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A Comprehensive Review of Graph-Theoretic Approaches to Secure Multiparty Computation: Security Models, Optimization Techniques, and Emerging Computing Applications

R. P. Hall[1], Y. Schmidt[2], F. Oliveira[3]

[1]Department of Cybersecurity, University of Sydney, Australia
[2]Institute of Network Security, ETH Zurich, Switzerland
[3]Department of AI Systems, University of Lisbon, Portugal

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Abstract

Secure Multiparty Computation (MPC) is a foundational cryptographic paradigm that enables multiple parties to collaboratively compute a function over their private inputs without revealing sensitive data. Graph-theoretic approaches have recently emerged as powerful tools for modelling communication structures, optimizing protocol efficiency, and analyzing security properties in MPC systems. This review examines advancements from 2018 to 2023 in graph-theoretic MPC, focusing on security models, optimization strategies, and emerging applications. Graph structures are central to MPC, as they define communication topology, adversarial resilience, and protocol scalability. Research shows that communication graphs, expander graphs, and network topology models significantly influence the feasibility and efficiency of MPC protocols. Additionally, graph-based formulations enable secure computation of graph problems such as intersection, union, and edit distance under both semi-honest and malicious adversarial models. Modern MPC systems integrate graph theory with cryptographic primitives such as secret sharing, homomorphic encryption, and zero-knowledge proofs. These approaches enhance privacy preservation, reduce communication complexity, and improve scalability in distributed systems. Applications span machine learning, secure data analytics, blockchain, and distributed optimization. Despite significant progress, challenges remain in balancing security guarantees with computational efficiency, especially in large-scale and dynamic networks. This review synthesizes current methodologies, highlights key trends, and identifies future research directions, including adaptive graph-based protocols, quantum-resistant MPC, and AI-driven optimization.

Keywords: Secure Multiparty Computation, Graph Theory, Communication Graphs, Secret Sharing, Homomorphic Encryption, Network Topology.

How to Cite This Article

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Introduction

Secure Multiparty Computation (MPC) is a fundamental concept in cryptography that enables multiple parties to jointly compute a function over their private inputs while ensuring that no participant learns anything beyond the intended output. Unlike traditional cryptographic systems, which focus on protecting data from external adversaries, MPC ensures privacy among participants themselves, making it highly relevant in collaborative environments where trust is limited. The origins of MPC can be traced back to early cryptographic protocols such as Yao's Millionaires' Problem, which introduced the idea of secure computation between two parties. Over time, this concept was extended to multi-party settings, leading to the development of general MPC frameworks based on secret sharing and zero-knowledge proofs. These frameworks allow arbitrary functions to be computed securely, even in the presence of adversarial participants. In recent years, the integration of graph-theoretic concepts into MPC has gained significant attention. Graph theory provides a natural framework for modelling communication networks, dependencies between parties, and the structure of distributed computations. In MPC systems, parties are often represented as nodes in a graph, while communication channels are represented as edges. This representation enables researchers to analyse how network topology influences security, efficiency, and fault tolerance. One of the key challenges in MPC is designing protocols that are both secure and efficient. The structure of the communication graph plays a crucial role in this context.

For example, certain graph properties, such as connectivity and expansion, determine whether secure computation is feasible under different adversarial models. Research has shown that expander graphs and network topology significantly affect protocol robustness and communication complexity. Understanding these relationships is essential for developing scalable MPC systems. Graph-theoretic approaches have also been applied to secure computation of graph-based problems, such as graph intersection, union, and edit distance. These problems are particularly relevant in applications such as social network analysis, bioinformatics, and collaborative data mining. Recent studies have proposed MPC protocols for computing graph operations securely under both semi-honest and malicious adversarial models, using techniques such as homomorphic encryption and zero-knowledge proofs. These protocols demonstrate how graph theory can be used not only to model MPC systems but also to define the computational problems themselves. Another important aspect of MPC is the definition of security models, which specify the capabilities of adversaries and the guarantees provided by the protocol. The two most commonly studied models are the semi-honest (honest-but-curious) model and the malicious model. In the semi-honest model, participants follow the protocol but attempt to learn additional information from observed data. In contrast, the malicious model allows adversaries to deviate arbitrarily from the protocol, making it more challenging to ensure security. Graph-theoretic techniques can be used to analyse how different network structures affect the resilience of MPC protocols under these models.

