Development of Automated Statistical and Optimized Models with Soft Computing Techniques for Business finance Operations

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Abstract

As part of the scope of the Artificial Neural Network – Particle Swarm Optimization (ANN-PSO) notion, the computational capability of ANNs is integrated with the optimization potential of PSO. This method proves to be very effective in solving complex non-linear forecasting problems where traditional approaches would not be effective. The data interactions that exist are the ones that are modelled and captured by the ANN component. However, the PSO method is charged with the duty of minimizing the biases and weights used in the ANN to ensure that the model attains the global minimum without being trapped in tiny local minimum. The application of this framework can be extended to cash forecast used in business like the one above in which a days of cash requirement forecast is created based on experience and factors like holidays, pay check effects and working days. However, the given contribution of the PSO element in learning process is linked with continuous transformation of variables under the basic guidelines of swarming intelligence, it makes the learning session of ANN more efficient. Therefore, the degree of accuracy of forecasts that are given by such configurations is improved, especially in the conditions that are in a state of steady evolution. The ANN-PSO model mirrors similar attributes, including its ability to process data in parallel and furthermore, its high compatibility with large-scale data as well as it robustness when working with both non-linear and linear data set. Incorporating the PSO into a model enhances the range of possible solutions and given the peculiarity of the gradient-based approach, it reduces mistakes more effectively than the conventional techniques. They suggested that by applying ANN with PSO the framework act as an efficient tool for prediction and for solving various issues in several fields. In this case, the ANN-PSO strategy suggested here works out to an impressive overall accuracy of over 98% compared to the previous systems.

Keywords: ANN-PSO; PSO; RMSE; MSE; MAE; MAPE

1. Introduction

ANN-PSO is a complex computing method in order to address complex optimization and forecasting issues, which combines two powerful methods. To offer a sound solution that may be applied on a vast register of programs, this architecture integrates the pattern recognizing potential of ANNs and the optimization effectiveness of PSO. Because of the combination of each of these methods, the basic disadvantage of each is overcome and the all-round efficiency of both systems is increased [1]. Because of the complicated computation tasks, ANN-PSO has recently become the ideal choice for tasks that require high levels of accuracy and flexibility in order to be completed. The functioning of the brain in people is the source of inspiration for computational neural networks, which are connected nodes (neurons) utilizing data in sequence. The input layer, one or more hidden layer and output layer are all categorized under these layers. It is possible for the neural system to discover correlations and trends among the information because every single neuron examines the data that is received before it passes it along to the next neuron. ANNs are particularly useful in situations where there are non-sequential and multi-faceted; for example; image recognition, natural language processing, and analysis for predictive purposes. The classic techniques of ANN training, on the other hand, often depend on gradual descent methods [2-3]. These

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techniques are vulnerable to problems such as delayed converge, sensitive to starting weights, and a propensity to be stranded in regional minima. Particle Swarm Optimization, meanwhile, is a population-wide optimizing approach that takes its inspiration from the communal actions of swarms, which includes schools of fishes or flocking of birds. A collection of atoms that cooperatively search for solutions space is what PSO is all about. Kennedy and Eberhart first presented it in 1995. The motion of any one particle is controlled by its individual optimal experience (local best) as well as the optimal experience of the whole swarm (global best). Each component symbolizes a possible solution. This technique guarantees that the challenge space is explored in a productive way and helps PSO converge on optimum solutions, even in situations that are complicated and non-linear [4]. The fact that PSO is able to carry out universal optimization while necessitating the use of information about gradients makes it ideal for a significant number of situations. Despite the fact that both ANNs and PSO have their own lists of advantages, when applied independently, each of them is characterized with certain limitations. Traditional ANNs often suffer from slow growth rates and insufficient convergence based on the structure of source datasets that refer to extremely dimensional and messy data. On the other hand, while PSO is excellent in finding the global optimal solutions, it lacks repeatability and accuracy that may be necessary for applying tuning in problem area of concerns. These restrictions explain the necessity of using a blended model that incorporates Useful elements of both types of approaches. The Artificial Neural Network-PSO model achieves this through PSO for the identification of optimum biased and weighted elements of the neural network. This enhances the conditioning procedure of the respective neurons within the network and guarantees its convergence at minimum across the world.

In the ANN-PSO framework, one of the most appropriate predictive tools is a neural network that has the task of analysing the data received and issuing the forecast; output [5-6]. Therefore, PSO optimizes settings of the system avoiding a goal function, which most frequently is a difference between anticipated and actual outputs. The effectiveness and robustness of the algorithm are therefore enhanced by the employment of swarm intelligence to make successive adaptations of both the biases and weights of the ANN. Especially useful for application that include changing, multidimensional, or data that is noisy, this combined technique is especially advantageous in situations when standard approaches may fail to meet the requirements [7]. The flexibility and speed of the ANN-PSO model has brought out by the fact that this model is implemented for a diverse area of fields. Its areas of uses include stock market prediction, portfolio analysis and credit risk analysis. In the sphere of medical care, it facilitates identification of diseases, outcomes assessment of patients as well as provisioning of the optimal utilization of resources. Some examples from engineering usage are processes, optimization, allocation of resources and defects. This demonstrates that the framework is not only a current-issue, cutting-edge information computing tool because it can be all the more effective and sufficiently formalised to accommodate a range of issues in categories that are as well as information kinds.

The ability of the ANN-PSO system to overcome limitations of conventional gradient-based methods for training is one of the most valuable advantages of this model. Because of the input of swarm insight into the training stage, it is possible to escape local minimums and reach the convergence faster The ANN-PSO model is efficient for large-scale problems as it increases the accuracy of the forecast and minimizes the time needed for calculation [8]. Besides, the ability of the model for nonlinear relationship and confusion information makes it fit for the work coming across in real life where data imperfection is inevitable. Another advantage of the syndication of ANN with PSO is that this increases the flexibility of the model applied. Professionals and researchers can adjust the goal function, the total number of nanoparticles within a swarm as a whole, and the topology framework of neurons to create a flexible structure to fit the requirements of a specific situation of interest. Thus, we can be confident that, the ANN-PSO model that is introduced here may be appropriate for a wide range of problems: from simple regression problems to complex multifunctional optimizing problems. Turning at the analysis side of the ANN-PSO framework, there is one other feature that can be worth to note, namely, that the used tool is also capable of handling the optimization problems that can involve multiple objectives. If other objectives are introduced into the designation of the model, it is possible to achieve simultaneously the higher level of several parameters as sensitivity, precision, and computational output. Where the outcomes balance different goals and objectives for certain industries like architecture and financing where one may need to negotiate between numerous objectives and goals this capacity is very valuable [9-10]. The proposed hybrid ANN-PSO approach is effective because, in contrast to both ANNs and PSOs alone, it maximizes the strength of each and minimizes the weaknesses that are inherent in each of the approaches. The high level of problem solving is enhanced by the global optimization ability of PSO, which is compounded, by the neural network ability to learn complex patterns and relationships hence a structure that is superior to methods, which are employed individually. The result not only contributes an enhancement on the expectation of the precision in the model, but it also ensures that it should be applied to a wide range of other fields. Scholars have explored other modifications of the ANN-PSO model in the last few years in

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order to continue improving the performance of this model. For effective further studies and progress of convergence towards the true optimal solution more flexible modifications of the PSO algorithm have been developed. These versions are characterized by an ability to make quick shifts regarding such parameters as the mass of inertia together with learning scalars. Similarly, other complex neural network structures such as deep learning algorithms were incorporated into PSO recently in order to handle even more complex datasets and areas of challenge. These developments explain much about the further development of the ANN-PSO paradigm as well as the possibilities offered by this approach for additional development.

