ISSN: 3008-1394

Big-Data Multimodal Power System Analysis with Markov Temporal Modeling for Community Detection

Tomas Ryan[1,*], Arash Mousaei[1]

[1]University of Glasgow, Department of Computer Science, Glasgow, UK

[*] Corresponding Author

Abstract

Modern power systems generate massive volumes of heterogeneous data from sensors, meters, supervisory devices, market platforms, and environmental services. Extracting stable structural patterns—especially community structures—from such big-data environments is essential for understanding grid behavior, enhancing situational awareness, and supporting reliable operation. However, existing community detection approaches often fail to capture the non-stationary temporal dependencies and multimodal heterogeneity inherent in large-scale power networks.

To address these challenges, this study proposes a big-data multimodal learning framework for power system community detection, integrating electrical measurements, topological descriptors, environmental indicators, and operational event logs into a unified representation. A Markov temporal prior is employed to model sequential dependencies and suppress unstable transitions across evolving power system states, thereby improving temporal consistency. The framework further incorporates scalable data processing, adaptive modality fusion, and topology-aware clustering techniques tailored for large and complex power grids.

Experiments conducted on both real-world and synthetic datasets demonstrate that the proposed framework achieves superior accuracy, robustness, and temporal stability compared with state-of-the-art baselines. The detected community structures align closely with physical grid regions, operational partitions, and disturbance propagation patterns, confirming the method's practical interpretability.

This work provides a scalable and data-driven solution for community detection in large power systems, offering valuable insights for grid monitoring, anomaly localization, reliability assessment, and intelligent decision-making.

Keywords

Big data analytics; power system data mining; multimodal learning; community detection; Markov temporal modeling; spatiotemporal grid analysis; power network topology; data-driven stability assessment; large-scale energy systems; intelligent grid monitoring.

1. Conclusion

Modern power systems are undergoing rapid digital transformation, driven by large-scale deployment of smart meters, phasor measurement units (PMUs), distributed energy resources (DERs), and supervisory control infrastructures. These developments have led to unprecedented volumes of heterogeneous operational data, encompassing electrical measurements, grid topology, environmental conditions, and event logs. The resulting big-data

ISSN: 3008-1394

ecosystem provides new opportunities for improving grid resilience, enhancing situational awareness, and enabling data-driven decision-making. However, the explosive growth of multimodal data also introduces substantial challenges in extracting coherent structural patterns that reflect the physical, operational, and temporal characteristics of the power grid.

A central task in power system data analytics is the identification of community structures—cohesive groups of buses, feeders, or regions that share similar dynamic behavior or functional roles. Kovachki et.al. community detection plays an increasingly important role in grid monitoring, stability assessment, anomaly localization, and infrastructure planning. Yet, most existing methods rely heavily on static snapshots of the network and typically assume quasi-stationary operating conditions. These assumptions are often violated in real-world environments, where load variations, renewable fluctuations, topology changes, and operational interventions create highly non-stationary, temporally dependent patterns [1].

Furthermore, modern power system datasets are inherently multimodal. Electrical measurements capture physical states; topology data encode network connectivity; environmental factors influence renewable outputs; and operational logs record switching actions or contingencies. Traditional single-modality approaches struggle to integrate these heterogeneous signals, leading to incomplete or unstable representations of grid behavior [2]. The challenge is further compounded by the need for scalability, as large regional and national grids contain thousands of nodes and generate massive continuous data streams.

To address these limitations, recent research has begun exploring big-data fusion techniques and machine learning models for power system analysis. While these methods have produced promising results, most fail to incorporate the temporal dependence that governs grid evolution. Power system states evolve in a manner consistent with physical constraints, operational schedules, and historical patterns—making it essential to model sequential dependencies [3]. In this context, Markov temporal priors offer a principled way to enforce temporal consistency, reduce instability in sequential predictions, and prevent abrupt community transitions caused by noise or short-term fluctuations.

Motivated by these challenges, this work develops a big-data multimodal learning framework for community detection in large-scale power systems, designed to capture multimodal dependencies while embedding Markov-based temporal regularization. The framework integrates various data modalities into a unified representation, processes them at scale, and infers stable community structures that align with real-world operational behavior. Through extensive experimentation on synthetic benchmarks and real grid datasets, the proposed approach demonstrates superior robustness, stability, and interpretability compared with existing baselines[4].

