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Data-driven control and a prey–predator model for sourcing decisions in the low-carbon intertwined supply chain

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Abstract

This paper addresses the challenges of low-carbon sourcing in intertwined supply chains by proposing a data-driven control framework and a prey–predator model for sourcing decisions. The objective is to optimize low-carbon objectives and reduce environmental impact. Existing static models fail to capture the dynamic nature of supply chain systems and overlook the ripple effects when sourcing decisions propagate throughout the interconnected network. To bridge this gap, our study develops a dynamic model that explicitly captures the bullwhip effect and leverages real-time and historical data. This model conceptualizes suppliers as prey and manufacturers and consumers as predators, employing an ecological analogy to decipher the intricate interactions and dependencies within the supply chain. Through this approach, we identify strategies to promote sustainable practices and motivate suppliers to adopt low-carbon measures. We assess two data-driven algorithms, the nonlinear auto-regressive exogenous (NARX) network and sparse identification of nonlinear dynamic systems with input variables (SINDYc). The results reveal that SINDYc outperforms prediction accuracy and control, offering significant advantages for rapid decision-making. The study highlights how shifts in market demands and regulatory pressures critically influence the strategies of chemical firms and fertilizer markets. Moreover, it discusses the economic challenges in transitioning from high carbon footprint suppliers (HCFSs) to low carbon footprint suppliers (LCFSs), exacerbated by a notable cost disparity where HCFSs are approximately 30% cheaper. By advancing beyond conventional static models, this research provides a deeper understanding of the environmental impacts and operational dynamics within supply chains, emphasizing the significant “ripple effect” where decisions at one node profoundly affect others within the chain.

KEYWORDS

data-driven control, dynamic modeling, low-carbon sourcing intertwined supply chains, optimization algorithms, prey–predator model

Abbreviations: ANN, Artificial Neural Networks; CFs, Chemical Firms; FMs, Fertilizer Markets; FSs, Fertilizer Suppliers; GHG, Greenhouse Gas; HCFSs, High Carbon Footprint Suppliers; LCFSs, Low Carbon Footprint Suppliers; LCISCs, Low-Carbon Intertwined Supply Chains; MSE, Mean Square Error; NARX, Nonlinear Auto-Regressive Exogenous; NACF, North African Company Of Fertilizers; SCN, Supply Chain Network; SD, System Dynamics; SINDY, Sparse Identification Of Nonlinear Dynamic Systems; SINDYc, Sparse Identification Of Nonlinear Dynamics With Control.

1 | INTRODUCTION

The recent increasing insistence on confronting the challenges posed by climate change and its environmental ramifications has elevated sustainable practices to the forefront of global priorities (Brandenburg, 2015; Peng et al. 2020). Firms across diverse supply chain sectors progressively recognize the significance of implementing low-carbon strategies across their supply chains (Halat & Hafezalkotob, 2019; Shaharudin et al., 2019). Sourcing decisions are critical in determining a supply chain's overall carbon footprint (Correia et al., 2013; Govindan & Sivakumar, 2016). Thus, developing effective strategies to optimize these decisions is paramount in achieving low-carbon supply chain objectives (Ma et al., 2022).

While considerable advancement has been made within individual segments of the supply chain, such as transportation (Cariou et al., 2019; Xun et al., 2022) or manufacturing (Xia et al., 2022), the interconnected nature of the elements of the supply chains in the low-carbon sourcing problem requires a comprehensive approach for modeling and analysis (Ivanov & Dolgui, 2020; Patil et al., 2023). Different methods have been proposed to model low-carbon issues in supply chains, including deterministic, stochastic, economic game-theoretic, and simulation-based models (Sarimveis et al., 2008). However, most existing models are static and focus on average performance or steady-state conditions, failing to capture the dynamic nature of supply chain systems. Such models are ill-suited for addressing the low carbon sourcing problem, especially in intertwined supply chains (Ivanov & Dolgui, 2020; Kumari & Bera, 2023), characterized by complex interdependencies and dynamic interactions among multiple stakeholders. Indeed, intertwined supply chains refer to complex networks where the entities involved are highly interdependent in logistics and operations and their strategic and environmental impacts (Feizabadi et al., 2023; Mahapatra et al., 2010). These supply chains are characterized by multiple layers of suppliers, manufacturers, and consumers whose decisions and actions are closely linked, creating a web of direct and indirect relationships. This interconnectivity often leads to intricate dynamics where decisions at one node can significantly influence operations and outcomes at several other points in the system. In these intertwined supply chains, decisions related to sourcing play a critical role in achieving low-carbon objectives and reducing environmental impact. The low-carbon sourcing problem in intertwined supply chains can give rise to the "ripple effect" (Lamba & Singh, 2019; Patil et al., 2023). This effect occurs when changes in sourcing decisions at one point in the supply chain propagate and amplify throughout the interconnected network, leading to increased carbon emissions, excessive waste, and inefficient resource utilization (Cariou et al., 2019). Consequently, static models fail to consider these ripple effects and overlook the potential for reducing carbon footprints through strategic sourcing decisions (Govindan & Sivakumar, 2016; Kumari & Bera, 2023; Ma et al., 2022).

Developing dynamic models that account for time-varying supply chain dynamics is crucial. This study addresses this gap by proposing a dynamic model that captures the bullwhip effect in low-carbon sourcing decisions for intertwined supply chains. We leverage data-driven control techniques, utilizing real-time and historical data for informed decision-making. Our model incorporates a prey–predator analogy, viewing suppliers as prey and manufacturers and consumers as predators. This ecological perspective helps analyze carbon dynamics, highlighting the balance and interdependencies akin to natural ecosystems. It illustrates how disruptions ripple through the network, explaining how small changes cause major fluctuations. By examining these dynamics, we gain insights into interactions and dependencies affecting environmental performance. This approach helps identify strategies to promote sustainable practices and incentivize suppliers to adopt low-carbon initiatives.

This paper has two main objectives. First, we develop a data-driven control model using real-time and historical data to optimize sourcing decisions in an LCISC. Second, we identify the most suitable algorithm for applying the prey–predator model to low-carbon sourcing in these complex supply chains. Moving beyond traditional static models, we capture dynamic interactions and ripple effects within the network, demonstrating how decisions at one node impact the entire supply chain. To achieve this, we explore two data-driven algorithms: the nonlinear auto-regressive exogenous (NARX) network and the sparse identification of nonlinear dynamics with control (SINDYc). We evaluate their suitability for addressing the complex dynamics of the prey–predator model. Thus, this study is an effort to assist both manufacturing and service supply-chain practitioners in building a model that analyzes carbon dynamics by addressing two main research questions (RQs):

> **Research Question 1.** How can a dynamic model that employs a data-driven control framework and a prey–predator analogy be developed to capture the ripple effects and optimize low-carbon sourcing decisions in intertwined supply chains?

> **Research Question 2.** Which data-driven algorithm, between the nonlinear auto-regressive exogenous (NARX) network and sparse identification of nonlinear dynamic systems with input variables (SINDYc), is more effective in addressing the complexity inherent in the prey–predator model within the context of low-carbon intertwined supply chains?

The remainder of the paper is organized as follows: Following the introduction, Section 2 presents a comprehensive literature review. Section 3 introduces our prey–predator model for sourcing decisions in LCISC, elaborating on our data-driven methodology comprising the NARX and SINDYc methods. Section 4 delves into the context and problem formulation, setting the stage for the subsequent analysis. Section 5 details the process of solving the prey–predator model using the NARX and SINDYc approaches, showcasing the practical application of these methodologies. Section 6 is dedicated to thoroughly discussing our results and dissecting their significance and implications. Section 7 presents the theoretical and managerial implications, providing insights into the broader impact of our study.

Finally, the paper concludes in Section 8 with a summary of our findings, current study limitations, and future research directions.

2 | LITERATURE REVIEW

2.1 | Advancing decision support systems in dynamic low-carbon supply chains

The modeling of supply chains is vital in decision-making processes, particularly for enhancing operational efficiency and effectiveness. A growing focus has recently been formalizing sustainable and eco-friendly supply chain models (Li et al., 2020). These models incorporate various methodologies, including optimization algorithms (Halat & Hafezalkotob, 2019; Xia et al., 2022), simulation techniques (Xia et al., 2022), and programming strategies (Brandenburg, 2015; Jabbarzadeh et al., 2019). In the realm of intertwined supply chains, companies often form complex networks by connecting within and across diverse industries, resulting in interconnected ecosystems of suppliers. These low-carbon intertwined supply chains (LCISCs) are dynamic and structurally different from traditional linear and static green supply chains (Tan et al., 2023). This complexity necessitates novel modeling approaches, leading researchers to explore system dynamics (SD) modeling (Francis & Albert, 2023; Wang & Yao, 2021).

Several studies exemplify the application of SD modeling in this field. Rebs et al. (2019) developed an SD model that captures the intricate dynamics of supply chain systems, including the influence of external stakeholder pressures from entities like governments and shareholders. Dolgui et al. (2020) used SD modeling to design blockchain technology's smart contracts, employing a dynamic, event-driven approach for task and service composition. Vlachos et al. (2007) proposed capacity planning policies for reverse supply chains in remanufacturing, considering both economic and environmental factors, such as legislative mandates and the impact of a company's green image on consumer demand. Olivares-Aguila and ElMaraghy (2021) introduced a system dynamics framework to analyze supply chain behavior and assess the impact of disruptions on various business metrics. Golroudbary and Zahraee (2015) evaluated the system behavior of an electrical manufacturing company using SD to simulate a closed-loop supply chain. Similarly, Tian et al. (2014) used an SD model to guide subsidy policies in China to promote the diffusion of green supply chain management. Trappey et al. (2012) also use SD modeling to simulate and identify green product redesigns with low carbon footprints during manufacturing. Such research aims to find the best ways to reduce carbon footprints in green product development and production.

Despite these advancements, literature indicates significant challenges in constructing SD models for complex supply chains, primarily due to their intricacy (Cui et al., 2022; Nguyen et al., 2022). To address this, recent research has pivoted toward data-driven SD modeling (Peng et al., 2020). This approach has seen varied applications, such as Pereira and Frazzon's (2021) alignment of demand and supply in omnichannel supply chains using machine learning and simulation-based optimization and Huber et al.'s (2019) use of regression and neural networks for dynamic inventory decision-making. Notably, the exploration of data-driven SD modeling in environmentally focused supply chains is still emerging, with notable efforts by Tseng, Ha, et al. (2022) and Tseng, Bui, et al. (2022) in circular and sustainable supply chains. Moreover, while AI models, including linear regression and artificial neural networks (ANN), are central to this new wave of data-driven SD modeling (Cui et al., 2022; Pereira & Frazzon, 2021), evidence of their effectiveness in highly interconnected systems is still forthcoming (Huber et al., 2019; Kraus et al., 2020). Additionally, customizing AI models for SD support demands careful consideration of various factors, including the degree of interconnection and uncertainty in the system (Erkip, 2022).

