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Macroscopic and Energy-Based Greenhouse Gas Emissions Predictions: Current Techniques and Future Directions

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***Abstract*— Predicting greenhouse gas emissions is a crucial effort in mitigating climate change and reducing the harmful effects of these gases. Various machine learning models have been employed for intelligent prediction of greenhouse gas emissions, both at a macroscopic level and through energy demand forecasting. The most popular models include Long Short Term Memory (LSTM), Back Propagation Neural Network (BPNN), Support Vector Machine (SVM), Extreme Learning Machine (ELM), and Random Forest (RF). To enhance the performance of these models, numerous optimization techniques have been utilized, with those from the swarm intelligence group being particularly prominent. Current research challenges involve selecting the appropriate machine learning model and optimization technique, addressing dependency on official data, overcoming model interpretability limitations, and dealing with training data constraints. Future research opportunities lie in discovering or modifying existing machine learning models and optimization techniques, utilizing transfer learning to mitigate limited training data issues, and leveraging quantum computing-based optimization techniques to refine existing machine learning models.**

Keywords — greenhouse gas emission, machine learning, sustainability,

I. Introduction

Greenhouse gas emissions refer to the total emissions of greenhouse gases (GHG) produced by an individual, product, service, place, event, or organization, expressed in units of carbon dioxide equivalent (CO2e) [1]. The Greenhouse Gas Protocol [2] defines several greenhouse gases: carbon dioxide (CO2), methane (CH4), nitrous oxide (N2O), hydrofluorocarbons (HFCs), perfluorocarbons (PCFs), sulfur hexafluoride (SF6), and nitrogen trifluoride (NF3), which are expressed in units of CO2e (carbon dioxide equivalent). Each type of GHG has a different source, characteristics, and global warming potential (GWP). These GHG emissions can be categorized into direct and indirect emissions and divided into three emission scopes that can be mapped to these two emission categories [2]. Figure 1 shows scopes 1, 2, and 3 of greenhouse gas emissions.

Predicting greenhouse gas emissions is crucial for mitigating climate change and formulating intervention strategies. Accurate predictions enable targeted efforts, such as policy changes or behavioral adjustments, to address emission drivers.

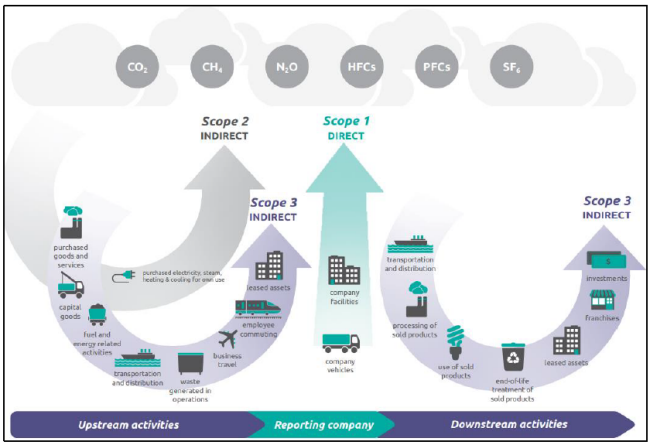


Figure 1. Scope 1, Scope 2, and Scope 3 of GHG emissions

Recent research on greenhouse gas (GHG) emissions prediction has explored a range of methodologies, each offering unique insights into the complex dynamics of emission sources and impacts. Studies utilizing deep learning [3] [4] [5] [6] and multiple learners [7] [8] have shown promise in enhancing the accuracy of emission forecasts, particularly by capturing non-linear patterns in large datasets. Research focused on China, the world's largest GHG emitter, has provided valuable case studies [9] [10] [11] [12] [13] [14] [15], offering crucial insights into regional emissions prediction. Additionally, efforts have been made to develop models for predicting daily emissions [16] [17] [18], which are essential for real-time monitoring and mitigation strategies. Several review papers [19] [20] [21] [22] [23] have also examined both macroscopic and energy-based emissions prediction techniques, highlighting both the strengths and limitations of existing approaches. Despite these developments, significant challenges persist in optimizing existing models and addressing current limitations, underscoring the need for continued research to enhance GHG emissions prediction methods.

