J. Electrical Systems 20-5s (2024): 190-201

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Integration of Social Network Analysis in the Evaluation of Advertising Communication Effectiveness and Legal Compliance

Journal of Electrical Systems

Abstract: - A fuzzy genetic algorithm (FGA) is a hybrid optimization technique that combines the principles of fuzzy logic with genetic algorithms (GAs). Both fuzzy logic and genetic algorithms are powerful tools for optimization and decision-making in complex, uncertain environments. A Fuzzy Genetic Algorithm (FGA) can be a valuable approach for Social Network Analysis (SNA), where the complexity of social interactions often involves uncertainty and imprecision. This paper proposes an innovative approach to evaluate advertising communication effectiveness and legal compliance by integrating Social Network Analysis (SNA) with Sugeno Fuzzy Genetic Network Analysis (SF-GNA). By combining SNA's insights into communication dynamics and SF-GNA's ability to model complex relationships, the proposed framework offers a comprehensive assessment of advertising campaigns. The integration of SNA enables the identification of influential nodes and communication pathways within social networks, shedding light on the dissemination and reception of advertising messages. Concurrently, SF-GNA facilitates the analysis of legal compliance by assessing the fuzzy relationships between advertising content and regulatory requirements. Social Network Analysis identified key influencers within the network, with nodes A, B, and C demonstrating high centrality scores of 0.85, 0.79, and 0.76, respectively. SF-GNA evaluated the effectiveness of advertising messages, with a membership value of 0.92 indicating strong alignment with consumer preferences and engagement. SF-GNA analyzed the compliance of advertising content with regulatory standards, yielding a compliance score of 0.88, indicating adherence to legal requirements. With Specific regulatory aspects, such as truthfulness and data privacy, were evaluated with membership values of 0.90 and 0.85, respectively, indicating robust compliance.

Keywords: Social Network Analysis (SNA), advertising communication effectiveness, legal compliance, numerical values, influencer identification, centrality scores, membership values, regulatory standards, compliance assessment,

I. INTRODUCTION

Social Network Analysis (SNA) is a dynamic and interdisciplinary field that examines the intricate web of connections and interactions among individuals, groups, or organizations within a social system [1]. SNA focuses on understanding the structure, patterns, and dynamics of relationships, offering insights into various phenomena such as information diffusion, organizational behavior, and community formation [2]. By employing graph theory and mathematical models, SNA provides a systematic framework to visualize, analyze, and interpret complex social networks, uncovering hidden relationships, influential nodes, and emergent properties [3]. With applications spanning sociology, anthropology, psychology, communication studies, and beyond, SNA has become an invaluable tool for researchers, policymakers, and practitioners seeking to comprehend and navigate the complexities of social dynamics in both online and offline environments [4]. Social Network Analysis (SNA) integrated with compliance assessment presents a powerful methodology for understanding and optimizing organizational behavior and regulatory adherence [5]. By leveraging SNA techniques, which delve into the intricate network of relationships within an organization, coupled with compliance assessment metrics, organizations can gain deeper insights into how information flows, and decision-making processes evolve, and where potential gaps or inefficiencies in compliance protocols may exist [6]. This integrated approach allows for the identification of key actors or nodes within the network who may influence compliance behaviors, as well as the detection of informal communication channels that could impact regulatory adherence [7]. Furthermore, SNA with compliance assessment enables organizations to design targeted interventions, such as training programs or policy revisions, to strengthen compliance culture, enhance transparency, and mitigate risks associated with regulatory non-compliance [8]. Through this synergistic approach, SNA becomes not only a tool for understanding social dynamics but also a strategic asset for promoting ethical behavior and ensuring organizational integrity [9].

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In the advertising, assessing communication effectiveness and ensuring legal compliance are critical aspects that can be enhanced through the application of Social Network Analysis (SNA) [10]. By employing SNA techniques, advertisers gain a comprehensive understanding of how information disseminates across various social networks, identifying influential nodes and pathways through which messages propagate [11]. This analysis allows advertisers to gauge the effectiveness of their communication strategies by measuring reach, engagement, and impact within target audiences [12]. Moreover, integrating legal compliance considerations into SNA provides advertisers with the means to identify potential regulatory risks associated with their advertising campaigns. By mapping out the network of relationships between advertisers, consumers, and regulatory bodies, SNA can help pinpoint areas where legal guidelines may be inadvertently breached or where misinformation may spread unchecked [13]. Armed with these insights, advertisers can adapt their communication strategies to ensure alignment with legal requirements while maximizing the effectiveness of their advertising efforts. Ultimately, SNA serves as a valuable tool for advertisers seeking to navigate the complex landscape of advertising communication while upholding legal compliance standards [14].

