A hybrid DEA-BPNN framework for performance modelling of Indonesian listed furniture and wood processing firms

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Abstract

This study proposes a hybrid Data Envelopment Analysis-Backpropagation Neural Network (DEA-BPNN) framework to evaluate and predict the efficiency performance of furniture and wood processing firms listed on the Indonesia Stock Exchange (IDX). As a strategic manufacturing sector, the industry faces challenges related to cost volatility, scale inefficiencies, fluctuating market demand, and increasing global competition. Conventional efficiency evaluation methods are often limited in capturing nonlinear relationships and predictive insights. To address these limitations, this study integrates frontier-based efficiency measurement with machine learning-based prediction. Using panel data from six IDX-listed firms during the 2020-2024 period, efficiency scores were estimated using CCR and BCC DEA models with total assets, cost of goods sold, and operating expenses as inputs, and revenue and profit as outputs. The findings reveal heterogeneous efficiency performance, where several firms achieve full BCC efficiency, indicating strong pure technical efficiency, while lower CCR scores indicate scale inefficiencies. The developed BPNN model with a 5-8-2 architecture demonstrates strong predictive capability, achieving an MSE of 0.0145, MAPE values below 2%, and Pearson correlation coefficients above 0.90. Overall, the hybrid DEA-BPNN framework provides an effective tool for efficiency evaluation and predictive performance modelling in Indonesia's furniture and wood processing industry.

***Keywords**: Performance modelling, DEA, BPNN, furniture, wood processing*

Introduction

The furniture and wood processing industry represents a strategic pillar of the Indonesian economy, contributing significantly to value creation, exports, and employment across a resource-based supply chain (Amarta & Ma'rifah, 2023). Characterized by both labour intensive and capital-intensive activities, firm performance in this sector depends heavily on effective input management, cost control, operational efficiency, and responsiveness to global market dynamics. Recent challenges, including shifting consumer preferences, raw material price volatility, and increasing demands for compliance with international sustainability standards, have intensified operational complexity (Amarta et al., 2026; Ma'rifah & Amarta, 2023). These conditions underscore the importance of robust, data driven performance evaluation frameworks to enhance competitiveness and long-term resilience.

In addition to its economic contribution, the furniture and wood processing industry also supports regional industrial development and employment generation in Indonesia. The industry operates through interconnected supply chain systems involving forestry resources, raw material suppliers, manufacturers, logistics providers, and export-oriented distribution networks. Consequently, inefficiencies occurring at the firm level may affect

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broader industrial performance, including production continuity, delivery reliability, and market competitiveness. As global competition intensifies, firms are increasingly required to optimize operational efficiency and improve productivity to maintain sustainable business performance.

International studies consistently show that furniture and wood processing firms often operate below optimal efficiency levels. Evidence from Slovakia, Bulgaria, and Serbia reveals persistent technical inefficiencies driven by imbalanced input-output utilization, particularly among small and micro enterprises (Krišt'Aková et al., 2021; Lazarević et al., 2022; Neykov et al., 2024). Cross country analyses attribute efficiency disparities to structural characteristics within the industry (Sedliačiková et al., 2024), while longitudinal studies in Slovenia demonstrate that financial volatility and productivity instability weaken firm competitiveness (Kropivšek & Grošelj, 2019). Collectively, these findings highlight the need for expanded empirical research on efficiency evaluation in this sector.

Another important issue concerns the increasing pressure for sustainability and environmentally responsible production practices. International markets increasingly demand certified raw materials, energy-efficient manufacturing systems, and environmentally sustainable production processes. Firms that fail to adapt to these standards may experience declining competitiveness and limited market access. Therefore, efficiency analysis becomes increasingly important because it provides insights into how firms utilize resources effectively while maintaining operational sustainability under competitive pressures.