2.2 | Sourcing decisions in low-carbon intertwined supply chains

Intertwined supply chains, as defined by Ivanov and Dolgui (2020), represent a network of interlinked supply chains collaboratively working to ensure the steady provision of goods and services to markets and customers. Within this framework, LCISCs specifically focus on minimizing greenhouse gas (GHG) emissions throughout all supply chain stages, including production, transportation, and disposal (Liu et al., 2020; Xia et al., 2022). Central to the concept of LCISCs are sourcing decisions, which play a pivotal role in achieving the goal of reducing carbon emissions across the supply chain (Shaharudin et al., 2019). These decisions encompass strategies for acquiring goods and services while consciously minimizing the carbon footprint of their life cycle, from production to end use (Peng et al., 2020; Shaharudin et al., 2019). Adopting low-carbon sourcing practices is increasingly seen as a vital corporate strategy, aiding organizations in lessening their environmental impact and supporting the transition toward sustainable supply chain models (Correia et al., 2013). There has been a growing body of research on sourcing decisions in LCISC in recent years, with numerous studies examining its benefits and challenges (Lamba & Singh, 2019; Ma et al., 2018).

Recent research, including that by Ma et al. (2022), has underscored the importance of sourcing decisions in reducing carbon emissions within LCISCs, highlighting their significant influence on the overall environmental performance of the supply chain. A critical component of these sourcing decisions is the selection of suppliers. Opting for suppliers committed to sustainable practices can substantially reduce the carbon footprint of the focal firm (Singh et al., 2018). This can involve a range of strategies, such as choosing suppliers that utilize renewable energy sources, have effective energy efficiency measures in place, or have a demonstrable record of reducing carbon emissions (Govindan & Sivakumar, 2016; Shaw et al., 2012; Singh et al., 2018). However, transitioning to low-carbon sourcing is fraught with challenges, as the literature indicates (Ma et al., 2022). Many companies face initial cost barriers, such as the need for investment in new technologies or processes, which may not be immediately feasible (Brandenburg, 2015; Liu et al., 2020). Additionally, there can be resistance from suppliers reluctant to adopt new, low-carbon practices, and implementing such initiatives within the supply chain can be challenging (Govindan & Sivakumar, 2016). Moreover, the lack of incentives for suppliers to transition to low-carbon practices, such as through carbon pricing or regulatory frameworks, further complicates adopting these practices (Ma et al., 2018).

This paper seeks to bridge the gap between the challenges above and the potential solutions advanced modeling techniques offer. Specifically, we aim to enhance the support of SD models in LCISCs through data-driven methods, particularly under conditions of high interconnection. We focus on a sourcing problem within an LCISC, utilizing the well-known prey–predator SD model as a basis (Ivanov & Dolgui, 2020; Nagurney & Nagurney, 2012; Turken et al., 2020).

3 | DATA-DRIVEN SD MODELING METHODOLOGY

This study aims to enhance sustainable supply chain management, focusing on LCISCs, by improving decision-making through advanced SD modeling techniques. We employ a dynamic model incorporating a prey–predator framework, using an ecological analogy to represent complex supply chain interactions, with suppliers as prey and manufacturers and consumers as predators. This approach effectively captures competitive and cooperative dynamics, illustrating significant ripple effects from shifts at any node. Central to this model is a data-driven decision-making framework that leverages real-time and historical data for accurate and timely sourcing decisions, utilizing advanced algorithms like the nonlinear auto-regressive exogenous (NARX) network and sparse identification of nonlinear dynamic systems with control (SINDYc).

The basic idea behind applying the data-driven control framework and the prey–predator model for sourcing decisions is to leverage real-time and historical data to simulate and optimize the complex dynamics within a supply chain network (SCN). The data-driven control framework uses data analytics and control theory to create decision-support systems that adapt to supply chain fluctuations and uncertainties. Analyzing extensive datasets on variables such as customer demand, inventory levels, and production capacity enables informed and timely decisions on sourcing strategies, inventory management, and production planning. The prey–predator model views suppliers as “prey” and manufacturers/consumers as “predators,” highlighting their dependency on each other and competition for resources. Indeed, the prey–predator model is particularly suited for describing the complex interactions and dependencies in low-carbon intertwined supply chains (LCISCs) due to its ability to capture the competitive and cooperative dynamics inherent in such systems. In LCISCs, suppliers, manufacturers, and consumers are interdependent, where suppliers provide essential resources to manufacturers and consumers who compete for these limited resources. This ecological analogy effectively illustrates how shifts or disruptions at one point in the supply chain can propagate and magnify throughout the network, like ecological systems where the population dynamics of prey and predators are closely linked. Moreover, this model helps elucidate phenomena like the “bullwhip effect,” where small changes in demand or supply at one node can cause significant fluctuations throughout the chain.

By applying the prey–predator framework, the study offers a nuanced perspective on how interdependencies and feedback loops in LCISCs impact overall performance, enabling more precise and dynamic decision-making essential for managing sustainability and efficiency in these complex networks. The model also incorporates dynamic feedback loops to reflect the nonlinear interactions and dependencies within the supply chain, emphasizing how decisions in one part of the chain can amplify effects elsewhere. These loops are crucial for understanding the interconnected nature of LCISCs and predicting the outcomes of various operational and strategic decisions. Moreover, the model is designed to accommodate various external factors that influence the supply chain, such as fluctuations in market demand, changes in commodity prices, and variations in supplier performance.

The NARX method was selected for its expertise in forecasting and managing nonlinear systems, effectively processing data influenced by previous output values and multiple exogenous variables. In LCISCs, these inputs include market factors like commodity prices, demand fluctuations, and supplier performance metrics. NARX's structure integrates these dynamics, providing a sophisticated tool for modeling the impact of external factors on sourcing decisions. Simultaneously, the SINDYc method excels in identifying the governing equations of a dynamical system using sparse regression, which is particularly beneficial for complex, high-dimensional data typical in supply chain analysis. SINDYc identifies both passively observed and actively controlled systems, making it invaluable for exploring robust and adaptable low-carbon sourcing strategies in LCISCs. This paper compares NARX and SINDYc, analyzing their strengths and limitations in LCISCs. Our study aims to enhance sustainable supply chain management by understanding how data-driven models improve decision-making in complex, intertwined supply chains with low-carbon objectives. The comparative analysis delineates each method's strengths and limitations, providing insights into their appropriateness and efficiency for LCISC modeling.

To strengthen the methodological rigor of our study, we implemented a comprehensive validation procedure for both the NARX and SINDYc models, focusing on their performance in real-world scenarios within low-carbon intertwined supply chains (LCISCs). We employed several key metrics to evaluate these models to ensure a thorough assessment of their accuracy and reliability. The primary metric used was the mean square error (MSE), which measures the average of the squares of the errors between predicted and actual values, clearly indicating each model's precision. Additionally, we utilized error histograms to visualize the distribution and magnitude of errors, which allowed us to identify patterns, variance, and skewness, offering insights into areas needing improvement. We also analyzed the models' convergence behavior by examining their ability to minimize errors through iterative training processes. Furthermore, our validation process included testing the models against unseen real-world data from the same supply chains they are intended to serve. This step was crucial for assessing the models' robustness and reliability under actual operational conditions, ensuring their capability to generalize beyond the training data. This comprehensive evaluation highlights the practical applicability and effectiveness of the models in making informed decisions under the dynamic and unpredictable conditions characteristic of LCISCs.

3.1 | NARX neural networks

The NARX neural network is a logical extension of artificial neural networks that are designed for time series prediction problems, where the current output of the system depends on past input and output values as well as on exogenous variables (Alshater et al., 2022; Gao et al., 2023; Trapero et al., 2012). ANN models usually outperform conventional approaches when the time series is noisy, and the underlying dynamical system is nonlinear and challenging to analyze. In these circumstances, the ANN's superior prediction performance seems to be explained by its ability to draw complicated nonlinear correlations from actual experimental data and learn from them (Ebadi Jalal et al., 2016; Shahbaz et al., 2020). In addition to being computationally robust in principle, NARX neural networks also provide several practical benefits. One of the critical advantages of NARX networks is that they are more effective at learning than other neural networks due to their use of gradient-descending learning algorithms. NARX networks are known to converge much faster and generalize better than other networks. For instance, Lin et al. (1996) assert that NARX networks have a higher potential for gradient-descent learning than different recurrent designs with "hidden states." Furthermore, NARX networks are particularly adept at discovering long-term dependencies, making them ideal for modeling complex systems. This contrasts with conventional recurrent neural networks, which can struggle with capturing long-term dependencies. Indeed, NARX networks can effectively capture long-term dependencies due to their use of output delays. This allows the network to consider the impact of past inputs on current outputs, thereby enabling it to model complex relationships over extended periods. As shown in Equation (1), the desired value of the output at the NARX model's $(n+1)^{th}$ element is given mathematically by $\widehat{X}(n+1)$, where $\widehat{X}(n+1)$ is the output value, at the $(n+1)^{th}$ element (Ebadi Jalal et al., 2016).

$$\widehat{X}(n+1) = F\left(\widehat{X}(n),\cdots,\widehat{X}(n-k+1),u(n),\cdots,u(n-k+1)\right), \quad (1)$$

where u is the input sequence, $\widehat{X}$ is the projected output sequence, and F represents a nonlinear function. The accuracy of this value is critical in ensuring the model's effectiveness.

3.2 | SINDy

SINDy is a method for mathematically deducing sparse dynamics from data to study complex systems using snapshot data $\boldsymbol{y}(t) \in Rn$. A critical step in building an SD model is identifying the relationships among the system's components, known as parse identification. This article will discuss the parse identification process and its importance in describing, analyzing, and explaining supply chain system issues. SINDYc is an extension of the SINDy framework, where "*c*" denotes the inclusion of control terms. SINDYc is used explicitly for systems where external control inputs influence the dynamics.

