Modeling Energy-Related CO_2 Emissions with Backpropagation and Metaheuristics

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***Abstract*—In this paper, we propose a model that combines Backpropagation Neural Network (BPNN) with a metaheuristic algorithm to predict carbon dioxide (CO_2) emissions. The model utilizes input variables directly influencing carbon dioxide emissions. Our objective is to monitor CO_2 emissions based on energy consumption resulting from production processes driven by the corresponding energy demand. Model training and testing are conducted to identify the most suitable model. The results demonstrate that machine learning with the Particle Swarm Optimization (PSO) model achieves an optimal avoidance rate. To assess model accuracy using Mean Square Error (MSE) and Mean Absolute Error (MAE) the smallest error indicates a more precise prediction. Following established guidelines, this document aids managers in making informed business decisions and devising energy management policies that effectively monitor carbon emissions.**

Keywords— CO_2 Emissions Prediction, Backpropagation Neural Network, Metaheuristic Algorithms, Particle Swarm Optimization

I. Introduction

Global warming refers to the phenomenon in which the Earth's average temperature increases due to the greenhouse effect, a well-known process characterized by the accumulation of greenhouse gases [1]. This effect is primarily attribute to human activities, specifically the release of carbon dioxide (CO_2) resulting from the combustion of various fuels in energy consumption processes. Key factors contributing to global warming include the heightened emissions of pollutants, resulting in increased permeability of the atmosphere to solar radiation. This phenomenon is known as the greenhouse gas effect.

The critical greenhouse gases that require reduction include carbon dioxide (CO_2), and the escalation of CO_2 emissions is related to final energy consumption from various sources such as coal and coal products, crude oil and petroleum products, gas, and electricity. The challenges posed by global warming have prompted countries to address the management of energy needs and the reduction of greenhouse gas emissions. Accurate predictions of energy requirements and CO_2 emissions are crucial for effectively addressing the challenges and planning energy management strategies.

The application scope of machine learning is extensive, with neural networks emerging as a widely embraced technique for predictive modeling, particularly in scenarios demanding high prediction accuracy, such as medical data and scientific research. Neural Networks offer an alternative approach to predictive modeling, extensively employed in various forecasting tasks. Among these, the Multi-Layer Perceptron (MLP), a prevalent type of Neural Network (NN), has found widespread application across diverse practical challenges. Neural networks exhibit superior learning capabilities from unstructured data compared to other methods, owing to their distinct learning architecture, differing from general machine learning algorithms. However, training MLPs for specific applications presents challenges, often grappling with issues concerning local optima, overfitting problem, encompassing convergence rate, training speed, and sensitivity to initialization. Numerous studies have demonstrated the efficacy of several methods in predicting carbon dioxide emissions [2][3][4][5][6][7][8]. This article aims to address these challenges by employing five metaheuristic algorithms to train MLPs, specifically focusing on predicting carbon dioxide emissions in Thailand.

II. Backpropagation Algorithm

The supervised learning model is extensively used in machine learning, wherein a model undergoes training on a dataset. The Multi-Layer Perceptron (MLP) represents a neural network of higher complexity compared to a single perceptron, featuring interconnected hidden layers that form a mathematical model simulating the relationship between data and desired outcomes [9]. MLP offers various advantages such as classification, prediction, and problem-solving capabilities. In this approach, neurons within the hidden layer adjust their weights based on computed results, typically initialized randomly. Another notable learning model is reinforcement learning, which involves multiple layers and employs a feed-forward connectivity system. When dealing with multiple layers and a feed-forward connectivity system, the process is termed the backpropagation (BP) algorithm [10]. This learning mechanism entails transmitting error information during result computation, facilitating the adjustment of weights between layers to optimize computational efficiency [11][12][13].

III. Metaheuristic Algorithm

Metaheuristics are applied to enhance performance in modified and adaptable problem domains [14]. They provide significant benefits when handling large-scale problems that are impractical for exhaustive analysis or comprehensive surveying. Employing metaheuristics addresses and enhances solutions for diverse optimization problems, considering challenges stemming from incomplete or limited data and computational resources. Metaheuristics encompass a range of algorithms that aim to efficiently explore solution spaces, aiming for near-optimal or optimal solutions without exhaustively evaluating all possible solutions. Metaheuristics algorithm often involve iterative processes that explore different parts of the solution space, balancing exploration and exploitation to efficiently converge on good solutions [15][16][17].

