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Review

Reducing Emissions Using Artificial Intelligence in the Energy Sector: A Scoping Review

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Abstract: Global warming is a significant threat to the future of humankind. It is caused by greenhouse gases that accumulate in the atmosphere. CO_2 emissions are one of the main drivers of global warming, and the energy sector is one of the main contributors to CO_2 emissions. Recent technological advances in artificial intelligence (AI) have accelerated the adoption of AI in numerous applications to solve many problems. This study carries out a scoping review to understand the use of AI solutions to reduce CO_2 emissions in the energy sector. This paper follows the PRISMA-ScR guidelines in reporting the findings. The academic search engine Google Scholar was utilized to find papers that met the review criteria. Our research question was "How is artificial intelligence used in the energy sector to reduce CO_2 emissions?" Search phrases and inclusion criteria were decided based on this research question. In total, 186 papers from the search results were screened, and 16 papers fitting our criteria were summarized in this study. The findings indicate that AI is already used in the energy sector to reduce CO_2 emissions. Three main areas of application for AI techniques were identified. Firstly, AI models are employed to directly optimize energy generation processes by modeling these processes and determining their optimal parameters. Secondly, AI techniques are utilized for forecasting, which aids in optimizing decision-making, energy transmission, and production planning. Lastly, AI is applied to enhance energy efficiency, particularly in optimizing building performance. The use of AI shows significant promise of reducing CO_2 emissions in the energy sector.

Keywords: artificial intelligence; emission reduction; energy sector; scoping review

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1. Introduction

Global warming, driven by the accumulation of heat-trapping greenhouse gases such as carbon dioxide (CO_2), poses a significant threat to our planet. As sunlight is reflected from the surface of the earth, the atmosphere reflects most of it back, trapping that energy in. This is called the greenhouse effect [1]. This challenge has motivated researchers to find mitigation strategies for CO_2 emission from, e.g., buildings [2], agriculture [3], air travel [4] and energy supply [5]. Furthermore, human activity in a modern society requires energy produced by means that add to the CO_2 emissions, such as fossil fuel combustion energy plants [6] (p. 4). The energy sector, responsible for approximately 34% of global CO_2 emissions, significantly contributes to this problem [7]. Reducing these emissions is critical for mitigating climate change and its severe impacts.

In addition to societal change, technological solutions have been introduced to reduce emissions. The use of computing technologies in this task has been proposed to optimize processes. There has also been research to identify ways to create optimized solutions to counter the emissions [8–10]. Recent advances in artificial intelligence (AI) offer promising solutions by optimizing energy consumption, improving the efficiency of renewable energy sources, and better managing energy demand [11]. The use of modern AI techniques could provide optimization strategies to reduce emissions in any domain, including the energy sector. The use of AI to optimize industrial processes has proven to be a viable option. For example, AI has been leveraged to control quality in industrial vision-based application [12] and to provide decision support [13]. The core promise of AI-based technologies is efficiency, which should be applicable to the energy sector. However, the multitude of research articles related to both emissions and AI make it difficult to identify the current state of AI usage to combat CO_2 emissions.

Understanding how AI can be utilized in the energy sector to reduce CO_2 emissions is crucial for driving environmental benefits, informing policy and investment decisions, and enabling continued innovation [14]. We argue that such understanding can be found in the current research literature. This paper aims to explore the current applications of AI in the energy sector, evaluate their effectiveness in reducing CO_2 emissions through optimizing energy generation, demand forecasting and optimizing energy usage efficiency, and identify future opportunities for leveraging AI to combat climate change. By examining these aspects, we can gain a deeper understanding of the role of AI in fostering a sustainable energy future. This leads to the research question of the present article.

- RQ: How is artificial intelligence used in the energy sector to reduce CO_2 emissions?

The research question is broad. However, we believe that having a high-level overview of the subject can be beneficial to the research field by providing an introduction to existing studies covered by the topic. The broadness of the research question means that the systematic review methodology is not a good fit to answer the question. Recommended reporting guidelines for systematic reviews include practical recommendations based on the findings. Nevertheless, our study is targeted as an introduction to studies covered by the topic; therefore, the scoping review methodology is a better fit for this study [15]. The paper follows the PRISMA-ScR reporting guidelines for scoping reviews [16].

The unique contribution of this research is that it uses the scoping review framework to describe the current status of AI research to prevent emissions. Furthermore, it strictly considers one domain (energy) and uses specific criteria to identify relevant literature. As a result, a concise list of relevant articles is produced. The articles satisfying the scoping criteria are also categorized, and their contents are discussed.

Next, this article considers related studies that have identified AI as a tool for the energy sector. Subsequently, the scoping review methodology of this study is explained. In the results section, our findings are presented, and finally, a section discussing the results concludes the article.

Related Studies

To our knowledge, no review papers exist with the same scope as our study. However, some papers explore related areas. These papers discuss AI usage in the energy sector in general or in some particular use cases in the energy sector. This section lists these types of research papers. The immediately following papers are narrative style reviews that do not report the review methodology. At the end of this section, methodologically more sound papers are presented. Our article's contribution in relation to existing literature is that it is a scoping review unlike most of the related literature. Moreover, the identified methodologically sound papers focus on various aspects of the energy sector, while our article specifically focuses on CO_2 emissions.