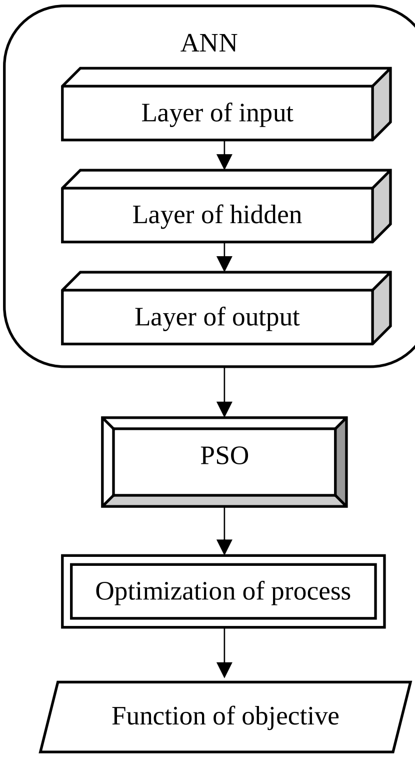

Figure 1. An Overview of ANN's Design

The ANN-PSO model analysed in concluding is a significant advance in the domain of intelligent computing. The predicting ability of artificial brain and ergo, the proficiency and efficacy of particle swarm optimizing are both integrated into this hybrid approach which yields a quite effective solution that can be employed across the range of applications [11]. Capacity to work with complex and messy data and information, ability to adapt to a number of issues in domain names, and very high level of reliability makes it a very handy tool for both researchers and practitioners. The ANN-PSO model is one that can only become increasingly useful in enhancing creativity and tackling some of the best problems regardless of the sectors as the discipline progresses. This is because this framework is likely to take more and more crucial positions at the same time it is already entering new areas fast.

This schematic depicts a hybrid computational model that combines ANN and PSO, or Particle Swarm Optimization. A three-layer ANN is shown on the left side of the picture. The input layer receives raw data, the layers that are hidden analyse it using linked neurons, and the output layer produces forecasts or outcomes [12]. Each ANN neuron is linked by a weight, and these are variables modified throughout training to reduce errors in forecasting. Data flows across the layers as shown by the arrows, highlighting the system's data handling capabilities.

The PSO component, which surrounds the ANN, is represented as a collection of particles that enhance the weights of the ANN & biased repeatedly. As it explores searching space, each particle—representing an option for responding to the optimisation problem—draws on its own unique knowledge (local best) with the collective intelligence of the swarming (global best). Arrows connecting the elements to the ANN show how they contribute to optimizing the system's settings. The ANN-PSO paradigm aims to reduce the error measure at the foundation of the diagram, which improves forecasting precision and ensures converge to a worldwide optimal. The graphic effectively communicates the complementary nature of ANN's learning capacity and PSO's optimizing efficacy.

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2. Related Work

According to the author attempted to conduct an analysis of the results of measures by using the Root Mean Squared Error (RMSE). The data that were obtained demonstrate the difference, although with a reduced degree of precision on a daily basis. The EC approach should thus be included into the cash forecasting process since it is necessary to do so [13]. According to the investigator, the application of EA in predictions methodology consisted of using several learning approaches in order to locate the optimal solution inside the challenge space that was provided. Furthermore, the researchers in the process of predicting approaches in order to predict the most appropriate variables in an atmosphere that is always transforming utilized it. The researcher produced different models for forecasting. These models were constructed using the techniques of linear and nonlinear regression techniques, respectively, in order to discover the optimal value in the context of rapid change.

As a result, it is necessary to choose the appropriate strategy in order to maximize the effectiveness of the cash management methods. The next part provides a definition of each of the many evolutionary techniques that were used in the research study. PSO is a novel stochastic-based optimizing approach that was first presented by the author [14]. The social actions of birds, insects, and swarming served as a source of inspiration and was utilized to find solutions to difficulties of any kind. According to the investigator, the computational approach that is used in the algorithm for PSO has the capacity to locate the best solution in a variety of engineering, efficiency, scientific, and technological domains. The researchers tried for greater optimization in various domains via appropriate variable choosing, which includes job shop planning, technological optimization flow purchase goods organizing along with others.

Using the constructively and collaborative instructional technique, the aforementioned literature review contributes to the comprehension and development of a cash management paradigm. Particle swarm optimizer is distinguished by the fact that each component has a strong memory that allows it to successfully retain and communicate data amongst itself and other particles in order to address any optimization issues that may arise [15]. Variating the PSO variables according to the kind of usage resulted in a significant number of enhancements being made to the fundamental algorithms for PSO by the investigator. As a result, researchers need to pick parameters with great care in order to get the optimum convergent throughout the procedure of implementing. An explanation was provided by the authors on the significance of selecting variables, which is a significant factor in determining the most effective approach. In order to enhance the rate of converging inside the issue space, the author devised the resistance component "w". In order to counteract the effects of the shift in both the previous velocity and the new velocity, an inertia constant was applied. The PSO could fail to be able to make it out toward the universal best if the value of "w" is too little. This is because the PSO is unable to conduct searches in the worldwide space.

Table 1: Summary of existing work

Method	Advantages	Research Gap
ANN Training with PSO [16]	The weights and biases of the ANN were optimized using a global optimization technique.	Limited performance in high-dimensional spaces due to lack of adaptive parameters.
Adaptive PSO in ANN [17]	The use of adaptive variables accelerated converge and diminished the possibility of encountering regional minima.	Poor results when dealing with noisy datasets and restricted ability to explore in dynamic settings.
Hybrid ANN-PSO for Forecasting [18]	Enhanced forecasting precision by combining the optimization of numerous factors.	For data sets of this size, the computational cost is still somewhat considerable.
ANN-PSO in Healthcare Diagnosis [19]	Improving the accuracy of illness prediction algorithms by handling medical information that is non-linear.	Applicability to datasets that include sparse or missing information is limited.