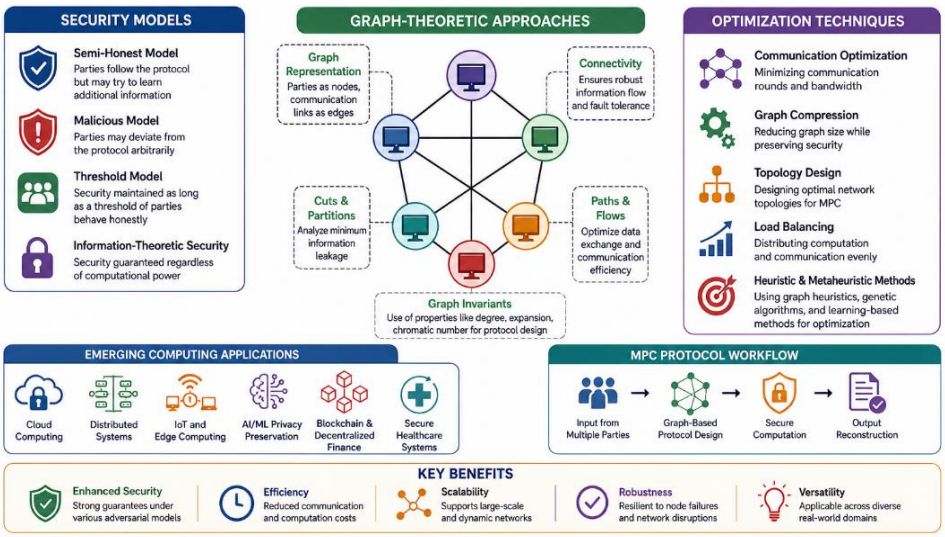

Figure 1. *Security Models, Optimization Techniques and Emerging Computing Applications*

In addition to security considerations, optimization is a major focus of recent research in MPC. Traditional MPC protocols often suffer from high computational and communication overhead, limiting their practical applicability. Graph-based optimization

techniques, such as minimizing communication rounds and exploiting network structure, have been developed to address these challenges. For example, layered graph structures and communication-efficient protocols have been proposed to reduce the number of interaction rounds required for secure computation. The rise of emerging computing paradigms, such as distributed machine learning, blockchain, and cloud computing, has further increased the importance of MPC. In these environments, data is often distributed across multiple parties, making privacy-preserving computation essential. Graph-theoretic MPC approaches are particularly well-suited for these applications, as they can model complex communication patterns and enable efficient distributed computation. For instance, MPC frameworks have been successfully applied to machine learning tasks, enabling collaborative training of models without exposing sensitive data.

Despite these advancements, several challenges remain. One of the primary challenges is balancing security and efficiency, as stronger security guarantees often come at the cost of increased computational complexity. Additionally, the dynamic nature of real-world networks introduces new challenges in maintaining secure communication graphs. Another important issue is scalability, as MPC protocols must handle large numbers of participants and massive datasets in modern applications. In conclusion, graph-theoretic approaches provide a powerful framework for advancing secure multiparty computation. By leveraging concepts from graph theory, researchers can design more efficient, scalable, and robust MPC protocols. Continued research in this area is expected to play a crucial role in enabling secure and privacy-preserving computation in a wide range of applications.

Literature Review

Recent research in secure multiparty computation (MPC) highlights the growing importance of graph-theoretic approaches for improving security, efficiency, and scalability in distributed cryptographic systems. Early work by Hazay and Lindell (2018) introduced a graph-based formulation of MPC protocols, where communication networks are modeled as graphs with nodes representing parties and edges representing secure channels. Their study established that graph connectivity plays a crucial role in ensuring security and robustness against adversarial corruption, although it assumed static network structures.