Ahmad et al. [17] and Ahmad et al. [18] provided an overview of how AI technologies are used in different parts of the energy sector, covering a wide range of topics from energy production, transmission, storage, and consumption. In a separate review, Ahmad et al. [19] studied real-time applications of probabilistic machine learning (ML) models in the energy sector's core technologies and energy distribution. A similar high-level overview of AI usage in the energy sector was conducted by Babatunde et al. [20], which covers the AI usage in the energy sector related to forecasting, diagnosis, control, and optimization topics. Forootan et al. [21] ended up mainly covering the same topics in their review, same as Zhou [22], who mainly included the same topics while focusing on research about AI usage in energy systems in carbon neutral district communities.

Makala and Bakovic [23] conducted a review of AI usage in the energy sector, which includes examples of AI-aided fault prediction and detection, energy usage optimization, disaster recovery, and power theft detection. Rangel-Martinez et al. [24] reviewed the impact of machine learning on renewable energy production (solar, wind, and hydro), chemical catalysis design, and power storage and distribution. Cheng and Yu [25] reviewed the impact of new-generation AI technologies on smart energy and electric power systems. Kanase-Patil et al. [26] reviewed research on the integration of renewable energy systems in smart cities with a focus on AI usage on renewable sizing problem.

Nemitallah et al. [27] reviewed the research concerning AI usage for boilers to optimize the boiler performance and AI usage to reduce boiler NO_x emissions. Zahraee et al. [28] reviewed AI methods for optimizing the design, planning, and control of hybrid energy systems that combine renewable energy production with backup energy production from traditional non-renewable energy sources. Al-Othman et al. [29] focused on reviewing AI methods in renewable energy systems with integrated hydrogen fuel cell-based energy generation capabilities. Prince and Hati [30] reviewed methods to reduce energy usage in ventilation systems covering the use of AI to predict airflow and control the ventilation systems. Pérez-Gomariz et al. [31] reviewed publications related to AI usage for saving energy in refrigeration systems.

Mehmood et al. [32] reviewed publications related to the application of AI to building energy efficiency. Nyangon [33] reviewed AI usage in the energy sector with a focus on preventing electricity asset stranding by utilizing AI technologies. Ali and Choi [34] reviewed the components of the smart grid and the role of AI in improving performance, reducing power losses, enhancing power quality, as well as easing the management of the smart grid. Mohammad and Mahjabeen [35] presented many ways in which AI can be used for solar energy generation, management, and grid integration to improve efficiency, cost effectiveness, and scalability. Seyedzadeh et al. [36] provided a review on the four main ML approaches including artificial neural network, support vector machine, Gaussian-based regressions, and clustering methods to forecast and improve building energy performance.

In addition to narrative style reviews, more systematic studies that explore the related areas also exist. The following review articles report their review process. Mhlanga [37] reviewed the existing research around AI usage in the energy sector, focusing particularly on emerging markets where the energy sector is not yet fully developed and faces challenges such as constant power outages. Saheb et al. [38] focused on AI and sustainability in the energy sector. Franki et al. [39] reviewed companies that use or develop AI technologies in the power sector. Aguilar et al. [40] focused on the consumption side of the energy sector and reviewed studies related to smart building energy management with ML technologies. A similar study was conducted by Halhoul Merabet et al. [41], where the authors reviewed research related to AI building control systems where the goal is to save energy while maintaining occupant comfort. Mosavi et al. [42] focused on reviewing what different ML models are used in energy system applications and what those applications are. Wei et al. [43] reviewed AI models for forecasting energy usage. Pandey et al. [44] described the different parts of the power system and the potential of AI techniques for optimizing, planning and controlling their operation.

2. Methodology

The review was conducted by utilizing the Google Scholar (https://scholar.google.com/ accessed on 14 January 2025) academic search engine. The search phrases were identified by first familiarizing ourselves with the topic by conducting a broad search around the subject and finding common terms used in the research papers that clearly fit in the topic of reducing CO_2 emissions using AI methods in the energy sector. The search phrase “reducing emissions in energy sector using artificial intelligence” was identified as a good candidate for finding the relevant research papers. The Google Scholar search algorithm clearly includes some fuzzy searching logic as the search phrase also returned papers that used near-synonyms for the keywords in the search phrase. However, we decided not to trust the algorithm blindly and instead came up with one near-synonym for each of the keywords that were often used in the papers that were discovered in the preliminary searching stage. Figure 1 presents the used keywords and their near-synonyms and illustrates the logic of how the search phrases were constructed by concatenating the identified keywords with fixed components “in” and “using”. This resulted in 8 distinct search phrases, such as “reducing emissions in energy sector using artificial intelligence”, “reducing emissions in energy sector using machine learning”, and so on.

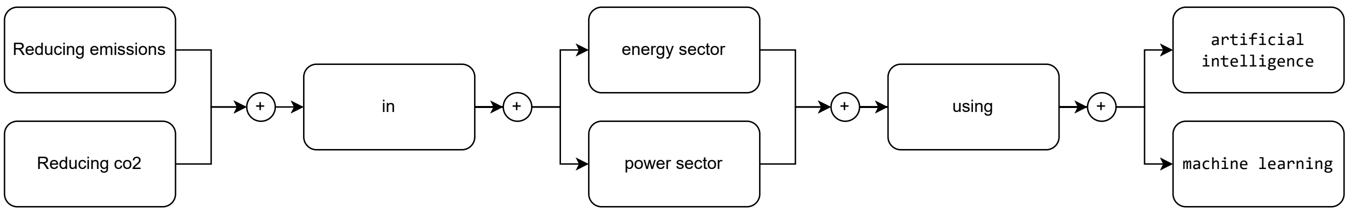

Figure 1. Image describing the search phrase construction. The search phrases were created by combining different keywords to full search phrase sentences with concatenating them together with fixed words “in” and “using”.