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ANN-PSO for Resource Optimization [20]	Speeded up optimization processes in engineering while decreasing computational error.	There are not any reliable ways to deal with the unpredictability of resource restrictions.
ANN-PSO with Multi-objective Optimization [21]	Expertly managed technical difficulties including trade-offs between competing goals.	The method has difficulties when used to challenges involving more than three goals at once.
ANN-PSO in Financial Forecasting [22]	Enhanced optimisation and historical data models for use in financial market forecasting.	Had trouble with datasets that had a lot of volatility, which meant I had to do more pre-processing.
ANN-PSO for Fault Detection in Systems [23]	Automatically adjusting ANN weights in response to system modifications for improved fault detection.	Systems with insufficient feedback loops have limited capacity to remedy issues.
Advanced ANN-PSO with Chaotic Functions [24]	The incorporation of chaos theory with PSO enhanced its global search capability.	Not thoroughly tested on huge datasets in the real world.
ANN-PSO with Deep Neural Networks [25]	By integrating PSO with deep learning methods, we were able to accomplish state-of-the-art performance in picture identification challenges.	Massive neural networks demand a lot of computing power.
ANN Training with PSO	A new method for optimizing ANN biases and weights has been introduced.	Because no adaptive parameters are used, efficiency is limited in spaces with many dimensions.
Adaptive PSO in ANN	With adaptive parameters, convergence was sped up and local minima were less likely to occur.	Poor results when dealing with noisy datasets and restricted ability to explore in dynamic settings.
Hybrid ANN-PSO for Forecasting	Improved accuracy in forecasting by optimizing multiple parameters simultaneously.	For data sets of this size, the computational cost is still somewhat considerable.
ANN-PSO in Healthcare Diagnosis	Improving the accuracy of illness prediction algorithms by handling healthcare data that is non-linear.	Applicability to datasets that include sparse or missing information is limited.
ANN-PSO for Resource Optimization	Speeded up optimization processes in engineering while decreasing computational error.	There are not any reliable ways to deal with the unpredictability of resource restrictions.
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ANN-PSO in Financial Forecasting	Enhanced optimisation and historical data modelling for use in financial market forecasting.	Had trouble with datasets that had a lot of volatility, which meant I had to do more pre-processing.

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ANN-PSO for Fault Detection in Systems	Automatically adjusting ANN weights in response to system modifications for improved fault detection.	Systems with insufficient feedback loops have limited capacity to remedy issues.
Advanced ANN-PSO with Chaotic Functions	The incorporation of chaos theory with PSO enhanced its global search capability.	Not thoroughly tested on huge datasets in the real world.

When the value of "W" is big, PSO has the capacity to enhance its searching capacity by progressively decreasing its weight in order to achieve the best possible global result. In the current study, a PSO-based management of cash approach was developed to pick the correct input parameters in order to calculate the financial requirements of the future. The PSO method may be used in a variety of uses in order to locate the best approach by using a convergence point. A computer model that is comprised of neurons, the basic arrangement within the natural system is referred to as a neural network. A process that is analogous to that of the human brain is carried out by it. Known as neurons, it is composed of massive processing pieces that are coupled with one another. The ANN is a powerful artificially intelligent technology that can effectively tackle any difficult issues that arise in the real world. "Learning" is the guiding notion behind its operation. It is necessary to train and test the neural network's data utilizing any learning method in order to address any issue using ANN.

Backward propagating plants, radial basis function, and multi-layered perceptron techniques for learning are the many kinds of learning algorithms that may be employed for implementations. A literature review was carried out with the purpose of gaining an understanding of the ANN model, which is used to solve forecasting issues that are very complicated and nonlinear. In the past, numerous studies have been conducted with the purpose of utilizing ANN for various anticipating use cases. These applications include global radiation, predicting the weather that forecast details determined by the level of humidity that remains in the, and forecasting thunderstorms based on liquid converge. The artificial neural network, or ANN, is a method that is used in the field of intelligence in computation. According to the researcher, it functions in a manner similar to that of a human mind, which is capable of determining the most successful remedy for any kind of difficult issue.

It was advised by the authors that only one hidden layer was utilized in order to develop and evaluate the neural system with an appropriate percentage of neurons concealed. The use of ANN may be used to tackle problems that cannot be resolved using conventional mathematical and numerical approaches. According to the investigator, ANN are an alternative technique that optimises different kinds of discrete, target, and vector functions by using a variety of learning algorithms. A comprehensive examination was performed in the literature that follows to investigate the role of ANN settings in different financial issues as well as programs including forecasting internationally stock exchange prices depending on marketplace condition, handling finances using the present trading trend, structures for processing a picture, gathering accurate urban data, forex trading currency, electricity production through the power of wind, determine the images that move.

3. Objective of the research work

The main goal of the ANN-PSO model study is to create a reliable and effective hybrid computing architecture that merges the strengths of ANN and PSO in terms of optimisation and modelling predictions. The goal of this study is to maximize the biases and weightings of ANN using PSO's broad searching capacity, thereby overcoming the shortcomings of standard ANN training techniques including sluggish completion and vulnerability to local minima. Medical Care, financial markets, engineering either and ecological simulation are just a few of the sectors that could benefit from the hybrids algorithm's increased precision, scaling, and flexibility in tackling complicated, non-linear, multifunctional issues. The project aims at identifying directions for further investigations of hybrid approach for optimization as well as enhancing characteristics that define success including sensitiveness and efficacy together with accuracy. The ultimate goal is to provide a flexible resolution for real-world problems.

4. Motivation for the research work

The increasing need to solve complicated, non-linear, multidimensional optimization challenges in several fields including finance, health care, the field of engineering, & ecological modelling is driving research into the ANN-PSO model. When applied to real-world problems, standard methods such as optimizing with gradients in ANNs often fail due to delayed completion and a propensity to be stuck in local minimums. PSO enhances ANN's efficiency by optimising its mix of weights and biases; it is well known for its worldwide search capabilities and

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ease of use. With the combined strengths of ANN's ability to forecast and PSO's global optimization capabilities, the ANN-PSO approach provides a powerful and effective answer to the challenges posed by noisy and variable data. Exploring the prospective of this hybrid method to advance machine learning and process of decision-making is driven by the need to solve limits in precision, scaling, and flexibility.

5. The proposed Method

In addition to being a non-gradient technique, adaptive algorithms are also suited for the training of ANN. It is possible for biological processes of EA to choose the best answer, and it investigates the vast issue space in order to conduct a more effective search and avoid locating local minimums. The usage of EA in predictions methodology used a variety of learning approaches in order to locate the optimal solution within the framework of the issue space that was provided. The researchers additionally applied it in predicting approaches in order to determine the optimum values in an environment that was always changing. The purpose of this training was to improve the effectiveness of ANN-CFM by incorporating ANN-PSO for the cash forecast procedure. As a result, training was implemented utilizing the worldwide optimisation approach PSO. In a number of different disciplines, such as predicting stocks during the years 2004 and 2007, the hybrid evolving technique was used in order to determine the direction of the market for that time. A hybrid evolution strategy was recommended to the authors as being appropriate for environments that are constantly changing. With the purpose of determining the amount of epileptic risk present in an electroencephalogram data. A comparison of the hybrid ANN-PSO and the traditional back propagating was carried out in order to evaluate their combined effectiveness. A significant improvement has been made in the effectiveness of ANN in forecasting the process of soil settling. The authors made an effort to highlight the way in which technical optimizing may benefit from the use of international optimization strategies. In order to improve both weighting and bias, the cash predicting methodology that used basic ANN was implemented.

