IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 14, No. 5, October 2025, pp. 3528∼3541
ISSN: 2252-8938, DOI: 10.11591/ijai.v14.i5.pp3528-3541

Efficiency search: application of nature-inspired algorithms in artificial intelligence forecasting models

José Rolando Neira Villar, Miguel Ángel Cano Lengua
Facultad de Ingeniería de Sistemas e Informática, Universidad Tecnológica del Perú, Lima, Perú

Article Info

Article history:

Received Jan 13, 2025
Revised Jul 26, 2025
Accepted Aug 6, 2025

Keywords:

Artificial intelligence
Demand forecasting
Multi-space optimization
Nature-inspired optimization algorithm
Quantization

ABSTRACT

This study reviews how nature-inspired optimization algorithms (NIOAs) have been applied to artificial intelligence-based demand forecasting, using preferred reporting items for systematic reviews and meta-analyses (PRISMA) and clustering analysis to examine 36 selected articles. The findings reveal that NIOAs, particularly genetic algorithms and swarm intelligence methods, including their hybrids, have been frequently applied to long short-term memory (LSTM) and other backpropagation neural network models (BPNN). A key insight is the differentiated application of NIOAs depending on network depth: In shallow networks, they have been effectively used to optimize trainable parameters, whereas in deep networks, their role has focused primarily on hyperparameter optimization due to the prohibitive dimensionality of trainable weights. In all studies, NIOA-optimized models consistently outperform conventional baselines based on backpropagation. However, persistent challenges such as excessive execution times and slow convergence have led to the development of more efficient hybrid strategies and adaptive mechanisms for automated exploration-exploitation control. By mapping explored and unexplored pathways, summarizing key outcomes and techniques, and identifying promising methodologies, this review offers a practical foundation to guide future experiments and implementations involving NIOA-based optimization strategies in neural network models. As a conceptual contribution, it also proposes an innovative use of multispace optimization to address one of the most critical challenges identified: the optimization of trainable parameters in deep neural networks.

Corresponding Author:

Miguel Ángel Cano Lengua
Facultad de Ingeniería de Sistemas e Informática, Universidad Tecnológica del Perú
Jr. Natalio Sanchez 125, Lima, Perú
Email: mcanol@unmsm.edu.pe

1. INTRODUCTION

Accurate demand forecasting is crucial for managing business operations and supply chains, enabling effective resource planning while avoiding costly issues such as stockouts and the bullwhip effect. It also supports financial, human resource, and marketing planning, thereby significantly enhancing competitiveness [1]-[4]. In light of this importance, recent years have witnessed the emergence of advanced machine learning approaches, particularly deep learning-based models, which have consistently demonstrated superior predictive performance [4], [5]. However, a major limitation of these models lies in the highly complex optimization problems they generate: specifically, the need to optimize both the network architecture and hyperparameters [6]-[8], as well as trainable parameters such as synaptic weights and biases. These problems typically involve vast search spaces that are often explored manually through trial and error, as exhaustive search methods are computationally prohibitive [9], [10].

These optimization challenges manifest at both the parametric and hyperparameter levels. Parametric optimization is traditionally performed using backpropagation gradient descent, which faces notable challenges such as the vanishing of the gradient - that is, a loss of effectiveness as the depth of the network increases [11] - and the difficulties of navigating multiple local optima, often failing to reach the global optimum [7]. In contrast, hyperparameter optimization cannot rely on gradient-based methods such as backpropagation, as the objective functions are unknown. These black-box optimization problems are typically noisy, lack analytical expressions, and are computationally expensive to solve [6], [8]. Thus, it is evident that although sophisticated machine learning models significantly improve forecast accuracy, they require new optimization techniques capable of overcoming their optimization drawbacks [7].

In this context, nature-inspired optimization algorithms (NIOAs) have gained significant popularity. These algorithms mimic natural processes to efficiently solve complex problems, providing good approximate solutions within reasonable time limits. Their key advantage is that they require no detailed knowledge of the problem, making them ideal for black-box optimization. Furthermore, they perform well in non-convex, noisy, and stochastic search spaces, further driving their widespread adoption [12], [13]. Notable successes include their scalable application in the search for high-performance neural architectures and hyperparameter configurations [13], [14]. However, in parametric optimization, NIOAs have yet to match the computational efficiency of gradient-based algorithms, presenting a promising avenue for future research [7]. In general, the range of NIOAs applications is expanding and diverse, although some domains remain underexplored.

Some emerging areas within NIOAs include neuroevolution, multi-objective optimization, multitask optimization, and multispace optimization. Neuroevolution applies NIOAs to evolve deep neural network architectures, enabling the identification of efficient configurations tailored to specific tasks. This approach often achieves better results compared to manually tuned models, including those adjusted by experts [6]. Multi-objective evolutionary optimization, on the other hand, focuses on simultaneously optimizing typically conflicting goals, such as maximizing model accuracy while minimizing computational cost, which is particularly valuable in hyperparameter tuning [6], [8]. Multitask evolutionary optimization deserves special attention, as it aims to create synergies between different optimization tasks by transferring knowledge across search spaces, avoiding unproductive regions, and sharing promising solutions. This method has shown strong potential for significantly improving the efficiency of NIOAs [14]. Expanding on this idea, recently proposed multispace optimization algorithms introduce simplified auxiliary search spaces to support the optimization of large, complex domains, with the knowledge gained being transferred back to the original space [15], [16]. Amid the promising convergence between machine learning and NIOAs, this study explores the application of these advanced techniques in the design of machine learning models for demand forecasting. It analyzes the outcomes achieved, uncovers recent NIOAs approaches that remain untapped in this context, and highlights key research gaps, inviting further exploration of their potential in addressing complex neural network optimization problems and advancing some of the most promising lines of investigation in the field.

2. METHOD

This study applies the preferred reporting items for systematic reviews and meta-analyses (PRISMA) methodology to systematically review the state of the art on the use of NIOAs in artificial intelligence-based demand forecasting models, with the aim of identifying research gaps. Within the PRISMA framework, NIOAs are treated as interventions, while their impact on forecasting model performance is considered as the outcome. PRISMA ensures the trustworthiness of the review by providing a transparent process for article selection and synthesis of findings [17]. To enhance the objectivity of the latter, an automatic agglomerative hierarchical clustering technique was employed to classify the reviewed studies.

2.1. Research questions

As recommended by the PRISMA methodology [18], the research questions were explicitly and concisely posed to help evaluate the coherence of the study in all its parts. To do so, after the main question was posed, the population, intervention, comparator, outcome and context (PICOC) framework was used to make the secondary questions explicit. Table 1 shows the results of this process.

Table 1. Research questions

Code	Question
Main	How have NIOAs been used in recent years in the development of AI-based demand forecasting models?
P	What are the characteristics of the AI models in which NIOAs have been involved?
I	What type of NIOAs have been used to intervene in AI-based forecasting models?
C	What metrics and models have been used to measure and compare the performance of models built with NIOAs?
O	What is the performance of the models built with NIOAs in relation to the established models?
C	In which economic sectors have they been applied and what main problems have been attempted to be solved with the models built with NIOAs?

