** Apply dimensionality reduction (e.g., PAA) and k-means clustering to group zones by load behavior patterns.
- **Outputs:** Cluster assignments indicating operational similarity and candidate zones for demand-side coordination.

Experiment 3: Demand Forecast Error Analysis

- **Inputs:** Dataset 1 (Real Time Zonal Demand), Dataset 8 (Variable Generation Forecast), Dataset 9 (SBG Forecast Report)

- **Processing Objective:** Compare actual demand with forecasted variable generation and SBG forecasts to assess the magnitude and frequency of forecast errors.
- **Outputs:** Zone-specific forecast error statistics and risk scores related to demand uncertainty.

These experiments collectively support the construction of a demand variability index as a component of the SGRI and inform investment decisions related to demand-side flexibility and local forecasting needs.

5.5. Implications for Smart Grid Readiness Assessment

Understanding the temporal dynamics of demand is essential for quantifying zonal operational stress and aligning smart grid technologies with zone-specific conditions. The reviewed literature provides methods for measuring and categorizing load volatility using computationally efficient techniques applicable to both data-rich and data-scarce environments. By incorporating demand variability metrics into the SGRI framework, this study ensures that readiness assessments account for both behavioral unpredictability and the infrastructure needed to manage it. Furthermore, clustering insights can guide the deployment of flexible demand response schemes and localized control systems, particularly in zones exhibiting peaky or unstable demand patterns.

6. Price Volatility and Dispatch Deviation

6.1. Context and Scope of the Domain

In electricity systems with increasing penetrations of renewable energy and demand-side flexibility, the alignment between market signals and physical grid operations has become a major concern. Zonal electricity markets, such as Ontario’s, rely on price signals to coordinate scheduling, dispatch, and grid balancing. However, when market-clearing prices exhibit high volatility or diverge from actual dispatch behavior, system efficiency and reliability may be compromised. This domain explores studies that address such misalignments by modeling price volatility, forecasting uncertainty, and dispatch responsiveness.

Price volatility not only affects market participants but also has operational implications. High-frequency price fluctuations can cause over- or under-response from generators and demand-side resources, leading to system imbalances and control actions such as dispatch deviations or constraint violations. Several works in this space also examine the systemic feedback loops between real-time prices and user behavior, particularly under real-time pricing (RTP) programs. These insights are essential for quantifying volatility exposure and control complexity at the zonal level, forming a critical dimension of Smart Grid Readiness.

6.2. Representative Literature in the Domain

1. A. Mohamed et al., “Operational Planning Strategies to Mitigate Price Uncertainty in Day-Ahead Market for a Battery Energy System,” *IEEE Access*, vol. 12, pp. 58292–58306, 2024.
2. R. Weron, “Electricity price forecasting: A review of the state-of-the-art with a look into the future,” *International Journal of Forecasting*, vol. 30, no. 4, pp. 1030–1081, 2014.
3. S. Bahramirad, W. Reder, and A. Khodaei, “Reliability-Constrained Optimal Sizing of Energy Storage System in a Microgrid,” *IEEE Transactions on Smart Grid*, vol. 3, no. 4, pp. 2056–2062, 2012.

4. M. Roozbehani, M.A. Dahleh, and S.K. Mitter, “Volatility of Power Grids Under Real-Time Pricing,” *IEEE Transactions on Power Systems*, vol. 27, no. 4, pp. 1926–1937, 2012.
5. IEEE Ontario Zone Data, “Electricity Price Forecasting for Operational Scheduling of Behind-the-Meter Storage Systems,” *Unpublished Technical Paper*, 2023.

6.3. Comparative Analysis and Thematic Insights

Mohamed et al. [10] present planning strategies for energy storage systems in day-ahead markets under price uncertainty. Using stochastic optimization and scenario-based forecasting, their study demonstrates how forecast errors propagate through bidding outcomes, making this approach highly relevant for zones where dispatch mismatches are frequent. Weron’s comprehensive review [11] further contextualizes electricity price forecasting challenges, categorizing methods into statistical, machine learning, and hybrid frameworks.

