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REVIEW

A Comprehensive Overview of PSO-LSTM Approaches: Applications, Analytical Insights, and Future Opportunities

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Abstract

The combination of particle swarm optimization algorithm with long short-term memory has led to new horizons in data analysis and solving complex problems. The particle swarm optimization has been used to solve complex and hard optimization problems since 1995 and has gained extraordinary popularity among researchers. The combination of particle swarm optimization-long short-term memory is carried out in order to simultaneously utilize the global search capability and convergence ability of the particle swarm optimization to optimize long short-term memory in modeling long-term temporal dependencies. The goal of the particle swarm optimization-long short-term memory model is to increase the prediction accuracy and reduce the error in solving complex and dynamic real-world problems. In this paper, a comprehensive and structured look at the scientific literature of particle swarm optimization-long short-term memory models between 2019 and June 2025 has been conducted. By categorizing the articles according to the publication date and place of publication, it was found that prominent publishers such as MDPI, Springer, Elsevier, and IEEE played a major role in the publication of particle swarm optimization-long short-term memory models in 2024. This paper aims to provide a clear overview of the potential applications of particle swarm optimization-long short-term memory in various domains. particle swarm optimization-long short-term memory has been widely used in engineering systems design, time series forecasting, and the oil and gas industry. This paper analyses the strengths and weaknesses, as well as the challenges of complexity in hybrid architectures, and issues related to scalability and optimization. Finally, future directions are proposed with an emphasis on performance enhancement and development of adaptable solutions for real-world problems.

1 Introduction

In today's world, with the increasing complexity and multidimensionality of data, the need for innovative solutions to tackle various scientific and industrial challenges is more pressing than ever. One of the practical approaches in this regard is the use of machine learning and Deep Learning (DL) methods to analyze, model, and predict the behavior of complex systems [1]. Algorithms such as linear regression, decision trees, or Artificial Neural Networks (ANNs), including MLP and RBF, exhibit acceptable performance in fundamental problems; however, they struggle to provide adequate accuracy when confronted with nonlinear structures and long-term time dependencies [2]. Algorithms such as Convolutional Neural Networks (CNN) [3], LSTM [4], Transformers, and Gated Recurrent Unit (GRU) have been proposed as efficient alternatives to traditional methods. These models enable more accurate predictions by understanding temporal sequences and capturing long-term dependencies; however, they still require optimization to improve their accuracy when dealing with large and noisy datasets. For example, ANNs require careful feature design to achieve optimal performance, but LSTMs can automatically extract complex temporal patterns from raw data. In training ANNs on sequence data, the problem of vanishing gradient becomes more severe, especially in long sequences, while LSTM effectively mitigates this problem by using gating mechanisms [5]. ANNs are unable to incorporate

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information about previous examples into learning the current example, which severely affects their performance in applications such as machine translation or natural language analysis.

1.1 Motivation

The optimization process in deep learning models is crucial not only for selecting the appropriate architecture but also for fine-tuning parameters, learning rates, and cost functions. In many cases, using conventional algorithms to train LSTM models does not lead to the desired prediction accuracy, because these models have difficulty finding the optimal minimum of nonlinear functions with a large number of parameters [6, 7]. Conventional training algorithms, such as Stochastic Gradient Descent (SGD) or Adam, often get trapped in local minima and struggle to perform well in solving complex problems with high noise or unbalanced data. Therefore, utilizing advanced optimization algorithms, such as evolutionary algorithms, adaptive gradient algorithms, or combining machine learning methods with metaheuristic methods, can significantly enhance LSTM results [8].

In recent decades, the increasing complexity of real-world problems, the emergence of nonlinear, multi-objective, and unstable systems, have led to the decline in the efficiency of classical methods based on deterministic optimization and local search [9]. In this regard, metaheuristic algorithms, which are inspired by natural, biological, and social phenomena, have been proposed as flexible, scalable, and robust methods for tackling complex and uncertain search spaces. By eliminating the traditional dependence on differentiability, continuity, or convexity of objective functions, these algorithms have opened new horizons in solving NP-hard problems. Metaheuristic algorithms, unlike classical techniques, are based on directed random search [10, 11]. At the applied level, the implementation and application of metaheuristic algorithms have expanded in a wide range of fields, including industrial engineering, structural design, computer networks, bio computation, machine learning, and even computational economics [12]. Many previous studies have only focused on individual applications of PSO [13, 14] or LSTM [15], while a comprehensive and systematic investigation of PSO-LSTM combinations in different domains is still limited.

1.2 Contributions

One of the fundamental challenges in using LSTM networks is selecting the optimal hyperparameters. Manual or empirical tuning, which relies on repeated trial and error by experts, is a common approach. However, this method not only significantly increases the complexity and execution time of modeling but also often prevents achieving the highest prediction accuracy. Inappropriate selection of hyperparameters leads to overfitting, which means the model performs well on the training data but struggles to generalize to new data sets. These weaknesses make the need for more efficient approaches to optimizing hyperparameters more apparent than ever. The particle swarm optimization (PSO) [16] as a powerful and metaheuristic optimization solution, it has become an effective tool for solving complex optimization problems. This algorithm attempts to locate the global optimum by systematically exploring the search space through a swarm of particles, with each particle encoding a candidate solution. Each particle updates its position and velocity based on its own best position and the best position found by the entire population. The performance of each particle is evaluated by the root mean square error (RMSE). The PSO can adjust various hyperparameters adaptively by analyzing the RMSE value in the LSTM model. The main contributions of this paper are as follows:

- This paper is the first systematic and comprehensive review of PSO-LSTM models from 2019 to June 2025. A comprehensive review of PSO-LSTM was not found in the search process. In this study, the progress made in various domains, hybrid architectures, and improvements applied to PSO in combination with LSTM are analyzed in detail.
- An extensive analysis was performed on 238 papers to provide statistically meaningful insights into publication trends and application areas. The papers are collected from authoritative sources (Springer, Elsevier, MDPI, Wiley, IEEE, World Scientific, Emerald, and Taylor & Francis).
- PSO-LSTM models are thoroughly reviewed in 30 application areas based on their advantages and disadvantages. Studies show that PSO-LSTM models have been increasingly utilized in various fields, including time series forecasting, water resources management, wind speed forecasting, and engineering systems design.
- The combination of PSO-LSTM models shows that the use of PSO has led to the optimization of LSTM parameters and increased prediction accuracy and performance.

The general structure of this paper is as follows: Section 2 provides a detailed description of the search methods used to locate documents in key sources. Section 3 describes basic concepts, including the PSO and LSTM algorithms. In sect. 4, the application of PSO-LSTM models in 30 different areas is thoroughly reviewed. Section 5 reviews the application areas and analysis of the PSO-LSTM model. Finally, in sect. 6, conclusions, challenges, limitations and future directions are presented.

2 Search Methodology

Figure 1 shows the steps of extracting and collecting PSO-LSTM papers. In the first step, PSO-LSTM papers are collected from two distinct source categories. The first category includes databases from reputable scientific publishers such as Springer, Elsevier, Wiley, MDPI, IEEE, Taylor & Francis, World Scientific, and Emerald. The second category includes scientific search engines and indexing databases such as PubMed, Scopus, Google Scholar, ACM,

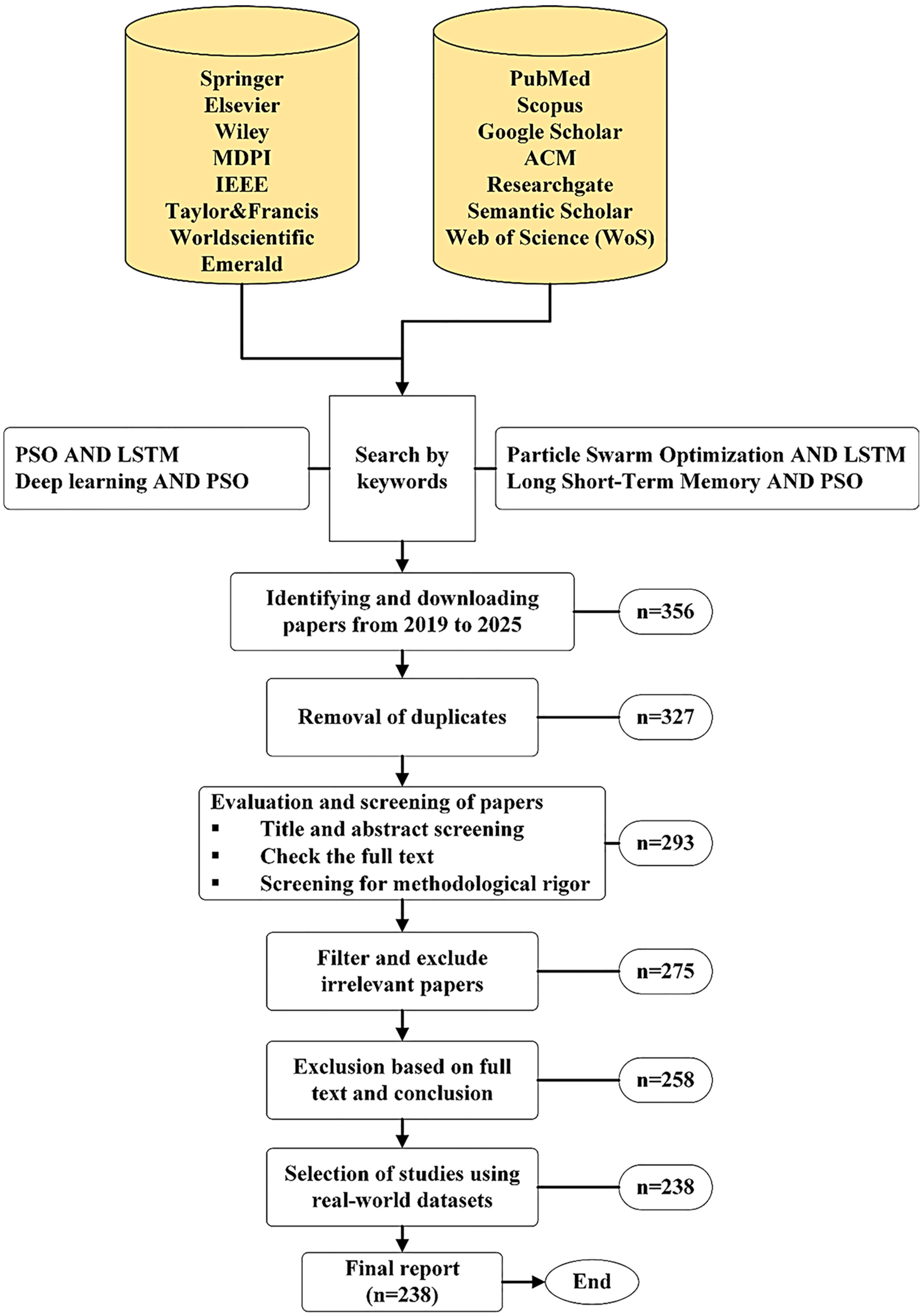


Fig. 1 The steps of extracting and collecting PSO-LSTM papers

ResearchGate, Semantic Scholar, and Web of Science (WoS). The papers were searched using keywords such as “PSO AND LSTM”, “Deep learning AND PSO”, “particle swarm optimization and LSTM”, and “long short-term memory and PSO”. After the initial search, 356 papers were identified and downloaded. Then, in the duplicate removal stage, 29 duplicate papers were removed, reducing the number of papers to 327. In the next step, the initial evaluation and screening of the papers is performed, which includes reviewing the title and abstract, reading the full text of the paper, and evaluating its scientific quality. After this stage, an additional 34 papers are discarded, resulting in a total of 293 papers. Then, to filter out irrelevant papers, an additional 18 papers are deleted, reducing the remaining number to 257 papers. Filtering of articles is done based on the following two factors: 1) Lack of hyperparameter settings (e.g., number of layers, batch size, learning rate). 2) Lack of real and normalized data. In the next stage, a more detailed review is conducted based on the full content and conclusions of the papers, resulting in the deletion of an additional 17 papers, which brings the final number of papers to 258. Then, papers with real datasets are selected. The number of these articles is 238 papers. Finally, the 238 selected papers are included in the final report, and the analysis process is now complete.

Figure 2 shows the distribution of PSO-LSTM papers across different publishers. The most significant percentage of documents comes from MDPI, which leads the way in publishing PSO-LSTM papers, at 32%. This indicates that MDPI has provided a suitable platform for publishing new research in the fields of artificial intelligence and optimization through its journals, such as Applied Sciences, Sensors, and Mathematics. Springer is in second place, publishing 20% of the papers in this field. Springer typically publishes high-quality journals in the fields of basic science, engineering, and computer science, making it a suitable choice for documents with a theoretical, applied, or algorithmic approach. Elsevier is in third place with 18%. Given the wide range of Elsevier journals in artificial intelligence, machine learning, software engineering, and intelligent systems, this publisher is well-suited for papers presenting advanced statistical analyses or applied case studies. IEEE, which is specifically active in the fields of electrical, computer, and telecommunications engineering, has a 15% share. This reflects the high interest of technical researchers in publishing in prestigious IEEE conferences and journals such as IEEE Access, IEEE Transactions on Neural Networks, and IEEE Transactions on Systems, Man, and Cybernetics. Publisher Wiley is in fifth place with 9%. This publisher also works in interdisciplinary and applied fields, and its journals usually focus on detailed methodological and industrial applications. Taylor & Francis has a relatively small share (3%) of the total papers. This publisher is better known for its focus on theoretical studies, complex systems,

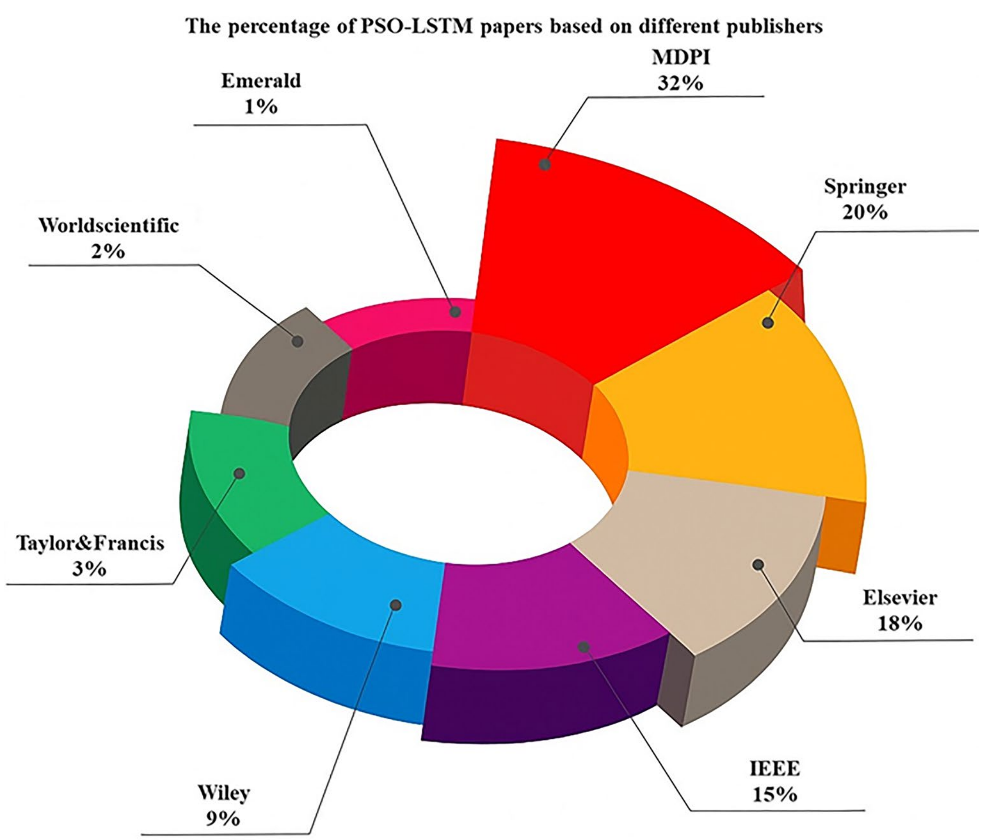


Fig. 2 The percentage of PSO-LSTM papers based on different publishers

and interdisciplinary applications. World Scientific published only 2% of the documents.

Figure 3 shows a chart of the number of PSO-LSTM papers based on publishers and year of publication. The trend of PSO-LSTM paper publication in 2023 and 2024 has seen significant growth. In 2023, 32 papers were published by MDPI, and this trend has reached 25 documents in 2024. Springer and Elsevier have published a large number of documents in 2024 and 2025. The rising demand for highly accurate and adaptive approaches in domains such as forecasting, intelligent control, signal processing, and decision support systems has driven researchers to develop and apply hybrid models, among which PSO-LSTM is a prominent example. Therefore, the increase in the number of papers in 2023 and 2024 is not only an indication of the technical growth of this field but also a reflection of the scientific community's appreciation of the application potential of this model.

Figure 4 shows a chart of the number of PSO-LSTM papers based on the year of publication. In 2019, only nine papers were published in this area, marking the initial stage of research on combining PSO with LSTM networks. In 2020, this number increased slightly to 11 papers, indicating limited but gradual growth in interest in this hybrid approach. In 2021, the number of publications increased to 17, reflecting growing attention from the scientific community to the use of PSO for enhancing the performance of deep learning models. In 2022, the number of papers reached 18, representing a modest increase compared to the previous year and indicating relative stability in the publication of related studies during this period. The central turning point occurred in 2023, when the number of papers reached 55, representing a significant increase compared to previous years. This growth can be attributed to the greater maturity of DL concepts, increased access to advanced computing infrastructure, and the proliferation of programming frameworks such as TensorFlow and PyTorch. This upward trend peaked in 2024, with 75 papers published—the highest number to date. This remarkable growth highlights that the PSO-LSTM field has become a major focus of interdisciplinary research. Finally, in the first half of 2025 (until June), 53 papers were published, which is an important number considering that only half of the year has passed. This indicates that the growing trend of attention to this field continues, and the number of papers is expected to exceed previous years by the end of this year.