Parallel to these observations, methodological developments emphasize analytical models capable of capturing dynamic, multistage, and network-oriented performance structures. Dynamic network Data Envelopment Analysis (DEA) provides deeper insights into operational interdependencies and sustainability performance (Kahi et al., 2017). Hybrid approaches combining DEA with Artificial Neural Networks (ANN), including three stage DEA and Backpropagation Neural Network (BPNN) models, have demonstrated improved benchmarking accuracy and reduced evaluative bias (Kwon et al., 2016, 2017). ANN based models have also proven effective in diverse engineering and industrial applications, such as infrastructure risk prediction, structural response modelling, and furniture demand forecasting, confirming their versatility in modelling complex systems (Akbal, 2018; Bibaud-Alves et al., 2019; Suryanita et al., 2019).

The growing complexity of industrial operations has encouraged the development of integrated analytical approaches capable of combining efficiency assessment and predictive analytics. Traditional statistical approaches are often limited by restrictive assumptions related to data distribution and linearity. In contrast, DEA and ANN models provide greater flexibility in evaluating multidimensional relationships and nonlinear interactions among operational variables. This flexibility makes hybrid DEA-ANN frameworks particularly suitable for manufacturing industries characterized by uncertain market conditions and fluctuating operational costs.

Recent extensions of hybrid and network-based DEA further enhance performance evaluation across industrial contexts. Integrating ANN with metaheuristic algorithms improves assessments in complex environments such as container terminals (Fri et al., 2020), while advances in network DEA theory offer more realistic representations of multistage production systems (Shi et al., 2021). Empirical evidence also links efficiency outcomes to smart, green, resilient, and lean production practices (Abdullah et al., 2023). Systematic reviews confirm the growing prominence of network DEA and hybrid DEA-ANN models in operations research (Anamika et al., 2014; Ratner et al., 2023).

DEA remains one of the most widely applied tools for efficiency evaluation in settings involving multiple inputs and outputs. Its nonparametric structure facilitates benchmarking across sectors such as manufacturing, energy, transportation, banking, and the wood industry (Akgöbek & Yakut, 2014; Azadeh et al., 2015; Kwon, 2017; Lazarević et al., 2022; Park & Kim, 2016; Tsolas et al., 2020). However, DEA's reliance on historical data and static frontiers limits its predictive capability, prompting the integration of ANN models to capture nonlinear and dynamic performance patterns.

BPNN models have been successfully applied in process optimization, sales forecasting, and energy consumption modelling within hybrid DEA frameworks (Amarta et al., 2019; Amarta & Ma'rifah, 2021; Olanrewaju, 2021). More advanced machine learning techniques, including LSTM, further demonstrate strong predictive performance in industrial contexts (Abbasimehr et al., 2020). Empirical studies confirm that training ANN models using DEA efficiency scores enhances forecasting accuracy and mitigates best practice bias across industries such as electronics manufacturing, telecommunications, transportation, higher education, banking, and manufacturing (Jauhar et al., 2023; Kwon, 2014; Kwon et al., 2016; Singh & Pant, 2018; Tsolas et al., 2020; Zhu et al., 2021). Recent reviews reaffirm the growing relevance of DEA-machine learning integration in efficiency research (Zhang et al., 2022).

Within the Indonesian context, empirical studies examining the efficiency of listed furniture and wood processing firms remain relatively limited compared to other manufacturing sectors. Existing studies generally focus on productivity measurement, supply chain management, or financial performance separately without integrating predictive modelling into efficiency evaluation. Consequently, there remains a significant research gap regarding the development of analytical frameworks capable of simultaneously evaluating current efficiency conditions and predicting future performance trends in this industry.

Despite these advancements, applications of hybrid DEA-ANN frameworks remain limited in Indonesia's furniture and wood processing industry, particularly among firms listed on the IDX. More importantly, prior studies have predominantly focused on efficiency measurement without integrating predictive modelling capabilities within this specific industrial context. These firms face mounting challenges related to supply chain coordination, raw material dependency, cost pressures, profitability volatility, and global competition. Therefore, this study introduces a novel contribution by integrating DEA and BPNN not only for efficiency evaluation but also for predictive performance modelling, which remains underexplored in the Indonesian context. To address this gap, this study proposes a Hybrid DEA-BPNN framework to evaluate and predict the efficiency of IDX listed furniture and wood processing firms. This dual analytical approach distinguishes the present study from prior research that primarily emphasizes static efficiency assessment.

