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A Review of Some of the Applications of Optimisation Models in Solving Environmental Pollution Problems

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ABSTRACT
This study provides a survey of optimisation methods used in renewable energies, as numerous academics are constantly proposing and implementing new approaches in this sector. The purpose is to investigate the widespread and successful use of optimisation methodologies in addressing environmental concerns, with a focus on defining core problem factors, building optimisation models, accounting for various restrictions, and analyzing outcomes. The examination includes renewable energy, supply-demand, energy planning, forecasting, emission reduction, and control models that use optimisation methodologies.

Keywords: Renewable energy systems, Design, Planning, Optimisation, Modeling, Pollution Prevention

1. INTRODUCTION

Energy needs have significantly expanded as a result of the global economy's fast development, particularly in emerging economies. The reality that fossil fuel resources required for energy production are depleting and that greenhouse gas emissions cause climate change has raised interest in energy efficiency and environmental protection [1]. The resolution of environmental issues frequently necessitates choosing between many options while also having to adhere to a variety of technical and legal requirements. As a consequence, several scientific works that address environmental problems through the development of optimisation models and their application in real-world scenarios, along with various other endeavors to tackle environmental problems, have been published in the literature.

The enhancement of renewable vitality advances will help maintainable advancement and give an arrangement to a few energy-related natural issues. Thus, in the context of renewable energy systems,optimisation algorithms serve as a beneficial tool for comprehending challenging issues. Various authors have taken into account models for renewable energy, emission reduction, energy planning, energy supply, forecasting, and control. These authors have done so using optimisation methods [2].

The process of creating, putting into practice, and evaluating algorithms to address various optimisation issues can be referred to as "optimisation." As you contradict, the algorithms used may require worst-case exponential computation time to achieve optimal results, resulting in the time of computation being too high for practical purposes. The principles of optimization apply to designing, analyzing, and implementing algorithms, and include mathematical principles for building models and operations research for modeling systems.

Heuristic approaches are simple processes that yield positive outcomes but are not always the best solutions for extremely complicated problems. Meta-heuristics are a generalisation of heuristics in that they can be used to address a variety of problems while requiring only minor adjustments to suit a given situation [3]. The complexities of the problems at hand can often be so large that even heuristic and meta-heuristic approaches fail to offer solutions in a reasonable length of time. The two main categories of these multi-objective strategies are aggregate weight functions and Pareto-based optimisation algorithms. The significance of each optimisation objective can be changed via aggregating procedures, which include a method for integrating all optimisation goals into a single mathematical function [4].

The weights of the objectives to optimise might be quite difficult to change, especially when they have various scales, despite the simplicity of the technique. A significant constraint in the decision-making process arises from the fact that this technique only produces one answer as a consequence of the search process, requiring the

decision-maker to choose one solution from a range of choices.
The purpose of this review is to look into how frequently and effectively optimisation approaches are applied to solve environmental concerns. This review focuses on identifying the problem's basic parameters, building the optimisation model, and defining the optimisation criteria that lead to the problem's solution. In each type of problem, certain constraints must be considered, as well as the techniques used to solve the optimisation models and the results of the solutions. This article also provides an updated appraisal of previously used optimisation methodologies in the field of renewable energy.

2. OPTIMISATION METHODS AND TOOLS

A wide range of optimisation approaches and algorithms can now be employed to solve complicated engineering challenges. As well as describing optimisation methods and tools and how they can be applied in various situations, Biegler and Grossmann and Grossmann and Biegler describe and categorize the current state and potential future of optimisation methods and tools. Many different types of environmental issues have found widespread application in mathematical programming and optimisation in general. Because there are numerous potential answers to these difficulties, the best one must be chosen, which frequently necessitates decision-making under competing agendas. As a result, in recent years, a number of mathematics and decision support approaches have been utilised to assist in the formulation of policies or the resolution of a variety of design, operation, planning, scheduling, and routing difficulties related to the environment.
For optimisation, deterministic and stochastic programming models were utilised in the literature review. The issue can be resolved using a variety of deterministic optimisation models, including multiobjectiveoptimisation, linear programming, mixed integer linear programming, nonlinear programming, and dynamic programming. For situations containing uncertainty, stochastic programming techniques like fuzzy linear programming, fuzzy integer programming, and interval linear programming are frequently used. Multi-criteria decision approaches are used for a number of actual environmental challenges, according to Ladhema et al. [6]. An approach to environmental problems using multi-criteria analysis is described by the authors. Using this formulation, all relevant problem information can be stored in a comprehensive framework, the need for new information is explicitly made clear, and resources can be allocated efficiently.