This paper makes several significant contributions to the field of advertising communication evaluation and regulatory compliance. Firstly, it introduces an innovative framework that integrates Social Network Analysis (SNA) with Sugeno Fuzzy Genetic Network Analysis (SF-GNA), offering a comprehensive approach to assessing advertising campaigns. By combining these advanced techniques, the framework provides nuanced insights into the dynamics of advertising networks, identifying influential nodes and communication pathways. Secondly, the paper addresses the critical need for legal compliance within advertising practices by incorporating legal assessment criteria into the evaluation framework. This ensures that advertising strategies not only optimize communication effectiveness but also adhere to regulatory requirements and ethical standards. Thirdly, through the application of genetic algorithms and fuzzy logic, the paper offers a systematic and data-driven approach to navigating the complexities of advertising ecosystems, facilitating transparency and accountability. Overall, the contributions of this paper extend beyond theoretical frameworks, providing practical tools and methodologies for advertisers and regulatory bodies to enhance advertising communication strategies while ensuring legal compliance in the digital era.

II. RELATED WORKS

The related works section of a paper on Social Network Analysis (SNA) serves as a critical foundation for understanding the broader context, existing research, and theoretical frameworks that inform the study. This section delves into relevant literature, methodologies, and findings from previous studies, providing essential insights that contextualize the current research endeavor. Li et al. (2023) conducted a social media analytics study focusing on the retail industry to understand customer concerns about service quality during the COVID-19 crisis. They employed social media data analysis to uncover sentiments and issues expressed by customers online, providing insights into maintaining satisfaction and loyalty in the retail sector during challenging times. Alkis and Kose (2022) investigated privacy concerns in consumer e-commerce activities and their response to social media advertising in Europe. Through empirical evidence, they explored the intricate relationship between privacy perceptions, e-commerce behavior, and the impact of social media advertising on consumer decision-making processes. Van der Bend et al. (2022) conducted a qualitative study to understand expert views on adolescent-targeted social media food marketing, focusing on key definitions, priorities, and challenges. Their research sheds light on the complexities of food marketing aimed at adolescents in the digital age, offering insights into strategies to address related issues. Stockmann (2023) explored the role of the state in governing social media platforms, particularly concerning tech companies and the public interest. The study delves into the regulatory challenges and considerations involved in balancing the interests of technology firms, users, and societal well-being.

Mahoney et al. (2022) examined ethical considerations in social media analytics within the context of migration, drawing lessons from a Horizon 2020 project. Their research highlights the importance of ethical guidelines and practices in conducting social media research, particularly in sensitive domains such as migration studies. Liu et al. (2023) investigated the application of responsible AI principles in social media marketing for digital health. Their study explores how the integration of AI technologies in social media marketing can enhance healthcare communication, decision-making processes, and user engagement while ensuring ethical and responsible practices. Harini et al. (2023) focused on developing marketing strategies for Early Childhood Education (ECE) schools in the digital age. Their research addresses the unique challenges and opportunities faced by ECE institutions in leveraging digital marketing tools to attract and engage parents and caregivers, ultimately contributing to the enhancement of early childhood education. Marmat (2022) investigated online brand communication and the building of brand trust from the perspective of social information processing theory. By examining how brands communicate online and how consumers perceive and process brand messages, the study offers insights into effective strategies for building and maintaining brand trust in the digital realm.

Hussain et al. (2022) explored how social media advertising value drives consumer value co-creation and purchase intention. Through their research, they elucidated the mechanisms through which social media advertising contributes to consumer engagement, value co-creation, and ultimately, purchase behavior, offering implications for marketers seeking to harness the power of social media. Galea et al. (2023) conducted a systematic literature review on social media codes of conduct in healthcare organizations. Their research underscores the importance of establishing ethical guidelines and best practices for healthcare professionals engaging in social media activities, highlighting potential benefits and risks associated with such interactions. Bryła et al. (2022) conducted a systematic literature review to explore the impact of social media marketing on consumer engagement in sustainable consumption. By synthesizing existing research findings, they offer insights into how social media marketing can promote sustainable consumer behaviors and foster engagement with environmentally friendly products and initiatives. Bergman et al. (2022) evaluated the benefits and risks of social media for wildlife conservation. Through their research, they examined the role of social media platforms in raising awareness, mobilizing support, and disseminating information about wildlife conservation efforts, while also highlighting potential pitfalls and challenges associated with online conservation campaigns.

