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Coal Energy Production Efficiency Improvement Strategy with Integrated Genetic Algorithm and Its Economic Impact Assessment

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Abstract

INTRODUCTION: Global energy systems heavily rely on coal energy generation, particularly in emerging nations.
OBJECTIVES: Strategies that maximize the efficiency of coal energy generation while limiting environmental harm are essential to addressing these issues. With an emphasis on increasing productivity and minimizing environmental effects, this study suggests an integrated strategy for optimizing coal energy production processes using Genetic Algorithms (GA).
METHODS: Key factors, including GDP growth rate, pollution abatement investment, coal intensity, and clean technology efficiency, are all optimized using GA in the suggested approach. Finding the best combination of these factors to maximize coal production efficiency while reducing CO2 emissions and other pollutants is made possible by GA-based optimization. A Social Cost-Benefit Analysis (SCBA) and environmental impact appraisal are also included to assess various scenarios' economic and environmental consequences. The findings show that, particularly in situations with slower GDP growth, more pollution abatement expenditures and cleaner technology adoption result in notable emissions reductions and increased overall efficiency.
RESULTS: The results show how crucial it is to balance environmental sustainability and economic prosperity. The study offers insightful information to industry executives and regulators, highlighting GA's potential to maximize the efficiency of coal energy generation.
CONCLUSION: Scenario A provided the best economic advantages, with a greater GDP growth rate and higher environmental costs.

Keywords: Coal Energy Production, Genetic Algorithms, Economic Impact, Environmental Impact, Pollution Abatement, Social Cost-Benefit Analysis.

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1. Introduction

Coal energy production has a very significant share in the energy scene globally. Using coal-fired power plants in developing countries becomes essential in meeting growing energy demands [1]. However, the widespread reliance on coal manifests with environmental challenges from emissions and the respective increase in greenhouse gases and the ensuing air pollution, damage to the ecosystem, etc [2]. Coal energy is critical for emerging countries because of its availability, low cost, and economic progress. These countries rely heavily on coal to fulfil rising electrical demand, typically with limited access to cleaner energy sources. This dependence produces a vicious cycle in which rising coal production fuels GDP growth, increasing energy consumption. Limited financial capacity and high initial costs impede investments in alternative energy and clean technologies, increasing dependency on coal. The coal sector generates major employment and government money, making it politically and economically difficult to replace.

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The paper advises utilizing Genetic Algorithms to increase coal production efficiency while decreasing pollution. Scenario analyses show moderate economic growth with high investment in pollution control and clean technologies yields the best environmental benefits, while high-growth scenarios incur greater ecological costs. The transition towards sustainable coal production is not limited purely to better coal extraction and processing; it also places a considerably wider lens on the environmental consequences of it [4], [5]. In seeking this balance, there is a need for innovative technological advancements, complemented by effective policies and strategies demanding reduced emissions and lesser pollution, and finally, working towards a more sustainable and responsible coal energy industry [6]. Coal is vital in global energy dynamics, particularly in developing countries, where it contributes to energy security and drives economic growth. Numerous countries depend on coal to fulfil their rising energy needs, which is important for industrial development. With ongoing industrialization, coal continues to be essential to their energy mix because of its cost-effectiveness and availability. A significant relationship exists between GDP growth and coal output, fueling increased demand as countries seek to enhance their economies. At the same time, there is a push to lessen coal's environmental effects through cleaner technologies such as carbon capture and storage. However, these approaches encounter significant expenses and gradual adoption, particularly in developing areas. Innovations like enhanced energy efficiency methods are crucial for these countries to integrate economic growth with environmental goals. Shifting to renewable energy poses obstacles, such as restricted financial resources and infrastructure, which further complicate the move away from dependence on coal. Despite worldwide trends supporting renewables, coal remains a safeguard against energy deficits, offering reliable and faster solutions than large-scale renewable initiatives. Therefore, developing nations struggle to find an equilibrium between promoting economic expansion and addressing the environmental impacts of coal. Approaches to improve coal efficiency, invest in cleaner technologies, and gradually integrate renewables are essential as these countries manage their energy security and climate obligations.

The long-term economic and structural relationship between the growth of coal demand, production, and consumption entails certain steps to be taken together [7]. There is a lot of work around clean coal technologies and energy-efficient mining methodologies that have reduced the carbon footprint of coal production, but those improvements are quite limited [8], [9]. High costs of building integrated cleaner coal technologies, coupled with minimal investments in research and development, further decelerate the rhythm [10]. Furthermore, political and economic factors, such as changing energy policies and shifting global markets, further complicate the transition toward cleaner practices [11]. There is a need for a holistic modal for intervention and to mount well-coordinated responses that will combine technological innovations, economic incentives, and institutionalized environmental policies to address these challenges with the optimum efficiency of coal production processes [12]. AI and MI are transforming coal production by enhancing efficiency, increasing economic advantages and minimizing environmental effects. AI enhances every phase of coal production, including exploration, processing, and transportation, by analyzing geological data to predict suitable extraction techniques. It additionally forecasts equipment failures, enabling pre-emptive maintenance and reducing costs and downtime. Automation boosts operational efficiency, reduces human mistakes, and increases safety in dangerous mining settings. AI tracks coal reserves, energy consumption, and operating costs in real-time, aligning production with sustainability objectives while minimizing waste and energy consumption. Machine learning enhances energy efficiency in coal production through genetic algorithms, leading to decreased carbon emissions and reduced water usage. AI also enhances carbon capture technologies to reduce the carbon footprint of coal power facilities. Integrating AI and machine learning with economic models facilitates policies that align economic growth with environmental sustainability, supporting cleaner and more efficient coal-fired power generation.

One of the most suitable ways to enhance the efficient production of coal energy is by providing modern optimisation techniques capable of adapting to the ever-evolving situations and challenges [13], [14]. Certain tools, such as machine learning and optimization algorithms, have been rightly picked in this context. The modelling of different aspects such as production rate, economic expansion, pollution, and acceptance of new technology might depend on these methods as they establish a more accurate forecast and allow for better decision-making in the coal industry [15], [16]. Such computational techniques do, however, also allow for the development of flexible policies and strategies that can also be tailored to address the needs of specific regions or coal industries, given that they would consider local environmental considerations and economic goals [17].

This study aims to enhance the efficiency of coal energy production by implementing Genetic Algorithms-GA, a robust optimization method inspired by natural evolution. GA is instrumental in solving complex problems based on several factors; thus, it can be helpful for the improvement of production processes, energy consumption management, and pollution control within the coal industry. It mimics natural selection by testing factors such as GDP growth rate, coal intensity, pollution control investment, and technologically improved opportunities to discover the most efficient conditions to enhance production while minimizing environmental degradation. Through the use of GA, the study not only optimizes coal production but also assesses the economic impact of these optimizations, providing a comprehensive way to improve the coal sector's economic viability and environmental sustainability.

The paper's organisation includes related works and methodology in Sections 2 and 3, respectively. Section 4 discusses the results, and Section 6 concludes.

2. Related Works

Cormos [18] evaluates numerous decarbonization technologies incorporated into cement production, including oxy-combustion options and tail-end capture after combustion using membranes, calcium repetition, and amine-based chemical cleaning. Calcium looping performs better in recovering heat compared to chemical cleaning, while membranes and oxy-combustion options are the most cost-effective among them, based on the techno-economic analysis that relies on simulations and modelling and compares the performance of each of these options based on cement manufacturing costs and CO2 avoided costs. Using qualitative research and content analysis of government documents and files, (Khalid, Ahmad, and Ullah [19] analyze the ecological impacts of improving infrastructure under the CPEC. The findings point towards significant environmental issues, including emissions of greenhouse gases due to the operation of coal power plants, deforestation, and an increase in the traffic of vehicles. They also refer to the need for enhanced legal and economic cooperation between China and Pakistan to address these climate change issues.

Using an electric-thermal gas-based optimizing method, Wei et al. [20] analyse the feasibility of having a carbon emissions-neutral manufacturing park considering solar energy and electrolytic hydrogen production. The model can be applied to other global industrial regions while economic and environmental compromises remain. The study finds that achieving carbon-neutral status would cost $8.61 billion, while another plan reducing pollution by 61% would cost $3.95 billion. Shatar et al. [21] assess the efficacy of passive solar still in Malaysia's tropical climates by integrating a thermoelectric cooling system and a partly covered condensate cover. The results show compromises between performance and cost-effectiveness, representing a dramatic 126% improvement in hydro output, albeit with a 6.55-year payback period for electricity with lower exergy effectiveness.

