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Chapter: Economic Dimensions of Sustainable Development

QUANTITATIVE MODEL OF MULTILEVEL ECONOMIC NETWORK SYNERGY IN CORPORATE MERGERS AND ACQUISITIONS BASED ON DEEP LEARNING

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Annotation. This study explores synergies in multilevel economic networks within corporate mergers and acquisitions, introducing an innovative quantitative model. With the evolving global economy, mergers and acquisitions present challenges tied to synergies and economic networks. In contrast to conventional approaches, our focus is on establishing corporate economic networks based on complex network theory. Through a comprehensive exploration of synergies and the implementation of machine learning and deep learning methods, we propose the multi-DAG model, seamlessly integrating multilevel network structures with directed acyclic graph neural networks. Experimental results conclusively demonstrate Multi-DAG-NN's superior performance in predicting synergy values. Furthermore, this study contributes by innovatively integrating multilevel network structures and neural network models, offering a practical quantitative methodology to study the synergetic effect of corporate mergers and acquisitions.

Keywords: mergers and acquisitions, multilevel economic networks, deep learning, directed acyclic graph neural network, synergy.

JEL classification: C13, C53, C55, G15, G34.

Introduction

In today's globalised economy, corporate mergers and acquisitions (*Ms and As*) have become a pervasive business strategy. Ms and As relate to transactions between two firms that are joined in some form. Although Ms and As appear to share meaning, they are legally distinct terms. When two similar firms are joined to create a new single entity, the term "merger" is utilised. Alternatively, an acquisition occurs once a comparatively larger company acquires a smaller one, resulting in the absorption of the smaller one. Ms and As agreements appear in two forms, namely, friendly or hostile, relying on the companies' approval by the board of directors. There are three distinct types of Ms and As: vertical, horizontal, and conglomerate. The horizontal ones occur between two firms that belong to the same industry. The competitiveness can either exist or not between them. The vertical ones are observed between firms and their suppliers or customers to secure their operations' supply chains. The firms aim to take a higher position with their supply chain, thus unifying their position. The diversification is the main objective of these transactions, and the firms can be in distinct industries.

There are several objectives of Ms and As. Firstly, statutory Ms are generally observed when the acquirer is bigger than the target firm, and their assets and liabilities are bought at the end of the agreement. Then the

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target companies' separate entity characteristics eventually end. Secondly, the target firms become the acquirers' subsidiaries; however, they continue to operate their business. This lead to both firms concluding their legal entity status, and a new firm is established when the deal is finalised.

Ms and As are observed for a number of reasons. One of them relates to the unlocking of synergies, as the shared motivation for Ms and As is based on synergy creation. By doing so, a joint firm is worth more than the two firms separately. Synergies aim to reduce cost or increase revenue. The scale economy can lead to cost synergies, while opportunities such as cross-selling, increasing the share in the market, or higher prices help increase revenue. The quantification and calculation of cost synergies can be done. Another reason argues for the achievement of a higher growth rate. Ms and As can easily lead to inorganic growth, and it is an easy way of achieving higher revenues when organic growth is considered. A company can gain the upper hand on the latest capabilities by not taking risks to achieve the same capabilities when Ms occur. A higher growth rate is not the only achievement of Ms and As, for they also point to stronger market power. The finally formed firm can reach a higher share in the market and can gain the upper hand to affect prices. Vertical Ms also cause higher power in the market, once the firm controls its supply chain, therefore refraining from externally occurring shocks in the supply side. In addition, Ms and As allow to achieve diversification. Firms operating in cyclical industries need diversified cash flows to avoid important losses when the industry slows down. However, acquiring a target firm in a non-cyclical industry gives rise to a firm with lower market risks. Finally, Ms and As point to the gaining of tax benefits. While the former has an important amount of taxable income, the latter leads to tax loss for the future. Therefore, the acquirer uses the tax losses to decrease its tax liability.

There are two basic forms of M and A. The first is stock purchase when the acquirer pays the target firm's shareholders cash and/or shares in exchange for shares of the target company. Here, the target's shareholders receive compensation and not the target. There are certain aspects to be considered in a stock purchase such as (a) the acquirer absorbs all the assets and liabilities, including those not available on the balance sheet; (b) the majority of the shareholders in the target firms must ratify the transaction to receive the compensation, which is usually a time-consuming process; and (c) receiving compensation puts liabilities on the shareholders once taken directly. The second form is asset purchase when the acquirer buys the assets of the target firm, and direct payment is made to them. When assets are purchased, certain aspects should be taken into consideration, such as (a) due to the assets purchased only by the acquirer, there will be no assumed liabilities for the target firms; (b) since the target firm directly gets the payment, the approval of the shareholders is no longer required; however, if assets are substantial, namely, larger than 50%, then the requirement is applied; and (c) the target firm witnesses taxation due to the capital gain by the corporation Two payment methodologies are available, namely, stocks are given and cash is transmitted. Nevertheless, Ms and As generally utilise mixed methods. New shares are issued to pay for the stakeholders of the target firm. An exchange rate is concluded to avoid fluctuation in the stock price. The number of shares is decided based on this agreement. Cash is paid by the acquirer for the target firm's shares. However, avoiding taxes is not the only reason to merge firms.

International cross-border transactions are not only common, but also domestic mergers and acquisitions occur frequently (Schwert, 1996; Ping *et al*., 2024; Inho, Menmeng, 2021). This trend has triggered a cascade of economic network and synergy issues, profoundly impacting both companies and markets (Bradley, 1998). Previous investigations on the networks of Ms and As primarily focused on social networks, predominantly qualitative, but with a limited quantitative analysis perspective (Ivan *et al*., 2019; Ivanchenko *et al*., 2016). This paper distinguishes itself by exploring networks based on the complex network theory using the foundation of corporate economic networks**.**

The modern world infrastructures are composed of inevitably complex systems, represented by networks. To represent networks, a certain quantity of nodes and edges are unified concurrently (Asavathiratham *et. al*., 2011; Krebs, 2006; Hofstad, 2004). Social networks are forms created by human beings by establishing mutual links and social bonds to exchange information, opinions, and news. To illustrate, colleagues with a special training purpose, employers working in the same industries, and organisations sharing the same vision are networks (Newman *et al*., 1992). Organisational networks (Newman *et al*., 1992) are pivotal entities to hire employees, measure the performance of the workers, and gauge business success (Wasserman, Faust, 1994). Nodes in organisational networks are joined to create interdependence by one or more specific kinds, covering several objectives such as values, visions, ideas, financial exchange, friendship, or trade. More specifically, corporate networks provide a structure consisting of joined nodes and edges. While nodes represent entities, edges designate associations or interrelations. Thus, complex corporate actions are tried to be captured, such as production, sales, marketing, and human resources. To analyse complex networks, hidden patterns, features, and behaviours need to be uncovered. The related insights that shed light on social dynamics, production, merger, and acquisition processes, information flow, and transportation systems are derived. This type of analysis contributes to several advancements (Barabasi *et al*., 2006).