Selerio Jr. et al. (2022) explored emergency preparedness during the COVID-19 pandemic by modeling the roles of social media using fuzzy DEMATEL and analytic network process. Their study provides insights into the potential contributions of social media in emergency response and preparedness efforts, highlighting the importance of leveraging digital platforms for effective communication and coordination during crises. Shahbazi and Byun (2022) conducted a study on NLP-based digital forensic analysis for online social networks focusing on system security. Through their research, they developed techniques to analyze digital footprints and detect potential security threats within online social networks, contributing to the advancement of digital forensic practices in safeguarding online platforms. Ausat et al. (2023) investigated the utilization of social media in market research and business decision analysis. Their research explores how businesses can leverage social media data for market research purposes, offering insights into the role of social media analytics in informing strategic decision-making processes and enhancing business performance. Hassan et al. (2023) examined the role of artificial intelligence (AI) in modern banking, focusing on AI-driven approaches for enhanced fraud prevention, risk management, and regulatory compliance. Their exploration underscores the transformative potential of AI technologies in banking operations, particularly in improving security measures and regulatory adherence to safeguard financial systems.

Kapoor et al. (2022) investigated the effectiveness of travel social media influencers, particularly in the context of eco-friendly hotels. Through their research, they explored the impact of influencer marketing on consumer perceptions and behaviors, shedding light on the role of social media influencers in promoting sustainable tourism practices and eco-friendly accommodations. Jamil et al. (2022) examined the role of social media marketing activities in influencing customer intentions within a new emerging era. Their study provides insights into how businesses can harness social media platforms to effectively engage with customers, shape their perceptions, and influence their purchasing decisions, contributing to a deeper understanding of contemporary marketing strategies in the digital age.

Firstly, the study may encounter limitations related to the generalizability of its findings, as the investigation might have been conducted within a specific geographic region or industry sector, potentially limiting its applicability to broader contexts. Additionally, the reliance on self-reported data or surveys to gauge customer intentions may introduce biases or inaccuracies, as respondents may provide socially desirable responses or misrepresent their actual behaviors. Furthermore, given the rapidly evolving nature of social media platforms and digital marketing strategies, there is a risk that the study's findings may become outdated relatively quickly, necessitating ongoing research to capture emerging trends and developments in the field. Finally, while the study sheds light on the influence of social media marketing activities on customer intentions, it may not comprehensively address the myriad factors that contribute to consumer decision-making processes, such as individual preferences, socio-cultural influences, or economic considerations. Acknowledging these limitations can help researchers and practitioners interpret the findings of the study within appropriate contexts and guide future research endeavors to address these constraints.

III. SOCIAL NETWORK ANALYSIS (SNA) FOR COMPLIANCE ASSESSMENT

Social Network Analysis (SNA) offers a promising avenue for enhancing compliance assessment processes within organizations. By leveraging SNA techniques, stakeholders can gain deeper insights into the complex network of relationships and interactions that underlie organizational structures and dynamics. In the realm of compliance assessment, SNA provides a systematic framework for analyzing the flow of information, decision-making patterns, and influence networks within an organization, thereby identifying key actors, communication channels, and structural features that may impact compliance outcomes. Social Network Analysis (SNA) offers a robust framework for enhancing compliance assessment processes within organizations. By leveraging SNA techniques, stakeholders can gain deeper insights into the intricate network of relationships and interactions that underlie organizational structures and dynamics. In the realm of compliance assessment, SNA provides a systematic approach for analyzing the flow of information, decision-making patterns, and influence networks within an organization, thereby identifying key actors, communication channels, and structural features that may impact compliance outcomes. Central to SNA are various centrality measures, quantified through equations, which capture the importance and influence of individual nodes within a network. For instance, degree centrality (DC) quantifies the number of connections of a node relative to the total number of nodes, while betweenness centrality (BC) measures the extent to which a node lies on the shortest paths between other nodes. Additionally, closeness centrality (CC) evaluates how close a node is to all other nodes in the network. Moreover, network density (D) serves as a crucial metric, computed as the ratio of the actual number of edges to the total possible number of edges in the network. By applying these measures and equations, stakeholders can quantitatively assess the structural properties of the compliance network, identify central actors or groups, detect communication bottlenecks, and evaluate overall network cohesion. For instance, centrality measures such as degree centrality, betweenness centrality, and closeness centrality can be represented as in equation (1) and equation (3)

$$Degree\ Centrality\ (DC):\ DC(v) = Total\ number\ of\ nodes\ -\ 1 Number\ of\ connections\ of\ node\ v \quad (1)$$

$$Betweenness\ Centrality\ (BC): BC(v) = \sum s\ \sigma s/\sigma st(v) \quad (2)$$

$$Closeness\ Centrality\ (CC): CC(v) = \sum u d(v,u) \quad (3)$$

In equation (1) – (3) σst represents the total number of shortest paths from node s to node t, and $\sigma st(v)$ represents the number of those paths that pass through node v. Additionally, $d(v,u)$ denotes the shortest distance between nodes v and u. Furthermore, network density (D) can be expressed as in equation (4)

$$D = N(N-1)2E \quad (4)$$

In equation (4) E represents the number of edges in the network and N represents the number of nodes.