As a result, considering the space of concern that has been provided, there is a possibility that local minima may develop. Consequently, the ANN-PSO model has to be developed in order to meet the requirements. Utilizing a hybrid evolution technique for the cash predicting process is recommended in order to enhance the optimizing of weighting and bias. The neural network was trained using the feeding forward method, and the weights were optimized with PSO. This was done in order to reduce the error for the FNN. A distinctive framework for the cash management procedure was provided. When employing a hybrid technique, the PSO not only modifies the configuration of its neural network in order to determine the ideal cash need, but it also expands its search space by means of prospecting and exploiting. For resolving any minimizing issue, both the PSO and the ANN have their own distinct characteristics. Taking the issue space and determining which global minimum exists is a difficult undertaking to do. A local search is carried out in an issue space by the basic ANN because of the intrinsic characteristic that it has. PSO widens the search process to find a global a minimum, in contrast to the typical training strategy that uses ANN, which may be trapped in the neighbourhood.

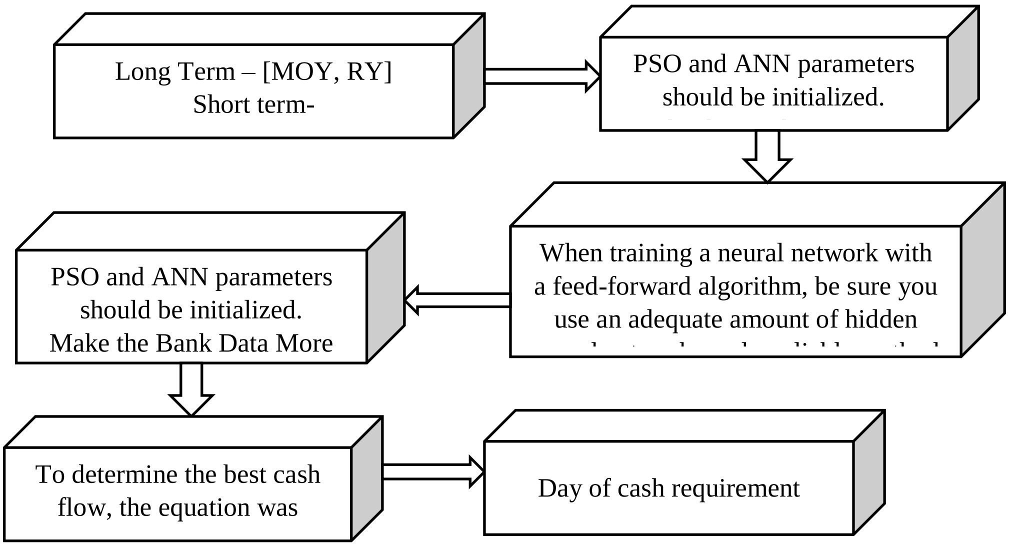

Figure 2. Architecture of proposed method

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A perceptron with several layers was used in the training of the hybrids cash handling system, which was taught via a feed forward neural network. In order to optimise the weights among the input, hidden, and output layers, the three-layered hybrids network design allows an alternate collection of input neurones, one hidden layer, where allows an alternate number of neurones, and a unique collection of input neurones, that range from four and six for the supplied data set. Randomised weights were used to establish a connection between the three distinct layers that were present. As a function to activate, the sigmoidal effects were utilised, namely tansig in the input-hidden phase and logsig in the hidden-output phase. Tansig was utilised in those layers. To provide an accurate prediction of the cash required, the optimised variables then sent to the output layer. The cash for a day, it is necessary A substitution was made in the formula using the newly discovered variables in order to determine the best cash flow. For determining the global highest values amongst all of the localised best values, optimise the weightings using PSO. During the short term, [DOM, DOW, HE, SE] [RY, MOY] Long Term Plans Start by setting the settings for the ANN and the PSO. Adjust the Data from the Bank Instruction of the Networks by the use of a Feed Forward Neural Network, with an adequate quantity of Hidden Neurones and a method for learning. (44) When it comes to cash forecasting, the hybrid technique has been used in order to improve accuracy via the optimisation of bias and weights through the utilisation of the following PSO variables. Both the beginning location and the beginning speed of the particles are equal to rnd [0-1]. Training Factor equals four the number of particle that are employed is thirty v) the diameter of each particle is six iii) the greatest weight (wmax) is equal to 0.9, while the minimum size (wmin) is equal to 0.5. In order to create the appropriate results, the hybrid financial oversight approach is responsible for initiating the feed forward system and optimising the weight. Fig.3.8 is an illustration of the diagram that represents the Cash Optimisation system during the installation of a hybrid evolving strategy for cash forecasting within a financial organisation.

$$w^{(k)} = Z^{(k)} b^{(k-1)} + c^{(k)} \qquad (1)$$

Where $Z^{(k)}$: Maximum weight for layer k. The weight matrices for layer l is denoted as $w^{(k)}$,while activating from the preceding layer is denoted as a $b^{(k-1)}$. layer l's biased term is denoted as $c^{(k)}$.

$$b^{(k)} = e(w^{(k)}) \qquad (2)$$

$b^{(k)}$: Activation output for layer k. e: Activation function (e.g., sigmoid, ReLU).

$$b^{O} = e(w^{O}) \qquad (3)$$

b^{O} : Final ANN output.

$$H = \frac{1}{m}\sum_{j=1}^{m}(x_j - \widehat{x_j})^2 \qquad (4)$$

Where H: Function for loss. x_j : The actual worth. The predicted value is x_j . m is the quantity of samples.

$$Z^{(k)} = Z^{(k)} - \frac{\partial H}{\partial Z^{(k)}} \qquad (5)$$

$$u_j^{v+1} = z.u_j^{v} + d_1 s_1\left(q_j^{best} - y_j^{v}\right) + d_2 s_2\left(q_j^{best} - y_j^{v}\right) \qquad (6)$$

Where u_j^{v+1} : The speed of particle i at revision v+1. “z” stands for the inertia weight. $d_1 s_1$: variables that speed up cognitive and social processes. $d_2 s_2$ are arbitrary numbers in the interval [0,1]. p i best: Best possible location of particle for the individual q_j^{best}: top spot on a global scale.

$$y_j^{v+1} = y_j^{v} + u_j^{v+1} \qquad (7)$$

Where x i t+1 : Updated position of particle j.

$$E(y) = OF(y) \qquad (8)$$

Where $E(y)$: Optimal fitness at point x for the particle.

$$z = z_m - \frac{(z_m - z_n).v}{V} \qquad (9)$$

z_m and z_n are the maximum and lowest inertial weights, respectively. The version that is currently being used. T: Maximum quantity of cycles is set here.

