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A Dynamic Competitive Intelligence Model for Achieving Sustainable Competitive Advantage in the Steel Industry

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Abstract. This study develops a nonlinear dynamic modeling framework to analyze and predict performance behavior in industrial environments using competitive-intelligence-related variables. Four organizational resource components are formulated as elements of a discrete-time state vector, and their influence on system output is modeled through a nonlinear state-transition function. Empirical observations collected from a steel manufacturing company were used to identify the unknown dynamics through a feed-forward artificial neural network trained via a gradient-based optimization procedure. Reliability of the measurement instrument was verified using Cronbach's alpha coefficients of 0.92 and 0.86 for the independent and dependent constructs, respectively. The identified model demonstrates stable convergence, with the minimum prediction error achieved near iteration 1500, and outperforms a linear baseline in mean-squared error and correlation accuracy. The proposed formulation provides a mathematically oriented approach for reconstructing performance-driven system behavior and establishes a foundation for future extensions involving adaptive estimation, robust analysis, and optimal control strategies in industrial systems.

Keywords. Dynamic modeling, Competitive intelligence, Optimization, Artificial neural networks, Simulation.

MSC. 90B50; 90C59.

1 Introduction

Rapid globalization and increasing competitive pressure have reduced the protective role of national industries, requiring organizations to operate within broader and more dynamic market environments [7]. In such conditions, firms must continuously enhance their decision-making capabilities and strategic responsiveness to sustain performance and leverage emerging opportunities. Access to timely and reliable knowledge regarding competitors, market actors, and external forces has therefore become a critical requirement for industrial systems [16].

The exponential growth of organizational data over recent decades has intensified the need for systematic mechanisms capable of transforming dispersed information into actionable insight. This development has contributed to the emergence of competitive intelligence, which functions as a structured process for collecting, analyzing, and interpreting external and internal information to support strategic decisions. Competitive intelligence is recognized as an influential contributor to long-term performance and sustainable competitive advantage [19], emphasizing the importance of coordinated planning, monitoring, and knowledge-based evaluation in contemporary industrial environments.

The increasing participation of domestic firms in global markets further reinforces the necessity of efficient decision-support systems. Traditional performance assessment practices, although historically widespread, are no longer sufficient to address the complexity and dynamism of modern competition. Organizations require systematic frameworks to guide competitive-intelligence-related decision-making [11]. Intelligent systems are designed to monitor environmental conditions and organizational activities, supplying relevant information to support adaptive responses.

Competitive intelligence represents a distinct domain that intersects but is not interchangeable with business intelligence or knowledge management. While these systems may share informational foundations, competitive intelligence is positioned as an enabling infrastructure through which sustained competitive capacity can be developed and maintained [3]. The strength and integration of such systems contribute to creating long-term organizational advantage and resilience [12].

Despite its strategic importance, existing studies predominantly examine competitive intelligence through descriptive or qualitative perspectives. These approaches do not provide mathematical modeling frameworks capable of capturing dynamic behavior, predicting system evolution, or supporting optimization-based analysis. To address this gap, the present work introduces a nonlinear dynamic modeling approach in which competitive-intelligence-related components are represented as system variables within a discrete-time formulation. The aim of the study is to develop and analyze a data-driven dynamic model that characterizes the evolution of these variables and evaluates their influence on organizational performance over time.

2 Literature Review

This section surveys the relevant theoretical and empirical literature on competitive intelligence to provide the conceptual basis for the proposed dynamic modeling framework. It first outlines the principal theoretical perspectives and economic foundations associated with sustainable competitive advantage, and then reviews influential prior studies addressing competitive intelligence and decision-support systems. Through this systematic examination, the section situates the present research within the existing literature and identifies critical gaps that justify the use of mathematical and dynamic system modeling approaches.

2.1 Theoretical Foundations

Competitive intelligence is defined as a systematic process for collecting and analyzing information about competitors to support both short- and long-term strategic planning [15]. Through this process, organizations can identify priority competitive activities and respond more effectively to external changes.