Table 1 illustrates the application of PSO-LSTM in various fields, as per Scopus. The three fields with the most use of the PSO-LSTM model are as follows: Engineering is the most widely used, with 820 cases (25.32%). This indicates the widespread adoption of this model in the design, control and prediction of engineering processes. Computer science is in second place with 739 cases (22.82%). This field is active due to its ability to process complex data and long-term time series in artificial intelligence, machine learning and machine vision problems. Mathematics also has a significant contribution with 380 cases (11.74%). This is due to the importance of mixed models in numerical analysis, random data modelling and optimization theories. Fields such as medical sciences, psychology, veterinary medicine,

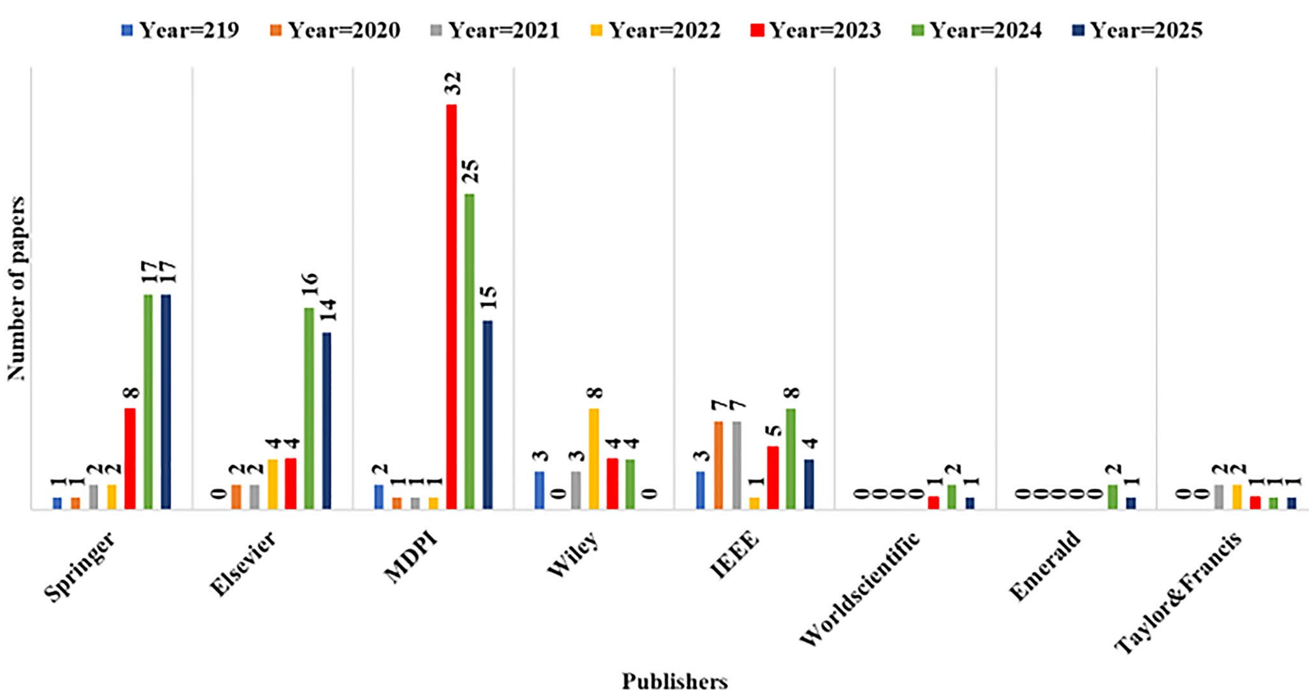


Fig. 3 Graph of the number of PSO-LSTM papers based on publishers and year of publication

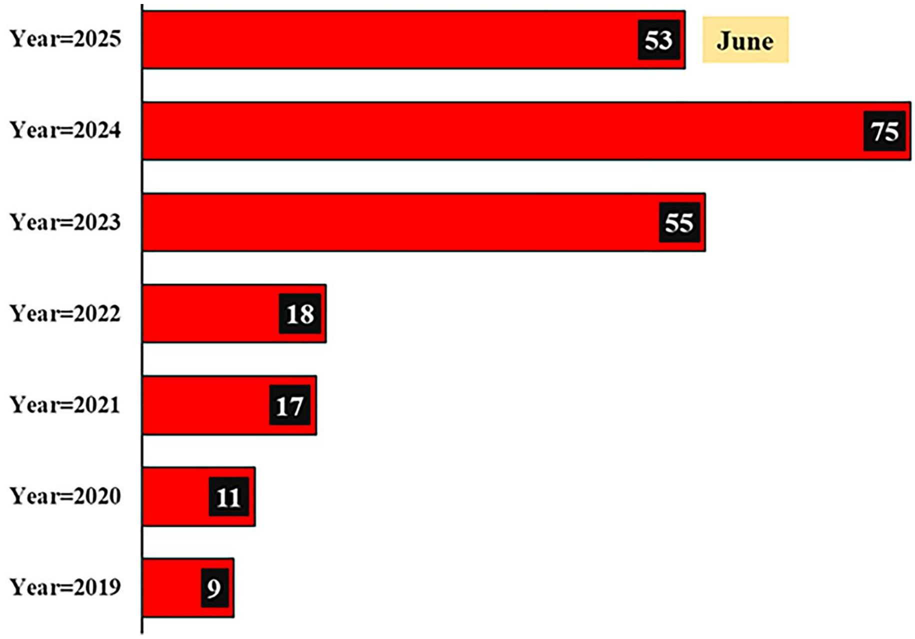


Fig. 4 Chart of the number of PSO-LSTM papers based on the year of publication

Table 1 The application of PSO-LSTM in various fields according to Scopus

subject area	Count	%	Proportion
Engineering	820	25.32٪	0.2532
Computer Science	739	22.82٪	0.2282
Mathematics	380	11.74٪	0.1174
Energy	268	8.28٪	0.0828
Physics and Astronomy	181	5.59٪	0.0559
Materials Science	152	4.69٪	0.0469
Environmental Science	146	4.51٪	0.0451
Decision Sciences	105	3.24٪	0.0324
Earth and Planetary Sciences	76	2.35٪	0.0235
Social Sciences	66	2.04٪	0.0204
Chemical Engineering	59	1.82٪	0.0182
Multidisciplinary	44	1.36٪	0.0136
Medicine	40	1.24٪	0.0124
Chemistry	35	1.08٪	0.0108
Biochemistry, Genetics and Molecular Biology	30	0.93٪	0.0093
Agricultural and Biological Sciences	29	0.90٪	0.0090
Business, Management and Accounting	28	0.87٪	0.0087
Economics, Econometrics and Finance	18	0.56٪	0.0056
Neuroscience	12	0.37٪	0.0037
Immunology and Microbiology	3	0.09٪	0.0009
Health Professions	2	0.06٪	0.0006
Psychology	2	0.06٪	0.0006
Veterinary	2	0.06٪	0.0006
Arts and Humanities	1	0.03٪	0.0003
Nursing	1	0.03٪	0.0003

nursing, and the humanities have fewer than 1% of applications. This decrease is likely due to limitations in data types, different conceptual structures and challenges in implementing DL models in these fields.

Table 2 presents the application of PSO-LSTM in various fields, as per the Web of Science (WoS). The three fields with the most use of the PSO-LSTM model are as follows: Electrical and electronic engineering is at the top, with 181 papers (14.27%). This is justified by the widespread need for signal prediction, time series analysis, and optimization in circuit and system design. Information systems in computer science (8.83%) and artificial intelligence (8.28%) also have high contributions, reflecting the application of the PSO-LSTM model in complex data processing, pattern recognition, and machine learning. The energy and fuels field is also of particular importance, with 8.28%, likely due to the use of PSO-LSTM in energy consumption forecasting, renewable energy system optimization, and energy market modelling. Multidisciplinary engineering, civil engineering, and multidisciplinary sciences each contribute approximately 3.5%, indicating the growing acceptance of the PSO-LSTM model in interdisciplinary projects. WoS data show that PSO-LSTM has been most widely used in areas requiring time series data analysis, system control, and process optimization.

The difference in the number of published papers between Scopus and WoS is rooted in the structure and indexing policies of these two databases. Scopus, as one of the most comprehensive scientific databases, covers a wide range of scientific journals and conferences across various disciplines, particularly engineering, computer science, energy, and applied sciences. However, WoS focuses on

Table 2 The application of PSO-LSTM in various fields according to WoS

subject area	Count	%	Proportion
Engineering Electrical Electronic	181	14.27٪	0.1427
Computer Science Information Systems	112	8.83٪	0.0883
Computer Science Artificial Intelligence	105	8.28٪	0.0828
Energy Fuels	105	8.28٪	0.0828
Telecommunications	87	6.86٪	0.0686
Environmental Sciences	65	5.13٪	0.0513
Instruments Instrumentation	54	4.26٪	0.0426
Engineering Multidisciplinary	47	3.71٪	0.0371
Engineering Civil	45	3.55٪	0.0355
Multidisciplinary Sciences	45	3.55٪	0.0355
Materials Science Multidisciplinary	42	3.31٪	0.0331
Automation Control Systems	38	2.99٪	0.0299
Computer Science Interdisciplinary Applications	38	2.99٪	0.0299
Physics Applied	38	2.99٪	0.0299
Computer Science Theory Methods	35	2.76٪	0.0276
Green Sustainable Science Technology	35	2.76٪	0.0276
Water Resources	34	2.68٪	0.0268
Geosciences Multidisciplinary	29	2.29٪	0.0229
Engineering Chemical	25	1.97٪	0.0197
Engineering Mechanical	22	1.74٪	0.0174
Thermodynamics	19	1.50٪	0.0150
Environmental Studies	17	1.34٪	0.0134
Mathematics Interdisciplinary Applications	17	1.34٪	0.0134
Operations Research Management Science	17	1.34٪	0.0134
Chemistry Multidisciplinary	16	1.26٪	0.0126

high-impact journals and applies strict criteria for indexing, resulting in only a limited number of papers on similar topics being included. One of the key factors in the statistical difference between these two databases is the broader coverage of international conferences in Scopus. Many PSO-LSTM-related papers are published in the proceedings of IEEE, Springer, and ACM conferences that are indexed in Scopus; however, in WoS, only specific and selected conferences are indexed.

The indexing process in Scopus is generally more flexible and faster, whereas WoS applies stricter criteria for scientific evaluation, publication stability, and impact metrics. As a result, many new or regional journals indexed in Scopus are not included in WoS. Scopus is particularly focused on technical and engineering fields such as electrical, computer, energy, and applied mathematics, which are precisely the fields that contribute the most to PSO-LSTM-based research. In contrast, WoS is more inclined towards basic sciences, medicine, and life sciences, which may have less overlap with typical PSO-LSTM applications. Finally, it should be noted that although the number of papers indexed in Scopus is higher, this does not necessarily imply superior quality; rather, it reflects the broader and more comprehensive coverage of the database. In contrast, WoS focuses on sources with a higher quality index. Therefore, in review or analytical studies, using both databases simultaneously can provide a more comprehensive and accurate view of the scientific and research process.

Figure 5 plots the number of PSO-LSTM papers published in different countries, as per Scopus. China is the clear leader in research in this particular area, with 880 papers, significantly ahead of other countries. India is in second place with 242 papers, indicating a significant contribution, but much less compared to China. Other countries show much lower numbers of publications. For example, Saudi Arabia and the United States both contribute in the range of 51–52 papers. Malaysia, Iran, South Korea, Taiwan, Australia, Turkey, Egypt and the United Kingdom each have between 24 and 40 papers. Countries such as Iraq, Pakistan, Vietnam, Canada, Indonesia, Jordan, Tunisia, Bangladesh, Japan, the United Arab Emirates, France, Germany, and Ethiopia have fewer than 20 papers, with some having as few as 7 or 8 papers. This distribution highlights China's position in PSO-LSTM research. India also shows significant activity, while most other countries have a relatively low presence.

Figure 6 plots the number of PSO-LSTM papers in various countries, as reported by WoS. Similar to Scopus data, China is the absolute leader in this research field, with 509 papers, although its number of papers in Web of Science is lower than that in Scopus. India is in second place with 103 papers, significantly behind China. Saudi Arabia is next, with 41 papers, followed by the United States with 38 papers. South Korea (30 papers), Iran (29 papers), Taiwan (27 papers), Australia (22 papers) and Egypt (21 papers) also make significant contributions. Malaysia is next with 17 papers, and the United Kingdom with 15 papers. Vietnam (13 papers), Canada (12 papers), Jordan (9 papers), United Arab Emirates (9 papers), Japan (8 papers), Pakistan (8 papers), France (7 papers), Spain (7 papers), Germany (6 papers), Iraq (6 papers), Bangladesh (5 papers) and Brazil (5 papers) have a lower number of publications. This chart clearly shows China's dominance in PSO-LSTM research. The high concentration of research in China and India highlights the primary centers of knowledge production in this field. Contributions from other countries are comparatively limited, which may reflect differences in investment, prioritization, or expertise in this specific area of machine learning and optimization.

Fig. 5 The number of PSO-LSTM papers in different countries according to Scopus

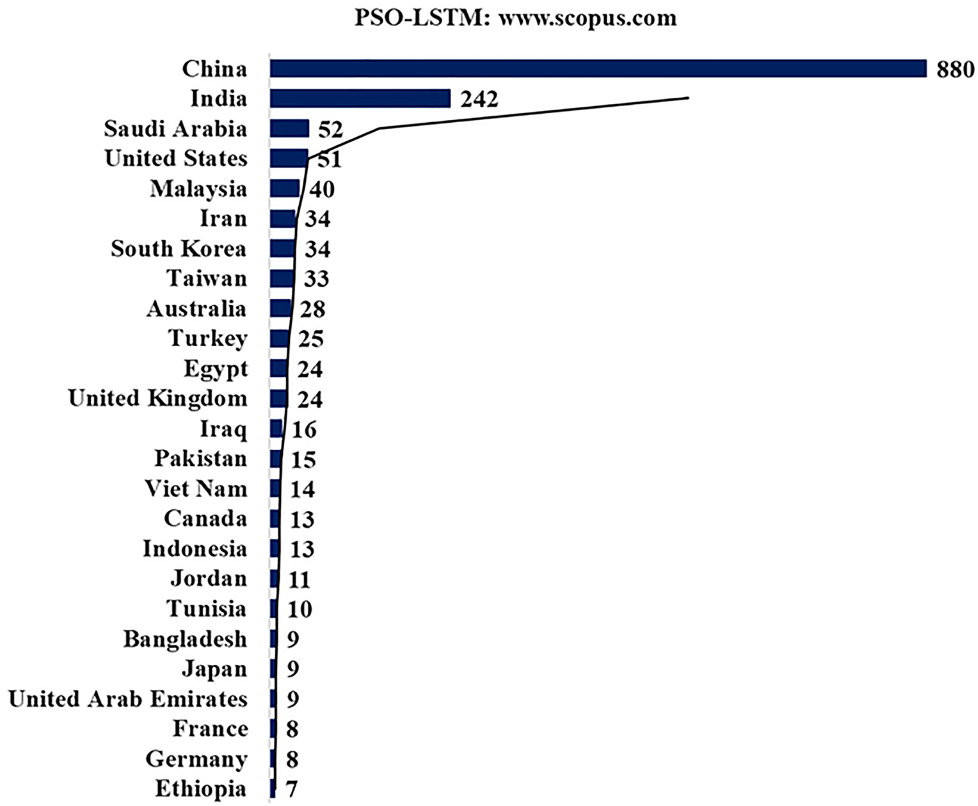
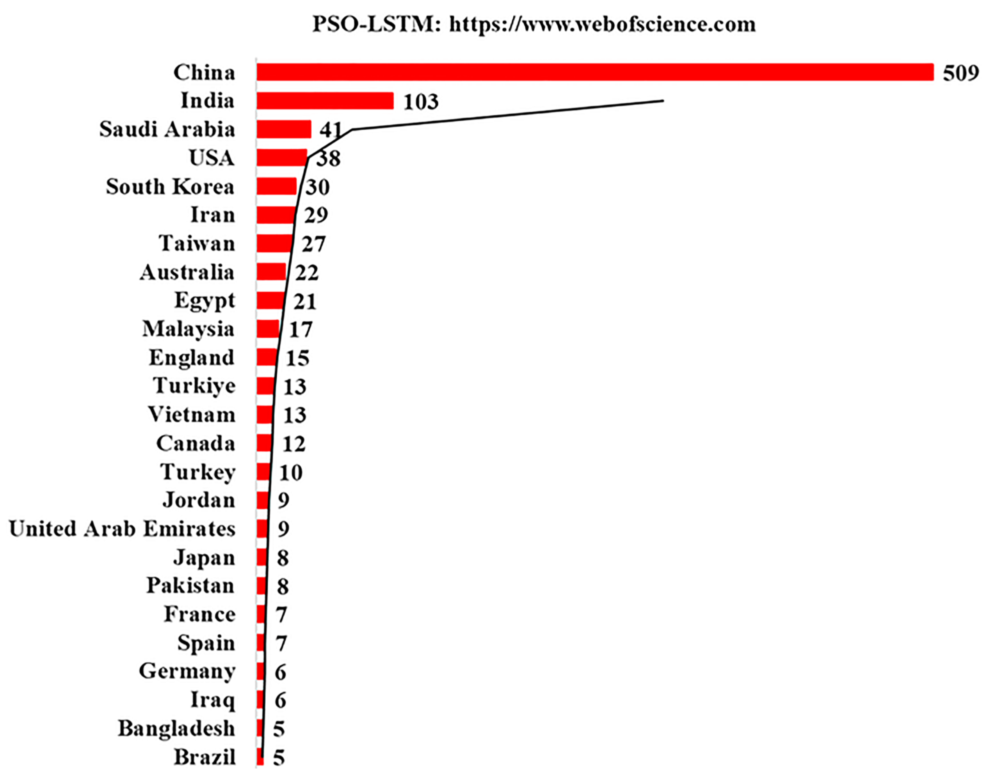


Fig. 6 The number of PSO-LSTM papers in different countries according to WoS



3 Basic Concepts

In this section, the PSO, LSTM, and the reasons for combining PSO with LSTM are explained.

3.1 Particle Swarm Optimization

The PSO is a stochastic and evolutionary optimization method inspired by modelling the social behaviour of living organisms, particularly the collective movement of birds and fish [16]. This algorithm seeks to find optimal solutions to complex problems by simulating the interactions between members of the population [17]. In this approach, each member of the population is represented as a particle that moves in a multidimensional search space, thereby representing a potential solution to the optimization problem. In this algorithm, particles act as independent yet dependent and cooperative components, and their positions are updated using a fitness function that determines their movement [18]. The fitness function serves as a criterion for evaluating the quality of solutions and guides the particles to improve them. In other words, each particle works based on two primary sources: the best position that the particle itself has ever seen (personal experience) and the best position discovered by other particles in the entire population (social experience). This two-way interaction between individual and collective knowledge causes the population to move towards the optimal regions of the search space gradually and eventually converge to the optimal or near-optimal solution. In the PSO, the position X_i^d and the velocity v_i^d are calculated as Eq. (1) and Eq. (2).

$$X_i^d\,(t+1) = X_i^d\,(t) + v_i^d\,(t+1) \tag{1}$$

$$\begin{aligned} v_i^d\,(t+1) = w\,(t) \times v_i^d\,(t) + c_1 r_1 \times \left(pbest_i^d - X_i^d\,(t)\right) \\ + c_2 r_2 \times \left(gbest_i^d - X_i^d\,(t)\right) \end{aligned} \tag{2}$$

The parameters of the PSO include several key elements that play a critical role in the performance and efficiency of the algorithm. In the mathematical formulation of particle motion, the coefficients c_1 and c_2 are defined as positive constants that represent the acceleration weights associated with personal experience (the individual's best position vector or $pbest$) and social experience (the collective best position vector or $gbest$), respectively. These coefficients determine the extent to which particles are influenced by individual knowledge or collective knowledge [19]. Typically, these coefficients are set between 1 and 2 to achieve a balance between exploration and exploitation in the search space. Another factor, the inertia weight w, controls the influence of a particle's previous velocity. This parameter causes the particles to maintain their previous direction of motion, thereby preventing excessive convergence. By adjusting w (which is usually in the range [0.4, 0.9]), the balance between exploration and extraction is improved. Specifically, larger values of w help increase exploration, while smaller values help improve extraction.

Also, r_1 and r_2 are two independent random variables whose values are generated uniformly in the range [0, 1]. These variables enable the PSO to incorporate randomization into the process of updating particle positions. These random components enable the algorithm to search the solution space dynamically and non-deterministically, helping it avoid getting stuck in local optima. In other words, r_1 and r_2 play a crucial role in enhancing search diversity and improving the algorithm's ability to discover new regions of the solution space. The parameter $pbest$ represents the best previous position of the particle i and $gbest$ represents the best previous position among all particles in the population. The main characteristics of the PSO are defined in Table 3.

Figure 7 shows the number of citations to the PSO based on Google Scholar data. The total citations from 1995 (the year PSO was introduced) to June 2025 have reached 96,248, indicating the widespread and enduring popularity of this algorithm in the scientific community. Over the years, the growth trend of citations to PSO has increased continuously and significantly, especially in the last decade, when its applications have expanded to areas such as machine learning [20], engineering optimization, and data mining. The highest number of citations was recorded in 2022, equal to 6,404 citations, indicating the prominent position and increasing influence of PSO in interdisciplinary research. From 2010 to 2022, the growth of citations has been continuous and accelerated, indicating the increasing popularity of this algorithm as a powerful and versatile optimization tool. The upward trend confirms the innovative role of PSO in solving complex and nonlinear problems in various scientific fields. High flexibility, simplicity in implementation, and fast convergence capability are among the factors that have made the PSO remain one of the most referenced and widely used meta-heuristic algorithms over the past three decades.

Table 4 compares PSO with other algorithms based on total citations and year.