Methods

This study adopts a two-stage quantitative framework to evaluate and predict the performance of furniture and wood processing firms listed on the IDX. The sample comprises six firms selected based on the completeness and continuity of their financial statements during the 2020-2024 period, as presented in Table 1. The use of consistent longitudinal data is essential to ensure the reliability of efficiency measurement and predictive modelling, as temporal discontinuities may introduce bias in both frontier based and machine learning analyses (Krišt'Aková et al., 2021; Kropivšek & Grošelj, 2019).

The selection of publicly listed firms provides several methodological advantages. First, listed companies are required to publish audited financial statements regularly, ensuring higher data consistency and transparency. Second, the use of publicly available financial indicators improves research replicability and comparability across firms and time periods. Third, the inclusion of multiple firms operating within related subsectors enables the identification of relative efficiency differences associated with managerial capability, production scale, and operational strategy. These considerations strengthen the reliability of the proposed analytical framework and support more objective benchmarking results.

Table 1. Indonesian Listed Furniture and Wood Processing Firms

No.	Firm Code	Business Fields
1	WOOD	Furniture and Wood Components
2	CINT	Furniture Manufacturing
3	GEMA	Furniture and Interior Components
4	IFI	Wood Processing
5	FWCT	Plywood Processing
6	SOFA	Wood and Metal Furniture

The first stage evaluates efficiency using DEA, a nonparametric method designed to assess the relative efficiency of decision-making units with multiple inputs and outputs. DEA is widely applied in manufacturing, energy, and service sectors due to its ability to identify best practice frontiers and sources of inefficiency (Akgöbek & Yakut, 2014; Lazarević et al., 2022; Park & Kim, 2016). Its applicability to wood-based industries has been demonstrated in studies examining resource utilization, cost structures, and productivity gaps (Azadeh et al., 2015; Sedliačiková et al., 2024). The selected input variables consist of total assets, cost of goods sold, and operating expenses, while revenue and profit are specified as output variables, reflecting firms' asset utilization, operational cost management, and output generation capability, consistent with established DEA modelling practices (Akgöbek & Yakut, 2014; Anamika et al., 2014).

The input and output variables were selected based on their relevance to manufacturing efficiency and prior DEA literature. Total assets represent firms' capital capacity and investment intensity, while cost of goods sold and operating expenses reflect operational resource consumption. Revenue and profit were selected as output indicators because they capture firms' ability to convert financial and operational resources into economic value. The combination of these variables allows the analysis to evaluate both operational productivity and financial performance simultaneously.

Efficiency scores were calculated using two classical DEA models: the Charnes, Cooper, and Rhodes (CCR) model assuming constant returns to scale, and the Banker, Charnes, and Cooper (BCC) model allowing for variable returns to scale. The use of both models enables a more comprehensive assessment of technical efficiency and scale effects, as recommended in prior efficiency studies across heterogeneous industrial contexts (Abdullah et al., 2023;

Jauhar et al., 2023).

The CCR model measures overall technical efficiency by assuming that all firms operate at an optimal production scale. Meanwhile, the BCC model separates pure technical efficiency from scale efficiency by incorporating variable returns to scale assumptions. The comparison between CCR and BCC results therefore enables the identification of whether inefficiencies originate from managerial limitations or inappropriate operational scale. Such distinctions are important in manufacturing industries where production scale, capital intensity, and market demand frequently fluctuate over time.