From an economic perspective, sustainable competitive advantage is achieved by improving performance efficiency relative to competitors. Under the synergistic viewpoint, competitive advantage results from the coordinated integration of organizational resources and capabilities [1]. Within the resource-based framework, firms that possess valuable and properly aligned resources can generate sustainable competitive capacity through synergistic interaction [17]. Organizational resources are commonly classified into four major categories. *Major organizational resources* refer to essential assets required for core operational activities [9]. *Environmental resources* represent externally accessible inputs that may be acquired or sourced with relative ease [14]. *Competitive resources* enable organizations to supply products or services with differentiated market value [10]. Finally, *strategic resources* are unique assets that contribute to distinct and defensible performance advantages [5]. These classifications form the conceptual basis for the dynamic modeling framework developed in this study. Value creation is a central mechanism through which firms transform their resource configurations into sustainable competitive advantage, particularly in dynamic and technology-driven environments [2].

2.2 Research Background

Previous studies have examined competitive intelligence from multiple perspectives. The work in [7] highlights its significance in knowledge-based organizations (KBOs) and proposes a model for implementing competitive intelligence processes, noting that KBO characteristics extend beyond products to encompass organizational purpose, processes, and strategic orientation.

In [16], competitive intelligence is approached as a critical factor for organizational success, particularly under conditions of economic instability. The authors emphasize the influence of organizational culture and outline practical, academic, and interdisciplinary perspectives within existing literature.

Further contributions expand the conceptual scope of competitive intelligence. The study in [19] investigates the relationship between business intelligence systems and semantic technologies, emphasizing the growing use of open-source information in competitive and marketing contexts. The work in [11] explores the interaction between information and communication technologies (ICT) and competitive intelligence, arguing that examining either domain in isolation does not fully capture their combined strategic role.

Additional analyses address organizational and cultural dimensions. The research in [3] identifies several analytical dimensions relevant to software companies, including distinctions between development approaches, talent versus technology-based competition, and the balance between shared and restricted intelligence data. Similarly, [12] reports on the integration of a competitive-intelligence framework within innovation management, reviewing historical developments and refining methodological stages.

Although these studies provide valuable conceptual insights, they predominantly adopt descriptive or qualitative approaches. Existing literature does not offer mathematical formulations capable of representing competitive-intelligence-related variables as dynamic systems. The absence of predictive modeling, system identification, and optimization-oriented analysis highlights a clear research gap addressed by the present study.

3 Research Methodology

This study adopts an applied research orientation, aiming to develop a data-driven dynamic modeling framework for analyzing the evolution of competitive-intelligence-related variables in an industrial setting. Empirical data were collected through a structured questionnaire designed to quantify the four resource components associated with competitive intelligence and the resulting level of sustainable competitive advantage.

The content validity of the measurement instrument was confirmed through expert review involving industry specialists, organizational managers, and academic faculty, with revisions completed in two iterative rounds. Reliability was assessed using Cronbach's alpha, yielding coefficients of 0.92 for the competitive intelligence construct and 0.86 for sustainable competitive advantage, indicating strong internal consistency. The dataset was subsequently used for model identification and analysis.

3.1 Statistical Population, Sampling, and Data Collection

The statistical population consisted of 316 employees of the Pipes and Profiles Company, representing managerial, operational, and production units. Using the Morgan sample size determination table, a sample of 175 participants was selected through simple random sampling. The collected dataset serves as the empirical basis for estimating the nonlinear dynamic model described in Section 4.

3.2 Research Hypotheses

Main hypothesis: There exists a significant relationship between competitive intelligence and sustainable competitive advantage.

Sub-hypotheses: There exists a significant relationship between:

- Major organizational resources and sustainable competitive advantage,
- Environmental resources and sustainable competitive advantage,

- Competitive resources and sustainable competitive advantage,
- Strategic resources and sustainable competitive advantage.