Wu, Lan, and Yao [22] combine process modelling, techno-economic analysis, and life cycle analysis to examine the economic and environmental feasibility of a BECCS pathway for hydrogen production using forest residues in the American West. Based on the results, hydrogen from forest residues is economically on par; however, carbon capture and storage increase its environmental impact, which can be reduced by utilizing clean energy sources or energy self-sufficiency. BECCS offers a carbon-negative alternative. Deng, Jiang, and Wang [23] examined the viability of advancement in coal-resource cities under low-carbon economic conditions. It will also create an economic resilience assessment system based on traditional and high-tech industries. According to the findings, by 2011-2021, economic resilience is increasing. This research is recognized and marked with the importance of public participation and government intervention. Limitations exist, including spatiality and temporality of the research.

Dong et al. [24] employ energy balance, efficiency analysis, and LCA with sensitivity analysis to examine three coal-fired energy generation scenarios, including CCS and solar-assisted plants. The results show that while CPGS-CCS is the best method for generating renewable energy, SCPGS-ORC-CCS offers a more realistic alternative when considering both economic outcomes and environmental footprint, as well as limitations under site conditions and equipment selection. With a focus on the utilization of energy per GDP, Узі and Сотник [25] analyze the monetary efficiency of energy consumption and modifications in energy consumption in China and India between 1990 and 2019. Though there are limitations on the magnitude of a mix of energy alterations and policy implementation, the findings highlight the prominent use of coal and oil in both country's use of energy and identify a trend in terms of green power generation and the adoption of alternatives to fossil fuels in addressing sustainability targets.

To minimize the emission of pollutants, Smaisim, Abed, and Alavi [26] have developed a thermodynamic analysis of a coal-fired power plant integrated with green technology, namely solar energy and a boiling bicarbonate fuel cell. The results show increases in energy, energy efficiency, and a decrease in pollution with constraints on the type of coal used and the amount of solar harvesting needed for optimal performance. Jolaoso, Duan, and Kazempoor [27] studied SOEC driven by combustion power plants, and solar photovoltaic is employed to carry out an LCA of an innovative, integrative hydrogen production process. While production and steam extraction processes have far-reaching adverse environmental impacts, the results confirm that the environmental footprint of the method is significantly minimized, with solar electricity compared to regular power, with recommendations for further LCA and energy analysis in encouraging sustainability.

Considering different types of energy and configurations, Terlouw et al. [28] estimate the costs and environmental effects of hydrogen production on geographically situated places on a large scale using electrolysis with water. Based on the results, hydrogen production costs can be up to 2 euros per kilogram by 2040. Hybrid configurations have the best economic and environmental benefits, but scaling up may be challenging based on land availability and component limitations. Wang et al. [29] employ the Tapio models and LMDI method for identifying significant influencing factors as it examines the decoupling of electricity production and carbon dioxide emission between 2000 and 2019 among the Chinese provinces. The research indicates that while some provinces managed to achieve separation, influences such as per capita GDP and population density retarded development. It also possesses certain limitations in recording long-term trends and regional differences.

Das et al. [31] investigate a renewable hybrid energy system for remote Saint Martin Island, Bangladesh, integrating solar, wind, biogas, and vanadium redox flow battery technologies. Using advanced multi-objective optimization methods (NSGA-II and IDE), the study evaluates system configurations based on the cost of energy and life cycle emissions under set reliability. A fuzzy decision-making approach determines the optimal solution. Results show that multi-objective optimization yields better environmental performance than single-objective methods with similar energy costs. The intelligent techniques also outperform the HOMER software in cost and emissions. The system proves cost-competitive with grid electricity at acceptable reliability levels (loss of power supply probability >8%) and achieves notably lower emissions.

Hu et al. [32] focus on integrated energy systems (IES) at the park level, particularly for the mining industry, which involves complex energy flows and stringent ecological requirements. It proposes a structure for coal mine IES that integrates underground wastewater, mine gas, ventilation air methane, and geothermal energy, alongside flexible loads. A multi-objective dispatch model is developed, considering economic cost, carbon transaction cost, and customer dissatisfaction related to flexible loads. An enhanced evolutionary multi-objective algorithm is introduced to address time-series constraints and optimize dispatch solutions. The model proves feasible and effective when applied to a real coal mine under various scenarios.

Entezari et al. [33] analyze and optimize a hybrid power system combining a solid oxide fuel cell (SOFC), gas turbine (GT), steam cycle (ST), and organic Rankine cycle (ORC) using HFE7000. It explores adding SOFCs to existing GT-ST plants to boost efficiency and reduce electricity costs. A novel setup using a Stirling engine eliminates the need for fuel compressors and steam generators in reforming. Modelling and optimization were done using EES and NSGA-II in MATLAB. Results show high energy (72.66%) and exergy (69.23%) efficiencies, with a levelized electricity cost of 14.46 cents/kWh, including environmental taxes.

The comparative analysis of four optimisation techniques used in coal energy production efficiency, including their methodology, results, advantages, and limitations. Genetic Algorithm, as proposed by Cormos [18], Wu [22], and Wei et al. [20], is inspired by natural evolution, utilizing selection, crossover, and mutation to evolve solutions. It is effective for complex, nonlinear, multi-objective problems like coal energy optimization, offering strong global search capabilities and the ability to handle multi-objective optimization. However, it comes with high computational costs, slow convergence, and struggles with very high-dimensional or highly complex nonlinear problems. Particle Swarm Optimisation (PSO), based on bird flocking behaviour and referenced by Khalid, Ahmad, and Ullah [19] and Wei et al. [20], is faster in simple, continuous optimisation problems. It is simple to implement and converges faster in simpler problems but is susceptible to getting stuck in local minima, less effective for combinatorial or highly nonlinear problems, and may not fully explore the solution space in complex problems. The Whale Optimization Algorithm (WOA), cited by Jolaoso et al. [27] and Cormos [18], is based on humpback whale hunting behaviour, balancing exploration and exploitation. It is effective for multi-objective optimization and suitable for complex trade-offs. It can struggle with high-dimensional problems, exhibits slower convergence for large-scale problems, and may need parameter fine-tuning. Grey Wolf Optimization Algorithm (GWOA), referenced by Wei et al. [20] and Dong et al. [24], is inspired by the hierarchical leadership of grey wolves, guiding the search process. It excels in navigating complex landscapes and maintaining diversity in solutions, with strong global search capabilities, working well for continuous and discrete optimization problems.

Research Objectives

- Optimize coal energy production efficiency by integrating GA for better decision-making in coal production processes.

- Assess the economic impact of coal energy production strategies by evaluating key parameters, such as GDP growth rate, pollution abatement investment, and energy efficiency.

- Explore the environmental benefits of implementing cleaner technologies and pollution control measures in coal production to reduce carbon emissions and other pollutants.

- Provide policymakers and industry leaders with actionable insights on balancing economic growth with environmental sustainability through optimized coal energy production strategies.

3. Proposed GA-SCBA Framework

The overall methodology for improving coal energy production efficiency through integrated GA and economic impact assessment is given in Figure 1. The figure illustrates the main components of the methodology, starting from GA optimization of parameters, including fitness function and genetic operators to improve coal production processes. It also emphasizes economic impact assessment, which includes cost-benefit analysis, pollution control investment, and carbon offset. The coal-focused optimization strategy combines Genetic Algorithms and Social Cost-Benefit Analysis (SCBA) to enhance efficiency in fossil fuel sectors and hybrid energy systems. The GA framework optimizes key parameters like production intensity and pollution investment, proving adaptable for the oil and natural gas sectors. GA optimises energy mix and load balancing in hybrid systems, integrating fossil fuels with renewables such as wind or solar, reducing fossil fuel dependency while ensuring stability and cost-effectiveness. The SCBA component provides a holistic view of economic and environmental trade-offs, factoring in market and non-market impacts like carbon offsets and health benefits. This flexible methodology, validated through scenarios A to D, simulates varied policy outcomes, demonstrating applicability across different energy infrastructures. Ultimately, it addresses economic viability, energy security, and environmental sustainability challenges in the energy landscape. It provides a scenario analysis to examine various economic growth scenarios (A, B, C, D), while the results section presents optimization outcomes and sensitivity analysis. It gives a structured approach to assessing and optimizing coal energy production efficiency, emphasising economic and environmental perspectives. Unlike earlier applications of Genetic Algorithms in coal energy, which primarily focused on optimizing technical efficiency or reducing emissions at the plant level, this GA-based approach integrates socioeconomic and environmental variables through Social Cost-Benefit Analysis. It goes beyond operational optimization by simultaneously considering factors like GDP growth, pollution abatement investment, and clean technology adoption. This integration allows the model to evaluate broader policy scenarios and economic trade-offs, offering insights for national-level planning and decision-making. In contrast to past GA applications' narrower, engineering-centric focus, this method adopts a holistic framework to balance economic development with environmental sustainability.