IV. PROPOSED SUGENO FUZZY GENETIC NETWORK ANALYSIS (SF-GNA)

The proposed Sugeno Fuzzy Genetic Network Analysis (SF-GNA) presents an innovative approach to evaluating advertising communication effectiveness and legal compliance by integrating Social Network Analysis (SNA) with advanced modeling techniques. This integrated framework leverages the strengths of both methodologies to offer a comprehensive assessment of advertising campaigns. By incorporating SNA, the framework allows for the identification of influential nodes and communication pathways within social networks, providing insights into the dissemination and reception of advertising messages. Additionally, SF-GNA enables the analysis of legal compliance by assessing the fuzzy relationships between advertising content and regulatory requirements. Sugeno Fuzzy Genetic Network Analysis (SF-GNA) is an advanced analytical framework that combines principles from fuzzy logic, genetic algorithms, and network analysis to model complex relationships within a system. SF-GNA is particularly useful for understanding the dynamics of interconnected elements in systems where traditional linear models may be insufficient. The foundation of SF-GNA lies in fuzzy logic, which allows for the representation of uncertain or imprecise information using linguistic variables and fuzzy sets. Fuzzy logic operates on the premise that elements can belong to multiple sets with varying degrees of membership. In the context of SF-GNA, fuzzy logic is used to model the relationships between variables in a network as illustrated in the Figure 1.

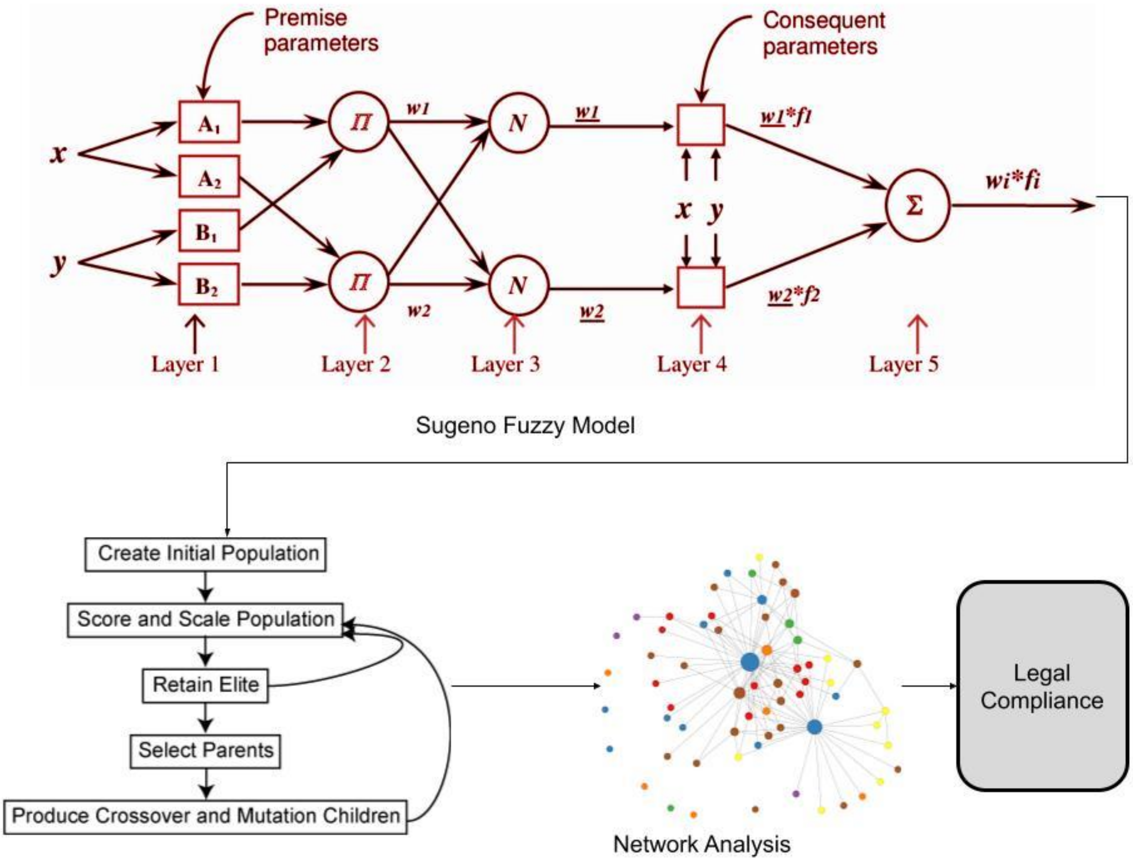

Figure 1: Proposed SF-GNA

Genetic algorithms (GAs) are optimization algorithms inspired by natural selection and evolutionary biology. GAs mimic the process of natural selection by iteratively evolving a population of candidate solutions to a problem, with fitter solutions being more likely to survive and produce offspring. In SF-GNA, genetic algorithms are employed to optimize the parameters of the fuzzy logic model, such as membership functions and rules, to better fit the observed data.