3.3 Research Conceptual Model

In this study, sustainable competitive advantage is treated as the dependent variable, while the four components of competitive intelligence, major organizational resources, environmental resources, competitive resources, and strategic resources, are considered independent variables. These components are incorporated into the state vector of the dynamic model. Figure 1 illustrates the conceptual framework.

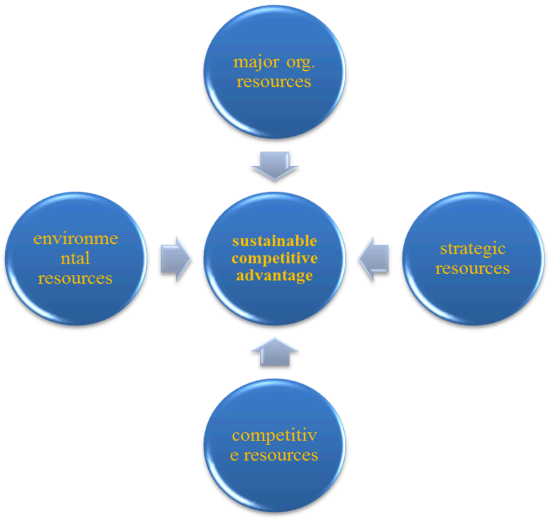

Figure 1: Conceptual model

4 Research Findings

4.1 Correlation Analysis

The primary hypothesis, examining the relationship between competitive intelligence and sustainable competitive advantage, was evaluated using the Pearson correlation coefficient. The results are presented in Table 1.

The correlation coefficient of $r = 0.563$ indicates a statistically significant positive association at the 99% confidence level. The coefficient of determination ($R^2 = 0.78$) suggests that approximately 78% of the variation in sustainable competitive advantage is explained by competitive intelligence. Table 2 reports the subordinate correlation results for individual components.

All four resource components exhibit statistically significant correlations with sustainable competitive advantage, confirming the directional assumptions of the research hypotheses.

Table 1: Correlation results for the main hypothesis

Main variables	Correlation	Sig.	R^2	Conclusion
Competitive intelligence → sustainable competitive advantage	0.563	0.000	0.78	Significant direct relationship

Table 2: Correlation results for subordinate hypotheses

Variables	Correlation	Sig.	R^2	Conclusion
Major organizational resources → SCA	0.439	0.019	0.16	Significant direct relationship
Environmental resources → SCA	0.375	0.028	0.14	Significant direct relationship
Competitive resources → SCA	0.509	0.005	0.25	Significant direct relationship
Strategic resources → SCA	0.488	0.030	0.23	Significant direct relationship

4.2 Dynamic Modeling Using Artificial Neural Networks

Recent methodological advances show that artificial neural networks are highly effective for modeling complex, multi-factor systems, particularly when domain-specific variables must be transformed into structured machine-learning inputs prior to training. Comparable ANN-based workflows have been successfully applied in data-intensive urban growth studies, where historical socioeconomic and environmental drivers are preprocessed, standardized, and evaluated through rigorous goodness-of-fit metrics to identify optimal network weights [8]. This methodological alignment reinforces the suitability of using an ANN framework for modeling competitive-intelligence–driven performance in industrial systems.

To model the nonlinear relationship between competitive intelligence components and performance outcomes, a feed-forward artificial neural network (ANN) was implemented. Nonlinear activation functions were selected to enable flexible approximation of complex input, output mappings and to enhance robustness against measurement disturbances.

Figures 2 and 3 provide schematic comparisons between biological neurons and the computational structure of the ANN.