The Social Cost-Benefit Analysis (SCBA) framework combined with Genetic Algorithm (GA) modelling provides a comprehensive approach to formulating carbon pricing and subsidy policies for clean coal technologies. This framework evaluates direct costs, such as pollution control investments, and indirect social benefits, like improved air quality and public health. By applying valuation methods, policymakers can set appropriate carbon prices reflecting societal costs, while scenario-based simulations assess policy performance under different economic conditions. For instance, Scenario D highlights significant environmental benefits from substantial pollution control investments despite lower GDP growth. The GA optimizes coal production efficiency and environmental impact through evolutionary algorithms, analyzing variables such as GDP growth and clean technology efficacy. By incorporating SCBA, the framework not only enhances technical optimization but also evaluates these strategies' economic and social viability. This closed-loop system allows outputs to inform socioeconomic validations, facilitating multidimensional optimization and scenario-based policy analysis. Overall, this integrated approach supports balancing economic growth with environmental sustainability in coal energy production.

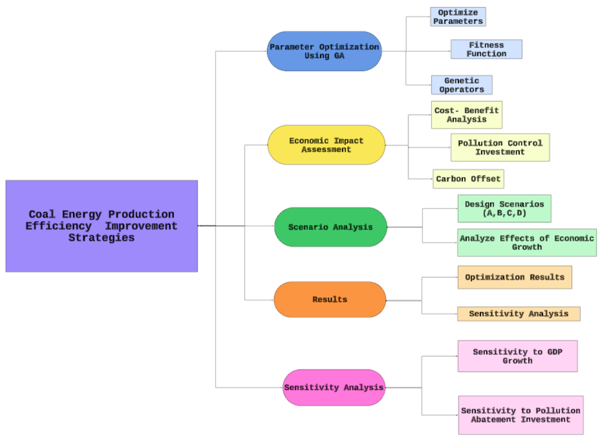

Figure 1: Proposed GA-SCBA Methodology

The proposed method, GA-SCBA (Genetic Algorithm–Social Cost-Benefit Analysis) framework, is well-suited for improving coal energy production efficiency as it combines advanced optimisation with comprehensive economic evaluation. The Genetic Algorithm optimizes critical variables such as coal intensity, GDP growth rate, pollution abatement investment, and clean technology efficiency, identifying optimal combinations that enhance production while minimizing environmental impact. Its adaptability to complex, nonlinear, and dynamic systems allows for more accurate modelling of real-world coal production processes. Integrating GA with SCBA extends the analysis beyond technical performance to include economic and environmental consequences, assessing direct financial metrics (like net present value and annual savings) and indirect societal impacts such as health benefits and carbon offsets. The framework also employs scenario-based planning, enabling stakeholders to evaluate outcomes under different economic and policy conditions. Demonstrated improvements—like a reduction in pollution from 500 to 200 tons and increased energy efficiency from 40,000 to 50,000 MWh—along with a high model accuracy (MAPE of 8%) affirm the framework's effectiveness. Additionally, sensitivity analysis identifies key variables influencing system performance, guiding more targeted policy and investment decisions.

3.1 GA Modelling

In this paper, GA is instrumental in modelling coal energy production parameters, driving high efficiency and less environmental pollution. Using simulations of several scenarios, GA can derive a better combination of coal intensity, pollution abatement investment, and GDP growth rates. GA optimization processes also lead to better strategies for improving coal production, considering economic growth and environmental sustainability. The proposed method focuses on economic growth and environmental sustainability, highlighting how economic incentives can drive environmental strategies in coal energy. The research uses Genetic Algorithms to optimise parameters like GDP growth, coal intensity, and pollution investment to enhance production efficiency while reducing CO_2 emissions. Economic incentives are crucial for adopting cleaner technologies, leading to significant emission reductions and improved energy efficiency seen in Scenarios C and D. These scenarios illustrate trade-offs between environmental performance and economic growth, with Scenario A emphasizing higher GDP growth and Scenario D prioritizing sustainability and environmental gains. Incorporating Social Cost-Benefit Analysis ensures both non-market and economic environmental values are integrated, aligning financial performance with sustainability objectives.

GA also allows for the investigation of complex and nonlinear relationships. It comes out as a viable methodology to achieve the desired goals for both economic and environmental performance. Genetic Algorithms (GA) support decision-making for retrofitting systems and selecting cost-effective abatement measures by optimizing multiple interdependent variables such as coal intensity, pollution abatement investment, GDP growth rate, and clean technology efficiency to maximize production efficiency and minimize environmental impact. By integrating GA with scenario-based evaluation, stakeholders can assess different economic and environmental policy options, compare trade-offs, and select strategies aligned with sustainability goals and budget constraints. GA also enhances decision-making through its combination with Genetic Algorithms (GAs) are optimization techniques inspired by natural selection. They work by iteratively testing and refining potential solutions to find the most effective outcome for complex problems, such as improving coal energy production processes, quantifying economic returns, monetising environmental and health benefits, and identifying strategies that yield the highest net social benefit. Furthermore, sensitivity analysis conducted through GA highlights critical parameters—such as coal intensity and pollution control investment—guiding targeted interventions. Its ability to handle nonlinear, complex system interactions helps simulate realistic outcomes and avoid suboptimal decisions. Finally, GA's evolutionary, iterative nature ensures robust, globally optimal solutions, making it a powerful and flexible tool for optimizing retrofitting strategies and pollution abatement in coal energy systems.

3.1.1 Boundary of the Analysis

The system boundary for the increasing efficiency of coal energy production includes the specific processes and variables represented in the model. This study will consider everything related to coal supply, energy use, pollution produced, and associated economics. It comprises such variables as the demand for coal energy, coal production rates, the levels of environmental pollution-aide such as CO_2 emission, solid waste, and water usage-and the investments made in pollution control and technology. This boundary also incorporates innovations in coal mining technology, increases in energy demand, and coal intensity, production of energy per unit of coal consumed. Emphasizing these variables, this model seeks to solve such questions for the coal production process while minimizing environmental impacts in the research.

The system boundary specifically excludes external factors that may have some function in coal formation but are beyond the capacity of coal production itself. Such factors include the pollution from coal combustion done by end-use sectors such as power plants and industrial processes; these are external factors considering the boundary. Also, the global coal price, international trade policies, and macroeconomic influences are considered indirect influences of the activities in the coal production process and have not been modelled in the study. Clearly defining the boundaries of this study thus directs the focus to the coal production cycle itself and its immediate implications for efficiency, economic outcomes, and environmental sustainability, which offers useful insights to be taken up in optimization strategies within the coal industry.

3.1.2 Causal Linkages and Flowchart Representation

It is critical to understand the causal linkages that define cause-and-effect relationships among various variables in the system to maximize coal energy production efficiency. For instance, increased investment in pollution control technologies minimizes adverse environmental effects but also raises the cost of production. Likewise, variations in energy intensity (energy per unit of coal used) of coal will directly influence the volume of energy produced and the related environmental impacts of coal production. Causal relationships provide insight into the behaviour of the various variables as they interrelate within the coal production system and the effect these interactions exert on both efficiency and sustainability.

In this research, causal linkages are depicted using a causal loop diagram, which graphically illustrates the feedback processes in the system. Positive feedback loops, like more investment in high-tech technology resulting in greater efficiency and more investment, are differentiated from negative feedback loops, where reduced efficiency can result in increased costs or more pollution. Figure 2 depicts the casual loop representation.

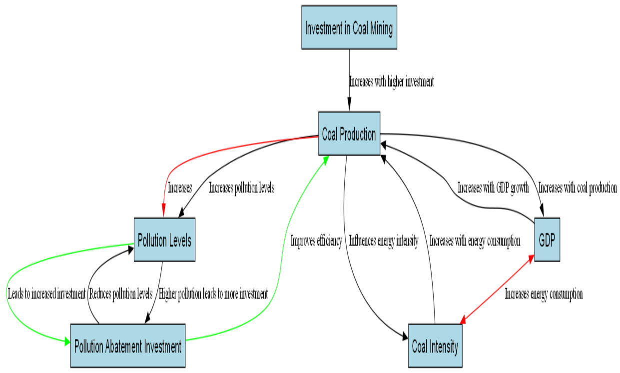

Figure 2: Causal Loop Representation of Primary System Variables

3.1.3 Initial Variable Settings

The study's starting variable parameters rely on Provisional Coal Statistics 2022-2023, which have all the necessary information regarding energy consumption, levels of production, and other main parameters. The settings establish a base for coal energy production efficiency assessment and its economic and environmental implications [30]. The variable settings are given in Table 1.