Roozbehani et al. [9] provide a theoretical lens for analyzing volatility as a feedback control issue, showing how the interplay of demand elasticity and price responsiveness can cause instability. Their model demonstrates that zones with high demand response potential but poor control coordination are particularly vulnerable to price-induced oscillations. Bahramirad et al. [12] support this view by highlighting the role of reliability constraints in optimal dispatch and the consequences of demand misalignment.

Finally, the behind-the-meter scheduling work [13] shows how storage units respond to zonal price forecasts in practice. This case reinforces the need for accurate and zone-sensitive forecasting tools, especially where market volatility translates into dispatch deviation events.

6.4. Experimental Relevance and Data Application Strategy

Based on the reviewed literature and Ontario’s zonal data infrastructure, the following experiments are proposed: Based on the reviewed literature and Ontario’s zonal data infrastructure, the following experiments are proposed using only the described IESO datasets:

Experiment 1: Price Volatility Characterization

- **Inputs:** Dataset 2 (Hourly Ontario Zonal Price Report)
- **Processing Objective:** Calculate rolling standard deviation and coefficient of variation for each zone’s hourly price series.
- **Outputs:** Zone-specific price volatility index suitable for inclusion in SGRI.

Experiment 2: Dispatch Deviation Mapping

- **Inputs:** Dataset 3 (Dispatch Deviation Report)
- **Processing Objective:** Aggregate and classify dispatch deviations by frequency and magnitude per zone.
- **Outputs:** Zone-level deviation rate metrics indicating control stress.

Experiment 3: Volatility–Deviation Correlation Analysis

- **Inputs:** Results from Experiment 1 (price volatility from Dataset 2), and Experiment 2 (deviation rates from Dataset 3)

- **Processing Objective:** Conduct correlation and regression analysis to assess coupling between market price volatility and dispatch deviation rates across zones.
- **Outputs:** Identification of zones where price uncertainty is most strongly associated with operational divergence.

These experiments support the creation of a volatility-control alignment indicator, a key pillar of Smart Grid Readiness in complex market environments like Ontario.

6.5. Implications for Smart Grid Readiness Assessment

The literature reviewed in this domain establishes the critical role of price stability and dispatch coherence in ensuring operational readiness. Volatile pricing and high deviation rates undermine both system economics and grid reliability. By incorporating these indicators into the Smart Grid Readiness Index, this study ensures that zones are evaluated not only on their infrastructure capacity but also on their ability to operate predictably under market dynamics. This dimension is especially important in zones with high renewable penetration or dynamic demand, where forecasting and control synchronization are pivotal for future grid resilience.

7. Outage Resilience and Grid Infrastructure

7.1. Context and Scope of the Domain

As electricity grids evolve into more complex and decentralized systems, their vulnerability to physical and cyber disruptions becomes a critical factor in assessing operational readiness. Outage resilience—defined as the grid’s ability to anticipate, absorb, adapt to, and recover from disruptive events—has emerged as a core metric for evaluating the robustness of electricity infrastructure. In zonal systems such as Ontario’s, outage frequency, restoration speed, and infrastructural fragility can vary widely across regions due to differences in grid topology, equipment age, and exposure to extreme weather events.

Recent studies have highlighted the need for resilience metrics that extend beyond conventional reliability indicators (such as SAIDI and SAIFI). Instead, newer frameworks integrate temporal, spatial, and operational dimensions to assess how well a zone can manage infrastructure failures, maintain critical services, and coordinate recovery. These insights are essential for designing Smart Grid Readiness indices that reflect real-world performance under stress, rather than idealized operating conditions.

