Energy and AI 18 (2024) 100417

Contents lists available at ScienceDirect

Energy and AI

journal homepage: www.sciencedirect.com/journal/energy-and-ai

Genetic modification optimization technique: A neural network multi-objective energy management approach

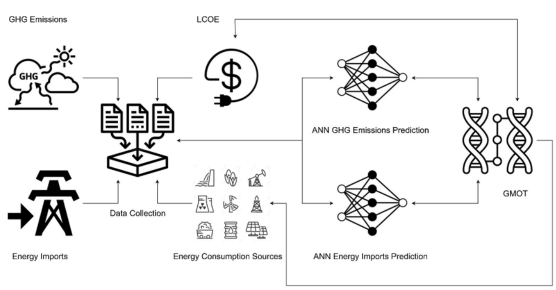
Mutaz AlShafeey [a,*], Omar Rashdan [b]

[a] Institute of Data Analytics and Information Systems, Corvinus University of Budapest, Budapest, Fővám tér 13-15, H-1093, Hungary
[b] Faculty of Pharmacy, Middle East University, Amman, Airport Rd. 11831, Jordan

HIGHLIGHTS

- Neural network-enhanced optimization technique introduced for energy management.
- Suggested method cut energy costs 46 % & emissions 9 % in European Union simulations.
- Human bias and subjectivity minimized through automated parameter settings.
- Superior performance and transparency over traditional methods validated.
- Potential applications in the energy sector and other industries highlighted.

GRAPHICAL ABSTRACT



ARTICLE INFO

Keywords:
Multi-objective optimization
Gene modification optimization technique
Greenhouse gas emissions
Energy management
Machine learning

ABSTRACT

In this study, a Neural Network-Enhanced Gene Modification Optimization Technique was introduced for multi-objective energy resource management. Addressing the need for sustainable energy solutions, this technique integrated neural network models as fitness functions, representing an advancement in artificial intelligence-driven optimization. Data collected in the European Union covered greenhouse gas emissions, energy consumption by sources, energy imports, and Levelized Cost of Energy. Since different configurations of energy consumption by sources lead to varying greenhouse gas emissions, costs, and imports, neural network prediction models were used to project the effect of new energy combinations on these variables. The projections were then fed into the gene modification optimization process to identify optimal configurations. Over 28 generations, simulations demonstrated a 46 percent reduction in energy costs and a 9 percent decrease in emissions. Human bias and subjectivity were mitigated by automating parameter settings, enhancing the objectivity of results. Benchmarking against traditional methods, such as Euclidean Distance, validated the superior performance of this approach. Furthermore, the technique's ability to visualize chromosomes and gene values offered clarity in optimization processes. These results suggest significant advancements in the energy sector and potential applications in other industries, contributing to the global effort to combat climate change.

* Corresponding author.
E-mail address: Mutaz.AlShafeey@uni-corvinus.hu (M. AlShafeey).

https://doi.org/10.1016/j.egyai.2024.100417

Available online 22 August 2024

1. Introduction

As concerns over climate change, pollution, and depleting fossil fuel reserves intensify, the quest for optimal energy source management has acquired significant interest in recent years. The Intergovernmental Panel on Climate Change (IPCC) underscores the urgency of limiting global warming to 1.5 °C, necessitating a swift shift from fossil fuels to renewables [1]. A primary challenge in the contemporary global energy landscape involves optimizing energy source consumption to achieve the lowest greenhouse gas emissions (GHG), minimize imports, and reduce operational costs, all while addressing the escalating global energy demand [2].

Fossil fuels such as coal, oil, and natural gas have long been the backbone of global energy systems due to their high energy density and easy accessibility [3]. The existing infrastructure and economic advantages associated with these energy sources have further lined their dominance in global energy markets [4]. However, their combustion releases substantial amounts of carbon dioxide and other pollutants into the atmosphere, contributing to high levels of greenhouse gas emissions (GHG) [5]. Additionally, the finite nature of fossil fuel reserves raises concerns over energy security and geopolitical conflicts [6]. Nuclear energy, while presenting an alternative with its relatively low GHG emissions during production, is not without challenges, such as the safe disposal of radioactive waste and prevailing public apprehensions [7]. The merits and drawbacks of nuclear energy continue to be highly debated in energy circles [8]. Renewable energy sources, on the other hand, such as solar, wind, hydropower, and bioenergy are starting to gain more attention due to their potential to mitigate GHG emissions and reduce environmental impact [9]. However, the intermittent nature of renewable energy sources poses a major challenge to their widespread integration into the existing energy infrastructure [10].