Networks, or graphs, are now widely used in economic and financial literature as they represent a natural way to study connections and systemic effects (Battiston *et al*., 2010). Under corporate networks, we consider all networks that describe interactions between firms, suppliers, and shareholders (Caldarelli, 2007).

In the study of complex networks (CNs), CNs are structures that are composed of interconnected nodes showing interdependencies in one form or another. Thus, the eventual graph-like structures are usually complicated forms. Nodes representing individuals, groups, or organisations and connections represented by links, edges, or ties designating relations are building blocks of complex networks. Various frameworks and methods are used to conceptualise nodes, but the fundamental units of the network remain to be nodes (Zanin *et al*., 2016). A real system is signified by a node that can be an entity or element. On the other hand, nodes are connected with, for example, lines showing the interrelatedness and associations. In a complex network, node betweenness measures the shortest path counts moving through a particular node among all pairs of nodes. This indicator helps evaluate the importance of the node, mirroring the degree of capacity to transfer and to connect. The significant correlations between the degree of a node and its closeness are important. The nodes that boast larger degree scores simply exhibit elevated betweenness levels. Complex networks are analysed by using clustering coefficients, which measure the degree of closeness and the community structure of the networks. The interconnectivity or density among the neighbours is specifically measured by this coefficient, giving insights into how tightly they are knit. Undirected networks are directly related to their application since the associations between nodes are bi-directional. To examine the topological structures of complex networks, the density of the network appears to be a significant indicator to outline the overarching characteristics of the network. This indicator efficiently shows the frequency and intensity of interactions among the nodes. As the network intensity increases, the node activities and their mutual interactions heighten (Wang *et al*., 2024).

In the structure of corporate networks, there are external networks (e.g., relationships with suppliers) and internal networks, including internal pipelines, shareholder social networks, and hierarchical multilevel structures, presented in *Figure 1*. In Ms and As, the networks of the acquiring target companies undergo integration and reconstruction, with nodes and pathways interacting in substitution, complementation, enhancement, independent operation, and conflict (Enrico *et al*., 2001). This process forms the economic network synergy of corporate Ms and As (Triegorgis, 1996). Managements use Ms and As to increase the profitability and performance of firms to achieve growth inorganically (Rashid, Naeem, 2017). A small company, lacking capital, can access greater capital and increase the firm's performance. Alternatively, a company having an advantage to better marketing of their products can aid in other companies' selling and eventually produce greater unified revenue (Frankel, Forman, 2017). Ms and As are justified when a synergy is foreseen in advance.

This is based on the distinct performance between the firm standing alone and the firms joined (Ross *et al*., 2016). Theoretically, synergy from operations affects firm performance internally. Internal firm performance is of great concern to management because it indicates the firm's profitability and sustainability (Septian, Dharmastuti, 2019). In addition, external parties also respond to Ms and As, particularly for firms that are publicly listed. Ms and As are big transactions and lead to market reactions, which affects firm performances. Apart from boosting the performance of the firms, Ms and As provide theoretical benefits to diversify business. Thus, companies increase the affiliated entities to minimise business risks. Nevertheless, synergy or business efficacy cannot be guaranteed by diversification (Dismukes, Deupree, 2016). Shareholders can choose a way to decrease their risks by buying shares from other companies so that their portfolios are diversified (Ross *et al*., 2016). Therefore, the claim that Ms and As are beneficial to diversify needs to be investigated further.

This paper focuses on multilevel economic networks in corporate mergers and acquisitions and proposes a quantitative model of synergy based on deep learning theory (Chatuverdi, Weigelt, 2024; Feiqiong *et al*., 2022).

When defining nodes in an economic network, specific research questions guide the selection of the appropriate scope of economic network nodes. In the multilevel network quantification research of corporations, the essence of each level's nodes differs, and the relationships between nodes across levels vary (Jarrel *et al*., 1980). Upper-level nodes in the lower level expand into a network (Jensen, Ruback, 1983; Newman *et al*., 1992). With the application of deep learning in areas such as image recognition, object detection, and economic regression analysis, its potential to address complex problems and improve the efficiency of the algorithms has become of interest of current research (Dixit, Pindyck, 1994; Cong *et al*., 2019).

1. Literature Review

Recent studies on corporate merger synergy include Yanan's (2023) cultural integration impact assessment, proposing a practical guidance framework. Interdisciplinary perspectives in organisational psychology focus on leadership teams, emphasising not only strategic aspects but also organisational culture and employee psychological states (Ang *et al*., 2019; Pennings, Natter, 2001). Sociology research analyses employee social networks, proposing a collaborative effect evaluation model (Rodríguez-Sánchez *et al*., 2018). Rozen-Bakher's (2018) theoretical framework emphasises resource dependence and organisational learning.

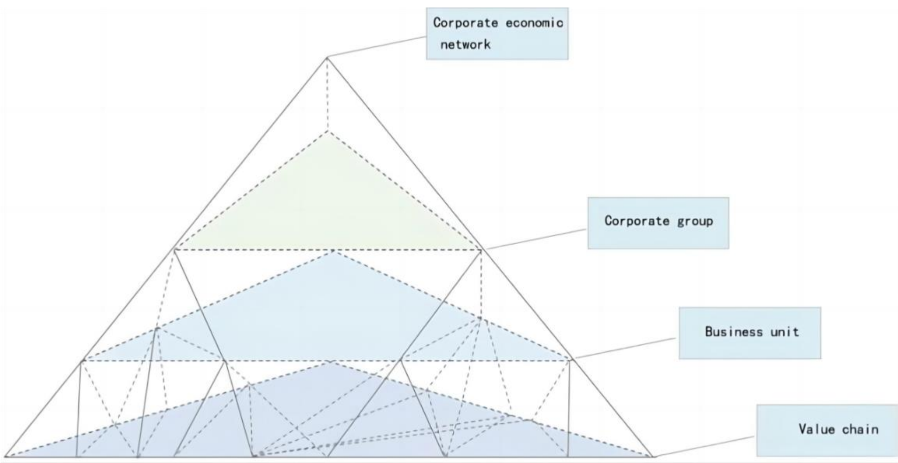

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Figure 1. **Multi-layer Structure of Corporate Networks**

Machine learning applications in corporate mergers, highlighted by Wei and Juan (2023), include a decision model that predicts a company's future target performance. Sentiment analysis in merger information mining correlates the sentiment index with subsequent merger performance, offering market feedback (Xiangjun *et al*., 2022; Ivanov, Vasilchenko, 2016). Chuqing *et al*. (2020) focus on machine learning in risk management, establishing a deep learning-based risk prediction model (Hong *et al*., 2022). While machine learning methods add value to the merger decision-making process, sentiment analysis, relationship dynamics, and risk management, attention must be based on data quality and model interpretability.