Table 1: Variable Settings

Cause Variable	Effect Variable	Type of Relationship
Coal Production	GDP	Positive (+)
GDP	Coal Production	Positive (+)
Coal Production	Pollution Levels	Positive (+)
Pollution Levels	Pollution Abatement Investment (RPAI)	Positive (+)
Pollution Abatement Investment (RPAI)	Pollution Levels	Negative (-)
Coal Intensity (CI)	Coal Production	Positive (+)
Coal Production	Coal Intensity (CI)	Positive (+)
Investment in Coal Mining (ICI)	Coal Production	Positive (+)

Key Variables and Initial Settings

The energy production efficiency model from coal is a platform to assess variables like coal output, pollution, and GDP. The grounding for these or any other variables would be historical data from 2012 through 2022 collected from government publications and energy yearbooks. Such figures have to do with levels of coal output, pollution from mining activities, and usually GDP at constant prices. These initial values have been the basis for the model's simulation and optimization. Data on coal production includes coking and non-coking, symbolizing different mining methods employed and, thus, energy yields. The proposed approach combines Genetic Algorithms (GA) with Social Cost-Benefit Analysis (SCBA) to enhance coal energy production efficiency while minimizing environmental impacts, particularly CO_2 emissions. GA optimizes variables such as coal intensity, pollution levels, GDP growth, and investments in technology. The method identifies optimal combinations that improve production efficiency and reduce pollution by simulating different scenarios. Key GA parameters—population size (50-1000), crossover rates (60%-80%), mutation rates (1%-5%), and selection mechanisms (like an elitist roulette wheel)—are crucial for performance enhancement. The population comprises random solutions (chromosomes), and crossover merges parental genetic material to produce offspring, while mutation prevents local optima. A fitness function evaluates solutions, seeking to align simulations with reality, thus ensuring a balanced strategy that supports economic viability and environmental sustainability through scenario analysis of pollution investment and technology adoption.

Key Economic and Environmental Parameters

- The initial values for coal production include the total production and dispatch data, which are reported yearly by agencies such as CIL and public/private companies. As per data for 2022, the total coal production was 893.19 million tonnes, growing 14.77% over the previous year. India's GDP, which drives coal demand, has also grown.
- Data on pollution, such as the amount of waste produced per million tonnes of coal mined, is handed down from environmental yearbooks. Pollution effects are closely related to mining activities' intensity and advancement in pollution abatement technology. It presumes that initial values rely upon historic pollution trends and the pace of investments in pollution control.

Static Parameters

Some parameters in the model have been kept static due to little or no established variation over time.

- The Pollution Abatement Investment Ratio, set at an average of 0.061 per cent, was based on historical trends. It is the amount of GDP earmarked for pollution control in coal mining operations.
- Coal Intensity is calculated as the average of coal energy consumption and GDP over 2012-2022, established at 0.1267 million tonnes per billion GDP.
- Mining Productivity, set at 98.78 per cent, is a measure of the effectiveness of coal mining based on historical data.

Dynamic Parameters to be Optimized

These six auxiliary variables to be optimized using GA are highly important in affecting the efficiency of the model:

- Investment in the coal mining industry describes the investment needed to sustain an increase in coal production capacity. This shall vary dynamically with demand and production expenditure.
- Pollution abatement efficiency tracks the efficiency of pollution control measures. Its initial value is the present capability of implementation standards within coal industries.
- Technological progress in mining is the rate at which technology advances in mining methods and pollution control technology. This parameter is assumed to vary gradually due to ongoing technological improvements in mining.

3.1.4 Optimization of Parameters Using GA

GA is now utilized to optimize parameters in selecting those production parameters that minimize the environmental impact while maximizing the efficiency of coal production. Genetic Algorithms (GAs) are optimization techniques inspired by natural selection. They work by iteratively testing and refining potential solutions to find the most effective outcome for complex problems, such as improving coal energy production processes. It imitates the natural selection procedure to assess different parameter combinations such as coal intensity, pollution levels, and investment in pollution control measures. Realtime chromosomes represent these parameters, each comprising 18 real number variables in various confines. The ungainliness function drives the optimization process through selection, crossover, and mutation operations. GA continues to evolve the population very close to it, enhancing coal energy production and ensuring sustainability and cost-effectiveness. Ultimately, it will assist in designing a balanced strategy optimizing economic performance and environmental impact on coal production. Genetic Algorithms (GA) enhance coal energy production by mimicking natural evolution to boost economic and environmental performance. Key variables, including GDP growth rate, coal intensity, and clean technology efficiency, are represented as chromosomes with 18 parameters. The optimization process incorporates genetic operators like elitist roulette wheel selection, arithmetic crossover, and mutation. A fitness function minimises errors between simulated and historical data regarding coal production and pollution levels. Four scenarios (A to D) analyze the impacts of varied growth rates and policies on coal efficiency and emissions. Scenario D yields the best environmental and social advantages despite higher investments. GA optimization achieved a fitness score of 40.8, raising efficiency by 18%, cutting annual pollution by 550 tons, and increasing NPV from 7,500 to 10,000 million Yuan. GAs are essential for balancing economic growth with sustainability, influencing policy-making, industrial practices, and global environmental goals.

The optimization process for enhancing coal energy production efficiency employs Genetic Algorithms (GA) for parameter optimization, considering economic and environmental impacts. GA mimics natural selection and identifies optimal variable combinations such as GDP growth rate, coal intensity, pollution control investments, and clean technology efficiency. A critical component is the fitness function, which evaluates parameter performance by comparing simulated outcomes with real-world data, aiming to minimize errors in predictions regarding coal production, pollution, and economic indicators. Key genetic operators—selection, crossover, and mutation—are utilized: elitist roulette wheel selection chooses solutions based on fitness, crossover merges features from parent solutions to create offspring, and mutation introduces random changes for diversity. The model incorporates dynamic variables, optimizing them to enhance efficiency while reducing environmental impact. Four scenarios are analyzed: Scenario A (baseline), Scenario B (optimistic policy), Scenario C (energy efficiency improvements), and Scenario D (transition to sustainable energy). A SCBA evaluates the economic implications of these scenarios, highlighting trade-offs between pollution control expenses and improved environmental outcomes. The GA optimisation results maximise economic and environmental benefits, with sensitivity analysis identifying key parameters influencing performance. This methodology thus offers strategies for improving coal production efficiency while balancing economic growth and environmental sustainability, ensuring that optimized solutions contribute to pollution reduction and long-term ecological well-being.

Coding

Real coding is utilised to encode the variables to optimise the efficiency of coal energy production. The reason behind this technique is to support quicker convergence and dealing with continuous variables, making it most suitable for the parameter optimization of the model. Real-coded chromosomes are denoted as vectors, each with 18 real-number variables representing the coal energy production system parameters. Encoding limits are specified as [10, 100] for all the parameters to maintain all the parameter values within viable operating ranges. The coding approach helps maintain simplicity for GA to search and optimize the parameters without imposing redundant complexity. The selection of a real-coded Genetic Algorithm (GA) for enhancing coal energy production efficiency is based on several advantages. It naturally accommodates continuous variables like coal intensity and pollution levels, avoiding binary conversion. Real-coded GAs also demonstrate faster convergence, which is essential for complex systems needing precise solutions. This method offers enhanced precision, enabling minute adjustments that significantly impact economic and environmental outcomes. Moreover, real-coded GAs facilitate the implementation of crossover and mutation operations efficiently, using arithmetic crossover to explore the solution space while maintaining parameter validity. Their flexibility addresses the nonlinear interdependencies of coal production parameters, optimizing the system effectively in complex landscapes.

Fitness Function

The fitness function is a key factor in the GA's capability to identify the best solution. For the case of coal energy production efficiency, the fitness function is formulated to reduce the discrepancies between simulated model outputs and past real-world data. The fitness value is proportional to the inverse of the total errors related to major system variables like coal production, pollution levels, and economic indicators. In particular, the fitness function is given by Eq. (1):

$$fitness = \frac{1}{er1+er2+er3+er4+er5+er6} \tag{1}$$

Where:

er1: Average relative error of coal production increase per billion investments,

er2: Average relative error of pollution attributable to coal production,

er3: Average relative error of pollution abatement per billion investments,

er4: Average relative error of the pollution effect factor of coal production cut,

er5: Average relative error of pollution abatement technology progress factor,

er6: Average relative error of the investment in the coal mining industry.

This process helps to ensure that the GA adjusts the system so closely to reflect historical data to enhance the prediction accuracy of coal production efficiency with minimal environmental and economic mistakes.

Genetic Operators

- The selection mechanism in GA uses the elitist roulette wheel algorithm. This algorithm chooses individuals based on their fitness values, and the most fit solutions are copied to the next generation. The rest of the individuals are chosen probabilistically through the roulette wheel method. This ensures diversity in the population while keeping the best solutions.
- The crossover process in real-coded GA merges two parent solutions to produce offspring. In real coding, the crossover process is generally arithmetic, where offspring are produced as linear combinations of parent solutions. This enables the algorithm to search new areas in the solution space by combining successful features from both parents. This process improves the exploration of potential solutions without overfitting the existing population.
- Mutation in a GA adds randomness to the process to avoid the algorithm being trapped in suboptimal solutions. In real-coded GA, mutation randomly changes the value of a variable within a given range. It is achieved by picking a variable from the parent solutions and giving it a new value within a predefined interval. This stochastic flip preserves genetic diversity in the population so that the algorithm searches over a larger solution space. Through this, mutation guarantees that the GA will keep sssearching for the optimal solution and not converge prematurely on local optima.