This literature review contributes to the field by providing a comprehensive analysis of current machine learning models used for predicting GHG emissions from a macroscopic and energy-based perspective. It explores the optimization techniques employed within these models, identifies key challenges in existing approaches, and proposes future research directions for advancing GHG emissions prediction.

II. Greenhouse Gas Emissions Prediction

Greenhouse gas emissions prediction is divided into two approaches: traditional and intelligent approaches using machine learning [19]. The traditional approach employs artificial empirical formulas and algorithms based on mathematical models. It is less integrated with current developing technologies, heavily reliant on expert experience, and often has slow update rates. On the other hand, the intelligent approach utilizes artificial intelligence that mimics human learning behavior. This approach relies on machine learning, which can autonomously learn from actual case data, resulting in much faster updates compared to mathematical models. This reduces dependence on human intervention.

A. Greenhouse Gas Emissions Prediction Models

According to [19], in the intelligent approach to predicting greenhouse gas emissions using machine learning, there are five models that are most commonly used. These models, ranked by popularity, are Long Short-Term Memory (LSTM), Backpropagation Neural Network (BPNN), Support Vector Machine (SVM), Extreme Learning Machine (ELM), and Random Forest (RF).

1) Long Short Term Memory (LSTM)

LSTM (Long Short-Term Memory) is a modification of the Recurrent Neural Network (RNN) algorithm that addresses issues like gradient disappearance and explosion, making it suitable for handling large datasets. To reduce the amount of processed information, the LSTM architecture incorporates a forget gate that selectively filters out irrelevant information from past time steps, decreasing the computational load needed.

LSTM has been used to predict greenhouse gas emissions, as noted in [3]. Furthermore, several variations of LSTM have been applied to greenhouse gas emission prediction, such as LSTM-STIRPAT [9], SSA-LSTM [24], and STIRPAT-ARIMAX-LSTM [25]. The integrity and accuracy of the data are key factors that influence the prediction accuracy of LSTM. Therefore, the recent improvements in GHG emission prediction using LSTM have focused on data processing and integration [19].

2) Back Propagation Neural Network (BPNN)

The Backpropagation Neural Network (BPNN) consists of three layers: the input layer, which receives and transmits essential information to the hidden layer for processing, and the output layer, which outputs the processed results. BPNN trains neural networks by minimizing empirical risk through a gradient descent mechanism.

The performance of BPNN is significantly influenced by the number of hidden layer and the number of neurons in its hidden layer. Choosing these numbers is vital in designing a BPNN to achieve a balance between model complexity and effective generalization [19]. BPNN has been employed to predict GHG emissions with varying numbers of hidden layers, ranging from 6 to 15, in studies referenced as [26], [10], [11], and [27]. These studies report accuracy results ranging from R^2 values of 0.90 to 0.99.

BPNN also exhibits constraints in GHG emission prediction models, such as slow convergence and prolonged training times, particularly when employing a low learning rate. BPNN is also susceptible to converging to local minima, which does not ensure the attainment of the global optimal solution [19].

3) Support Vector Machine (SVM)

Support Vector Machines (SVM) transform input vectors into a higher-dimensional space to create a hyperplane with maximum margin. SVM searches for a hyperplane that maximizes the distance between hyperplanes, assuming that greater distances yield better generalization performance [19].

SVM has been applied in various studies: [28] combines gross domestic product (GDP) data, urbanization rates, and coal fuel consumption from 1990-2015 in Henan province, China. [29] predicts greenhouse gas emissions using principal component analysis (PCA)-extracted features from education and economic data in Shanghai from 2000-2016. Meanwhile, [30] uses World Bank data on urban and rural populations in EU countries to predict GHG emissions from solid, liquid, and gas fuel combustion.

Prediction accuracy heavily depends on selecting penalty factor C and kernel function parameter gamma. A superior overall predictive performance is often achieved by employing the right kernel function.

Radial Basis Function (RBF) is a kernel function that shows a good performance in SVM-based models for predicting greenhouse gas emissions. Meanwhile, C and gamma are adjusted concurrently to discover optimal values. Initially, gamma ranges from 0.0001 to 10, and C ranges from 0.1 to 100. The best parameters are determined through hyperparameter tuning [19]. SVM optimization in [29] utilizes the Improved Chicken Swarm Optimization Algorithm (ICSO), and in [30], it employs the Firefly Optimization Algorithm (FFA).