Deep learning implementation in multilevel economic networks research includes Umer *et al*.'s (2011) successful research in capturing complex relationships. Jun *et al*.'s (2023) multilevel network model integrates social network theory and deep learning, accurately depicting relationships. Na and Bo's (2013) study on information dissemination constructs a model that integrates multiple data sources. Rayan and Islam (2021) focus on the dynamic evolution of corporate multilevel relationships using deep learning, providing a decision support framework.

In research on the collaborative effects, past studies focused on cultural integration, collaborative innovation, and leadership teams. The critical role of cultural integration in achieving collaborative effects is emphasised, but systematic quantitative research methods are lacking. Machine learning methods in mergers aim to enhance the intelligence of firms in decision-making and risk management. Some studies construct comprehensive models, but interpretability and data quality are essential. Research on multilevel economic networks explores issues such as the evolution of inter-firm relationships and information diffusion. While studies capture non-linear relationships, empirical validation is needed for effective deep learning methods. Despite significant progress, unresolved issues require more large-scale, data-driven research and attention to interpretability, data quality, and model complexity.

2. The Synergy of the Multi-layered Network Model

2.1 The Nodes of the Multi-layered Network

Value Chain Nodes and Resources: At the value chain level, large corporate groups optimise the industry chain by integrating resources from internal business units, enhancing competitiveness through resource integration, supply chain management, customer relationship management, and brand building (Shahzad *et al*., 2023). Additionally, they manage raw materials, production equipment, and human resources.

Business Unit Nodes and Resources: At the business unit level, large corporate groups ensure efficient operations through organisational structure optimisation, talent cultivation, incentives, business synergy, and innovation. They manage financial, technological, material, and information resources for effective utilisation.

Corporate Group Nodes and Resources: At the corporate group level, large corporate groups achieve strategic goals through strategic planning, resource allocation, and risk management. They focus on integrating and managing human, financial, technology, and material resources for the development of the entire group.

Corporate Network Nodes and Resources: At the corporate network level, large corporate groups form an industrial ecosystem through partner selection, innovation in cooperation models, and profit distribution mechanisms (Mostafa and Mahmoud, 1964). They focus on integrating and managing human, financial, technological, and material resources for the common prosperity and development of partner networks (Hillier, 1999).

2.2 The Correlation Analysis of the Multilevel Network Synergy

Pearson's correlation analysis was conducted to screen out the variables that are most relevant to the synergistic value computation, which allowed to improve the accuracy and robustness of the model. In addition, it is possible to gain a deeper understanding of the associations between distinct attributes and to better understand the operational mechanisms of the system. The results of the correlation analysis between different hierarchical network nodes within a corporation are provided in *Figures 2 and 3*.

a. Corporate network level

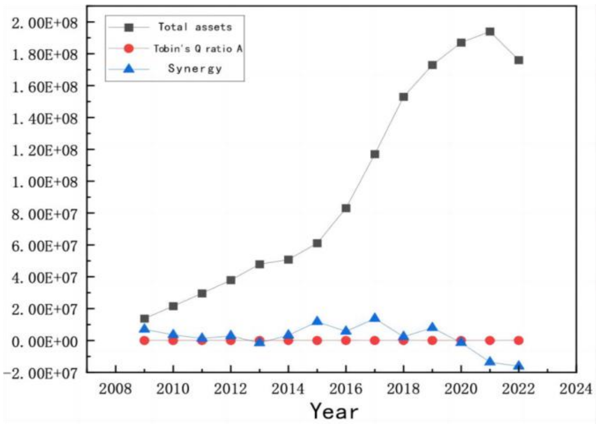

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Figure 2. **Data on Factors Influencing the Operation of Corporate Network Levels**

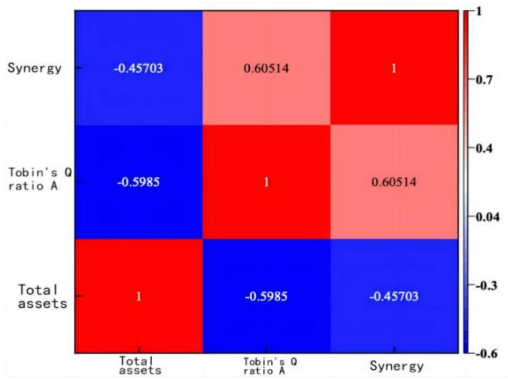

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Figure 3. **Pearson's Correlation Heatmap of Factor Data at the Corporate Network Level**

b. Corporate group level

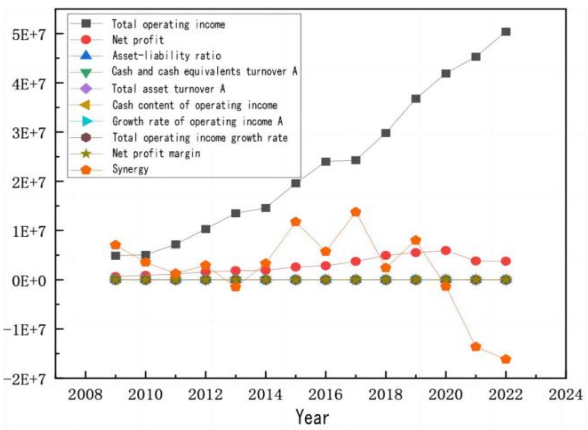

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Figure 4. **Data on Factors Influencing the Operation of Corporate Group Levels**