Optimizing energy utilization sources presents several challenges from economic, environmental, and social perspectives. Mathematically, one of the primary challenges is the nonlinear and non-convex nature of the problems involved. Specifically, the relationships between different energy sources, storage systems, demand patterns, and environmental constraints are nonlinear, making it difficult to find a single global optimal solution [11]. Moreover, the problem deals with a multi-dimensional decision space [12]; i.e. determining the optimal mix of energy sources, their capacities, and dispatch strategies, which requires considering numerous economic aspects leading to computationally intensive optimization processes [13]. Consequently, the demand for efficient algorithms and computational processes became crucial in obtaining practical solutions [14], especially since such interventions require decision-makers to make trade-off decisions based on their specific regional settings [15].

The European Union (EU) serves as an ideal model for analyzing energy utilization. The EU's strong environmental commitment, diverse energy mix, economic dynamics, and well-established policy framework provide a solid foundation for this study [16]. This region's mix of renewables, fossil fuels, and nuclear energy allows for a comprehensive assessment of emissions and costs associated with different energy sources which also allows for a robust test for the GMOT [17].

The optimization of energy source utilization has been recently in focus [18]. However, a common limitation in existing models is the human biases when balancing conflicting objectives. In technical terms, multi-objective optimization aims to identify a set of Pareto optimal solutions that best represent the trade-offs among conflicting objectives [19]. However, the process can be inadvertently influenced by human biases. For instance, scalarization methods might necessitate subjective weighting of objectives, potentially skewing the Pareto front towards certain objectives [20]. Evolutionary algorithms, widely used in multi-objective optimization, come with selection mechanisms and parameters (e.g. mutation rates), which if not set with objective rigor, can bias the search toward specific solution space [21]. furthermore, many models come burdened with a plethora of hyperparameters, often leading to complexities in tuning and potential overfitting [22]. Another challenge is that most optimization approaches incorporate uncertainties and approximation errors, particularly when ensuring constraints are met [23].

To address these gaps, this study introduces a Neural Network-Enhanced Gene Modification Optimization Technique (GMOT) by utilizing Artificial Neural Networks (ANN) as objective functions, GMOT minimizes human biases in trade-offs between conflicting objectives, streamlining the process and ensuring more objective decision-making for multi-dimensional problems. Additionally, GMOT significantly reduces the number of hyperparameters, which sidesteps the complications often associated with overparameterization. In short, GMOT ensures constraints are strictly adhered to, eliminating uncertainties and approximation errors that have been prevalent in earlier techniques. This integration of advanced AI methods with genetic optimization concept highlights the transformative potential of AI in addressing contemporary multi-dimensional challenges. In essence, this article stands out in its innovative approach to energy optimization in the EU, presenting a technique that combines precision, efficiency, and objectivity.

2. Background

Multi-objective optimization is a type of vector optimization where optimal decisions need to be taken in the presence of trade-offs between two or more conflicting objectives. To address optimization challenges, researchers have proposed various approaches; one common solution is to utilize metaheuristic algorithms, such as genetic algorithms, particle swarm optimization, or simulated annealing, which can explore the solution space and identify a set of Pareto-optimal solutions [24]. Another approach is to employ mathematical programming techniques like goal programming or fuzzy programming, which allow for the formulation and solution of Multi-objective optimization problems with imprecise or uncertain information [25]. Recently, there has been a growing interest in the integration of machine learning and optimization algorithms to tackle multi-objective optimization problems. Machine learning techniques, such as neural networks and support vector machines, can be employed to develop surrogate models that approximate the behavior of complex energy systems. These surrogate models can then be used within optimization algorithms to accelerate the search process and improve computational efficiency [26].