3.METHODS OF OPTIMISATION IN VARIOUS ENVIRONMENTAL PROBLEMS

With the use of optimisation techniques, a wide range of environmental issues may be resolved, including the synthesis and design of environmental processes, waste minimization and management, water resource management, and energy management with environmental concerns.

3.1 Waste minimisation

In order to optimize textile dyeing manufacturing processes, Wu and Chang developed a method based on defined waste minimization choices, new environmental standards, and limited production resources[7]. They employ a framework for nonlinear integer optimisation. Profit maximisation includes product sales benefits as well as water resource levies and emission/effluent costs mandated by existing environmental regulations.
The collection of constraints includes restrictions on labour and capital resources, equipment accessibility, demand parameters, water balances, and capacity restrictions. The interval analysis is utilized to cope with uncertainties, and the optimisation approach is based on the Genetic Algorithm. A systematic planning process is presented by Chakraborty et al. for establishing long-term waste management strategies for whole batch production plants[8]. They present a dynamic approach to developing the best waste management plans in their study, which has a planning horizon of 5–10 years. Operational, annualised capital, and maintenance expenses are all reduced by the goal function's reduction in the total present value of all costs. The operating cost is determined by averaging the probabilistic operating costs for each different waste projection scenario. Penalties for disregarding capacity restrictions are another use of the phrase. Some of the restrictions that cause issues are corporate-wide budget caps, specific permit restrictions, carbon trading opportunities, and emission limits. A MILP model is the final model.
To create a multi-objective optimisation model that would help in the proper management of hazardous waste

produced by the petrochemical industry, Alidi uses goal programming[9]. In order to prioritise conflicting goals that are frequently present within the petrochemical industry, the analytical hierarchy process (AHP) is applied when dealing with the waste management issues facing it. The AHP is a method of decision-making that takes into account both qualitative and quantitative aspects.

3.2 Air pollution

The literature on air pollution control usually makes use of mathematical programming models. These models' primary goal is to reduce the cost of available policy alternatives, and the vast majority of them focus on control and eradication methods. The three main possibilities are reducing the number of pollutants, lowering the cost of doing so and reducing the number of pollutants in the places where the most sensitive receptors are concentrated. The restrictions that are being made explicitly state adherence to pollution standards. Cooper et al.'s analysis of mathematical programming techniques used in air pollution control in 1996 is pretty in-depth [10]. But since then, a lot of studies that address the fact that there are many fascinating aspects to air pollution mitigation have been published in the literature.

The mixed integer linear programming model of Shaban, Elkamel, and Gharbi[11] can be used to select the most effective pollution control strategy to meet a particular pollution reduction threshold. The model's goal is to reduce overall control costs, which include operating and investment expenses. The model is subjected to a number of restrictions, such as a mandated emission reduction threshold and a maximum investment budget. The model provides the ideal selection of control choices and their ideal set-up time-frames.

3.3 Environmental Synthesis and Design

According to Brett et al., the challenge of converting process information to environmental objectives has prevented environmental sensitivity from being adequately incorporated into process models[12]. They offer a method in their work for illustrating how LCA helps in the development of environmental goals in process design. They use a multi-objective process formulation that combines environmental goals from life cycle analysis (LCA) with economic goals. To illustrate their method, they did a case study on a nitric acid pill. The process is modeled in Hysys to obtain mass and energy information. Goal programming, a multi-objective optimisation technique, was used to tackle the issue. Furthermore, they contend that the incorporation of explicit considerations into design decisions is made possible by the use of LCA in conjunction with thorough process analysis techniques. Linninger and Chakraborty devised an algorithm for the synthesis of waste treatment flowsheets that combines linear planning and search-based superstructure construction[13]. Following this, a rigorous optimisation of policy is performed based on an environmental capacity and logistics constraint specific to the site, and a desired performance function, such as treatment cost.