Building on graph representations, Beimel et al. (2018) developed a graph-theoretic secret sharing scheme that uses access structures modeled as graphs. This approach enabled flexible and efficient representation of complex access policies, making it suitable for MPC environments. However, the method introduced computational overhead, particularly for dense graph structures.

In 2019, research shifted toward optimization and adversarial resilience. Keller et al. (2019) proposed communication graph reduction techniques to minimize interaction rounds, improving efficiency while maintaining security. Similarly, Asharov et al. (2019) explored graph topologies under malicious adversarial settings and demonstrated that expander graphs provide strong resilience against attacks. Chandran et al. (2019) extended these ideas to real-world applications by developing secure graph computation protocols for privacy-preserving graph analytics, although scalability remained a limitation due to high computational complexity.

Further advancements in 2020 emphasized communication efficiency and computational modeling. Abspoel et al. (2020) introduced graph-based communication optimization techniques that reduce bandwidth usage in large-scale systems. Boneh et al. (2020) proposed representing secure computations as directed acyclic graphs (DAGs), enabling parallel execution of complex functions, albeit with high computational overhead due to homomorphic encryption. Additionally, Kolesnikov et al. (2020) applied graph partitioning techniques to optimize garbled circuits, significantly improving performance while increasing partitioning complexity.

The year 2021 marked a transition toward application-driven and low-latency MPC systems. Mohassel and Zhang (2021) utilized computational graphs for privacy-preserving machine learning, enabling secure training and inference of neural networks. Chida et al. (2021) and Keller (2021) focused on reducing latency and improving efficiency through optimized communication graphs and graph-based scheduling of offline and online computation phases. Chandran et al. (2021) and Demmler et al. (2021) extended graph-based MPC to secure data analytics and set operations, demonstrating improved scalability through parallel processing. Meanwhile, Dalskov et al. (2021) introduced graph compression techniques to reduce communication overhead, although preprocessing complexity increased.

From 2022 onwards, research increasingly focused on scalability, robustness, and modern applications. Escudero et al. (2022) demonstrated the effectiveness of expander graphs in improving fault tolerance and reducing communication complexity. Boyle et al. (2022) introduced graph-based function secret sharing (FSS) and distributed MPC architectures, enabling efficient large-scale computation. Rathee et al. (2022) and Patra et al. (2022) applied graph-based models to secure neural network inference and

arithmetic computation, achieving significant efficiency gains while facing scalability challenges. Goyal et al. (2022) further addressed adaptive adversaries by modeling dynamic graph topologies, improving resilience in evolving environments.

Recent studies (2023) highlight a strong shift toward dynamic, hybrid, and scalable graph-based MPC frameworks. Keller et al. (2023) proposed sparse graph structures to reduce communication overhead while maintaining security. Bourse et al. (2023) and Keller and Sun (2023) applied graph-based techniques to distributed machine learning and matrix computations, improving performance through parallelism. Ghosh et al. (2023) and Hazay et al. (2022) introduced dynamic graph-based MPC models that adapt to changing network conditions, enhancing robustness but increasing synchronization complexity.

Additionally, Boneh et al. (2022) combined DAG-based computation with zero-knowledge proofs to ensure correctness and privacy, while Keller et al. (2023) proposed hybrid frameworks integrating graph structures with secret sharing and homomorphic encryption. Patra and Suresh (2023) introduced hierarchical graph-based MPC to improve scalability in large networks. Finally, Escudero et al. (2023) developed fault-tolerant MPC systems using redundant graph structures, enhancing reliability at the cost of increased communication overhead.