Regardless of the utilized approach, choosing an appropriate cost or fitness function is a major challenge for any multi-objective optimization method, especially in high-dimensional problems; One such method is the global criterion method, which transforms a multi-objective problem into a single-objective problem by minimizing the distance between multiple reference points and viable destination areas where the reference point represents an ideal solution [27]. Another method is the weighted-sum method [28]; Which combines all objectives into one using a weighted vector where the weights are usually normalized [29]. However, this method has two inherent problems; difficulty in choosing weights for objectives with different magnitudes, and bias in finding trade-off solutions. Additionally, it may not be effective if the multi-objective problem is non-convex. To overcome this issue, the ε-constraint method can be used [24]; where it optimizes one objective while transforming the others into constraints [30]. By changing the ε vector, several optimal solutions can be obtained. However, for certain ε vectors, there may be no feasible solution [24].

In addition, the utilization of metaheuristic algorithms, such as genetic algorithms and particle swarm optimization, has proven effective in addressing complex multi-objective optimization problems. For example, the application of these algorithms in optimizing energy consumption and reducing greenhouse gas emissions has been explored extensively, demonstrating significant improvements in efficiency and sustainability [31]. However, these algorithms often require extensive parameter tuning and can be sensitive to initial conditions, which may limit their robustness and applicability in certain scenarios.

Furthermore, hybrid optimization techniques that combine multiple methods have shown promise in enhancing the robustness and applicability of multi-objective optimization models [32]. The integration of fuzzy programming and goal programming with traditional optimization techniques, for instance, allows for better handling of uncertainties and imprecise information, leading to more reliable and practical solutions [33]. Despite their advantages, these hybrid approaches can be complex to implement and may require specialized knowledge to ensure proper integration and operation.

Moreover, multi-objective optimization techniques have been extensively used to optimize energy consumption in various systems. For instance, a framework using the Improved Shuffled Frog Leaping Algorithm (ISFLA) has been proposed to optimize microgrid energy consumption with Distributed Energy Resources (DERs) [34]. Although ISFLA represents a novel optimization approach, it still exhibits several imperfections that require further refinement, such as parameter settings.

A system that combines Building Information Modeling (BIM), machine learning, and the non-dominated sorting genetic algorithm-II (NSGA II) model has been suggested to minimize energy consumption and maximize thermal comfort [35]. The suggested method has limitations in handling complex and highly nonlinear optimization problems as it relies on specific assumptions and models may not capture all the intricacies of the problem domain.

A Consumption-based Multi-objective Optimization Model (CMOM) has been proposed to minimize energy consumption while maintaining economic growth, using China as a case study [36]. The suggested CMOM model might have challenges in fulfilling. Its performance can be influenced by parameter settings, population size, and problem complexity. Another method used in multi-objective optimization within the energy sector, involves the integration of advanced machine learning algorithms with traditional optimization techniques. For instance, combining neural networks with optimization algorithms was utilized to enhance the performance of hybrid photovoltaic and fuel cell systems for green hydrogen and electricity production [37].

Given the aforementioned methods, the multi-objective optimization of energy consumption resources faces several major challenges that require further exploration and refinement to enhance the effectiveness and applicability of these techniques.

One significant challenge is the human factor in setting model hyperparameters, making assumptions, and deciding on trade-offs, all of which can influence the objectivity of the optimal solution. Hyperparameter tuning is often performed manually or with limited automation, introducing human bias into the optimization process [38]. This can result in suboptimal solutions that are not truly reflective of the best possible outcomes. Additionally, the assumptions made during the model formulation can significantly impact the results [39]. These assumptions often simplify complex real-world scenarios to make the problem more tractable, but they may also overlook critical factors, leading to less accurate or applicable solutions. Trade-off decisions, which are inherent in multi-objective optimization, further complicate this issue, as they require subjective judgment on the relative importance of different objectives [40]. Studies have shown that incorporating more automated and objective methods for setting these parameters can reduce bias and improve the robustness of the optimization outcomes [41].

Another challenge lies in the constraints of the optimization problems. These constraints must be maintained rigorously to ensure the feasibility and reliability of the solutions without introducing uncertainties and approximation errors [42]. In the context of energy management, constraints might include physical limits of the energy systems, regulatory requirements, and sustainability goals. Ensuring that these constraints are accurately represented and adhered to within the optimization models is crucial. However, many current methods struggle with maintaining strict constraint adherence, particularly in complex and dynamic environments. This can lead to solutions that are theoretically optimal but practically infeasible or suboptimal when applied in real-world scenarios [43].