2.2. Eligibility criteria

To define the scope of the article, the eligibility criteria [18] outlined in Tables 2 and 3 were established. These criteria were also used to verify the inclusion decisions of the review. The focus was on selecting recent, reliable empirical studies that propose demand forecasting models using AI and NIOAs.

Table 2. Inclusion criteria

Code	Description
I1	Studies that use Nature-inspired algorithms, as part of the proposed AI-based demand forecasting models
I2	Studies containing a detailed and comprehensive methodology related to Nature-inspired algorithms used
I3	Empirical studies with models validated with real data from companies
I4	Studies whose main objective is the development and validation of a demand forecasting model

Table 3. Exclusion criteria

Code	Description
E1	Articles published after 2018
E2	Other documents than scientific articles and conference papers
E3	Articles published in other idioms than English or Spanish or with full text not available
E4	Documents not related to the overall demand of a specific business market

2.3. Sources of information

In July 2024, the Scopus, Web of Science, and IEEE databases were consulted, as they are recognized for their reliability within the academic community. The queries were conducted through their respective platforms using the same search method for all three. At this stage, the temporal coverage of the search was not limited.

2.4. Search strategy

During the development of the search strategy, the population, intervention, comparison, output (PICO) framework guided the identification of relevant terms and their synonyms. These were linked using OR operators within each category. While the PICO components themselves were combined using AND operators to create the following search string, applied uniformly across all data sources: (”demand forecasting” OR ”demand prediction” OR ”demand prognostic” OR ”demand prognosis” OR ”demand estimation”) AND (”evolutionary computation” OR ”genetic algorithm” OR ”genetic programming” OR ”evolutionary programming” OR ”evolution strategies” OR ”neuro evolution” OR ”swarm intelligence”) AND (”artificial intelligence” OR ”machine learning” OR ”deep learning” OR ”reinforcement learning” OR ”neural networks”) AND (”error” OR ”performance” OR ”efficiency” OR ”robustness” OR ”accuracy” OR ”precision”).

2.5. Article selection process

The researchers independently assessed the search results for consistency and relevance to the inclusion and exclusion criteria. After resolving inconsistencies and making adjustments, the exclusion criteria were applied at the title and abstract level, and the inclusion criteria at the full text level. Only studies agreed upon by both researchers were included.

2.6. Data items and data collection

The authors identified the data required to answer the research questions and collaboratively developed an extraction matrix, with columns for data items and rows for included studies. Each article was independently reviewed and discrepancies were resolved through discussion. Extracted data encompassed: i) economic sector; ii) problem addressed and limitations of prior solutions; iii) NIOAs and their classification by [19]; iv) the role of NIOAs in the model; v) type of optimization performed; vi) machine learning methods employed; vii) optimization strategy (e.g., single-objective or multi-objective); viii) forecast model outline; ix) data description; x) performance metrics; xi) benchmarking models; xii) performance of the proposed model.

2.7. Synthesis method

The qualitative synthesis involved classifying articles based on similarities using the criteria described in subsection 2.6, specifically items iii), v), vi), vii), and ix). To reduce bias, hierarchical agglomerative clustering was applied using a feature table to compute Euclidean distances. The silhouette method was used to determine the optimal number of clusters. The implementation was carried out in Python, using scipy.cluster.hierarchy for linkage construction, sklearn.cluster for clustering execution, and sklearn.metrics for silhouette evaluation, adopting Ward's method to ensure clear separation between clusters. Subsequently, the clusters and sub-cluster are analyzed and grouped when the differences were minimal. This classification informed the synthesis by identifying contributions to the research questions and led to the development of a new conceptual model that integrates these insights and addresses key challenges using state-of-the-art tools.

3. RESULTS AND DISCUSSION

This section presents the results of the study selection process and the subsequent qualitative synthesis. The selection results are detailed, tracing the progression from the initial records identified in the search to the final number of studies included in the review. For the quantitative synthesis, this section reports the classification of the selected articles and provides answers to the research questions, offering insights into the key findings derived from the analysis.

3.1. Result of the studies selection

The search process initially retrieved a total of 282 records. After eliminating duplicates and systematically applying the exclusion and inclusion criteria, 36 studies were selected for the final analysis, as shown in Figure 1. Most of these studies were published in 2019, 2023, and 2024. In terms of application domains, the predominant sectors represented in the selected articles are electricity, water distribution, and retail.

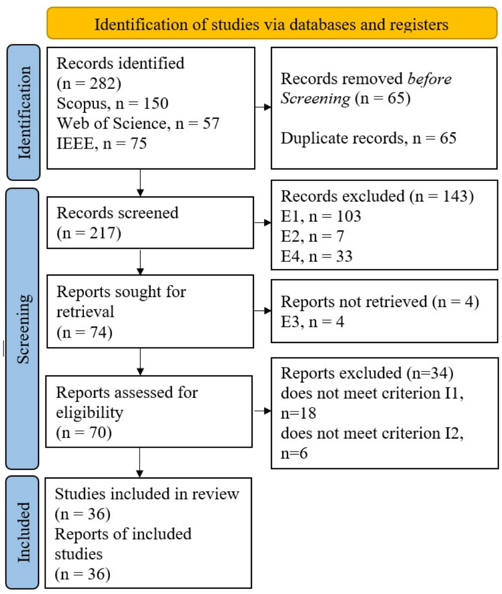

Figure 1. Results of article selection

3.2. Result of the qualitative synthesis

As a result of the analytical operations conducted on the collected information, such as automatic grouping, comparison, and categorization of articles, and subsequent confrontation of evidence with the respective research questions, significant findings were obtained, which are reported as follows:

3.2.1. Result of the classification of articles

After converting the relevant data items from the extraction matrix into dummy variables and eliminating the redundant variables, the features table for the calculation of the Euclidean distances between the articles was obtained. In relation to the optimal number of clusters, the silhouette method initially recommended 24, a high number relative to the 36 articles analyzed. Based on the best silhouette value in the range of two to five clusters, the authors selected four main clusters and used the 24 clusters as subclusters within these main clusters. After analyzing similarities and differences within and between them, subclusters with negligible differences were merged to align with the research objectives. Each class and subclass were then descriptively named. The final classification, along with the numbering of the automatic clusters, is presented in Table 4.