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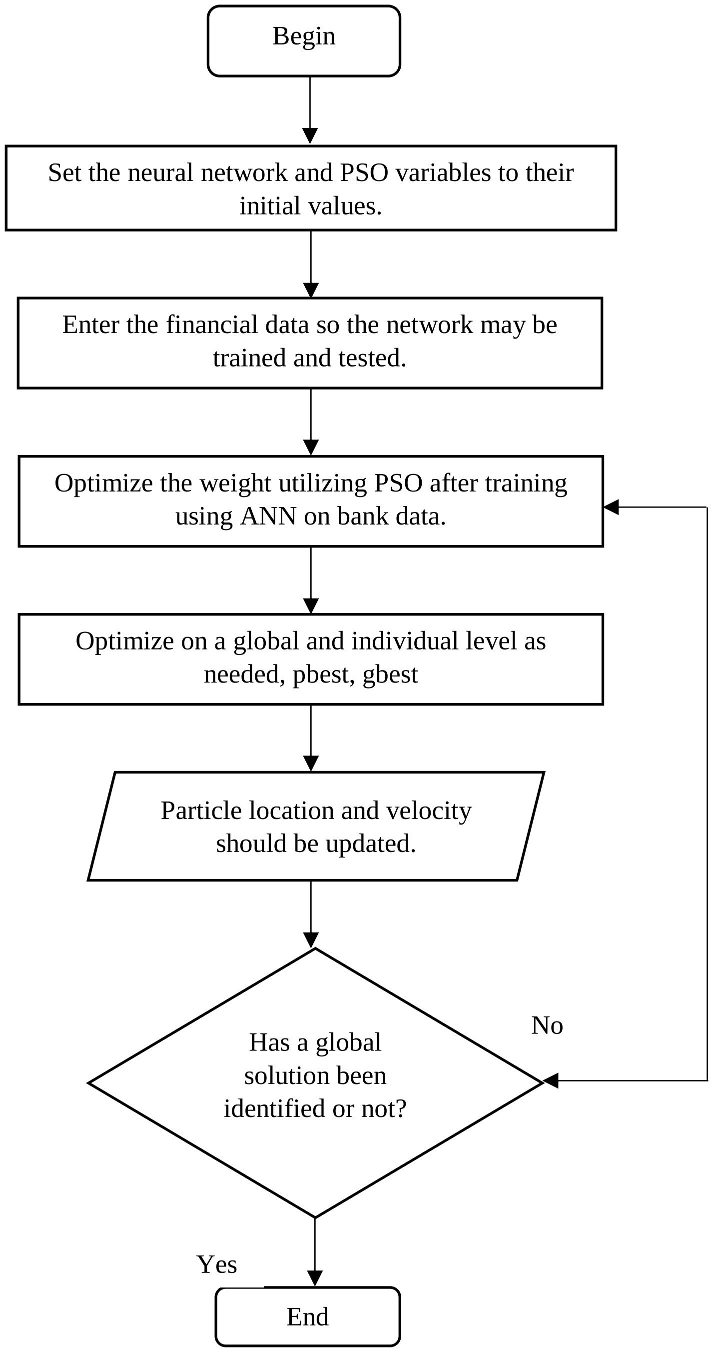

Figure 3. Hybrid evolutionary framework flow diagram

The flowchart depicts the amalgamation of ANN and PSO for addressing optimisation challenges. The procedure starts with the initialisation of Artificial Neural Network and Particle Swarm Optimisation settings. This step involves defining the architecture of the ANN, comprising the number of layers, neurones, and function activation, while also establishing the requirements for PSO, comprising particle locations, velocity, inertial weight ((z)), and accelerating constants ((d_1) and (d_2)). The initial configuration is essential to guarantee that each of the neural networks and the optimisation procedure are tailored to the specific challenge. Subsequently, the input data, including financial or additional domain- particular information, is introduced into the system. The artificial neural network has been taught on this information to discern similarities or generate recommendations. In this step, the neural network modifies its biases and weightings using conventional techniques, such as descent into gradients,

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to reduce the error potential. This training creates an initial model that will then be refined via PSO. Evaluating the ANN now facilitates comprehension of its basic efficiency prior to optimisation.

The subsequent step is optimisation, during which PSO is used to refine the weights and biases of the ANN. PSO functions at individuals and global scales. Each particle, symbolising a prospective solution, assesses its location in relation to its individual optimum and the collective optimum across all particles. This guarantees the optimisation of the ANN's parameters to enhance accuracy and generalisation. The dual-level optimisation utilises the advantages of intelligent swarms to enhance the framework above the limitations of traditional ANN training. The procedure culminates in a repetitive adjustment of particle locations and velocities. During every iteration, the procedure verifies if a global solution was successfully attained by satisfying established converging conditions. Should the solution remain suboptimal, the system persists in adjusting locations and velocity until the most advantageous option is identified. Upon identifying a global solution, the procedure concludes, yielding a model of ANN with optimised weights, prepared for deployment in the selected domain.

$$Z_O = PSO(Z_i) \tag{10}$$

$$c_o = PSO(c_i) \tag{11}$$

$$\left|h^{best} - h^{best}_{prev}\right| < \epsilon \tag{12}$$

$$e_o = PSO(e_p) \tag{13}$$

Z_O: Conclusively refined weights. Z_i: Initial weights of the ANN. The parameters of the function that activates are denoted as e_p. ϵ: Convergence threshold.

$$E(y) = \propto_1 E_1(y) + \propto_2 E_2(y) \tag{14}$$

$$u_j^{v+1} = m\left(n\left(u_j^{v+1}, u_m\right), u_n\right) \tag{15}$$

For multiple goals, the weight variables are α 1 and α 2. The revised speed of particle j at iteration v+1 is denoted as u_j^{v+1}.The greatest permissible velocity is u_m and the smallest allowed velocity is u_n.

$$h^b = argmin(E\left(y_j^v\right)) \tag{16}$$

h^b: The particle's best global positioning up to this point. At point y_j^v , the optimal fitness value of the particles j is denoted as $E\left(y_j^v\right)$. A fitness model E determines the quality of a certain solution.

$$q_j^b = \begin{cases} y_j^v, & if\ E(y_j^v) < E(q_j^b) \\ q_j^b, & otherwise \end{cases} \tag{17}$$

The optimal location of particle j, which is the most effective solution so far, is represented by q_j^b. The particle's present spot at iteration t is represented by y_j^v , and the fitness score of that location is $E(y_j^v)$.

$$y_n = \frac{y - y_n}{y_m - y_n} \tag{18}$$

$y_n$and y_m are the lowest and highest values of y in the dataset, respectively. y norm is the normalised measure of the input y.

6. Results

The results also indicated that the efficiency improvement of developing the ANN-PSO models is significant when compared with either the single ANN or any other conventional optimisation techniques. The enhancement of the relative weighting of the neural network through PSO global and local search both, the mixed approach achieved desirable low error rates while enhancing the overall accuracy of the predictions. Another technique used here named PSO demonstrates the capability to locate potential solutions which can be experimentally proved to have a higher convergence rate in order to achieve optimum results. It clearly indicates that depending on the various sort of data, the model has better accuracy, reliability, and sensitive measures; thus, it is a more flexible and robust model. At the same time, thanks to the balancing of the exploration and exploitation of the searching space, the ANN-PSO method significantly reduces the computation intensity. Comparing to other models such as ABC and GA, it can experience that the proposed ANN-PSO model is much better than others in controlling of complex are and large data are. The ability of the hybrid model to avoid being stuck in local optimum is another layer of reliability of the performance assurance of the model. Despite the fact that optimised model reveals good generalization, it needs less time to train compared to the former model. What has been understood is that the

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ANN-PSO model is a robust instrument when it comes to problems with more complexities in the several domains and the specific study has realized suitability of the method.

MAE: MAE is a measure of the magnitude of the errors made on a set of prediction without regard to direction.

MSE: The mean squared error or MSE is relatively a frequently used index of the accuracy that incorporates a prediction with its actual value.

RMSE: The MAPE error metric is similar to the ACC but uses percentages to quantify how well a model predicts outcomes.