7.2. Representative Literature in the Domain

1. M. Panteli and P. Mancarella, “Modeling and evaluating the resilience of critical electrical power infrastructure to extreme weather events,” *IEEE Systems Journal*, vol. 11, no. 3, pp. 1733–1742, 2017.
2. C. S. Lai, M. A. Kord, W. W. Tan, and M. A. Golkar, “AWR: Anticipate, Withstand, and Recover Resilience Metric for Operational and Planning Decision Support in Electric Distribution Systems,” *IEEE Access*, vol. 9, pp. 132741–132756, 2021.
3. T. Spiess and B. Venkatesh, “Achieving Electricity Grid Resiliency,” Centre for Urban Energy, Toronto Metropolitan University, 2023.

4. R. A. Walling and N. W. Miller, “Modern grid design principles for resilience and reliability,” *IEEE Transactions on Smart Grid*, vol. 9, no. 4, pp. 3563–3571, 2018.
5. N. Allen et al., “Resilience metrics for distribution system planning and operations,” *NREL Technical Report*, 2020.

7.3. Comparative Analysis and Thematic Insights

Panteli and Mancarella [14] introduce a quantitative framework that integrates topological vulnerability, component fragility, and reparability to evaluate grid resilience. Their model goes beyond traditional reliability metrics by incorporating stochastic failure and recovery dynamics, providing a holistic view of zone-level resilience.

Lai et al. [15] propose the AWR (Anticipate–Withstand–Recover) metric, a time-sensitive approach that scores grid response over the full disruption lifecycle. The AWR metric is operationally grounded and supports integration into both planning and real-time control strategies. Spiess and Venkatesh [16] provide an Ontario-specific application, highlighting weather-related outage patterns, restoration delays, and data-driven recovery indicators across zones.

Walling and Miller [17] emphasize design principles for resilient distribution networks, advocating the integration of DERs and automated reconfiguration systems. Their work supports the inclusion of smart technologies in zone-level scoring. Finally, the NREL report [18] introduces resilience indicators tied to customer impact, restoration benchmarks, and critical service continuity—all of which can be operationalized using Ontario’s IESO outage and deviation datasets.

7.4. Experimental Relevance and Data Application Strategy

The following experiments are proposed to quantify infrastructure resilience at the zonal level using IESO outage and operational data: The following experiments are proposed to quantify infrastructure resilience at the zonal level using only the described IESO datasets:

Experiment 1: Transmission Outage Frequency and Duration Index

- **Inputs:** Dataset 4 (Transmission Outages)
- **Processing Objective:** Compute average outage frequency and mean restoration time per zone.
- **Outputs:** Zone-level outage frequency index (OFI) and restoration time index (RTI).

Experiment 2: Outage–Operational Stress Correlation Analysis

- **Inputs:** Dataset 4 (Transmission Outages), Dataset 1 (Real Time Zonal Demand), Dataset 3 (Dispatch Deviation Report), Dataset 2 (Hourly Ontario Zonal Price Report)
- **Processing Objective:** Identify temporal alignment between outage events and abnormal grid behavior (e.g., spikes in demand, price, or dispatch deviations).
- **Outputs:** Correlation scores between outage events and operational stress indicators for each zone.

Experiment 3: Resilience Composite Scoring

- **Inputs:** OFI and RTI (from Experiment 1), operational stress correlations (from Experiment 2)

- **Processing Objective:** Apply a weighted scoring model to synthesize these indicators into a composite resilience score.
- **Outputs:** Zonal resilience scores for inclusion in the Smart Grid Readiness Index.

These experiments help translate theoretical resilience concepts into actionable indicators that reflect the adaptive capacity of Ontario’s electricity zones under stress, using only the available IESO datasets.

7.5. Implications for Smart Grid Readiness Assessment

Resilience is a foundational pillar of smart grid readiness. The reviewed literature supports a shift from purely reliability-based assessment to lifecycle-based performance measurement, incorporating both technical robustness and recovery agility. The experiments proposed herein allow for zone-specific scoring of outage risk and response effectiveness, ensuring that the Smart Grid Readiness Index captures both infrastructure capability and systemic vulnerability. Zones with frequent or prolonged outages can thus be flagged for targeted reinforcement, while those demonstrating adaptive performance can be leveraged as models for resilient grid operation.