Figure 8 presents a comparison of the trend of the PSO with that of the ant colony optimization (ACO) and differential evolution (DE) algorithms over the last 5 years (2020–2025). The y-axis ranges from 0 to 100. A value of 100 means that an algorithm has had the highest relative popularity (relative to the total searches performed in a week). A value of 50 means that an algorithm has had half the popularity in a week. A value of 0 means that there has been little or no interest in searches. The numbers on the

Table 3 Main characteristics of the PSO

Feature	Explanation	Advantage	Limitation	Type of issues
Algorithm type	Population-based metaheuristic	Suitable for complex and nonlinear problems	No need for parameter tuning	Objective function optimization, machine learning
Inspired	Bird flock movement	An algorithm with two main equations	No precise mathematical modeling	Problems with synergy between variables
Search type	Directed randomness	Power to pass through a local minimum	Possibility of early convergence	Non-convex or multi-point optimal problems
Principal components	Particles, velocity, position, memory	Easy implementation and simple structure	Needs proper manual tuning	Tuning neural network parameters
Objective function	Requires a non-derivative function value	Can be used for complex functions	Slowdown near the exact solution	Noisy data
Optimization type	Single-objective or multi-objective	High flexibility	Complexity in multi-objective design	Feature selection, neural network design
Computational complexity	Linear concerning particles and iteration	Scalable for medium problems	Slowness in huge problems	Low to medium dimensional problems
Key parameters	Number of particles, c_1, c_2, inertial weight	Ability to control algorithm behavior	Difficulty in optimal tuning	Dynamic and responsive algorithms
Parallelization capability	GPU-based	Increase training speed	Requires parallel infrastructure	DL, big data
Convergence	Fast but ultimately slow	High initial speed	Risk of getting stuck in local minima	Time-consuming problems with high evaluation cost

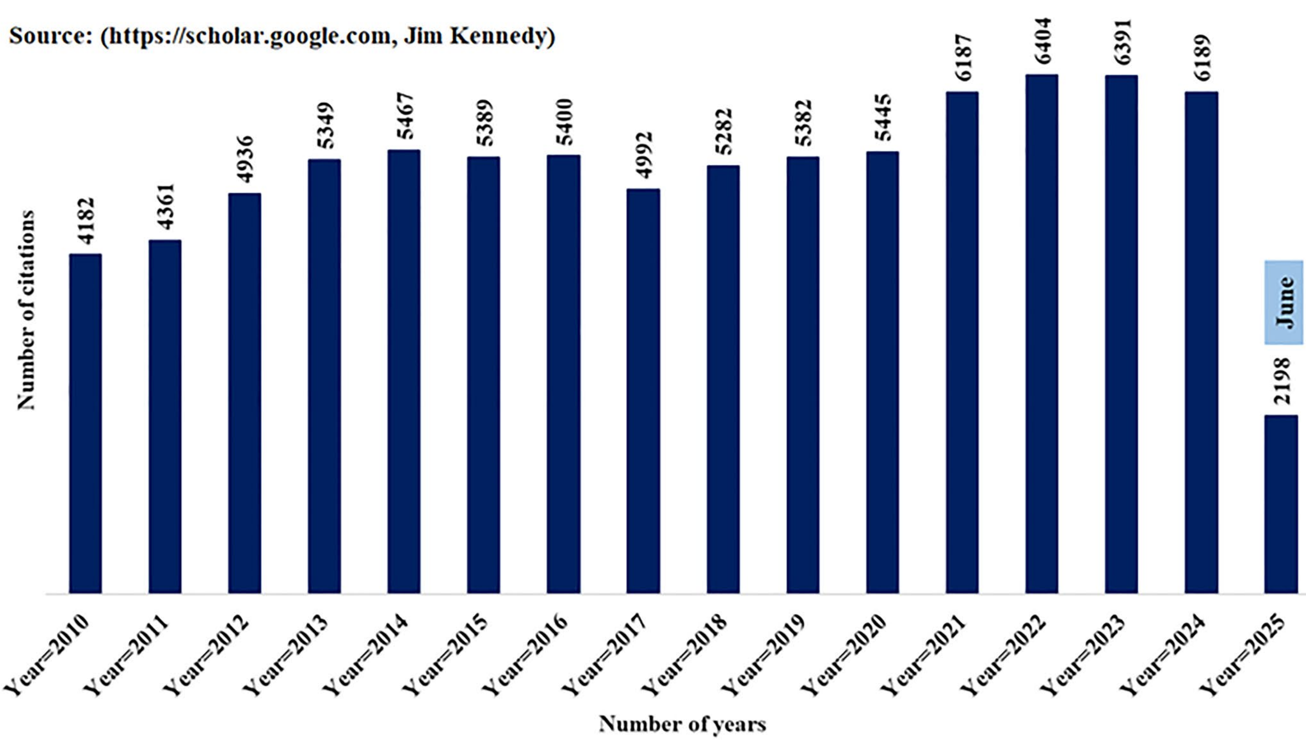


Fig. 7 Number of citations to PSO according to Google Scholar (source: https://scholar.google.com)

y-axis represent a percentage of total searches, not the absolute number of searches.

In Table 5, a comparison is made using the trend percentage between PSO, ACO and DE algorithms based on the last 5 years. The spread column is calculated based on the difference between the highest and lowest percentage (the dispersion index of interest). The variance column displays the percentage difference or dispersion of interest among the three algorithms: PSO, ACO, and DE.

Figure 9 illustrates the trend comparison of the PSO with the ACO and DE algorithms over the last 10 years (2015–2025). The results of the graph indicate that the PSO is more popular than ACO and DE.

Table 4 Comparison of PSO with other algorithms based on total citations and year

Years	Citation total	Other algorithms (abbreviation and citation total)
2014–2025	PSO=68726	grey wolf optimizer (GWO, 19,491) [21], symbiotic organisms search (SOS, 1748) [22], interior search algorithm (ISA, 494) [23], forest optimization algorithm (FOA, 263) [24]
2015–2025	PSO=59259	moth-flame optimization (MFO, 4734) [25], ant lion optimizer (ALO, 3678) [26], lightning search algorithm (LSA, 446) [27], invasive tumor growth optimization (ITGO, 81) [28].
2016–2025	PSO=53870	whale optimization algorithm (WOA, 13,770) [29], sine cosine algorithm (SCA, 5472) [30], dragonfly algorithm (DA, 3022) [31], multi-verse optimizer (MVO, 2964) [32], crow search algorithm (CSA, 2430) [33], water evaporation optimization (WEO, 380) [34], galactic swarm optimization (GSO, 204) [35], electromagnetic field optimization (EFO, 25) [36].
2017–2025	PSO=48470	Salp swarm algorithm (SSA, 5061) [37], grasshopper optimization algorithm (GOA, 2931) [38], thermal exchange optimization algorithm (TEOA,623) [39], satin bower bird optimization (SBO, 318) [40], electro-search algorithm (ES, 102) [41].
2018–2025	PSO=43478	emperor penguin optimizer (EPO, 741)
2019–2025	PSO=38196	Harris hawks optimizer (HHO, 5607) [42], henry gas solubility optimization (HGSO, 990) [43], sailfish optimizer (SFO, 608) [44], biology migration algorithm (BMA, 48) [45].
2020–2025	PSO=32814	slime mould algorithm (SMA, 2730) [46], marine predators algorithm (MPA, 2238) [47], Tunicate Swarm Algorithm (TSA, 1231) [48], manta ray foraging optimization (MRFO, 1004) [49], Political Optimizer (PO, 560) [50], artificial ecosystem-based optimization (AEO, 453) [51], red deer algorithm (RDA, 446) [52], barnacles mating optimizer (BMO, 408) [53], billiards-inspired optimization algorithm (BOA, 132) [54], bear smell search algorithm (BSSA, 65) [55].

Google Trends charts, such as Figs. 8 and 9, do not provide a reliable measure of the scientific importance or credibility of a paper. These graphs show non-academic audiences and industry executives how much attention a topic has received in the public space and among users.

3.2 Long Short-Term Memory

Recurrent neural networks with long-term memory are considered one of the most advanced types of neural networks in the field of time series and sequence data processing. Due to the special structure of memory cells, these networks can effectively identify and maintain long-term dependencies in data. The LSTM network was invented by $Hochreiter$ & $Schmidhuber$ in 1997. Each LSTM cell comprises various components, including input, output, and forget gates, which manage the flow of information in a controlled manner. In the LSTM network, important past information is retained for a more extended period, and unnecessary data is prevented from entering. This capability has made LSTM an ideal choice for problems related to time series forecasting, complex pattern recognition, and long sequence analysis. Numerous studies have demonstrated that LSTM networks outperform other traditional models and specific recurrent neural networks in identifying and modelling long-term relationships. The exact structure and details of the LSTM network are shown in Fig. 10.

The LSTM network has a complex and purposeful structure that includes two transition states and three main gates. These components play a key role in managing and processing information over time. In this architecture, the variable c represents the cell state, which acts as the network's long-term memory. The variable h represents the hidden state. The three important gates of the LSTM network include the Forget Gate, the Input Gate, and the Output Gate. The forget gate determines which parts of the previous information should be discarded; the input gate is responsible for entering new information into the cell state; and the output gate determines what information is transferred from the cell state to the hidden state and finally to the output. Using these control mechanisms, the LSTM network can maintain long-term dependencies in sequential data and overcome the limitations of traditional recurrent neural networks (RNNs) such as the vanishing gradient problem. This capability has made LSTM perform much better in applications such as natural language processing, speech recognition, and time series prediction. The internal calculations of this network are defined by specific mathematical relationships, which are expressed in Eq. (3).

$$\begin{cases} c_t = f_t \odot c_{t-1} + i_t \odot tanh\left(w_c\left[h_{t-1}, x_t\right] + b_c\right) \\ h_t = o_t \odot tanh\left(c_t\right) \\ f_t = \sigma\left(w_f\left[h_{t-1}, x_t\right] + b_f\right) \\ i_t = \sigma\left(w_i\left[h_{t-1}, x_t\right] + b_i\right) \\ o_t = \sigma\left(w_o\left[h_{t-1}, x_t\right] + b_o\right) \end{cases} \tag{3}$$

In this structure, x represents the input sequence; the symbol $\odot$ represents the element-by-element (Hadamard) multiplication between the vectors. The activation function in the output layer is denoted by tanh, which is used to limit the output value to the interval [−1,1]. Additionally, sigma represents the sigmoid function, whose output lies in the interval [0, 1] and serves as a gate to control the flow of

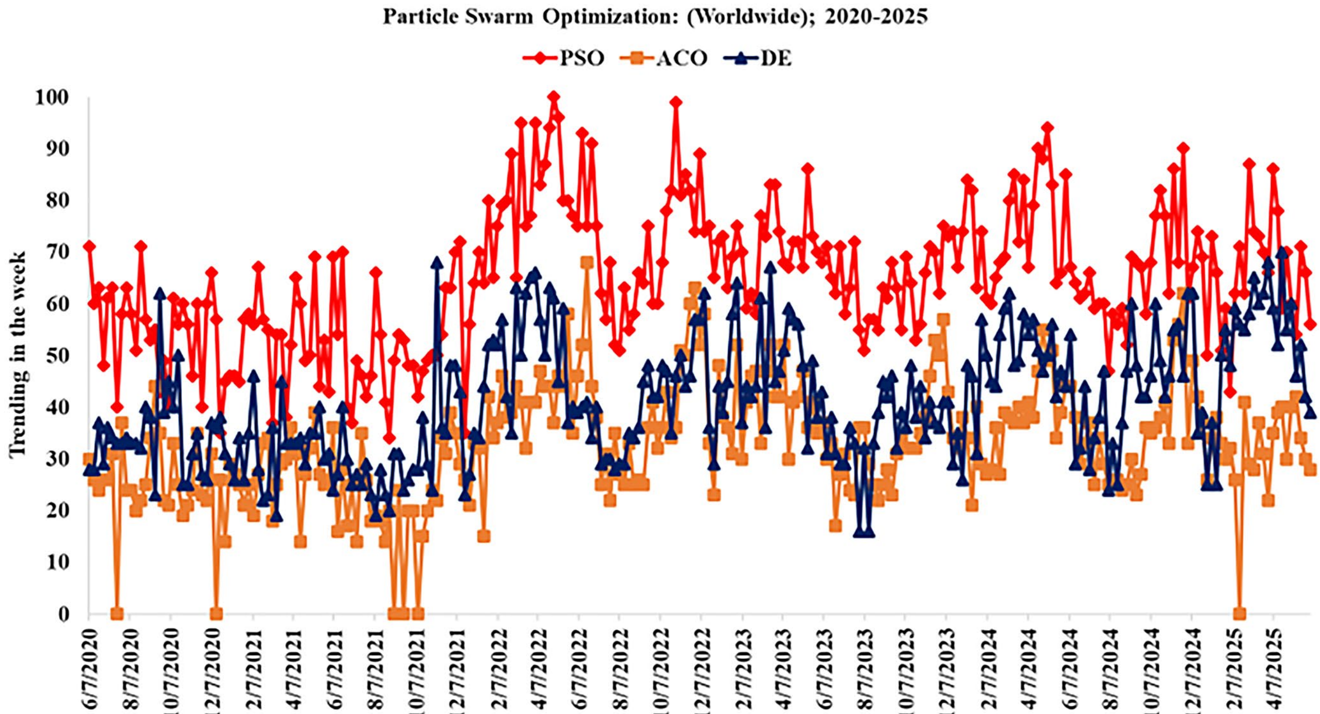


Fig. 8 Comparison of the trend of the PSO with the ACO and DE algorithms based on the past 5 years (2020-June 2025) (source: https://trends.google.com/trends)

information. The weight vector is denoted by w and the bias vector is denoted by b, which are trainable parameters of the network and help fine-tune the model's performance. These concepts are used in defining and calculating the various gates and updating the internal states of the LSTM.

Table 6 shows the number of citations to the original paper of the LSTM, titled Long Short-Term Memory, based on various sources. In 2015, the Semantic Scholar database received 585 citations and in Google Scholar, 736 citations. This trend has increased rapidly in subsequent years; in 2016, the number of citations reached 1922 in Semantic Scholar and 2250 in Google Scholar. In 2018, the number of citations reached 7181 in Semantic Scholar and 8643 in Google Scholar. In 2019, these numbers increased to 9,684 and 12,041, respectively. This upward trend has continued in 2020, with the number of citations reaching 11,350 in Semantic Scholar and 14,714 in Google Scholar. In 2022, the number of citations reached 11,494 in Semantic Scholar and 18,401 in Google Scholar. In 2023, they reached 11,909 and 18,980, respectively. The year 2024 recorded the highest number of citations, reaching 12,896 in Semantic Scholar and 19,959 in Google Scholar. The number of citations in 2025 is not yet complete, but the reported numbers are 5,564 and 7,902, respectively, indicating that 2025 is also approaching previous records.

3.3 Reasons for Combining PSO with LSTM

Compared with algorithms such as Genetic Algorithm (GA) and GWO, the PSO has advantages such as simplicity of implementation, faster convergence speed, and greater flexibility in multi-objective problems. These same features have led to it being combined with LSTM more than other algorithms in recent years and finding wider interdisciplinary applications. Second, the literature related to PSO-LSTM has reached a critical point between 2023 and 2025. Studies in areas such as energy and water resources have reported remarkable success. However, in areas such as financial data or noisy data, some studies have presented contradictory and weaker results. This heterogeneity in the results indicates an urgent need for a critical and analytical review that can reveal gaps and common patterns. Third, the increasing diversity of this model in areas such as engineering, energy, medicine, cybersecurity, and IoT-based systems has reached a stage of conceptual maturity. Therefore, a systematic and critical review is needed to clarify in which circumstances this model works successfully and in which areas it faces limitations.

Combining PSO with LSTM is a powerful approach for solving optimization problems, time series forecasting, and modelling complex systems. LSTM networks, like other neural networks, have numerous parameters and weights, and their performance depends heavily on the optimal

Table 5 A comparison using trend percentage between PSO, ACO, and DE algorithms based on the last 5 years

Countries	Interest percentage in algorithms			Spread (%)	Dominant	Variance (%)
	PSO	ACO	DE			
Lebanon	100%	0%	0%	100	PSO	3333.33
Syria	100%	0%	0%	100	PSO	3333.33
Ethiopia	83%	17%	0%	83	PSO	1922.33
Jordan	74%	0%	26%	74	PSO	1409.33
Kenya	73%	0%	27%	73	PSO	1362.33
Peru	65%	36%	0%	65	PSO	1060.33
Ghana	64%	29%	7%	57	PSO	826.33
Indonesia	63%	13%	24%	50	PSO	690.33
South Africa	62%	25%	13%	49	PSO	652.33
Turkiye	62%	21%	17%	45	PSO	620.33
Saudi Arabia	61%	21%	17%	44	PSO	592
Ecuador	60%	40%	0%	60	PSO	933.33
Tunisia	59%	25%	16%	43	PSO	514.33
South Korea	57%	17%	26%	40	PSO	440.33
Jordan	57%	25%	18%	39	PSO	432.33
Nigeria	57%	25%	18%	39	PSO	432.33
Pakistan	56%	28%	16%	40	PSO	421.33
Iran	56%	25%	19%	37	PSO	394.33
Egypt	56%	27%	17%	39	PSO	410.33
Bangladesh	56%	36%	8%	48	PSO	581.33
Algeria	55%	23%	22%	33	PSO	352.33
Malaysia	55%	29%	16%	39	PSO	394.33
Thailand	55%	21%	24%	34	PSO	354.33
China	53%	17%	30%	36	PSO	332.33
Taiwan	53%	19%	28%	34	PSO	310.33
Hong Kong	52%	18%	30%	34	PSO	297.33
Morocco	52%	32%	16%	36	PSO	325.33
Greece	52%	26%	22%	30	PSO	265.33
Colombia	51%	29%	20%	31	PSO	254.33
Argentina	50%	0%	50%	50	DE	833.33
India	49%	33%	17%	32	PSO	256
Singapore	49%	18%	33%	31	PSO	240.33
Sri Lanka	49%	51%	0%	51	ACO	834.33
Belgium	49%	19%	32%	30	PSO	226.33
Norway	48%	21%	31%	27	PSO	186.33
Finland	48%	18%	34%	30	PSO	225.33
Brazil	48%	21%	31%	27	PSO	186.33
Portugal	47%	28%	25%	22	PSO	142.33
Nepal	47%	53%	0%	53	ACO	842.33
United Arab Emirates	47%	30%	23%	24	PSO	152.33
Italy	47%	17%	36%	30	PSO	230.33
Hungary	47%	29%	24%	23	PSO	146.33
Vietnam	46%	28%	26%	20	PSO	121.33
New Zealand	46%	18%	36%	28	PSO	201.33
Japan	45%	17%	38%	28	PSO	212.33
Sweden	44%	28%	28%	16	PSO	85.33
Germany	44%	21%	35%	23	PSO	134.33
Denmark	43%	22%	35%	21	PSO	112.33
United Kingdom	43%	23%	34%	20	PSO	100.33
Serbia	43%	29%	28%	15	PSO	70.33
Chile	43%	23%	34%	20	PSO	100.33
Spain	43%	23%	34%	20	PSO	100.33
Ukraine	43%	37%	20%	23	PSO	142.33
Netherlands	42%	28%	30%	14	PSO	57.33

Table 5 (continued)

Countries	Interest percentage in algorithms			Spread (%)	Dominant	Variance (%)
	PSO	ACO	DE			
Switzerland	42%	22%	36%	20	PSO	105.33
Austria	41%	26%	33%	15	PSO	56.33
France	41%	22%	37%	19	PSO	100.33
Poland	40%	33%	27%	13	PSO	42.33
Russia	40%	23%	37%	17	PSO	82.33
Philippines	39%	18%	43%	25	DE	180.33
Canada	39%	19%	42%	23	DE	156.33
Australia	39%	18%	43%	25	DE	180.33
Mexico	39%	29%	32%	10	PSO	26.33
Romania	38%	45%	17%	28	ACO	212.33
Czechia	37%	23%	40%	17	DE	82.33
Ireland	36%	36%	28%	8	ACO	21.33
United States	31%	12%	57%	45	DE	510.33
Croatia	28%	25%	47%	22	DE	142.33

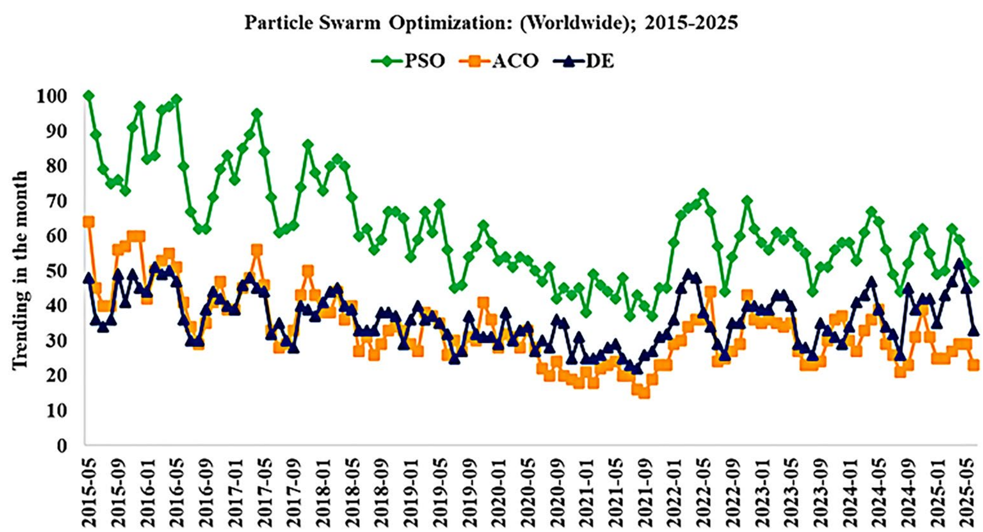


Fig. 9 Comparison of the trend of the PSO with the ACO and DE algorithms based on the past 10 years (2015-June 2025) (source: https://trends.google.com/trends)

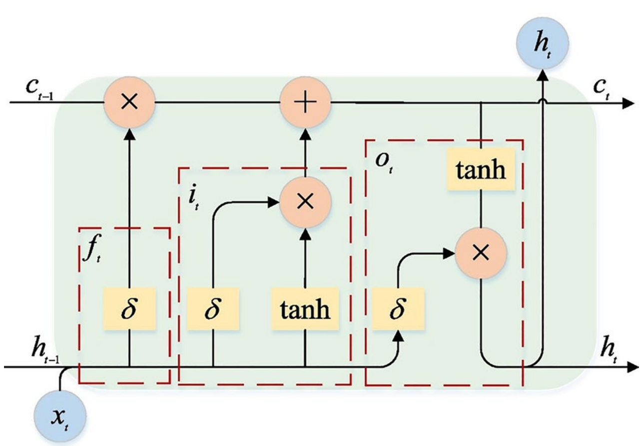


Fig. 10 Detailed structure and details of the LSTM network

Table 6 Number of citations to the original paper of the LSTM based on different sources

Years	Google Scholar	Semantic Scholar	Average
2015	736	585	660
2016	2250	1922	2086
2017	4737	4111	4424
2018	8643	7181	7912
2019	12041	9684	10862
2020	14714	11350	13032
2021	17592	11650	14621
2022	18401	11494	14947
2023	18980	11909	15444
2024	19659	12896	16277
2025	7902	5564	6733

values of these parameters. Typically, LSTM uses gradient-based optimization algorithms, such as Adam, RMSprop, or SGD, for the training process, which can become trapped in local optima. The four main reasons for combining PSO with LSTM are as follows:

Automatic parameter optimization: The PSO algorithm automatically and intelligently adjusts the key parameters of the LSTM, including the learning rate, number of neurons, and number of layers. This saves time and increases the accuracy of the model.