An additional challenge lies in the utilization of normalization and vectorization techniques. Although these methods are useful for simplifying complex optimization problems, they can lead to a loss of specificity and subjectivity in the analysis [44]. These techniques transform the original problem into a more manageable form, but this transformation can obscure important details and nuances of the problem. For example, normalization can lead to interpretability challenges, as the transformed problem might not reflect the original scale and context of the data [45]. This can make it difficult for decision-makers to understand and trust the optimization results, potentially hindering the adoption of these techniques in practice. Moreover, vectorization can sometimes lead to oversimplification, where the transformed problem loses critical interdependencies and relationships inherent in the original data. Addressing these challenges requires the development of advanced techniques that can retain the specificity and context of the original problem while still benefiting from the computational advantages of normalization and vectorization.

Adding to that, in the realm of energy system optimization, a significant challenge lies in navigating the extensive and complex search space of potential energy source configurations. Traditional optimization methods often rely on predefined and limited fitness functions. These methods typically operate on direct data or predefined mathematical functions, which can be restrictive and fail to capture the nuanced, non-linear interactions within energy systems. Consequently, they may lead to suboptimal solutions when dealing with the high dimensionality and intricate interdependencies inherent in real-world scenarios.

In this work, a Neural Network-Enhanced Gene Modification Optimization Technique for multi-objective energy resource management has been developed to optimize energy consumption sources in the EU. This novel approach concurrently minimizes costs, energy imports, and GHG emissions, ensuring that demand is strictly satisfied while addressing the challenges of hyperparameter tuning, constraint adherence, and specificity conservation. By integrating neural networks as fitness models, the proposed method enhances efficiency and robustness, effectively reducing human bias and improving constraint handling. Moreover, the potential use of this method extends beyond the energy sector into various optimization applications, such as manufacturing, logistics, and healthcare, demonstrating its versatility and broad applicability. The originality of GMOT lies in its unique combination of gene modification, neural networks, and evolutionary optimization, directly addressing key challenges in multi-objective optimization management.

3. Methods

To achieve the aims of this study, the method depicted in Fig. 1 was employed. First, data were collected as detailed in Section 3.1. Then, two Artificial Neural Networks (ANN) models were trained (Section 3.2) to predict GHG emissions and energy imports. Finally, a gene modification optimization technique was devised and employed to optimize energy utilization sources ensuring energy demand fulfillment while minimizing GHG emissions, Levelized cost of energy (LCOE), and energy imports (Section 3.3). All models were developed and implemented using Python Jupiter environment.

3.1. Data collection

EU data for energy consumption sources, GHG emissions, LCOE, and energy imports were collected from several sources; energy consumption by source and GHG emissions were collected from "Our World in Data" database spanning the period from 1965 to 2021. The energy consumption by source dataset was reported annually in terawatt-hours