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A. Biogeography-based optimization (BBO)

BBO is an evolutionary metaheuristic inspired by the dispersal behavior of living organisms across various islands [18]. Frequently, populations migrate from islands with high fertility to those with lower fertility, resulting in increased fertility on the settled island due to the introduction of a diverse set of species. In this analogy, islands can represent solutions to a balancing problem, where suboptimal solutions are more likely to adopt characteristics from others, particularly better solutions. While existing good solutions are less prone to acquiring traits from other solutions, they are expected to evolve and develop into even better solutions over time. Overall, the BBO algorithm capitalizes on this idea of emulating the natural dispersal and adaptation observed in living organisms across different environments, leveraging the concept of migration between islands to optimize and improve solutions in problem-solving scenarios [19][20][21].

B. Jaya Optimization (JAYA)

The Jaya Algorithm was devised to tackle extensive variable optimization challenges without specific targeting, conditions, or preset parameters [22]. It operates through a simulated natural population dynamics concept, randomly adjusting population variables to enhance suitability. These adaptations encompass the entire population, selecting variables to improve the target function and subsequently adjusting variables in the next generation. Its proficiency lies in resolving various constraint problems without complex parameter modification. Functioning as an inhibition-free search algorithm, it adeptly handles numerous parameters or computationally intense methods. Distinguished from other algorithms, the Jaya Algorithm emphasizes stability, adaptive enhancements, and efficacy in solving uncertain or diverse data problems. It remains an attractive choice for intricate optimization tasks across scientific and industrial domains dealing with extensive data, requiring minimal parameter adjustments, thereby asserting a significant role in the realm of optimization [23][24][25].

C. Particle Swarm Optimization (PSO)

PSO is a nature-inspired algorithm that emulates the collective behavior observed in swarms [26]. It employs particles or agents forming a swarm to explore a search space in pursuit of the optimal solution for a given problem. Initially, random positioning of particles represents potential solutions, which are iteratively refined by the algorithm. Each particle updates its position based on both its personal experience and the best position discovered by the entire swarm. This process involves adjusting particle velocity and position using a formula that integrates personal and global best positions. Over iterations, particles traverse the search space, progressively converging toward an optimal or nearly optimal solution. The fundamental strategy involves maintaining a balance between exploration, seeking new solution areas, and exploitation, leveraging promising regions, to effectively navigate and determine the best solution. PSO's effectiveness stems from its simplicity, ease of implementation, and its ability to explore intricate search spaces, rendering it a widely adopted optimization technique across diverse domains [27][28][29].

D. Shuffled Frog-Leaping Algorithm (SFLA)

SFLA is a metaheuristic optimization algorithm inspired by the behavior of frogs. It mimics the process of frogs hopping among lily pads to find the optimal solution for a given problem [30]. SFLA consists of a population of frogs, where each frog represents a potential solution to the optimization problem. The algorithm operates through a series of steps: initialization, grouping, memorization, shuffling, evaluation, selection and iteration. SFLA's core principle lies in the collaboration and exchange of information between frogs, resembling the way frogs leap between different lily pads to find better feeding spots. By combining local search and information sharing among frogs, SFLA aims to efficiently explore the search space and converge towards the optimal or near-optimal solutions for the given problem. Its adaptability and effectiveness in solving various optimization problems have made it a notable algorithm in the field of optimization [31][32][33].