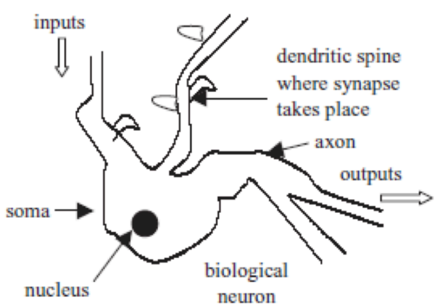

Figure 2: Biological neuron and conceptual ANN representation

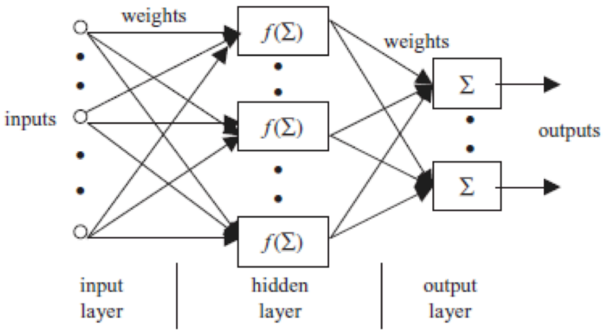

Figure 3: Feed-forward neural network architecture with one hidden layer

The notation used in the model is summarized below:

u_0**:** Input vector to the network

n_i**:** Number of input neurons

n_h**:** Number of hidden-layer neurons

n_o**:** Number of output neurons

W_1**:** Weight matrix (input to hidden layer)

W_{10}**:** Bias vector for hidden layer

W_2**:** Weight matrix (hidden to output layer)

W_{20}**:** Bias vector for output layer

M**:** Learning rate

Signals propagated from the input to the first hidden layer are given by

$$y_1 = W_1 u_0 + W_{10}, \qquad u_1 = f(y_1),$$

where u_0 is treated as the primary estimate of the weights. Here, y_1 denotes the vector of intermediate values, u_1 is the input to the hidden layer, and $f(y_1)$ is a nonlinear activation defined componentwise by

$$f(y_i) = \frac{1 - e^{-\lambda y_i}}{1 + e^{-\lambda y_i}} \quad \text{(equivalently } f(y_i) = \tanh\Big(\frac{\lambda y_i}{2}\Big)\text{)}.$$

Subsequently, the signal from the hidden layer to the output layer is computed as

$$u_2 = f(y_2), \qquad y_2 = W_2 u_1,$$

with u_2 representing the output-layer signal. The learning dynamics are governed by

$$\frac{dW}{dt} = -\,\mu(t)\,\frac{\partial E(W)}{\partial W},$$

where the output error is defined as

$$e = z - u_2,$$

and, under a quadratic loss, the gradient with respect to W_2 is

$$\frac{\partial E}{\partial W_2} = -\, f'(y_2)\, e\, u_1^T.$$

Here, u_1 serves as the gradient component corresponding to y_2, with the dependence on W_2 implied through $y_2 = W_2 u_1$.

The derivative of the activation f is

$$f'(y_i) = \frac{2\lambda e^{-\lambda y_i}}{(1 + e^{-\lambda y_i})^2} \quad \text{(equivalently } f'(y_i) = \frac{\lambda}{2}\,\text{sech}^2\left(\frac{\lambda y_i}{2}\right)\text{)}.$$

Consequently, the update rule for the output-layer weights can be written as

$$W_2(i+1) = W_2(i) \;+\; \mu\, e_2^b\, u_1^T \;+\; \Omega\,[W_2(i) - W_2(i-1)]\,,$$

where μ is the learning rate, e_2^b denotes the (buffered) output error, and Ω is a stabilizing term (e.g., a damping or momentum-like component).

4.3 Additional clarifications

To enhance transparency, reproducibility, and alignment with standard neural network notation, this subsection provides precise clarifications regarding the cost functional, error definition, gradient computation, and the learning update mechanism used in the proposed dynamic model.

Cost Functional and Error Definition

For a single training sample, the performance index is defined as the mean squared error (MSE) between the desired output $\mathbf{z}$ and the network output $\mathbf{u}_2$:

$$E(\mathbf{W}) = \frac{1}{2}\|\mathbf{z} - \mathbf{u}_2\|^2.$$

For a mini-batch of size B, the accumulated cost becomes

$$E(\mathbf{W}) = \frac{1}{2B}\sum_{b=1}^{B} \|\mathbf{z}^{(b)} - \mathbf{u}_2^{(b)}\|^2,$$

where $\mathbf{u}_2^{(b)}$ denotes the output corresponding to the b-th training sample.