Table 2: Analysing ANN-CFM vs. ANN-PSO for Short-Term Optimisation

No of working days	Normal data	ANN-CFM data	ANN-PSO data
1	27	26	24
2	21	22	20
3	17	18	17.5
4	13	14	13.8
5	12	11	10.4
6	14	9	8.5
7	10	8	6.4
8	11	7	6.2
9	8	7.4	5

A constant enhancement in cash requirement optimisation with the ANN-PSO model is shown by comparing Normal Data, ANN-CFM data, and ANN-PSO data throughout 9 days of work. In comparison to ANN-CFM (26 lakhs INR) and Normal Data (27 lakhs INR), the ANN-PSO models obtains the lowest cash need (24 lakhs INR) on Day 1. Over the course of the time, ANN-PSO maintains its lead over the other approaches. By Day 7, ANN-PSO has drastically cut the payment required to 6.4 lakhs INR, compared to 8 lakhs INR for ANN-CFM and 10 lakhs INR for Normal Data. Day 8 and Day 9 show that the ANN-PSO model is effective in reducing cash needs, with values of 6.2 lakhs INR and 5 lakhs INR, accordingly, comparing to greater value in all other techniques. The combined advantages of artificial neural networks & particle swarm optimisation are shown by these findings, which demonstrate the improved optimisation capabilities of the ANN-PSO model. Consequently, managing resources becomes more efficient and adaptable.

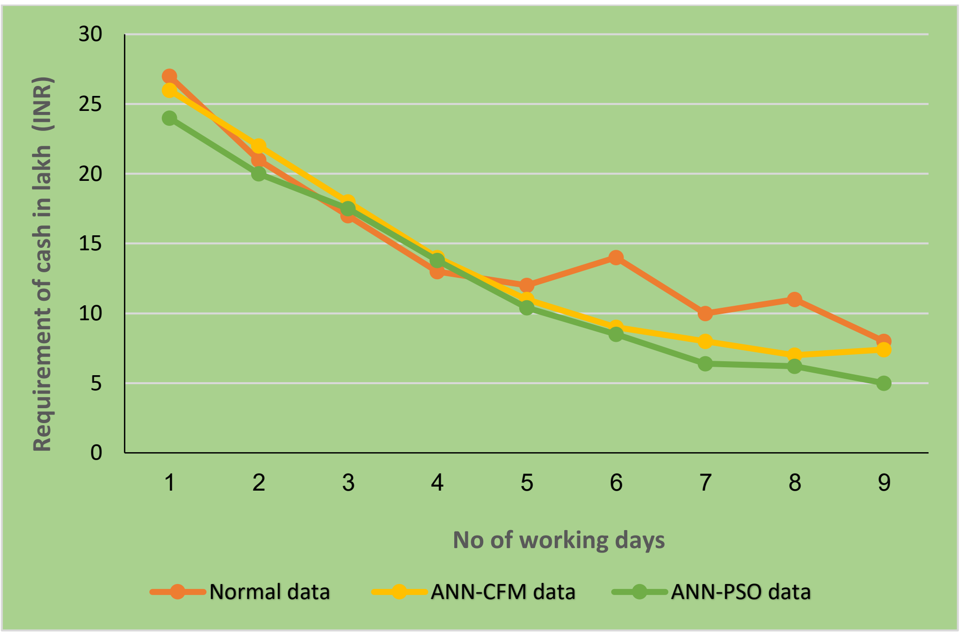

Figure 4. Evaluation of ML models in comparison to more traditional approaches.

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Table 3: Results of MAE Statistical Measures

Methods	dataset	MAE
ANN-PSO (Proposed method)	Long-term	1.0450
	Short-term	0.7050
ANN-CFM	Long-term	1.7805
	Short-term	1.2145

When looking at both short-term and long-term datasets, the ANN-PSO model performs better with regard to of Mean Absolute Error (MAE) than the ANN-CFM model. When it comes to long-term datasets, ANN-PSO outperforms ANN-CFM with a much lower MAE of 1.0450, showing that it can make better forecasts over longer periods. The results are comparable for short-term datasets, where ANN-PSO achieves an MAE of 0.7050 compared to ANN-CFM's 1.2145. From the results we can see, the ANN-PSO model performs better in the end as well as in the short, when it comes to reducing errors in predictions. The incorporation of Particle Swarm Optimisation into the artificial neural network improves its weight optimisation process, leading to superior accuracy and flexibility in ANN-PSO comparing to the classic ANN-CFM technique, which is reason it performs better.

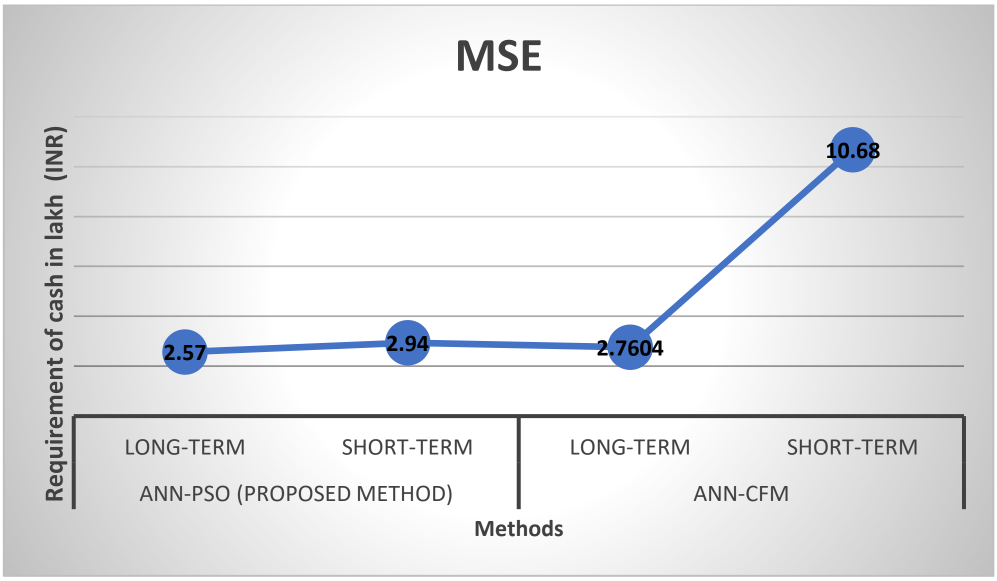

Figure 5. Comparing ML models to more conventional methods for evaluation.