The search phrases were executed individually using the default Google Scholar search view. A semi-automatic result collection system was developed using the Playwright (https://playwright.dev/ accessed on 14 January 2025) browser automation framework. The system automated the result collection to remove human errors in the repetitive task of copy-pasting the data from the result pages. The result collection system script was executed one search phrase at a time. The main author of this paper conducted the result collection and monitored the result collection script progress for any errors. The script opened a normal browser window, navigated to Google Scholar web page and performed the search using the search phrase. In the search result page, the script collected the relevant data from each of the search results. The collected data included publication name, APA citation, and link to the publication. The publication name was collected from the search result anchor texts on the result page. The link to the publication was the href URL of the result’s link. The APA citation was copied from the pop-up window that opens from the “Cite” button on the results page. Furthermore, for each of the search results, Google Scholar “Cited by”, “Related articles”, and “All versions” links were also collected just in case, but in the end, they were not used in this study.

The search results from the first five pages, resulting in 50 papers for each query, were collected and saved in JSON formatted files. The collected raw data from the JSON files were converted to an Excel worksheet to orchestrate the review process. An automatic duplicate removal was performed when the records from the JSON files were added to the Excel file using a Python script. The script compared the APA citation across the collected results and dropped the duplicates based on that. The number of unique APA citations in the collected raw data JSON files was independently replicated using a one-liner bash command that used command line tools `jq`, `sort`, `unique`, and `wl`. This number was compared to the number of entries that resulted from duplicate removal with the Python script to verify that the duplicate removal logic in the Excel file creation was bug-free. A few duplicates remained where the APA citation that Google Scholar provided did not match even when the publication was the exact same. Those duplicates were discovered and removed during the abstract screening phase. The abstract screening phase was conducted by the main author of this paper. All papers where the inclusion criteria were unclear were passed to the full text screening phase. During this phase, the search phrase effectiveness was also evaluated by observing how well the abstracts fit the inclusion criteria. As the number of included papers was sufficient in this phase, the search phrases were determined to be effective in finding the relevant studies. Each of the authors of this paper contributed to the full content screening process. In this phase, the reviewer read the full paper and compared the contents to the inclusion criteria. The review process was orchestrated in the Excel file, where the reviewer marked the paper to see whether it passed the inclusion criteria. If the paper did not pass the inclusion criteria, the reviewer wrote a short explanation in the Excel file. If the paper passed the inclusion criteria, the reviewer wrote an initial summary of the paper to the manuscript. The initial summaries were revisited at the final synthetization phase. The inclusion criteria for papers were agreed upon at the beginning of the review process. Weekly meetings between the research team were organized to discuss papers where the inclusion was unclear for the reader. The inclusion criteria were the following:

- Publication is related to the energy sector;
- Publication goal is to reduce CO_2 emissions;
- Publication uses artificial intelligence to achieve the goal.

These inclusion criteria were chosen to complement our research question, which we identified as lacking in existing reviews. The research question focuses on the energy sector and asks how AI is used to reduce CO_2 emissions. The inclusion criteria map directly to this research question.

The energy sector was defined to include electricity production, heat production, and energy storage systems. Papers related to energy consumption in the transportation sector were omitted from this study to reduce the already wide scope of the study. The CO_2 emission reduction needed to be clearly identified as one of the goals of the paper; however, it did not have to be the main focus. In this study, we defined artificial intelligence as limited to machine learning algorithms where a model was fitted with data. Papers where optimization algorithms were used for pure mathematical models were excluded from this study. This decision was made to ensure the paper's coherence and accessibility for readers with experience in machine learning. By focusing on machine learning models, we aimed to create a unified narrative that professionals familiar with these techniques can fully understand and appreciate. Only papers with full text available in English were included. Grey literature was also considered, and no publication year limit was set for the papers.

In the contents screening phase, many related review studies were identified, which were related to AI usage in energy sector. These studies are presented in the related studies section of this paper.

During the preparation of this study, the authors used Llama 3.1 70B Instruct generative AI model [45] to aid with the analysis of some of the papers and writing. The model directly wrote no text, and the authors take full responsibility for the validity of the text in this paper. The authors first read all the papers, and a general understanding of the contents was formed. The generative AI tool was used in the paper summarization phase to aid in understanding the paper and the authors' intentions.

Hallucinations are problematic when using generative AI to answer questions [46]. To make sure that the AI model did not hallucinate the responses, the following method was used to feed the paper to the AI model:

1. The pdf files were converted to text files using `pdftoppm` and `tesseract` [47] command line tools.

```
pdftoppm "${PDF_FILE}" "${WORKDIR}/output" -png
find "${WORKDIR}" -name "*.png" \
      -exec tesseract {} "$(basename {} .png)" --psm 1 \;
```