System identification is the process of identifying the variables, parameters, and relationships crucial to the behavior of the system being modeled. Creating an accurate and comprehensive SD model that can produce reliable predictions is essential. SINDy has been used successfully for model identification in various fields, including fluid flows, optical systems, chemical reaction dynamics, convection in plasma, structural modeling, and model predictive control (Hoffmann et al., 2019; Loiseau & Brunton, 2018; Zhang & Schaeffer, 2019). The SINDy framework has also undergone theoretical expansion to incorporate various models. Mangan et al. (2016) demonstrated the framework's ability to handle models with rational function nonlinearities. Additionally, Schaeffer et al. (2020) introduced models for partial differential equations, while Zhang and Schaeffer (2019) demonstrated the framework's applicability to hybrid dynamical systems and models for parametrically dependent dynamical systems. Moreover, the SINDy framework can combine physics and limitations that are not fully understood, as demonstrated by Loiseau and Brunton (2018). Furthermore, the framework can discover models using data from physically accurate sensors. The algorithm can be modified to handle missing or limited data or include integral terms for noisy data, as Schaeffer et al. (2020) show. Additionally, information criteria can be utilized to evaluate the selected modes. These theoretical advancements have expanded the scope of the SINDy framework, allowing it to handle a broader range of modeling problems and offer a sound basis for model discovery methods. Parse identification in system dynamics involves several steps. First, the system boundary is established to determine the model's scope. Next, relevant stocks and flows are identified, representing accumulations and rates of change within the system. Feedback loops are then placed, which can create dynamic behavior. Parameters that affect the system's behavior are also identified. Lastly, the specified variables, parameters, and relationships are translated into a mathematical model for simulation and analysis. The method seeks to identify a best-fit dynamical system with the fewest terms possible, represented by Equation (2), which describes the rate of change of the system's state variable y at a given time t, which is influenced by the input variable u and the current state $y(t)$.

$$\dot{y}(t) = G(y(t),u)\Xi. \quad (2)$$

Here, $G(y(t),u)$ represents a library of candidate functions of the state variables y and input variables u, and Ξ is a sparse coefficient matrix. This form explicitly highlights the sparse regression approach used in SINDY to identify the most relevant dynamics governing the system.

By finding the best-fit system, the method enables the modeling of complex systems with a more straightforward representation, facilitating analysis and prediction of system behavior.

4 | PROBLEM MODELING

4.1 | Context and problem formulation

In this paper, we delve into the sourcing decision problem within an African fertilizers supply chain, a quintessential example of an LCISC due to its complexity and sensitivity to the carbon footprint of products (Bouzekri et al., 2022; Hilali et al., 2022). The intertwined supply chain is modeled using a novel data-driven control framework and a prey–predator dynamic, where suppliers are "prey" and manufacturers and consumers are "predators." This ecological analogy highlights complex interactions and dependencies, capturing the "bullwhip effect" where decisions at one node impact the entire network. In ecological terms, prey–predator models illustrate resource dependency and competition, with prey providing essential resources for predators. Applied to supply chains, suppliers (HCFSs and LCFSs) are prey-providing raw materials, and manufacturers (CFs) are predators. Introducing super-predators, represented by fertilizer markets (FMs), adds complexity as FMs pressure CFs, who must optimize sourcing from HCFSs and LCFSs, creating a three-tier hierarchy similar to ecological systems. This analogy, despite lacking traditional cooperation, captures broader supply chain interactions, emphasizing competitive and cooperative dynamics. This approach enhances informed decision-making, reflects real-world complexities, and improves supply chain sustainability and efficiency.

Moreover, the paper discusses the economic challenges inherent in transitioning from HCFSs to LCFSs, particularly their notable cost disparity. This economic consideration poses a significant hurdle in achieving low-carbon objectives without compromising financial viability. The general structure of this supply chain, depicted in Figure 1, shows chemical firms (CFs) sourcing phosphate rock from various mining suppliers. These CFs then process the phosphate rock into products like phosphoric acid, feeds, and fertilizers, which are distributed to local and international fertilizer markets (FMs).

In the African fertilizers supply chain, phosphate rock is principally sourced from two distinct types of mining suppliers: low carbon footprint suppliers (LCFSs) and high carbon footprint suppliers (HCFSs). Traditionally, CFs have predominantly relied on HCFSs for their phosphate rock due to their widespread availability in Africa (Couth & Trois, 2010). However, recent developments in environmental legislation across several African nations have prompted a significant shift in this dynamic (Bouzekri et al., 2022; Olujobi et al., 2022). These new carbon footprint regulations are compelling HCFSs to reevaluate and modify their mining processes, increasingly transitioning toward practices characteristic of LCFSs (Tan et al., 2023). Concurrently, there is a growing emphasis within chemical firms (CFs) on reducing their products' carbon footprint by sourcing from low carbon footprint suppliers (LCFSs). However, this shift faces significant challenges, primarily due to the cost disparity between LCFSs and high carbon footprint suppliers (HCFSs). On average, sourcing from HCFSs is about 30% cheaper. This cost difference arises because LCFSs invest more in cleaner technologies and stricter environmental regulations, leading to higher production costs. In contrast, HCFSs often use older, fully amortized infrastructure with lower operational expenses. Additionally, many HCFSs benefit from economies of scale, producing goods more cheaply in large quantities. This disparity creates a complex economic landscape in the African fertilizers supply chain, affecting sourcing decisions. We propose a double-prey, predator, and super-predator interaction framework to model this complexity.

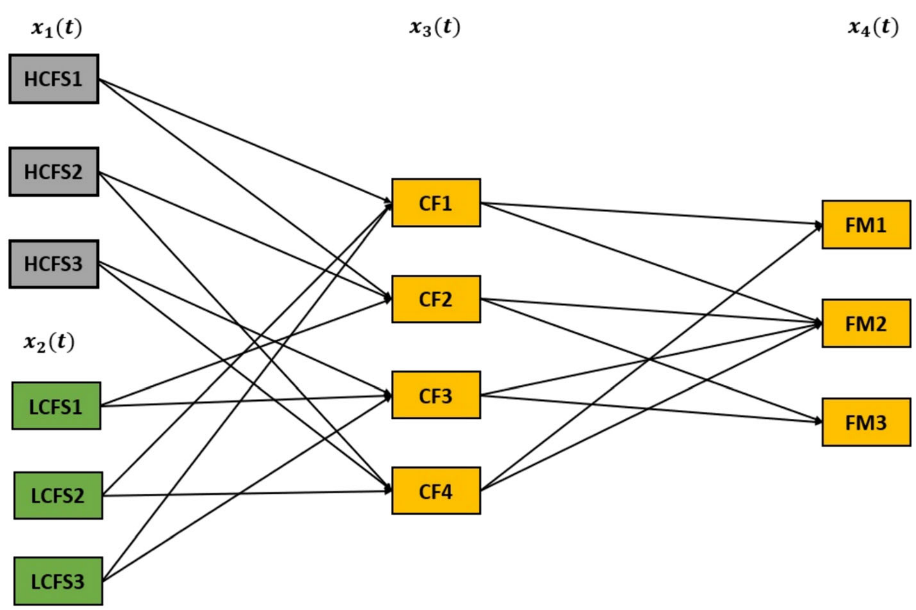


FIGURE 1 Structure of LCISC of fertilizers in Africa.

4.2 | Assumptions and modeling

In our model of the fertilizer supply chain, which includes fertilizer markets (FMs), chemical firms (CFs), and fertilizer suppliers (FSs), we establish several foundational assumptions for analysis. The supply chain is structured into three hierarchical levels: *FM*, *CF*, and *FS*. We treat the evolution of these levels as a deterministic process described by quadratic growth and death parameters, simplifying the model by assuming static parameters (u, v, w, and p) that do not change over time. This framework assumes a monopolistic market setting where market changes are gradual and disturbances are considered negligible, thus not affecting the system's dynamics significantly. This model also conceptualizes the dynamics between HCFSs and LCFSs (as prey), the CFs (as predators), and the FMs (as super-predators). We represent the carbon footprint of these entities at any given time t; the carbon footprint of prey (HCFSs and LCFSs), predator (CFs), and super-predator (FMs) are denoted as $x_{HCFSs}(t)$, $x_{LCFSs}(t)$, $x_{CFs}(t)$, and $x_{FMs}(t)$, respectively. The predator CFs and the prey LCFSs are both expected to play a role in the dynamic evolution of the prey HCFSs, while the predator CFs serve as prey for the supra-predator FMs. The logistic response function is used to model the interaction between these levels, capturing the consumption of resources (prey) by CFs and their impact on HCFSs and LCFSs while also considering the influence of FMs on CFs. This method allows the model to capture the ripple effects of decisions and behaviors across the supply chain. Indeed, using the logistic functional response for predator and super-predator population consumption of prey and predator (Equation 3), we can demonstrate this phenomenon.

$$\begin{cases} x'_{HCFSs}(t) = x_{HCFSs}(1 - u_{HCFSs}x_{HCFSs} - v_{HCFSs}x_{CFs} - px_{LCFSs}) + U, & (3.1) \\ x'_{LCFSs}(t) = x_{LCFSs}(1 - u_{LCFSs}x_{LCFSs} - v_{LCFSs}x_{CFs} + px_{HCFSs}), & (3.2) \\ x'_{CFs}(t) = x_{CFs}(-b + \alpha_{HCFSs}v_{HCFSs}x_{HCFSs} + \alpha_{LCFSs}v_{LCFSs}x_{LCFSs} - wx_{FMs}), & (3.3) \\ x'_{FMs}(t) = x_{FMs}(-c + wx_{CFs}). & (3.4) \end{cases} \tag{3}$$

We denote the set of model parameters (u_i, v_i, w, p, U) $\in U_{admissible}$, where $U_{admissible}$ is the bounded set of admissible control variables. These variables would entail behavioral strategies at businesses at various LCISC tiers. Accordingly, the internal strategy of companies is denoted by u_i, while v_j denotes the behavioral strategies of CFs toward their suppliers j (HCFSs or LCFSs). In addition, w represents the behavioral strategies of FMs toward CFs. Moreover, we included an exogenous system control, that is, the credit carbon buying capacity (denoted by U). We assume that HCFSs are intrinsically migrating to LCFSs under carbon neutrality pressures at a constant rate denoted by p. The intrinsic effort to reduce carbon footprint by CFs and FMs is $c > 0$ and $b > 0$. Finally, the physiological parameters α_{LCFSs} depict the transfer rate of carbon footprint between the intertwined levels. Table 1 summarizes the variables and parameters of the model.

To build the system of differential equations in our model, we start by transitioning from discrete-time data to continuous modeling. We represent the population of high carbon footprint suppliers (HCFSs) (Equation 3.1) with a differential equation that accounts for intrinsic growth adjusted for intraspecific competition, predation by chemical firms (CFs), migration to low carbon footprint suppliers (LCFSs), and external regulatory forces. The differential equation for LCFSs (Equation 3.2) includes similar terms but incorporates the positive influx of individuals transitioning from HCFSs. For CFs, Equation (3.3) reflects their efforts to reduce their carbon footprint, their benefits from consuming HCFSs and LCFSs, and the negative impact of interactions with fertilizer markets (FMs). Finally, the dynamics of FMs are modeled with a differential equation (Equation 3.4) that captures their growth due to the availability of CFs as a resource while considering their efforts to reduce their carbon footprint.

TABLE 1 Summary of variables and parameters.