Table 4. Classification of articles

Classification of articles	Cluster	Sub-cluster	Articles
a) Shallow learning optimizers	1		13
i) Evolutionary-swarm optimizers	1	1	3
ii) Shallow parameter optimizers	1	2, 3, 4, 5	8
iii) Shallow multi-objective optimizers	1	6	1
iv) Shallow ensemble optimizers	1	7	1
b) Evolutionary optimizers	2		16
i) Genetic programming models	2	13, 14	3
ii) Shallow hyperparameter optimizers	2	15	1
iii) Support vector machine (SVM) evolutionary optimizers	2	18	1
iv) Deep learning optimizers	2		11
- Deep structural optimizers	2	16, 17, 19	4
- Deep multi-objective optimizers	2	8, 9	3
- Deep parameter optimizers	2	10, 11	3
- Deep ensemble optimizers	2	12	1
c) Deep swarm optimizers	3	20, 21	3
d) SVM swarm optimizers	4	22, 23, 24	4

The following describes the classes and subclasses presented in Table 4.

a. Shallow learning optimizers: this class groups models based on shallow neural networks (only one hidden layer), where NIOAs primarily optimize trainable parameters, with differences across subclasses.

i) Evolutionary-swarm optimizers: this subclass combines genetic algorithms (GA) with swarm intelligence to optimize models. A key example is study in [20], where GA explores new weights and biases, and PSO exploits GA's best findings through continuous transfer learning. Similarly, studies in [21] and [22] use GA to pre-train initial weights and biases, improving the efficiency of gradient descent fine-tuning. They also employ Northern Goshawk optimization (NGO) and Gray Wolf optimization (GWO), respectively, to optimize other model hyperparameters.

ii) Shallow parameter optimizers: this subclass focuses on optimizing only the trainable parameters of shallow neural networks, mainly through evolutionary algorithms. Studies in [23]-[26] use the mind evolutionary algorithm (MEA), GA, and PSO respectively for pre-training backpropagation neural networks (BPNN), while studies in [27]-[30] apply differential evolution (DE), GA, and artificial immune system (AIS) algorithms respectively for full parameter optimization. These approaches reduce prediction errors compared to backpropagation, though at the cost of longer training. Notably, MEA improves both accuracy and execution time over GA.

iii) Shallow multi-objective optimizers: this subclass includes a single study proposing a multi-objective optimization to reduce lag inputs while minimizing error for a multilayer perceptron (MLP) model. An adaptative neuro-fuzzy inference system (ANFIS) further refines predictions, with both input selection and ANFIS parameters optimized by GA. The model outperforms standalone MLP and ANFIS in accuracy. Additionally, the authors claim that by reducing inputs, computational cost decreases, enabling real-time use, though no quantitative evidence is provided in [31].

iv) Shallow ensemble optimizers: this subclass includes a single study in [32] where PSO combines predictors, including an extreme learning machine (ELM), outperforming standalone components.

b. Evolutionary optimizers: this class is characterized by using only and exclusively evolutionary algorithms, leaving aside swarm intelligence. It is made up of four subclasses that are distinguished from each other by the type of optimization they perform, and the AI model that intervenes, where deep learning models are a prominent set.

i) Genetic programming (GP) models: this subclass applies GP to generate explicit mathematical expressions for demand forecasting, employing Canonical GP, Multi-Gene GP, and multi-expression programming in [33]-[35], respectively. These studies benchmark against ARIMA, artificial neural network (ANN), and ANFIS, consistently achieving lower errors. GP stands out for producing interpretable models, unlike the black-box nature of neural networks.

ii) Shallow hyperparameter optimizers: this subclass includes a single study from the water distribution sector [36], where GA optimizes structural and training hyperparameters of a shallow BPNN, including hidden neurons, learning rate, and validation criteria. The optimized model outperforms both standalone BPNN and ARIMA. The study highlights the effectiveness of GA for hyperparameter tuning, even with gradient-based parameter training.

iii) SVM evolutionary optimizers: this subclass includes a single study in [37] where GA optimizes the penalty (C) and kernel (gamma) parameters of an SVM for forecasting. GA adaptively tunes crossover and mutation rates, balancing exploration and exploitation as in [20]. The model improves accuracy, and the authors suggest faster convergence, though no quantitative evidence is provided.

iv) Deep learning optimizers: this is the largest subclass, with 11 studies focused on optimizing deep learning models, mainly using evolutionary algorithms. It includes four groups: two optimize hyperparameters, one targets trainable parameters, and one combines models using weighted averaging. Each group is described below.

- Deep structural optimizers: this group includes four studies on hyperparameter optimization of deep neural networks [38]-[41], covering both structural (layers, neurons) and training hyperparameters (dropout rate, batch size, learning rate). All combine one algorithm for exploration and another for refinement, such as Bayesian optimization (BO)-GA [38], GA-DE [39], and GA-scatter search (SS) [41]. All improve accuracy over standalone methods. Notably, GA-SS reduced execution time to 23 minutes compared to 58 minutes for GA alone and 480 minutes for trial-and-error.
- Deep multi-objective optimizers: this group includes three studies by the same author [42]-[44], applying non-dominated sorting genetic algorithm II (NSGA-II) to jointly maximize R^2 and minimize test error by optimizing structural hyperparameters of ANN, long short-term memory (LSTM), and Transformer models. Trainable parameters are refined via gradient methods. Accuracy and explanatory power improve across studies. To reduce computational cost, training time or epochs are limited during optimization, with final retraining of the best models for full convergence. These studies confirm the effectiveness of multi-objective optimization for neural network design.
- Deep parameter optimizers: this group focuses on parameter optimization in deep learning using neuroevolution, which starts from simple architectures with a single layer and few neurons, progressively evolving both structure and parameters. The studies apply neural network simultaneous optimization algorithm (NNSOA) [45] and neuro evolution of augmenting topologies (NEAT) [46]. Additionally, [47] uses GA for pre-training in a gray neural network (GNN), reportedly improving convergence, though without quantitative evidence.
- Deep ensemble optimizers: this is a group consisting of a single study in [48] in which GA is used to obtain the optimal weights to assemble a MLP in charge of forecasting trends, with an LSTM in charge of forecasting seasonality and other complex variations. The authors found that the proposed model obtains better error metrics than benchmark models.

c. Deep swarm optimizers: this class includes three studies that improve deep neural network pre-training by combining aggressive exploration with strong exploitation. Study in [49] uses the modified dragonfly algorithm (MDA), merging genetic operators with Dragonfly refinement. Study in [50] combines stochastic fractal search (SFS) for broad exploration with whale optimization algorithm (WOA) for precise exploitation, improving network accuracy and convergence. Study in [51] applies PSO to deep network, enhancing temporal memory and prediction accuracy.

d. SVM swarm optimizers: this class shows how swarm intelligence enhances SVM models by optimizing kernel parameters, regularization terms, and epsilon. Boosted multiverse optimizer (BMVO) improves Incremental SVM accuracy [52], while PSO boosts SVM and LSTM-SVM hybrid models [9], [53].

Study in [10] combines GA with swarm methods for SVM optimization in cloud demand forecasting. These studies demonstrate the versatility of swarm intelligence to improve non-neural models across sectors.

3.2.2. Result of the research questions

This section consolidates the insights from the classified articles to evaluate their contributions to the research questions shown in Table 1. It examines the application of NIOAs in AI-based forecasting models, highlighting the characteristics of the models, the specific NIOAs employed, the metrics and benchmarking models used, the performance achieved, and the primary challenges and sectors addressed.

Main question: how have NIOAs been used in recent years in the development of AI-based demand forecasting models? NIOAs have been predominantly applied to neural network optimization, representing 28 of the 36 studies reviewed. In addition, some applications have focused on the optimization of SVM and genetic programming (GP) models. Notably, no use of NIOAs was identified for other machine learning models beyond these categories.

Neural network optimization covers both shallow and deep learning, as shown in Figures 2 and 3. In these figures, the main branches, sub-branches, and leaves represent the optimization focus, applied technique, and specific NIOA with its corresponding study. In shallow networks, the focus is primarily on parametric optimization, achieved through pre-training or full training, mainly using GA. In deep learning, the emphasis shifts to hyperparameter optimization, where advanced techniques such as hybridization, adaptive mechanisms, and multi-objective approaches are applied. Notably, no studies address full parametric optimization of deep networks.