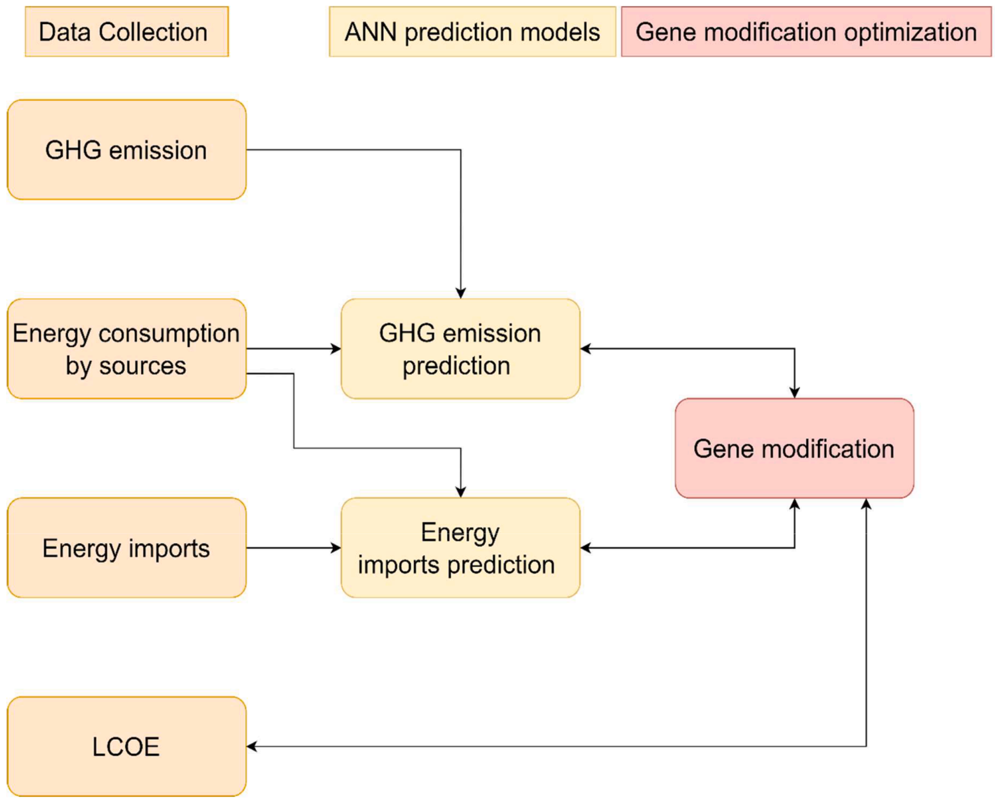


Fig. 1. Flowchart of the neural network GMOT for multi-objective energy resource management.

(TWh) for nine different sources (i.e. Geo biomass, Biofuels, Solar, Wind, Hydro, Nuclear, Gas, Coal, and Oil. The GHG emissions dataset comprised the annual emissions of carbon dioxide, methane, and nitrous oxide from all sources combined in metric tons. The energy imports dataset was collected from the World Bank DataBank annually reporting the proportion of imported energy from the total energy consumption for the period 1965 to 2015. The levelized costs of geo biomass, and biofuels were collected from the International Energy Agency (IEA) report [46]. While solar, wind, hydro, nuclear, gas, coal, and oil LCOE were collected from [47]. Table 1 summarizes the datasets utilized in this study alongside the variables of each dataset, the units, the period, and their corresponding sources. Note that SI units are provided in parentheses for each dataset variable where applicable.

Fig. 2 illustrates the trends in energy consumption by source and GHG emissions in the EU from 1965 to 2021. Key observations include that oil and coal have consistently been the largest sources of energy consumption, peaking around the 1970s and 1980s, respectively, before experiencing a general decline. Gas consumption has shown a steady increase over the years, while nuclear energy consumption has recently remained quite stable. Renewable energy sources like biofuels, solar, wind, and geothermal biomass have seen gradual increases, reflecting a shift towards more sustainable energy practices. GHG emissions have generally decreased since the early 1990s, indicating efforts to reduce environmental impact.

Fig. 3 illustrates the trends in energy imports as a percentage of total energy consumption in the EU from 1965 to 2015. Key observations include a peak in energy imports occurring in the late 1960s, reaching over 54 %. There was a notable decline in energy imports from the late 1970s to the early 1980s, dropping to around 44 %. A gradual increase in energy imports started in the late 1980s, with a significant rise during the 2000s, reaching a peak again around 2008. The trend shows fluctuations but generally indicates an increasing reliance on imported energy in recent decades.

Table 1
Summary of datasets, variables, units, time periods, and sources used in the study.

Dataset	Variable(s)	Unit	Period/ time	Source
Energy consumption by source	Geo biomass, biofuels, solar, wind, hydro, nuclear, gas, coal, and oil	Terawatt-hours (TWh) (3.6×10^{15} Joules)	1965 to 2021	Our world in data
GHG	GHG emissions	Metric tons (1000 kg)	1965 to 2021	Our world in data
LCOE	LCOE for each energy source	Dollars per Megawatt-hour (USD/MWh) (2.78×10^{-7} Dollars per Joule)	N/A	IEA [46] and [47]
Energy imports	Energy imports	Percentage (%) of total energy consumption	1965 to 2015	World bank DataBank

3.2. Artificial neural network (ANN)

Feedforward ANN with Levenberg-Marquardt backpropagation algorithm was utilized to train our two models (GHG emissions & energy imports) as depicted in Fig. 4.