Symbol	Interpretation
x_{HCFSs}	Population or state of high carbon footprint suppliers (HCFSs)
x_{LCFSs}	Population or state of low carbon footprint suppliers (LCFSs)
x_{CFs}	Population or state of chemical firms (CFs)
x_{FMs}	Population or state of fertilizer markets (FMs)
u_{HCFSs}, u_{LCFSs}	Internal strategies of companies (efficiency measures)
v_{HCFSs}, v_{LCFSs}	Behavioral strategies of CFs toward their suppliers (HCFSs or LCFSs)
w	Behavioral strategies of FMs toward CFs
p	Migration rate from HCFSs to LCFSs under carbon neutrality pressures
U	Exogenous control variable, representing external forces that can influence and control the behavior of x_{HCFSs}
$\alpha_{HCFSs}, \alpha_{LCFSs}$	Efficiency parameters reflecting the transfer rate of carbon footprint from HCFSs and LCFSs to CFs
b	Intrinsic effort by CFs to reduce their carbon footprint
c	Intrinsic effort by FMs to reduce their carbon footprint

5 | SOLVING THE PREY–PREDATOR MODEL OF SOURCING DECISIONS IN LCISC

5.1 | Data collection procedure

In our study, comprehensive data collection was paramount to analyzing the supply chain dynamics of African fertilizers. We obtained our primary dataset from the North African Company of Fertilizers (NACF), a pseudonym to preserve confidentiality. We utilized various internal digital sources within NACF, stored in a data lake, to collect a wide range of information. These sources included inputs from sensors and platforms, which provided in-depth insights into sourcing practices, carbon footprints, and market dynamics within the supply chain. Mainly, we focused on gathering data on sourcing phosphate rock by *CFs* from mining suppliers and distributing chemical products to local and international *FMs*. Data collection was done over approximately 4 years. This duration is necessary to adequately capture the temporal fluctuations and trends in the supply chain, including seasonal variations and long-term market shifts that impact the supply chain dynamics. Furthermore, data collection involved thousands of data points. These points span various metrics and periods to accurately capture the supply chain's evolving dynamics.

The data collection and preparation were intricately designed to align with and support the model in Equation (3), ensuring coherence between the data sources, content, and the theoretical framework. The first phase of data collection focused on assembling a broad array of information from various internal digital sources of NACF stored in a data lake. This data lake included inputs from sensors and platforms, providing in-depth insights into sourcing practices, carbon footprints, and market dynamics pertinent to the supply chain. Mainly, we gathered detailed information on the sourcing of phosphate rock by *CFs* from mining suppliers, along with data on the distribution of chemical products to local and international *FMs*. This phase involved cataloging data on the types of chemical products produced, identifying both *LCFSs* and *HCFSs*, and collating information on the carbon footprint at each stage of the supply chain. In the second phase, we conducted thorough assessments to quantify the carbon footprint of different supply chain components. This analysis encompassed data related to energy consumption, emissions, transportation, and production processes. We applied established carbon accounting methodologies to ensure the accuracy and comparability of our carbon footprint assessments.

Additionally, we gathered data on the pricing trends of phosphate rock sourced from both *LCPSs* and *HCFSs*. These data were complemented by market information from the international fertilizers marketplace to understand the factors influencing the sourcing decisions of *CFs*. The third phase was crucial in bridging our data collection with the prey–predator model outlined in Equation (3). We collected time series data, capturing the dynamic nature of the sourcing problem. These data were essential in representing the temporal fluctuations of carbon footprints within the supply chain entities, denoted as $x_{HCFSs}(t)$, $x_{LCFSs}(t)$, $x_{CFs}(t)$, and $x_{FMs}(t)$ (or simply $x_1(t)$, $x_2(t)$, $x_3(t)$, and $x_4(t)$).

By collecting data at various time intervals, we could track and analyze changes in the carbon footprints of *HCFSs*, *LCFSs*, *CFs*, and *FMs* over time. Moreover, we collected additional data on population dynamics, consumption rates, and other relevant parameters to calibrate the prey–predator model effectively. These parameters were instrumental in accurately depicting the interactions and dependencies within the supply chain system. By meticulously aligning our data collection and preparation with the model's requirements, we ensured that the empirical data substantiated and enriched the theoretical constructs of our model, thereby enhancing the robustness and applicability of our research findings.

5.2 | Solving the prey–predator model of sourcing decisions in LCISC using NARX

The NARX method is used to understand the complex dynamics of the prey–predator model described in Equation (3). This algorithm is designed for time series forecasting and provides valuable insights into the behavior of the system (Alshater et al., 2022; Ebadi Jalal et al., 2016). By utilizing historical data and external inputs, we will explore the capabilities of the NARX method to better understand the dynamics in Equation (3). Indeed, the collected data were meticulously aligned with each model parameter. The time series data, which captured the carbon footprints of *HCFSs*, *LCFSs*, *CFs*, and *FMs* at various time intervals, provided empirical values for parameters such as $x_{HCFSs}(t)$, $x_{LCFSs}(t)$, $x_{CFs}(t)$, and $x_{FMs}(t)$. These data were instrumental in representing the changes in carbon footprints within the supply chain over time. Additionally, data on population dynamics, consumption rates, and other relevant factors were crucial for effectively calibrating the prey–predator model.

The model's architecture, shown in Figure 2, facilitates data-driven predictive analysis by incorporating information from previous time steps and external factors. Before the initiation of the training process, specific parameters, such as $u_1 = 0.01$, $v_1 = 0.1$, $p_1 = 1$, $u_2 = 1$, $v_2 = 1$, $b = 1$, $w = 0.01$, and $c = 1$, are set as initial conditions. These initial values are fundamental in establishing the starting trajectory of the system, playing a significant role in shaping the behavior and subsequent evolution of the dynamic supply chain system. Moreover, these parameters reflect the behavioral strategies adopted by different levels within the supply chain, and their accurate determination is vital for the model's efficacy. We undertook a comprehensive data analysis process to ensure precision in setting these parameters. This iterative process aims to construct a model that accurately reflects the real-world behaviors and dynamics of the LCISC. The initial stage of this process involves the systematic collection of pertinent data, with a specific focus on behavioral aspects, such as sourcing decisions, supplier choices, carbon footprints, and pricing strategies, across the diverse levels of the supply chain. Once the data are compiled, a comprehensive preprocessing procedure involves data cleaning, standardization, and normalization to prepare it for subsequent exploratory analysis. Through exploratory analysis, trends and relationships are identified, and regression analysis is then employed to estimate the values of the parameters above.

The NARX model architecture is displayed in Figure 2. It highlights the key components, starting with the inputs marked as $x(t)$, representing the prey–predator interactions within the supply chain. These inputs are crucial data points that initiate the network's processing. The target output, labeled $y(t)$, signifies the network's desired output, encapsulating the modeled supply chain dynamics. Central to the neural network are the weights and biases, forming the foundation of the neural processing units. The architecture includes 10 hidden layers, each performing complex nonlinear transformations on the input data. These layers sequentially process and refine the information, preparing it for the final output prediction (Ebadi Jalal et al., 2016). The four output layers then compile and finalize this processed information, shaping the network's ultimate output to match the intended result. The figure also delineates the generation of the final output $y(t)$, utilizing the NARX method. This process uniquely updates the output, considering both the present input and past outputs, thereby capturing the dynamic and interconnected nature of the supply chain within our model.

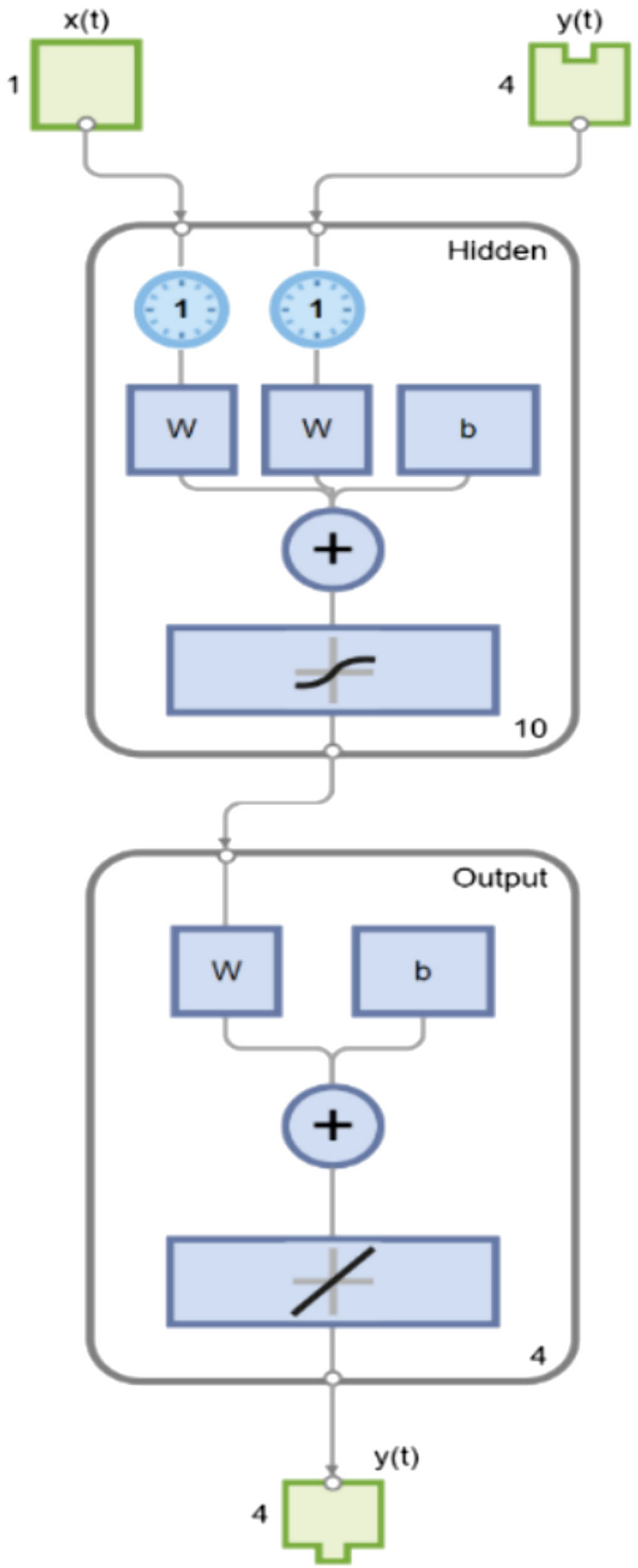


FIGURE 2 NARX model neural network architecture.

A rigorous evaluation process is conducted to analyze the performance of our NARX model. The main goal of this assessment hinges on a comparative analysis of the expected target state against the output state generated by the model. This juxtaposition serves two pivotal roles. Primarily, it offers an insight into the predictive prowess of the model, evaluating its capacity to make accurate forecasts. Second, it gauges the model's generalization capabilities, testing its ability to apply learned patterns to new, unseen data.

The training process involves multiple iterations, and with each iteration, the model refines its internal parameters to minimize the discrepancy between the target state and the output state. Thus, to effectively train a neural network to learn the nonlinear mapping from x_k to x_{k+1}, we use a diverse set of initial data to generate trajectories (Shahbaz et al., 2020). These trajectories are generated through the simulation of the system, which produces two matrices, namely, the input matrix and the output matrix (Trapero et al., 2012). The former is a matrix of the system at x_k, while the latter is the corresponding state of the x_{k+1} system advancement Δt. The neural network must learn the nonlinear mapping from x_k to x_{k+1} by analyzing these matrices. Figure 3 represents this iterative learning process, effectively showcasing the gradual improvement in the model's predictive capabilities during training.