Table 7 Benefits of combining PSO with LSTM

Feature	Explanation	Importance	Limitation
Automatic parameter optimization	Finding optimal values for learning rate and network structure using PSO	Reduce the need for trial and error	Automatic model tuning in stock price prediction
Increase prediction accuracy	Significant increase in LSTM accuracy after optimization with PSO	Improve model performance	Daily electricity consumption prediction
Avoid getting stuck in local minima	Passing local minima and achieving better solutions with PSO	Achieve more accurate results	User behavior modeling in recommender systems
No need for gradients	Ability to use PSO in non-differentiable functions	Suitable for complex functions	LSTM optimization in environments with discrete data
Better performance on noisy data	Increasing model resistance to noise through PSO group search	Increase stability on real data	Analysis of biological signals such as ECG
Model structure tuning	Optimizing the LSTM architecture structure using PSO	Save model design time	Automatic selection of the number of layers in sentiment analysis
Multi-objective optimization	PSO allows for multi-objective optimization, considering factors such as accuracy and execution time.	Balance between efficiency and speed	Application in real-time systems such as the Internet of Things
Model training stability	Reducing oscillations in the model training process using PSO	Prevent overfitting	Long-term weather forecasting
No dependence on accurate initialization	Reducing dependence on accurate initialization in optimization with PSO	Simplify the initial tuning process	Use in industrial environments with incomplete data
Easy parallelization	Ability to run the PSO in parallel on multiple CPUs or GPUs	Increase training speed	Model training in big medical data

Increased prediction accuracy: By utilizing PSO, the LSTM model is more effectively trained, leading to improved prediction accuracy, particularly in time series problems such as stock prices, weather, or energy consumption. Finding the optimal parameter set using PSO results in a reduction in prediction error.

Avoiding getting stuck in a local minimum: Conventional LSTM training methods may converge at points that are not the optimal solution. The PSO increases the probability of reaching the optimal solution (global minimum) due to its random and group search capabilities.

High applicability in real-world problems: The combination of PSO and LSTM is highly efficient and yields accurate results in various real-world applications, including electricity demand forecasting, sentiment analysis, disease diagnosis, and intelligent system control.

Table 7 illustrates the benefits of integrating PSO with LSTM.

Frameworks such as PyTorch and TensorFlow fully support parallel and distributed computing architectures, enabling efficient processing of large datasets. This feature is crucial for hybrid models that require the simultaneous execution of learning operations (such as LSTM training) and hyperparameter search (using PSO). Additionally, the use of visualization tools such as TensorBoard or Matplotlib enables you to visually monitor and analyze the convergence of the optimization algorithm, changes in the objective function, training error, and validation metrics during the learning process. The parameters of an LSTM network play a crucial role in determining its prediction accuracy and overall efficiency. In traditional approaches, these parameters are often set based on human experience and judgment. This results in a significant discrepancy between the actual accuracy of the model and its ideal accuracy. The PSO reduces the dependence on human interventions in parameter adjustment and paves the way for achieving optimal performance. The PSO employs an iterative process to identify a set of optimal parameters that optimize the LSTM network's parameters. Then, based on these values, the LSTM is trained to learn the temporal information in the data effectively. The flowchart of the PSO-LSTM is drawn in Fig. 11.

4 Applications

In this section, the applications of PSO-LSTM in 30 different domains are reviewed. The coverage of 30 domains demonstrates that the PSO-LSTM applies to a wide range of problems. The PSO-LSTM is a powerful solution to challenging problems. The PSO-LSTM has become a versatile and valuable tool in various fields due to the combination

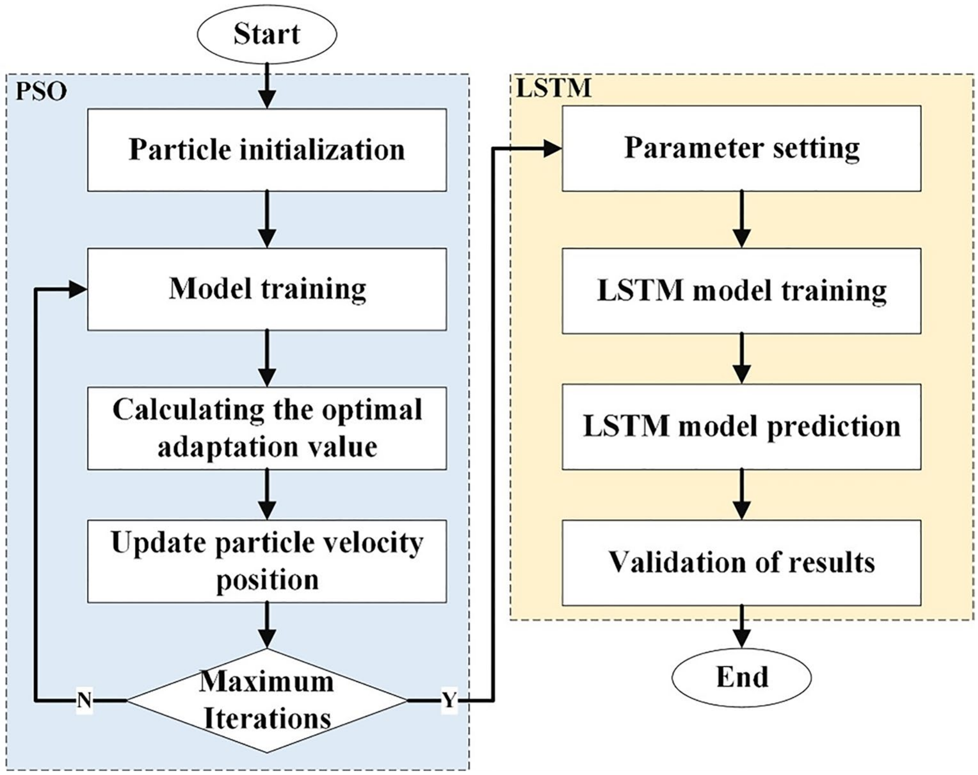


Fig. 11 PSO-LSTM model flowchart

of LSTMs powerful capabilities with the PSO. Table 8 illustrates the application of the PSO-LSTM across various areas by year.

4.1 Air Pollution Prediction

Due to the rapid growth of urbanization and the increase in industrial activities, transportation, and energy consumption, air pollution has become one of the most important environmental challenges in large cities [56]. Air pollution not only negatively impacts the overall health of the community but also poses significant risks to natural ecosystems and environmental sustainability. Therefore, accurate prediction of air quality index (AQI) and concentrations of specific pollutants, such as particulate matter with a diameter of less than 2.5 microns ($PM_{2.5}$), plays a vital role in urban planning, environmental management, and prevention of respiratory and heart diseases [58]. In recent years, machine learning approaches [294], such as intense learning models, have emerged as powerful tools for predicting air quality. These models can recognize complex, nonlinear, and random patterns in temporal air pollution data. However, there are challenges, such as determining the optimal input set, fine-tuning hyperparameters, and effectively integrating multi-source data. In this regard, hybrid models have been considered as a new solution. These models employ a combination of various techniques, including LSTM and BiLSTM networks, as well as metaheuristic optimizers such as PSO. Table 9 describes the application of the PSO-LSTM in the field of air pollution prediction.

Table 11 compares LSTM and PSO-LSTM on air pollution data [57]. PM_{10} refers to particulate matter with a diameter of less than 10 µm. These particles are small enough to enter the upper respiratory tract (nose and throat) and cause problems such as coughing or irritation of the respiratory tract. $PM_{2.5}$ refers to much smaller particles with a diameter of less than 2.5 µm. These particles penetrate deep into the lungs and even the bloodstream and cause more serious health effects, such as heart and lung diseases and even neurological problems. O_3 leads to eye and throat irritation, shortness of breath, exacerbation of lung diseases and damage to plants. The results of comparing the PSO-LSTM, LSTM and Random Forest (RF) models show that the combined PSO-LSTM model performs better than other methods in predicting various pollutants. For $PM_{2.5}$, the MAE error value for PSO-LSTM is 0.0014, which is lower than LSTM (0.00223) and RF (0.00228). For PM_{10}, the MAE value for PSO-LSTM is 0.0037, while LSTM and RF recorded errors of 0.00487 and 0.00475, respectively. The results for O_3 also confirm the superiority of PSO-LSTM.

4.2 Battery SOH Prediction

In modern electric transportation and energy storage systems, accurate prediction of lithium battery State of Health (SOH) [62] plays a vital role in ensuring the performance,

Table 8 The application of the PSO-LSTM in different areas based on the year

Applications	Refs	2019	2020	2021	2022	2023	2024	2025
Air pollution prediction	[56–61]	-	-	-	-	1	3	2
Battery SOH prediction	[62–66]	-	-	-	-	1	1	3
Classification	[67–72]	-	-	-	-	3	2	1
Cloud computing	[73, 74]	-	-	1	-	-	-	1
Cybersecurity	[75, 76]	-	-	-	1	1	4	-
Deformation prediction	[77–82]	-	-	-	1	1	4	-
Electric vehicles	[83–85]	-	-	-	-	1	-	2
Energy management and analysis	[86–92]	-	-	1	-	1	3	2
Engineering system design	[93–99]	-	-	-	-	-	-	7
	[100–113]	-	-	-	-	-	14	-
	[114–128]	-	-	-	-	15	-	-
	[129–132]	-	1	2	1	-	-	-
Hydrological time series	[133–135]	-	-	-	-	1	1	1
Image processing	[136, 137]	1	1	-	-	-	-	-
Industrial robot	[138–142]	-	1	-	-	-	3	1
Intrusion detection	[143–154]	1	-	2	-	1	3	5
Internet of Things	[155, 156]	-	-	-	-	-	1	1
Medical industry	[157–163]	-	1	-	1	2	2	1
Natural language processing (NLP)	[164–166]	1	1	1	-	-	-	-
Oil and gas industry	[167–177]	1	1	2	1	1	5	2
Photovoltaic power prediction	[178–181]	-	-	-	-	-	2	2
Predictive maintenance	[182–190]	-	1	-	1	-	2	5
Renewable energy optimization	[191–196]	-	-	-	-	1	3	2
Risk assessment	[197–199]	-	-	-	-	1	1	1
Runoff prediction	[200–202]	-	-	1	2	-	-	-
Signal processing	[203–211]	1	1	-	1	1	2	3
State of Charge (SOC) estimation	[212–216]	-	-	-	-	2	2	1
Stock price forecasting	[217–228]	1	-	2	3	2	3	1
Time series forecasting	[229–232]	-	-	-	-	-	-	4
	[233–243]	-	-	-	-	-	11	-
	[244–250]	-	-	-	-	7	-	-
	[251–260]	1	3	2	4	-	-	-
Traffic flow management	[261–266]	-	-	1	1	1	1	2
unmanned aerial vehicles (UAVs)	[267, 268]	-	-	-	-	-	1	1
Water resources management	[269–281]	1	-	1	1	5	4	1
Wind speed forecasting	[282–293]	2	1	1	1	5	1	1

safety, and lifespan of battery-based systems. Given the nonlinear behavior of batteries and the time dependence of various factors such as temperature, capacity, and internal resistance, developing accurate and robust models for estimating SOH is considered one of the important challenges in the field of battery management. In this regard, artificial intelligence-based approaches and intense neural networks have been proposed as powerful tools for identifying complex failure patterns and predicting battery degradation. Hybrid models based on PSO and LSTM have been proposed to estimate the SOH of lithium batteries [57] accurately. In these models, multidimensional health indicators are first extracted from voltage, current, and temperature curves during charge and discharge cycles. Then, using the Pearson correlation coefficient, the most effective features are selected to train the model.

In the SOH problem, the battery charge and discharge cycle data have nonlinear, unstable and noisy behaviors. These characteristics cause gradient algorithms such as Adam or SGD to often get stuck in local minima and the optimization of LSTM parameters is incomplete. In such situations, PSO provides the ability to bypass local minima and achieve more stable responses. For example, studies on lithium-ion battery data have shown that PSO significantly reduced the RMSE error by automatically adjusting the learning rate and the number of hidden layer neurons.

4.3 Classification

Classification includes issues such as image pattern recognition [67], classification of biological signal types, classification of ship types based on AIS data, as well as classification

Table 9 Application of the PSO-LSTM in the field of air pollution prediction

Refs	Application	Goals	key findings	Disadvantages	Publisher	Year
[56]	The hybrid approach is implemented using real-world pollution data collected from Tangshan and Beijing	PSO has successfully optimized the weights of the LSTM network.	RMSE values of 6.407 for Tangshan and 7.485 for Beijing are obtained.	Missing data in time series is often ignored or improperly addressed in many existing studies.	Elsevier	2025
[57]	The PSO-LSTM is applied to predict the concentrations of PM2.5, PM10, and O_3 using hybrid DL techniques.	PSO is integrated with LSTM to enhance parameter tuning in air pollutant forecasting.	The PSO-LSTM model outperforms both Random Forest and standard LSTM models in predicting PM2.5 levels.	PSO can sometimes converge prematurely.	Elsevier	2025
[58]	Quantum PSO (QPSO) is used to optimize the hyperparameters of the LSTM for AQI prediction.	A key goal is to address the limitations of traditional models in capturing nonlinear and stochastic patterns in air pollution data.	The use of QPSO has enhanced the convergence speed and parameter optimization of the LSTM network.	Missing or inconsistent data in environmental monitoring systems can degrade the effectiveness of predictive models.	Springer	2024
[59]	DL techniques have been applied to improve the accuracy of AQI and PM2.5 concentration forecasts.	PSO has been employed to optimize hyperparameters in the hybrid DL model, thereby enhancing its performance.	PSO-based optimization has enhanced the convergence speed and stability of DL models in AQI prediction.	Delays have hindered the real-time implementation of advanced models in data acquisition and processing.	Springer	2024
[60]	Modified PSO (MPSO) has been integrated with DL models to improve AQI forecasting accuracy.	The primary objective has been to predict the AQI for 15 major metropolitan cities in India.	The MPSO-LSTM-$BiRNN$ model has achieved an MSE of 0.000184, RMSE of 0.0135, mean absolute error (MAE) of 0.0088, and MAPE of 27.69%.	Hybrid models have become increasingly complex.	Elsevier	2024
[61]	Accurate air pollution forecasting has been used to support urban planning and promote environmental sustainability.	PSO and the Sparrow search algorithm (SSA) have been integrated with LSTM networks to enhance prediction accuracy.	In Batu Muda, the proposed model has reduced RMSE by 2.65% and MAE by 9.31% compared to existing models.	The integration of neighboring station data has increased model complexity and computational cost.	Elsevier	2023

In Table 10, a comparison of PSO-LSTM models in the field of air pollution prediction based on analytical indicators has been made. The results show that advanced models such as QPSO-LSTM and MPSO-LSTM have higher accuracy and stability. But they are also heavier in terms of complexity and parameter sensitivity. In contrast, simpler models such as PSO-LSTM have a better balance between efficiency and scalability and can be used in more diverse domains

Table 10 comparison of PSO-LSTM models in the field of air pollution prediction based on analytical indicators

Refs	Models	Domain Generalizability	Parameter Sensitivity	Complexity Level	Real-time Applicability	Robustness / Stability
[56]	PSO-LSTM	High	Medium	Medium	Medium	Medium
[57]	PSO-LSTM	High	Medium-High	Medium	Medium	Medium-High
[58]	QPSO-LSTM	Medium	High	High	Medium	High
[59]	PSO-LSTM	Medium-High	Medium	Medium	Low-Medium	Medium
[60]	MPSO-LSTM	Medium	High	High	Medium	High
[61]	PSO-SSA-LSTM	Medium	Medium-High	High	Medium	High

Table 11 Comparison of LSTM and PSO-LSTM on air pollution data

Type	Evaluation criteria	RF	LSTM	PSO-LSTM
PM2.5	MAE	0.00228	0.00223	0.0014
	RMSE	0.00466	0.00419	0.0033
	R^2	0.8356	0.8447	0.9486
PM10	MAE	0.00475	0.00487	0.0037
	RMSE	0.00847	0.00893	0.0077
	R^2	0.8299	0.8221	0.9419
O3	MAE	0.02394	0.02479	0.0113
	RMSE	0.02953	0.0304	0.0184
	R^2	0.8659	0.8629	0.9698

of the functional status of power system elements such as insulators and antennas. In all of these cases, accuracy, speed, and reliability play crucial roles in system classification. Table 12 describes the application of the PSO-LSTM in the field of classification.