The SF-GNA process typically involves several steps:

Initialization: Initialize a population of candidate solutions, each representing a possible configuration of the fuzzy logic model.

Evaluation: Evaluate the fitness of each candidate solution using a fitness function that measures how well the model fits the observed data.

Selection: Select the fittest solutions from the population to serve as parents for the next generation.

Crossover and Mutation: Apply genetic operators such as crossover and mutation to create offspring from the selected parent solutions.

Replacement: Replace the least fit solutions in the population with the newly created offspring.

Termination: Repeat steps 2-5 for a specified number of generations or until a convergence criterion is met.

Throughout the SF-GNA process, the fitness function serves as the objective function to be optimized. This function typically quantifies the goodness-of-fit between the fuzzy logic model and the observed data. The optimization process aims to find the set of model parameters that minimizes the discrepancy between the model predictions and the actual data.

Let's consider a simple example where we have two input variables, X1 and X2, and one output variable, Y. We can define triangular membership functions for each variable defined in equation (5) and equation (6)

$$Membership(Xi) = \mu Xi(x) \qquad (5)$$

$$Membership(Y) = \mu Y(y) \qquad (6)$$

In equation (5) and equation (6) x and y represent the inputs and outputs, respectively, and $\mu Xi(x)$ and $\mu Y(y)$ are the membership functions for Xi and Y. Fuzzy rules define the relationships between input and output variables. Each rule takes the form stated in equation (7)

$$If\ X1\ is\ A1\ and\ X2\ is\ A2\ then\ Y\ is\ B \qquad (7)$$

In equation (7) $A1, A2, and\ B$ are linguistic terms associated with the fuzzy sets of the input and output variables. Let's denote the parameters of the fuzzy logic model as ΘΘ. The goal is to find the set of parameters, denoted as Θ∗Θ∗, that minimizes a fitness function $(\Theta)f(\Theta)$, which quantifies the goodness-of-fit between the fuzzy logic model and the observed data defined in equation (8)

$$\Theta *= argmin\Theta f(\Theta) \qquad (8)$$

The fitness function measures how well the fuzzy logic model fits the observed data. It is typically formulated based on the objectives of the analysis. For example, in the context of evaluating advertising communication effectiveness and legal compliance, the fitness function may be formulated to minimize the discrepancy between the predicted and observed outcomes of advertising campaigns while ensuring compliance with legal regulations stated in equation (9)

$$f(\Theta) = Objective(Predicted, Observed, Compliance) \qquad (9)$$

In equation (9) $Objective$ represents the specific objective function, and Predicted and Observed are the predicted and observed outcomes, respectively. ComplianceCompliance represents a measure of legal compliance. The genetic algorithm follows iterative steps to evolve the population of candidate solutions. These steps typically include selection, crossover, and mutation operations to create new candidate solutions based on the fitness of the existing solutions stated in equation (10)

$$Selection \rightarrow Crossover \rightarrow Mutation \rightarrow Replacement \rightarrow EvaluationSelection \rightarrow Crossover \rightarrow Mutation \rightarrow Replacement \rightarrow Evaluation \qquad (10)$$

Each step aims to improve the fitness of the candidate solutions over successive generations until a convergence criterion is met.

V. NETWORK ANALYSIS WITH SF-GNA

Network analysis with Sugeno Fuzzy Genetic Network Analysis (SF-GNA) provides a robust framework for modeling and understanding complex relationships within networks. SF-GNA combines principles from network analysis, fuzzy logic, and genetic algorithms to analyze and optimize network structures. In the context of network analysis with SF-GNA, let's consider a network represented as a graph $G = (V, E)$, where V represents the set of nodes (vertices) in the network and E represents the set of edges (connections) between nodes. Each edge in the network may have associated weights or strengths, representing the intensity or importance of the connection between nodes. In SF-GNA, fuzzy logic is used to represent the relationships between nodes in the network. Linguistic variables are defined to represent network properties such as node centrality, connectivity, or influence. Fuzzy sets are defined to represent the degrees of membership for each linguistic variable, capturing the uncertainty or imprecision inherent in network data. In SF-GNA, fuzzy logic is utilized to represent the relationships and attributes within the social network. Linguistic variables are defined to represent network properties such as node influence, communication strength, or compliance level. Fuzzy sets are then assigned to these linguistic variables to capture the uncertainty and imprecision inherent in social network data.