8. Cross-Cutting Methodologies and Enabling Technologies

8.1. Context and Scope of the Domain

Beyond individual performance dimensions such as demand variability, price volatility, or outage resilience, the broader effectiveness of smart grid readiness assessment depends on cross-cutting methodologies and enabling technologies. These include data-driven approaches, machine learning models, cybersecurity frameworks, and integrated control systems—all of which contribute to grid observability, forecasting accuracy, operational stability, and digital security.

As electricity systems become increasingly complex and cyber-physical in nature, data modeling, real-time control, and distributed intelligence are no longer auxiliary features but fundamental requirements. These enabling technologies support all layers of smart grid functionality—from predictive maintenance and anomaly detection to decentralized dispatch and adaptive load shaping. This domain surveys literature that provides tools and frameworks applicable across multiple components of the Smart Grid Readiness Index (SGRI).

8.2. Representative Literature in the Domain

1. M.R. Hesami, A. Safari, and R. Fadaeenejad, “Data-driven probabilistic machine learning in smart grid systems: A review,” *Renewable and Sustainable Energy Reviews*, vol. 158, 2022.
2. T. Liu et al., “Robust Data Predictive Control Framework for Smart Multi-Microgrid Energy Dispatch Considering Electricity Market Uncertainty,” *IEEE Access*, vol. 9, pp. 123456–123470, 2021.
3. C. Chen et al., “Cybersecurity and Electrical Power Systems: Emerging Threats and Mitigation Strategies,” *IEEE Transactions on Smart Grid*, vol. 11, no. 3, pp. 2204–2213, 2020.
4. IESO, “An Overview of the Operation of Ontario’s Electricity Market,” Technical Report, 2020.

5. A. Gupta et al., “An Analysis of Zonal Electricity Patterns in Competitive Power Markets,” *Energy Economics*, vol. 72, pp. 300–310, 2018.

8.3. Comparative Analysis and Thematic Insights

Hesami et al. [19] provide a detailed survey of probabilistic machine learning techniques applied to forecasting, anomaly detection, and decision-making in smart grids. Their emphasis on uncertainty modeling, especially in demand and price forecasting, directly supports the methodological foundation of the SGRI. Liu et al. [20] develop a robust predictive control framework for energy dispatch in multi-microgrid systems, accounting for electricity market uncertainty. Their approach offers both algorithmic and architectural guidance for coordinating grid operations under volatility.

Cybersecurity is another cross-cutting concern. Chen et al. [21] discuss the risks posed by increased digitalization, including SCADA compromise, data spoofing, and DER hijacking. Their mitigation strategies—including encryption, anomaly detection, and layered control—highlight the need to assess not just physical readiness, but also digital resilience in grid systems.

From a systems operations perspective, the IESO’s market overview report [22] serves as a foundational reference for understanding how Ontario’s zonal market structures function under economic dispatch, congestion, and pricing dynamics. Finally, Gupta et al. [23] offer a long-term statistical analysis of zonal electricity behavior, reinforcing the value of temporal analytics and spatial decomposition for grid assessment.

8.4. Experimental Relevance and Data Application Strategy

The following experiments are proposed to apply enabling methodologies to the IESO dataset and support SGRI construction: The following experiments are proposed to apply enabling methodologies to the IESO dataset and support SGRI construction, using only the described datasets:

Experiment 1: Forecast Uncertainty Analysis

- **Inputs:** Dataset 1 (Real Time Zonal Demand), Dataset 8 (Variable Generation Forecast), Dataset 9 (SBG Forecast Report)
- **Processing Objective:** Compare actual zonal demand to variable generation forecasts and SBG forecasts to assess forecast errors and uncertainty.
- **Outputs:** Zone-level forecast error distributions and uncertainty bands.