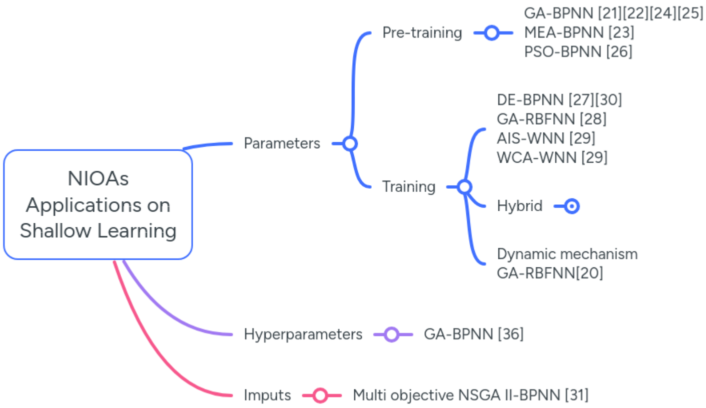

Figure 2. NIOAs applications on shallow learning

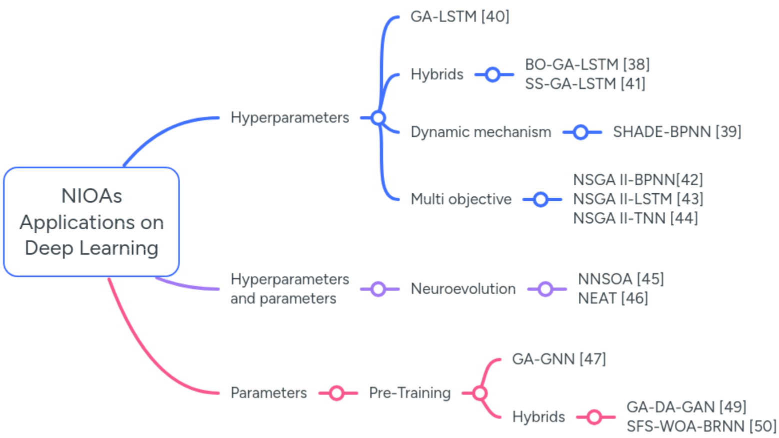

Figure 3. NIOAs applications on deep learning

P1: What are the characteristics of the AI models in which NIOAs have been involved?

The AI models predominantly optimized by NIOAs are neural network-based. Among these, half (14 studies) involve shallow neural networks, while the other half focus on deep neural networks. The shallow neural networks include fully connected single hidden layer BPNNs [21]-[27], [30], [31], [36], radial basis function neural networks (RBFNNs) [20], [28], and wavelet neural networks [29]. For deep learning models, most studies involve LSTM architectures [38], [40], [41], [43], [48], [50] and fully connected deep BPNNs [39], [42], [45], [46]. Other deep neural networks explored include transformer neural networks [44], generative adversarial networks (GANs) [49], Deep Echo State Networks [51], and GNN [47]. Finally, NIOAs have also been applied to models based on SVM [10], [37], [52], [53], and GP [33]-[35].

P2: What type of NIOAs have been used to intervene in AI-based forecasting models?

In shallow learning, parameter pre-training has predominantly relied on GA [21], [22], [24], [25] and its variants, such as MEA [23], with occasional use of PSO [26]. For complete parameter training, GA [28], DE [27], [30], AIS [29], and the hybrid GA-PSO [20] have been employed. Additionally, GA has been applied to hyperparameter optimization [36] and input selection [31]. In deep learning models, GA has been extensively used for optimizing structural and training hyperparameters, either independently [40], in combination with other algorithms such as SS [41], BO [38], and success-history-based parameter adaptation for differential evolution (SHADE) [39], or within the NSGA-II multi-objective optimization framework [42]-[44]. Neuroevolutionary algorithms like NNSOA [45] and NEAT [46] have been applied to simultaneously optimize hyperparameters and trainable parameters. For parametric pre-training of deep networks, GA has also been employed [47], along with hybrids such as MDA [49] and SFS-WOA [50]. For optimization of SVM-based models, both GA [37] and Swarm Intelligence algorithms [52], [53] have been used, as well as hybridization of both types of metaheuristics [10].

P3: What metrics and models have been used to measure and compare the performance of models built with NIOAs?

Root mean squared error (RMSE), mean absolute percentage error (MAPE), and mean absolute error (MAE) are the most used metrics to assess prediction accuracy and error normalization in both shallow and deep models. Correlation coefficients and NSE provide additional performance insights. Shallow models benchmark against regression, ARIMA, and BPNN, while deep models are compared to support vector regression (SVR), ANN, and non-optimized LSTM. In these models, advanced metrics like R^2 and SEP assess goodness-of-fit and robustness, especially for LSTM, GAN, and Transformers. In SVM models, RMSE and MAPE are the main metrics, with specific measures like the Bullwhip Effect used in inventory forecasting.

P4: What is the performance of the models built with NIOAs in relation to the established models?

The reviewed studies provide compelling evidence that NIOAs significantly improve forecasting accuracy in shallow and deep neural network-based models, as well as SVM-based models. In neural models, this improvement is consistent across hyperparameter optimization, trainable parameter optimization, or a combination of both, with notable examples from studies [20], [45]. While the primary focus of most studies is on reducing forecast errors, some authors also address computational efficiency concerns, proposing strategies such as hybrid approaches (e.g., BO-GA [38], SS-GA [41], MDA [49]) that enhance convergence speed and efficiency compared to standalone methods. However, hybrids like NEAT-NCS increase execution time [46], and others, such as SFS-WOA, reduce training time but add pre-training steps, leaving overall efficiency uncertain [50]. Additional efficiency-oriented strategies include adaptive algorithms with automatic parameter tuning [20], [37], [39], transfer learning mechanisms between GA and PSO [20], and input variable selection [31].

P5: In which economic sectors have they been applied and what main problems have been attempted to be solved with the models built with NIOAs?

The primary sectors utilizing NIOAs are electricity, water distribution, manufacturing, retail, and cloud computing. Across sectors, common challenges in forecasting include managing non-linear dynamics, reducing overfitting, and improving accuracy in dynamic systems. Traditional models, such as regression, ARIMA, and MLR, often fail to capture non-linearities, while standalone machine learning models like ANN, SVM, and BPNN struggle with overfitting and limited adaptability. To address these issues, machine learning models and hybrid frameworks have been introduced. LSTM models enhance accuracy but face difficulties with overfitting and hyperparameter tuning, while hybrid approaches, such as LSTM-SVR and GA-DE integrations, improve non-linear modeling but encounter computational efficiency limitations. NIOAs play a critical role in overcoming these limitations by enhancing hybrid frameworks' predictive accuracy, adaptability, and potentially computational efficiency. Techniques like PSO, GA, WOA, and DE optimize parameters and hyperparameters, addressing the shortcomings of traditional and standalone models. Sector-specific applications highlight these advancements: in electricity, NIOAs support dynamic forecasting for short-term and annual energy demands [33], [35]; in water distribution, they address agricultural and urban needs by managing nonlinear patterns in daily and hourly forecasts [23], [44]; in retail and manufacturing, they tackle the bullwhip effect and refine e-commerce demand predictions [9], [34]; and in cloud computing, NIOAs enhance resource demand forecasting and workload optimization in highly dynamic environments [10], [27], [29].