2. Line numbers were added with the `nl` command.

```
cat "${WORKDIR}"/output-*.txt | nl -s" " -w2 -ba > paper.txt
```

3. The following prompt was used to start the chat session:

```
The following is an OCR generated text from a scientific paper that is
originally created from two column pdf file using tesseract.  I want you to
answer questions about the paper.  Because the text was generated using an
OCR software, it is not 100% accurate, and there is illogical jumps between
text columns.  Also the text lacks images and only includes the image
captions.  Try your best to make sense about the whole.  Each text line is
started with a line number in following format:
1 Text on the line number one
2 Text on the line number two
And so on.  When you answer to a question, I want you to say which line(s)
contains the information that you refer to.  It is important that you
include all the lines that you refer.  If your answer includes references
to lines in the text, then start the sentence with ‘‘According to line’’ or
‘‘According to lines’’.  This is the OCR created text:
(the paper OCR extracted and line numbered text was pasted here)
```

After the reader had the general idea of the paper, the method was used to quickly find answers to the questions such as What dataset did the authors use in this paper? and What were the input and output variables of the model? The model answers were not trusted directly. Instead, the line numbers that the model included in the responses were used to locate the information in the original source paper. This way, any potential model hallucinations could be avoided. The following is an example of the model answering a question about a paper by Ashraf et al. [48]. The used model is the original version of the Llama 3.1 70B Instruct model, running with full 16-bit precision and using the greedy decoding strategy.

```
» What dataset did the authors use in this study?
According to lines 490-491, the authors used a dataset of approximately
31,200 observations averaged over 10-minute intervals taken from the
supervisory information system (SIS) for the power plant’s selected input
and output operating parameters.
```

As can be seen from the example, the model fully understands the instruction of adding the referred line numbers to the answer. Sometimes the line numbers were off by few lines. However, the information that the model referred to was always near the indicated lines. The model adds its own interpretation about the text to the answer. The model was never trusted directly, the user always checked the referred lines and made their own interpretation about the text. This way, the AI model was used only to find facts from the papers, but all the potential problems with model hallucinations were avoided. Furthermore, in the final result synthetization phase, the same model was used to suggest categories based on the written summarizations.

3. Results

Figure 2 illustrates the number of papers in different phases of the review process. The large drop of the initial 186 screened papers to the final 16 summarized papers shows that it is hard to come up with specific search phrases that return papers that fit our inclusion criteria. Therefore, we needed to search through many publications to find the fitting papers.

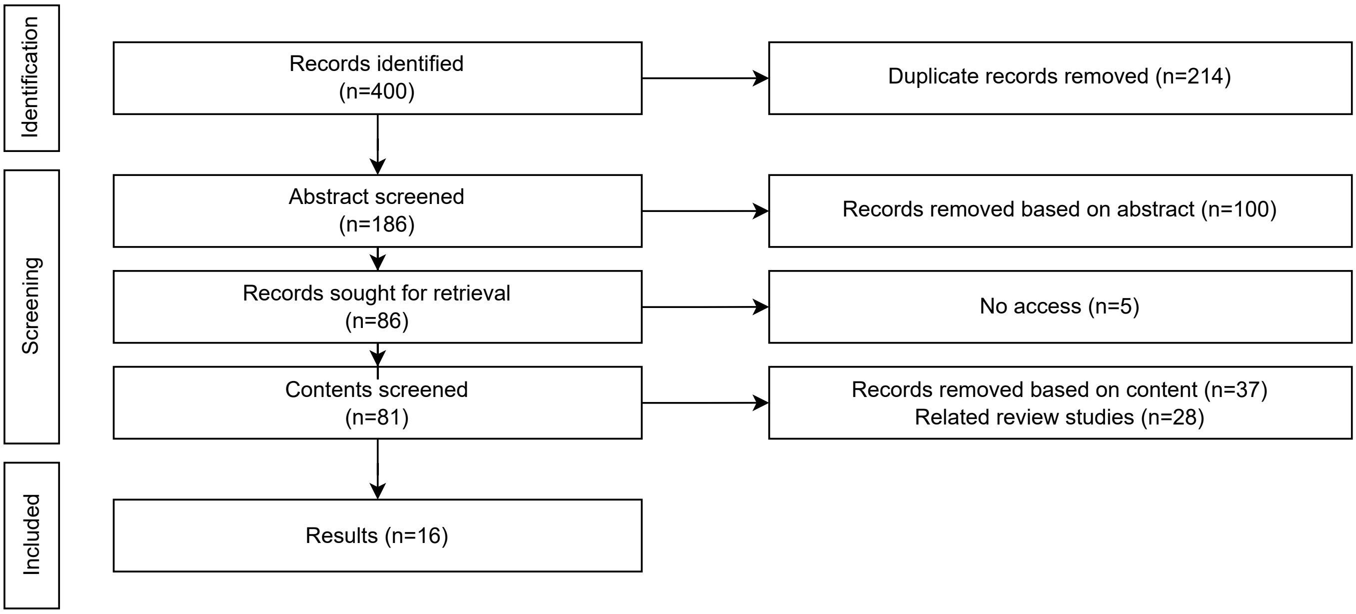

Figure 2. PRISMA flowchart illustrating the number of papers through different phases of the review process. The related review studies that were identified in the contents screening phase are listed in the related studies section of this paper.

The results of this study are presented by categorizing the papers into three different categories based on their content. AI is used to optimize energy production, forecast the future for decision-making and policy setting, and optimize energy usage on the end-user side of the energy sector. The following sections summarize the relevant studies in more detail. A summary and a table are provided at the end.

3.1. AI Applications in Energy Generation for Emission Reduction

The largest category with the most papers contains studies related to energy generation optimization with AI methods. A common theme between most of the papers is to fit a machine learning model to a dataset that is collected from the energy generation process and use an optimization algorithm to find the optimal input parameters for the model. Different variants of artificial neural networks were the most common method for modeling the processes, although many of the studies tested multiple methods for process modeling. Different optimization algorithms were used in the studies, such as Particle Swarm Optimization, nonlinear programming methods, Monte Carlo simulation, and Ant Colony Optimization.