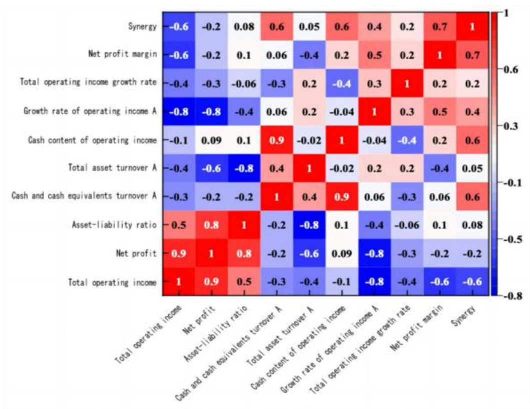

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Figure 5. **Pearson's Correlation Heatmap of Factor Data at the Corporate Group Level**

Figures 2 and 3 present that factors positively correlated with collaborative values include Tobin's Q value (A) at the corporate network level. In contrast, the factor negatively correlated with collaborative values is total assets. Employing an absolute correlation coefficient exceeding 0.5 as a criterion, it is evident that Tobin's Q value (A) exhibits a robust correlation with collaborative values, while other factors demonstrate weaker associations. Notably, the correlation between Tobin's Q value (A) and collaborative values is found to be the most pronounced. This observation strongly suggests that alterations in Tobin's Q value (A) significantly influence collaborative values in corporate network collaborations, as shown in *Figures 4 and 5*.

At the corporate group level, *Figures 4 and 5* highlight factors positively correlated with synergy value: net profit margin, operating cash content of revenue, cash and cash equivalents turnover rate A, operating income growth rate A, total operating income growth rate, debt-to-equity ratio, and total asset turnover rate A. Conversely, negatively correlated factors include operating income and net profit. Using an absolute correlation coefficient above 0.5 as a benchmark, net profit margin, operating cash content of revenue, and cash turnover rate display strong correlations with synergy value, emphasising their importance in determining corporate synergy during mergers, as depicted in Figures *6* and *7*.

c. Business unit level:

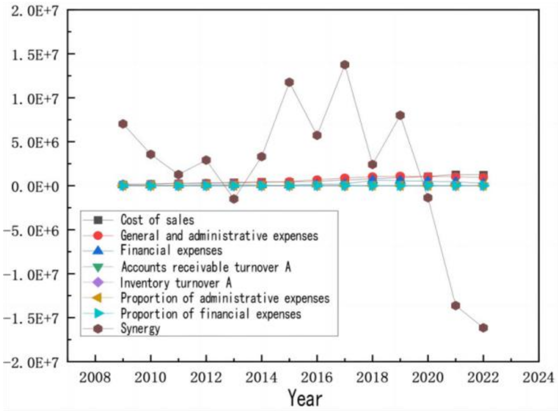

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Figure 6. **Factors Affecting Business Unit Operational Factors Data**

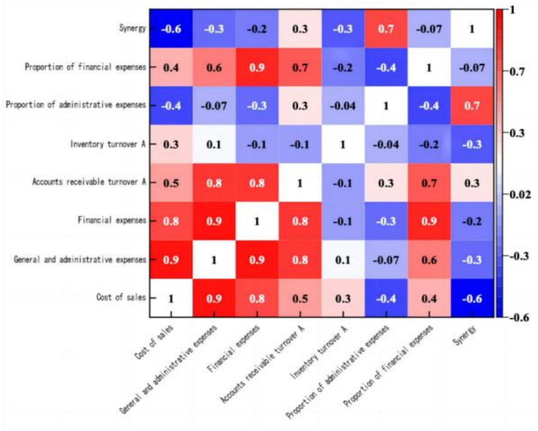

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Figure 7. **Pearson's Correlation Heatmap of Business Unit Level Factor Data**

Figures 6 and 7 depict the trends of expenses, financial expenses, and financial expense ratio. The management expense ratio, selling expenses, and synergy value exhibit robust correlations, while others show weaker associations. The correlation between the management expense ratio and synergy value stands out as the most pronounced, emphasising the direct influence of the extent of business management integration on synergy value benefits in the corporate merger, as shown in figures *8* and *9*.

d. Value chain level:

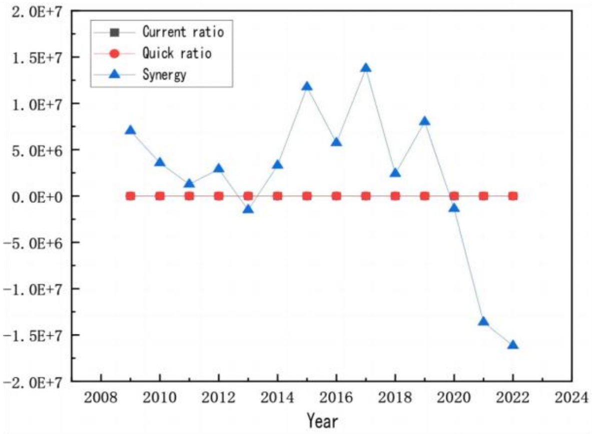

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Figure 8. **Factors Affecting Value Chain Operational Factors Data**

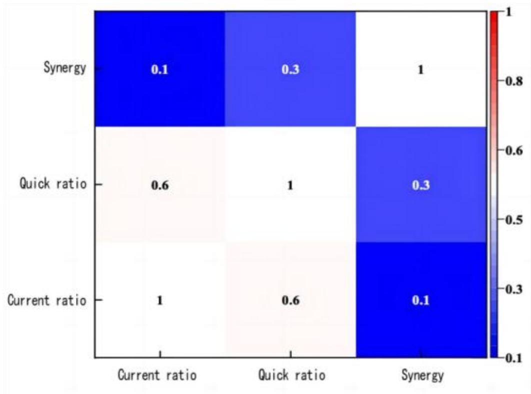

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Figure 9. **Pearson's Correlation Heatmap of Value Chain Level Factor Data**

As depicted by *Figures 8 and 9*, the analysis of the Pearson's correlation heatmap at the value chain level reveals factors positively correlated with synergy value: quick ratio and current ratio. Conversely, no factors at this level exhibit negative correlations with synergy value. Applying a criterion based on an absolute correlation coefficient greater than 0.5, it is evident that both the quick ratio and current ratio display weak correlations. Notably, the highest correlation exists between the quick ratio and synergy value. This observation suggests that value chain-level factors have a limited impact on corporate synergy in the merger of two companies. However, generally speaking, the quick ratio holds greater importance.

3. Deep Learning Prediction Model

3.1 Directed Acyclic Graph Neural Network Prediction Model

A Directed Acyclic Graph Neural Network (DAG-NN) is a unique neural network characterised by a directed acyclic graph structure, featuring unidirectional connections between nodes and mergers (Lie *et al.,* 2023; Yang *et al.,* 2023). This distinctive architecture enforces a clear temporal sequence during training. DAG-NNs are primarily employed for processing sequential data in tasks such as text classification, speech recognition, and dialogue generation, as presented in *Figure 10*. They systematically capture chronological information by propagating it from the initial to the current step.