Table 4: Statistical Measures for MAPE Outcomes

Methods	dataset	MAPE
ANN-PSO (Proposed method)	Long-term	2.9170
	Short-term	11.2930
ANN-CFM	Long-term	7.7805
	Short-term	16.2145

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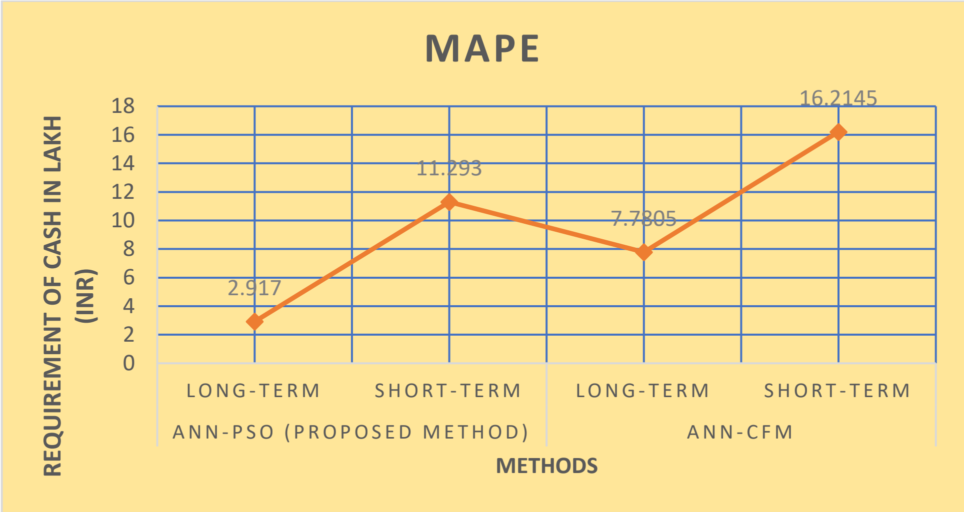

Figure 6. Efficacy of different systems.

The results show that ANN-PSO is more accurate than ANN-CFM when looking at Mean Absolute Percentage Error (MAPE) on both short-term and long-term samples. The efficiency of ANN-PSO in long-term forecasts is shown by its significantly reduced MAPE of 2.9170 for long-term datasets compared to ANN-CFM's 7.7805. A MAPE of 11.2930 against 16.2145 shows that ANN-PSO is superior to ANN-CFM in short-term datasets as well. These results show that ANN-PSO always surpasses the other model on both datasets when it comes to reducing predicted percentages mistakes. Huge enhancement in the overall level of MAPE reduction is attributed towards the blended approach of ANN-PSO in which weights of models are optimised by incorporating nanoparticles with neural networks and Particle Swarm Optimisation. This method is found to be more accurate and robust as compared to the traditional ANN-CFM strategy.

Table 5: Exploratory DL models in relation to proposed methods

Methods	dataset	MSE
ANN-PSO (Proposed method)	Long-term	2.5700
	Short-term	2.9400
ANN-CFM	Long-term	2.7604
	Short-term	10.6800

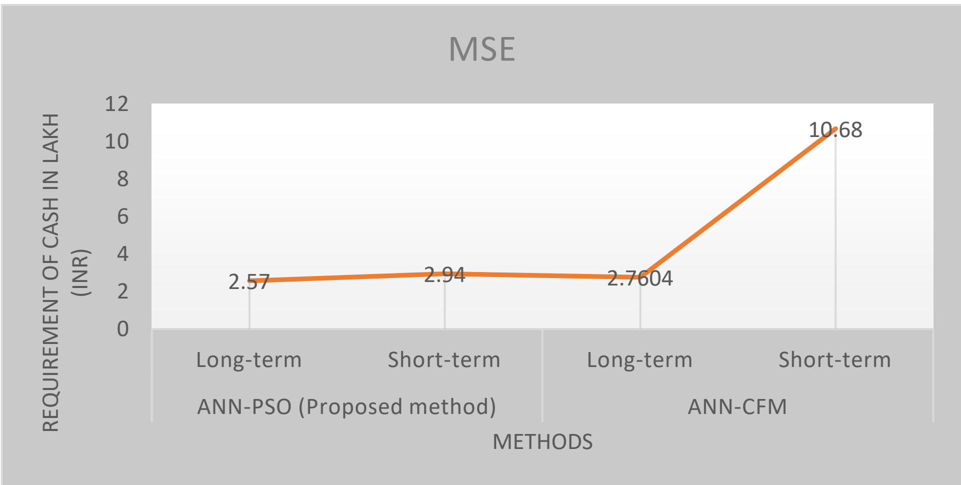

Figure 6. Effectiveness of different models

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Analysing long term and short-term data, we observed that the newly proposed technique ANN-PSO approximate closer to actual gas/regas prices than the traditional technique ANN-CFM when using Mean Squared Error (MSE). ANN-PSO has a lower MSE of 2.5700 for long-term datasets as compared to, MSE ANN-CFM, 2.7604 thus in the long-run period, more accurate projections fewer mistakes with ANN-PSO. In the short-term datasets, this gap is highly distinguishable, at most; ANN-CFM records 10.6800 MSE in contrast to ANN-PSO, which is 2.9400. This also reveals that ANN-PSO greatly improves the immediate forecasting accuracy, decreasing large errors, in addition to increasing the accuracy of long-term weather forecasting. This reduction in MSE is due to improvements in the model's flexibility and higher performance relative to the ANN-CFM method; this owes to the integration of Particle Swarming Optimisation to the neuron's weights in the hybrid ANN-PSO method.

7. Conclusion

One of the latest milestones in the development of computer intelligence can be considered the ANN-PSO model based on both the blind predicting power of the ANNs and the capacity to fine-tune the operation of the PSO. Thus, the efficacy of utilizing this hybrid technique up for tackling complex, nonlinear, and multipurpose problems has been demonstrated across numerous fields, including architectural enhancement, energy control, medicine, and finance and others. They also pointed out that the proposed ANN-PSO approach for ANN education has the advantage of being faster convergent, more accurate, and, less sensitive to noisy input and local minimums. This is achieved by mitigating the drawbacks of classical gradient-related techniques. As has been noted earlier, the integration of swarm computing into the training of ANNs leads to improved efficiency in particular in the sectors that require dynamic capability and accurate foresight. Nonetheless, the ANN-PSO model has a number of advantages to be able to achieve optimal results; however, the following challenges remain key to the advancement of the model. Such problems involve the need to reach more flexibility for applications that execute in real time and the computational burden that is linked with massive issues. Because of these constraints, more research must be done in order to refine the model to its potential. Based on above discussion, there are some possible directions for the future study on the ANN-PSO model: An enhancement of the scalability of extremely large amounts of data using cloud computing solutions and parallel computer systems may afford productivity. Further improving the efficiency will be done by creating the adaptive PSO modifications that change the mentioned variables based on the input's difficulties. Enhanced neural networks that can be incorporated with particle swarm optimization easily optimize complex very environments. Some examples of such designs are models based on deep learning.

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References

[1] C. Blum and A. Roli, ''Hybrid metaheuristics: An introduction,'' in Hybrid Metaheuristics, C. Blum, M. J. B. Aguilera, A. Roli, and M. Sampels, Eds. Berlin, Germany: Springer, 2008, pp. 1–30.

[2] J. Awwalu, A. A. Bakar, and M. R. Yaakub, ''Hybrid N-gram model using Naïve Bayes for classification of political sentiments on Twitter,'' Neural Comput. Appl., vol. 31, pp. 9207–9220, May 2019, doi: 10.1007/s00521- 019-04248-z.