After the training phase, the model advances to the validation phase, where it predicts outputs for a new dataset it has not encountered during the training phase. In this stage, we employ a two-pronged approach. First, we examine the model's performance under various specific initial conditions. These initial conditions, deliberately selected for their relevance and importance to the supply chain dynamics, allow us to test the model's predictive competence in scenarios that are of particular interest (Alshater et al., 2022; Ebadi Jalal et al., 2016). This validation method offers an in-depth evaluation of how well the model performs under conditions deemed crucial in the sourcing problem within the LCISC context. Simultaneously, we extend our validation process to examine the model's performance under randomly chosen initial conditions. This aspect of our validation phase tests the model's resilience and generalization capability across a wide range of initial states, thereby closely mirroring real-world situations where initial conditions can vary significantly (Trapero et al., 2012). Figure 4a offers a visual representation of the first stage of the validation phase, and Figure 4b represents the second stage with randomly chosen initial conditions, highlighting the model's accuracy in predicting unseen data points.

Despite the promising structure and theoretical capabilities of the NARX method, its performance has not lived up to expectations. The error between the target and output states remains significantly large, failing to converge to zero. This indicates that the model struggles to encapsulate the complexities of the underlying system within the interval (0, 10), leading to an inability to minimize error effectively. The error magnitude surpasses the threshold of 10, suggesting a substantial deviation from the expected accuracy. This observation is corroborated by the model's behavior during the validation phase, as shown in Figure 4. The model's output increasingly diverges from the exact model, indicating an apparent discrepancy between the model's predictions and the actual dynamics of the system.

To complete our performance analysis, Figure 5 displays an error histogram with 20 bins, representing the distribution of errors

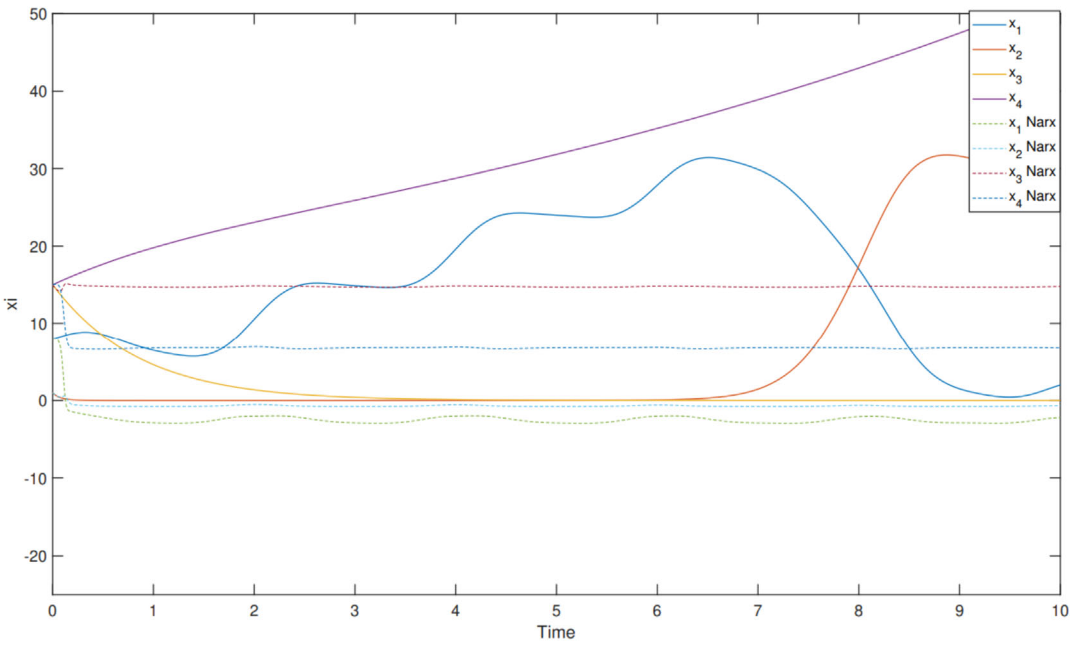


FIGURE 3 The training phase of the NARX model.

between the target and output states. By examining the histogram, it's possible to gain insights into the variability, magnitude, and frequency of errors generated by the NARX method. These insights can be crucial for identifying potential issues and planning necessary improvements in the model (Alshater et al., 2022).

As shown in Figure 5, the analysis reveals the limitations of the NARX method in accurately capturing the intricate dynamics of the sourcing mechanisms in the LCISC model. Indeed, the inability to converge and the substantial error values highlight the limitations of the NARX method in accurately capturing the desired dynamics. These findings suggest that alternative approaches or modifications may be necessary to achieve better performance and improve the model's accuracy.

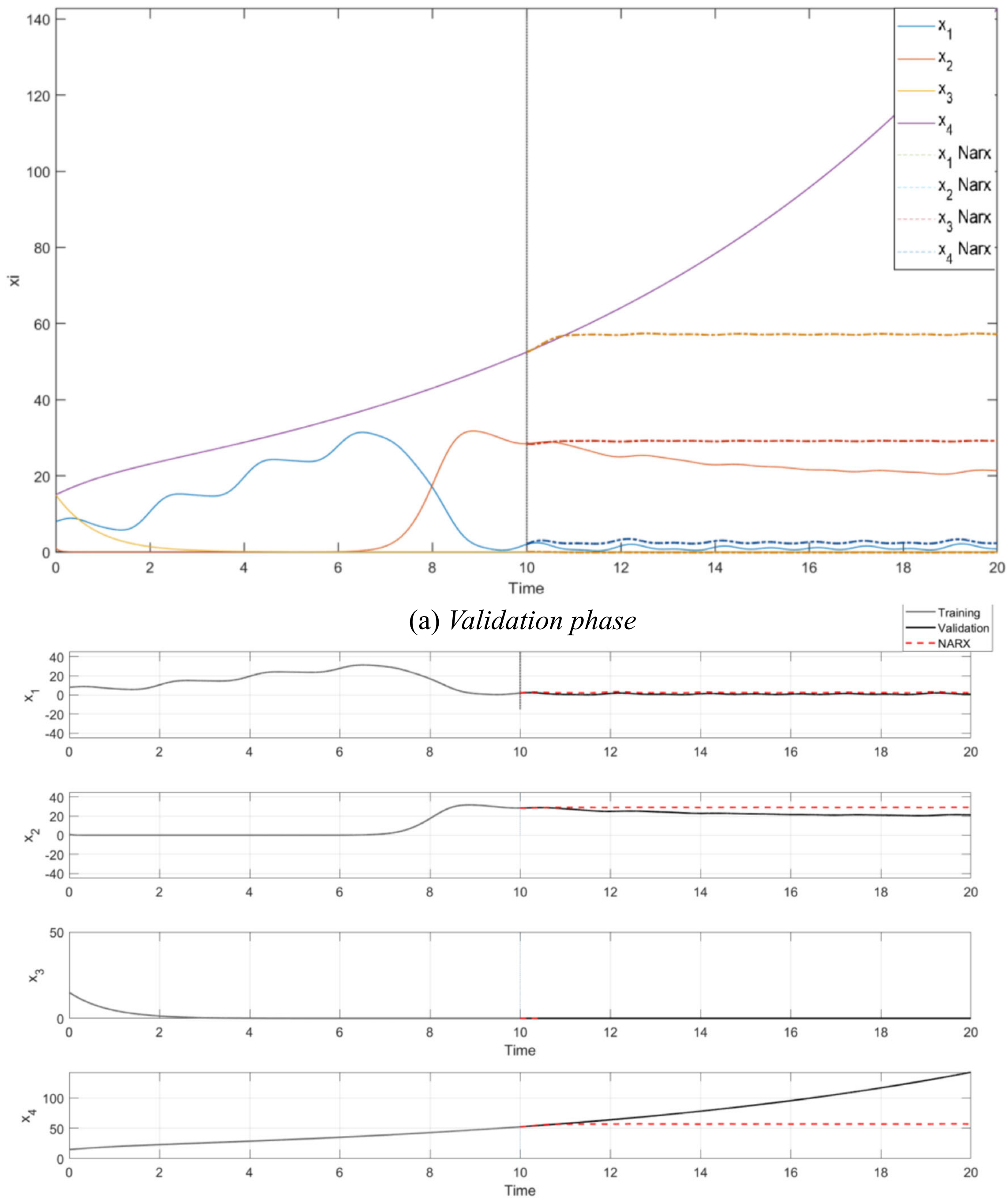
5.3 | Solving the prey–predator model of sourcing decisions in LCISC using SINDYc

Our study on nonlinear dynamics starts by outlining the system boundary and defining the model's dimensions. We identify "stocks" and "flows" key variables for system accumulations and changes. In our African fertilizers supply chain study, stocks include the quantities of raw materials such as phosphate rock; the inventory of produced chemical products like phosphoric acid, feeds, and fertilizers; and the populations of different actors within the supply chain, including CFs, LCFSs, and HCFSs. Simultaneously, we have identified "flows" within this system. These encompass the rates at which raw materials are converted into chemical products, the pace at which these products are supplied to local and international FMs, the rate of transition from HCFSs to LCFSs spurred by carbon neutrality pressures, the tempo of carbon credit buying capacity, which may fluctuate over time, and the transfer rate of the carbon footprint across different stages of the supply chain.

Once we have a clear understanding of the stocks and flows within our system, we proceed to identify feedback loops. Feedback loops are inherent aspects of many dynamic systems that can engender complex, sometimes unexpected, behaviors over time (Loiseau & Brunton, 2018; Zhang & Schaeffer, 2019). In this regard, several feedback loops and parameters were identified in Table 2 within the context of our African fertilizers supply chain system.

Having identified the integral components of our system, the next step involves translating these components into a mathematical model. This model, represented by Equation (3), describes the rate of change of the system's state variable y, influenced by the input variable u and the current state $y(t)$. This mathematical representation aids in encapsulating the complexity of our system into a more straightforward, more analyzable form.

Sparse regression, by design, strives to identify a model that captures the essential behavior of a system with the fewest possible active terms, thereby providing a more manageable and streamlined representation of complex systems (Loiseau & Brunton, 2018). To implement this methodology, "snapshots" of the system are considered. The snapshots are not merely collected but are systematically arranged or "stacked" together to form what we refer to as data matrices. This arrangement of data is executed with an underlying assumption that the derivatives of these snapshots are either already available or can be computed from the data. Derivatives, in this context, signify the rates of change of the system's state variables over time. These derivatives offer valuable insights into the system's dynamic behavior, informing us how the system evolves as time progresses. The constructed Y and Y' matrices are presented as follows.