2. Conclusion

Information Retrieval and Graph-Based Modeling

Research in information retrieval has long explored probabilistic ranking, query expansion, and scalable search architectures. Within this field, Zhang et.al work by has played an important role in establishing modern principles for large-scale retrieval systems[9]. Their research introduced effective models for ranking optimization, distributed search, and efficient processing of heterogeneous web-scale datasets. Although originally developed for search engines, these ideas are closely related to the challenges of big-data processing found in contemporary power systems, where massive multimodal signals must be analyzed in real time and under strong dynamic constraints.

Big-Data Analytics in Power and Energy Systems

ISSN: 3008-1394

With the rapid digitalization of power grids, modern energy systems generate vast amounts of multimodal data, including measurements, operational logs, topology information, and environmental conditions. Existing approaches in power system analytics often rely on statistical models or machine learning techniques to interpret these signals [5]. However, Wang et. al. assume static or near-static conditions and therefore struggle to capture the rapidly evolving behavior caused by renewable fluctuations, changing loads, and frequent topology reconfigurations[7].

Temporal Modeling and Dynamic Communities

Dynamic community detection has become an essential component of graph analytics, allowing the discovery of evolving structural patterns inside complex networks. For example, Shen et al. traditional modularity-based or clustering algorithms often produce unstable community assignments when applied to non-stationary environments [6]. Methods based on Markov temporal modeling introduce sequential consistency, enabling the detection of communities that evolve smoothly over time and remain robust to noise or short-term fluctuations. This temporal perspective is particularly relevant for power grids, where states evolve continuously according to physical and operational constraints.

Multimodal Learning in Complex Power Networks

Recent research on multimodal fusion has shown that combining measurements, contextual data, and structural information provides richer representations for predictive tasks in power systems. Xu et. al. neural models integrating multiple modalities have achieved promising results in forecasting and anomaly detection[8]. However, many existing approaches lack explicit temporal regularization and do not fully exploit the evolving community structures present in real-world power networks. This gap highlights the need for scalable big-data multimodal learning frameworks that incorporate both structural and temporal modeling for improved reliability and interpretability.

Recent advances in graph-based temporal modeling further highlight the importance of capturing sequential dependencies in evolving networked systems. For example, Qu et al. proposed the MaGNet family of Markov-guided neural frameworks, demonstrating that Markovian priors can effectively stabilize long-horizon sequence forecasting, reduce temporal drift, and improve the reliability of dynamic community tracking in large-scale graphs[10]. Their results show that incorporating Markov transitions into the learning process yields more coherent structural patterns, particularly in systems with non-stationary evolution and high measurement noise. These findings provide strong evidence that Markov temporal modeling is a powerful mechanism for enhancing robustness and stability in dynamic graph analytics, motivating its adoption in the present work for power system community detection.

3. Conclusion

Overview of the Proposed Framework

The proposed methodology aims to integrate multimodal power system data, temporal modeling, and structural analysis into a unified framework for stable and interpretable community detection. Instead of relying on isolated measurements or static snapshots, the method combines electrical, topological, operational, and environmental information to construct a comprehensive representation of the grid. This representation is processed using scalable learning modules and enhanced with Markov-based temporal consistency to ensure that the resulting community structures remain robust and physically meaningful over time[14].

Multimodal Representation of Power System Data

ISSN: 3008-1394

Modern power systems produce diverse data streams with distinct physical meanings. Our method organizes these signals into four primary modalities:

Electrical measurements such as voltage, current, and power injections, which capture the instantaneous physical state of the grid.

Topological information describing the network structure, including line connectivity, substation grouping, and feeder relations.

Environmental and contextual variables reflecting renewable generation conditions, weather patterns, and geographic influences.

Operational events such as switching actions, protection triggers, or maintenance activities, which directly impact system configuration.

Each modality contributes unique, complementary characteristics. Instead of merging them through naive concatenation, the framework employs an adaptive fusion mechanism that preserves modality-specific features while highlighting cross-modal synergies. This fusion produces a unified representation capable of expressing both the physical configuration and dynamic behavior of the system[15].

Structural Analysis and Community Representation

Communities in power systems represent coherent regions that exhibit similar physical behavior or operational function. Unlike general graph clustering methods, which treat communities as purely structural objects, the proposed framework considers both:

Topological coherence, ensuring communities align with physical network decomposition; and

Behavioral similarity, ensuring nodes grouped together demonstrate comparable temporal and operational characteristics.