4) Extreme Learning Machine (ELM)

The Extreme Learning Machine (ELM) enhances the BPNN algorithm and utilizes simpler parameter settings to increase learning efficiency [31]. During the ELM learning process, only weights in the output layer are optimized and modified, while the hidden layer node weights are either randomly assigned or manually set and remain unchanged [19].

Several studies optimize ELM models using specific optimization techniques. Optimization of ELM using Genetic Algorithm is demonstrated in [12], while optimization using Particle Swarm Optimizer (PSO) is shown in [32]. Optimization of ELM models using Mantaray Foraging Optimization (MRFO) is discussed in [13], and optimization using Improved Salp Swarm Optimization (ISSA) is presented in [16].

5) Random Forest (RF)

Random Forest is an enhanced version of the decision tree algorithm that employs multiple decision trees that operate independently to improve prediction accuracy. Decisions are made through an ensemble learning process, by combining the predictions from multiple trees, resulting in a more accurate and robust model than using a single decision tree.

Predictions made with RF are well-suited for efficiently handling multidimensional data. While its accuracy may not match that of some other models, its rapid processing speed is a significant advantage, making it highly promising for wider application [19].

RF models are widely used for predicting GHG emissions, particularly in predicting emissions from buildings. In [33], GHG emissions were predicted based on data from 38 buildings in the Pearl River Delta region of China. Additionally, RF was used in [34], achieving an improved prediction accuracy with an R^2 value of 0.94, by considering spatial factors and the building structure.

B. Model Performance Metrics

If N is the number of prediction trials, X_i represents the actual value for the i^{th} trial, and Y_i represents the predicted value for the i^{th} trial, then the performance of the greenhouse gas emission prediction model can be measured using the following metrics[35][20]:

1) RMSE (Root Mean Squared Error)

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_i - Y_i)^2} \quad (1)$$

RMSE represents the square root of the mean of the squared differences between predicted and actual values. RMSE values range from 0 to ∞, with a lower RMSE indicating a more accurate model.

2) Mean Absolute Error (MAE)

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|X_i - Y_i| \quad (2)$$

MAE calculates the mean of the absolute differences between predicted values and actual values. The range of MAE values is from 0 to ∞. A more accurate model is indicated by a smaller MAE.

3) R-Squared (R2)

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(X_i - Y_i)^2}{\sum_{i=1}^{N}(\bar{Y} - Y_i)^2} \quad (3)$$

R^2 indicates how much of the variation in the actual values (dependent variable) can be accounted for by the predicted values (independent variable) in a regression model. According to formula (3), R^2 values range from -∞ to 1. The closer R^2 is to 1, the better the model performs.

4) MAPE (Mean Absolute Percentage Error)

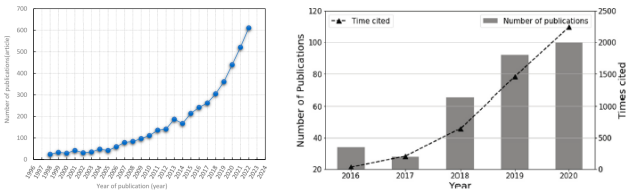
$$MAPE = \frac{1}{N} - \sum_{i=1}^{N}\left|\frac{Y_i - X_i}{Y_i}\right| \quad (4)$$

MAPE measures the average percentage of absolute error between predictions and actual values. It is used to assess the level of relative error in predictions. The range of MAPE values is from 0 to ∞. A more accurate model is indicated by a smaller MAPE.

In addition to the four most popular metrics explained, other evaluation metrics that can be used to measure the performance of GHG emission prediction models include Normalized Root Mean Square Error (NRMSE), Coefficient of Variation of Root Mean Square Error (CV-RMSE), Adjusted R2, Mean Absolute Deviation (MAD), etc [20].

III. Macroscopic and Energy-Based Greenhouse Gas Emissions Predictions

GHG emissions prediction is closely related to predicting energy consumption in buildings. Both are closely intertwined as building energy consumption represents a significant portion of global energy consumption [21], with buildings contributing to one-third of GHG emissions [22].



(a) (b)

Figure 2. The number of publications on macroscopic greenhouse gas emissions predictions [19] and building energy consumption prediction models using ANN [23]

Machine learning has been used to predict GHG emissions, both directly by using emissions causes on a macro scale (macroscopic) and indirectly by predicting energy consumption and demand of buildings (energy-based). Figures 2(a) and 2(b) show the increase in the number of publications on macroscopic GHG emission prediction and energy-based GHG emissions prediction. The upward trajectory shown in both figures signifies that research on macroscopic and energy-based greenhouse gas emissions is progressive and worth further investigation.