Chen et al. [49] studied how to optimize the scheduling of an adjustable post-combustion carbon capture (PCC) system in a coal fired power plant (CFPP) with integrated renewable power generation. The PCC system works by absorbing the CO_2 to a solvent. The CO_2 is released from the solvent when it is heated, therefore regenerating the solvent for reuse. Some of the energy required for solvent heating can be generated with renewables, such as wind or solar. The operational limits of the CFPP, renewable power availability, PCC system adjustment, CO_2 emissions, and load demand create a complex optimization problem with different solutions for different objective functions. In this paper, the authors optimized the PCC system timings so that the regional power grid operating costs were minimized. One part of the optimization target was the penalty costs of CO_2 emissions. The authors used a PCC system modeling platform to create a dataset with 3000 samples. A total of 2000 samples were used to train a deep belief network (DBN) and the rest were used for model validation. The authors used the Particle Swarm Optimization method on the DBN model to optimize the objective function. The authors reported that when the PCC system is optimally scheduled, the whole CFPP-PCC system renewable power curtailments can be reduced by 51% with CO_2 emission reductions by 80% when compared to standalone CFPP.

Hong et al. [50] optimized the steam methane reforming (SMR) process for hydrogen production to produce less CO_2 emissions. Even though hydrogen fuel cells do not produce emissions when the gas is converted to electricity, there are multiple ways to produce hydrogen gas and some of them do produce CO_2 emissions. SMR is one such method where fossil fuels are used to produce hydrogen. In this paper, authors modeled an SMR production plant using deep neural networks (DNNs). The dataset was collected from an SMR pilot plant which included 66 data collection points. However, the pilot plant did not include measurements for composition and flow rate of CO_2; therefore, those measurements needed to be simulated with a process simulation model. Two DNN models were trained with the data, which the authors named the operation DNN model and the simulation DNN model. The operation model was trained with the data that were collected from the pilot plant. However, because the collected data did not have values for the composition and flow rate, the simulation model training data included simulated values for those variables. The operation model was used in simulation model validation since many of the output variables were shared between the two models. The authors used a multi-objective particle swarm optimization method to optimize the input parameters for the simulation DNN model. The optimization targets were to maximize the thermal efficiency and minimize CO_2 emissions. The authors reported values between 77.5% and 87.0% in thermal efficiency and values between 577.9 t/y and 597.6 t/y in CO_2 emissions in the Pareto-optimal front. The authors suggested that the results contribute to improvements in low-carbon production of hydrogen using the SMR method.

Ashraf et al. [48] studied the optimization and emission reduction in a 660 MW super-critical coal fired power plant. The authors modeled the power plant heat rate with seven plant operating parameters as the input features. The tested ML techniques were artificial neural network (ANN), support vector machine (SVM), and AutoML platform where Light Gradient Boosting on the ElasticNet Predictions model was used. The training dataset consisted of approximately 31,200 samples of historical data from the power plant supervisory information system. The model performances were validated with an external validation dataset. The ANN achieved the best results. The authors conducted a parametric study for the plant operating parameters using the Monte Carlo simulation technique with the ANN and SVM models and compared the results to the AutoML platform feature impact analysis. Based on the parametric study, the authors optimized the operating parameters of the power plant and estimated that the optimized operation parameters would reduce CO_2 emissions by 173.4 kt/y, 220.7 kt/y, and 204.9 kt/y in 50%, 75%, and 100% power generation modes, respectively.

In a separate study, Ashraf and Dua [51] used artificial neural networks to model presumably the same 660 MW coal plant operation and used nonlinear programming methods to find the optimal parameters where the model generated a maximum amount of power under the defined constraints. The model explanatory variables were Coal Flow Rate, Main Steam Temperature, Main Steam Flow Rate, and Reheat Steam Temperature. The target variable for the model was the power production of the coal plant. The optimized parameters were tested in a real setting by running the power plant while trying to maintain the parameters around the optimized values. The optimization achieved 3 t/h savings in Coal Flow Rate, 1.3% improvement in thermal efficiency, and estimated 50.5 kt/y accumulated emission reductions when compared to a business-as-usual setting where the plant is run with non-optimized parameters.

In a third study, Ashraf et al. [52] proposed two advanced AI modeling algorithms to improve the isentropic efficiency of a high-pressure (HP) steam turbine. The authors tested artificial neural network (ANN) and support vector machine (SVM) algorithms to model the process. Both models were trained and validated with a dataset that was collected from the power plant's supervisory information system, which includes data from the fuel combustion system, turbines, and reheating systems. The dataset contains hundreds of parameters of operational data of which the model input parameters were selected based on literature review and recommendations by the power plant operation and performance engineers. The modeled output parameter was the HP turbine efficiency. The authors used Monte Carlo methods to conduct a sensitivity analysis on the input variables and used nonlinear programming methods to find the optimal operating parameters under specific constraints. The results indicate that the efficiency of the HP turbine can be enhanced by 1.43%, 5.09%, and 3.40% for half-load, mid-load, and full-load power generation modes, respectively, when compared to the average input parameter values. Additionally, the annual CO_2 reduction is projected to be 58.3, 123.5, and 70.8 kilotons per year (kt/y) for half-load, mid-load, and full-load modes, respectively. Furthermore, SO_2, CH_4, N_2O, and Hg emissions saw significant reductions across all three power generation modes of the power plant.