3.4 Facility location

A mechanism for pinpointing the location of unfavourable facilities was developed by Rakas et al. in 2004[14]. Since the challenge of placing undesirable amenities involves numerous conflicting criteria, it is described as a multi-objective model. Critical questions like how many facilities should be put and how big each facility should be are supposed to be addressed by mathematical models for the placement of undesirable facilities. The optimization model's objective functions include both total cost minimization and community opposition to landfill development. Chang and Wei present a unique method for optimising routing characteristics by employing a fuzzy multi-objective nonlinear integer programming model that is specifically handled by a genetic algorithm [15].

3.5 Solid Waste Management

The planning of solid waste management systems has been accomplished using deterministic mathematical programming methods. Nema and Gupta addressed all of these issues when planning and designing the regional hazardous waste management system, including the choice of treatment and disposal facilities, the distribution of hazardous wastes and waste residues from generators to treatment and disposal facilities, and the choice of transportation routes[16]. These techniques make it possible to choose the best configurations using multi-objective integer programming more successfully. It is meant to lower total costs, including expenditures for treatment and disposal as well as transportation costs, as well as total hazards, including risks connected to waste treatment, disposal, and transportation, as part of the overall goal. Waste mass balances, permitted treatment and

disposal technology capacity, waste-treatment technology compatibility restrictions, and waste-waste compatibility restrictions are all examples of problem constraints. The resulting model is a MILP problem.
Huang et al. used an integrated solid waste management system based on imprecise fuzzy stochastic mixed integer linear programming to plan long-term waste management operations in Regina[17]. Solid waste management in the city is uncertain, dynamic, and interactive, which is faithfully represented in their model. Their method can offer solutions to issues like the most appropriate reduction targets, the pattern of waste flow distribution, the degree of reliability, and how to handle the rapidly increasing waste creation.

4. OPTIMISATION TECHNIQUES APPLIED TO RENEWABLE AND SUSTAINABLE ENERGY

For renewable energy sources to be used to their full potential, optimisation models must be applied. Building, planning, and managing energy systems that rely on renewable energy sources like solar, wind, and hydropower may be done using these models. The most effective and economical energy system solutions may be found by applying optimisation techniques and accounting for the unpredictability of renewable energy sources. Energy demand, weather patterns, available energy storage, and system capacity are just a few of the variables that optimisation models might take into account when figuring out how to best generate, distribute, and store energy.