(a) *Validation phase*

(b) *Validation phase for randomly initial conditions*

FIGURE 4 Validation phase of the NARX model. (a) Validation phase. (b) Validation phase for randomly initial conditions.

$$\mathbf{Y} = \begin{pmatrix} y_1(t_1) & y_2(t_1) & \cdots & y_n(t_1) \\ y_1(t_2) & y_2(t_2) & \cdots & y_n(t_2) \\ \vdots & \vdots & \ddots & \vdots \\ y_1(t_m) & y_2(t_m) & \cdots & y_n(t_m) \end{pmatrix}, \ \dot{\mathbf{Y}} = \begin{pmatrix} \dot{y}_1(t_1) & \dot{y}_2(t_1) & \cdots & \dot{y}_n(t_1) \\ \dot{y}_1(t_2) & \dot{y}_2(t_2) & \cdots & \dot{y}_n(t_2) \\ \vdots & \vdots & \ddots & \vdots \\ \dot{y}_1(t_m) & \dot{y}_2(t_m) & \cdots & \dot{y}_n(t_m) \end{pmatrix}, \tag{4}$$

$$Y = (y_j(t_i))_{m \times n}. \tag{5}$$

Once these data matrices are established, they are a reference point for identifying potential candidate functions that describe the system's dynamic behavior. This process involves creating a library of potential candidate functions, which are then tested against the data matrices. The goal is to find those functions that best fit the data and maintain the model's simplicity by including as few terms as possible

(Hoffmann et al., 2019). Indeed, with $\mathbf{Y},\dot{\mathbf{Y}} \in \mathbb{R}^{m \times n}$. We can create an extensive library of p probable candidate basis functions with unknown values. After making the library of potential candidate basis functions, we formulate a regression problem using the library to solve approximately the overdetermined linear system of equations:

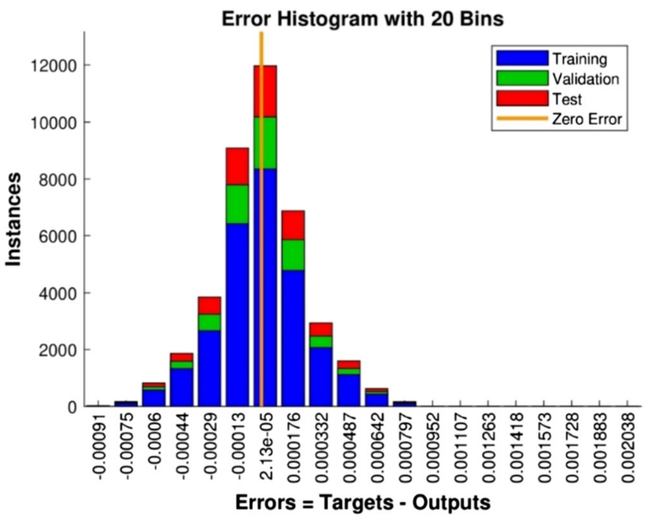


FIGURE 5 Error histogram with 20 bins.

$\mathcal{G}(\mathbf{Y}) = [\mathbf{G}_1(\mathbf{Y}) \cdots \mathbf{G}_p(\mathbf{Y})] \in \mathbb{R}^{m \times p}$, where each $\mathbf{G}_j$ is an alternative term for a basis function or model.

$$\mathrm{G}_i(\nu) = \left[1\ x_1\ \ x_2\ \cdots\ x_1^2\ x_2^2\ \cdots\ x_1x_2\ \ x_2x_3\ \cdots\ x_2^3\ x_3^3\ \cdots\ x_3^4\ x_4^4\ \cdots\right]. \quad (6)$$

Since we assume that $m \times p$ makes the number of data snapshots significantly more significant than the number of potential library functions, it may be necessary to sample transient dynamics and multiple initial conditions to increase the condition number of the library functions (Loiseau & Brunton, 2018). This gives us a sparse representation of the system dynamics, represented as

$$\dot{\mathbf{Y}} = \mathcal{G}(\mathbf{Y})\boldsymbol{\Lambda}, \quad (7)$$

where the set of coefficients for the unknown matrix $\boldsymbol{\Lambda} = (\boldsymbol{\lambda}_1 \boldsymbol{\lambda}_2 \cdots \boldsymbol{\lambda}_n) \in \mathbb{R}^{p \times n}$ is the set of coefficients that determine the active terms from $\mathcal{G}(\mathbf{Y})$ in the dynamics $\mathbf{G}$.

As we venture deeper into system modeling, we extend our horizons to a more encompassing approach by implementing SINDy. As an advanced iteration of the SINDy method, SINDYc broadens the scope of the original method by incorporating inputs and controls into the equation (Zhang & Schaeffer, 2019). This expansion, however, comes with an additional requirement: to capture both the state "Y" and the input signal "u." In other words, SINDYc necessitates a dual

TABLE 2 SINDYc's model loops and parameters.

	Key elements	Description	Validation
Feedback loops	Market demand and production loop	The demand for fertilizers in the market influences the production rate at the CFs. As demand increases, the production rate also escalates to meet the requirement, which might affect market demand.	Analyzing market demand data and production rates from historical records
	Carbon footprint and legislation loop	As the carbon footprint of the HCFSs increases, stricter carbon footprint laws are prompted. These laws then shift toward LCFSs, reducing the overall carbon footprint.	Examining the legislative changes and their impact on HCFSs' carbon footprint
	Supply–demand balance loop	The balance between supply (from LCFSs and HCFSs) and demand (from CFs) for phosphate rock influences the prices, which in turn affects the sourcing decisions of the CFs and the market competitiveness.	Examining price elasticity studies and how changes in phosphate rock prices impact CFs' sourcing decisions and market competitiveness
Parameters that influence the behavior of the system	Carbon credit buying capacity	This affects the rate at which HCFSs can transition to becoming LCFSs.	Analyzing the transition trends of HCFSs to LCFSs about available carbon credits
	Carbon neutrality pressures	The intensity of these pressures can significantly affect the migration rate from HCFSs to LCFSs.	Assessing migration trends from HCFSs to LCFSs against the backdrop of increasing carbon neutrality pressures
	Market demand for fertilizers	Fluctuations in this demand can influence production rates and, thus, the rates of raw material transformation.	Analyzing the correlation between market demand fluctuations and production rate changes
	Regulatory parameters	The stringency of carbon footprint laws in different African countries can impact the operations of both HCFSs and LCFSs, affecting the overall supply chain dynamics.	Analyzing how changes in carbon footprint laws impact the operations of HCFSs and LCFSs

set of measurements to encapsulate the broader dynamics it aims to represent. This dual measurement process informs the creation of our extended library of candidate functions, underpinning the new dimensions that SINDYc seeks to explore. In the quest for parsimonious models, we employ sparsity-promoting regression to ensure that the resultant models are both simple and understandable. We use a sequentially thresholded least squares technique to testify to the SINDy algorithm's robustness in obtaining the coefficients. The approach is presented in Equation (8).

$$\lambda_k = argmin_{\lambda_k'} \left\| \dot{Y_k} - \mathcal{G}(\mathbf{Y})\lambda_k' \right\| + \lambda \|\lambda_k'\|. \quad (8)$$

This equation succinctly articulates our pursuit of finding coefficients that minimize the sum of the residuals' square and the regularized term $\lambda\|\lambda_k'\|$.

The final step involves simulating the model using given initial conditions and parameters. This facilitates the production of input and output matrices, wherein the former represents the system's state at x_k and the latter represents the system's state at x_{k+1} advanced $t = 0.01$. The simulation of the model with these conditions permits the NN to learn the nonlinear mapping from x_k to x_{k+1}. From our collected data, the simulation of the previous model with initial conditions is given by $x_1 = 7$, $x_2 = 1$, $x_3 = 15$, and $x_4 = 14$ and the parameters $u_1 = 0.01$; $v_1 = 0.1$; $p = 1$; $u_2 = 1$; $v_2 = 1$; $b = 1$; $w = 0.01$; $\alpha_1 = \alpha_2 = 0.01$; $c = 0$. Using these initial conditions and parameters, we modelized the studied architecture in Figure 6.

The following steps aim to identify the underlying dynamics of a system by leveraging sparsity-promoting techniques. A training and validation process is launched to recover the input U. Figure 8 illustrates the training and validation process employed to recover this input U. During the training phase, the SINDy algorithm analyzes the training data. It uses a sparse regression approach to identify the essential terms in the dynamic equations. The algorithm searches for the optimal terms that best represent the system dynamics while promoting sparsity. In other words, it aims to identify the minimum number of terms necessary to capture the system behavior accurately.

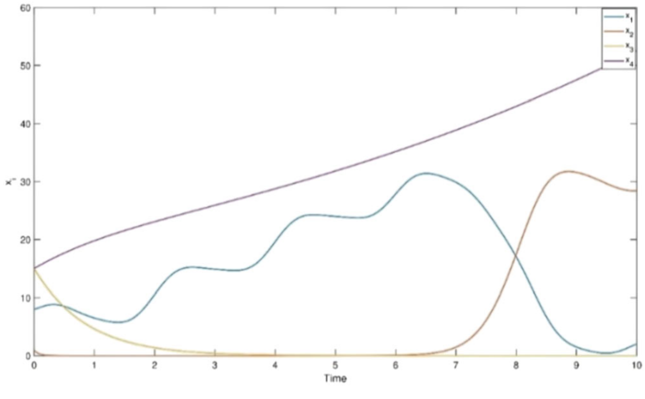


FIGURE 6 Model simulation using given initial conditions and parameters.

Figure 7 illustrates the control variable, a key factor representing incentives for reducing CO_2 emissions. An intriguing observation from the figure is the diminishing trajectory of the control variable beyond time 10, which suggests a decreasing need for incentives to sustain low CO_2 emission levels. This trend offers valuable insights into the system's evolving nature of emission control strategies. Further analysis of Figure 7 reveals the SINDy method's increasing proficiency in accurately capturing and representing the system's dynamics through its iterative process. With every iteration, SINDy increasingly focuses on identifying the most crucial terms and relationships that dictate the system's behavior. This methodical refinement leads to an increasingly accurate depiction of the supply chain dynamics, as evidenced by the narrowing gap between the predicted outcomes and observed data. This accuracy demonstrates the SINDy method's capability to effectively decipher the underlying dynamics of the system, even amidst potential noise and complexity inherent in the data. The culmination of this process is showcased in Figure 8, where the resultant sparse model is presented. This model adeptly encapsulates the intricacies of the supply chain dynamics into a more streamlined and manageable format.