In the second stage, a predictive model was developed using a BPNN. All financial indicators employed in the DEA analysis served as input variables, while the CCR and BCC efficiency scores functioned as learning targets. This hybrid DEA-ANN approach aligns with established methodologies that combine DEA's benchmarking capability with ANN's strength in capturing nonlinear relationships (Kwon, 2014; Kwon et al., 2016; Singh & Pant, 2018). Prior studies also support the use of neural networks for performance forecasting in energy, construction, and furniture related industries (Amarta et al., 2019; Bibaud-Alves et al., 2019; Olanrewaju, 2021).

The dataset was partitioned into training (75%), validation (15%), and testing (15%) subsets to ensure robust learning performance. This partitioning strategy follows standard machine learning practices to prevent overfitting and ensure model generalization. The finalized network architecture consists of five input neurons, eight hidden neurons, and two output neurons representing predicted CCR and BCC efficiency scores, as illustrated in Figure 1. A tangent sigmoid (tansig) activation function was applied in the hidden layer to capture nonlinear patterns, while a pure linear (purelin) function was used in the output layer to generate continuous efficiency predictions. The number of hidden neurons was determined through simulation-based tuning to minimize prediction error (Abbasimehr et al., 2020; Suryanita et al., 2019).

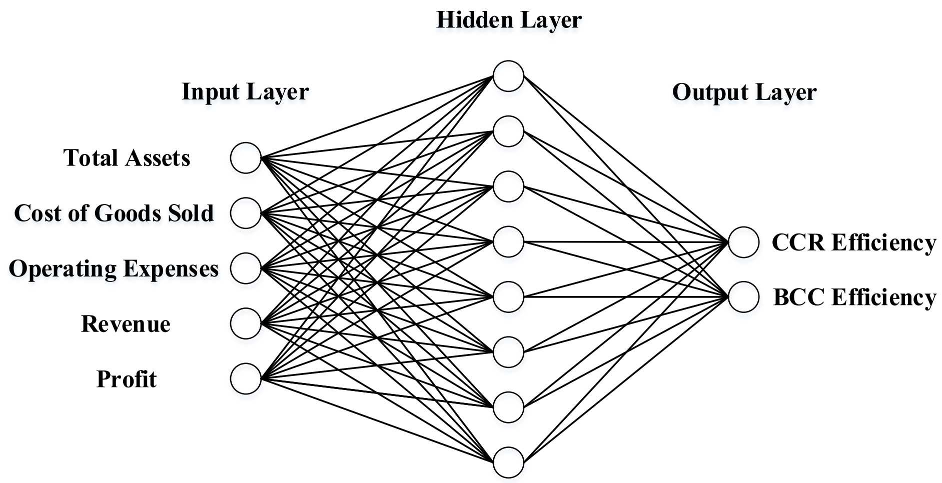

Figure 1. Architecture of Developed Network (5-8-2)

Before model training, all variables were normalized to improve network stability and accelerate convergence during the learning process. Data normalization is essential in neural network modelling because large differences in variable scales may distort weight adjustment and reduce predictive performance. The training process was conducted iteratively until the model achieved stable convergence with minimum prediction error. Several alternative hidden layer configurations were also evaluated during preliminary simulations before selecting the final 5-8-2 architecture based on predictive accuracy and computational efficiency.

Model training utilized the Levenberg-Marquardt algorithm, which is recognized for its fast convergence and reliability in financial and operational modelling (Olanrewaju, 2021). Network parameters, including a learning rate of 0.05, a performance goal of 0.0001, a maximum gradient threshold of 0.00001, a maximum of 10,000 epochs, and a computational iteration limit of 200 seconds, were iteratively adjusted to ensure stable convergence and optimal learning performance. The resulting BPNN demonstrated strong capability in learning and reproducing DEA derived efficiency patterns, consistent with evidence that hybrid DEA-ANN frameworks improve predictive accuracy and reduce evaluative bias compared to standalone approaches (Fri et al., 2020; Zhang et al., 2022; Zhu et al., 2021).

The Levenberg-Marquardt algorithm was selected because of its effectiveness in handling nonlinear optimization problems and medium-sized datasets. Compared to conventional gradient descent approaches, this algorithm generally provides faster convergence and more stable training performance. These advantages are particularly important in efficiency prediction models where small prediction errors may significantly influence benchmarking interpretation and managerial recommendations.