A. Macroscopic Greenhouse Gas Emissions Prediction

Macroscopic greenhouse gas emission predictions commonly utilize data on economic development, population, urbanization energy consumption, industrial structure, and technological advancement [19]. These data can be enriched with traffic load data, import and export scale, and education levels, to improve the accuracy of the greenhouse gas emission prediction models [19].

The machine learning models are often optimized using optimization techniques. Optimization can be carried out at both the algorithm level and the data level, or at both levels simultaneously. Table I shows some greenhouse gas emission prediction models that have been optimized at both the data level and the algorithm level.

TABLE I. Macroscopic Greenhouse Gas Emissions Prediction Model

Ref	Model	Level	Optimization Technique
[25]	LSTM	Data	Principal component analysis
[24]	LSTM	Algorithm	Sparrow Search Algorithm
[7]	BPNN	Data	Genetic algorithm
[10]	BPNN	Algorithm	Particle Swarm Optimization
[36]	SVM	Data	Principal component analysis
[36]	SVM	Algorithm	Butterfly Optimization
[37]	SVM	Algorithm	Lion Swarm Optimizer
[14]	SVM	Algorithm	Improved Marine Predator Algorithm
[16]	ELM	Data	Ensemble empirical model decomposition
[15]	ELM	Data	Logarithmic average division
[32]	ELM	Algorithm	Particle Swarm Optimization
[13]	ELM	Algorithm	Manta Ray Foraging Optimization
[34]	RF	Data	Pearson Test
[38]	RF	Data	Generalized additive model

B. Energy-based Greenhouse Gas Emissions Prediction

Several approaches are available to conduct energy-based greenhouse gas emissions prediction: statistical analysis, machine learning, and deep learning [20]. Statistical analysis is considered easier to implement but not suitable for nonlinear problems and is very affected by outlier data. Machine learning is considered to have a relatively fast training process, but its accuracy is highly influenced by feature selection. Deep learning can automatically select features, handle nonlinear problems, and is suitable for large, complex data, but its training process is very long, requires high computational resources, and needs extensive hyperparameter optimization. Universities are the most common type of building studied, followed by residential, commercial, and office buildings. Most of the training data used is building energy consumption data from the last 1-2 years, and some focus on electrical energy consumption. The most popular models used are MLR for statistical analysis approaches, SVR for machine learning approaches, and LSTM for deep learning approaches [20]. Table II shows some examples of models used for each approach to greenhouse gas emission prediction through building energy consumption prediction.

TABLE II. ENERGY-BASED GREENHOUSE GAS EMISSIONS PREDICTION

Approach	Model	Reference
Statistical Analysis	ARIMA	[8]
	ARIMAX	[17]
	MLR	[39]
	LR	[40]
	ARMA	[41]
Machine Learning	RF	[42], [41]
	SVM	[4]
	ANN	[43]
Deep Learning	LSTM	[5], [44]
	RNN	[6]
	CNN	[17]
	Hybrid LSTM	[45], [18]

A more detailed comparative analysis of 324 articles on the Web of Science about building energy consumption prediction using deep learning approaches with artificial neural networks (ANN) is presented by [23]. Three groups of ANN architecture were identified, namely Feedforward Neural Network (FFNN), Convolutional Neural Network (CNN), and Recurrent Neural Network (RNN). Meanwhile, optimization algorithms used to improve the prediction model were categorized into 5 categories; Evolutionary-based algorithm, Physical or Math-based algorithm, Human-based algorithm, and Swarm Intelligence-based algorithm. A detailed elaboration of these algorithms is presented in [23]. The ANN models are optimized to improve the accuracy of the prediction results. These optimization techniques are applied to optimize three types of parameters in ANN: (i) weights and biases; (ii) input parameters; and (iii) hyperparameters. Most studies use swarm intelligence-based optimization [23]

C. The Potential of Transfer Learning

Transfer learning (TL) involves creating a new model for task B by utilizing an existing model initially developed for task A as a foundation. The motivation behind the study of transfer learning is the observation that humans can use previously acquired knowledge to address new problems more efficiently or with superior solutions [46].