Next, we train and validate using actual data collected from the African fertilizers supply chain. The process entails the model learning from and then benchmarking its predictions against the factual data, commonly represented by a solid line in visual representations. The data used include but are not limited to historical data chronicling quantities of raw materials, production volumes of chemical products, the evolving population of CFs, shifts in migration rates, and changes in carbon credit purchasing capacity, among other factors. These data encapsulate the complexity and intricacies of the African fertilizers supply chain. With the training dataset in place, the SINDYc algorithm is deployed on these data. The objective is to generate a sparse dynamical system that aligns closely with the observed data. The obtained sparse dynamical system is formulated in Equation (9).

$$\begin{cases} \dot{x_1} = 0.1x_1 + u - 0.0001x_1^2 - 0.1x_1x_2 - 0.1x_1x_3 \\ \dot{x_2} = 0.1x_2 - 0.01x_2^2 - 0.1x_2x_1 - x_2x_3 \\ \dot{x_3} = 0.7x_3 - x_1^2 - x_1x_2 - x_1x_3 \\ \dot{x_4} = 0.8x_4 + x_4^2 - x_1x_2 - x_1x_3 \end{cases} . \quad (9)$$

The mathematical equations provided exhibit the dynamics of a complex system governed by four state variables $\left(\dot{x_1}, \dot{x_2}, \dot{x_3}, \dot{x_4}\right)$ and an external input u. Each state's change rate is portrayed through differential equations, encapsulating a set of nonlinear interactions between the variables and the input. These equations embody the underlying dynamics the SINDY method strives to learn and reproduce. The proficiency of the SINDY model's decoder in reconstructing these complex dynamics is conveyed through the calculated mean square error. On a test dataset that comprises trajectories derived from randomly chosen initial conditions, this error is less than 2.10^{-6} of the input variance fractions. Such a minimal value signifies an exact reproduction of the system's dynamics by the SINDY model. Moreover, when examining the dynamics across the lifetime of trajectories within the training data, the SINDY method's simulations demonstrate

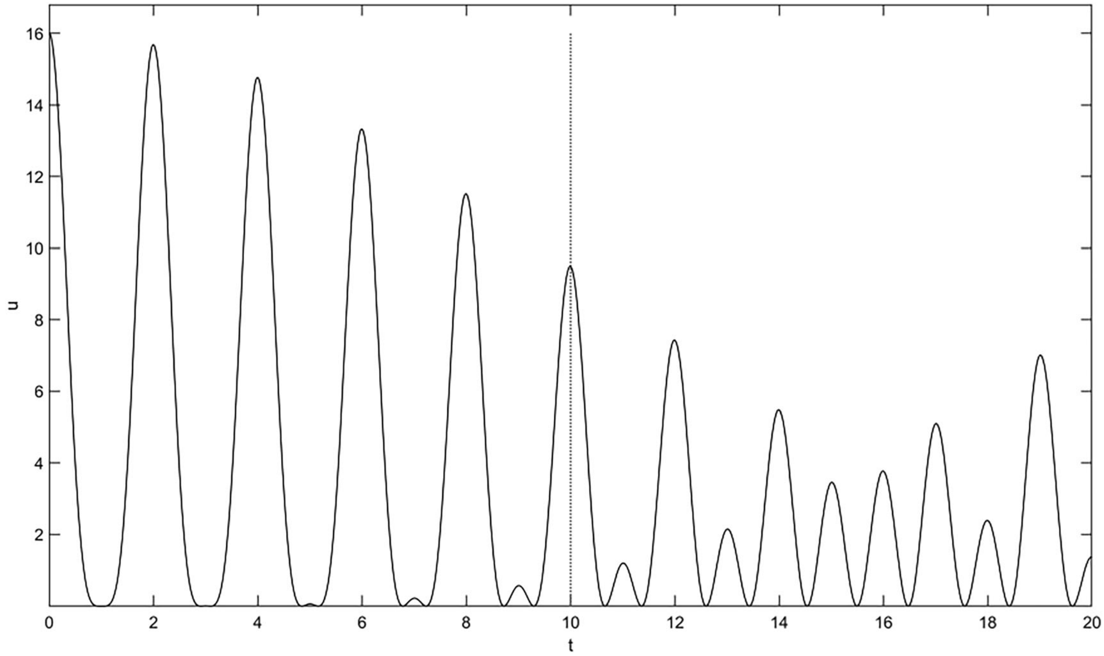


FIGURE 7 Training and validation to recover the input *U*.

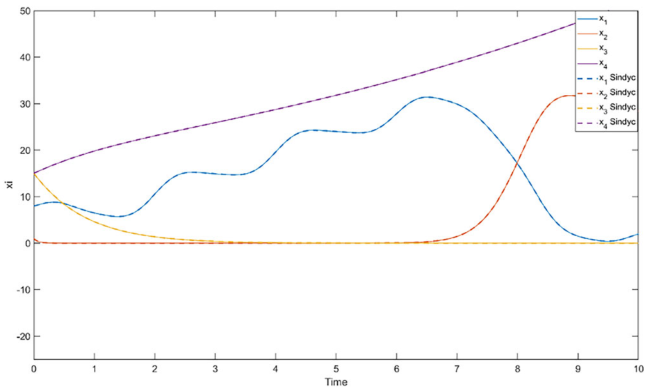


FIGURE 8 Training SINDYc for supply chain model.

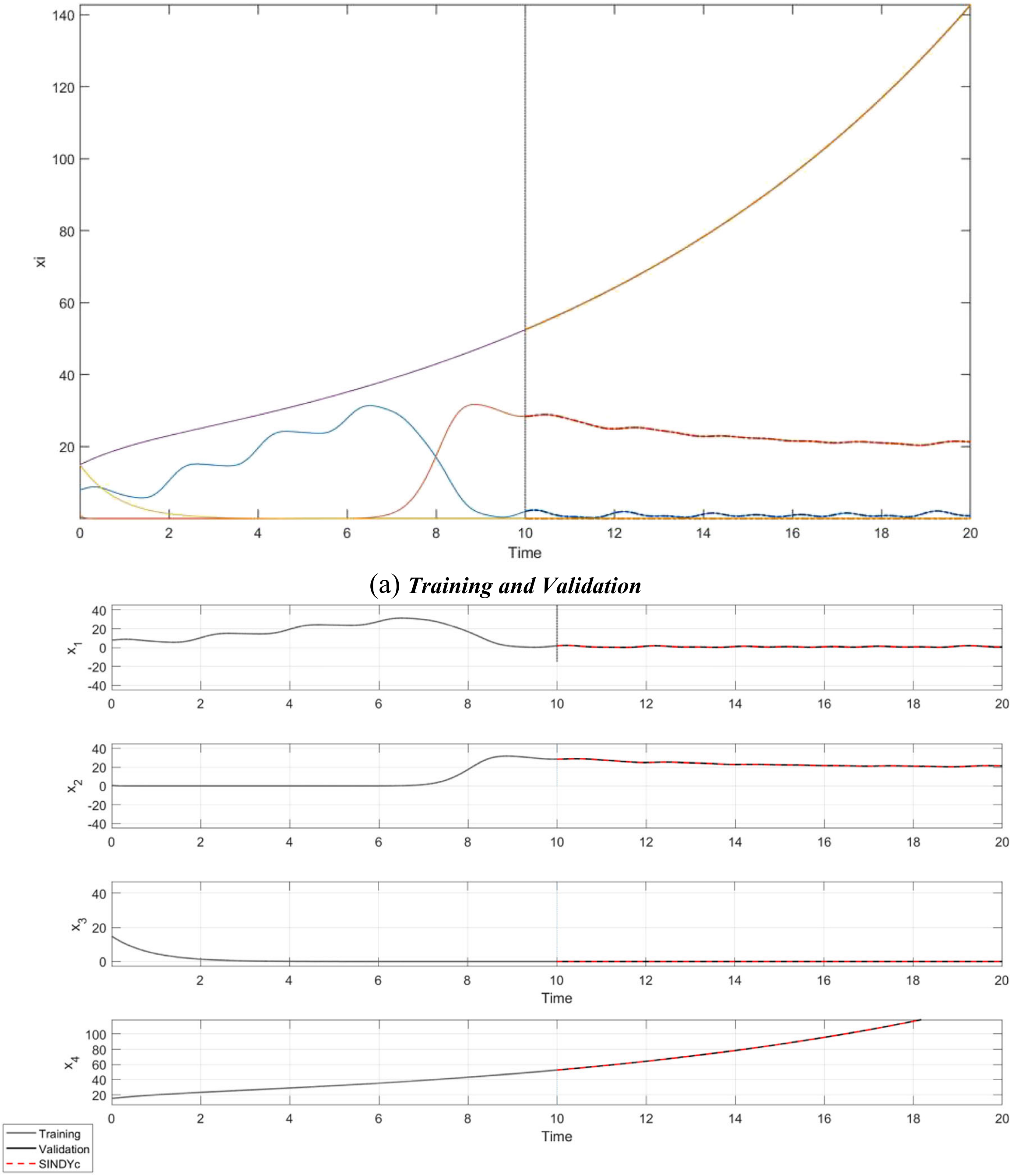
prowess in reconstructing the dynamics of a solitary trajectory. The associated accuracy here is less than 0.005, further solidifying the exceptional precision of the SINDY approach. The training and validation phases, the two crucial stages of the model development process, are visually traced in Figure 9.

The trained model is tested against unseen real-world data from the same supply chain. The predictions the model makes, often depicted as a dashed line, are juxtaposed against the actual data, represented by a solid line. This comparison affirms the model's aptitude to accurately encapsulate and forecast real-world system dynamics. The attained accuracy in the model is notably high, with the error during the continuous validation phase being less than 10^{-5}. This insubstantial error reemphasizes the fidelity of the SINDY method in capturing the system's dynamics (Olivares-Aguila & ElMaraghy, 2021; Zhang & Schaeffer, 2019).

6 | DISCUSSION

This research addressed a sourcing decision problem within an African fertilizer supply chain, exemplifying an LCISC characterized by complexity and sensitivity to carbon footprint (Ivanov & Dolgui, 2020). Our study aimed to understand the challenges and dynamics of sustainable sourcing decisions. We modeled interactions between HCFSs, LCFSs, CFs, and FMs using a double-prey, predator, and super-predator model, capturing the nuanced supply chain dynamics and carbon footprint interplay. The study highlighted the impact of carbon neutrality pressures, showing a shift from HCFSs to LCFSs driven by parameter *p*. It also demonstrated how market demand (*w*) and regulatory parameters (*U*) significantly influence supply chain dynamics, affecting production rates, sourcing decisions, and strategies of CFs and FMs. Additionally, the model revealed efforts by CFs and FMs to reduce their carbon footprint in response to market and regulatory demands. However, a key challenge identified is the 30% cost disparity between HCFSs and LCFSs, presenting a hurdle that influences sourcing decisions and necessitates balancing economic viability with environmental sustainability. The study underscores the complexities of achieving sustainability goals within the economic landscape of the supply chain.