Shakibi et al. [53] studied how machine learning methods can be used to model and optimize a system with combined solar/natural gas power and freshwater cogeneration system. The authors modeled the cogeneration process with Engineering Equation Solver software and used the model to create a dataset. A hyperparameter-optimized Support Vector Regression (SVR) model was fitted to the dataset, and a Multi-Objective Grasshopper Optimization Algorithm was used to find optimal parameters for the system. The authors tested different optimization targets with double- and triple-optimization experiments. The optimal scenario prioritized exergy efficiency, total product cost rate, and CO_2 emissions, achieving an exergy efficiency of 45.6%, a total product cost rate of 2.716 \$/GJ, and a freshwater consumption of 30.26 kg/s.

Amjad et al. [54] used ML methods to predict the lower heating value of different fuel blends. The authors prepared fuel blends where good quality coal was used as a base, and 10%, 20%, 30%, 40%, and 50% concentrations of lower quality coal, rice husk, and sugarcane bagasse were mixed into the blend. The authors measured the characterized properties of all the mixes and of each of the ingredients in full concentration. The measured properties were moisture content, ash content, volatile matter, sulfur content, fixed carbon content, hydrogen content, and lower heating value. The authors used Ridge Regressor, Nyström Kernel SVM Regressor, and Linear Regressor to model the fuel blend lower heating value based on the characterized properties. The authors discovered that Ridge Regressor was the best performing model and reported R^2 values of 0.993, 0.979, and 0.983 for validation, cross-validation, and holdout experiments, respectively. The authors claimed that the model can be used to suggest the most suitable fuel blend where the percentage of the coal is replaced with biomass, thus reducing carbon footprint.

Arumugham et al. [55] proposed an approach to make smart grids more sustainable and reliable by effectively integrating renewable energy sources with conventional power generation methods. The authors used deep learning-based methods to model a microgrid with integrated wind and solar cell power generation. The optimal response of the model was solved using the Multi-Objective Ant Colony Optimization (MOACO) method. The authors claimed that the developed microgrid model can be used to forecast demand and supply, schedule power delivery according to demand, and provide actionable insights of the operation of the smart grid system. The test results were evaluated across various scenarios to optimize operating costs using the MOACO. The authors showed that simulations of demand response based on the developed models reduce solar and wind power operating costs.

3.2. AI Applications in Energy Demand Forecasting and Optimization for Emission Reduction

In addition to directly affecting energy generation, another way to use AI for emission reduction in the energy sector is to forecast the future. A clear prediction of the future can be used to set policies and better plan the actions based on the prediction. When planned correctly, the policies and actions can reduce emissions from the energy sector. Forecasting the future can be beneficial on multiple levels. The following section includes studies that used forecasting at national, power grid, and end-user levels to reduce emissions.

Chen et al. [56] tested Linear Regression, Support Vector Regression, and Random Forest Regression algorithms to forecast the electricity demand at a regional level in Guandong Province, China. The ML algorithms used economic data and weather data as explanatory variables, in addition to electricity consumption and production from neighboring provinces and the electricity production of the Guandong province. The authors suggested that by forecasting the future electricity demand, the power generation firms can better plan the required electricity production in advance, therefore producing the electricity in more optimized manner, thus potentially lowering the greenhouse gas emissions.

Staudt et al. [57] studied the prediction of power plant redispatch events that were caused by transmission congestion. During the congestion events, the power plants in front of the congestion need to ramp down their production (negative redispatch), and the plants behind the congestion need to ramp up their production (positive redispatch). The authors tested multiple different ML methods for redispatch event prediction and discovered that artificial neural network (ANN) and extra-tree classifier performed the best. The authors trained separate models for negative and positive redispatch types. The model output was the probability that the power plant is redispatched during the following day. The authors reported the average F_1-scores of 0.47 for the ANN and 0.42 for the extra tree; however, the score varied significantly between the different power plants. The authors argued that the proposed method can be used to prepare for plant redispatch events, and the transmission system operator can therefore identify power plants that can be completely ramped down for the duration of the congestion instead of ramping down the production of multiple plants by small amounts. This can reduce emissions since the other power plants can continue running with optimal power output.

Truong et al. [58] proposed additive artificial neural networks (AANNs) for energy consumption estimation and prediction in residential buildings. In addition to AANN models, the authors also tested other AI models, such as two flavors of support vector regression (SVR) models and a classical artificial neural network. The dataset was sourced from residential buildings that used solar photovoltaic system as a renewable energy source.

The dataset had a one-hour resolution (sampling time). The predictive accuracy of the different AI methods was compared with Mean Absolute Percentage Error, Mean Absolute Error, Root Mean Square Error and Correlation Coefficient. The AANN was identified as the best performing forecasting model to predict buildings' energy consumption. The authors claimed that building energy consumption prediction is the basis for building performance optimization and therefore building energy reduction. Energy usage reduction leads to less energy used; thus, it can lead to emission reductions.