4.4 Cloud Computing

Cloud computing systems have been required to optimize resource utilization in response to the growing demand for

Table 12 Application of the PSO-LSTM in the field of classification

Refs	Application	Goals	key findings	Disadvantages	Publisher	Year
[67]	Monitoring agricultural pests in real-time using DL-based classification systems.	Developing a robust framework capable of functioning in complex environmental conditions.	Achieving 91.2% classification accuracy using a hybrid PSO-CNN architecture.	Relying on $ConvLSTM$ and adaptive layers potentially introducing latency in specific applications.	Elsevier	2025
[68]	Applying 3D CNNs for spatiotemporal feature learning in video authenticity classification.	Developing a novel PSO algorithm incorporating multiple enhancement strategies for global search efficiency.	Optimizing CNN-RNN topologies and 3D CNN hyper-parameters using the enhanced PSO approach.	Facing scalability challenges when applied to ultra-high-resolution or long-duration video sequences.	Elsevier	2024
[69]	Classifying real-time leakage currents to prevent pollution flashover in high-voltage transmission systems.	Capturing temporal dependencies in leakage current data through LSTM-based sequence modeling.	Proving the effectiveness of IPSO in optimizing hyperparameters for LSTM-CNN model configurations.	Increasing computational complexity due to the integration of LSTM and CNN components.	Elsevier	2024
[70]	Predicting landslide displacement using LSTM neural networks enhanced with optimized hyperparameters.	Balancing exploration and exploitation in PSO using fuzzy multi-attribute decision-making.	Successfully integrating feature selection and hyperparameter optimization within a unified framework for LSTM modeling.	Needing extensive calibration to achieve optimal balance between exploration and exploitation phases.	Springer	2023
[71]	Classifying maritime vessels using location and movement data from automatic identification systems (AIS).	Introducing a boosted version of PSO (BPSO) for more efficient search processes.	Reaching a mean square error (MSE) of 0.000098 in vessel trajectory prediction using LSTM.	Showing sensitivity to missing or noisy data points that may affect both classification and forecasting tasks.	MDPI	2023
[72]	Classifying motor imagery tasks using adaptive frameworks based on evolutionary algorithms.	Enhancing model performance through parameter tuning using GA and PSO.	Reaching 81.4% accuracy with CNN-LSTM	There are limitations in real-time implementation due to model complexity and processing latency.	Wiley	2023

scalable services [73]. A hybrid ensemble meta-learning framework based on PSO has been proposed for predicting dynamic cloud workloads. In this framework, PSO is used to optimize the weights assigned to the inputs of the LSTM, leading to improved predictive performance. LSTM-based DL models have been applied for time-series forecasting of cloud load to improve resource allocation efficiency [74]. Variational Mode Decomposition (VMD) has been employed to preprocess complex time-series data for enhanced forecasting accuracy. The performance of LSTM models with and without attention layers has been evaluated for cloud load forecasting. The modified PSO algorithm has been used to optimize the hyperparameters of the LSTM-based models. Experimental results have shown significant improvements in mean squared error (MSE), R^2 coefficient, MAE, and index of agreement.

4.5 Cybersecurity

Protecting confidential information, controlling access, and preventing intrusion into systems have always been considered significant challenges in the field of cybersecurity. With the rise of advanced threats, including sophisticated malware, manipulation of cryptographic algorithms, and intrusions into critical infrastructures, there is a growing need for intelligent and advanced approaches to analyzing security data. Hybrid models based on DL have shown high efficiency, especially in the field of threat identification, attacker behavior analysis, and optimization of cryptographic systems [75, 76]. One effective method in this field is the use of a hybrid model combining PSO with LSTM. This model, capable of learning complex temporal patterns in security data, is used to identify intrusions, analyze suspicious traffic, and detect anomalies in cryptographic processes. In cryptography, the PSO-LSTM is employed to evaluate the authenticity of encrypted transactions, detect attempts to breach codes, and identify weaknesses in cryptographic algorithms. For example, in examining the security of encrypted channels or key exchange algorithms, LSTM can identify unusual time patterns and provide reliable performance through parameters optimized by PSO. Additionally, when analyzing malware that seeks to bypass cryptographic algorithms, this model can detect unauthorized activities with high accuracy, based on either source code or behavioral data.

4.6 Deformation Prediction

In recent years, with the expansion of construction projects in areas with complex geotechnical conditions, the importance of accurately predicting deformations of rock and soil environments, especially in tunnels and deep excavations, has become essential [79]. In this context, intelligent models and deep learning networks have been considered as advanced tools for predicting nonlinear and unstable deformation behavior. The most commonly used methods include LSTM and GRU models, which are well-suited to process complex time sequences and uncover hidden patterns in deformation dynamics data. Additionally, PSO has been employed to enhance their performance and mitigate the inherent uncertainties in measurements from geological environments. This integrated approach is designed to enhance the accuracy and stability of forecasting under various conditions by optimizing the initial parameters of forecasting models, while strengthening their convergence capability. These methods have successfully managed challenges such as noise in the measured data, instability in time sequences, and high dependence on initial conditions.

The proposed approaches have found wide application in challenging environments such as shallow tunnels in clay zones, deep excavations in unstable soils, and underground roads at high altitudes and great depths. These models can consider the effects of various environmental, structural, and temporal factors in the prediction process due to their ability to manage both local and global parameters. As a result, researchers and engineers can predict deformations more accurately without the need for complex mechanical models. Also, the use of signal decomposition methods such as VMD (Variable Mode Analysis) along with intelligent models has effectively helped to improve the prediction accuracy [77]. By decomposing the original data into static and stable underlying components, these methods have enabled the identification of hidden relationships and temporal patterns, thereby improving the performance of prediction models. Overall, these integrated models and methods, as modern and efficient tools in the field of geotechnical engineering and underground structures, have solved the challenges in predicting ground deformations with high accuracy and reliability. Table 13 describes the application of the PSO-LSTM in the field of deformation prediction.

4.7 Electric Vehicles

PSO-LSTM is used to optimize energy management and accurately estimate the charging status and energy consumption in electric vehicles. The model simulates the complex dynamics of battery charging and discharging based on driving patterns, temperature, and road conditions [83]. PSO-LSTM significantly enhances the accuracy of estimates and predictions, which directly impacts the efficiency

Table 13 Application of the PSO-LSTM in the field of deformation prediction

Refs	Application	Goals	key findings	Disadvantages	Publisher	Year
[77]	Monitoring vertical deformation in tidal flat terrains using MEMS sensor arrays	Predicting periodic and trend components of vertical deformation (VD) using LSTM	Validating the hybrid PSO-VMD-LSTM model showed consistent performance with RMSE <0.15 and $R^2>0.90$	Processing large volumes of time-series VD data demands high computational power and extended processing times	IEEE	2024
[78]	Predicting deformation behavior in deep foundation pits using advanced machine learning techniques.	Improving the accuracy of deformation prediction in complex geotechnical environments.	Reducing computational time while maintaining high prediction precision in multi-step forecasting.	Incurring complexity in model implementation due to the integration of multiple algorithms.	MDPI	2024
[79]	Analyzing deformation behavior in tunnel portal slopes located in weak and water-rich geological conditions	Improving prediction accuracy of slope displacement using hybrid PSO-LSTM modeling techniques.	Achieving high prediction accuracy with the PSO-LSTM ($R^2=91\%$).	Lacking generalization potential without recalibration for tunnels in different geological settings.	MDPI	2024
	Applying multifractal theory to characterize the fluctuation features of tunnel deformation data.	Enhancing the accuracy and stability of tunnel settlement forecasting through model optimization.	Demonstrating the superior performance and stability of the PSO-LSTM in predicting tunnel settlement.	This requires extensive preprocessing of raw deformation data before applying multifractal analysis.	MDPI	2024
[81]	Isothermal deformation experiments are conducted to investigate the hot working behavior of Hastelloy C276 alloy.	Developing accurate models for simulating and forecasting the hot deformation characteristics of Hastelloy C276.	The PSO-optimized LSTM model demonstrates superior prediction accuracy compared to the physics-based constitutive model.	Encountering difficulties in modeling extreme deformation conditions not covered in training data.	MDPI	2023
[82]	Predicting roadway deformation to support information-based construction in high-altitude and deep-buried soft rock environments.	Integrating PSO with LSTM to enhance predictive performance in complex geological conditions.	Demonstrating that the PSO-LSTM achieves higher prediction accuracy compared to traditional models.	Requiring continuous maintenance and calibration of monitoring systems in harsh, high-altitude environments.	Wiley	2022

of the battery management system (BMS), increases the vehicle range, and improves the user experience. Table 12 describes the application of the PSO-LSTM in the field of electric vehicles. The detailed applications are summarized in Table 14.

4.8 Energy Management and Analysis

The PSO-LSTM is used in energy optimization in smart buildings, industrial networks, and power distribution systems [86]. PSO-LSTM models capture complex and dynamic consumption patterns by accurately predicting hourly energy demand. These predictions are essential for optimal resource allocation, generation scheduling, implementing demand response strategies, and identifying opportunities for energy savings. PSO increases the accuracy of the hybrid model in adapting to sudden and seasonal changes in energy consumption. Table 15 describes the application of the PSO-LSTM in the field of energy management and analysis.

4.9 Engineering System Design

The PSO-LSTM is utilized in the design phase of engineering systems to predict the system's future performance under various operating conditions. For example, in the design of control systems, it is used to predict the system's response to specific inputs or environmental disturbances. By analyzing simulation data or prototype tests, this model helps designers optimize the performance of the system before physical construction. An advanced aerodynamic prediction framework based on the combination of an LSTM network and a PSO is presented [119]. The primary objective of this approach is to accurately model aerodynamic forces under transient and variable conditions and to extract flight dynamic derivatives with high precision and computational efficiency. The PSO-LSTM model can predict dynamic derivatives with an error of less than 1% compared to linear analyses. Additionally, compared to traditional numerical methods, the PSO-LSTM model achieves a nearly 70% increase in computational speed. One of the highlights of this approach is its ability to achieve high generalization even in conditions with limited training data, making it an effective tool for predicting aerodynamic characteristics in complex and variable scenarios.

In order to accurately analyze the resistance of a wheel loader in contact with soil masses, a hybrid model based on PSO-LSTM is presented [114]. A correct understanding of the resistance plays an important role in preventing wheel slippage, reducing excess energy consumption, and increasing the useful life of mechanical components. In order to increase the accuracy and stability of the model, the hyperparameters of the LSTM are optimized using the PSO. Numerical results show that the PSO-LSTM performs better than the LSTM in terms of prediction accuracy, numerical stability, generalizability, and noise resistance.

4.10 Hydrological Time Series

The PSO-LSTM is utilized to predict hydrological phenomena, including river discharge, dam water levels, and rainfall. It predicts complex and nonlinear patterns caused by climate change, seasonality, and extreme climate events. The PSO-LSTM [269] is a crucial tool for developing hydrogeological forecasting models and making informed, sustainable decisions in the management of the most vital natural resource. Accurate groundwater level prediction will directly contribute to optimizing water management, increasing resilience to climate change, and ensuring water security for future generations.

4.11 Image Processing

One of the fundamental and long-standing challenges in the field of signal and image processing is the denoising of medical images. A new model for denoising is designed

Table 14 Application of the PSO-LSTM model in the field of electric vehicles

Refs	Application	Goals	key findings	Disadvantages	Publisher	Year
[83]	Integrating electric vehicles into power systems to support dynamic grid scheduling and infrastructure planning.	Utilizing hybrid PSO-LSTM models for accurate and adaptive load forecasting in seasonal variations.	A decrease of 6.57% in MAE	Depending heavily on the quality and preprocessing of input time-series data.	MDPI	2025
[84]	Administering lithium-ion batteries to enhance the performance and longevity of electric vehicles.	Developing reliable battery management systems	Optimizing DL architectures for better convergence and generalization in battery forecasting.	Suffering from overfitting risks when models are trained on insufficient or non-representative battery cycles.	MDPI	2025
[85]	Implementing model predictive control strategies for motion control in distributed drive electric vehicles.	Improving the driving experience by optimizing motion control parameters across different driving modes.	Confirming the ability of the LSTM to classify driving feel under various control configurations.	high computational	MDPI	2023

Table 15 Application of the PSO-LSTM model in the field of energy management and analysis

Refs	Application	Goals	key findings	Disadvantages	Publisher	Year
[86]	Prediction of the remaining useful life of lithium	Optimizing model parameters through PSO	PSO enhances convergence and generalization	Evaluating model performance depends heavily on the quality and representativeness of the test dataset.	MDPI	2025
[87]	Develop an advanced framework to detect unusual patterns in electricity usage	Combining PSO with LSTM to enhance prediction reliability.	Detecting irregular electricity usage behaviors with greater efficiency compared to baseline models.	Highly dependent on precise parameter configuration for optimal results.	world scientific	2025
[88]	Tackling complex urban rail energy demand patterns using an integrated model.	Integrating $LightGBM$ and LSTM models to improve prediction accuracy.	Minimizing prediction errors in nonlinear and non-stationary environments.	Challenging model maintenance and updating	Springer	2024
[89]	This study combines PSO, LSTM, GRU, and PID control to improve real-time prediction of hydraulic system positioning.	Employing PSO for optimizing neural network hyperparameters	Reducing energy consumption through intelligent prediction-driven control strategies	Increasing system complexity through the integration of multiple algorithms	MDPI	2024
[90]	Energy consumption estimation based on motor efficiency and driving patterns.	Enhancing driving mileage by reducing energy consumption during vehicle operation	Reducing average energy consumption by 11.11% using the proposed framework	Requiring large-scale data to train accurate LSTM-based trajectory prediction models	Elsevier	2024
[91]	Forecasting customer-side electricity load using LSTM	Intelligent energy storage allocation to reduce annual electricity costs.	Solving the cost minimization problem with PSO	Requiring high-quality historical and real-time data for proper load prediction	MDPI	2023
[92]	Forecasting short-term heat pump electricity loads using LSTM models	Developing an optimized energy management strategy by combining neural networks with PSO	Demonstrating the superiority of LSTM over classical and machine learning models	Achieving the lowest average MAPE of 1.59% using LSTM for test datasets	Elsevier	2021

based on the combination of LSTM and PSO [137]. Lung CT scan images are input into the system, and the PSO algorithm is used to determine the optimal size of the dataset. To improve the denoising process and reduce internal variations in the data distribution, the LSTM-based batch normalization technique is employed. The performance of the proposed model is evaluated based on standard criteria, including the peak signal-to-noise ratio (PSNR) and the mean square error (MSE). The experimental results show that this method has higher efficiency and accuracy compared to other conventional denoising algorithms. Therefore, this model has considerable potential for enhancing the quality of medical images and improving the accuracy of clinical diagnoses. Figure 12 depicts the steps of the PSO-LSTM model for image classification.

4.12 Industrial Robot

In industrial robotics, PSO-LSTM is used to predict robot trajectories, mechanical errors, and the states of robot joints based on time-series sensor data. PSO-LSTM facilitates optimal motion planning, predictive maintenance, and improves both the accuracy and safety of robotic operations. In the rehabilitation process of patients with lower limb motor disorders, accurate and real-time recognition of the individual's movement plays a key role in increasing the effectiveness of human-robot interaction. The input of the PSO-LSTM includes multi-channel electromyographic signals from the muscles of the thigh and knee region [138]. These signals represent the electrical patterns of the muscles during the execution of joint flexion and extension movements, providing accurate information about the patient's motor intention. After training the PSO-LSTM using the data, the network output includes continuous and real-time estimates of the angles of the hip and knee joints. This output is directly injected into the control module of the rehabilitation robot to generate precise torque or position commands by the patient's intention. The high prediction accuracy of the PSO-LSTM reduces latency, enhances coordination between human and robot movements, and improves safety during the rehabilitation process.

4.13 Intrusion Detection

In intrusion detection systems (IDS), the combination of PSO and LSTM is suitable for environments such as Internet of Things (IoMT) networks [143], wireless sensor networks [147], and mobile ad hoc networks [145] with heterogeneous and dynamic data. Other application areas of PSO-LSTM include analyzing traffic flows in wireless

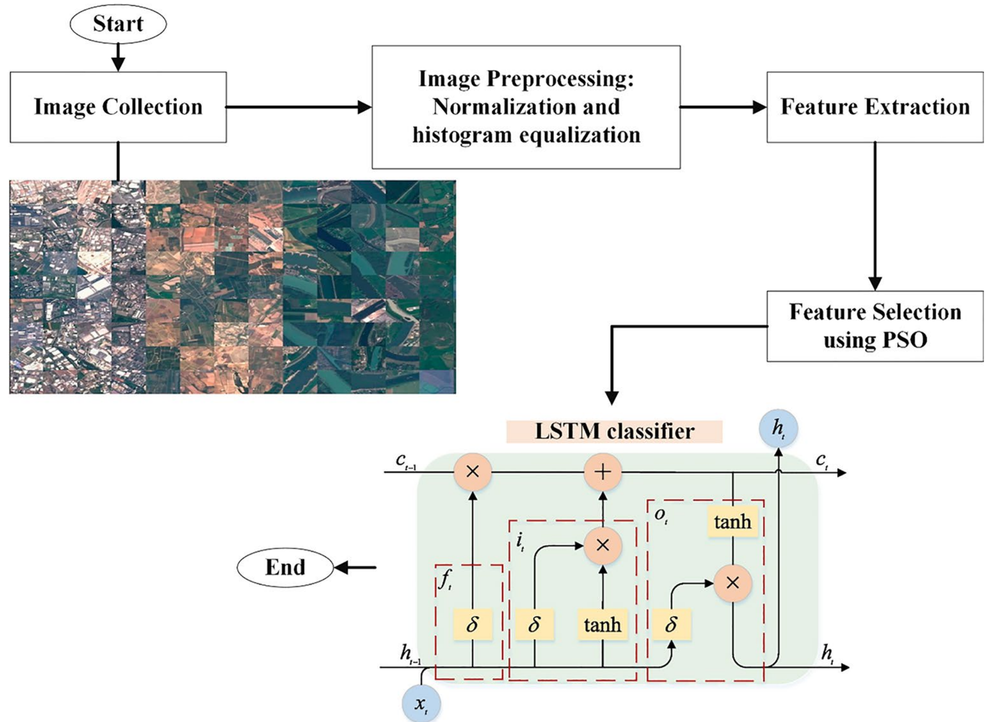


Fig. 12 The steps of the PSO-LSTM model for image classification [136]

networks, detecting malicious nodes in mobile networks, and detecting suspicious activities in systems without infrastructure. Another application of the PSO-LSTM model is in designing low-latency threat detection systems in high-traffic networks. In this regard, PSO, by dynamically and automatically adjusting the parameters of the LSTM model, enables the implementation of lightweight and fast systems with real-time execution. Ultimately, the application of PSO-LSTM in security systems serves as a comprehensive solution, enhancing network security levels, facilitating the early detection of complex attacks, and improving the overall performance of intrusion detection and cyber defense systems. The pseudocode of the PSO-LSTM model for intrusion detection, as expressed in algorithm (1), is presented.

Table 16 The advantages and disadvantages of the PSO-LSTM model in the field of IoT

Properties	Features	Description
Advantages	Increasing prediction accuracy	PSO helps optimize LSTM parameters, thereby increasing the model's accuracy in predicting sequences.
	Reducing energy consumption	In network applications, more accurate predictions lead to the optimal use of limited energy resources.
	Increasing adaptability to dynamic conditions	PSO can quickly adapt to environmental and network changes in LSTM learning.
	Identifying complex and nonlinear patterns	The ability of LSTM to understand temporal dependencies and PSO is effective in adjusting the model's structure.
	Improving stability in decision-making	In routing and resource allocation, decisions made through the model are less volatile.
	Application in network security	The ability to identify threats and anomalies in IDSs is a key predictor of accurate and predictable results.
Disadvantages	Need to tune sensitive parameters.	Incorrect PSO settings (such as population size or inertia weight) may lead to poor convergence.
	High initial energy consumption in the training phase	Especially in nodes with limited resources.

Algorithm 1: Pseudocode of the PSO-LSTM model for intrusion detection

```
01: Start
02: Reading intrusion detection datasets
03: Define hyperparameter search space using PSO
3.1. Define bounds
  {
  learning_rate: [0.0001, 0.01],
  num_units: [50, 200],
  batch_size: [16, 128],
  num_layers: [1, 3],
  dropout: [0.0, 0.5]
  }
3.2. position =
  [
  random.uniform(0.0001, 0.01)
  random.randint(50, 200)
  random.randint(16, 128)
  random.randint(1, 3)
  random.uniform(0.0, 0.5)
  ]
3.3. velocity =
  [
  random.uniform(-0.001, 0.001)
  random.uniform(-15, 15)
  random.uniform(-11.2, 11.2)
  random.uniform(-1, 1)
  random.uniform(-0.05, 0.05)
  ]
04: Initialize PSO parameters
    swarm_size = N
    max_iterations = T
    inertia_weight = w
    cognitive_coeff = c1
    social_coeff = c2
05: Initialize swarm
For each particle i in swarm:
  Randomly initialize position[i] within bounds
  Initialize velocity[i] = 0
  Evaluate fitness[i] = Evaluate_LSTM(position[i])
  personal_best[i] = position[i]
  personal_best_score[i] = fitness[i]
  global_best = particle with best personal_best_score
06: PSO main loop
For iteration in 1 to max_iterations:
  For each particle i:
6.1. Update velocity
    For each dimension d in hyperparameters:
      r1, r2 = random numbers in [0, 1]
      velocity[i][d] = (
        w * velocity[i][d]
        + c1 * r1 * (personal_best[i][d] - position[i][d])
        + c2 * r2 * (global_best[d] - position[i][d])
      )
6.2. Update position
    position[i] = position[i] + velocity[i]
    Adjust to bounds (position[i] within bounds)
6.3. Evaluate fitness
    fitness[i] = Evaluate_LSTM(position[i])
6.4. Update personal best
    If fitness[i] < personal_best_score[i]:
      personal_best[i] = position[i]
      personal_best_score[i] = fitness[i]
6.5. Update global best
    If fitness[i] < best_global_score:
      global_best = position[i]
      best_global_score = fitness[i]
07: Final model training with optimal hyperparameters
08: Train the final LSTM model using the global best hyperparameters
09: Return the final trained model and performance
```

4.14 Internet of Things

In the IoT ecosystem, the PSO-LSTM model is used to predict device behavior patterns, energy consumption, sensor status, or anomaly detection in large, real-time data streams. IoT data is often noisy and has complex temporal dependencies. LSTM models these patterns, and PSO performs optimization to ensure high performance in distributed and scalable IoT environments. Routing optimization with quality of service (QoS) in Internet of Things (IoT) networks has been performed by PSO-LSTM [155]. LSTM is used to intelligently predict future path behavior and network load. This prediction helps in improving convergence and stable parent selection. PSO is responsible for automatically tuning parameters and optimizing routing and scheduling processes. Table 16 presents the advantages and disadvantages of the PSO-LSTM model in the field of IoT.