3.3. Proposed conceptual model

This section introduces a new optimization model to address the key issue identified: optimizing trainable parameters in deep learning models. The model incorporates advanced tools like heuristic hybridization and adaptive parameter control, while addressing the main gap: the lack of evolutionary multitasking applications.

3.3.1. Foundational studies

This model adopts the multi-space evolutionary search for large-scale optimization [15], a variant of evolutionary multitasking optimization. It generates an auxiliary search space with simplified versions of the original space to ease the search process. Insights learned from the auxiliary space guide the original space search, enhancing effectiveness and efficiency, while the best results from the original space return to enrich the auxiliary search.

On the other hand, the model draws inspiration from low-bit quantization optimization [54] for constructing the auxiliary search space. Quantization, a deep network compression technique, discretizes continuous variables representing neural network weights, reducing possible weight values and bit requirements, thereby simplifying optimization. Recent advances have shown that low-bit-width models can maintain high accuracy by applying quantization to both activations and weights [55]. The model is also influenced by metaheuristic hybridization [49], [50], and adaptive mechanisms for mutation and crossover control in GA [20], [39].

3.3.2. Model components

Model components are the key elements that define the search strategy, adaptive mechanisms, and hybrid techniques of the optimization framework.

- Original search space. This search space encompasses all possible values for the weights and biases of a deep neural network. This continuous space has dimensions equal to the total number of weights and biases in the network.
- Auxiliary quantized search space. This space discretizes the dimensions of the original space based on the range of the initial population. It allows generating values beyond the initial ranges but within feasible limits. The number of possible values per dimension is governed by the bit width (m-bit); higher m-bit values permit more possibilities, with the binary dimension (2-bit) representing the most extreme case.
- GA with adaptive mechanism. This search algorithm explores the discretized auxiliary space using mutation and crossover, guided by an adaptive mechanism that promotes aggressive exploration in the early stages and shifts to exploitation as fitness improves.
- SFS-WOA hybridization. This hybrid algorithm searches the original space using insights from the auxiliary space, combining the exploration strength of SFS with the refinement capabilities of WOA.
- Automatic granularity adjustment mechanism. This mechanism adjusts the m-bit in the auxiliary space, starting with low m-bits for efficient exploration of large regions and increasing the value during evolution for finer exploration of promising areas.

3.3.3. Operational dynamics

The model employs multi-task optimization with transfer learning. The auxiliary space, driven by aggressive GA and low m-bit values, rapidly explores large regions and identifies promising areas. This information directs the more precise but less aggressive SFS-WOA algorithms in the original space to exploit these areas and refine the search for optimal solutions. The best candidates from the original space are then transferred back to the auxiliary space to adjust the m-bit and enhance exploration. Figure 4 illustrates the operation of the proposed model.

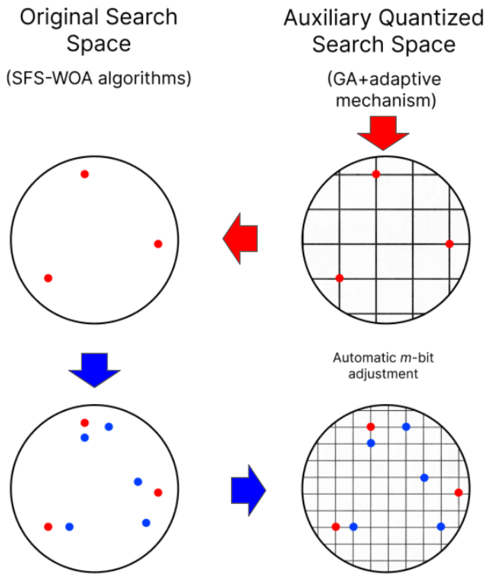

Figure 4. Schematic of the proposed model

3.3.4. Expected outcomes

The simultaneous search across two spaces, the use of multiple NIOAs, and the dynamic resizing of the auxiliary space via m-bit adjustments are expected to incur significant computational costs. However, the rapid convergence facilitated by the auxiliary space is anticipated to accelerate optimization in the original space, maintaining precision and avoiding local optima. This efficiency could drastically reduce execution times, a critical factor for practical applications of deep neural networks in demand forecasting across various industries.

3.4. Discussion

NIOAs are primarily applied to neural network optimization. In shallow networks, the focus is on parameter optimization, including pre-training [21]-[26] and full training [20], [27]-[30]. In deep networks, parameter optimization is rare due to high computational costs and is limited to neuro evolution [45], [46] or advanced pre-training methods [47], [49], [50]. Neuro evolution reduces complexity by progressively increasing network size, starting with a single layer, but remains resource-intensive. In contrast, hyperparameter optimization is more common in deep learning, with seven studies in [38]-[44] applying techniques such as hybridization, adaptive mechanisms, and multi-objective optimization. In shallow networks, only one study in [36] addresses hyperparameter tuning, as parameter optimization offers greater gains. This contrast reflects the higher practicality and impact of hyperparameter optimization in deep learning, given the difficulty of parameter-level optimization.

Despite their differences, shallow and deep networks share similar optimization strategies, especially hybridization. In shallow models, [20] applies a GA-PSO hybrid for complete RBFNN training, while deep learning studies use BO-GA and SS-GA for LSTM hyperparameter tuning [38], [41], and GA-DA and SFS-WOA for pre-training [10], [49]. Adaptive mechanisms are also common: [20] applies them to shallow parameter optimization, and [39] to deep hyperparameter tuning. Multi-objective optimization with NSGA-II is used in both shallow [31] and deep networks [42]-[44].

While the main goal of NIOAs is to improve model accuracy, several studies acknowledge their high computational cost, primarily due to intensive neural network evaluations. To address this, different efficiency-oriented strategies have been proposed. In shallow networks, studies in [26], [31] highlight that selecting relevant input variables reduces model complexity and improves efficiency. [26] proposes grey relational analysis for input selection, while [31] uses a multi-objective evolutionary algorithm that jointly minimizes forecast error and selects inputs. Although these approaches are expected to improve efficiency, no quantitative validation is provided. Efficiency is also explored through the selection of specific NIOAs, with [23] finding MEA more efficient than GA for shallow network pre-training, and [29] showing water cycle algorithm (WCA) surpassing AIS in training efficiency, though at the cost of accuracy. Adaptive mechanisms in GA are another approach to improving efficiency. Studies in [20], [37] dynamically adjust mutation and crossover rates, encouraging exploration early and shifting to exploitation as fitness improves. In deep learning, [39] applies similar adaptive mechanisms to DE parameters based on historical success. These mechanisms are expected to accelerate convergence; however, the reviewed studies do not provide quantitative validation.