During training, the input data is fed forward through the network using the following equations [48]:

$$a(1) = x \tag{1}$$

$$a(l) = \sigma(h(l)) \tag{2}$$

$$a(l) = \sigma(w(l-1)a(l-1) + b(l-1)) \tag{3}$$

The initial input data x is processed through the network to produce the output. Activation vectors and weighted input vectors for layer l are

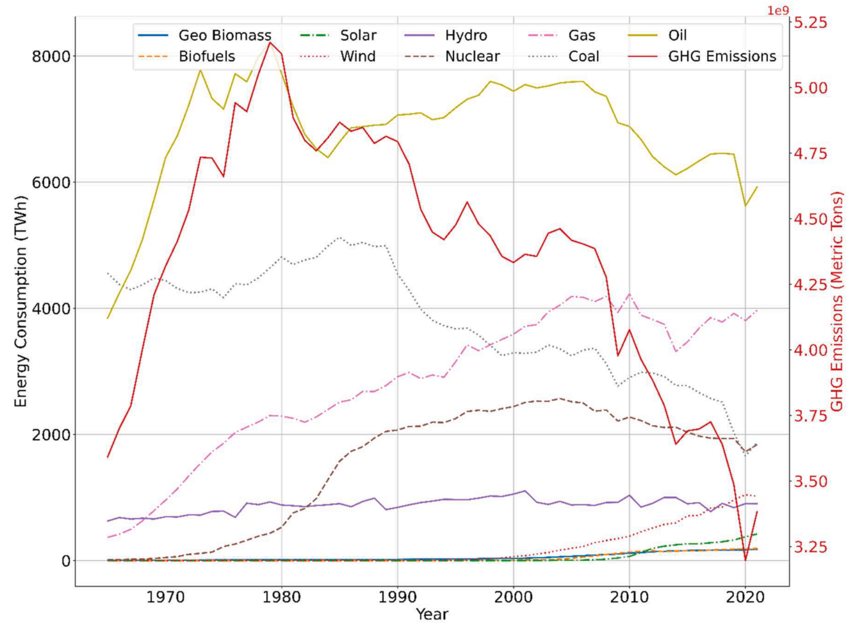


Fig. 2. Trends in energy consumption and GHG emissions in the EU (1965–2021).

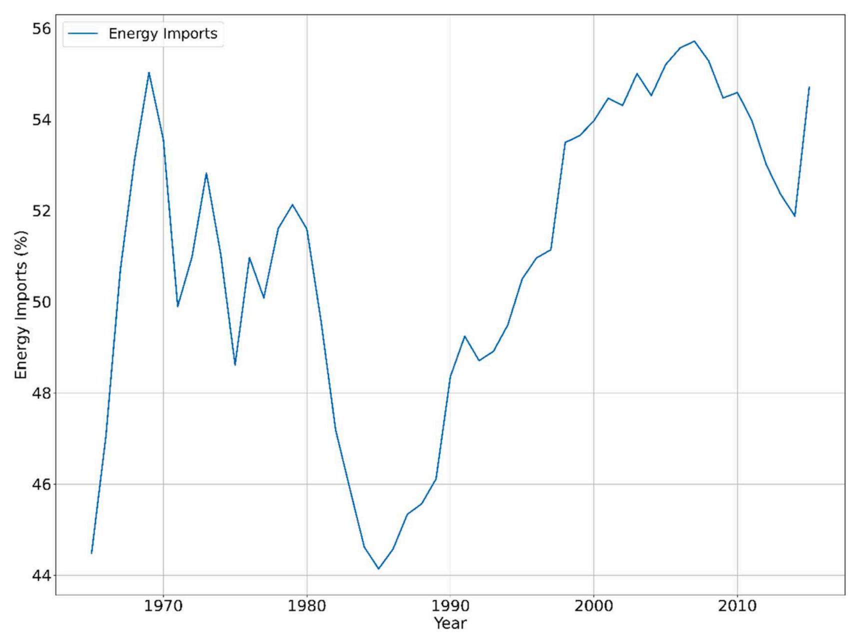


Fig. 3. Trends in energy imports in the EU (1965–2015).

represented by (l) and $h(l)$ respectively, with weight matrix $w(l-1)$ and bias vector $b(l-1)$ connecting layers. The activation function is given by σ. After output generation, its error against the target is calculated. The Levenberg-Marquardt algorithm then updates weights and biases using backpropagation.