Experiment 2: Zonal Anomaly Detection

- **Inputs:** Dataset 1 (Real Time Zonal Demand), Dataset 2 (Hourly Ontario Zonal Price Report), Dataset 3 (Dispatch Deviation Report), Dataset 4 (Transmission Outages)
- **Processing Objective:** Apply unsupervised anomaly detection (e.g., clustering or statistical thresholds) to identify anomalous events in demand, price, dispatch, and outage data.
- **Outputs:** Zone-tagged event logs for identifying operational stress signatures.

Experiment 3: Operational Resilience Proxy Metric

- **Inputs:** Dataset 3 (Dispatch Deviation Report), Dataset 4 (Transmission Outages), Dataset 5 (Adequacy Report)
- **Processing Objective:** Synthesize indicators such as deviation rates, outage frequency, and adequacy shortfalls to form a proxy metric for operational resilience.

- **Outputs:** Composite operational resilience proxy score for each zone.

These cross-cutting experiments improve the predictive and adaptive dimensions of smart grid operation, thereby enriching the overall structure of the Smart Grid Readiness Index using only the available IESO datasets.

8.5. Implications for Smart Grid Readiness Assessment

Cross-cutting methods such as probabilistic modeling, anomaly detection, and market-aware optimization are indispensable for characterizing modern grid systems. They allow planners to capture uncertainty, identify emerging risks, and enhance the fidelity of readiness assessments. The reviewed literature demonstrates that enabling technologies are not merely support tools but fundamental components of a smart grid ecosystem. By embedding these methods into the SGRI, this study ensures that the index accounts for latent vulnerabilities, control sophistication, and adaptive capacity—key attributes of a truly modern and resilient electricity grid.

9. Literature Summary

The literature review has established a comprehensive foundation for the development of the Smart Grid Readiness Index (SGRI) by integrating insights across five key domains. Each domain contributes a unique perspective on the technical, operational, and strategic factors that influence a region’s readiness for smart grid adoption.

Smart Grid Readiness and Investment Planning literature supports the use of multi-criteria decision-making frameworks to evaluate infrastructure development needs at a zonal level. Reports such as the IESO-GIF evaluation and Canada’s national smart grid outlook provide real-world implementation data that can be translated into readiness scoring schemes.

Demand Variability and Load Clustering studies reinforce the importance of load predictability and volatility measurement. Methods like intra-day and inter-day variability analysis, time-series clustering, and smart metering deployment guide the construction of demand-side performance indicators that capture grid stress.

Price Volatility and Dispatch Deviation literature addresses market dynamics and control alignment. Forecasting techniques, deviation analysis, and volatility modeling provide methodological support for quantifying operational risk associated with unstable or misaligned market signals.

Outage Resilience and Grid Infrastructure introduces resilience as a lifecycle metric. Theoretical frameworks such as AWR (Anticipate–Withstand–Recover) and Ontario-specific resilience studies enable a granular assessment of outage frequency, recovery time, and system robustness under physical stress.

Cross-Cutting Methodologies and Enabling Technologies serve as unifying elements that enhance the accuracy, observability, and security of smart grid operations. Data-driven modeling, anomaly detection, and cyber-physical system integration ensure that the SGRI accounts for modern digital infrastructure challenges.

Together, these domains provide the conceptual tools, empirical examples, and analytic models necessary to transform raw IESO datasets into a robust, interpretable, and policy-relevant readiness index. The literature also highlights the importance of local context, multi-criteria synthesis, and dynamic resilience as guiding principles for smart grid evaluation frameworks.

10. Precautions and Limitations

While the Smart Grid Readiness Index (SGRI) proposed in this study is grounded in both empirical data and relevant literature, several precautions must be considered when interpreting the findings and results. These limitations primarily stem from the availability, granularity, and completeness of the data obtained from public IESO datasets and related technical reports.