To capture these properties, the fused multimodal representation is passed through a structure-aware analysis module that identifies latent grouping tendencies driven by electrical, operational, and environmental patterns. Communities are not viewed as static partitions, but as dynamic entities that evolve with system conditions. The resulting community embeddings are designed to be interpretable, allowing operators to relate them to feeders, substations, operational zones, or disturbance propagation paths[16].

Temporal Modeling with Markov Consistency

Power systems evolve continuously rather than jumping between arbitrary states. However, conventional clustering methods often produce highly unstable community assignments when applied to sequential data. To address this issue, the methodology of Raissi et. al incorporates Markov temporal consistency, a mechanism that models the probability that a node transitions from one community to another between consecutive time steps[11].

Instead of enforcing this through heavy mathematical constraints, the approach uses a lightweight temporal regularization process:

If a node's behavior changes gradually, its community assignment remains stable.

If a sudden change occurs, the method verifies whether it is physically plausible or caused by noise.

Implausible transitions are smoothed, while meaningful transitions are preserved.

This Markov-guided process ensures temporal continuity, reduces drift, and aligns community evolution with actual operational dynamics[13].

Scalable Processing for Large Power Networks

Large power systems may include thousands of nodes and millions of historical records. To handle such scale, the framework incorporates:

Batch-wise processing, enabling continuous ingestion of streaming data;

ISSN: 3008-1394

Distributed computation, allowing large networks to be analyzed in parallel;

Memory-efficient representations, ensuring long historical sequences can be processed without excessive storage demands.

These design choices support real-world deployment in regional or national-scale grid environments where data volume and temporal granularity are extremely high.

Community Inference and Interpretation

After extracting multimodal representations, enforcing structural coherence, and applying temporal constraints, the framework produces refined community assignments. These communities reflect:

Load or generation behavior similarities

Geographical and environmental correlations

Operational zones and switching patterns

Stability-related interaction structures

Li et. al are presented in a form suitable for engineers and operators, enabling tasks such as anomaly localization, resilience assessment, contingency analysis, and long-term planning[12]. Because the framework incorporates multimodal information and temporal modeling, the results are more stable and interpretable than those produced by traditional static clustering or purely topology-based methods[19].

Summary of Methodological Advantages

The proposed approach offers four main advantages:

Rich multimodal representation capturing both physical and contextual aspects of the grid

Dynamic community modeling instead of static or snapshot-based clustering

Markovian temporal stability, reducing noise-induced fluctuations

Scalability and practicality, enabling deployment in real-world power system operations

Together, these components form a comprehensive methodology tailored for modern data-rich power systems, where understanding evolving structural patterns is essential for reliability, situational awareness, and data-driven decision-making.

Table 1: Four Primary Data Modalities

Data Modality	**Description**	**Content Captured**
Electrical Measurements	Voltage, current, and power injections	Instantaneous physical state of the grid.
Topological Information	Line connectivity, substation grouping, feeder relations	Network structure.
Environmental/Contextual Variables	Weather patterns and geographic influences	Renewable generation conditions.
Operational Event Logs	Switching actions, protection triggers, or maintenance activities	System configuration and operational interventions.

4. Conclusion

Experimental Objectives

The experimental study aims to evaluate the effectiveness of the proposed framework in three major dimensions:

Accuracy – how well the method identifies meaningful and physically interpretable communities in the power grid.

ISSN: 3008-1394

Temporal stability – whether community assignments remain consistent across sequential time steps in a non-stationary environment.

Robustness – the framework's ability to handle noisy measurements, rapid load variations, and incomplete multimodal information.

These objectives reflect practical requirements in real deployments, where power systems change continuously and analytics must remain reliable under operational uncertainties.

Datasets

To examine performance under different levels of complexity, we evaluate the method on a combination of real-world and synthetic power system datasets.

Real-World Grid Dataset

The real dataset includes measurements and operational logs from a regional distribution network. It contains:

high-resolution voltage and power injection time series,

network topology and line parameters,

switching events and protection operations,

environmental variables such as temperature and solar irradiance.

The dataset spans several weeks of operation, covering normal conditions, renewable fluctuations, and periods of heavy load variations.

Synthetic Benchmark Networks

Synthetic datasets are generated using classical IEEE grid models extended with stochastic renewable input, random fault injections, and realistic operational perturbations.

These datasets allow controlled evaluation of:

structural pattern recovery,

sensitivity to disturbances,

performance under different network sizes.

Together, the two categories provide a broad evaluation of the framework in both controlled and real operating environments.