By integrating DEA for efficiency assessment and BPNN for performance prediction, this study proposes a comprehensive analytical framework that combines diagnostic and predictive perspectives. The hybrid DEA-BPNN approach not only identifies firms' current efficiency positions but also enables forward looking performance evaluation, providing data driven insights to support strategic decision making aimed at strengthening competitiveness and long-term resilience in Indonesia's furniture and wood processing industry.

The integration of DEA and BPNN within a unified analytical framework offers several methodological advantages. DEA provides relative efficiency benchmarks without requiring predefined functional forms, whereas BPNN enhances predictive capability through nonlinear learning mechanisms. Combining both approaches enables the framework to function not only as a retrospective evaluation tool but also as a predictive decision-support system. Such integration is particularly beneficial for industries facing high uncertainty and operational volatility, where strategic decisions increasingly rely on data-driven forecasting and performance anticipation.

Result and Discussions

The DEA efficiency results provide a comprehensive overview of performance dynamics among the six sampled furniture and wood processing firms during the 2020-2024 period. The combined use of CCR and BCC models enables a multidimensional assessment capturing both managerial efficiency and scale effects. As illustrated in Figure 2 and 3, efficiency scores vary considerably across firms, reflecting differences in cost structures, capacity utilization, demand stability, and strategic responses to market fluctuations. This heterogeneity is consistent with prior findings in wood-based industries, where operational complexity and market dependence generate substantial efficiency disparities (Krišt'Aková et al., 2021; Neykov et al., 2024).

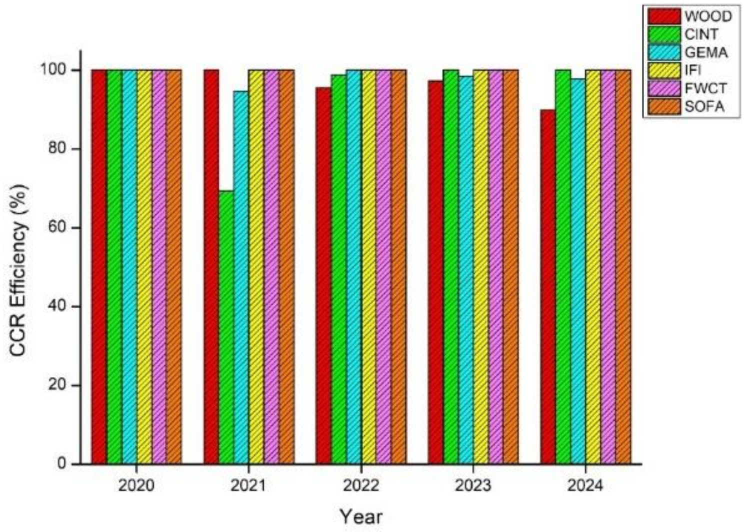

Figure 2. DEA Result (CCR Efficiency)

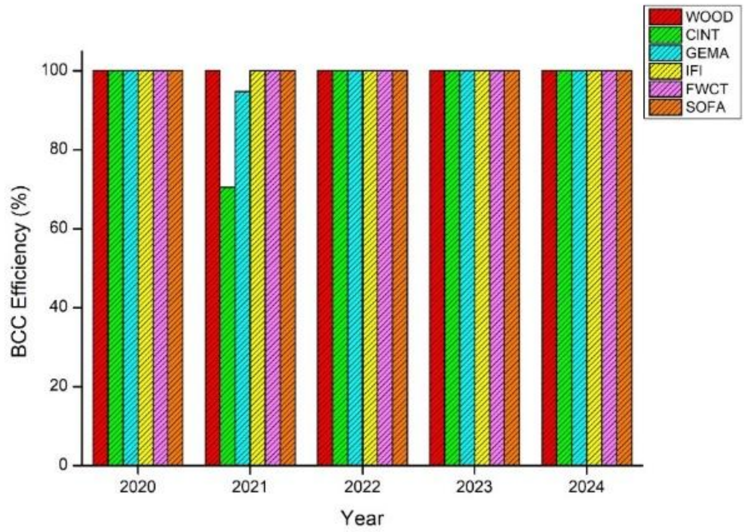

Figure 3. DEA Result (BCC Efficiency)