The per-sample error vector is defined as

$$\mathbf{e}^{(b)} = \mathbf{z}^{(b)} - \mathbf{u}_2^{(b)}.$$

When using a batch update, the aggregated error is given by

$$\mathbf{e}_{batch} = \frac{1}{B}\sum_{b=1}^{B} \mathbf{e}^{(b)}.$$

Gradient Regarding the Output-Layer Weights $\mathbf{W}_2$

Given the hidden-layer activation $\mathbf{u}_1$, and the output-layer pre-activation

$$\mathbf{y}_2 = \mathbf{W}_2\mathbf{u}_1, \quad \mathbf{u}_2 = f(\mathbf{y}_2),$$

the gradient of the cost with respect to $\mathbf{W}_2$ for a single sample is

$$\frac{\partial E}{\partial \mathbf{W}_2} = -\, f'(\mathbf{y}_2) \odot \mathbf{e}\, \mathbf{u}_1^\top,$$

where $\odot$ denotes the Hadamard (elementwise) product and

$$\mathbf{e} = \mathbf{z} - \mathbf{u}_2.$$

For a mini-batch, the gradient is averaged over all samples.

Learning Rule

The continuous-time gradient descent update is expressed as

$$\frac{d\mathbf{W}}{dt} = -\mu(t)\frac{\partial E}{\partial \mathbf{W}},$$

where $\mu(t)$ is a (possibly time-varying) learning rate.
In discrete-time form, the iterative update becomes

$$\mathbf{W}_2(k+1) = \mathbf{W}_2(k) + \mu(k)\, \Delta\mathbf{W}_2(k),$$

with

$$\Delta\mathbf{W}_2(k) = -f'(\mathbf{y}_2(k)) \odot \mathbf{e}(k)\, \mathbf{u}_1(k)^\top + \Omega\big[\mathbf{W}_2(k) - \mathbf{W}_2(k-1)\big],$$

where Ω is a stabilizing term (e.g., momentum coefficient) introduced to improve convergence behavior and reduce oscillations during training.

4.4 Case Study

The proposed modeling framework is applied to a real industrial setting in the steel sector, specifically within a steel pipe and profile manufacturing company. This environment provides a suitable context for evaluating the dynamic behavior of competitive-intelligence–driven performance, as the industry is characterized by high market volatility, resource dependency, and frequent strategic adjustments. To capture expert knowledge and encode nonlinear interactions among the competitive intelligence components, an ANN is employed as the core dynamic model.

Model Inputs and Outputs

The ANN is designed to map multidimensional competitive intelligence indicators to a normalized performance index. The model inputs consist of field data representing:

- major organizational resources,
- environmental resources,
- competitive resources,
- strategic resources.

The output of the model is a continuous score in the range $[-1, 1]$, where values closer to $+1$ indicate stronger competitive advantage potential. This normalized output facilitates comparison across scenarios and supports performance-based decision-making.

Network Architecture

The ANN architecture is selected to balance representational flexibility and computational tractability. Key structural attributes are:

- *Network type:* feed-forward multilayer perceptron.
- *Hidden layers:* the number of layers is chosen based on the complexity of the input–output mapping and validated through experimental tuning.
- *Neurons per layer:* determined via iterative search to optimize the performance function.
- *Activation function:* a sinusoidal transfer function is employed in the hidden layer to enhance nonlinear expressiveness.

The model aims to reach a target error on the order of 10^{-6}, reflecting high fidelity between predicted and expert-evaluated outputs.