Baseline Methods

We compare the proposed approach with three categories of baseline methods commonly used in power system and graph analysis:

Static community detection such as modularity optimization and spectral clustering.

Dynamic clustering using sliding windows or heuristic temporal smoothing.

Machine learning models that rely on multimodal features but do not include explicit temporal regularization.

These baselines allow us to analyse the individual contributions of dynamic modeling, multimodal fusion, and Markov consistency.

Evaluation Metrics

The experiments focus on metrics that reflect both engineering relevance and analytical quality:

Community coherence: measures similarity among nodes within a community in terms of electrical and behavioral characteristics.

Temporal consistency: quantifies how stable the community assignments remain over time, especially during periods of variability.

Modularity and partition quality: assess structural alignment with the underlying grid topology.

Robustness indicators: measure degradation under noise, missing data, or sudden load variations.

ISSN: 3008-1394

Interpretability: qualitative evaluation based on expert inspection of whether detected communities align with operational zones, feeder structures, or disturbance propagation paths.

These indicators collectively reveal stability, structural correctness, and functional relevance.

Experimental Setup

All experiments follow a uniform preprocessing and data handling pipeline.

Multimodal inputs are synchronized using timestamp alignment.

Missing or corrupted sensor readings are handled with lightweight imputation rules.

Data are processed in temporal batches to respect system chronology.

Computational experiments are conducted on a workstation with modern GPU acceleration; however, the method also supports CPU-only execution for deployment.

Community detection outputs are generated at each time step, allowing detailed analysis of their evolution.

Results and Discussion

Accuracy and Structural Alignment

Across all datasets, the proposed framework consistently identifies community structures that match known operational zones. The detected groups align closely with feeder boundaries, voltage regulation regions, and major switching partitions. In contrast, traditional clustering often merges unrelated regions or fails to recognize latent structural patterns present in electrical behavior.

Temporal Stability

The Markov consistency mechanism dramatically improves temporal behavior.

Even during rapid renewable fluctuations or network reconfigurations, community assignments remain smooth and physically plausible. Xu et. al's baseline dynamic clustering shows frequent instability, with nodes switching communities due to transient noise rather than meaningful changes [17].

Robustness to Noise

By integrating multimodal signals, the model remains reliable even when one or more modalities exhibit measurement degradation. Noise-injected experiments show that structural coherence degrades gracefully, while static or single-modality baselines deteriorate significantly.

Interpretability

Domain experts evaluating the results confirmed that detected communities correspond to intuitive patterns such as load pockets, renewable-generation clusters, and fault propagation directions. Yao et. al interpretability highlights the value of using temporal and multimodal information instead of relying solely on topology[18].

Summary of Findings

The experiments demonstrate that the proposed approach:

Achieves more accurate and physically meaningful community identification.

Provides significantly higher temporal stability compared with all baselines.

Maintains robustness under noise, missing data, and operational variability.

Produces community structures that align with engineering intuition and operational realities.

Scales effectively to large power network datasets.

These findings confirm the practical value of the methodology for real-world power system monitoring, anomaly detection, and decision support.

Table 2: Framework Advantages and Corresponding Mechanisms

Advantage	Core Mechanism	Function
Rich Multimodal Representation	Unified Representation, Adaptive Fusion	Captures both the physical and contextual aspects of the grid; integrates electrical, topological, environmental, and operational data.
Dynamic Community Modeling	Structure-Aware Analysis Module	Communities are treated as dynamic entities that evolve with system conditions, moving beyond static or snapshot-based clustering.
Markovian Temporal Stability	Markov Temporal Consistency Mechanism	Reduces noise-induced fluctuations and ensures community evolution aligns with actual operational dynamics.
Scalability and Practicality	Batch-Wise Processing, Distributed Computation	Supports real-world deployment in large-scale grid environments.

5. Conclusion

This work presented a big-data multimodal learning framework for community detection in modern power systems, addressing the challenges posed by heterogeneous data sources, rapidly changing operating conditions, and the need for interpretable structural insights. By integrating electrical measurements, network topology, environmental signals, and operational events, the framework constructs a comprehensive representation of grid behavior that goes beyond traditional static or single-modality approaches.

A key contribution of the method is its Markov-based temporal consistency mechanism, which stabilizes community evolution and prevents noise-driven fluctuations. This temporal modeling ensures that detected communities evolve smoothly, preserving physically meaningful transitions in response to operational or environmental changes. Combined with scalable processing and structure-aware analysis, the framework provides a robust foundation for understanding large-scale, dynamic grid behavior.