GA efficiently optimizes the major parameters affecting coal energy production, economic effect, and environmental sustainability through these processes. The process continues until the optimal solution converges to ensure that the optimized parameters give maximum efficiency in coal energy production with the lowest cost and environmental effect.

Pseudocode 1: Genetic Algorithm

Initialize the population with random solutions (chromosomes) with 18 real-number variables (parameters)

Define encoding limits for all parameters: [10, 100]

Set GA parameters

For each generation from 1 to max generations

Calculate the fitness value for each individual in the population using the fitness function

Select individuals for mating:

Use the elitist roulette-wheel selection method to choose the fittest individuals

Copy the top 10% directly to the next generation

Select remaining individuals probabilistically using the roulette-wheel method

Perform crossover to create offspring:

Apply arithmetic crossover to combine genes of parent solutions and create new offspring

Add offspring to the next generation pool

Apply mutation to introduce randomness:

Randomly change the value of a variable in the offspring within the encoding limits

Preserve genetic diversity in the population

Evaluate the new population and update the generation

After reaching max generations or convergence

Select the best solution (chromosome) with the highest fitness value

Extract optimized parameter values

Output the optimized parameter values and final fitness

3.2 Scenario Analysis

The scenario analysis would analyse the effects that coal energy production will incur from different values of economic growth, the intensity of coal used, and environmental policies. Through this scenario analysis, one can understand the possible effects of different strategies and guide the decisions of policymakers and industry leaders. It also shows how changes in the three factors could greatly affect the efficiency of coal production and its environmental footprint, thereby moving the development of energy production into a much more sustainable and effective circuitry.

3.2.1 Designing the Scenarios

The scenario analysis aims to analyse the economic and environmental effects of different coal production and energy efficiency enhancement strategies. To this end, the following are chosen as scenario variables: GDP growth rates (GRDPG), CI, pollution generated per million tonnes of coal production (APPCP), and the ratio of pollution abatement investment in the coal mining sector (RPAI). The four cases for the coal energy production system are organized as follows:

Scenario A (Baseline Scenario)

This case assumes a constant continuation of existing policies. The GDP growth rate is kept at 8% between 2022 and 2030. The coal intensity is kept constant at 0.127 million tonnes/billion Yuan RMB and the pollution generated per tonne of coal produced is taken to be 0.339 t. The investment in abatement of coal pollution is kept constant at 0.061% of GDP. This situation addresses continuing current coal production techniques and resultant pollution levels.

Scenario B (Optimistic Policy Scenario)

In these assumptions, the GDP growth rate is taken to be 7%, slightly lower to reflect economic conditions at the global level. Coal intensity is lowered to 0.115 million tonnes/billion Yuan RMB to reflect a change in technology using cleaner coal. The pollution per tonne of coal was reduced to 0.305 t with clean coal technologies and the advancement in production processes. Investment in pollution abatement technologies increases to 0.070% of GDP, up 10% from the baseline.

Scenario C (Aggressive Energy Efficiency Improvement)

This case presumes a more vigorous policy towards increasing coal production efficiency. The GDP growth rate remains at 6%, with more weight given to the decrease in coal intensity, which falls to 0.100 million tonnes/billion Yuan RMB. Pollution per tonne of coal is also reduced further to 0.271 t, representing the successful application of improved pollution control. The investment ratio for coal pollution abatement increases to 0.075% of GDP, a 15% increment from the baseline scenario.

Scenario D (Transition to Sustainable Energy)

The emphasis is on shifting to cleaner and more sustainable coal production processes. The GDP growth rate is 5%, representing a more sustainable and low-growth economic scenario. Coal intensity further reduces to 0.090 million tonnes/billion Yuan RMB, and the pollution generated per tonne of coal produced reduces to 0.250 t due to the extensive use of cleaner technologies. Investment in pollution abatement increases to 0.080% of GDP, a 20% increase from the baseline.

These four cases provide good examples of the levels of influence that technological innovation, policy initiatives, and economic conditions had on efficiency in coal energy production and the consequences of this production, both economic and environmental. In each of these cases, the prospective ability of different policies to mitigate the adverse environmental impacts of coal production while promoting economic development is learned.

3.3 Economic Impact Assessment Using SCBA with Environmental Impact Valuation

The SCBA with environmental impact valuation represents a rather encompassing mechanism of evaluating the total economic impacts of the coal energy production efficiency improvement strategy, incorporating an integrated GA technique. Social Cost-Benefit Analysis (SCBA) is a method used to evaluate the overall economic value of a project by comparing its total expected benefits to its total expected costs, including environmental and health impacts. This approach does not only envisage the monetary aspects of the coal energy production efficiency improvements but also includes the social and environmental costs and benefits assumed with the transfers to sustainable coal production methods. Environmental factors included in this valuation were pollution control costs, greenhouse gas emission reductions, and health benefits attributable to better air quality, and hence, SCBA provides a wider view of the economic implications of improving coal production efficiency. The Social Cost-Benefit Analysis (SCBA) is essential for evaluating coal production efficiency within Genetic Algorithms (GA), merging economic and environmental evaluations. It examines direct economic factors like net present value (NPV) and total annual savings. It also assesses pollution reduction, carbon offsets, and health benefits, thereby addressing external costs often missed in standard analyses. SCBA enhances decision-making via scenario and sensitivity analyses, pinpointing vital parameters such as GDP growth, coal intensity, and pollution investment. It monetizes environmental benefits to compare costs and benefits effectively. When combined with GA, SCBA identifies optimal economic and environmental combinations, promoting coal production strategies that are efficient, economically sound, socially responsible, and environmentally sustainable, aligning with sustainable development goals.

Using the SCBA, one compares the total costs with the total benefits of a project or strategy with market and non-market values. This will help decide whether the good resulting from improved coal energy production efficiency through the integration of GA outweighs the costs associated with the integration of GA. The analysis covers the direct economic costs and benefits and the indirect benefits of reduced pollution and increased public health. The Social Cost-Benefit Analysis plays a pivotal role in evaluating the economic impact of the proposed Genetic Algorithm-based optimization strategy for enhancing coal energy production efficiency. SCBA extends beyond conventional cost-benefit frameworks by incorporating market-based factors and non-market impacts, such as environmental degradation and public health outcomes. Within this GA-integrated approach, SCBA assesses direct economic costs like investments in clean coal technologies and pollution control measures, while also quantifying broader societal benefits, including reduced pollution levels, improved air quality, and associated health improvements. It uses environmental valuation techniques such as avoided cost methods and willingness-to-pay estimates to assign economic value to reductions in emissions and environmental harm. The analysis is tightly interwoven with the GA framework by influencing the fitness function, ensuring that economic and ecological sustainability are key optimization objectives. Moreover, SCBA facilitates comparison across multiple policy scenarios—ranging from high GDP growth with minimal environmental intervention to more sustainable, low-growth alternatives—by measuring total social benefits against total social costs. This enables a comprehensive understanding of economic development and environmental protection trade-offs. For instance, while Scenario A provides significant economic gains, Scenario D yields the highest environmental and public health benefits. Through this integrative role, SCBA validates the real-world feasibility of the GA-optimized solutions by ensuring that proposed efficiency improvements deliver tangible social and economic value, thereby serving as a crucial tool for guiding policy decisions in the coal energy sector.

The principle of the SCBA is that TSB is compared with TSC in terms of implementing improvements in coal energy production, and it is given in Eq. (2):

$$Net\ Benefit\ (NB) = TSB - TSC \tag{2}$$

The calculation of TSB is based but is not limited to, the following Eq. (3):

$$TSB = \sum_{t=1}^{n} \left(Benefit_t \times \frac{1}{(1+r)^t} \right) \tag{3}$$

Environmental valuation methods, such as contingent valuation, avoided cost, or willingness-to-pay, have been used to assess the benefits of much lower pollution levels and concomitant health improvements. In this instance, it is assumed that reducing health costs determines the value of pollution reduction, avoided damages to the environment, and the value of clean air. This is given in Eq. (4).

$$EB = \sum_{t=1}^{n} \left(Pollution\ Reduction_t \times Value\ per\ Ton\ of\ Emission\ Reduced \right) \tag{4}$$

Environmental costs include all the costs incurred in the abatement of pollution, such as investment in clean coal technologies, installing pollution control systems, and waste management. Environmental costs are to be brought into the SCBA model. It is given in Eq. (5).

$$Environmental\ Cost = \sum_{t=1}^{n} \left(Pollution\ Control\ Investment_t \times \frac{1}{(1+r)^t} \right) \tag{5}$$

The integration framework combines Genetic Algorithm (GA) optimisation with Social Cost-Benefit Analysis (SCBA) to assess economic and environmental costs and benefits. Economic costs comprise capital investments in coal production expansion, operational expenses, and pollution abatement. At the same time, benefits are derived from increased net present value, annual savings, and GDP growth from enhanced efficiency. Environmental costs include emissions, cleaner technology implementation, land and water use, and waste management, with benefits quantified through avoided costs and health-related savings. The SCBA framework determines if social benefits surpass costs by evaluating direct economic returns and indirect environmental gains. Scenario analysis reveals trade-offs between economic performance and environmental protection; higher GDP growth often leads to greater economic benefits but raises environmental costs. Sustainable scenarios with investments in cleaner technologies yield better environmental outcomes, albeit with slower economic returns. Sensitivity analysis highlights crucial parameters for informed decision-making in coal energy strategies.