During training, DAG-NNs employ error backpropagation and gradient descent algorithms to adjust parameters, progressively enhancing prediction accuracy. The intricate DAG structure introduces a heightened non-linear representation, making these networks effective in addressing complex, non-linear problems. This study focuses on utilising DAG-NNs for the regression prediction of collaborative values in corporate networks. Unlike classification, regression prediction demands a network structure with increased non-linearity to fit the data adequately. Limited data volume in the business domain poses challenges, motivating the construction of a DAG-NN structure tailored to the specific data volume for regression prediction. The foundational network structure is illustrated in *Figure 10*, with detailed configurations elaborated in the subsequent subsection.

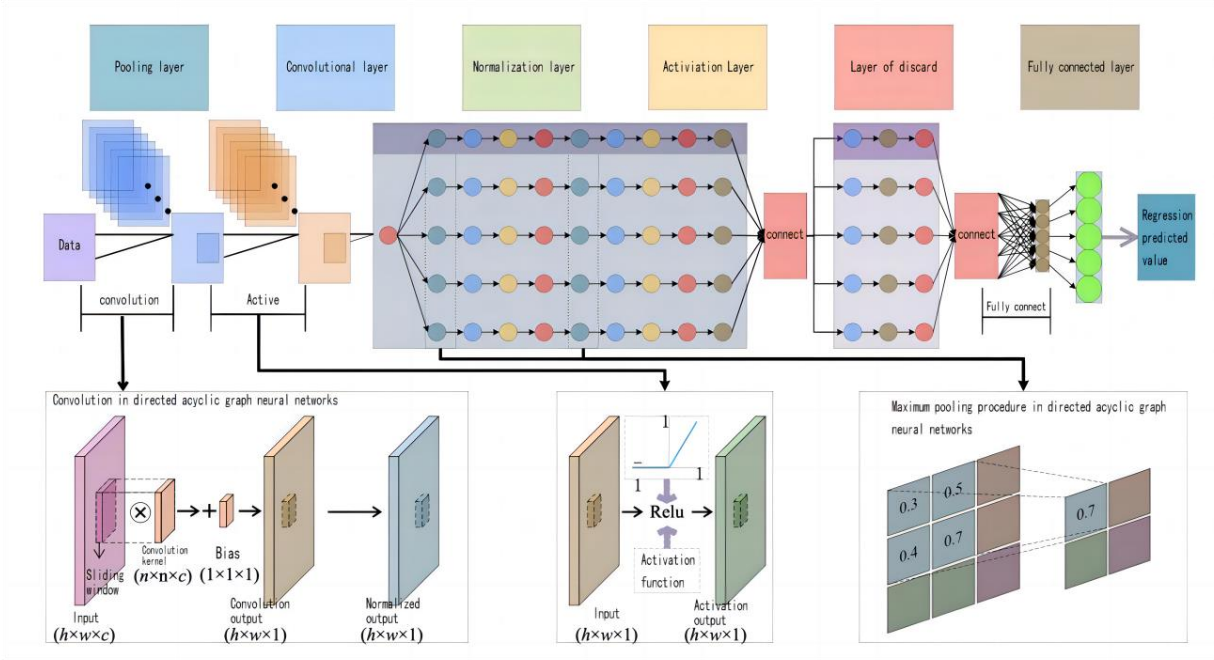

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Figure 10. **A Directed Acyclic Graph Neural Network Structure**

3.2 Multilevel Collaborative Quantisation of Directed Acyclic Graph Neural Networks

The study identified a substantial resemblance between the multilevel network structure of corporations and neural networks. However, a notable distinction lies in the fully connected inter-layer structure of neural networks, contrasting with the non-fully connected structure of corporate multilevel networks. Specifically, within a corporate entity, a given business unit (A) cannot encompass all the value chains, and those excluded are not linked to business A. Section 2 analyses the corporate multilevel network model, revealing that a large corporation can be hierarchically divided into four nodes: value chain, business unit, corporate group, and corporate network. There are critical interrelationships and mutual influences between these nodes that affect the collaborative value change in the corporate network.

By leveraging the corporate multilevel network node model and the directed acyclic graph neural network algorithm, this study introduces a directed acyclic graph neural network algorithm for the quantitative synergy of multilevel economic networks (Multi-DAG-NN). This model predicts relationships using node factors as input and collaborative value as output. The detailed model structure is presented in *Figure 11*.

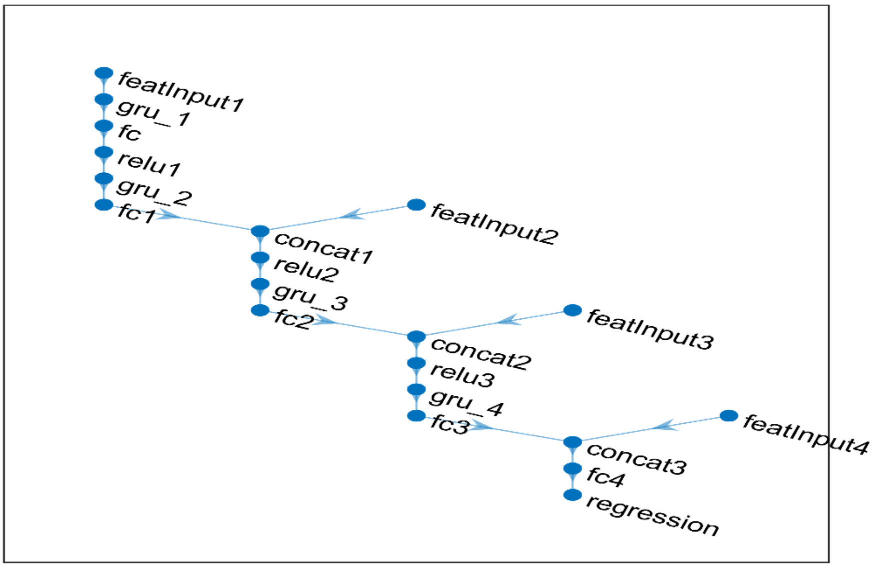

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Figure 11. **Multilevel Economic Network Synergy Model**

The model for quantifying collaboration in multilevel economic networks, which uses a directed acyclic graph neural network, consists of four layers. The first layer, featinput1, includes value chain level factors: quick ratio and current ratio. The second layer, featinput2, contains business-unit-level factor data, including selling expenses, administrative expenses, financial expenses, accounts receivable turnover rate A, inventory turnover rate A, administrative expense ratio, and financial expense ratio. The third layer, featinput3, contains group-level factor data, such as operating income, net income, gearing ratio, cash and cash equivalents turnover rate A, total assets turnover rate A, operating income cash content, operating income growth rate A, total operating income growth rate, and net income margin. The fourth layer, featinput4, integrates factor data from the corporate network level, including total assets and Tobin's Q value (A).