The BCC results indicate that IFI, FWCT, and SOFA consistently achieve high pure technical efficiency across multiple years. Their repeated attainment of full efficiency suggests effective resource utilization, minimal waste, and well aligned production processes. High BCC efficiency reflects strong managerial capability and operational discipline, characteristics commonly associated with structured cost management and stable production planning systems (Akgöbek & Yakut, 2014; Lazarević et al., 2022). These firms appear resilient to sectoral volatility, including raw material price fluctuations and seasonal demand changes.

Consistent efficiency achievement also indicates the presence of effective internal control systems and better coordination between operational and financial functions. Firms capable of maintaining stable efficiency over time generally possess stronger strategic planning capabilities and more disciplined resource allocation practices. Such conditions enable firms to maintain operational continuity despite external market pressures and changing production environments.

In contrast, the CCR results reveal more nuanced performance patterns. WOOD, the largest firm in the sample, consistently records perfect BCC scores but exhibits fluctuating CCR efficiency, with values of 95.50 in 2022, 97.30 in 2023, and 89.90 in 2024. This divergence indicates scale inefficiency, suggesting that despite sound managerial practices, the firm operates at a suboptimal scale. Such inefficiencies often arise from high overhead costs, oversized fixed assets, or coordination challenges in large scale production systems, a phenomenon widely documented in manufacturing industries (Kropivšek & Grošelj, 2019; Shi et al., 2021).

Scale inefficiency may also indicate that certain firms have expanded operational capacity beyond optimal production requirements. In manufacturing industries, excessive production capacity may increase maintenance costs, idle resources, and coordination complexity, ultimately reducing overall efficiency. Therefore, achieving operational scale balance becomes essential for maintaining long-term competitiveness. Firms operating under volatile demand conditions must continuously evaluate production capacity utilization to avoid inefficiencies associated with underutilized resources.

CINT and GEMA also demonstrate variability in CCR efficiency, though with differing patterns. CINT experienced a sharp decline in both CCR and BCC efficiency in 2021, with scores falling to 69.30 and 70.50, respectively. This decline likely reflects an internal or external shock, such as rising costs or weakened demand. However, the subsequent recovery to full efficiency indicates effective managerial intervention, potentially through cost restructuring or improved production control. Temporary efficiency deterioration followed by rapid recovery has been identified in prior hybrid DEA-ANN studies as an indicator of managerial agility and long-term resilience (Fri et al., 2020; Jauhar et al., 2023).

GEMA exhibits relatively stable BCC efficiency but fluctuating CCR scores, suggesting sound technical performance alongside persistent scale optimization challenges. Such patterns may stem from strategic capacity adjustments, technological adoption, or changes in product mix. Similar scale related inefficiencies have been reported in wood processing firms in Europe and Asia, where misalignment between production volume and market demand affects overall efficiency (Park & Kim, 2016; Sedliačiková et al., 2024).

Overall, IFI, FWCT, and SOFA emerge as the most stable and consistently efficient firms under both DEA models. Their near perfect scores indicate strong financial controls, effective cost allocation, and production capacities well matched to market conditions. This consistency positions them as benchmark firms within the sample, aligning with evidence that sustained efficiency is supported by sound governance, workforce investment, and balanced production scales (Abdullah et al., 2023; Azadeh et al., 2015).

The integration of the BPNN model enhances the analytical depth by enabling predictive performance assessment. The BPNN successfully captures nonlinear relationships between financial inputs and DEA derived efficiency scores, achieving a low Mean Squared Error (MSE) of 0.0145. Predictive accuracy for both CCR and BCC efficiencies is further supported by Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and Pearson correlation metrics reported in Table 2. These results indicate strong generalization capability, consistent with prior studies employing neural networks for efficiency and performance forecasting (Abbasimehr et al., 2020;

Amarta & Ma'rifah, 2021; Tsolas et al., 2020).