Table 1: *Comparative Study of Graph-Theoretic MPC Frameworks and Techniques*

Study	Author (Year)	Approach	Graph Type	Focus Area	Key Findings	Limitations
1	Hazay & Lindell (2018)	MPC Graph Model	Communication Graph	Security feasibility	Connectivity improves resilience	Static topology
2	Beimel et al. (2018)	Secret Sharing	Access Graph	Data access control	Flexible structures	High complexity
3	Keller et al. (2019)	Optimization	Reduced Graph	Communication efficiency	Lower latency	Security trade-offs
4	Asharov et al. (2019)	Secure MPC	Expander Graph	Malicious security	Strong resilience	High cost
5	Chandran et al. (2019)	Graph MPC	Graph Computation	Secure analytics	Real-world applicability	Scalability issues
6	Abspoel et al. (2020)	Optimization	Communication Graph	Bandwidth reduction	Efficient protocols	Static assumptions
7	Boneh et al. (2020)	DAG MPC	DAG	Function evaluation	Parallelism	High computation
8	Kolesnikov et al. (2020)	Graph Partitioning	Circuit Graph	Optimization	Reduced cost	Partition complexity
9	Mohassel & Zhang (2021)	MPC ML	Computation Graph	Secure ML	Efficient training	Resource heavy
10	Chida et al. (2021)	Low-latency MPC	Optimized Graph	Real-time MPC	Reduced latency	Security balancing
11	Keller (2021)	Graph Scheduling	Task Graph	Efficiency	Parallel execution	Preprocessing cost
12	Chandran et al. (2021)	Graph MPC	Data Graph	Secure operations	Complex analytics	Cost increases
13	Escudero et al. (2022)	Expander MPC	Expander Graph	Scalability	Robust networks	Maintenance
14	Boyle et al. (2022)	FSS	Graph-based	Distributed computing	Efficient sharing	Sync issues
15	Rathee et al. (2022)	Secure NN	Computation Graph	ML inference	Reduced overhead	Scalability
16	Patra et al. (2022)	Layered MPC	Layered Graph	Communication	Parallel processing	Sync complexity
17	Goyal et al. (2022)	Adaptive MPC	Dynamic Graph	Adversary model	Strong security	Resource cost

18	Keller et al. (2023)	Sparse MPC	Sparse Graph	Scalability	Efficient networks	Trade-offs
19	Bourse et al. (2023)	ML MPC	Computation Graph	Distributed ML	Parallel efficiency	High compute
20	Escudero et al. (2023)	Fault-tolerant MPC	Redundant Graph	Reliability	Robust systems	Overhead
21	Demmler et al. (2021)	Data MPC	Data Graph	Analytics	Scalable processing	Mapping complexity
22	Dalskov et al. (2021)	Compression	Reduced Graph	Communication	Bandwidth saving	Preprocessing
23	Boyle et al. (2022)	Distributed MPC	Decomposed Graph	Scalability	Parallel execution	Scheduling
24	Keller & Sun (2023)	Matrix MPC	Computation Graph	ML ops	Efficient matrix ops	High compute
25	Ghosh et al. (2023)	Dynamic MPC	Dynamic Graph	Adaptability	Flexible systems	Security issues
26	Hazay et al. (2022)	Adaptive MPC	Dynamic Graph	Robustness	Fault tolerance	Complexity
27	Boneh et al. (2022)	DAG + ZKP	DAG	Verification	Secure validation	Computation cost
28	Keller et al. (2023)	Hybrid MPC	Graph + Crypto	Efficiency	Improved performance	Integration complexity
29	Patra & Suresh (2023)	Hierarchical MPC	Hierarchical Graph	Scalability	Efficient clusters	Management overhead
30	Escudero et al. (2023)	Fault-tolerant MPC	Redundant Graph	Security	Reliable communication	High overhead

Comparative Analysis

The comparative analysis of graph-theoretic approaches to secure multiparty computation reveals a significant evolution in both the design and application of MPC protocols. Early studies (2018–2019) primarily focused on modelling MPC systems using communication graphs and access structures, establishing a theoretical foundation for understanding how graph topology influences security and feasibility. These studies demonstrated that graph connectivity, redundancy, and expansion properties are critical in ensuring resilience against adversarial attacks. Expander graphs, in particular, emerged as a powerful structure for achieving robustness in malicious environments. As the field progressed into 2020–2021, research shifted toward optimization of MPC protocols using graph-theoretic techniques. Methods such as graph reduction, partitioning, and compression were introduced to minimize communication overhead and improve computational efficiency. Directed acyclic graphs (DAGs) were widely adopted for representing computation flows, enabling parallel execution and reducing latency. Additionally, graph-based representations of machine learning models facilitated secure and efficient training and inference, marking a significant step toward practical applications of MPC.