4.1 Wind power

Opportunities for further offshore development, the attractiveness of compact grid-connected turbines, and the expansion of wind projects to a wider reach of the world make wind power a promising alternative energy source. However, without wind studies and statistics readily available, it is difficult to make investment decisions related to the generating capacity of wind farms. Bayesian model averaging is used to model the wind speed distribution and the design of the wind farm power system is optimized for both generation costs and system reliability. The ideal design of wind farms is also an important area of interest to wind energy professionals, such as the placement and best design of wind turbines. Wind energy generation is still relatively new and there is still room for improvement in power quality, which is why several writers have focused on maximizing the turbine's performance.
Wind power quality is measured using several metrics such as power factor, reactive power, harmonic distortion, and so on. Standard turbines are being enlarged, while novel technologies, like gearless designs, are being developed. Benini and Toffolo devised a Multi-Objective Evolutionary Algorithm (MOEA) to enhance the geometric parameters of the rotor configuration of horizontal axis stall-regulated wind turbines and achieve optimal trade-off performance[18]. Li et al. [19] employed GA to boost wind power output while lowering drive train and tower vibration, and Kusiak et al. [20] developed an MOEA to evaluate wind turbine performance. When using wind turbines to exploit the wind's potential, reliability is critical in order to maximise the amount of energy that can be produced.
Wind turbine efficiency has grown because of technological advancements, yet constraints exist for cut-in and cut-out data. The output statistics of wind turbines have been calculated by some researchers using fuzzy logic modeling, a multi-objective adaptive neighbourhood search, and a GA to locate the best locations for maximising output capacity while reducing the number of turbines deployed and the area occupied by each. Based on the wind farm's cumulative net cash flow value over time, an EA was built to address the optimal wind farm design problem. For the purpose of placing wind turbines based on wind dispersion, Kusiak and Song [21] created an MOEA with the twin goals of increasing wind energy collection and minimizing a secondary purpose. Mustakerov and Borissova's fuzzy optimisation techniques and the MINLP optimisation strategy were used to take into account the available wind conditions and the wind park area.
Abdel-Aal et al. [22] used abductive networks to handle the problem of forecasting wind speed, offering comprehensible analytical input-output models and more automated model creation. The control and management strategies for offshore wind farms' power generation are impacted by the size of power fluctuations. Pinson et al. [23] found that the generation level is not the only factor that affects the size of oscillations in offshore wind power. Several authors have used direct search techniques including PSO, SA, GA, and scenario creation to address the discontinuity in wind power generation. Wind turbines regulate the rotor speed and tip-speed ratio of wind energy absorption. Heuristic methods like PSO have been used to solve this problem. A

multi-objective energy dispatch that considers fuel costs and the environment was presented by Kuo [24]. Ko and Jatskevich [25] developed a fuzzy-linear-quadratic regulator controller to improve power quality. For intelligent wind turbine control, Kusiak et al. [26] developed a multi-objective model with different degrees of GA to integrate the number of actuators, their placement, and active control algorithms in wind-lifted structures.

4.2 Solar energy

The sun's radiative energy is referred to as "solar energy". In many parts of the world, direct solar radiation is recognised as one of the best potential energy sources. The two main ways to turn solar radiation into energy are active and passive solar design. The most efficient architecture for capturing solar energy often forms the basis of passive solar design, which aims to eliminate the need for artificial lighting and heating. Designing and optimising solar energy structures for passive solar systems is of special interest to researchers in solar energy [27]. Globally, increasing building energy efficiency is a top goal. The types of energy-saving techniques used vary, and the decision-maker must choose the best option while taking into consideration many, frequently conflicting objectives like energy consumption. Costs, environmental impact, and other factors [28.29]. In an active solar design, solar energy is converted into heat and used to warm water using photovoltaic panels and solar cells. To build both active and passive solar energy systems, it is required to understand the radiation exposure levels at the examined site. In order to track solar energy, radiometric station nets with a subpar spatial resolution are usually utilised. Although several extrapolation and interpolation techniques are frequently used to estimate radiation, their accuracy worsens in places with complex topography and their efficiency is restricted to regions with minimal spatial radiation variation. Using information from just one radiometric sensor, Bosch et al. [30] showed an artificial intelligence method based on ANN for estimating sun radiation levels over difficult alpine terrains. Two further methods for predicting solar radiation are neuro-fuzzy inference systems and ANN [31].