Within the network model, a Gated Recurrent Unit (GRU) module is introduced to regulate information flow. The reset gate determines retained information, and the update gate governs hidden state updates based on current and previous inputs. The candidate hidden state stores the hidden state of the current moment, allowing the GRU to capture long-term dependencies without introducing additional parameters. In the model, the ReLU function serves as an activation function, addressing the vanishing gradient problem and enabling the learning of complex mapping relationships. Traditional activation functions, such as Sigmoid and Tanh, are prone to vanishing gradient issues. ReLU mitigates this by setting negative values to zero, preserving only the positive part. The model incorporates the Fully Connected Layer (FC), a fundamental neural network structure that connects the previous layer's output to the next layer's inputs. The FC is essential for extracting high-level abstract representations or combining features. The Concat layer concatenates tensors of information from multiple nodes along a given dimension, addressing occasions where information combination is required. This layer is crucial for handling sequence or image data and serves as a special fully connected layer. Finally, the Regression layer calculates the regression model's root mean square error loss, optimising model parameters through backpropagation.

3.3 LSTM and GRU Estimation Models

Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models are extensively used in economics and statistics for processing time series data and making predictions. LSTM, known for handling long-term dependencies, incorporates a "memory cell" structure crucial for retaining past information. It includes the input, forget, and output gates, regulating new information, discarding irrelevant data, and propagating relevant information.

In contrast, GRU, a simplified model, employs the update gate and reset gate to manage current information storage and decides on memory retention. Both models find widespread use in financial market predictions such as stock prices, exchange rates, and commodities, alongside forecasting macroeconomic indicators like GDP, inflation, and unemployment rates. They excel in capturing complex relationships within data, adaptively forecasting patterns across different time steps.

In economics and statistics, these models are vital for identifying trends, predicting future trajectories, and aiding decision-making. Thus, LSTM and GRU serve as prevalent neural network models, potent for processing time series data, making predictions, and adapting to diverse economic scenarios.

4. Results

After selecting performance evaluation indicators and sorting the correlations and importance of data, the next step is the experimental validation. In this section, machine learning models such as Support Vector Machine Regression, Random Forest Regression, and Artificial Neural Network are utilised to estimate the corporate network synergy values of Company A before and after the merger, as summarised in *Table 1* and *Figure 12*.

Table 1. Performance Indicator Comparison of Different Algorithms

	LSTM	GRU	Multi-DAG
MAE	8.0761e+06	8.0841e+07	8.4632e+05
MSE	8.4539e+13	6.6518e+15	1.2594e+12
RMSE	9.1945e+06	8.1558e+07	1.1222e+06

Source: created by the authors.

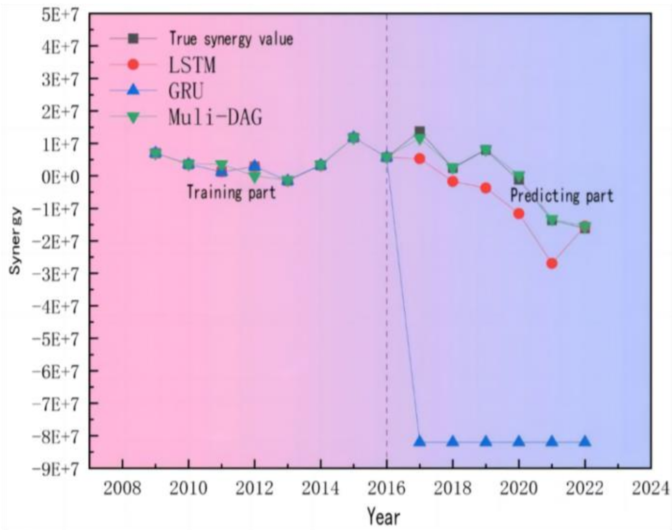

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Figure 12. **Experimental Results**

It can be concluded that the proposed Multilevel Economic Network Synergy Quantification-Directed Acyclic Graph Neural Network model significantly enhances predictive performance compared to LSTM and GRU, as shown in *Table 1* and *Figure 12*. The proposed model shows a remarkable reduction of approximately 90% to 99% in average absolute error and root mean square error in collaborative value prediction, highlighting its superior accuracy. Also, the analysis of the graph indicates that the Multi-DAG model outperforms other algorithms in both collaborative value transition and stable change phases, effectively capturing changing trends and making accurate predictions in diverse scenarios. Overall, the Multi-DAG model exhibits substantial improvement in predictive performance attributed to its multilevel structure and directed acyclic graph characteristics. Through the demonstration of stability and robustness, it holds broad potential for practical applications, providing reliable support for decision-making in economics.

Conclusions

This paper undertakes a central research on the economic network within a corporate group, delineating four hierarchical nodes: the value chain, the business unit, the corporate group, and the corporate network. These nodes are established based on various resource elements and their interrelationships, exploring the correlation between different hierarchical nodes and collaborative values. It also extracts and prioritises the core factors that influence collaborative values across different hierarchical nodes.

By applying a hybrid approach, we construct a directed acyclic graph neural network model to quantify multilevel economic network synergy. This model integrates characteristics of a multilevel corporate network node model and a directed acyclic graph neural network, utilising identified core factors as inputs and collaborative values as outputs. Comparative evaluations against LSTM and GRU models reveal the superior predictive performance of the Multi-DAG model. Acknowledging limitations in data volume and machine learning algorithms, we suggest potential improvements with increased data availability.

The potential of the Multi-DAG model in the economic landscape is highlighted, offering a profound analysis and aiding decision-makers in informed decision-making and planning. As technology advances, this model is anticipated to significantly impact future decision-making processes.