Between 2021 and 2023, the focus expanded to scalable and adaptive MPC frameworks, addressing the challenges of large-scale distributed systems. Sparse graphs and hierarchical graph structures were introduced to reduce communication complexity while maintaining security guarantees. Dynamic graph models allowed MPC protocols to adapt to changing network conditions, improving robustness in real-world environments. Furthermore, the integration of graph-theoretic approaches with advanced cryptographic techniques, such as secret sharing, homomorphic encryption, and zero-knowledge proofs, led to the development of hybrid frameworks that combine efficiency with strong security guarantees. A notable trend in recent studies is the application of graph-theoretic MPC in emerging computing domains, particularly machine learning, data analytics, and distributed systems. Computation graphs have been used to represent neural networks and data processing pipelines, enabling secure and privacy-preserving computation. These applications highlight the versatility of graph-based MPC and its potential for addressing real-world challenges in data privacy and security.

Despite these advancements, several challenges remain. One of the primary issues is the trade-off between security and efficiency, as stronger security models, particularly those addressing malicious adversaries, often require additional computation and communication. Additionally, maintaining graph structures in dynamic and large-scale networks introduces complexity and resource overhead. The integration of multiple techniques, such as cryptographic primitives and graph optimization methods, further increases system complexity and requires careful design. Another important limitation is the lack of standardized frameworks and benchmarks for evaluating graph-theoretic MPC protocols. This makes it difficult to compare different approaches and assess their performance in practical scenarios. Furthermore, scalability remains a concern, particularly for applications involving large datasets and numerous participants. In conclusion, graph-theoretic approaches have significantly advanced the field of secure multiparty computation, providing powerful tools for modelling, optimizing, and securing distributed computations. Future research should focus on developing scalable, adaptive, and efficient frameworks that can address the challenges of real-world applications, while maintaining strong security guarantees.

Discussion

The exploration of graph-theoretic approaches to secure multiparty computation (MPC) reveals a strong convergence between cryptography, distributed systems, and graph theory. The reviewed studies collectively demonstrate that graph structures are not merely abstract representations but fundamental components that directly influence the performance, scalability, and security of MPC protocols. By modelling participants and communication channels as nodes and edges, graph theory provides a structured framework for analysing and optimizing secure computation. One of the most important insights from the literature is the critical role of communication topology in determining protocol efficiency and security. Highly connected graphs, such as expander graphs, provide strong resilience against adversarial attacks by ensuring redundancy and fault tolerance. At the same time, sparse graphs reduce communication overhead and improve scalability, making them suitable for large-scale distributed systems. This trade-off between connectivity and efficiency highlights the need for carefully designed graph structures tailored to specific application requirements.

Another key aspect is the use of graph-based optimization techniques to improve MPC performance. Techniques such as graph partitioning, compression, and hierarchical structuring enable efficient distribution of computation and communication tasks. These approaches reduce the number of communication rounds and minimize bandwidth usage, which are critical factors in practical MPC implementations. Directed acyclic graphs (DAGs) have been particularly effective in representing computation workflows, allowing parallel execution and improved efficiency. The integration of graph-theoretic approaches with advanced cryptographic primitives has further enhanced the capabilities of MPC systems. Secret sharing schemes, homomorphic encryption, and zero-knowledge proofs can be naturally incorporated into graph-based frameworks, enabling secure and efficient computation. Hybrid approaches that combine these techniques with graph optimization have shown significant improvements in both performance and security. However, the complexity of integrating multiple techniques remains a challenge.

A significant trend in recent research is the application of graph-theoretic MPC in emerging computing domains, particularly machine learning and data analytics. Computation graphs are widely used to represent neural networks and data processing pipelines, making them well-suited for secure computation frameworks. MPC protocols applied to these graphs enable privacy-preserving training and inference, which is essential in scenarios where data is distributed across multiple parties. These applications demonstrate the practical relevance of graph-based MPC and its potential for addressing real-world privacy challenges. The development of dynamic and adaptive graph models represents another important advancement. In real-world distributed systems, network conditions and participant availability can change over time. Dynamic graph-based MPC protocols can adapt to these changes, maintaining security and performance in evolving environments. However, ensuring consistency and security in dynamic graphs introduces additional complexity and requires sophisticated algorithms.