Data Preparation and Training Procedure

A total of 85% of the available data is used for model training, while the remaining 15% is reserved for performance evaluation. The mean squared error (MSE) is used as the primary performance metric. For each observation with actual value y and model estimate $\hat{y}$, the squared error is computed as

$$e = y - \hat{y},$$
$$SE = (y - \hat{y})^2,$$
$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2.$$

The comparison between ANN and a linear benchmark model is made based on their relative MSE values.

Figure 4 illustrates the overall network structure.

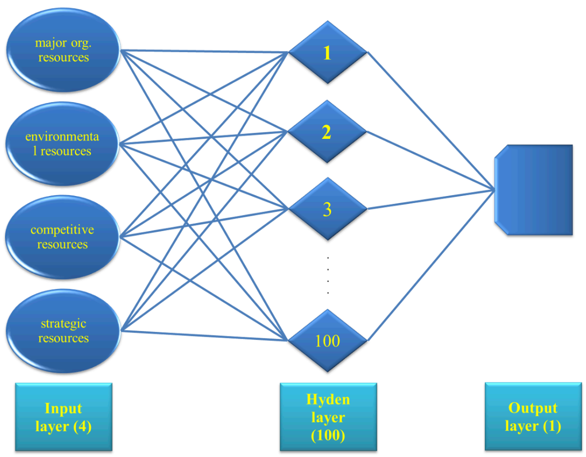

Figure 4: Structure of the artificial neural network used in the study

Training Dynamics and Prediction Capability

After specifying the network architecture, the ANN undergoes supervised training where each input vector is paired with expert-determined target values. Learning is achieved by updating connection weights to minimize prediction error. The evaluation of predictive capability is essential to ensure that the model generalizes beyond the training data.

A schematic representation of the simulation workflow is depicted in Figure 5.

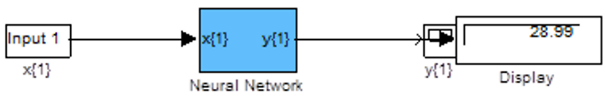

Figure 5: Process diagram of the ANN simulation system

Figures 6 and 7 present internal layers and weight-function mappings, respectively, highlighting the hierarchical organization used to extract nonlinear relationships.

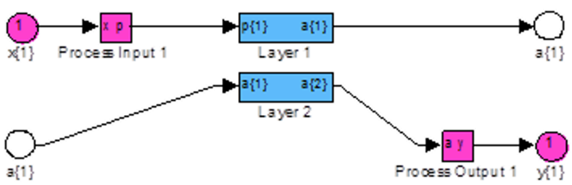

Figure 6: Internal layer configuration of the ANN

Network weights are initialized using a uniform distribution in the interval

$$\left[-\frac{2.4}{F_i}, \frac{2.4}{F_i}\right],$$

where F_i denotes the number of input connections to neuron i. This approach improves convergence and stability during training. Figure 8 illustrates the weight determination mechanism.