E. Teaching-Learning-Based Optimization (TLBO)

TLBO is a metaheuristic algorithm inspired by the teaching and learning process observed in a classroom. It simulates the learning environment where a teacher and students interact to improve learning [34]. In TLBO, the population is divided into teachers and learners. Teachers represent the best solutions, and learners are solutions that need improvement. The algorithm iteratively improves the learner's solutions based on the teacher's guidance. It consists of two phases: First, Teacher Phase: The best solutions (teachers) share their knowledge with other solutions (learners). The teaching process involves updating the learners based on the teacher's quality, allowing learners to improve towards better solutions. Second, Learner Phase: In this phase, learners assimilate knowledge from their teachers. They update their solutions by considering the information received from teachers, aiming to enhance their performance. TLBO operates by fostering collaboration and knowledge sharing among solutions to optimize the objective function. Its simplicity, ease of implementation, and ability to solve complex optimization problems make it a popular choice in various domains [35][36][37].

IV. EXPERIMENTS AND RESULTS

Our objective is to monitor CO_2 emissions resulting from energy consumption by seeking an accurate prediction with the lowest error. The dataset selected for this purpose pertains to Thailand and encompasses various dimensions, including GDP, population, coal and coal products, crude oil and petroleum products, gas, electricity, and CO_2 emissions, spanning the years from 1990 to 2020. The data was collected from the World Databank [38] and The Expert Group on Energy Data and Analysis (EGEDA)[39]. In this experiment, as mentioned earlier, the dataset was utilized to split the data into a training set and testing set, with proportions of 85% and 15%, respectively. The neural network architecture consists of three layers: 1) the input layer, 2) Hidden layer 1, starting with 5 nodes and incrementing by 5 nodes up to 20 nodes, and 3) the output layer representing carbon dioxide emissions. The hyperparameters, including the learning rate and momentum, were set to identical values, specifically 0.1. The number of iterations was fixed at 1000, and the weight values ranged from -1 to 1. The population size of all metaheuristic algorithms is 50. Various indices are typically used to evaluate and validate prediction models and algorithms. The MSE and MAE indices were used in study to validate the prediction accuracy of the six machine learning algorithms and the multi-objective mathematical model. Annual CO_2 emissions target data are shown in Figure 1.

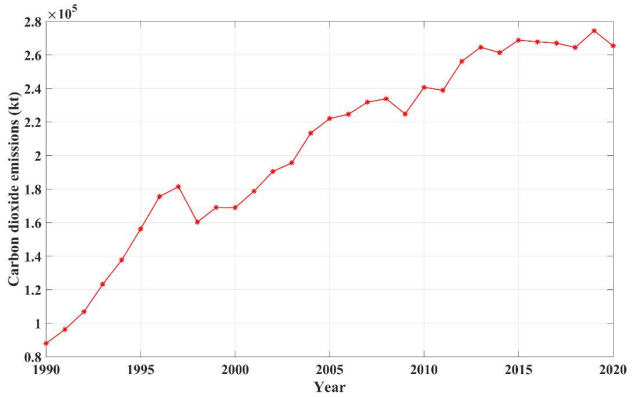


Fig. 1. Annual CO_2 emissions in Thailand (1990–2020)

The Pearson correlation coefficient (R) was employed to examine the dependency between each input variable and the annual output. All relevant R-values are presented in Table I.

From Table I, it is evident that the R-values for each input are close to 1, indicating a positive correlation and a direct linear relationship between the inputs and outputs.

TABLE I. THE RELATIONSHIPS (R) BETWEEN INPUT PARAMETERS AND OUTPUT

GDP	**Population**	**Coal and coal products**	**Crude oil and petroleum products**	**Gas**	**Electricity**
0.9857	0.8809	0.8167	0.9676	0.9167	0.9685

MSE was applied to calculate the minimize objective function performance during training as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(X_i - Y_i)^2$$

The MAE was evaluated for the reliability as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|X_i - Y_i|$$

Where X_i and Y_i are actual value and predicted value, respectively; n is the number of observations.

The result from all architectures according to the MSE values obtained from the training, and the MAE from the test dataset are summarized in Table II, as follows.