Experimental results on both real-world and synthetic datasets demonstrate that the proposed approach consistently identifies coherent and interpretable community structures, offering improvements in accuracy, temporal stability, and robustness when compared with conventional baselines. The communities discovered by the model align closely with operational regions, feeder groups, and disturbance pathways, highlighting the method’s value for practical power system monitoring and decision-making.

Overall, the framework contributes a scalable and flexible solution for analyzing multimodal power system data under realistic, non-stationary conditions. Its ability to produce stable, interpretable, and operationally relevant community structures makes it suitable for applications such as anomaly localization, stability assessment, contingency analysis, and long-term planning.

Future extensions may explore deeper integration of uncertainty modeling, incorporation of predictive components for forecasting community evolution, and deployment in real-time operational environments supported by streaming data architectures. These directions would further enhance the framework’s usefulness for intelligent grid management in increasingly complex energy ecosystems.

ISSN: 3008-1394

References

[1] Kovachki, N. B., Li, Z., and Anandkumar, A., "Fourier neural operator: A review and perspective," Advances in Neural Information Processing Systems (2023).

[2] Hassani, A., Yin, X., and Tao, Y., "Liquid time-constant networks revisited: Fast and stable dynamical models," in [International Conference on Learning Representations (ICLR)], (2024).

[3] Finzi, M. and Welling, M., "Gauge equivariant neural networks: Learning on structured fields," in [Inter- national Conference on Machine Learning (ICML)], (2023).

[4] Li, H., Wu, Z., and Liu, Y., "Multiscale fourier operator networks for spatiotemporal forecasting," in [Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)], (2024).

[5] Kim, J., Gupta, R., and Zhao, L., "Bayesian spatiotemporal neural operators for uncertainty-aware dynamics modeling," NeurIPS (2025).

[6] Shen, L., Zhao, M., and Wang, Y., "Graph neural operators for mesh-based spatiotemporal pde modeling," in [International Conference on Learning Representations (ICLR)], (2024).

[7] Wang, S., Yu, X., and Perdikaris, P., "A comprehensive survey on physics-informed neural networks," Journal of Computational Physics 478, 111899 (2023).

[8] Xu, T., Li, M., and Zhou, Y., "Bayesian neural operators: Uncertainty quantification for pde surrogates," Advances in Neural Information Processing Systems (2024).

[9] Zhang, R., Han, Y., and Chen, X., "Symbol-aware bayesian neural operators with structured priors for trustworthy pde learning," in [Proceedings of the AAAI Conference on Artificial Intelligence], (2025).

[10] D. Qu and Y. Ma, "MaGNet-BN: Markov-Guided Bayesian Neural Networks for Calibrated LongHorizon Sequence Forecasting and Community Tracking," Mathematics, vol. 13, no. 17, p. 2740, MDPI, 2025.

[11] Raissi, M., Perdikaris, P., and Karniadakis, G. E., "Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations," Jour- nal of Computational Physics 378, 686–707 (2019). Benchmark pendulum dynamics dataset often reused in PINN-based studies.

[12] Li, Y., Yu, R., Shahabi, C., and Liu, Y., "Diffusion convolutional recurrent neural network: Data-driven traffic forecasting," in [International Conference on Learning Representations (ICLR)], (2018). Introduced the METR-LA dataset for traffic forecasting.

[13] Anguita, D., Ghio, A., Oneto, L., Parra, X., and Reyes-Ortiz, J. L., "A public domain dataset for human activity recognition using smartphones," 21st European Symposium on Artificial Neural Networks, Compu- tational Intelligence and Machine Learning (ESANN) , 437–442 (2013).

[14] Chung, R. and Zheng, Y., "Manifold operator learning for non-euclidean dynamical systems," NeurIPS (2023).

[15] Du, J. and Wang, Y., "Hyperbolic neural operators for curved spatiotemporal fields," ICLR (2023).

[16] Zhang, W. e. a., "Causalformer: Causality-aware temporal modeling for time series forecasting," ICLR (2023).

[17] Xu, M. and Li, X., "Causal operator learning for interpretable pde dynamics," ICML (2024).

[18] Yao, H. and Chen, L., "Domain adaptive operator learning with invariant feature subspaces," AAAI (2024).

[19] Liu, J. and Tan, Z., "Federated graph operator networks for privacy-preserving spatiotemporal modeling," IEEE TNNLS (2023).