Jahangiri et al. [59] investigated whether an ML model is capable of finding the least-cost and robust pathways to achieve a net-zero electricity system in Canada by 2050. The model input variables included estimates such as carbon tax, demand growth and annualized capital costs for different energy sources like wind, solar, coal, and nuclear energy. The authors used the capacity expansion mixed-integer linear planning (COPPER) model in this study. The ML model minimizes the system costs while taking into account variables such as carbon pricing, decarbonization policies, and distribution network evolution. Almost all scenarios to achieve the least-cost pathways to net-zero electricity system resulted in substantial deployment of wind power. Natural gas is maintained mostly to guarantee electricity system reliability and reserve requirements. Furthermore, only a very limited amount of new natural gas capacity needs to be added. The results achieved in this study can be used by policymakers to support decision making to achieve net-zero in the Canadian electricity system.

3.3. AI Applications in Energy Efficiency for Emission Reduction

A third notable trend in leveraging AI for emission reduction within the energy sector is the optimization of building energy consumption. According to the European Environment Agency indicator, building energy usage represents 34% of energy-related greenhouse gas emissions in the EU in 2022 [60]. Moreover, Lamb et al. [7] estimated that buildings contributed 6% of global CO_2 emissions in 2018. By targeting the energy efficiency measures in the building sector, significant gains in reducing overall CO_2 emissions could be achieved.

Zekić-Šušac et al. [61] studied building energy efficiency in the public sector and tested machine learning models to predict the specific energy consumption (SEC) of the buildings. SEC expresses the energy consumed per m^2 while taking into consideration external influences, such as the heating season length, thus enabling the comparison of different buildings in different climates [62]. The dataset for this research was sourced from the Croatian Energy Management Information System. The authors evaluated deep neural networks, CART decision trees, and random forests for predicting the building SEC. The authors discovered that random forest was the best performing model for the task. The authors suggested that the models can be used to predict the energy consumption of new buildings, thus aiding planning and therefore reducing future energy usage and emissions.

Thrampoulidis et al. [63] trained artificial neural networks to predict building retrofit solutions with the focus on reducing the building CO_2 emissions while considering the optimal cost. The retrofit solutions included considerations for heating, building insulation, renewable installation, and energy storage. The idea of this study was to replace an existing complex modeling software with a lighter and faster neural network model that achieves the same accuracy with reduced computational requirements and a reduced number of required input variables that are hard to obtain. The authors conducted a case study for buildings in Zurich, Switzerland by collecting information about buildings in this area from multiple different data sources and combining that information to urban building energy modeling data to train the neural networks. The proposed method predicted ten solutions from the Pareto front of multi objective solutions of reducing CO_2 emissions with optimal cost. The authors suggested that the simpler and computationally lighter model accelerates the adoption of CO_2 emission-friendly retrofit solutions, and therefore contributes to the reduction in CO_2 emissions.

Alpan et al. [64] presented a global model for reducing carbon emissions in residences. The study demonstrated how IoT and AI could be used globally to reduce carbon emissions caused by the energy consumption of cities. The authors envisioned a global model where data are gathered from IoT devices, and AI can intervene in device energy usage with minimal interference to the residents. The proposed system is constructed from multiple levels, the highest of which is the global unit. The global unit contains multiple country units, which in turn contain multiple city units, which in turn contain multiple residence units. The proposed topology focuses on minimizing data from the IoT devices that are connected to the centralized and hierarchical AI units. The authors suggested that the proposed topology minimizes the computational resources required for transferring and processing the data between the hierarchical levels. Otherwise, the amount of data gathered from billions of devices would require a significant amount of computing power. The authors tested a Decision Tree model in simulated setting and discovered that the visioned system is capable of reducing the carbon emissions up to 21%.

Marasco and Kontokosta [65] developed a machine learning classifier to predict building energy conservation measures (ECMs) using energy audit data from over 1100 buildings. The classifier is a user-facing falling rule list (FRL) that utilizes binary features derived from the energy audit data. This method improves the utility of building energy audit data to predict building-specific eligibility for energy conservation. The developed and trained FRL classifier performs well, achieving ROC AUC values of 0.72–0.86 for predicting the most important ECM opportunities. The developed method provides an effective and low-cost method to predict and determine energy conservation, potential savings, and reduction in greenhouse gas emissions on a larger scale.

3.4. Summary of AI Use in the Energy Sector

In energy generation optimization, AI techniques, such as artificial neural networks, support vector machines, and deep neural networks, have been effectively used to optimize the operation of power plants and other energy generation systems. These optimizations lead to reductions in CO_2 emissions by improving the efficiency of energy generation processes and integrating renewable energy sources. In energy demand forecasting and optimization, machine learning models, including linear regression, support vector regression, random forest regression, etc., are employed to forecast electricity demand. Accurate demand forecasting enables better planning and optimization of energy production, which can reduce greenhouse gas emissions by minimizing the need for inefficient, last-minute energy generation. In energy efficiency improvements, AI models are applied to enhance the energy efficiency of buildings and other infrastructure. Techniques such as decision trees, random forests, and additive artificial neural networks help predict energy consumption and identify opportunities for energy conservation, leading to reduced CO_2 emissions. Findings about the various AI models in these categories are presented in Table 1.

Table 1. Articles discussing emission reduction using AI.