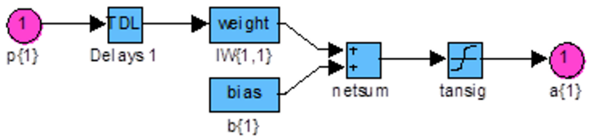

Figure 7: Weight adaptation mechanism inside the neural network

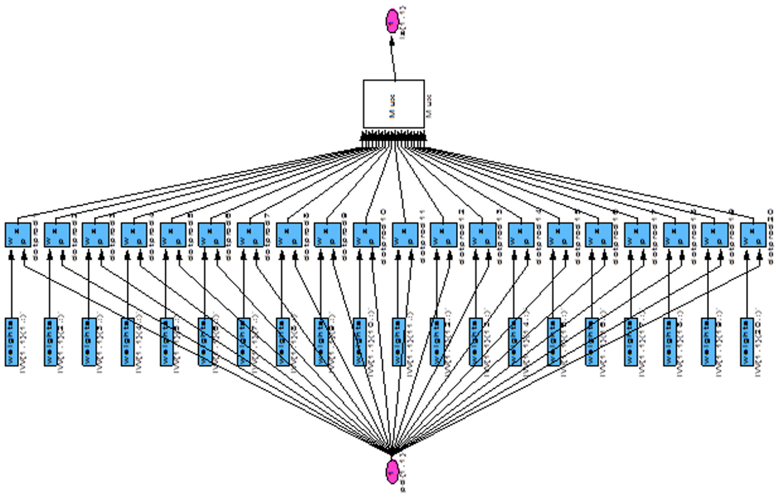

Figure 8: Mechanism for determining weight functions

Back propagation neural networks are made active by using active inputs

$$x_1(p), x_2(p), \ldots, x_n(p),$$

and favorable outputs

$$y_{d,1}(p), y_{d,2}(p), \ldots, y_{d,n}(p).$$

Real outputs of neurons in the hidden layer are calculated by

$$y_j(p) = \text{sigmoid}[\sum x_i(p) w_{ij}(p) - \theta_j],$$

for all I and real outputs of neurons in the output layer are calculated by

$$y_k(p) = \text{sigmoid}[\sum x_{jk}(p) w_{jk}(p) - \theta_k],$$

for all I, where n denotes number of inputs of neuron j in the hidden layer and m denotes number of inputs of neuron k in the output layer.

MATLAB software partitions the data into 80% training, 10% validation, and 10% testing, as visualized in Figure 9.

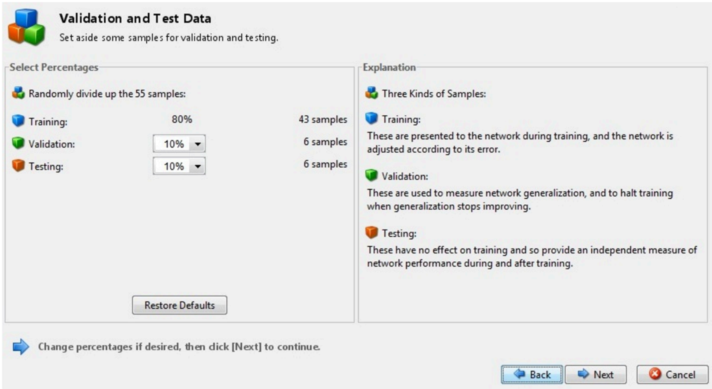

Figure 9: Training, validation, and test data segmentation

Model Performance

The trained network achieves an MSE of 0.044 and a correlation coefficient of $R = 0.99$, indicating a strong linear association between predicted and actual values. Figure 10 presents the sum of squared errors during training, while Figure 11 shows the regression fit.

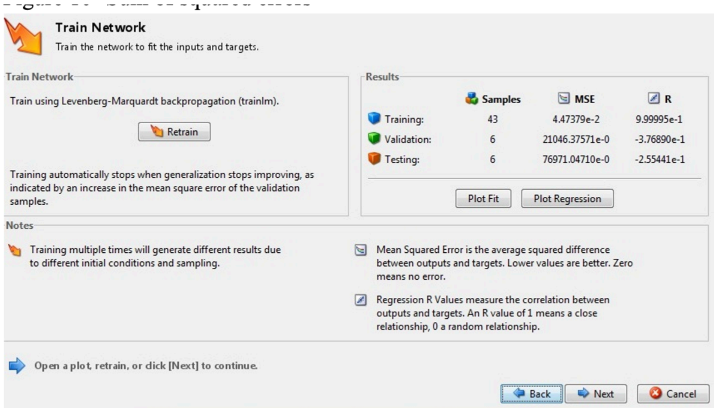

Figure 10: Sum of squared errors during network training

Table 3 reports the training error measured every 100 cycles. The minimum error occurs at approximately 1500 iterations, which is therefore adopted as the convergence point for the final model.

The model's convergence at cycle 1500, coupled with its low prediction error and high correlation, provides strong evidence supporting its suitability as a dynamic mechanism for evaluating competitive-intelligence–driven performance in industrial systems.