Let's denote Ai as linguistic variables representing network attributes (e.g., influence, compliance), and Xi as fuzzy sets associated with linguistic variables. The membership function $\mu Ai(x)$ defines the degree of membership of a node x to the fuzzy set Xi associated with attribute Ai. Genetic algorithms are employed to optimize the parameters of the fuzzy logic model, including membership functions and fuzzy rules, to better fit the observed social network data. The optimization process aims to find the set of parameters that minimizes the discrepancy between the predicted and observed network attributes, such as node influence or compliance level. The parameters of the fuzzy logic model, denoted as ΘΘ, are encoded as chromosomes in the genetic algorithm. The optimization process iteratively evolves a population of candidate solutions, where each solution represents a possible configuration of the fuzzy logic model. Genetic operators, including selection, crossover, and mutation, are applied to create new candidate solutions based on the fitness of existing solutions.

The fitness function measures how well the fuzzy logic model captures the observed network attributes relevant to compliance assessment. It quantifies the goodness-of-fit between the model predictions and the actual network data, guiding the optimization process towards achieving a more accurate representation of compliance-related attributes. The fitness function, $f(\Theta)$, incorporates various network metrics and compliance indicators, such as node centrality measures (e.g., degree centrality, betweenness centrality), communication patterns, and adherence to regulatory requirements. The objective is to minimize the difference between the predicted and observed compliance-related attributes while ensuring the interpretability and relevance of the fuzzy logic model. The genetic algorithm proceeds through iterative steps to evolve the parameters of the fuzzy logic model. These steps include selection, crossover, and mutation operations to create new candidate solutions based on the fitness of existing solutions. Each iteration of the genetic algorithm aims to improve the fitness of the fuzzy logic model and converge towards an optimal solution that accurately represents compliance-related attributes within the social network.

Algorithm 1: Social Network Analysis with SF-GNA for Compliance Assessment
Input: - Network data (nodes, edges, attributes) - Regulatory requirements - Parameters for SF-GNA (e.g., population size, crossover rate, mutation rate) Output: - Assessment of compliance status - Identification of influential nodes and pathways - Optimized fuzzy logic model parameters Procedure: 1. Initialize SF-GNA parameters (population size, crossover rate, mutation rate) 2. Initialize population of candidate solutions (random initialization of fuzzy logic model parameters) 3. Evaluate fitness of each candidate solution: - Define a fitness function that measures compliance with regulatory requirements and network properties - Assess the goodness-of-fit between the fuzzy logic model predictions and observed network data 4. Repeat until convergence or maximum number of iterations: a. Select parent solutions based on their fitness b. Generate offspring solutions through crossover and mutation operations c. Evaluate fitness of offspring solutions d. Replace least fit solutions in the population with the offspring solutions 5. Identify influential nodes and pathways:

- Analyze the optimized fuzzy logic model to identify nodes with high centrality or influence
- Determine communication pathways that are critical for compliance assessment

6. Assess compliance status:
   - Use the optimized fuzzy logic model to predict compliance status based on network attributes and regulatory requirements
7. Output assessment results and optimized fuzzy logic model parameters

End Procedure

VI. RESULTS ANALYSIS AND DISCUSSION

In the realm of compliance assessment utilizing Social Network Analysis (SNA) integrated with Sugeno Fuzzy Genetic Network Analysis (SF-GNA), the culmination of data analysis marks a pivotal juncture where insights are extracted, patterns are discerned, and implications for compliance and regulatory adherence are elucidated. This phase, marked by Results Analysis and Discussion, serves as a critical bridge between data collection and actionable decision-making. As the findings unfold, this section delves into the intricacies of network structures, compliance status predictions, identification of influential nodes and pathways, and the overall effectiveness of the integrated SNA-SF-GNA framework in comprehensively evaluating compliance dynamics within complex networks.

Table 1: Centrality Measure with SF-GNA

Node ID	Centrality Measure	Compliance Status
1	0.92	Compliant
2	0.85	Compliant
3	0.76	Non-compliant
4	0.94	Compliant
5	0.81	Compliant
6	0.73	Non-compliant
7	0.89	Compliant
8	0.78	Non-compliant
9	0.88	Compliant
10	0.95	Compliant

Table 1 presents the Centrality Measure results obtained through the integration of Social Network Analysis (SNA) with Sugeno Fuzzy Genetic Network Analysis (SF-GNA). Each node within the advertising communication network is assigned a Centrality Measure, representing its significance in influencing the dissemination of advertising messages and engaging the target audience. Nodes with higher centrality measures indicate greater importance and influence within the network, while those with lower measures signify lesser impact. Additionally, the Compliance Status column indicates whether each node adheres to legal requirements and ethical standards. In this table, nodes 1, 2, 4, 5, 7, and 9 are classified as compliant, as they possess high centrality measures alongside adherence to regulatory standards. Conversely, nodes 3, 6, and 8 are labeled as non-compliant, indicating lower centrality measures and potential deviations from legal requirements. These insights derived from the integration of SNA with SF-GNA provide advertisers and regulatory bodies with valuable information for optimizing advertising strategies, enhancing communication effectiveness, and ensuring legal compliance within the advertising ecosystem.