An attractive strategy for improving efficiency is the hybridization of metaheuristics, particularly in deep learning. In [38], Bayesian optimization (BO) enables rapid exploration, with solutions refined by a GA. Similarly, [41], [49], [50] combine GA or SFS with refinement algorithms such as scatter search (SS), dragonfly algorithm (DA), or WOA, improving both accuracy and convergence, with supporting runtime and convergence curve analysis reported in [41] and [49]. A standout example is [20], where the authors combine adaptive GA mechanisms with PSO in a transfer learning framework, claiming accelerated convergence and reduced execution time, though without detailed quantitative validation.

Another approach to improve efficiency is limiting training during the optimization phase, as shown in [42], [43]. The first study applied time-constrained training to prioritize faster-converging models, reducing computational effort and enabling broader exploration. The second limited training epochs, accelerating the identification of promising models while maintaining feasibility. In both cases, the best models were retrained without constraints to ensure full convergence. For neural network pre-training, studies in [49], [50] report reduced training times, as gradient-based methods start from near-optimal values. However, the additional pre-training stage raises questions about overall efficiency. Across these techniques, quantitative evidence remains scarce, highlighting the need for further research focused on systematically measuring efficiency gains and final model performance, particularly in deep learning.

Notably, most advanced NIOA techniques have already been applied to AI forecasting, including hybridization [20], [38], [41], [49], [50], parameter control [20], [39], multi-objective optimization [31], [42]-[44], and neuro evolution [45], [46]. In contrast, evolutionary multitasking—designed to accelerate convergence by sharing information across tasks—remains largely unexplored. The only partial example is study in [20], which incorporates transfer learning, a key element of multitasking. This gap highlights an opportunity for future research to apply evolutionary multitasking in NIOA-based forecasting models to improve both efficiency and performance.

Additionally, this paper also contributes to the debate on backpropagation limitations. Strong evidence shows that NIOAs outperform backpropagation in reducing error metrics for shallow networks, reinforcing the relevance of the local optima stagnation problem and questioning the claim in [6] that local optima often approximate global optima. A similar performance gap in deep learning would further expose gradient vanishing issues. However, the high computational cost of applying NIOAs to deep networks limits research in this area.

Finally, this study has two key limitations. First, there is limited quantitative evidence to support the efficiency claims of the proposed techniques. Second, the predominance of studies from the electrical sector in the final selection may have biased the observed applications of NIOAs. This could be due to the inclusion of the IEEE database, or alternatively, it may reflect that the electrical sector is where NIOAs have seen the greatest development.

4. CONCLUSION

This review has comprehensively addressed the research questions, showing that NIOAs are mainly applied to parametric optimization in shallow neural networks and hyperparameter optimization in deep networks. The most common techniques include hybridization, adaptive parameter control, multi-objective optimization, and neuro evolution. Optimized models are mostly BPNNs and LSTMs, with GA as the main NIOA, often combined with swarm methods. Building on these findings, models optimized with NIOAs consistently outperform reference models, though often at the expense of higher computational costs. Some studies propose strategies to improve efficiency, but most lack quantitative validation. Despite these challenges, NIOAs are applied in various sectors, mainly in the electric power, water distribution, and retail industries. In terms of future research opportunities, significant gaps were identified, such as the lack of comprehensive parametric optimization studies for deep neural networks, the limited application of evolutionary multitasking optimization, and the absence of quantitative studies aimed at improving the efficiency of NIOA-based optimization. To bridge this gap, the authors introduce a new model that utilizes these methodologies to improve the optimization of parameters in deep neural networks.

ACKNOWLEDGMENTS

The authors would like to thank the Universidad Tecnológica del Perú, from Lima, Perú, for their cooperation in realizing the present work.

FUNDING INFORMATION

The authors declare that no funding was received to support the research, authorship, or publication of this article.

AUTHOR CONTRIBUTIONS STATEMENT

The individual contributions of the authors are detailed below following the CRediT (Contributor Roles Taxonomy) framework.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
José Rolando Neira Villar	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	
Miguel Ángel Cano Lengua	✓	✓			✓					✓		✓		

C	: **C**onceptualization	I	: **I**nvestigation	Vi	: **Vi**sualization
M	: **M**ethodology	R	: **R**esources	Su	: **Su**pervision
So	: **So**ftware	D	: **D**ata Curation	P	: **P**roject Administration
Va	: **Va**lidation	O	: Writing - **O**riginal Draft	Fu	: **Fu**nding Acquisition
Fo	: **Fo**rmal Analysis	E	: Writing - Review & **E**diting		

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, MACL, upon reasonable request.

REFERENCES

[1] L. J. Krajevsky and M. K. Malhotra, *Operations management: processes and supply chains*, 13th ed. Pearson, 2022.

[2] S. Kim, "Innovating knowledge and information for a firm-level automobile demand forecast system: a machine learning perspective," *Journal of Innovation and Knowledge*, vol. 8, no. 2, 2023, doi: 10.1016/j.jik.2023.100355.

[3] B. Rolf, I. Jackson, M. Müller, S. Lang, T. Reggelin, and D. Ivanov, "A review on reinforcement learning algorithms and applications in supply chain management," *International Journal of Production Research*, vol. 61, no. 20, pp. 7151–7179, 2023, doi: 10.1080/00207543.2022.2140221.

[4] M. Muth, M. Lingenfelder, and G. Nufer, "The application of machine learning for demand prediction under macroeconomic volatility: a systematic literature review," *Management Review Quarterly*, June 2024, doi: 10.1007/s11301-024-00447-8.

[5] J. R. N. Villar and M. A. C. Lengua, "A systematic review of the literature on the use of artificial intelligence in forecasting the demand for products and services in various sectors," *International Journal of Advanced Computer Science and Applications*, vol. 15, no. 3, pp. 144–156, 2024, doi: 10.14569/IJACSA.2024.0150315.

[6] E. Galván and P. Mooney, "Neuroevolution in deep neural networks: current trends and future challenges," *IEEE Transactions on Artificial Intelligence*, vol. 2, no. 6, pp. 476–493, 2021, doi: 10.1109/TAI.2021.3067574.

[7] A. D. Martinez *et al.*, "Lights and shadows in evolutionary deep learning: taxonomy, critical methodological analysis, cases of study, learned lessons, recommendations and challenges," *Information Fusion*, vol. 67, pp. 161–194, 2021, doi: 10.1016/j.inffus.2020.10.014.

[8] F. Karl *et al.*, "Multi-objective hyperparameter optimization in machine learning—an overview," *ACM Transactions on Evolutionary Learning and Optimization*, vol. 3, no. 4, 2023, doi: 10.1145/3610536.

[9] M. Mittal, P. R. Swain, and H. Rana, "A nature inspired optimisation method for supply chain management problem," in *2019 Amity International Conference on Artificial Intelligence (AICAI)*, Feb. 2019, pp. 505–509. doi: 10.1109/AICAI.2019.8701393.

[10] N. Sanjay and S. Sreedharan, "Hybrid bio-inspired optimization-based cloud resource demand prediction using improved support vector machine," *International Journal of Advanced Computer Science and Applications*, vol. 15, no. 1, pp. 773–782, 2024, doi: 10.14569/IJACSA.2024.0150177.