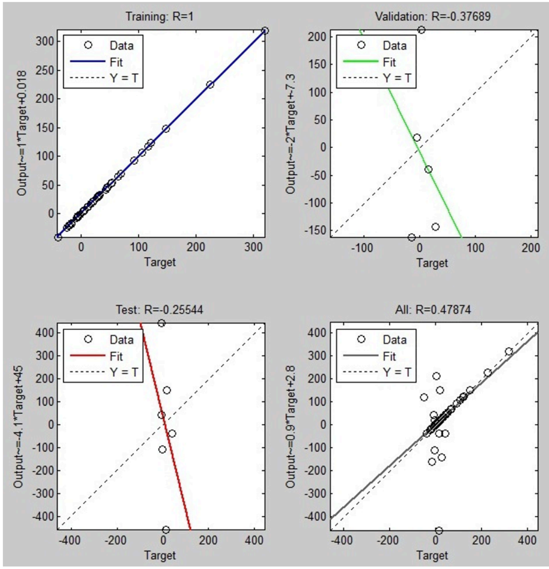

Figure 11: Regression diagrams showing the fit between actual and predicted values

Table 3: Training error values across 2000 iterations

Cycle	Error	Cycle	Error	Cycle	Error
100	0.0131925	200	0.0131916	300	0.0131866
400	0.0131786	500	0.0131715	600	0.0131584
700	0.0131573	800	0.0131581	900	0.0131581
1000	0.0131554	1100	0.0131555	1200	0.0131551
1300	0.0131530	1400	0.0131547	1500	0.0131517
1600	0.0131534	1700	0.0131544	1800	0.0131550
1900	0.0131533	2000	0.0131524		

5 Conclusions

This study proposed and empirically evaluated a dynamic competitive intelligence model aimed at strengthening sustainable competitive advantage in the steel industry through the application of an artificial neural network (ANN). Competitive intelligence was conceptualized across four dimensions—major organizational resources, environmental resources, competitive resources, and strategic resources. The correlation analysis revealed that all four dimensions are positively and significantly associated with sustainable competitive advantage, with correlation coefficients of 0.439, 0.375, 0.509, and 0.488, respectively. These findings provide empirical support for the relevance of competitive intelligence components and validate their integration into a dynamic modeling framework. Following the validation of these relationships, an ANN-based framework was designed to capture nonlinear dependencies and to simulate the dynamic behavior of competitive-intelligence–driven performance. The model achieved strong predictive accuracy, exhibiting a low mean squared error (MSE) and a correlation coefficient of $R = 0.99$, which aligns with the findings of prior research (e.g., [4, 6, 13, 18]). The training process, showed that the minimum error occurred at approximately 1500 iterations, and this convergence point was adopted for the final model configuration. The results confirm that ANN-based dynamic modeling is an effective tool for analyzing competitive intelligence and forecasting its contribution to sustainable competitive advantage. The approach offers a robust foundation for future decision-support systems in resource-intensive industries.

Directions for Future Research

- The present study examined the linear associations between competitive intelligence variables and sustainable competitive advantage prior to dynamic modeling. Future research may extend this framework by incorporating additional variables or exploring nonlinear relationships using advanced learning architectures.
- Application of the proposed ANN model across different industrial contexts, both manufacturing and service sectors, would enable comparative error analysis and enhance generalizability.
- This study did not operationalize specific indicators for sustainable competitive advantage. Subsequent investigations are encouraged to develop explicit indices for sustainable competitive advantage and to model their interaction with competitive intelligence metrics in greater detail.

Declarations

Availability of Supporting Data

All data generated or analyzed during this study are included in this published paper.

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Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

Artificial Intelligence Statement

Artificial intelligence (AI) tools, including large language models, were used solely for language editing and improving readability. AI tools were not used for generating ideas, performing analyses, interpreting results, or writing the scientific content. All scientific conclusions and intellectual contributions were made exclusively by the authors.

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