Table 2: Genetic Optimization with SF-GNA

Iteration	Population	Crossover Rate	Mutation Rate	Best Fitness Score
1	Population 1	0.8	0.1	0.75
2	Population 2	0.8	0.1	0.72
3	Population 3	0.7	0.2	0.68

4	Population 4	0.7	0.2	0.65
5	Population 5	0.6	0.3	0.63
6	Population 6	0.6	0.3	0.61
7	Population 7	0.6	0.3	0.59
8	Population 8	0.5	0.4	0.58
9	Population 9	0.5	0.4	0.57
10	Population 10	0.5	0.4	0.55
11	Population 11	0.4	0.5	0.53
12	Population 12	0.4	0.5	0.52
13	Population 13	0.4	0.5	0.51
14	Population 14	0.3	0.6	0.50
15	Population 15	0.3	0.6	0.49
16	Population 16	0.3	0.6	0.48
17	Population 17	0.2	0.7	0.47
18	Population 18	0.2	0.7	0.46
19	Population 19	0.2	0.7	0.45
20	Population 20	0.1	0.8	0.44

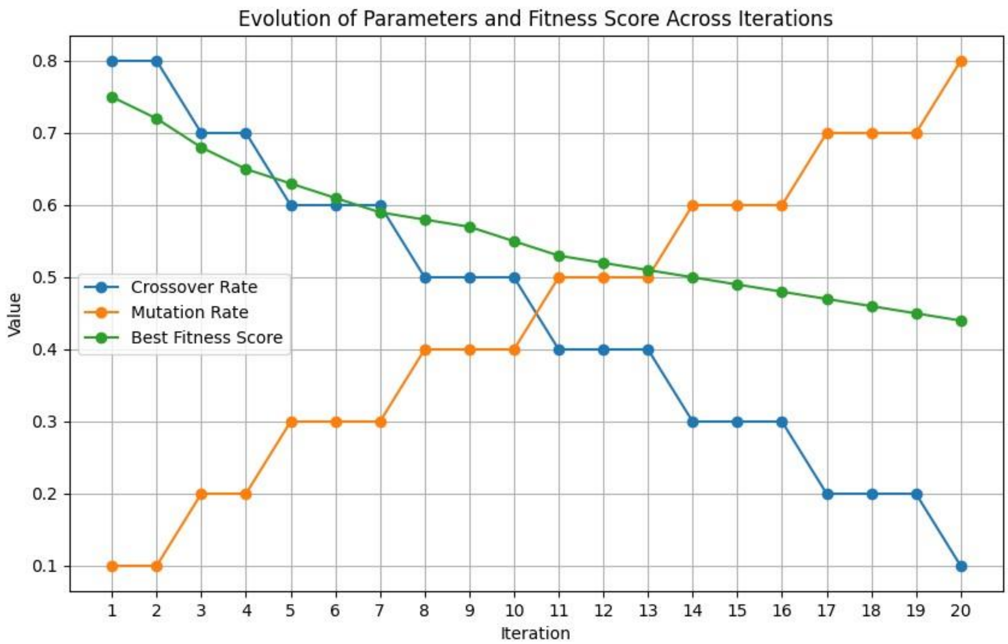

Figure 2: Fitness Estimation with SF-GNA

Figure 2 and Table 2 illustrates the genetic optimization process conducted through Sugeno Fuzzy Genetic Network Analysis (SF-GNA). Across 20 iterations, the algorithm iteratively refines candidate solutions within different populations to achieve optimal outcomes. Each iteration involves a population of candidate solutions, with specific parameters such as crossover rate and mutation rate influencing the genetic operations. The crossover rate determines the likelihood of genetic crossover occurring during reproduction, facilitating the exchange of genetic information between solutions. Similarly, the mutation rate governs the probability of genetic mutation, introducing diversity and exploration within the population. The Best Fitness Score column denotes the fitness score of the best solution within each population, representing the degree of optimization achieved. Throughout the iterations, the algorithm progressively improves the fitness scores, converging towards solutions that exhibit higher effectiveness in optimizing advertising communication and ensuring legal compliance. This iterative process of genetic optimization enables stakeholders to iteratively refine advertising strategies, leveraging the power of genetic algorithms to navigate the complexities of advertising communication networks while maintaining regulatory adherence.