[11] S. Skansi, *Introduction to deep learning: from logical calculus to artificial intelligence*. in Udergraduate Topics in Computer Science. Zagreb, Croatia: Springer International Publishing AG, 2018. [Online]. Available: http://www.springer.com/series/7592

[12] A. Kumar, M. Nadeem, and H. Banka, "Nature inspired optimization algorithms: a comprehensive overview," *Evolving Systems*, vol. 14, no. 1, pp. 141–156, 2023, doi: 10.1007/s12530-022-09432-6.

[13] V. Bharti, B. Biswas, and K. K. Shukla, "Recent trends in nature inspired computation with applications to deep learning," in *Proceedings of the Confluence 2020 - 10th International Conference on Cloud Computing, Data Science and Engineering*, 2020, pp. 294–299. doi: 10.1109/Confluence47617.2020.9057841.

[14] E. Osaba, J. Del Ser, A. D. Martinez, and A. Hussain, "Evolutionary multitask optimization: a methodological overview, challenges, and future research directions," *Cognitive Computation*, vol. 14, no. 3, pp. 927–954, 2022, doi: 10.1007/s12559-022-10012-8.

[15] L. Feng, Q. Shang, Y. Hou, K. C. Tan, and Y.-S. Ong, "Multispace evolutionary search for large-scale optimization with applications to recommender systems," *IEEE Transactions on Artificial Intelligence*, vol. 4, no. 1, pp. 107–120, Feb. 2023, doi: 10.1109/TAI.2022.3156952.

[16] Q. Shang *et al*., "Multi-space evolutionary search with dynamic resource allocation strategy for large-scale optimization," *Neural Computing and Applications*, vol. 34, no. 10, pp. 7673–7689, May 2022, doi: 10.1007/s00521-021-06844-4.

[17] M. J. Page *et al*., "The PRISMA 2020 statement: an updated guideline for reporting systematic reviews," *BMJ*, vol. 372, Mar. 2021, doi: 10.1136/bmj.n71.

[18] M. J. Page *et al*., "PRISMA 2020 explanation and elaboration: updated guidance and exemplars for reporting systematic reviews," *BMJ*, vol. 372, Mar. 2021, doi: 10.1136/bmj.n160.

[19] J. Stork, A. E. Eiben, and T. Bartz-Beielstein, "A new taxonomy of global optimization algorithms," *Natural Computing*, vol. 21, no. 2, pp. 219–242, 2022, doi: 10.1007/s11047-020-09820-4.

[20] Z.-Y. Chen and R. J. Kuo, "Combining SOM and evolutionary computation algorithms for RBF neural network training," *Journal of Intelligent Manufacturing*, vol. 30, no. 3, pp. 1137–1154, 2019, doi: 10.1007/s10845-017-1313-7.

[21] X. Wang, X. Li, J. Wang, J. Gao, and L. Xin, "Short-term power grid load forecasting based on optimized VMD and GA-BP," *International Journal of Low-Carbon Technologies*, vol. 19, pp. 980–986, 2024, doi: 10.1093/ijlct/ctae039.

[22] X. Xia *e*t al., "An interval water demand prediction method to reduce uncertainty: a case study of Sichuan Province, China," *Environmental Research*, vol. 238, 2023, doi: 10.1016/j.envres.2023.117143.

[23] H. Huang, Z. Zhang, Z. Lin, and S. Liu, "Hourly water demand forecasting using a hybrid model based on mind evolutionary algorithm," *Water Supply*, vol. 22, no. 1, pp. 917–927, 2022, doi: 10.2166/ws.2021.228.

[24] J. Li and B. Cao, "Seasonal tourism demand forecasting based on machine learning in big data environment," *Journal of Network Intelligence*, vol. 9, no. 2, pp. 1032–1045, 2024.

[25] Q. Luo, "logistics demand forecasting based on BP neural network model optimized by genetic algorithm," in *2023 4th International Conference on Computer, Big Data and Artificial Intelligence (ICCBD+AI)*, 2023, pp. 445–450, doi: 10.1109/ICCBD-AI62252.2023.00082.

[26] M. Liu, Z. Xie, J. Gu, J. Wang, W. Xiang, and N. Zhu, "Electricity consumption forecasting in Jiangxi Province based on GRA-PSO-BP," in *2023 IEEE 11th Joint International Information Technology and Artificial Intelligence Conference (ITAIC)*, Dec. 2023, pp. 900–904. doi: 10.1109/ITAIC58329.2023.10408854.

[27] J. Kumar and A. K. Singh, "Cloud resource demand prediction using differential evolution based learning," in *2019 7th International Conference on Smart Computing & Communications (ICSCC)*, June 2019, pp. 1–5. doi: 10.1109/ICSCC.2019.8843680.

[28] D. Marcek, "Comparison of predictive statistical learning accuracy with computational intelligence methods," in *2019 IEEE 15th International Scientific Conference on Informatics*, Nov. 2019, pp. 000317–000322. doi: 10.1109/Informatics47936.2019.9119308.

[29] S. Jeddi and S. Sharifian, "A water cycle optimized wavelet neural network algorithm for demand prediction in cloud computing," *Cluster Computing-The Journal of Network Software Tools and Applications*, vol. 22, no. 4, pp. 1397–1412, Dec. 2019, doi: 10.1007/s10586-019-02916-2.

[30] O. Oyebode and D. E. Ighravwe, "Urban water demand forecasting: A comparative evaluation of conventional and soft computing techniques," *Resources*, vol. 8, no. 3, 2019, doi: 10.3390/RESOURCES8030156.

[31] A. Jadidi, R. Menezes, N. De Souza, and A. C. De Castro Lima, "Short-term electric power demand forecasting using NSGA II-ANFIS Model," *Energies*, vol. 12, no. 10, 2019, doi: 10.3390/en12101891.

[32] M. Ren, J. Dai, W. Zhu, and F. Dai, "Combined modelling for iron ore demand forecasting with intelligent optimization algorithms," *Gospodarka Surowcami Mineralnymi / Mineral Resources Management*, vol. 37, no. 1, pp. 21–38, 2021, doi: 10.24425/gsm.2021.136293.

[33] A. D. Mehr, F. Bagheri, and R. Reşatoğlu, "A genetic programming approach to forecast daily electricity demand," in *13th International Conference on Theory and Application of Fuzzy Systems and Soft Computing — ICAFS-2018. ICAFS 2018. Advances in Intelligent Systems and Computing*, vol 896. Cham, Switzerland: Springer, 2019, pp. 301–308, doi: 10.1007/978-3-030-04164-9-41.

[34] S. Jaipuria and S. S. Mahapatra, "A study on behaviour of bullwhip effect in (R, S) inventory control system considering DWT-MGGP demand forecasting model," *Journal of Modelling in Management*, vol. 14, no. 2, pp. 385–407, 2019, doi: 10.1108/JM2-04-2018-0053.

[35] A. Fallahpour, K. Wong, S. Rajoo, and G. Tian, "An evolutionary-based predictive soft computing model for the prediction of electricity consumption using multi expression programming," *Journal of Cleaner Production*, vol. 283, Feb. 2021, doi: 10.1016/j.jclepro.2020.125287.