The delta rule is used to calculate the error at each layer [49]:

$$\delta(L) = \nabla h(L)\mathscr{L} \odot \sigma'(h(L)) \tag{4}$$

$$\delta(l) = ((w(l))T\delta(l+1)) \odot \sigma'(h(l)) \tag{5}$$

Where $\nabla h(L)\mathscr{L}$ is the loss gradient relative to the network output, $\odot$ denotes element-wise multiplication, and σ' is the activation function's derivative. $\delta(L)$ is the output layer error, while $\delta(l)$ is the error at layer l, ranging from 1 to $L-$ 1. Weights and biases are updated using the following equations [50]:

$$w^l := w^l - \Delta w^l \tag{6}$$

$$b^l := b^l - \Delta b^l \tag{7}$$

For layer l, the updates for the weights and biases are calculated using regularized Gauss-Newton equations. These equations help determine the tradeoff between the gradient descent and Gauss-Newton steps [48].

$$\Delta w^l = \left(J^T J + \lambda I\right)^{-1} J^T \delta^{l+1} \left(a^l\right)^T \tag{8}$$

$$\Delta b^l = \left(J^T J + \lambda I\right)^{-1} J^T \delta^{l+1} \tag{9}$$

Where Δw^l and Δb^l represent the updates for the weights and biases,

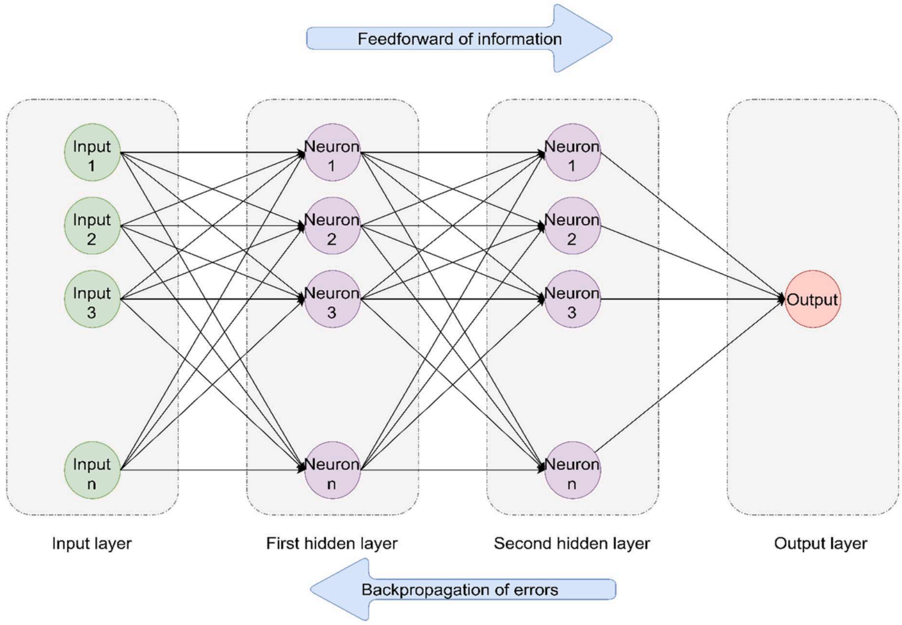


Fig. 4. Architecture of neural network model with n inputs and one output.

respectively, for layer l. The Levenberg-Marquardt parameter is represented by λ and J represents the Jacobian matrix. The Jacobian matrix is defined as follows [51]:

$$\mathrm{J}_{\mathrm{ij}}^{(\mathrm{l})} = \frac{\partial \mathrm{h}_{\mathrm{i}}^{(\mathrm{l})}}{\partial \mathrm{w}_{\mathrm{ij}}^{(\mathrm{l}-1)}} \tag{10}$$

$$= \frac{\partial}{\partial w_{ij}^{(l-1)}}\left(\sum_k w_{ik}^{(l-1)} a_k^{(l-1)} + b_i^{(l-1)}\right) \tag{11}$$