Conclusions drawn hold notable implications for future research and practical applications. Firstly, analysing collaborative values across hierarchical levels in multilevel corporate networks provides a superior understanding of the influence of hierarchical corporate network factors on collaborative values resulting from mergers. Investors can leverage this understanding to establish relationship models, combining high-order topological characteristics and financial data for enhanced merger and acquisition decisions. Secondly, the construction of a directed acyclic graph neural network model facilitates theoretical analysis and quantitative predictions of collaborative values, bolstering the precision and interpretability of merger and acquisition forecasts. Thirdly, integrating data into practical corporate merger and acquisition prediction models serves as a reference for various predictive analyses in financial forecasting and corporate decision-making systems, enhancing predictions of future developmental trends.

Literature

Ang, L., Shan-Na, F., Zhen-Hong X. (2019), “Study on risk assessment of overseas merger and acquisition knowledge integration based on character-weighted set pair”, *Cluster Computing*, Vol. 22, No 2s, pp.2689-2700.

Asavathiratham, C., Roy, S., Lesieutre, B., Verghese, G. (2011), “The Influence Model”, *IEEE Control Systems*.

Barabasi, A.-B., Newman, M., Watts, D. (2006), *The Structure and Dynamics of Networks, Princeton*, NJ: Princeton University Press.

Bradley, M., Desai, A., Kim, E.H. (1988), "Synergistic gains from corporate acquisitions and their division between the stockholders of target and acquiring firms", *Journal of Financial Economics*, Vol. 21, No 1, pp.3-40, DOI:10.1016/0304-405X(88)90030-X.

Battiston, S., Glattfelder, J. B., Garlaschelli, D., Lillo, F., Caldarelli, G. (2010), *The structure of financial networks, Network Science,* Berlin: Springer, pp.131–63.

Caldarelli, G. (2007), *Scale-free Networks: Complex Webs in Nature and Technology,* Oxford: Oxford University Press. https://doi.org/ 10.1093/acprof:oso/9780199211517.001.0001).

Chaturvedi, T., Weigelt, C. (2024), "Operating synergy and post-acquisition integration in corporate acquisitions: A resource reconfiguration perspective", *Long Range Planning*, Vol. 57, No 3, p.102428.

Chuqing, Z., Han, Z., Dunnan, L.A. (2020), "Contrastive Study of Machine Learning on Energy Firm Value Prediction", *IEEE Access*, Vol. 8, pp.11635-11643.

Cong, C., Xiaoming, Y., Fuming, J., Yang Z. (2023), "How to Synergize Different Institutional Logics of Firms in Cross-border Acquisitions: A Matching Theory Perspective", *Management International Review*, Vol. 63, No 3, pp.403-432.

Dismukes, D.E., Deupree, M.W. (2016), "The challenges of the regulatory review of diversification mergers", *The Electricity Journal*, Vol. 29, pp.8–14.

Dixit, A., Pindyck, R. (1994), "*Investment under uncertainty*", Princeton: Princeton University Press.

Frankel, M.E., Forman, L.H. (2017), *Mergers and Acquisitions Basics: The Key Steps of Acquisitions, Divestitures, and Investments*, 2nd Edition, New Jersey: John Wiley & Sons, Inc.

Feiqiong, C, Wenjing, W, Jieru, Z. (2022), "How do firms upgrade innovation capabilities through the coevolution of post-merger integration and network reconstruction? A multiple-case study of Chinese companies", *Journal of Organizational Change Management*, Vol. 35, No 3, pp.630-650.

Hillier, M.S. (1999), "Product commonality in multiple-period, make-to-stock systems", *Naval Res. Logist*, Vol. 46, pp.737–751.

Hofstad, R. (2007), "Random Graphs and Complex Networks", *Kaleidoscoopdag*, Leiden

Hong, X., Lin, X., Fang, L., Gao, Y., Li, R. (2022), "Application of Machine Learning Models for Predictions on Cross-Border Merger and Acquisition Decisions with ESG Characteristics from an Ecosystem and Sustainable Development Perspective", *Sustainability*, Vol. 14, No 5, pp.2838-2838.

Inho, S, Mengmeng, W. (2021), "Does target firm insider trading signal the target's synergy potential in mergers and acquisitions?", *Journal of Financial Economics*, Vol. 142, No 3, pp.1155-1185.

Ivan, M., Lidiya, S., Liudmyla, R., Mytsenko, V., Reshytko, T. (2019), "Investment security models in mergers and acquisition agreements for international corporations", *Journal of Security and Sustainability*, Vol. 9, No 1, pp.185-198.

Ivanchenko, H.F., Ahmad, D.B.O. (2016), "Synergistic Coherence of Bifurcation Evolutionary Processes of Mergers and Acquisitions of Enterprises", *Problemi Ekonomiki*, Vol. 3, pp.3293-299.

Ivanov, A.E., Vasilchenko, A.A. (2017), "Economic efficiency evaluation of mergers and acquisitions in the sector of industry based on a nonlinear model of synergistical growth of an industrial corporation value", 3rd International Conference on Industrial Engineering (ICIE-2017), Vol. 35, No 01099, pp.1-5. https://doi.org/10.1051/shsconf/20173501099.

Jarrell, G., Brickley, J.A., Netter, J. (1980), "The Market for Corporate Control: The Empirical Evidence Since 1980", *Journal of Economic Perspectives*, Vol. 2, pp.49-68. DOI:10.1257/JEP.2.1.49.

Jensen, M.C, Ruback, R.S. (1983), "The market for corporate control", *Journal of Financial Economics*, Vol. 11, No 1–4, pp.5-50.

Jun, Q., Dexuan, M., Cuiping, L., Pan Y., Zhu, X. (2023), "Multilevel optimization of economic dispatching in active distribution network based on ADMM", *Front. Energy Res.* Vol. 10, No 1088255. doi: 10.3389/fenrg 2022.1088255.

Krebs, V. (2006), *Social Network Analysis*: A Brief Introduction.

Mostafa, M.D., Mahmoud, M.W. (1964), "On the problem of estimation for the bivariate lognormal distribution", *Biometrika*, Vol. 51, pp.522–527.

Na, T., Bo, G. (2022), "Sustainable Reuse Strategies of Enterprise Financial Management Model Following Deep Learning Under Big Data", *Journal of Organizational and End User Computing* (JOEUC), Vol. 34, No 8, pp.1-18.

Newman, M. E. J., (2003), "The structure and function of complex networks", *SIAM Rev*., Vol. 45, pp.167-256.

Newman P.K., Milgate M., Eatwell J. (1992), "*The New palgrave dictionary of money & finance"*, Macmillan Press Ltd.

Pennings, E., Natter, M. (2001), "Strategic diversification and capacity utilization", *International Journal of Production Economics*, Vol. 72, No 3, pp.261-272. https://doi.org/10.1016/S0925-5273(00)00161-4.