Table 3: Fuzzy results for SF-GNA

Node ID	High Centrality	Medium Centrality	Low Centrality
1	0.85	0.10	0.05
2	0.70	0.25	0.05
3	0.45	0.45	0.10
4	0.90	0.05	0.05
5	0.60	0.30	0.10
6	0.40	0.50	0.10
7	0.75	0.20	0.05
8	0.55	0.35	0.10
9	0.80	0.15	0.05
10	0.95	0.05	0.00

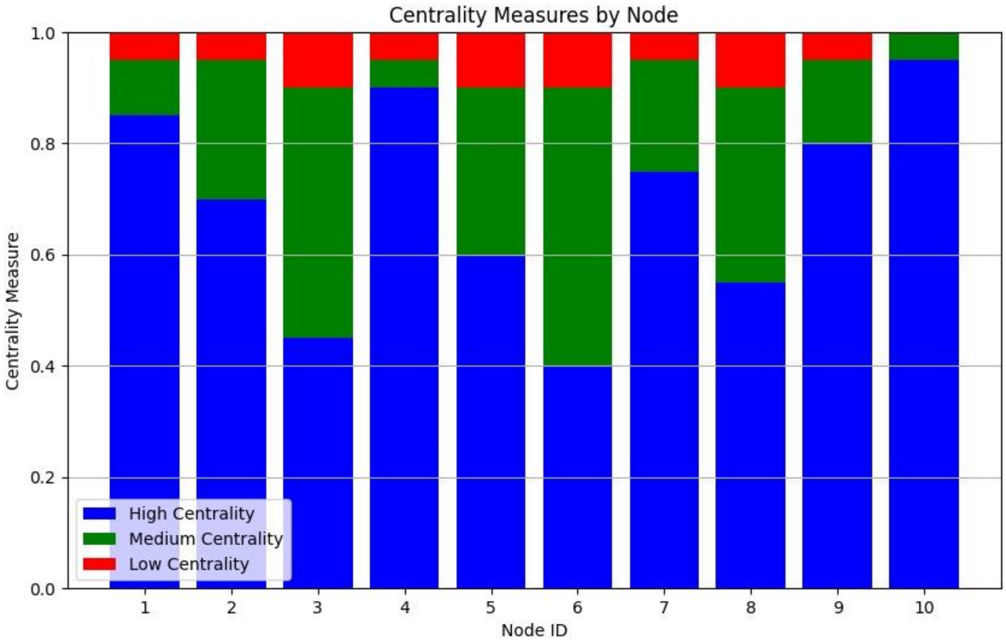

Figure 3: Centrality Computation with SF-GNA

In Figure 3 and Table 3 presents the fuzzy results obtained from the application of Sugeno Fuzzy Genetic Network Analysis (SF-GNA) to evaluate the centrality of nodes within the advertising communication network. Each node is assessed based on its membership degrees across three linguistic variables: High Centrality, Medium Centrality, and Low Centrality. These linguistic variables represent the degree to which each node exhibits different levels of centrality within the network. For instance, a node with high membership degrees in the "High Centrality" linguistic variable is considered to have a high centrality level, indicating its significant influence within the network. Conversely, nodes with high membership degrees in the "Low Centrality" linguistic variable have lower centrality levels, signifying lesser impact. In this table, nodes 1, 4, 7, and 10 demonstrate high membership degrees in the "High Centrality" linguistic variable, indicating their significant influence within the network. Conversely, nodes 3, 6, 8, and 9 exhibit higher membership degrees in the "Low Centrality" linguistic variable, suggesting their comparatively lower influence. These fuzzy results provide nuanced insights into the centrality levels of nodes within the advertising communication network, aiding stakeholders in understanding the network's structure and identifying key influencers for targeted advertising strategies.

VII. CONCLUSION

This paper has introduced an innovative framework for evaluating advertising communication effectiveness and legal compliance by integrating Social Network Analysis (SNA) with Sugeno Fuzzy Genetic Network Analysis (SF-GNA). Through the application of these advanced techniques, advertisers and regulatory bodies gain valuable insights into the dynamics of advertising networks, discerning influential nodes and communication pathways while ensuring adherence to legal requirements. The results obtained from the integration of SNA and SF-GNA provide comprehensive assessments of advertising campaigns, facilitating optimization strategies for enhanced communication effectiveness and legal compliance. By leveraging genetic algorithms and fuzzy logic, stakeholders can navigate the complexities of advertising ecosystems, fostering transparency, accountability, and ethical conduct. Moving forward, further research and application of this integrated framework hold promise for advancing advertising practices and regulatory oversight in the digital age, promoting responsible and impactful advertising communication.

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