In developing our dynamic model for low-carbon sourcing in intertwined supply chains (LCISCs), we drew on key studies in supply chain management and data-driven modeling (Dolgui et al., 2020; Peng et al., 2020; Tseng, Bui, et al., 2022; Tseng, Ha, et al., 2022). These studies provided foundational concepts in real-time data integration, stochastic modeling techniques, and sustainable supply chain management indicators, highlighting gaps our research addresses. Our



(a) ***Training and Validation***

(b) ***Training and Validation of Real Data***

FIGURE 9 Training and validation using the SINDYc method. (a) Training and validation. (b) Training and validation of real data.

model builds on these insights but differs significantly by focusing on optimizing low-carbon sourcing through ecological analogies and advanced data-driven algorithms. Our approach addresses the complex reality of intertwined supply chains, characterized by pronounced interdependencies and dynamic interactions. Unlike existing studies that propose system dynamics models without resolving them, our work presents an adapted system dynamics model for LCISCs. It resolves this problem using advanced algorithms like NARX and SINDYc. This allows us to account for time-varying dynamics and provide practical solutions for optimizing sourcing decisions.

To delve deeper into the capabilities of these algorithms, we examined the NARX method and the SINDy model. The NARX method excels in time series analysis, capturing nonlinear relationships between a target and multiple exogenous variables, making it superior to traditional autoregressive (AR) models (Alshater et al., 2022). Conversely, the SINDy model uncovers underlying dynamic systems in time series data, assuming sparsity to focus on critical terms influencing system behavior. This involves solving an optimization problem to identify sparse differential equations best describing system dynamics. Our analysis revealed that while NARX is robust in time series analysis, SINDy outperformed in prediction accuracy and control performance. Indeed, the performance metrics for the NARX model indicated significant limitations, as evidenced by the error histogram with 20 bins, which showed a wide distribution of errors between the target and output states. This substantial deviation from expected accuracy highlighted the model's inability to accurately capture the system's intricate dynamics, with errors remaining significantly large and failing to converge to zero. In contrast, the SINDYc model demonstrated superior quantitative performance. The mean square error on test datasets with randomly chosen initial conditions was less than 2.10^{-6}, indicating a precise reproduction of system dynamics. Additionally, the accuracy for trajectories within the training data was exceptionally high, with errors less than 0.005. Further validation against unseen real-world data from the same supply chain confirmed the robustness of the SINDYc model, with predictions showing high accuracy and continuous validation phase errors being less than 10^{-5}. Moreover, data requirements differed significantly as NARX needed a larger dataset for effective training (250 short trajectories with 1000 snapshots each, totaling 25,000 instances), while SINDYc performed comparably with just 104 instances from a single trajectory. Despite limited training data, this demonstrates SINDYc's robustness and effectiveness in learning system dynamics.

The study also employs ecological analogies to manage supply chains under low-carbon and environmental sustainability constraints. Suppliers are modeled as prey and manufacturers and consumers as predators, illustrating the competitive and cooperative dynamics within the supply chain. This analogy highlights the need for suppliers to adapt to manufacturers' and consumers' demands, aligning with low-carbon initiatives. Decisions at one node can ripple throughout the chain, akin to ecosystem changes affecting species populations, helping managers anticipate and mitigate potential negative impacts. Additionally, employing real-time and historical data to make informed sourcing decisions mirrors how natural ecosystems adjust to environmental changes in real time. This enhances the supply chain's ability to quickly adapt to market and environmental shifts. Using data-driven algorithms like NARX and SINDYc to predict and control supply chain dynamics improves decision-making accuracy and operational efficiency, similar to how ecologists use models to manage and conserve ecosystems effectively. By applying these ecological insights to supply chain management, the paper provides a novel perspective on navigating the complexities of intertwined supply chains in an environmentally conscious and economically viable manner.

To enhance the generalizability of our model, it is crucial to consider potential modifications or expansions across different economic sectors and geographical areas. Customizing the model to align with specific industry practices and market conditions is essential for broadening its applicability. For instance, adapting the model for the European automotive sector would necessitate adjustments to account for the stringent environmental regulations and sustainability practices prevalent in the EU. Similarly, tailoring the model for the East Asian electronics industry would require considering the region's rapid technological advancements and competitive manufacturing landscape. Incorporating variables such as local environmental policies, economic conditions, and unique supply chain characteristics can provide deeper insights and increase the model's applicability in diverse contexts. These adaptations would enhance the model's relevance, flexibility, and utility, supporting informed and sustainable decision-making across various industries worldwide. Consequently, expanding our model in this manner could make it a more versatile tool in strategic planning, thereby contributing more effectively to global sustainability efforts.

7 | THEORETICAL AND MANAGERIAL IMPLICATIONS

Our study advances the theoretical understanding of sustainable supply chain management, particularly in the context of LCISCs. This research transcends the conventional static frameworks by employing a novel double-prey, predator, and super-predator interaction model, offering a dynamic and nuanced perspective to capture the complex interdependencies and the consequential ripple effects within such supply chains. Theoretical advancements can be represented in several key areas. First, our research provides a groundbreaking approach to modeling the complexities of LCISCs. Traditional models often present a static view, focusing on average performance or steady-state conditions. In contrast, our dynamic model integrates supply chain elements' interconnected and evolving nature, offering a more comprehensive understanding of supply chains' environmental impact and operational dynamics. Second, the study elucidates the "ripple effect" in supply chains, where changes at one supply chain node have amplified effects throughout the network. Furthermore, by adopting an ecological analogy, our study breaks new ground in applying the prey–predator model to analyze carbon dynamics within supply chains. This approach highlights the balance and sustainability, mirroring the delicate interdependencies found in natural ecosystems, and offers a comprehensive method to manage the interplay between economic activities and environmental impact.

Exploring data-driven algorithms like NARX and SINDYc represents a significant theoretical advancement. These models, particularly SINDYc, emphasize sparse data and enhance predictive accuracy and operational efficiency. Their application in supply chain management introduces a new pathway for real-time decision-making based on dynamic data inputs. Additionally, the research provides theoretical insights into strategic decision-making within supply chains, highlighting the need to balance economic viability with environmental sustainability. This challenges traditional profit-centric approaches and advocates for integrated decision-making frameworks that consider environmental impact. The study offers a valuable roadmap for managers to optimize sourcing strategies that balance economic viability with environmental sustainability. A key finding is the need to balance sourcing between HCFSs and LCFSs. Despite a 30% cost advantage of HCFSs, the study advocates for a gradual shift toward sustainable LCFSs. It suggests collaborating with LCFSs to enhance cost-effectiveness through technological investments or long-term contracts, mitigating cost disparities and ensuring a smoother transition to sustainable practices.

Moreover, the study underscores the importance of proactive adaptation to market trends and regulatory changes. It advocates for agile sourcing strategies that swiftly respond to the dynamic market and regulatory environment, ensuring competitive advantage and compliance. Another critical implication is using data-driven decision-making tools such as NARX and SINDYc. These methods are instrumental in enhancing decision-making processes by accurately predicting the impact of external factors on the supply chain, thereby aiding in strategic planning and risk management. Updating and refining these models with real-time data are essential for maintaining their effectiveness. The study also highlights the importance of balancing profitability with sustainability (Chevrollier et al., 2023). Managers are encouraged to integrate environmental considerations into their economic decision-making frameworks. Though initially costlier, the research suggests that investments in cleaner, more efficient technologies can offer long-term sustainability and regulatory compliance benefits.

Additionally, our research leverages dynamic modeling techniques to address the complexities of LCISCs, offering insights applicable across various industries. The innovative double-prey, predator, and super-predator interaction model, while developed for LCISCs, is useful for any supply chain facing rapid changes or significant environmental impacts. This model enhances understanding of dynamic interdependencies and can be integrated into broader supply chain management theories, emphasizing adaptability and resilience under external pressures like market fluctuations and regulatory shifts. The strategic decision-making insights, supported by advanced data-driven tools like NARX and SINDYc, lay the groundwork for integrated decision-making frameworks that balance economic viability with environmental sustainability. These frameworks can guide managers in low-carbon sourcing and other supply chain decisions, influencing policymaking and strategic planning across sectors. Furthermore, integrating our findings into educational programs and training for supply chain management ensures that future managers are equipped with the knowledge and tools to implement sustainable practices effectively.

Our study also presents several ethical and social implications. By applying our model, businesses can make decisions that positively impact local communities, promoting community engagement and fostering stronger stakeholder relationships. Additionally, our model addresses environmental justice by guiding companies to reduce their carbon footprint and mitigate environmental impacts, particularly in vulnerable and marginalized communities. This dual focus on community engagement and environmental justice underscores our approach's broader social benefits and ethical considerations.

8 | CONCLUSION

Our study provides critical insights into the African fertilizers supply chain, representing LCISCs in an environmentally conscious era. We developed an innovative model capturing complex interactions between supply chain entities, featuring a unique double-prey, predator, and super-predator dynamic. This model highlights the balance between economic viability and environmental responsibility in sustainable sourcing decisions. Unlike traditional static models, our dynamic approach offers a comprehensive view of environmental impacts within the supply chain, illustrating the ripple effect of decisions across the chain. The study also highlights the significant cost difference between HCFSs and LCFSs, with HCFSs being cheaper, creating a complex decision-making scenario for managers balancing sustainability and economic goals. We suggest a gradual transition to LCFSs, facilitated through collaborations to improve cost competitiveness. Our exploration of data-driven algorithms, NARX and SINDYc, revealed that while NARX is robust for analyzing complex time series data, SINDYc outperformed it in prediction accuracy and control performance, especially in real-time applications. The efficiency of SINDYc, even with limited data, underscores its potential as a powerful tool for supply chain managers, enabling rapid responses to market changes and regulatory developments.

While our study provides valuable insights into sourcing decision challenges within the African fertilizer supply chain, addressing its limitations is essential to enhance transparency and reliability. Our methodology, though robust and adaptable, is specifically tailored to this industry and region. Different market dynamics, regulatory environments, and structural nuances in other sectors or regions may require significant modifications. Second, our research heavily relies on estimating model parameters, which depend on the availability and quality of historical data. The precision of these estimates is influenced by the selection of appropriate algorithms and the representativeness of the data. This highlights the need for rigorous data selection and algorithm testing to ensure model accuracy and reliability.

Addressing these limitations requires further research. Our study presents several promising research opportunities, such as exploring advanced or alternative data-driven models to enhance predictive accuracy and operational efficiency in LCISCs. Future studies could integrate AI techniques for more nuanced analyses and better handling human decision-making complexities. Additionally, applying our model to various sectors and geographical contexts is a valuable direction, which would involve adapting the model to different market dynamics, regulatory environments, and supply chain structures. This expansion could help validate the model's versatility and robustness across diverse applications. Developing practical tools and frameworks to assist managers in implementing model insights is also crucial. Future work could focus on creating user-friendly software or decision-support systems that encapsulate the model's capabilities, making it easier for managers to apply these insights in real-world scenarios. This could include interactive dashboards, simulation tools, and visualization techniques to provide managers with actionable information and facilitate informed decision-making. Furthermore, collaborating with industry stakeholders to pilot these tools in real-world settings could provide valuable feedback and drive continuous improvement. By pursuing these directions, future research can enhance our modeling approach's practical applicability and impact, contributing to more efficient and sustainable supply chain management practices.

CONFLICT OF INTEREST STATEMENT

The authors declare no potential conflict of interest.

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