Table 2. BPNN Accuracy

Error Metrics	CCR Efficiency	BCC Efficiency
MAE	1.20	0.88
RMSE	2.02	1.59
MAPE	1.22%	0.89%
Pearson correlation	0.94	0.96

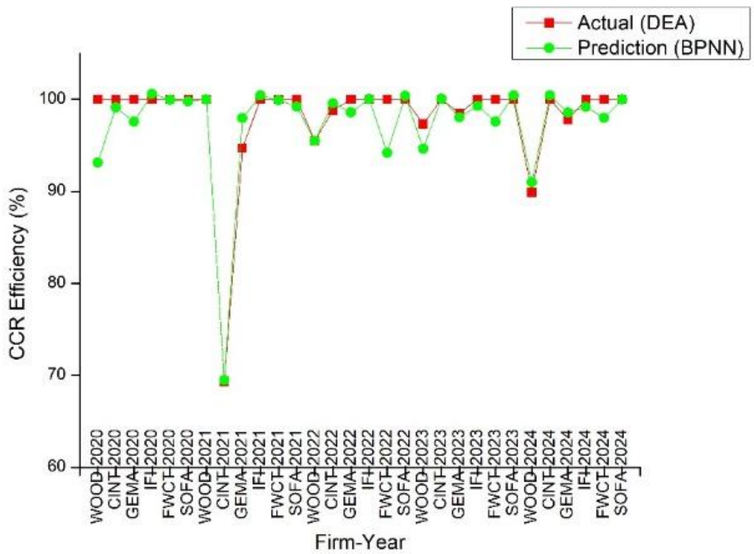

Figure 4. CCR Efficiency Comparison

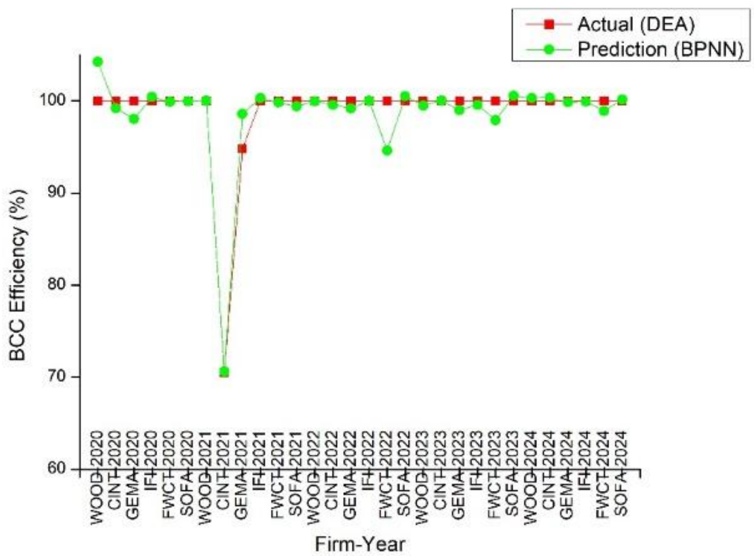

Figure 5. BCC Efficiency Comparison

Comparisons between actual and predicted efficiency scores, illustrated in Figure 4 and 5, further confirm prediction quality. For instance, in CINT's 2021 downturn, predicted CCR and BCC scores (69.48 and 70.63) closely match actual values (69.30 and 70.50), demonstrating the model's ability to replicate extreme efficiency variations. Slightly larger deviations observed for WOOD in 2024 reflect the tendency of neural networks to smooth abrupt fluctuations, a generalization effect well documented in machine learning literature (Zhang et al., 2022; Zhu et al., 2021).