Another frequently used term in transfer learning is domain adaptation. It involves modifying one or more source domains to transfer knowledge and enhance the target learner's performance. Various fundamental concepts of transfer learning are discussed in [46], while the latest developments in domain adaptation are discussed in [47].

A common scenario in utilizing transfer learning is when there is a large amount of labeled example data available or a well-trained model in the source domain is available, but only a few labeled examples from the target domain. In this case, the goal of transfer learning is to learn a more accurate decision function in the target domain.

The need for transfer learning may also arise when data quickly becomes outdated [46]. The current data for forecasting GHG emissions is highly intricate, and only a few areas possess adequate monitoring systems for these emissions. Most regions do not have enough data to create accurate prediction models. Transfer learning can considerably decrease the data requirements, making it a crucial tool for overcoming the challenges associated with GHG emission models and paving the way for further research opportunities.

D. The Potential of Quantum-Based Optimization

Quantum computing uses the principles of quantum mechanics to process information, through the phenomenon of superposition and entanglement that allows quantum computers to have an advantage in the speed of complex calculations compared to classical computers [48]. This makes quantum computing emerge as an innovation with the potential to accelerate and even change the approach to handling greenhouse gas emissions.

Quantum computing offers potential applications in various fields and has been widely studied in various literature reviews [49] [50] [51]. Quantum machine learning is a result of combining quantum information processing with classical machine learning[52]. Some quantum machine learning algorithms are quantum versions of existing machine learning algorithms. These algorithms can be pure quantum algorithms, hybrid classical-quantum algorithms, or quantum-inspired algorithms, and some of them in certain cases show better performance than their classical machine learning versions [52].

Classical GHG emission prediction models can be optimized using several types of optimization techniques, both at the data level and algorithm level [19], which are currently still dominated by swarm intelligence-based optimization [23].

One quantum computing approach that can be used for optimization tasks is Quantum Annealing (QA). QA utilizes the principles of quantum mechanics and is designed to find the global minimum of a cost function to solve optimization problems [53]. QA has been implemented in various optimization tasks, for example, to optimize real-time traffic light control[54], assist bike-sharing operators in optimizing bike load balancing processes [55], and optimize energy consumption in buildings [56]. The wide application scenarios and its advantages in certain examples indicate that QA has advantages and flexibility in various use cases and has great potential to be used to optimize greenhouse gas emission prediction models.

IV. Current Challenges and Opportunities

Both macroscopic and energy-based GHG emission predictions face several challenges, namely:

1. Dependence on official data such as GDP and demographic data that are available in limited quantities and require official release by the authorities.
2. Limited interpretability of the models, especially if the models are based on neural networks or deep learning
3. The need for suitable model architecture, particularly for models using artificial neural networks, especially in determining the number of hidden layers and the number of neurons per layer.
4. The need for better optimization techniques
5. Limited data training is available.

Therefore, several future research opportunities can be identified, namely:

1. Utilizing local monitoring systems to enrich official data
2. Improving the accountability of prediction models through the application of explainable AI (XAI),
3. Discovering new optimization techniques to achieve better model performance,
4. Utilizing quantum computing-based optimization to optimize existing machine learning models,
5. Utilizing transfer learning to address the lack of available training data.

V. Conclusion

Current research shows that macroscopic greenhouse gas emissions prediction often employs models based on LSTM, BPNN, SVM, ELM, and RF, each with its own advantages and disadvantages. Meanwhile, energy-based greenhouse gas emissions prediction is often made using artificial neural networks with three architectural groups: FFNN, CNN, and RNN. Both macroscopic greenhouse gas emission predictions and energy-based greenhouse gas emissions prediction have been optimized using various optimization techniques. The most popular optimization techniques used come from the swarm intelligence algorithm group.

Some challenges faced in predicting greenhouse gas emissions include (1) dependence on official data; (2) limited interpretability of the machine learning models; (3) choosing the best neural network architecture; (4) the need for optimization of existing models; and (5) limited training data available. Future research opportunities to address these challenges include utilizing local monitoring systems to enrich official data, implementing explainable AI, discovering new optimization techniques or modifying existing optimization techniques to improve model prediction performance, utilizing transfer learning to address the limited available training data, and leveraging quantum computing-based optimization techniques to optimize existing machine learning models.

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