TABLE II. COMPARISON OF THE MSE VALUES OBTAINED FROM TRAINING AND THE MAE VALUES OBTAINED FROM TESTING

Algorithm	MSE from Training				MAE from Testing			
	6-5-1	6-10-1	6-15-1	6-20-1	6-5-1	6-10-1	6-15-1	6-20-1
BPMLP	0.0118	0.0020	0.0017	0.0014	8.1821	2.6573	3.5633	3.7163
BPBBO	0.0133	0.0056	0.0064	0.0088	0.1154	0.0746	0.0799	0.0940
BPJAYA	0.0001	0.0389	0.0800	0.0524	0.2319	0.1972	0.2829	0.2290
BPPSO	0.0047	0.0042	0.0046	0.0039	0.0687	0.0648	0.0676	0.0626
BPSFLA	0.0076	0.0075	0.0054	0.0054	0.2162	0.2077	0.3199	0.3431
BPTLBO	0.0468	0.0431	0.1023	0.1177	0.0871	0.0868	0.0732	0.0737

Table III displays the average ranks resulting from the Friedman test conducted among the six competing algorithms. Lower scores indicate better performance. The results revealed that BPMLP had a lower MSE than BPPSO when evaluated on the training dataset. However, in the case of the MAE on the testing dataset, BPMLP exhibited a higher value compared to BPPSO. This divergence may suggest a scenario of overfitting in BPMLP.

TABLE III. COMPARISON OF THE MSE VALUES OBTAINED FROM TRAINING AND THE MAE VALUES OBTAINED FROM TESTING

Algorithm	Ranking	
	MSE	MAE
BPMLP	1.75	6.00
BPBBO	4.00	2.75
BPJAYA	4.00	4.25
BPPSO	2.00	1.00
BPSFLA	6.00	4.75
BPTLBO	3.25	2.25

The results indicate that BPPSO effectively determines an appropriate search agent among all the compared methods. Observing the experimental outcomes, it's evident that the MSE and MAE rank values are the lowest for BPPSO, surpassing most values obtained by BP, except for the MSE training value, which might indicate an overfitting issue. These findings demonstrate the superior performance of BPPSO in solving the problem.

Furthermore, the evaluation of the annual CO2 emissions through Table II and III reveals distinct patterns in the predictive accuracy of various algorithms. The BPPSO architecture within the artificial neural network stands out prominently, showcasing unparalleled promise in minimizing errors associated with CO_2 emission predictions. Its robust performance, as indicated by the convergence curves in Figure 2, substantiates its superiority over alternative algorithms.

The MSE convergence curves depicted in Figure 2 provide a visual representation of the model's learning dynamics across different optimization techniques. It is evident from these curves that the neural network model, when trained by BBO, JAYA, PSO, SFLA, and TLBO, converges toward optimal solutions. Notably, the curve corresponding to PSO exhibits a distinct convergence pattern, underscoring the effectiveness of the PSO technique in minimizing the mean squared error.

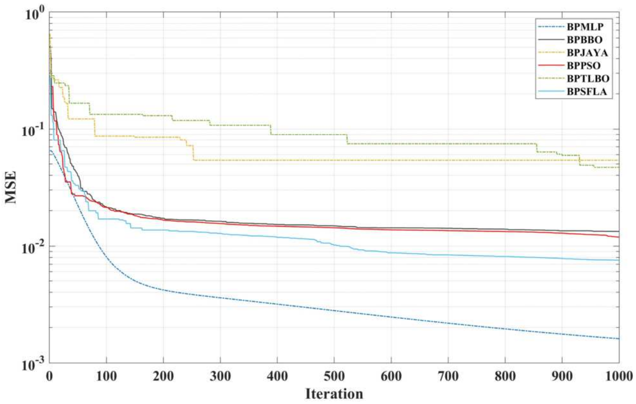
The success of PSO in integrating solutions is evident from the convergence of the MSE curve towards the best-fit function, highlighting the algorithm's adeptness in navigating the solution space. Comparative analysis accentuates the competitive edge of PSO over other optimization algorithms utilized in this study. Its consistent and efficient convergence demonstrates superior performance, emphasizing its viability for optimizing neural network models in predicting CO_2 emissions.

In conclusion, the comprehensive analysis of Table II, Table III, and Figure 2 underscores the supremacy of the BPPSO architecture and the effectiveness of PSO in enhancing the accuracy of CO_2 emission predictions. These findings offer valuable insights into leveraging specific neural network architectures and optimization algorithms for addressing environmental concerns associated with CO_2 emissions.