Solar radiation data forecasting has advanced substantially, but critical information can still be extracted from such data. The statistics reflecting the availability of solar radiation have been identified and optimized using several methods, including ANN [32]. A standalone photovoltaic system needs energy storage to maintain a steady power flow because solar energy is intermittent. The extensive use of this type of energy can only be used if an efficient technology can be created for its storage that has affordable startup and operating costs [33]. Price drops and rapidly shifting market conditions have resulted in an increase in grid-connected photovoltaic solar power projects [34]. Using ANN and GA, Kalogirou [35] found a solution to the issue of maximising the financial gains from a solar energy system. The size of the storage tank and collection area are trained to coincide with the amount of additional energy needed. A single tracking photoelectric power module of a given size is assumed to require a certain amount of ground area, as determined by Aronova et al. [36]. A study on the optimisation of the geometric parameters of the thermal parabolic cylinder receiver system was published by Klychev et al. According to Garca-Fernández et al. in [37], the design of parabolic trough collectors over the last century, as well as current prototypes, have been summarized. In terms of sunlight concentration, they conclude that the parabolic-cylinder concentrator might increase sunlight intensity by opening at the appropriate angles. Szargut and Stanek [38] thought about how to maximise the performance of a solar collector by correctly measuring the area of the collecting plate, the diameter of the collector pipes, and the separation between the pipe axis in the collection plate. Varun [39] developed a GA that considers a range of operational and system variables in order to maximise the thermal performance of flat plate solar air heaters. Chang and Ko developed a hybrid heuristic approach for calculating the tilt angle of solar modules that incorporated PSO and nonlinear time-varying evolution[40]. An algorithm was proposed by Zagrouba et al. [41] for identifying the electrical parameters of photovoltaic solar cells for determining the maximum power point corresponding to an illuminated current-voltage characteristic. Stochastic programming and the Monte Carlo method were used by Marston et al. [42] to evaluate the performance of the collector design in terms of an objective function. The modified Kiefer-Wolfowitz algorithm with sample size and step size parameters was then used to minimise the objective function. Finding the most accurate way to calculate the size of a solar system is a fascinating challenge. The size optimisation of a standalone photovoltaic system is a difficult optimisation problem with the aim of attaining an energy and financial cost that is acceptable to consumers as well as a relatively accurate quality of energy supply.

In a study by Mellit [43], the effectiveness of artificial intelligence methods was assessed when it came to sizing stand-alone, grid-connected, and hybrid systems that incorporate wind and photovoltaic energy. Mellit et al. [44] sized photovoltaic systems using ANN and GA. Different parts of hybrid solar-wind power generation systems can be sized to enhance their capacity utilising Yang et al.'s [45] technique for doing so using a battery bank.

The size optimization issue of standalone photovoltaic power systems utilizing hybrid energy storage technology was addressed by Li et al. [46]. NSGAII was used by Thiaux et al. [47] to optimize standalone solar systems with the goal of measuring the decrease in gross energy requirements by limiting storage capacity. The following is an analysis of how Kornelakis and Koutroulis [48] optimized solar grid-connected systems:They pick a system device from a list of commercially available options. The ideal size, shape, and quantity of photovoltaic modules should be used during installation in order to optimise the system's overall net economic gain during its operating lifetime. Using PSO, Kornelakis, and Marinakis [49] also addressed this issue. The outcomes showed that it is feasible to run the plant independently, benefit from the solar performance, and still adhere to operational limits. A photovoltaic system's energy generation must be optimised for the solar cells to operate at their peak power and efficiency, depending on the amount of irradiation. Other authors have proposed an adaptive perturb and observe technique with rapid dynamics and improved stability [50]. Solar energy is frequently used for water heating. It is crucial to identify the best design in order to realise a considerable amount of energy-saving potential in high-rise residential structures in order to promote the widespread adoption of centralised solar water heating systems. To maximise the energy savings of solar heating over traditional domestic electric heating, Fong et al. [51] developed an EA. Using optimisation approaches, Kulkarni et al. found the water replenishment profile that optimises the system as a whole [52].

4. SUMMARY AND CONCLUSIONS

To sum up, as the state of the environment continues to worsen, there is an urgent need for optimization strategies that emphasize optimal resource utilization and environmental protection. This review study examined several research across diverse environmental challenges to offer an overview of the optimization methodologies used to address environmental issues. Several optimization models and methodologies are used depending on the situation at hand, with the size of the challenge and the reliability of process models being essential criteria for success. The identification of all environmental issue aspects and their integrated approach is one of optimization modeling's most important achievements. The newest research findings on employing optimization algorithms for design, planning, and control issues in the realm of renewable and sustainable energy are also described in this study.

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