4.15 Medical Industry

The PSO-LSTM model is used in the analysis of time-series medical data such as electrocardiogram (ECG) signals for diagnosing heart diseases, electroencephalogram (EEG) signals for diagnosing epilepsy or sleep patterns, as well as predicting the progression of diseases (such as Alzheimer's). Epilepsy is a common neurological disorder caused by abnormal activity of brain neurons [158]. EEG signals are usually used to diagnose this disorder. The analysis and interpretation of these signals, particularly in the early stages of diagnosis by humans, are often prone to errors. The combination of fuzzy clustering (FCM), PSO, and LSTM has been proposed as FCM-PSO-LSTM for epilepsy diagnosis. The second model is a direct combination of the PSO algorithm with LSTM, referred to as PSO-LSTM. In both models, PSO is responsible for optimizing the LSTM network's parameters to enhance the model's performance in the early detection of epileptic seizures. The experimental results show that both models have excellent performance in the early detection of epileptic seizures related to stress and anxiety. The PSO-LSTM model has recorded accuracies of 97% and 98.5%, respectively. Figure 13 depicts the steps of PSO-LSTM in the medical industry.

4.16 Natural Language Processing (NLP)

In NLP, LSTM is widely used to model sequences of words in text. PSO-LSTM is used in applications such as machine translation, text generation, sentiment analysis, and text summarization [164]. PSO improves the model's performance in learning grammatical and semantic dependencies in long sentences and documents by optimizing the LSTM parameters (e.g., the number of LSTM units and the learning rate). By using language modeling techniques and combining them with neural networks, hidden patterns in user comments are identified [166]. The primary goal is to design a neural network architecture based on language modelling,

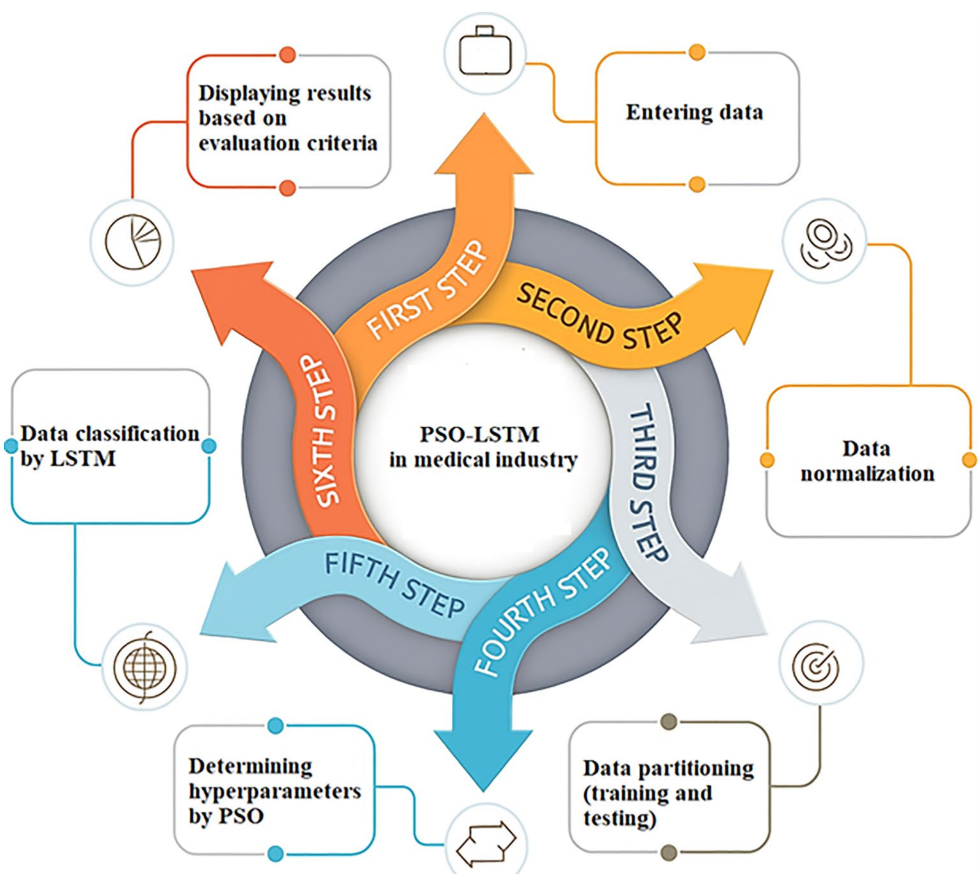


Fig. 13 The steps of PSO-LSTM in the medical industry

utilizing recurrent neural networks, particularly LSTM, to predict the course of conversations. To feed the LSTM layers, the distribution of hidden topics obtained from the trained Latent Dirichlet Allocation (LDA) model is used. To optimize the system's performance, the PSO algorithm is employed. The findings show that the combined model, incorporating LSTM and PSO optimization capabilities, performs significantly better than the basic methods.

4.17 Oil and Gas Industry

The PSO-LSTM model is used in forecasting oil and gas production from reservoirs, forecasting crude oil prices [167], analyzing well logs, and optimizing drilling operations. The data in this industry often have a high level of noise, a nonlinear nature, and complex time dependencies. LSTM models these patterns, and PSO improves forecast accuracy for strategic and operational decisions in the oil and gas industry by optimizing parameters [172].

4.18 Photovoltaic Power Prediction

The combination of PSO and LSTM is an advanced and efficient solution for power forecasting of photovoltaic systems [179]. This combination is used to improve forecast accuracy and enhance stability against severe fluctuations in solar data. The volatility and stochastic nature of wind speed and solar radiation pose significant challenges in predicting the power generation of wind and solar resources. The instability in the forecast has led to a decrease in planning accuracy in power networks and a degradation in the performance of power plants. To overcome this problem, the Quantum PSO (QPSO) algorithm is used for the structure and parameters of the LSTM network [178]. An optimized model based on LSTM has been developed for forecasting the short-term power generation of wind and solar resources. This model was first tested using real data, and the results were then compared with those of the model without optimization. The results show that the proposed model based on QPSO-LSTM has higher prediction accuracy and provides better performance than the reference models.

4.19 Predictive Maintenance

The PSO-LSTM model is used to predict the failure time of industrial components or equipment based on sensor data (vibration, temperature, pressure) over time [184]. This model extracts degradation patterns and predictive failure signals from noisy time series data. The PSO algorithm improves prediction accuracy and reduces operating costs. The combination of PSO with an LSTM network in the field of predictive maintenance has better performance than traditional ANN models [188]. A fundamental limitation of artificial neural networks is their inability to capture time dependencies and long-term trends in time series data. In predictive maintenance applications, detecting gradual failures, recurring patterns in sensor data, and analyzing the long-term behavior of machinery are essential. As a static model, ANN lacks internal memory and processes each input independently; therefore, it does not correctly understand the temporal relationships between data. This limitation reduces the accuracy of prediction in conditions where the process of component degradation occurs gradually and nonlinearly.

4.20 Renewable Energy Optimization

In recent years, the use of hybrid models to enhance forecast accuracy in the renewable energy sector has garnered significant attention. One of these innovative models is the hybrid structure of PSO-LSTM, which has a much faster convergence rate compared to the basic PSO [192]. In the field of wind power management, the LSTM-PSO model has demonstrated remarkable performance in mitigating the fluctuations and uncertainties inherent in wind turbine output power. By considering factors such as forecast error and production losses due to deviations, this model determines the optimal output of wind farms with high accuracy, thereby increasing the grid's efficiency. In the field of solar energy, where the stability and predictability of solar radiation are crucial, the CPSO-LSTM model emerges as a more advanced alternative. In this model, the chaotic PSO (CPSO), as an intelligent searcher, optimizes the sensitive parameters of the LSTM [191]. The primary objective of this model is to significantly reduce solar radiation forecasting errors, thereby enhancing the efficiency of solar energy generation systems. The results of implementing this model indicate a significant improvement in accuracy compared to other forecasting methods. Therefore, the CPSO-LSTM model is considered not only as an advanced computational tool but also as a strategic solution for solar power plant operators and electricity distribution companies. Because it enables the stability of a clean energy supply. The overall structure of the PSO-LSTM process is illustrated in a flowchart format in Fig. 14.

4.21 Risk Assessment

In the fields of finance, insurance, and engineering, PSO-LSTM is used to assess future risks based on time series of historical data (such as market volatility, failure rates, safety data) [197]. PSO increases the accuracy of risk prediction. A multi-stage model for credit risk assessment using deep networks is presented. In the credit risk assessment

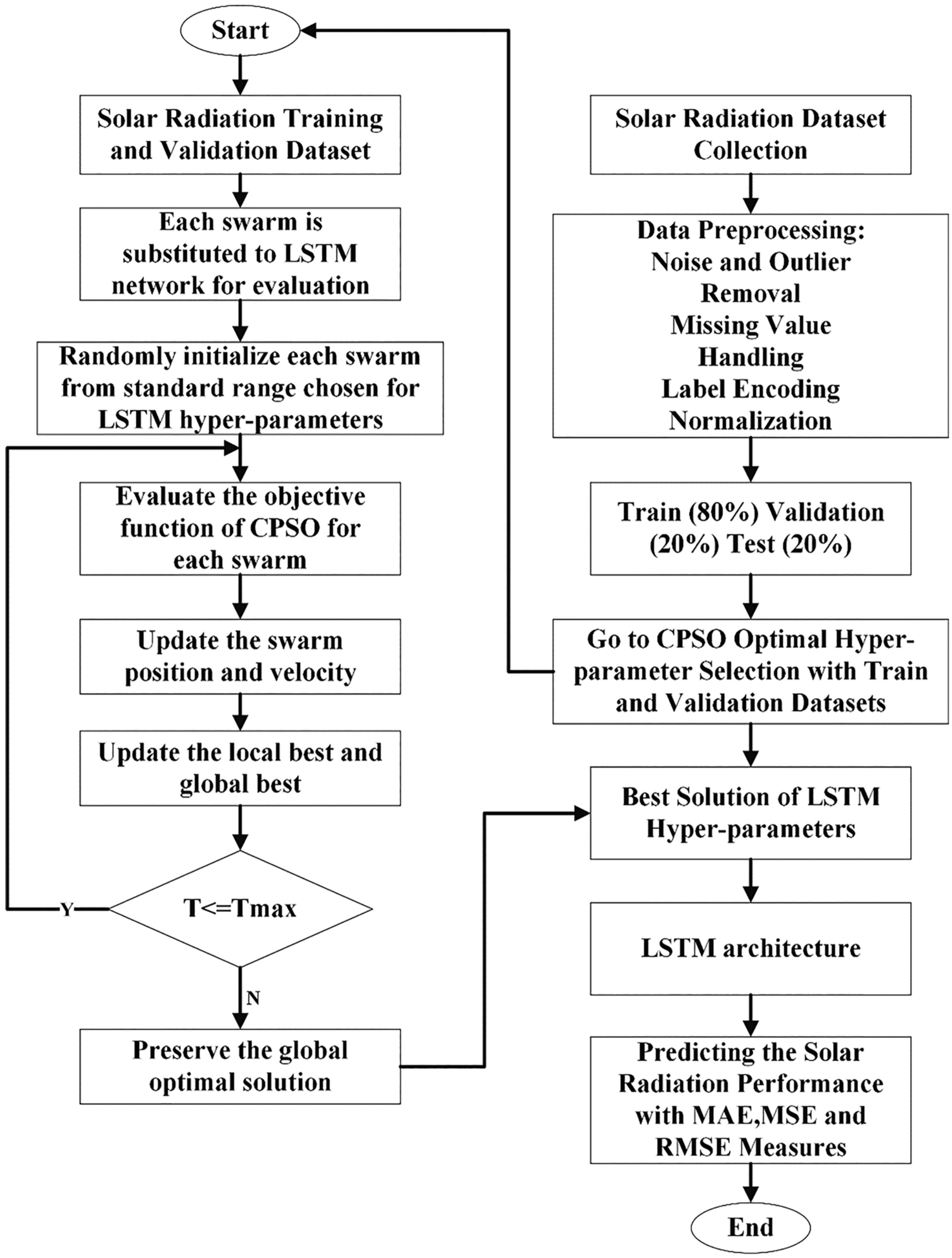


Fig. 14 Flowchart of CPSO-LSTM model for solar irradiance prediction [191]

problem, the data is usually unbalanced, meaning there are many more good debtors than bad debtors. To address this problem, techniques such as SMOTE or under-sampling are employed. In the PSO-LSTM model, the PSO is used to find the optimal combination of LSTM parameters [198]. This enables the model to achieve higher prediction accuracy and prevent performance degradation resulting from inappropriate parameter selection. In the final stage, the model performance is evaluated based on indicators such as Accuracy, Recall, F1 score, and AUC. Navigation risk assessment has been performed through PSO-LSTM [295]. The results show that the error value of PSO is less compared to GA and WOA.

4.22 Runoff Prediction

The PSO-LSTM model is used in hydrology to predict the volume of runoff from rivers and watersheds [200, 201]. This model models complex and nonlinear relationships between variables by analyzing historical data (such as precipitation, temperature, soil moisture, and runoff). Optimization using PSO enhances the accuracy of forecasting for flood management, water resource planning, and dam operations.

4.23 Signal Processing

The PSO-LSTM model is used in applications such as noise filtering, pattern recognition, and prediction of complex signals (such as audio signals, radar signals, or communication signals) [203]. LSTM is very suitable because of its ability to learn temporal dependencies in signals [209]. PSO optimizes the parameters of LSTM to extract meaningful information from noisy and dynamic signals.

4.24 SOC Estimation

Specifically, the PSO-LSTM model is used to accurately estimate the SOC of batteries in real time based on voltage, current, and temperature data [212, 215]. The model successfully handles the challenges of sensor noise and nonlinear battery dynamics. PSO ensures that the LSTM, with the best settings, provides the highest accuracy in SOC estimation under operational conditions.

4.25 Stock Price Forecasting

Various data such as open and close prices, daily highs and lows, trading volume, as well as technical indicators such as RSI, MACD, and Bollinger Bands are fed into the LSTM network as market behavioral signals [218]. LSTM, with its memory gate mechanism, analyzes the underlying relationships between these variables layer by layer, providing a clearer forecast of future prices. Financial markets, particularly the stock market, behave like dynamic and unpredictable systems. These markets are influenced by a complex system of thousands of internal and external factors, and their movements often do not follow simple, linear rules. Meanwhile, using traditional machine learning algorithms to predict price trends faces fundamental challenges. Because the data of these markets is usually accompanied by noise, irregularity, and statistical chaos. In such a complex context, the IPSO-LSTM model works as an innovative and intelligent approach [227]. This model not only leverages the LSTMs ability to extract deep temporal patterns, but also expands the search range for optimal parameters by combining it with an improved version of PSO (with an adaptive mutation factor). In other words, IPSO is like a skilled guide that diverts the network's training path away from low-value paths and local dead ends, guiding it towards the best possible settings. The innovation of the IPSO-LSTM model lies in its use of adaptive mutations to uncover the hidden relationships between variables. This dynamic process makes the model not only more statistically accurate, but also more robust in terms of resistance to unpredictable market fluctuations. Testing this model on real data from the Australian Stock Exchange (ASX) showed that its performance is significantly improved compared to classical models such as SVR, LSTM, and PSO-LSTM.

Table 17 shows a comparison between the PSO-LSTM model and data mining algorithms for stock price prediction. In the field of stock price forecasting, data is often nonlinear, dynamic, and influenced by multiple factors. Therefore, selecting an accurate and appropriate model is crucial for informed financial decision-making. By comparing different algorithms such as ANN, Logistic Regression (LR), Decision Tree (DT), Random Forest (RF), Multiple Linear Regression (MLR), and PSO-LSTM hybrid model, it is found that the PSO-LSTM model has an outstanding performance in all important forecasting criteria. The PSO-LSTM model exhibits higher stability and robustness in forecasting compared to ANN and other traditional models. Models such as RF and DT, which perform better in interpreting results, are not suitable for time series data. Additionally, compared to MLR and LR, which can only model linear relationships, PSO-LSTM is well-equipped to learn

Table 17 A comparison between the PSO-LSTM and data mining algorithms on stock price prediction

Features	PSO-LSTM	ANN [230]	LR	DT	RF	MLR
Forecast accuracy	Very good	Average	Low	Average	Average	Low
Processing temporal data	Very good	Poor	Very poor	Average	Average	Weak
Ability to adapt to nonlinear patterns	Very good	Good	Weak	Good	Good	Weak
Resistance to noisy data	Good	Average	Low	Good	Good	Low
Learning speed	Average	Average	Fast	Fast	Slow	Very fast
Computational complexity	Average	Average	Low	Low	Average	Very low
Requires fine-tuning of parameters	Yes	Yes	Good	Yes	Yes	No
Interpretation ability	Poor	Low	Average	Good	Average	Good
Long-term performance	Good	Poor	Very poor	Poor	Average	Weak
Scalability	Good	Good	Good	Average	Good	Very good
Requires large amounts of data	Yes	Yes	Low	Low	Average	Low
Robustness	Good	Average	Good	Average	Good	Low
Time dependence analysis	Good	Inadequate	Inadequate	Average	Average	Weak
Application in stock price forecasting	Adequate	Low	Adequate	Adequate	Adequate	Limited

complex nonlinear patterns in financial data and provide more accurate forecasts.

4.26 Time Series Forecasting

Nonlinearity and high noise in time series pose significant challenges, especially in price forecasting (such as stock prices, cryptocurrencies, or commodities) [231]. These factors lead to the failure to identify hidden patterns in the data. Combining the power of modeling complex relationships and temporal dependencies of LSTM with the automatic and efficient optimization capabilities of PSO, the PSO-LSTM model is a comprehensive and robust solution for accurate and stable price forecasting in time series. The main reasons for using the PSO-LSTM model are as follows:

Non-linearity: The relationships between factors affecting price (economic news, political events, market sentiment, trading volume, etc.) are rarely linear. Small changes in one factor led to significant and unpredictable fluctuations in price [237]. Traditional models built on linear assumptions are unable to model complex and nonlinear relationships. Due to its specialized architecture, which includes input, forget, and output gates, the LSTM network is capable of learning and modelling complex nonlinear relationships and long-term temporal dependencies in the data. This capability enables the LSTM to identify hidden and nonlinear patterns in price data, even in the presence of significant fluctuations.

High Noise: Time series often contain a large amount of noise, which is caused by random factors, market manipulations, or irrelevant information [241]. Noise obscures real patterns and disrupts model training. The LSTMs ability to filter out noise and focus on meaningful information through its internal memory mechanisms enables it to skip past irrelevant information and emphasize important signals. This feature makes the model less affected by noise and provides more stable predictions.

Long-term Dependencies: Current prices depend not only on recent prices, but also on events and patterns from the distant past. Traditional models, such as ARIMA models struggle to deal with these long-term dependencies [243]. LSTM is inherently designed to handle long-term dependencies. Its built-in memory allows it to store and retrieve information from the distant past, which is critical for identifying long-term trends and recurring patterns in price time series.