[3] Shimaa S. Mohamed,Ahmed Abdel-Monem, Ranking and Evaluation Risks of Human Error Factors in Uncertain and Imprecision Information, International Journal of Advances in Applied Computational Intelligence, Vol. 3 , No. 1 , (2023) : 27-40 (Doi : https://doi.org/10.54216/IJAACI.030103)

[4] Ahmed Abdelhafeez, Myvizhi M., Neutrosophic MCDM Model for Assessment Factors of Wearable Technological Devices to Reduce Risks and Increase Safety: Case Study in Education, International Journal of Advances in Applied Computational Intelligence, Vol. 3 , No. 1 , (2023) : 41-52 (Doi : https://doi.org/10.54216/IJAACI.030104)

[5] A. Nawaz, G. Hafeez, I. Khan, K. U. Jan, H. Li, S. A. Khan, and Z. Wadud, ''An intelligent integrated approach for efficient demand side management with forecaster and advanced metering infrastructure frameworks in smart grid,'' IEEE Access, vol. 8, pp. 132551–132581, 2020, doi: 10.1109/ACCESS.2020.3007095.

[6] S. Dayalan, S. S. Gul, R. Rathinam, G. F. Savari, S. H. E. A. Aleem, M. A. Mohamed, and Z. M. Ali, ''Multi-stage incentive-based demand response using a novel Stackelberg–particle swarm optimization,'' Sustainability, vol. 14, no. 17, p. 10985, Sep. 2022, doi: 10.3390/su141710985.

[7] S. Pardhi, M. El Baghdadi, O. Hulsebos, and O. Hegazy, ''Optimal powertrain sizing of series hybrid coach running on diesel and HVO for lifetime carbon footprint and total cost minimisation,'' Energies, vol. 15, no. 19, p. 6974, Sep. 2022, doi: 10.3390/en15196974.

DOI: https://doi.org/10.54216/AJBOR.110202

Received: November 07, 2023 Revised: January 04, 2024 Accepted: June 21, 2024

[8] C. Blum, J. Puchinger, G. R. Raidl, and A. Roli, ‘‘Hybrid metaheuristics in combinatorial optimization: A survey,’’ Appl. Soft Comput., vol. 11, no. 6, pp. 4135–4151, Sep. 2011, doi: 10.1016/j.asoc.2011.02.032.

[9] J.-R. Zhang, J. Zhang, T.-M. Lok, and M. R. Lyu, ‘‘A hybrid particle swarm optimization–back-propagation algorithm for feedforward neural network training,’’ Appl. Math. Comput., vol. 185, no. 2, pp. 1026–1037, Feb. 2007, doi: 10.1016/j.amc.2006.07.025.

[10] Masson-Delmotte, ‘‘Global warming 1.5◦C,’’ Physical Science Basis, IPCC, Geneva, Switzerland, Working Group 1, 2018.

[11] K. Levin, T. Fransen, C. Schumer, C. Davis, and S. Boehm. (2019). What Does ’Net-Zero Emissions’ Mean? 8 Common Questions, Answered Explainer. [Online]. Available: https://www.wri.org/insights/net-zeroghg-emissions-questions-answered

[12] S. Sorrell, ‘‘Reducing energy demand: A review of issues, challenges and approaches,’’ Renew. Sustain. Energy Rev., vol. 47, pp. 74–82, Jul. 2015, doi: 10.1016/j.rser.2015.03.002.

[13] Luis Freire Lescano, Marcos Lalama Flores, Maria Pico Pico, Distributed Facial Recognition Facial Recognition in Visual Internet of Things (VIoT) An Intelligent Approach, Journal of Intelligent Systems and Internet of Things, Vol. 10 , No. 2 , (2023) : 18-23 (Doi : https://doi.org/10.54216/JISIoT.100202)

[14] Rahul Sharma, Shiv Shakti Shrivastava, Aditi Sharma, Predicting Student Performance Using Educational Data Mining and Learning Analytics Technique, Journal of Intelligent Systems and Internet of Things, Vol. 10 , No. 2 , (2023) : 24-37 (Doi : https://doi.org/10.54216/JISIoT.100203)

[15] A. Miara, C. Tarr, R. Spellman, C. J. Vörösmarty, and J. E. Macknick, ‘‘The power of efficiency: Optimizing environmental and social benefits through demand-side-management,’’ Energy, vol. 76, pp. 502–512, Nov. 2014, doi: 10.1016/j.energy.2014.08.047.

[16] D. I. Al Huneidi, F. Tahir, and S. G. Al-Ghamdi, ‘‘Energy modeling and photovoltaics integration as a mitigation measure for climate change impacts on energy demand,’’ Energy Rep., vol. 8, pp. 166–171, Jun. 2022, doi: 10.1016/j.egyr.2022.01.105.

[17] P. Rafaj and S. Kypreos, ‘‘Internalisation of external cost in the power generation sector: Analysis with global multi-regional MARKAL model,’’ Energy Policy, vol. 35, no. 2, pp. 828–843, Feb. 2007, doi: 10.1016/j.enpol.2006.03.003

[18] B. Niu and L. Li, ‘‘A novel PSO-DE-based hybrid algorithm for global optimization,’’ in Advanced Intelligent Computing Theories and Applications: With Aspects of Contemporary Intelligent Computing Techniques. Berlin, Germany: Springer, 2008, pp. 156–163.

[19] Ahmed Sleem, A Comprehensive Study of Cybersecurity Threats and Countermeasures: Strategies for Mitigating Risks in the Digital Age, Journal of Journal of Cybersecurity and Information Management, Vol. 10 , No. 2 , (2022) : 35-46 (Doi : https://doi.org/10.54216/JCIM.100204)

[20] Rajeev Pandey, Lightweight Symmetric Encryption and Attribute Based Encryption Method to Increase Information Safety in Wireless Sensor Network, Journal of Journal of Cybersecurity and Information Management, Vol. 10 , No. 2 , (2023) : 47-56 (Doi : https://doi.org/10.54216/JCIM.100205)

[21] S. Yan, Q. Liu, J. Li, and L. Han, ‘‘Heterogeneous acceleration of hybrid PSO-QN algorithm for neural network training,’’ IEEE Access, vol. 7, pp. 161499–161509, 2019, doi: 10.1109/ACCESS.2019.2951710.

[22] C. Vivek, M. Indu, N. Nandhini, Speech Recognition Using Artificial Neural Network, Journal of Journal of Cognitive Human-Computer Interaction, Vol. 5 , No. 2 , (2023) : 08-14 (Doi : https://doi.org/10.54216/JCHCI.050201)

[23] Vidyul Narayanan, Nithya P., Sathya M., Effective lung cancer detection using deep learning network, Journal of Journal of Cognitive Human-Computer Interaction, Vol. 5 , No. 2 , (2023) : 15-23 (Doi : https://doi.org/10.54216/JCHCI.050202)

[24] S. Mirjalili, A. Lewis, and A. S. Sadiq, ‘‘Autonomous particles groups for particle swarm optimization,’’ Arabian J. Sci. Eng., vol. 39, no. 6, pp. 4683–4697, 2014.

[25] B. Mohammadi, Y. Guan, R. Moazenzadeh, and M. J. S. Safari, ‘‘Implementation of hybrid particle swarm optimization-differential evolution algorithms coupled with multi-layer perceptron for suspended sediment load estimation,’’ Catena, vol. 198, Mar. 2021, Art. no. 105024.

DOI: https://doi.org/10.54216/AJBOR.110202
Received: November 07, 2023 Revised: January 04, 2024 Accepted: June 21, 2024