Ping, Z., Na, C., Jieying, G. (2024), "Mergers and Acquisitions, Synergy, and Corporate Innovation: Evidence from China", *Emerging Markets Finance and Trade*, Vol. 60, No 5, pp.870-898.

Rashid, A., Naeem, N. (2017), "Effects of mergers on corporate performance: An empirical evaluation using OLS and the empirical Bayesian methods." *Borsa Istanbul Review*, Vol. 17, No 1, pp.10-24.

Rayan, H.A., Islam, H.E-A. (2021), "Stock Prices of Architectural, Engineering, and Construction Firms as Leading Economic Indicator: A Computational Deep-Learning Econometrics Model to Complement the Architecture Billings Index", *Journal of Architectural Engineering*, Vol. 27, No 4. doi: 10.1061/(ASCE)AE.1943-5568.0000519.

Rodríguez-Sánchez, J., Mora-Valentín, E., Ortiz-de-Urbina-Criado, M. (2018), "Successful Human Resources Management Factors in International Mergers and Acquisitions", *Administrative Sciences*, Vol. 8, No 3, pp.45-45.

Ross, S.A., Westerfield, R.W., Jaffe, J., Jordan, B.D. (2016), *Corporate Finance,* 11th Edition, New York: McGraw-Hill Education.

Rozen-Bakher, Z. (2018), "Comparison of merger and acquisition (M&A) success in horizontal, vertical, and conglomerate M&As: industry sector vs. services sector", *The Service Industries Journal*, Vol. 38, No 7-8, pp.492-518.

Septian, S., Dharmastuti, C.F. (2019), "Synergy, diversification and firm performance in mergers and acquisitions", *Advances in Economics, Business and Management Research*, Vol. 100, pp.1-5.

Shahzad, U., Mohammed, K.S., Schneider, N., Faggioni, F., Papa, A. (2023), "GDP responses to supply chain disruptions in a post-pandemic era: Combination of DL and ANN outputs based on Google Trends", *Technological Forecasting & Social Change*, Vol. 192, No 122512. https://doi.org/10.1016/j.techfore.2023.122512.

Schwert, G.W. (1996), "Markup pricing in mergers and acquisitions", *J. Financial Econom*. Vol. 42, No 2, pp.153–192.

Xiangjun, H., Xian, L., Laitan, F., Geo, Y., Li, R. (2022), "Application of Machine Learning Models for Predictions on Cross-Border Merger and Acquisition Decisions with ESG Characteristics from an Ecosystem and Sustainable Development Perspective", *Sustainability*, Vol. 14, No 5, pp.2838-2838.

Wang, C.; Zhang, T.; Jia, J.; Wang, J.; Ren, S. (2024), "Complex Network-Based Resilience Assessment of the Integrated Circuit Industry Chain", *Sustainability*, Vol. 16, No 5163. https://doi.org/10.3390/su16125163.

Wasserman, S., Faust, K. (1994), *Social Network Analysis: Methods and Applications*, Cambridge: Cambridge University Press.

Wei, T., Juan, H. (2023), "Can Digital Transformation Facilitate Firms' M&A: Empirical Discovery Based on Machine Learning", *Emerging Markets Finance and Trade*, Vol. 59, No 1, pp.113-128.

Trigeorgis, L. (1996), "*Real Options, Managerial Flexibility and Strategy in Resource Allocation"*, The MIT Press, Cambridge, MA.

Yanan, Y. (2023) "Chinese multinationals' post-merger integration evolutions in developed markets from autonomy to actual-form integration: a lens of ambidexterity", *Chinese Management Studies*, Vol. 17, No 5, pp.1085-1116.

Yang L., Shen X., Zhong C., Liao Y. (2023), "On-demand inference acceleration for directed acyclic graph neural networks over edge-cloud collaboration", *Journal of Parallel and Distributed Computing*, Vol. 171, pp.79-87. https://doi.org/10.1016/j.jpdc.2022.09.005.

Zanin, M., Papo, D., Sousa, P.A., Menasalvas, E., Nicchi, A., Kubik, E., Boccaletti, S. (2016), "Combining Complex Networks and Data Mining: Why and How", *Phys. Rep*., Vol. 635, pp.1–44.

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KIEKYBINIS SINERGIJOS MODELIS ĮMONIŲ SUSIJUNGIMUOSE IR ĮSIGIJIMUOSE, TAIKANT DAUGIAPAKOPĮ EKONOMINĮ TINKLĄ IR GILŲJĮ MOKYMĄSI

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Santrauka. Globalioje ekonomikoje įmonių susijungimai ir įsigijimai tapo plačiai paplitusia verslo strategija. Jau įprasti ne tik tarptautiniai tarpvalstybiniai sandoriai, bet dažnai vyksta ir vidiniai susijungimai bei įsigijimai. Ši tendencija sukėlė daug ekonominių tinklų ir sinergijos problemų, kurios stipriai veikia įmones ir rinkas. Ankstesni tyrimai, skirti susijungimų ir įsigijimų tinklams, daugiausia buvo sutelkti į socialinius tinklus iš kokybinių tyrimų perspektyvos, o kiekybinė analizė buvo ribota. Šiame tyrime siūlomas kryptinio aciklinio grafo neuroninis tinklo modelis (angl. *Multi-DAG*), pagrįstas keturiais hierarchiniais mazgais, tokiais kaip vertės grandinė, verslo vienetas, įmonių grupė ir įmonių tinklas, siekiant kiekybiškai įvertinti daugiapakopę ekonominio tinklo sinergiją. Šiame modelyje kaip įvestis naudojami nustatyti pagrindiniai veiksniai, o kaip išvestis – bendradarbiavimo vertės. Lyginamieji vertinimai, atlikti su LSTM ir GRU modeliais, atskleidė, kad siūlomas metodas užtikrina geresnį prognozavimo našumą, padeda sprendimų priėmėjams priimti pagrįstus sprendimus planavimo etapuose, veiksmingai fiksuoti kintančias tendencijas ir tiksliai prognozuoti įvairius scenarijus tiek bendradarbiavimo vertės perėjimo, tiek stabilių pokyčių etape. Todėl Multi-DAG modelis rodo žymų prognozavimo našumą.

Reikšminiai žodžiai: susijungimai ir įsigijimai; daugiapakopiai ekonominiai tinklai; gilusis mokymasis; kryptinio aciklinio grafo neuroninis tinklas; sinergija.