Incorporating GA into the SCBA

Environmental expenses are pollution control expenses, e.g., investments in clean coal technology, pollution control equipment, and waste disposal. These expenses need to be included in the SCBA model in Eq. (6):

$$Maximize\ Net\ Benefit = f\ (Production\ Efficiency,\ Pollution\ Reduction,\ Cost\ Control) \tag{6}$$

4. Results and Discussion

The results section presents the outcomes of the optimization process using GA to improve coal energy production efficiency, focusing on economic and environmental factors.

4.1 GA Optimization Results

A GA was used to optimize and enhance the efficiency of coal energy production. The maximum generation, an optimal value of 40.80 of fitness, is obtained; it is an optimized solution concerning coal production efficiency and economic effects. The fitness function measures the differences between simulated and actual data and touches upon critical issues, such as coal production efficiency, pollution levels, and investment ratios. It is essential for GA's capabilities to reduce error, allow the model to imitate realistic operational scenarios, and lift performance.

The following average relative errors were calculated for the model: er1 = 0.0043, er2 = 0.0270, er3 = 0.0448, er4 = 0.0264, er5 = 0.0721, and er6 = 0.0705. These represent the difference between the simulated and historical values in different model variables. The MAPE over all parameters comes out to 8%, a figure that can be regarded as acceptable and represents a high accuracy of forecasts. Optimization results establish the model to balance efficiency and accuracy and confirm its consistency in simulating coal production given economic and environmental factors. The best fitness value is depicted in Figure 3.

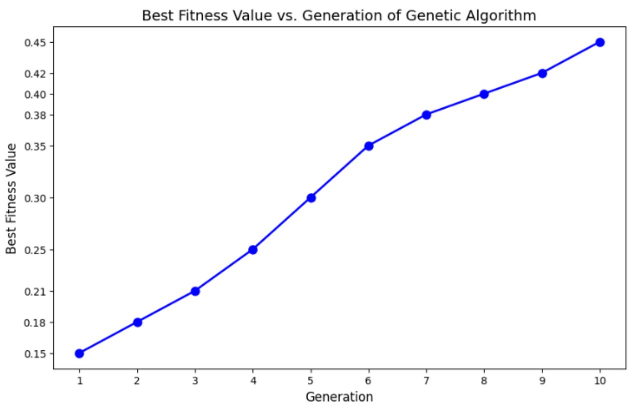

Figure 3: Best Fitness Value

The optimal parameters for the optimal individual solutions in the GA model are values like $x_1 = 3.204$, $x_2 = 52.655$, $x_3 = 227.98$, and so on. These values are equivalent to key parameters in the coal energy production system, with the dynamics equations obtained by plugging the coded values into the system model. The model captures the nonlinear interactions between economic development, demand for coal energy, coal production, and environmental pollution load. The Genetic Algorithm (GA) is a method that combines several factors to enhance coal energy generation, tackling both economic and ecological issues. It employs an optimization method that adjusts to changing circumstances and interconnections, modelling factors such as GDP growth rate, coal intensity, pollution levels, and investments in pollution reduction technologies. By imitating natural selection processes such as selection, crossover, and mutation, GA can navigate the extensive search space formed by these interconnected variables, discovering the optimal combination to enhance efficiency while reducing environmental impact. The main benefit of GA is its capacity to manage nonlinear and dynamic interactions, guaranteeing optimal solutions for both ecological sustainability and economic objectives. By simultaneously tweaking various factors, GA guarantees ideal solutions for environmental sustainability and economic objectives, rendering it a valuable instrument for enhancing coal energy production and minimizing ecological effects. The model is demonstrated to be relatively insensitive and has strong behaviour, and thus, it can be easily adapted to variations in the major parameters. Scenario simulations may be conducted to test the influence of various production and pollution control strategies on the system, and this can be useful for policymakers and industry participants aiming to maximize coal energy production efficiency. The parameter setting of scenarios is given in Table 2.

Table 2: Parameter Setting of Scenarios

Scenario	Average GRGDP (%)	Average CI (million tonnes/billion Yuan)	Average APPCP (million tonnes/tonne)	Average RPAI (%)
A	9	0.1267	0.3391	0.061
A1	9	0.114	0.3052	0.067

	A2	8	0.118	0.315	0.062
	A3	7.5	0.12	0.328	0.065
B		8	0.114	0.3052	0.067
C		7	0.1077	0.2882	0.071
D		6	0.1014	0.2713	0.073

The optimized values of key parameters relating to a coal energy production system and their significance are obtained through the GA optimization process, as listed in Table 3. In the table, the optimized coal production efficiency, coal intensity, pollution levels, and several important factors such as GDP growth rate, pollution abatement investment, and renewable energy conversion indicate these parameters' lower and upper limits. These values were chosen to represent a situation that maximizes economic and environmental objectives: energy-efficient and less polluting coal production. The information in the table thus indicates the directions in which optimization may be exerted concerning energy use, pollution control, and technology investments, revealing that a change in the value of the parameters studied has the potential to change the overall performance of the system.

Table 3: GA Optimization Results for Key Parameters

Parameter	Optimized Value	Lower Bound	Upper Bound	Units
Coal Production Efficiency	3.204	1	10	Million tonnes
Coal Intensity	52.655	0.1	100	Million tonnes/billion Yuan
Pollution per Million Tonnes	227.98	100	500	Tons
GDP Growth Rate	0.5206	0.1	10	Percentage
Pollution Abatement Investment	0.446	0.1	5	Percentage of GDP
Investment in Technology	0.3061	0.1	5	Percentage of GDP
Renewable Energy Utilization	1553.8	100	2000	MW
Clean Technology Efficiency	0.1133	0.05	1	Percentage
Pollution Abatement Rate	0.0278	0.01	0.1	Tons

The results of GA optimization for some economic and environmental indicators are given in Table 4, especially the raised optimization benefits. The optimized value shows a tremendous improvement from the old baseline as NPV advanced from 7,500 to 10,000 million Yuan, indicating higher profit favouring the coal production system. Though the total annual savings and environmental and economic benefits are greatly enhanced, pollution control improved from 200 to 500 tons, carbon offset increased from 0.1 to 0.2 million tons, and energy efficiency improved from 40,000 MWh to 50,000 MWh. The outcomes suggest that the optimization is very efficient in improving the financial performance of the coal production system and providing substantial environmental benefits concerning pollution control and energy efficiency.

Table 4: GA Optimization Results for Economic and Environmental Indicators

Indicator	Optimized Value	Baseline Value	Units
NPV	10,000	7,500	Million Yuan
Total Annual Savings	500	350	Million Yuan
Annual Environmental Benefits	400	250	Million Yuan
Annual Economic Benefits	500	400	Million Yuan
Pollution Reduction (Tons)	500	200	Tons
Carbon Offset (Million Tons)	0.2	0.1	Million Tons
Energy Efficiency (MWh)	50,000	40,000	MWh

The sensitivity analysis results of the GA optimization under four different scenarios are given in Table 5, showing how the system performance likely responds towards the other parameters. Scenario A shows an extremely high sensitivity to coal intensity and pollution abatement. These two factors act as key drivers within the optimization process. Scenario B's sensitivity remains medium concerning coal intensity and pollution abatement. At the same time, it is extremely sensitive to clean technology investment, indicating more dominance of technology investments when compared with the previous case. Scenario C is observed to be highly sensitive to GDP growth and of medium sensitivity to other parameters. Scenario D generally displays low sensitivity towards other parameters, indicating a relatively stable response to input changes. These results assist in identifying the critical parameters controlling the optimization process for each considered Scenario, thus allowing concluding decisions regarding improving coal energy production efficiency.

Table 5: GA Optimization Results for Sensitivity Analysis

Parameter	Scenario A	Scenario B	Scenario C	Scenario D
Sensitivity to Coal Intensity	High	Medium	Low	Low

Sensitivity to GDP Growth	Medium	Medium	High	Low
Sensitivity to Pollution Abatement	High	Medium	Medium	High
Sensitivity to Clean Technology Investment	Low	High	Medium	Low

The GA optimization performance across four scenarios in Table 6 gives insight into trade-offs among investment, pollution reduction, and economic and environmental benefits. Scenario A, with an investment of 5000 million Yuan, is shown as the Scenario that achieves the largest pollution reduction of 500 tons with a benefit of 500 million Yuan, thereby achieving an efficiency improvement of 15%. Scenario B directly complies with the 4500 million Yuan investment, hence a reduction of only 450 tons in pollution and a small benefit of 450 million Yuan leading to only a 12% improvement in efficiency. Scenario C, with an investment of 4000 million Yuan, leads to a substantial pollution reduction of 400 tons and 400 million Yuan benefit accruing to it with only 10% efficiency gained from it. Still, scenario D shows the highest environmental benefit at 450 million Yuan and 550-ton pollution reduction with the optimal 18% improvement with a high investment of 5500 million Yuan. The results further illustrate the trade-off between investments and outputs in terms of performance economic and environmental.