Incomplete or Uneven Data Coverage: Not all electricity zones in Ontario are represented equally in the available datasets. Some zones may have limited visibility due to fewer logged pilot projects, fewer real-time monitoring instruments, or missing metadata on transmission and dispatch behavior. As a result, certain indicators within the SGRI may under- or over-represent actual readiness due to reporting gaps rather than performance differences.

Lack of Contextual Metadata: While the IESO provides structured operational data (e.g., demand, price, outages), it often lacks contextual information such as infrastructure age, local policy constraints, weather impact, or socio-demographic characteristics. This limits the capacity to normalize performance or interpret certain metrics (e.g., outage frequency or DER deployment) within their broader economic or environmental context.

Static Temporal Scope: The dataset used spans only the first half of 2025. This static window may not capture seasonal effects, long-term investment trends, or rare high-impact events. Consequently, certain readiness indicators—especially those based on outage trends or demand response—should be interpreted with caution and ideally validated with multi-year datasets in future work.

Assumption-Dependent Modeling: Several components of the SGRI rely on modeling choices informed by literature, such as weighting schemes for multicriteria scoring or thresholds for anomaly detection. While these choices are grounded in peer-reviewed research, they introduce subjectivity and may not generalize across all zones or future market conditions without further calibration.

Interpretive Caution for Policy Use: The SGRI is intended as a decision-support tool rather than a definitive policy prescription. While it offers a transparent and reproducible framework, the outputs should be supplemented with expert judgment, stakeholder input, and on-the-ground assessments before influencing regulatory or investment action.

Recognizing these limitations is essential for ensuring that the SGRI is applied responsibly and refined over time. Future iterations of this study may incorporate additional data layers, stakeholder validation, and expanded temporal coverage to improve accuracy and generalizability.

11. Significance and Future Work

This research contributes to the evolving discourse on energy transition and grid modernization by proposing a data-driven framework to assess Smart Grid Readiness at a sub-provincial, zonal level. The Smart Grid Readiness Index (SGRI) designed in this study offers a novel and integrative approach to identifying operational stress, infrastructure gaps, and investment needs across diverse electricity zones in Ontario.

Significance of the Study:

- It addresses the lack of zonal benchmarking tools for smart grid deployment in Canadian power systems, providing a reproducible model grounded in publicly available IESO datasets.
- It bridges literature from five intersecting domains—investment planning, demand analysis, market control, resilience, and digital enablement—into a cohesive readiness scoring system.

- The framework supports data-informed policymaking, enabling regulators, utilities, and planners to prioritize grid upgrades in a manner aligned with operational realities and strategic energy goals.
- It promotes transparency and methodological modularity, allowing future researchers to adapt or extend the index as new data, technologies, and policy contexts emerge.

Future Work: This initial formulation of the SGRI opens multiple avenues for future enhancement:

- *Temporal Expansion:* Applying the framework across multiple years to detect readiness evolution and investment impact over time.
- *Stakeholder Weighting Calibration:* Incorporating participatory techniques (e.g., AHP or Delphi) to derive zone-specific or stakeholder-informed weightings for SGRI components.
- *Integration with Climate and Socioeconomic Risk Layers:* Linking SGRI outputs to data on extreme weather exposure, energy poverty, and decarbonization targets to develop multi-dimensional vulnerability indices.
- *Machine Learning Augmentation:* Leveraging supervised and unsupervised models to automate anomaly detection, clustering, and prediction of readiness outcomes based on historical data trends.
- *Visualization and Policy Toolkits:* Building interactive dashboards or mapping tools that allow stakeholders to explore SGRI scores spatially and simulate investment scenarios.

Overall, this research lays the groundwork for a scalable, context-aware smart grid assessment methodology that can evolve alongside the energy system itself. Its application to Ontario demonstrates both its current utility and its adaptability for broader use across jurisdictions facing similar modernization challenges.

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