Category	Article (n = 16)	AI Methods
Energy Generation	Chen et al. [49]	DBN, Particle Swarm Optimization
	Hong et al. [50]	DNN, Particle Swarm Optimization
	Ashraf et al. [48]	ANN, SVM, Gradient Boosted ElasticNet, Parametric Significance Analysis
	Ashraf and Dua [51]	ANN, Nonlinear Programming
	Ashraf et al. [52]	ANN, SVM, Parametric Significance Analysis
	Shakibi et al. [53]	SVR, Grasshopper Optimization
	Amjad et al. [54]	Ridge Regressor, SVR, Linear Regressor
	Arumugham et al. [55]	DNN, Ant Colony Optimization
Energy Demand Forecasting	Chen et al. [56]	Linear Regressor, SVR, Random Forest Regressor
	Staudt et al. [57]	ANN, Extra-Tree Classifier
	Truong et al. [58]	SVR, ANN
	Jahangiri et al. [59]	COPPER
Energy Efficiency	Zekić-Šušac [61]	DNN, CART, Random Forest
	Thrampoulidis et al. [63]	ANN
	Alpan et al. [64]	Decision Tree
	Marasco and Kontokosta [65]	FRL Classifier

4. Discussion

This scoping review on reducing CO_2 emissions using artificial intelligence in the energy sector highlights the potential of AI technologies to contribute to emission reduction efforts. The review categorizes the applications of AI into three main areas: energy generation for emission reduction, energy demand forecasting and optimization for emission reduction, and energy efficiency for emission reduction.

Although our research question was broad, the inclusion criteria of the study were quite effective in reducing the number of relevant studies. This suggests that there is not a substantial number of articles that address the use of AI to reduce CO_2 emissions in the energy sector. Our search phrases found many publications focusing on AI usage in the energy sector in general; however, these were most often narrative-style reviews about the subject and lacked the experimental and technical details.

Most of the articles that were found with our search phrases and matched to our criteria were published in recent years. This is an interesting result. This could indicate that the possibility of using AI for emission reduction in the energy sector has just recently been discovered. There could be several reasons for this, such as the recent Ukraine conflict, which greatly impacted European energy production [66]. This could have increased research around the topic. Moreover, the COVID-19 pandemic and the transition to green energy might also be the reason for the increased research. Other potential explanations for most of the papers being from recent years could be the global rise in the number of published papers [67] or that the Google Scholar search algorithm used to find the articles may favour the most recent publications. However, the Google Scholar bias should be accounted for by our strategy of including 50 search results from each search.

There is a need for more realistic and more expansive datasets. Studies are being conducted using restricted datasets coming from singular sources, which often suffer from limitations in availability, quality, and bias. The lack of publicly accessible, diverse datasets hinders the research community's ability to test AI methods using standard benchmarks and reduces the generalizability of the findings. Moreover, using small and specialized datasets leads to less scalable AI solutions, affecting the solution's reliability in production. Despite the common goal of emission reduction, the varied focus areas of the reviewed articles make it difficult to create standardized datasets. Additionally, as emission reduction is a global challenge, common factors like weather patterns and energy production resources vary significantly across regions, further complicating the development of unified datasets.

The identified articles come from various geographical areas, and some of the results of the research are applicable only in the original research setting. Challenges in this field vary widely based on location and energy production methods, which are often shaped by country-specific political decisions. Moreover, researchers' access to energy infrastructure for testing AI solutions differs across regions. This can lead to a situation where local research in energy production lags behind global standards. To address this issue, we recommend implementing policies that provide researchers with enhanced access to energy infrastructure for their work.

Integrating AI with emerging technologies, including the Internet of Things (IoT), offers significant potential to improve energy management and reduce emissions. Implementing these solutions in real-world scenarios is crucial to uncover practical challenges and benefits. However, technologies like IoT are often closed resources, thus making real-world integration and data acquisition impractical. Additionally, further research is needed to explore the application of AI in underdeveloped areas of the energy sector, such as energy storage and distribution, to maximize its impact on reducing CO_2 emissions.

Although many papers fitting our inclusion criteria used neural networks and deep learning models in their research, the model architectures were based on traditional multilayer perceptron or convolutional neural network architectures. Recent advancements in natural language processing (NLP) have been achieved with the transformer neural network architecture, which is also successfully applied to other application areas in addition to NLP. Furthermore, a recent trend is to use pre-trained foundation models as a base for new AI solutions [68]. An example of this is the use of large language models for various different applications such as classification. We identified a potential gap in the existing research in this area. None of the included papers used these technologies yet.

Our search phrases focused on finding the research papers that explicitly stated CO_2 emission reduction as the goal of the study. However, in the energy sector, CO_2 emission reductions can also be achieved while optimizing towards other goals, such as cost. Cost is mainly driven by energy usage, and by reducing energy usage, indirect reduction to CO_2 emissions can be accomplished. These types of papers did not fit our inclusion criteria. Nevertheless, this paper includes many references to related studies which cover this shortcoming. Furthermore, because the goal of this study was to provide an overview of existing studies covering the topic, we ended up conducting this study using the scoping review methodology. Scoping review is a more suitable methodology than systematic review for a broad research question such as ours. However, a scoping review is not as comprehensive as systematic reviews in the literature retrieval phase; thus, it is impossible to say if all the existing research fitting the criteria is covered.

Based on the findings, some recommendations can be made to improve technologies to reduce emissions. Firstly, without access to the process, it is difficult for researchers to improve them. Having more datasets, especially open datasets, would provide more opportunities to offer AI solutions. Furthermore, hosting challenges to provide the best optimization could be a viable way of finding new solutions. Secondly, standardized interfaces and process descriptions could provide more opportunities to use AI solutions in this domain.

AI has demonstrated promise in reducing CO_2 emissions in the energy sector through optimization, forecasting, and efficiency improvements. Continued research and development, along with real-world implementation, are key factors to achieve sustainable energy goals and mitigate climate change.

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