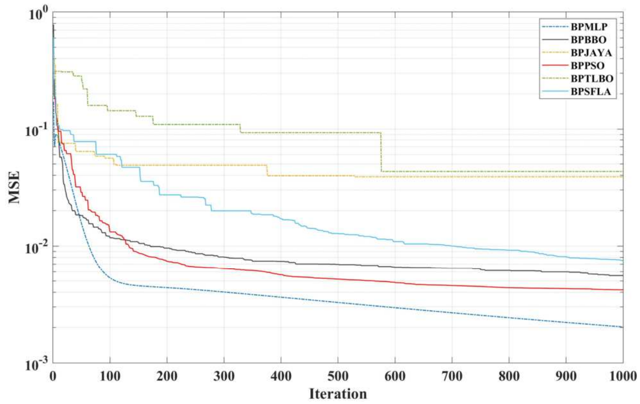
V. Conclusion

In this article, BPMLP was used to predict carbon dioxide emissions, employing a metaheuristic algorithm for initializing the weights of MLP. The aim of the training problem was to avoid overfitting while converging to the best possible solution. From the evaluation of various predictive models applied in conjunction with BP, namely BBO, JAYA, PSO, SFLA and TLBO, the BPPSO model exhibited the low MSE on the training dataset and the lowest MAE on the testing dataset when compared to BPMLP and other metaheuristic algorithms. BPPSO method has been proven suitable for forecasting annual carbon dioxide emissions, supporting precise energy management policies.

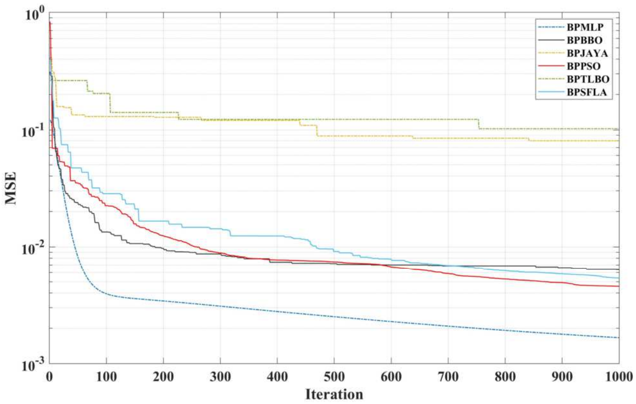
In future investigations, it is planned to conduct a comprehensive comparison among various metaheuristic algorithms. Furthermore, the application of neural networks in conjunction with these metaheuristic algorithms can be extended to address a diverse array of challenges beyond carbon emissions prediction. This could encompass tackling finance-related complexities, strategic planning, or solving various other problem domains. Exploring these applications could unveil the versatility and robustness of the proposed approach in handling a wide spectrum of real-world issues.



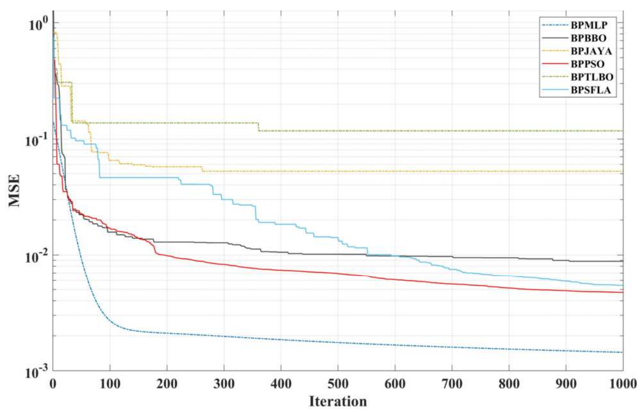
Convergence curves of 6-5-1 architecture



Convergence curves of 6-10-1 architecture



Convergence curves of 6-15-1 architecture



Convergence curves of 6-20-1 architecture

Fig. 2. Convergence curves of metaheuristic methods based on the MLP architecture during training for MSE

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