Hyperparameter tuning: The ultimate performance of an LSto predict wind speeds in wind farms accurately hyperparameters. Manually determining these parameters (such as the number of neurons, learning rate, and batch size) is a time-consuming, experimental, and often inefficient process that leads to unstable results. Therefore, the PSO identifies the best combination of LSTM parameters by intelligently and automatically searching the parameter space [244]. This automatic optimization not only significantly increases prediction accuracy but also enhances the stability and reliability of the model.

Long-term memory: The defining feature of LSTM is its ability to retain long-term memory. The network is inherently designed to understand and model autocorrelation over time. The network does not just look at the previous moment in time; LSTM stores information from the past several days, weeks, or even months in its memory cells. It identifies and exploits long-term dependencies that exist in autocorrelated price patterns. For example, if the price of a stock increases during a particular season every year, the LSTM learns this seasonal pattern through long-term autocorrelation.

Figure 15 shows the PSO-LSTM papers in the field of time series forecasting based on the percentage of different publishers. Elsevier has the highest share with 31%. MDPI is in second place with 22%. Wiley, with 19%, and IEEE, with 16%, are in third and fourth place, respectively. Springer, with 9%, and Taylor & Francis, with 3%, have the lowest number of papers published in this field. This distribution indicates that most papers related to PSO-LSTM in the field of time series forecasting have been published in journals affiliated with Elsevier and MDPI, which suggests the scientific credibility and focus of these publishers on the fields of artificial intelligence and DL.

4.27 Traffic Flow Management

The PSO-LSTM model helps intelligent traffic management systems by predicting traffic volume, speed, and travel time on road or rail networks [261]. The model models daily and weekly traffic patterns and the impact of events. PSO improves prediction accuracy for optimal routing, traffic signal control, and congestion reduction. Network traffic assessment and prediction lead to the identification of network anomalies. The PSO-LSTM prediction model is proposed to handle the special characteristics of network traffic, such as real-time mutation and time dependence [265]. The network traffic data is modeled as a non-negative matrix X of dimensions N by T, where N represents the number of nodes and T represents the number of sampled time intervals. Each column in the data matrix represents the amount of network traffic at a specific node during a particular time interval. Fig. 16 shows the PSO-LSTM model for network traffic prediction.

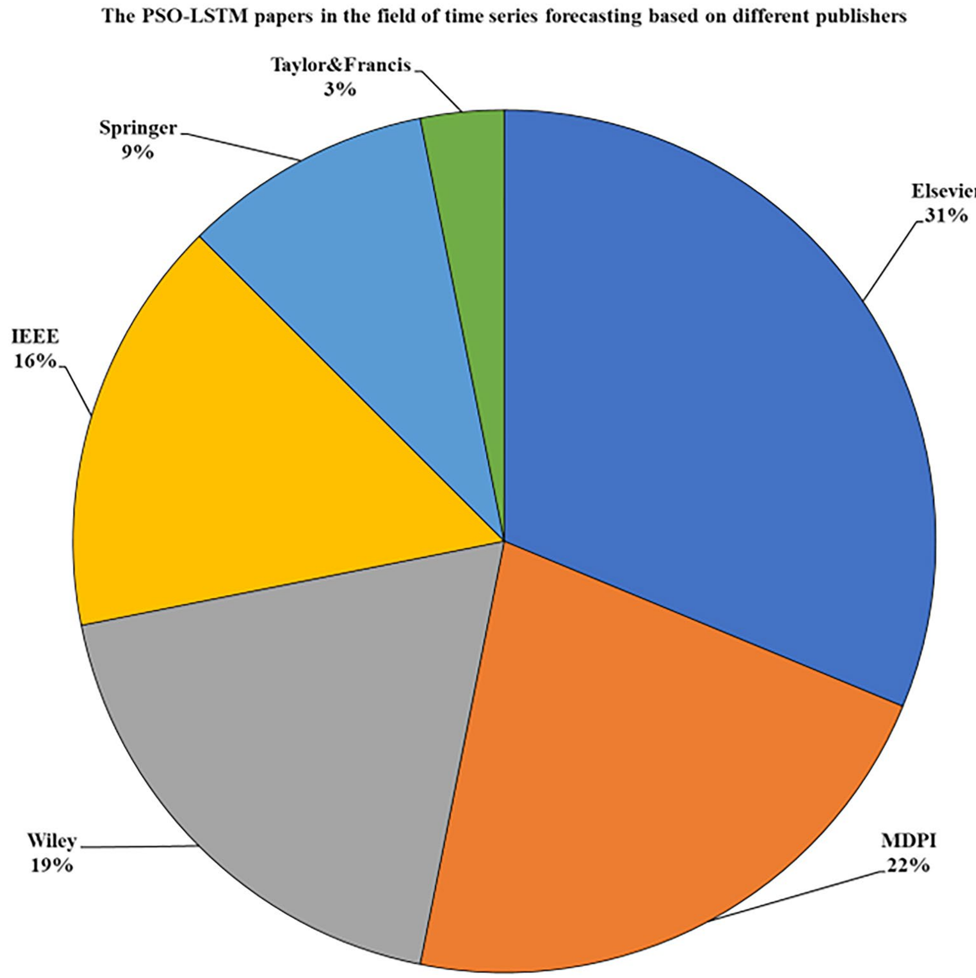


Fig. 15 The PSO-LSTM papers in the field of time series forecasting based on the percentage of different publishers

4.28 Unmanned Aerial Vehicles

The PSO-LSTM model is utilized in UAVs to predict flight paths, estimate battery power consumption, assess component health, and analyze flight sensor data to detect anomalies and enhance safety. LSTM models are used to capture flight dynamics and environmental factors. At the same time, PSO optimizes the parameters to improve the accuracy and stability of predictions in variable flight conditions. First, the QUAV flight data, including variables such as 3D position, angular velocity, linear acceleration, gyroscope outputs, GPS data, and inertial sensors, are collected and preprocessed [267, 268]. Preprocessing involves normalizing the data and removing outliers to prepare it for input to the LSTM network. The final PSO-LSTM model is trained on the training data and then evaluated on the test set. The model's performance in predicting future states of the QUAV (e.g., velocity, position, or yaw angles) is compared with real data to determine its accuracy.

4.29 Water Resources Management

The PSO-LSTM model is used to predict water demand, reservoir water levels, and water quality in water resource management systems [271]. The model models seasonal patterns, trends, and impacts of climatic and anthropogenic factors. PSO optimization facilitates the making of optimal decisions for water allocation, drought and flood management, and maintaining water quality.

Quantum PSO (QPSO) offers a significant improvement over traditional PSO [273]. This approach enhances the exploration of the solution space, thereby preventing premature convergence and increasing the likelihood of finding global optima. QPSO updates the positions of particles based on personal best solutions and global best solutions. Due to the probabilistic behavior of quantum particles, more exploratory moves are possible. This process continues until the algorithm converges to an optimal or near-optimal set of hyperparameters. The PSO-LSTM model is proposed to predict flood dynamics using observed water level data from stations located along the rivers of Bangladesh [276].

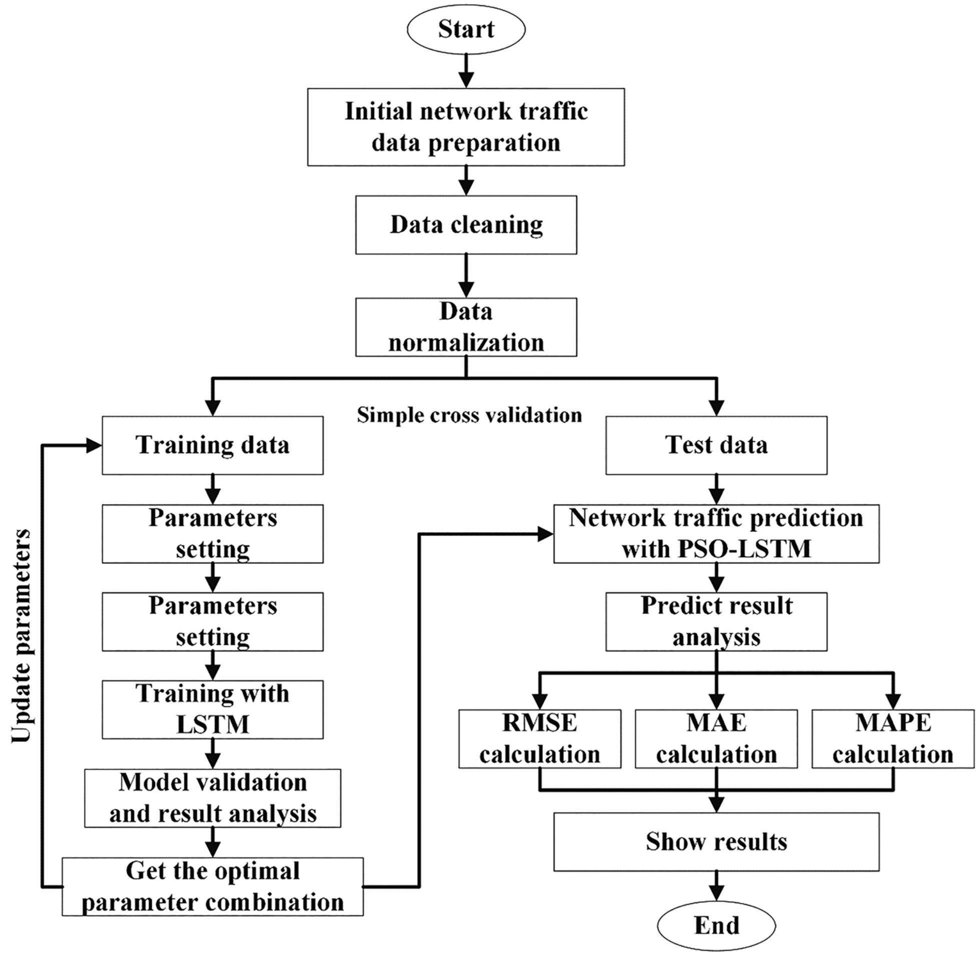


Fig. 16 PSO-LSTM model for network traffic prediction [265]

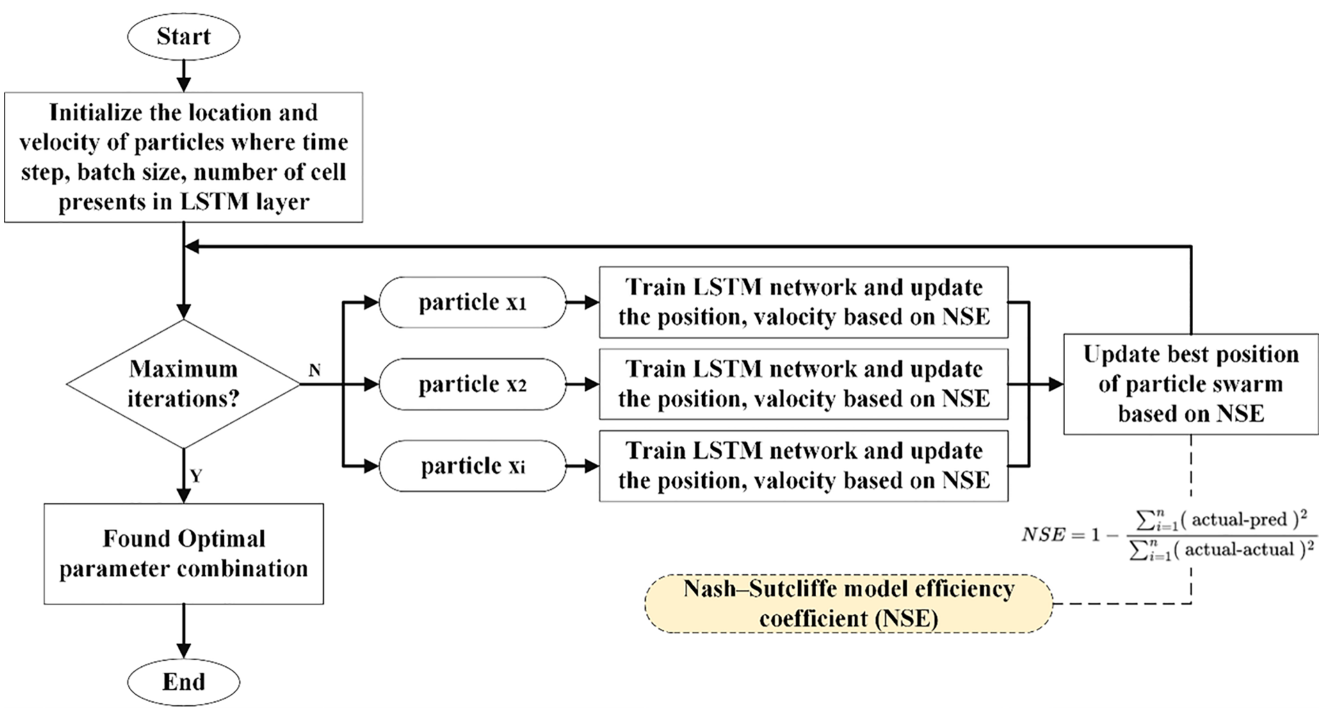


Fig. 17 Flood dynamics prediction by PSO-LSTM model on Bangladesh rivers [276]

Fig. 17 shows flood dynamics prediction by PSO-LSTM model on Bangladesh rivers.

4.30 Wind Speed Forecasting

In the wind energy industry, the PSO-LSTM model is used to accurately predict wind speeds in wind farms. This prediction is crucial for power generation estimation, grid planning, and optimal wind turbine management. LSTM significantly increases the prediction accuracy by modeling the nonlinear and complex fluctuations of wind speed (affected by climatic and geographical factors). Wind speed data from measurement stations at regular intervals (such as every ten minutes or hours) are used as input to the PSO-LSTM model [282, 285]. After preprocessing, including normalization, noise removal, and dispersion correction, these data are prepared for training in successive windows. After determining the optimal values for the hyperparameters, the LSTM model is trained using the wind data and used to predict wind speeds in future time intervals [292]. The model output is presented in the form of predicted wind speed values. It is compared with the actual data and evaluated using indicators such as MAE, RMSE, and coefficient of determination (R^2) [289].

5 Discussion

LSTM networks have revolutionized the field of time series prediction, including passenger flow prediction, due to their ability to learn complex patterns and long-term time dependencies [252]. The performance of LSTMs is highly dependent on the fine-tuning of hyperparameters. These parameters, such as learning rate, batch size, number of hidden units, or dropout rate, determine the training path of the model and ultimately the accuracy of the prediction. Manually determining these parameters is an empirical, time-consuming process that is highly dependent on expertise and intuition. In an urban rail transportation system that serves millions of passengers daily, even slight fluctuations in predictions can lead to inefficient scheduling, overcrowding, delays, or even safety issues. To solve this problem, IPSO intelligently searches the parameter space to find the best combination for the LSTM [245]. This approach not only reduces human error but also enables the LSTM model to reach its full potential, providing more stable and accurate predictions.

The parameter tuning process with IPSO is as follows [245]: First, the LSTM parameters (e.g., number of layers, number of neurons per layer, learning rate, forgetting rate, batch size) are specified and then optimized by IPSO. For each parameter, a reasonable range (minimum and maximum) is defined. IPSO searches for the best combination within this range. A minimum objective function is defined to evaluate the performance of each parameter combination. Usually, this function is determined based on prediction evaluation criteria such as RMSE, MAE, or mean absolute percentage error (MAPE). The IPSO model iterates the search process multiple times. In each iteration, particles move through the search space and update their positions based on their best individual performance and best group performance, thereby converging towards the global optimum. At the end of the process, the best combination of LSTM parameters with the lowest prediction error is selected and used for the final training of the LSTM model. The experimental results show that the prediction accuracy of the PSO-LSTM model is higher than that of the LSTM model [245]. In addition, the comparison of the IPSO-LSTM model with the PSO-LSTM model also highlights the significant improvement in the performance of the improved model. During the off-peak period (regular hours), the evaluation criteria MAE, RMSE, and MAPE decreased by 20.53%, 26.00%, and 16.20%, respectively. Also, in the peak traffic hours, this reduction has been achieved by 11.66%, 10.87% and 9.62%, respectively [245]. Additionally, the execution time of the IPSO-LSTM model is shorter than that of the PSO-LSTM. This indicates that the improved model has better efficiency and performance in predicting passenger flow.

Figure 18 shows the applications of PSO-LSTM in different fields based on the number of papers. A 40-paper study on engineering systems design demonstrates the wide application of the PSO-LSTM model in modelling and optimizing technical and industrial systems. Time series forecasting with 32 papers is ranked second. Therefore, the ability of the PSO-LSTM model to learn time dependencies and optimize forecast performance is confirmed. In the next rankings, applications such as water resources management, intrusion detection, stock price forecasting, wind speed forecasting, and those in the oil and gas industries are featured. These areas are primarily based on variable and dynamic data, requiring algorithms with DL capabilities and automatic parameter adjustment. Some areas, such as electric vehicles, natural language processing, risk assessment, cloud computing, cybersecurity, the Internet of Things, and drones, with a smaller number of papers (mainly 2 or 3), indicate that they are still in the early stages of utilizing intelligent models.

Analysis of 238 papers shows that 153 papers compared the PSO-LSTM model with the base LSTM. The results of the papers showed that the PSO-LSTM model achieved better accuracy compared to LSTM. Also, 85 papers compared the PSO-LSTM model with other models and machine learning algorithms.

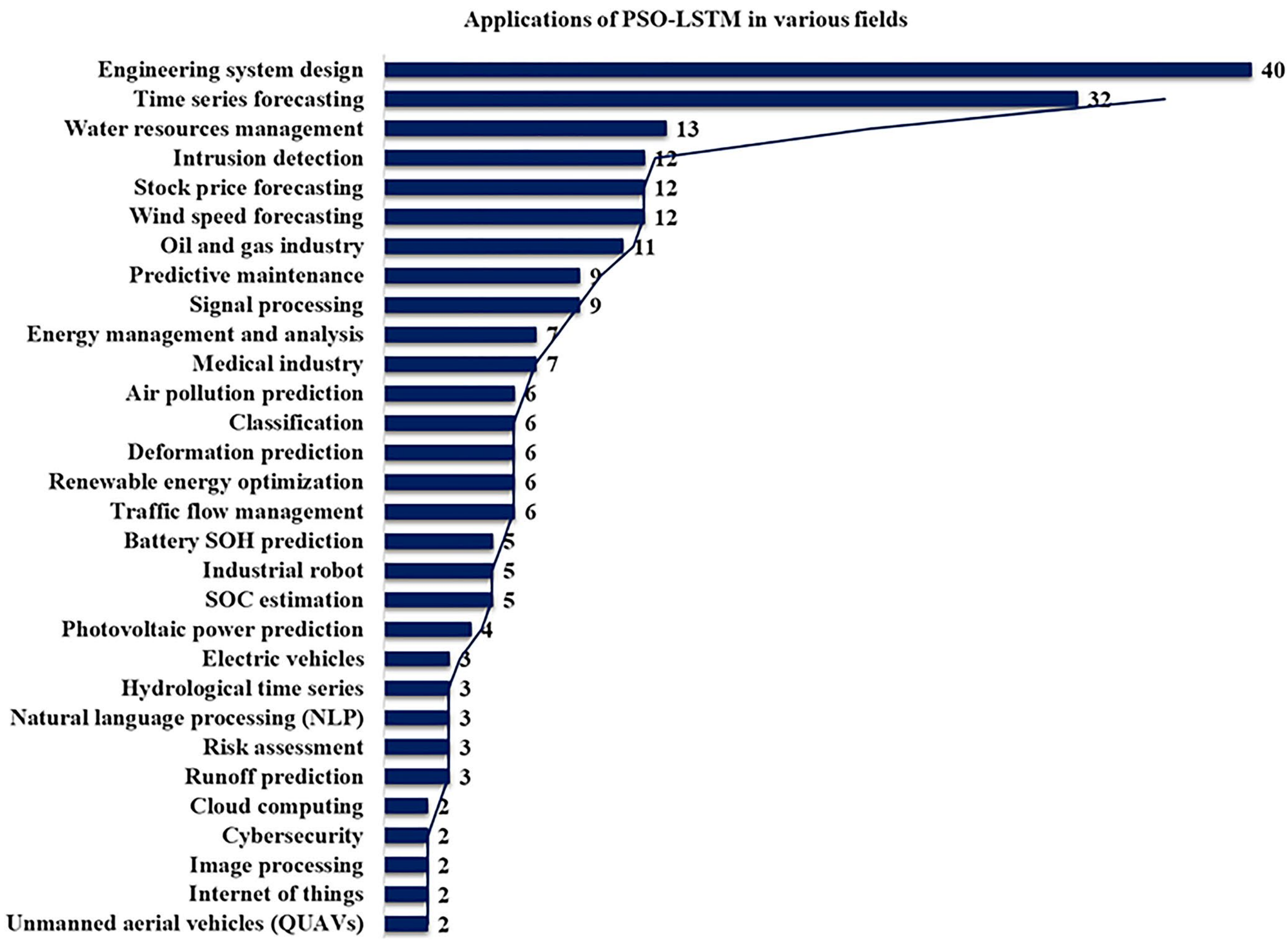


Fig. 18 The applications of PSO-LSTM in different fields based on the number of papers (https://www.scopus.com)

5.1 PSO Enhancement

Despite the high efficiency of PSO in many applications, this algorithm faces challenges in its basic form that reduce its performance in complex problems. Among the most important problems of PSO are getting stuck in local optima, reducing population diversity over time, premature convergence, and dependence on the selection of appropriate parameters. These weaknesses are especially evident in optimization problems with multidimensional search spaces, such as training recurrent neural networks and those with long-term memory (LSTM). To increase the efficiency of PSO, its improved versions should be used. One of the most effective methods for improving PSO is to utilize chaotic maps instead of traditional random distributions. This method increases the diversity of the initial population and prevents premature concentration of particles in a specific region of the search space [296]. OBL strategy, as a method to simultaneously evaluate the current and opposite positions of each particle, has been shown to accelerate convergence and improve the quality of responses. The use of Lévy flights or quantum versions of PSO (QPSO) leads to increased movement diversity and a reduced likelihood of getting stuck in local optima [297]. Fig. 19 illustrates the flowchart of the improved PSO, which employs various strategies.