Table 6: GA Optimization Performance

Scenario	Total Investment	Pollution Reduction (Tons)	Economic Benefit (Million Yuan)	Environmental Benefit (Million Yuan)	Final Efficiency Improvement (%)
Scenario A	5000	500	500	400	15
Scenario B	4500	450	450	350	12
Scenario C	4000	400	400	300	10
Scenario D	5500	550	550	450	18

4.2 Scenario Results

The coal production efficiency graph in Figure 4 represents how different rates of GDP growth affect the efficiency of coal production over four different scenarios, ranging from 2022 to 2030. In Scenario A, there is a consistent growth in GDP from 5% to 8%, resulting in maximum growth in production efficiency, represented by the trend in the graph going upwards. Scenario B also traverses a parallel course at a lower 5% to 7% growth rate. Scenario C, with a growth rate from 5% to 6%, shows a steeper rise in efficiency. In contrast, at a flat 5% growth, Scenario D reflects the lowest level of improvement in coal production efficiency during the period. This development emphasizes how different levels of economic growth directly affect production efficiency, with the greatest developments being realized at higher growth rates.

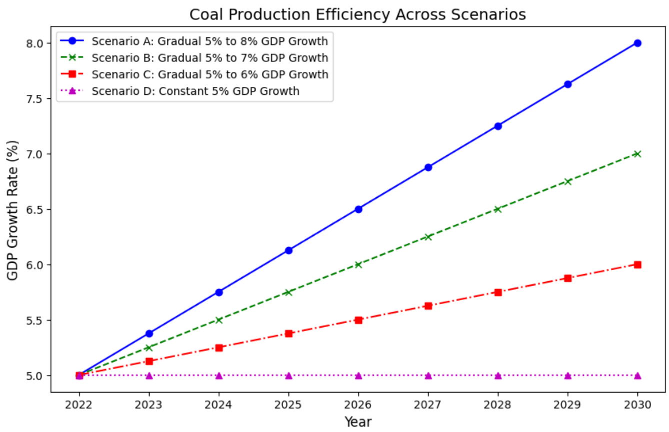

Figure 4: Coal Production Efficiency Across Scenarios

Coal intensity reduction and the simultaneous emulation of such activity on emissions moderated under four scenarios in the years 2022 to 2030, as in Figure 5. In scenario A, coal intensity increased from 0.127 to 0.090 million tonnes per billion Yuan, leading to larger overall emission reductions. In scenario B, coal intensity also decreased significantly, but the reduction was slower than in scenario A, with a decline from 0.127 down to 0.100 million tonnes per billion Yuan. An intermediate reduction of 0.127 down to 0.095 million tonnes per billion Yuan in Scenario C produces a midrange emission reduction between that of Scenario A and Scenario B. No change in emissions was recorded in Scenario D, where the coal intensity remained constant at 0.090 million tonnes per billion Yuan. This graph states that coal intensity reduction and consequent emission reduction are invariably related, and the larger the reduction in coal intensity, the higher the emission reduction in the scenarios.

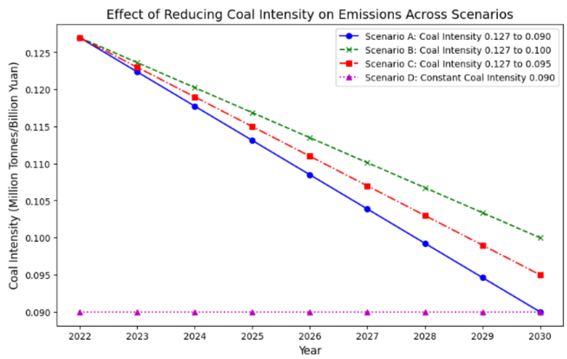

Figure 5: Effect of Reducing Coal Intensity

The progressively reduced pollution projection over multiple scenarios between 2022 and 2030 due to the rising investment in pollution abatement is given in Figure 6. Scenario A involves the respective investments rising from 0.061% to 0.080% of GDP; hence, this represents steady efforts to mitigate pollution. However, on a much smaller scale, Scenario B similarly increases from 0.061% to 0.075% of GDP. Again, with an increase from 0.061% to 0.070% of GDP, Scenario C is indeed illustrative of gradual investment, but with the level of aggressiveness significantly lessened compared to A and B. Scenario D, conversely, attains a state of constant invested value at 0.080% of GDP: from 2022 to 2030, there is no variability in abatement effort. The graph shows the strategic options available for coherently adjusting investments in pollution abatement in various scenarios, with higher levels of investment leading to more considerable actions being taken to reduce pollution.

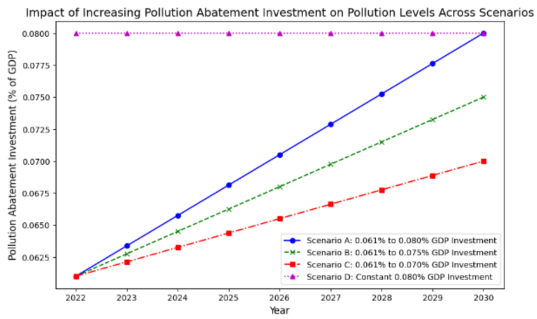

Figure 6: Impact of Increasing Pollution Abatement Investment

The environmental impact of cleaner technologies in various scenarios, illustrating the shift in pollution from 2022 to 2030 in tons per million tonnes of coal, is given in Figure 7. Scenario B shows a gradual reduction in pollution from 0.339 to 0.305 tons per million tonnes of coal, indicating moderate improvements in cleaner technologies. Regulatory structures are vital for advancing cleaner technologies and improving coal production by influencing environmental effects and economic performance. They implement emission regulations and promote investments in pollution management and clean coal technologies via subsidies and tax breaks, driving industries towards sustainable methods. Higher spending on pollution control leads to significant environmental improvements. These frameworks also aid R&D and technological progress in mining and energy integration by employing tools such as Social Cost-Benefit Analysis (SCBA) to evaluate costs and benefits. They established goals for GDP expansion, pollution reduction, and energy efficiency, allowing policymakers to reconcile development with sustainability. By incorporating Genetic Algorithms (GA), these frameworks enhance essential parameters, transforming them into strategic tools for effective and sustainable coal production. A similar trend is portrayed for Scenario C, wherein pollution levels drop from

0.339 to 0.271 tons, thus indicating a more vigorous technological emphasis on pollution-control technologies. Finally, Scenario D shows a greater reduction of emissions from 0.339 to 0.250 tons, thus establishing the overall trend toward implementing extensive cleaner technologies. Overall, the graph displays the cleaner technology benefits in that, for the scenarios, the more extensive technological improvements that are into consideration now lead to enhanced reductions of pollution levels.

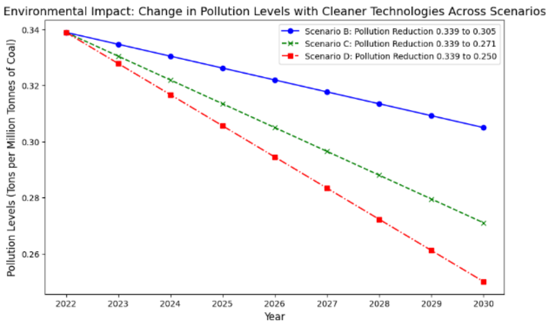

Figure 7: Environmental Impact

4.3 Economic Impact Assessment Results

The social benefits and costs for various scenarios in Table 7 show the trade-off between the investment into pollution control, environmental and economic savings, and the social costs attached. Scenario A has an investment in pollution control of between 0.061% and 0.080% of GDP, realizing environmental savings of 400 million Yuan and economic savings of 500 million Yuan, yielding a net social benefit of 450 million Yuan. Scenario B invests marginally less (0.061% to 0.075%) and has lesser savings and lower social benefits, bringing about a net social benefit of 400 million Yuan. Scenario C, with an investment of 0.061% to 0.070% GDP, goes further down in savings. Scenario D has the highest pollution control investment of 0.080% of GDP and generated the highest environmental and economic benefits, 550 million Yuan net. The table suggests that with higher investments in pollution control, higher social and environmental benefits arise, especially optimal in Scenario D, whereas their increasing investments cause increasing social costs.