These findings confirm that the hybrid DEA-BPNN framework functions as both a diagnostic and predictive tool, capable of anticipating efficiency shifts under changing financial conditions. In industries characterized by cost volatility and uncertain global markets, such as furniture manufacturing and wood processing, this predictive capability is particularly valuable. Similar benefits have been reported in hybrid DEA-ANN applications across energy, logistics, and manufacturing sectors, where early detection of performance deterioration supports timely managerial intervention (Akbal, 2018; Anamika et al., 2014; Kwon, 2017).

From a managerial perspective, three key implications emerge. First, predictive efficiency monitoring enables early identification of potential performance decline, enhancing organizational resilience. Second, firms with persistent inefficiencies can identify specific cost, asset utilization, or scale related issues requiring targeted intervention, consistent with prior empirical findings (Azadeh et al., 2015; Jauhar et al., 2023). Third, the integrated DEA-BPNN results provide valuable insights for investors, analysts, and policymakers in assessing firm competitiveness, financial stability, and growth potential within an asset intensive industry.

Overall, the results demonstrate the practical relevance of the hybrid DEA-BPNN framework. By integrating frontier-based efficiency analysis with machine learning prediction, the approach provides a holistic understanding of both current efficiency conditions and future performance trajectories. This dual capability makes the framework particularly suitable for strategic decision making in volatile industrial environments where foresight and adaptability are essential for sustaining long term competitiveness.

Conclusion

This study evaluates and predicts the efficiency performance of furniture and wood processing firms listed on the IDX by integrating DEA with BPNN. The proposed hybrid framework overcomes key limitations of traditional frontier analysis, particularly its static orientation and limited predictive capability. Using a two-stage quantitative approach, the study provides both diagnostic and forward-looking insights into firm efficiency over a five-year period marked by market volatility, sustainability pressures, and cost fluctuations.

DEA results indicate substantial heterogeneity in efficiency performance across firms. IFI, FWCT, and SOFA consistently exhibit high technical and scale efficiency, reflecting effective cost control, stable revenue generation, and alignment with optimal production scales. In contrast, WOOD, CINT, and GEMA show greater variability driven by scale inefficiencies, cost shocks, and operational adjustments. The comparison of CCR and BCC models highlights the importance of jointly assessing technical and scale efficiency to capture performance dynamics more comprehensively.

The findings also demonstrate that predictive efficiency modelling can serve as an early warning mechanism for firms operating in highly competitive and volatile industrial environments. Managers may use predictive efficiency information to identify potential operational weaknesses before they significantly affect financial performance. Furthermore, the framework may support investment analysis and policy evaluation by providing more comprehensive insights into firms' operational sustainability and competitiveness.

The integration of BPNN further enhances the analysis by enabling accurate efficiency prediction with low error rates. The neural network successfully captures nonlinear relationships between financial inputs and efficiency scores, supporting its role as a predictive and early warning tool for managerial decision-making. However, this study has several limitations. The sample is limited to six IDX-listed firms, which may affect generalizability. The analysis relies only on financial indicators, excluding operational or non-financial factors. Additionally, the focus on a single industry limits broader comparisons.

Future research is encouraged to expand the sample size, incorporate additional variables such as sustainability and operational indicators, and explore more advanced machine learning techniques such as LSTM or hybrid metaheuristic-ANN models. Comparative studies across industries or countries may also provide broader insights into efficiency dynamics. Overall, the findings confirm that the hybrid DEA-BPNN framework is a robust approach for evaluating and anticipating efficiency performance in resource-dependent and volatility-prone industries, offering practical insights for practitioners and a methodological foundation for future research.

In addition, the integration of DEA and BPNN contributes to the advancement of hybrid analytical methodologies in industrial performance research. The framework combines the benchmarking strength of DEA with the adaptive learning capability of neural networks, producing a multidimensional approach suitable for evaluating complex manufacturing systems. Therefore, this study not only offers empirical evidence from the Indonesian furniture and wood processing industry but also provides a methodological reference for future efficiency and predictive performance studies in other industrial sectors.

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