The PSO exhibits limited and unstable performance in many DL applications, particularly in the optimal adjustment of LSTM parameters, due to its tendency to converge prematurely and become stuck in local optima. These limitations are especially evident in complex problems with nonlinear and high-dimensional search spaces. For this reason, improved versions of PSO aim to enhance the global search power and improve the escape from stagnation areas by incorporating mechanisms such as Chaotic Map-PSO (CMPSO), OBLPSO, Quantum-PSO (QPSO), Levy Flight-PSO (LFPSO), Mutation-PSO (MUPSO) [298], and Crossover-PSO (COPSO). Models such as QPSO and LFPSO have enhanced the accuracy of the model and reduced its dependence on initial values by expanding the search space and creating diverse motion dynamics, particularly in the field of time series prediction. For advanced DL-based

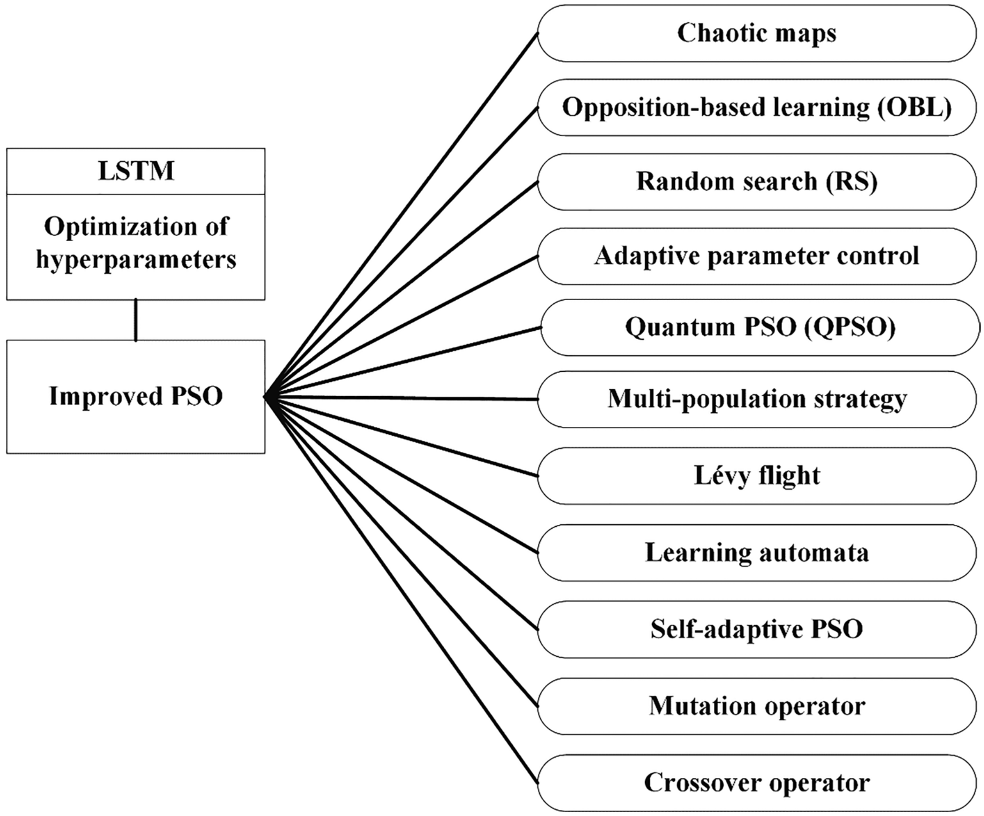


Fig. 19 The flowchart of improved PSO by different strategies

Table 18 The computational complexity for different PSO-LSTM models

Models	Computational complexity
PSO	$O\,(N \cdot D \cdot T)$
PSO-LSTM	$O\,(N \cdot D \cdot T + M \cdot P)$
QPSO-LSTM	$O\,(N \cdot D \cdot T \cdot \log D + M \cdot P)$
OBLPSO-LSTM	$O\,(2 \cdot N \cdot D \cdot T + M \cdot P)$
LFPSO-LSTM	$O\,(N \cdot D \cdot T + N \cdot D + M \cdot P)$
MUPSO-LSTM	$O\,(N \cdot D \cdot T + N \cdot D + M \cdot P)$
COPSO-LSTM	$O\left(N \cdot D \cdot T + N^2 \cdot D + M \cdot P\right)$

N: number of particles. D: problem dimensions. T: number of iterations. M: number of training samples. P: number of LSTM parameters

applications, such as time series data analysis, financial forecasting, or intelligent controls, combining LSTM with IPSO models is a promising and effective approach for optimizing parameters and extracting more accurate patterns.

In the PSO, three main parameters, including inertia weight (w), cognitive coefficient (c_1), and social coefficient (c_2), play a key role in the efficiency of the model. The inertia weight value is usually chosen between 0.4 and 0.9. Larger values lead to better global search, and smaller values lead to faster convergence. The common method is to linearly decrease this value from 0.9 to 0.4 during iterations. The cognitive coefficient, which determines the particle's confidence in its individual experience, is usually in the range of 1.5 to 2.0, and the social coefficient, which indicates the particle's confidence in the best collective position, is also chosen in the same range. For the stability of the particle's movement, the sum of c1 and c_2 is usually considered close to 4. Conventionally, the combination of w = 0.7, c_1 = 1.5, and c_2 = 1.5 has been used as appropriate and stable values in many studies.

Table 18 shows the computational complexity for different PSO-LSTM models. The simplest and least expensive case is related to PSO, whose complexity is O(NDT). With the addition of the LSTM network in the PSO-LSTM model, the cost of training the network with the order of O(MP) is added to the overall complexity and becomes heavier than the simple PSO. In the QPSO-LSTM model, the complexity has grown more due to the use of quantum calculations and logarithmic relations. The OBLPSO-LSTM model costs twice as much as PSO due to the use of OBL. In the LFPSO-LSTM and MUPSO-LSTM models, the additional cost due to Lévy movements and the mutation operation is added to the overall complexity as O(ND). Finally, the highest complexity is related to COPSO-LSTM. Because the merging operation is performed between pairs of particles and adds an order of O(N^2D) to the complexity.

Although PSO was introduced in the mid-1990s and is considered one of the old algorithms, it has continued to be widely used and appreciated due to its simplicity, ease of implementation, and efficiency in solving various optimization problems. Despite the introduction of new algorithms, PSO continues to be a strong foundation and reference point and is widely used in various fields such as neural network training, engineering designs, and hybrid methods (such as OBLPSO, QPSO, and PSO-LSTM hybrid models). Features such as adaptability, extensibility through various improved versions, and stable performance in reference and real-world problems are the main reasons for its survival and competitiveness to this day.

5.2 Important Criteria for Pso-Lstm Evaluation

In studies on PSO-LSTM [264, 269], common indicators such as RMSE, mean absolute percentage error (MAPE), MAE, and correlation coefficient (r) are used to evaluate the prediction. Various statistical measures are used to assess the accuracy of forecasting models. The MAE is one of the simplest and most reliable of these indicators, which is obtained by calculating the absolute difference between the actual values and the predicted values in the entire dataset. This measure is widely used in many analyses because it is not affected by the direction of error (negative or positive) and gives equal weight to all points. The Pearson correlation coefficient (r) indicates the strength and direction of the linear relationship between two variables. This coefficient produces a value between −1 and 1, where a value of 1 indicates a perfect positive correlation, a value of −1 indicates a perfect negative correlation, and a value of 0 means no linear relationship exists [242]. The correlation coefficient is one of the important tools for measuring the degree to which the model's forecasting process matches statistical realities. Also, Explained Variance (EV) examines the dispersion of predicted data relative to the mean of actual values, as a measure of model quality. Table 19 defines the main criteria for predicting PSO-LSTM models in different applications. In the evaluation of predictive models, Y_P represents the predicted value, Y_A represents the original (actual) value, and n is the number of data sets. These symbols are used to define and calculate evaluation indices.

Table 19 Main criteria for predicting PSO-LSTM models in different applications [264]

$$RMSE = \sqrt{\frac{1}{n}\sum^{(Y_P - Y_A)^2}} \tag{4}$$

$$MAE = \frac{1}{n}\sum^{|Y_P - Y_A|} \tag{5}$$

$$MAPE = \frac{1}{n}\sum \frac{|Y_P - Y_A|}{Y_A} \tag{6}$$

$$r = \frac{n\sum^{(Y_P * Y_A)} - \sum^{(Y_A)} * \sum^{(Y_P)}}{\sqrt{\left(n\sum^{(Y_A)^2} - \left(\sum^{(Y_A)}\right)^2\right)} * \sqrt{\left(n\sum^{(Y_P)^2} - \left(\sum^{(Y_P)}\right)^2\right)}} \tag{7}$$

$$EV = 1 - \frac{\mathrm{var}(Y_P - Y_A)}{\mathrm{var}(Y_A)} \tag{8}$$

$$canR^2 = 1 - \frac{\sum_{i=1}^{n}(Y_A - Y_P)^2}{\sum_{i=1}^{n}(Y_A - Y_P)^2} \tag{9}$$

$$\mathrm{CosineSimilarity} = \frac{\sum_{i=1}^{n} Y_A \times Y_P}{\sqrt{\sum_{i=1}^{n} {Y_A}^2} \times \sqrt{\sum_{i=1}^{n} {Y_P}^2}} \tag{10}$$

A review of the literature showed that nonparametric tests have been used in the PSO-LSTM combination to evaluate and compare the performance of the models. Usually, the Wilcoxon signed-rank test is used to compare the performance of PSO-LSTM with other machine learning models or neural networks [70, 74]. Also, the Friedman test has been used in situations where several different algorithms are compared simultaneously. The use of these tests, due to their independence from the assumption of normality of the data and the ability to analyze experimental results, allows for a more accurate and reliable evaluation of the performance of PSO-LSTM compared to competing models [149, 299].

Data normalization plays a very important role in improving the accuracy of predictions, so all the datasets are scaled to a range between zero and one using the Min-Max Normalization technique [272]. This method enables the PSO-LSTM model to work with more uniform and homogeneous data, thereby avoiding problems caused by different scales. Min-Max normalization is defined by Eq. (11). Each input value is mapped to the range 0 to 1 using the lowest and highest values in the training data. This technique enables the PSO-LSTM model to learn more effectively and mitigate the impact of large fluctuations in the data during the training process. Additionally, by preserving the ratios and relative differences between the data, the original information is maintained, allowing the model to better understand the existing patterns.

$$n' = d_{min} + (d_{max} - d_{min}) + \left(\frac{x - x_{min}}{x_{max} - x_{min}}\right) \tag{11}$$

In this formula, n' represents the normalized value, which is in the range between d_{min} and d_{max}. The symbol x is the original data value, and x_{min} and x_{max} are the minimum and maximum values in the data set, respectively, that need to be normalized. Using these definitions makes the data uniform and comparable, and avoids problems caused by differences in the range of values.

5.3 Superiority of the Pso-Lstm

Comparison of the PSO-LSTM with other hybrid algorithms such as Whale Optimization Algorithm-LSTM (WOA-LSTM), Grey Wolf Optimization-LSTM (GWO-LSTM), Harris Hawks Optimization-LSTM (HHO-LSTM) and Genetic Algorithm-LSTM (GA-LSTM) in many studies

Table 20 A comparison between the PSO-LSTM model and other models

Features	PSO-LSTM	**WOA-LSTM** [241]	GWO-LSTM	HHO-LSTM	GA-LSTM
Convergence speed [295]	High	Average	Average	Average	Low
Ultimate accuracy of the model	Good	Good	Good	Very good	Good
Algorithm complexity	Low	Average	Average	High	Average
Ease of implementation [300]	High	Average	Average	Low	Average
Ability to escape from local optima	Average	High	High	High	Very High
Need to adjust parameters.	Low	Average	Average	High	Average
Global search capability	Average	High	High	High	High
Computing resource consumption	Low	Average	Average	High	High
Ability to integrate with DL models	High	High	High	High	Average
Resistance of results [186]	Good	Average	Good	Average	Low
Sensitivity to initial parameters	Low	Average	Average	High	Good
Suitable for big data [242]	Good	High	Average	Average	Average
Search diversity	Average	Good	High	High	Average
Ability to improve multiple parameters	Good	Limited	Good	Good	Very High
Widely applicable to various problems	Very Extensive	High	Limited	Limited	Average
Noise-resistant	Average	High	High	High	High
Ability to converge global optima [246]	Average	Average	High	High	High
Ability to explore the search space	High	Average	Average	Average	Average
Ability to exploit the search space	Low	Average	Average	Average	Low
Ability to automatically adjust parameters	High	Good	Average	Very good	Good

shows significant differences in performance, accuracy and convergence speed. The advantages of the PSO-LSTM are in the convergence speed and simplicity of implementation, which have led to faster optimal solutions in many problems. However, algorithms such as WOA and GWO often offer higher search diversity. The HHO, which is based on the hunting behavior of falcons, has been able to show excellent performance in finding a balance between exploration and exploitation of the search space in some cases and has performed better than PSO in some applications. However, the complexity of the HHO and the need for more precise parameter tuning may limit its application in some projects. On the other hand, GA-LSTM, which uses a genetic algorithm for optimization, provides good diversity in the search population by utilizing selection, crossover, and mutation operations and can avoid getting stuck in local optima, but it usually has a longer computational time than PSO and may be slower in convergence.

In general, the choice of the best algorithm for optimizing LSTM parameters depends mainly on the type of problem, the complexity of the data, and the available computational resources. PSO-LSTM is a suitable choice for many applications due to its simplicity, speed, and acceptable efficiency. However, in special problems or for data with complex structures, algorithms such as WOA-LSTM, GWO-LSTM, or HHO-LSTM may perform better. Also, combining or integrating several optimization algorithms leads to better and more stable results. Therefore, a careful examination of the problem's characteristics and needs, along with conducting comparative experiments, provides a good guide for choosing the appropriate algorithm. In Table 20, a comparison is made between the PSO-LSTM and other models. This comparison has been prepared based on the review of 238 papers.

5.4 Applied and Industrial Concepts

PSO-LSTM models can provide more accurate predictions on complex and nonlinear data than traditional models. Using PSO to optimize the LSTM weights and parameters enables the model to learn complex patterns and unpredictable fluctuations. One of the key considerations for data managers in the energy industry is the flexibility and adaptability of PSO-LSTM models in response to environmental changes and input data. Due to the LSTM structure, these models can identify long-term patterns and unpredictable fluctuations in the data. Of course, appropriate preprocessing, including data cleaning, normalization, and missing value management, is essential to achieve optimal performance. Industrial implementation of PSO-LSTM requires expert teams to tune hyperparameters, monitor performance, and continuously update to prevent accuracy loss over time. As a result, managers must consider the operational and human resource requirements necessary to maintain the continuous performance of the model in their decisions, in addition to the benefits of higher accuracy.

For data managers in the stock market, PSO-LSTM models are powerful tools for predicting price trends, market volatility, and asset behavior, as these models are able to identify complex, long-term patterns in financial data. Financial data often contains noise and unpredictable events that affect model performance, so careful preprocessing, incomplete data management, and continuous evaluation are of particular importance. From an operational perspective, implementing PSO-LSTM in trading environments requires powerful processing resources, adequate scheduling for model training, and expert teams for continuous optimization and monitoring. At the strategic decision-making level, managers should consider these models as auxiliary tools to enhance human analysis and decision-making, not as a complete replacement.

5.5 Scientific Challenges and Limitations

Despite their strengths, PSO-LSTM models also face challenges and limitations. The most important of these include high complexity, high computational resource consumption, sensitivity to initial parameter values, and the lack of standard frameworks for evaluating the performance of the models. In addition, the lack of quantitative analyses, the lack of sensitivity tests in most studies, and the limited in-depth evaluation of the robustness of the models under noisy or incomplete data conditions have also been identified as major weaknesses. Combining PSO with LSTM in some cases leads to performance degradation on real data, because PSO requires fine-tuning of parameters; this is especially evident when the training data is limited or noisy. As a result, finding a balance between prediction accuracy and generalizability is a key challenge.

6 Conclusion, Research Contributions, Practical Advantages, and Future Directions

In recent years, the integration of metaheuristic algorithms with deep learning structures has become one of the most active research areas in artificial intelligence. The PSO-LSTM model, with its ability to model deep temporal dependencies, has attracted the attention of many researchers. The theoretical implications of this study show that this combination leads to an increase in the convergence speed and improves the prediction accuracy. The PSO-LSTM model provides a robust framework for the analysis of nonlinear and dynamic systems.

6.1 Research Contributions

The main goal of this article was to provide a structured and analytical review of scientific studies published between 2019 and June 2025 on PSO-LSTM models. The findings indicate a rapid and significant growth trend in this field, particularly in 2023 and 2024, resulting in a peak in the number of published articles in 2024. This model is used as an advanced method for solving complex problems. A review of 238 papers published in eight internationally recognized scientific databases reveals that the application of this model is not limited to a specific field, but has also been utilized in 30 interdisciplinary fields characterized by high complexity. A statistical review of the articles shows that the most significant research focus has been on the design and optimization of engineering systems, with 40 papers dedicated to this technical field.

6.2 Practical Advantages

In the analyses conducted, it was found that the PSO-LSTM model has been used in a wide range of problems, including time series forecasting, energy resource management, and engineering systems. Combining PSO with LSTM in modeling deep temporal dependencies has led to increased prediction accuracy and reduced error in many scenarios. This shows that PSO-LSTM has found a reliable place in technical and industrial environments due to its features such as high accuracy for modeling complex dynamics and the ability to optimally adjust parameters.

6.3 Future Directions

Future research directions should focus on developing adaptive and intelligent approaches to improve the performance of PSO-LSTM models. Suggestions for future directions are as follows:

1) Developing self-adaptive PSO-LSTM algorithms to reduce the dependence on initial settings and improve the stability of performance in real and dynamic environments. 2) Combining PSO-LSTM with Reinforcement Learning to design models that learn and make decisions progressively in interactive and complex environments. 3) Using multi-objective optimization frameworks to optimize accuracy, complexity, and execution time simultaneously. 4) Developing lightweight and low-cost computational models for implementation in edge devices and IoT-based systems. 5) Creating standardized and comparable benchmark databases to more accurately evaluate the performance of PSO-LSTM models in real-world scenarios. 6) Integrating Reinforcement Learning (RL) with PSO-LSTM leads to increased accuracy [301]. RL dynamically adjusts the PSO parameters or LSTM structure during execution, and the model interacts with the learning environment in a self-adaptive manner. The extension of PSO-LSTM to IoT-based systems leads to increased energy efficiency and sustainability in Fog and Edge architectures [156].

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