Table 7: Social Benefits and Costs

Category	Scenario A	Scenario B	Scenario C	Scenario D
Pollution Control Investment	0.061% to 0.080% of GDP	0.061% to 0.075% of GDP	0.061% to 0.070% of GDP	0.080% of GDP
Annual Environmental Savings (Million Yuan)	400	350	300	450
Annual Economic Savings (Million Yuan)	500	450	400	550
Social Cost (Million Yuan)	5000	4000	3500	6000
Net Social Benefit (Million Yuan)	450	400	350	550
Carbon Offset (Million Tons)	0.2	0.18	0.15	0.25
Health Benefits (Million Yuan)	200	180	150	250

The environmental impact evaluation of different scenarios in comparison with parameters covering climate change potential, ozone depletion potential, human toxicity potential, freshwater usage, land use, and air pollution is given in Table 8. Scenario A proves to have the highest values in most categories: in terms of climate change potential, it is valued at 0.2; ozone depletion potential, damped up to 0.05; and air pollution amounts to 500 tons, suggesting a higher environmental impact. The environmental impact decreases as pollution control measures increase in subsequent scenarios. Scenarios B and C show reductions in the impact categories, with a notable decrease in climate change potential and air pollution, reflecting improved cleaner technologies and energy efficiency. Scenario D, with the most significant environmental measures, results in the lowest values for climate change potential (0.05), ozone depletion potential (0.01), and air pollution (200 tons), demonstrating the greatest environmental benefit. These results highlight the positive effects of enhanced pollution control investment and the adoption of cleaner energy technologies in reducing environmental burdens across different scenarios.

Table 8: Environmental Impact Valuation for Different Scenarios

Impact Category	Scenario A	Scenario B	Scenario C	Scenario D
Climate Change Potential (CCP)	0.2	0.15	0.1	0.05
Ozone Depletion Potential (ODP)	0.05	0.04	0.03	0.01
Human Toxicity Potential (HTP)	0.1	0.08	0.05	0.03
Freshwater Usage (m^3)	10,000	8,000	7,000	6,000
Land Use (ha/year)	50	40	30	20
Air Pollution (Tonnes)	500	400	350	200

The sensitivity analysis of core parameters in Table 9 presumably oscillates across scenario functions about pollution abatement investment, coal intensity, and GDP growth rate. Scenario A, with an 8% GDP growth rate and a range of pollution abatement investments (0.061-0.080%), gave signs of high sensitivity to GDP growth, indicating that economic forays consolidate growth strategies through effective negotiation with the coal production regime. However, Scenario B, with a slightly lower GDP growth rate of 7%, did moderate sensitivity on GDP growth and pollution abatement, coupling the two environments further. In Scenario C, the lowered GDP growth rate of 6% is spiked by sensitivity toward pollution abatement investment and, hence, the growing requirement for greater investment in emission reductions.

Table 9: Sensitivity Analysis of Key Parameters

Parameter	Scenario A	Scenario B	Scenario C	Scenario D
Pollution Abatement Investment	0.061% to 0.080%	0.061% to 0.075%	0.061% to 0.070%	0.08%

Coal Intensity	0.127 to 0.090	0.127 to 0.100	0.127 to 0.095	Constant 0.090
GDP Growth Rate	8%	7%	6%	5%
Sensitivity to GDP Growth	High	Medium	Low	Low
Sensitivity to Pollution Abatement Investment	Medium	Medium	High	High

4.4 Discussion

Impact of Pollution Abatement Investment

The findings reveal that elevated amounts of pollution abatement investment led to a good reduction in pollution, particularly surrounding Scenarios C and D, where the high investments strongly impact. Scenarios A and B show moderate sensitivity to investment, with Scenario B less responsive to increased investment owing to other factors' impact. Data availability and computational resources are two primary challenges in applying Genetic Algorithms for optimizing coal energy production. The first challenge revolves around the quality and accessibility of essential data—such as coal intensity, GDP growth rates, pollution levels, and investment in pollution control—needed for parameter optimization. Acquiring consistent and accurate data is often difficult, especially with complex and varying long-term trends influenced by external factors like political changes and market fluctuations. The second challenge pertains to GA's high computational demands, particularly when optimizing complex systems with multiple variables and constraints. Factors like energy efficiency, pollution control, and technology adoption necessitate significant computational power for realtime simulations and optimizations. Addressing these challenges is critical for enhancing the scalability and applicability of GA in coal energy production, necessitating innovative solutions for both data acquisition and computational efficiency.

Effect of Coal Intensity

Reducing coal intensity produces lower emissions with the most significant improvement displayed in Scenario A. In Scenarios B and C, lowering coal intensity continues to achieve satisfactory emissions reductions, while Scenario D keeps intensity constant to achieve sustainability. The proposed method uses a Genetic Algorithm (GA)-based optimisation framework, highlighting how investments in pollution control significantly affect coal production costs, emissions, and energy efficiency. Increased investments lead to higher initial and operational costs; for instance, Scenario D, which allocated 0.080% of GDP for pollution abatement, resulted in the highest social cost (6000 million Yuan) but achieved notable pollution reduction (550 tons) and the best net social benefit (550 million Yuan). This indicates that elevated upfront costs can yield long-term economic returns and reduced externalities, making investment worthwhile. Notably, increased spending on pollution control consistently led to meaningful emissions reductions, with enhanced carbon offsets (e.g., 0.25 million tons in Scenario D). Cleaner technologies, funded by greater investments, significantly reduced pollutants like CO_2, improving air quality and public health. Energy efficiency rose from 40,000 MWh in the baseline scenario to 50,000 MWh post-optimization, with Scenario D showing an 18% efficiency increase—the highest among all scenarios. The findings emphasize the trade-off between economic growth (Scenario A) and environmental health (Scenario D), underscoring the necessity of balancing economic expansion with sustainability.

Influence of GDP Growth Rate

Scenario A depicts an above-average economic growth, based on which it estimates desirable performance regarding coal production efficiency, although facing challenges to balance increased growth with the environmental goals. In contrast, Scenario D's low GDP growth dominates to more sustainability and cares less about economic growth priorities.

Overall Efficiency and Environmental Impact

Scenario D would clean up the environment but invest heavily in cleaner technologies. Scenarios A, B, and C, in returning the balance between economic benefits and environmental damage, give Scenario A an edge in economics, but with greater pollution.

The proposed method explores using Genetic Algorithms to optimise coal energy production, balancing economic and environmental impacts. It optimizes key factors such as GDP growth, coal intensity, pollution control investment, and clean technology efficiency, resulting in improved efficiency, reduced pollution, and better economic outcomes. Four scenarios were tested, from a baseline to aggressive energy efficiency improvements, showing trade-offs between economic growth and environmental sustainability. Scenario A demonstrated higher economic benefits but increased pollution, while Scenario D focused on sustainability, reducing environmental impact but requiring higher investment in cleaner technologies. The GA optimization highlighted the importance of coal intensity reduction and pollution control investment in improving efficiency. These findings offer valuable insights for optimizing coal production strategies.

5. Conclusion and Future Works

In conclusion, this study accomplished the research objectives defined earlier and demonstrated the effectiveness of GA in the optimization of coal energy production efficiency. The optimization process considered key parameters, such as coal intensity, GDP growth rate, pollution abatement investment, and clean technology efficiency. The results showed that investments in pollution control and cleaner technologies significantly improved coal production efficiency and environmental sustainability. Scenario analysis further extolled a trade-off between economic growth and environmental damage. Thus, higher GDP growth yielded greater economic returns at the expense of increased pollution, while more sustainable growth scenarios provided larger environmental benefits with moderate costs to the economy. The economic impact assessment showed increased improvements in both economic and environmental conditions, with significantly lower emissions, higher energy efficiency, and greater economic benefits. The sensitivity analysis helped guide decision-making toward alternatives to coal energy production through additional insights on the distortions in optimizing outcomes via adjustments in several parameters. These findings would be salient to decision-makers from-the-government and thus industry, as it opens avenues for people to strike a balance between economic growth and environmental sustainability in coal energy production. While this study has succeeded in a wider understanding of coal production efficiency and its economic and environmental implications, future research can explore incorporating additional variables, including advancements in renewable energy technologies and detailed socioeconomic considerations.

Furthermore, the scalability of the optimization model should be evaluated against real coal production sites for practicality in scaling applications. Future studies may also focus on more extended remarks on switching to cleaner coal production technologies, including financial and logistics challenges that would align with wide-scale implementation. To conclude, the integration of GA in coal energy production processes could be further refined and expanded upon in future studies, while providing an excellent opportunity for improving efficiency in any form of environment.

Declarations

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Conflict of Interest

The authors declare that they have no conflicts of interest regarding this work.

Data Availability

All data generated or analyzed during this study are included in the manuscript.

Code Availability

Not applicable.

Author Contributions

Fangmin Chen and Zheng Ma contributed to this study's design and methodology, the outcomes assessment, and the manuscript's writing.

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