[36] M. G. Shirkoohi, M. Doghri, and S. Duchesne, "Short-term water demand predictions coupling an artificial neural network model and a genetic algorithm," *Water Science and Technology: Water Supply*, vol. 21, no. 5, pp. 2374–2386, 2021, doi: 10.2166/ws.2021.049.

[37] Z. Bai, W. Ma, and T. Wu, "Ride-hailing demand prediction based on hotspot areas," in *2023 2nd International Conference on Artificial Intelligence, Human-Computer Interaction and Robotics (AIHCIR)*, Dec. 2023, pp. 477–482. doi: 10.1109/AIHCIR61661.2023.00084.

[38] P. Suryawanshi, S. Gaikwad, A. Kumar, A. Patlolla, and S. K. Jayakumar, "A hybrid bayesian-genetic algorithm based hyperparameter optimization of a LSTM network for demand forecasting of retail products," in *International Joint Conference on Computational Intelligence*, pp. 230–237 2023, doi: 10.5220/0012182900003595.

[39] A. Vakhnin, I. Ryzhikov, C. Brester, H. Niska, and M. Kolehmainen, "Weather-based prediction of power consumption in district heating network: case study in Finland," *Energies*, vol. 17, no. 12, 2024, doi: 10.3390/en17122840.

[40] H. Su, E. Zio, J. Zhang, M. Xu, X. Li, and Z. Zhang, "A hybrid hourly natural gas demand forecasting method based on the integration of wavelet transform and enhanced Deep-RNN model," *Energy*, vol. 178, pp. 585–597, 2019,

doi: 10.1016/j.energy.2019.04.167.
[41] A. Kantasa-ard, M. Nouiri, A. Bekrar, A. Ait el cadi, and Y. Sallez, "Machine learning for demand forecasting in the physical internet: a case study of agricultural products in Thailand," *International Journal of Production Research*, vol. 59, no. 24, pp. 7491–7515, 2021, doi: 10.1080/00207543.2020.1844332.
[42] R. G. Perea, E. C. Poyato, P. Montesinos, and J. A. R. Díaz, "Optimisation of water demand forecasting by artificial intelligence with short data sets," *Biosystems Engineering*, vol. 177, pp. 59–66, 2019, doi: 10.1016/j.biosystemseng.2018.03.011.
[43] R. G. Perea, I. F. García, E. C. Poyato, and J. A. R. Díaz, "New memory-based hybrid model for middle-term water demand forecasting in irrigated areas," *Agricultural Water Management*, vol. 284, 2023, doi: 10.1016/j.agwat.2023.108367.
[44] R. G. Perea, E. C. Poyato, and J. A. R. Díaz, "Attention is all water need: multistep time series irrigation water demand forecasting in irrigation disctrics," *Computers and Electronics in Agriculture*, vol. 218, 2024, doi: 10.1016/j.compag.2024.108723.
[45] R. Brattin, R. S. Sexton, W. Yin, and B. Wheatley, "A neural network solution for forecasting labor demand of drop-in peer tutoring centers with long planning horizons," *Education and Information Technologies*, vol. 24, no. 6, pp. 3501–3522, 2019, doi: 10.1007/s10639-019-09939-7.
[46] Z. Yichen, C. Yang, and A. Ghandar, "Evolving neural networks for prediction with negative correlation search: application in consumer demand forecasting," in *2020 IEEE Symposium Series on Computational Intelligence (SSCI)*, Dec. 2020, pp. 384–391. doi: 10.1109/SSCI47803.2020.9308565.
[47] W. Wei and J. Chuan, "A combination forecasting method of grey neural network based on genetic algorithm," in *Procedia CIRP*, pp. 191–196, 2022, doi: 10.1016/j.procir.2022.05.235.
[48] K. Zhu, S. Zhang, W. Zhang, and Z. Zhang, "A novel hybrid deep learning model for taxi demand forecasting based on decomposition of time series and fusion of text data," *Journal of Intelligent and Fuzzy Systems*, vol. 41, no. 2, pp. 3355–3371, 2021, doi: 10.3233/JIFS-210657.
[49] Y. Ling, X. Li, C. Li, and T. Chen, "An intelligent adversarial deep forecasting model for load demand using hybrid modified DA-GAN," in *2023 IEEE/IAS Industrial and Commercial Power System Asia (I&CPS Asia)*, July 2023, pp. 1340–1345. doi: 10.1109/ICPSAsia58343.2023.10294656.
[50] A. A. Salamai, A. A. Ageeli, and E.-S. M. El-Kenawy, "Forecasting e-commerce adoption based on bidirectional recurrent neural networks," *Computers, Materials and Continua*, vol. 70, no. 3, pp. 5091–5106, 2022, doi: 10.32604/cmc.2022.021268.
[51] N. Sinha and C. Lucheroni, "Double-reservoir deep echo state network architecture for short-term electricity demand forecasting," in *2022 18th International Conference on the European Energy Market (EEM)*, Sept. 2022, pp. 1–6. doi: 10.1109/EEM54602.2022.9921048.
[52] A. Huang, Q. Bi, L. Dai, and H. Hosseinzadeh, "Developing a hybrid technique for energy demand forecasting based on optimized improved SVM by the boosted multi-verse optimizer: investigation on affecting factors," *Heliyon*, vol. 10, no. 7, 2024, doi: 10.1016/j.heliyon.2024.e28717.
[53] H. Li, P. Li, Y. Zhang, W. Zu, and Y. Zheng, "Research on electricity demand forecasting based on LSTM-SVR," in *2022 2nd International Conference on Algorithms, High Performance Computing and Artificial Intelligence (AHPCAI)*, Oct. 2022, pp. 233–239. doi: 10.1109/AHPCAI57455.2022.10087856.
[54] R. Zhou and P. Quan, "Optimization ways in neural network compression," *Procedia Computer Science*, vol. 221, pp. 1351–1357, Jan. 2023, doi: 10.1016/j.procs.2023.08.125.
[55] A. Alqahtani, X. Xie, and M. W. Jones, "Literature review of deep network compression," *Informatics*, vol. 8, no. 4, 2021, doi: 10.3390/informatics8040077.

BIOGRAPHIES OF AUTHORS

José Rolando Neira Villar He is a professor at the Universidad Tecnológica del Peru (UTP) and at CENTRUM, the postgraduate school of the Pontificia Universidad Católica del Peru. He has a degree in industrial engineering from the National University of Callao, and a master in Business Administration from the Pontificia Universidad Católica del Perú, he is currently a doctoral student in systems engineering and computer science at the National University of San Marcos. He works on the use and applications of AI in operations management and supply chains. He can be contacted at email: jose.neirav@unmsm.edu.pe.

Miguel Ángel Cano Lengua is a Ph.D. Engineering of Systems and Computer Science from the Universidad Nacional Mayor de San Marcos, a Master's in systems engineering from the Universidad Nacional del Callao (UNAC), a profesor at the Universidad Tecnologica del Peru (UTP) and teaching researcher in the Universidad Nacional Mayor de San Marcos (UNMSM), has a degree in Mathematics. He works on continuous optimization, AI algorithms, conical programming, numerical methods, methodology, and software design. He can be contacted at email: mcanol@unmsm.edu.pe.