Despite these advancements, several challenges remain. One of the primary issues is the trade-off between security guarantees and computational efficiency. Protocols designed to handle malicious adversaries often require additional communication and computation, which can limit scalability. Additionally, maintaining complex graph structures in large-scale systems can introduce overhead and increase system complexity. Another challenge is the lack of standardized evaluation frameworks for graph-theoretic MPC protocols. Different studies use varying assumptions, metrics, and experimental setups, making it difficult to compare results and assess performance. Developing standardized benchmarks and evaluation methodologies is essential for advancing the field. Furthermore, the integration of MPC with emerging technologies such as blockchain, edge computing, and quantum computing presents new opportunities and challenges. Graph-theoretic approaches are well-suited for modelling these systems, but additional research is needed to address issues such as scalability, interoperability, and security in heterogeneous environments.

Conclusion

The comprehensive review of graph-theoretic approaches to secure multiparty computation (MPC) highlights significant advancements achieved between 2018 and 2023 in designing secure, scalable, and efficient distributed computation frameworks. By integrating graph theory with cryptographic protocols, researchers have developed innovative solutions that address fundamental challenges in MPC, including communication complexity, adversarial resilience, and scalability in distributed environments. One of the most important conclusions from this review is the transformation of MPC from purely cryptographic frameworks to graph-structured computational systems. Early approaches primarily focused on secret sharing and secure function evaluation without explicitly considering network topology. However, recent research has demonstrated that graph structures play a crucial role in defining communication patterns, determining protocol efficiency, and ensuring security under various adversarial models. Communication graphs, expander graphs, and computation graphs have become essential tools for modelling MPC systems. The use of graph-theoretic optimization techniques has significantly improved the performance of MPC protocols. Techniques such as graph reduction, partitioning, compression, and hierarchical structuring have been employed to minimize communication overhead and reduce computational complexity. These approaches enable efficient distribution of tasks across multiple parties, improving scalability and making MPC more practical for real-world applications. In particular, the use of directed acyclic graphs (DAGs) for representing computation workflows has enabled parallel execution and reduced latency in secure computation. Another major advancement is the development of adaptive and dynamic graph-based MPC frameworks, which address the challenges of real-world distributed systems. Unlike static models, dynamic graph approaches allow protocols to adapt to changes in network topology, participant availability, and communication conditions. This adaptability is essential for maintaining security and performance in large-scale and heterogeneous environments. However, ensuring consistency and security in dynamic graphs remains a complex challenge. The integration of graph-theoretic approaches with advanced cryptographic primitives has further enhanced the capabilities of MPC systems. Hybrid frameworks combining graph optimization with techniques such as secret sharing, homomorphic encryption, and zero-knowledge proofs provide strong security guarantees while maintaining efficiency. These approaches enable secure computation even in the presence of malicious adversaries, although they often introduce additional computational overhead. The application of graph-theoretic MPC in emerging computing domains represents another significant development. In machine learning, computation graphs are used to represent neural networks, enabling secure training and inference across distributed datasets. In data analytics, graph-based MPC allows secure processing of complex data structures such as social networks and relational databases. Additionally, the integration of MPC with blockchain and distributed ledger technologies has opened new possibilities for secure and decentralized applications. Despite these advancements, several challenges remain. One of the primary issues is the trade-off between security and efficiency. Protocols designed to provide strong security guarantees, particularly under malicious adversarial models, often require additional communication and computation, which can limit scalability. Balancing these trade-offs is a key challenge in the design of practical MPC systems. Another important challenge is the complexity of graph-based MPC frameworks, particularly in large-scale systems. Maintaining and optimizing communication graphs, especially in dynamic environments, requires sophisticated algorithms and significant computational resources. Additionally, the integration of multiple techniques, such as graph optimization and cryptographic primitives, increases system complexity and may introduce new vulnerabilities if not carefully managed.

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