$$= a_j^{(l-1)} \tag{12}$$

$$\delta^{(L)} = J^{(L)}\left(f\left(h^{(L)}\right) - y\right) \tag{13}$$

$$\delta^{(l)} = \left(J^{(l)}\right)^T\left(J^{(l)}\left(J^{(l)}\right)^T + \mu I\right)^{-1}\delta^{(l+1)} \tag{14}$$

$$\frac{\partial E}{\partial w_{ij}^{(l)}} = a_j^{(l-1)}\delta_i^{(l)} \tag{15}$$

$$\frac{\partial E}{\partial b_i^{(l)}} = \delta_i^{(l)} \tag{16}$$

The error vector at the output layer is represented by $\delta^{(L)}$. The Jacobian matrix of layer l is represented by $J^{(l)}$. The step size is controlled by a regularization parameter, μ. I represents the identity matrix. The calculation of the derivative of the cost function with respect to the weights and biases is performed as follows [51]:

$$\frac{\partial E}{\partial w_{ij}^{(l)}} = \frac{\partial E}{\partial h_i^{(l)}}\frac{\partial h_i^{(l)}}{\partial w_{ij}^{(l)}} \tag{17}$$

$$= \delta_i^{(l)} a_j^{(l-1)} \tag{18}$$

$$\frac{\partial E}{\partial b_i^{(l)}} = \frac{\partial E}{\partial h_i^{(l)}}\frac{\partial h_i^{(l)}}{\partial b_i^{(l)}} \tag{19}$$

$$= \delta_i^{(l)} \tag{20}$$

In each iteration, the following rules are used to update the weights and biases [51]:

$$w_{ij}^{(l)} := w_{ij}^{(l)} - \eta\frac{\partial E}{\partial w_{ij}^{(l)}} \tag{21}$$

$$b_i^{(l)} := b_i^{(l)} - \eta\frac{\partial E}{\partial b_i^{(l)}} \tag{22}$$

The learning rate, denoted by η, controls the step size of the weight and bias updates. The algorithm is applied repeatedly until either the error converges or a maximum number of epochs is reached.

As elaborated above, feedforward ANN with Levenberg-Marquardt backpropagation was used (Eqs. (1)–22) for predicting GHG emissions and energy imports from the energy consumption of different sources. By testing different combinations of hyperparameters, the algorithm can find the optimal set and improve the model's performance. Table 2 shows the values of the ANN parameters tested; number of inputs, number of outputs, number of hidden layers and neurons, the maximum number of epochs, maximum training time, performance goal, learning rate, activation function, and cross-validation.

Table 2
Hyperparameter values and descriptions for neural network optimization.

Parameter	Description	Tested values during ANN optimization
Number of inputs	Number of input data variables	9
Number of outputs	Number of output forecasted variables	1
Number of hidden layers	Number of hidden layers	2–10
Number of hidden neurons	Number of hidden neurons	2–10
Maximum epochs	Max. number of training iterations before training is stopped	1000
Performance goal	The minimum target value of MSE	0
Learning rate	A positive value controlling the model's speed of adjustment to error during weight updates	0.001, 0.01, 0.1
Activation function	The activation function to be used in the hidden layers	'relu', 'tanh'
Cross-validation	Cross-validation folds to be used during the grid search	5

3.3. Gene modification optimization technique (GMOT)

In this section, a novel gene modification technique is designed for optimizing multiple conflicting objectives problems simultaneously. The proposed gene modification technique aims to enhance the exploration and convergence capabilities of the conflicting multiobjective optimization process.

3.3.1. Gene representation

Initially, an appropriate gene representation scheme is carefully selected and tailored to the problem domain. The chromosome consists of n number of genes belonging to the domain of real numbers, represented as floating-point values. In the particular case of optimizing the nine energy consumption sources in the EU, the chromosome consists of nine genes, each representing the value of a specific energy consumption source as can be seen in Fig. 5.

3.3.2. Objective selection

The initial step in devising a fitness function involves identifying and selecting the objectives that define the optimization problem [52]. As this study aims to reduce GHG emissions, costs (LCOE), and energy imports by optimizing the nine energy consumption sources; three separate fitness functions (each with nine genes) must be optimized. The trained ANN models were used to obtain values for GHG emissions and energy imports associated with different combinations of consumption from these nine energy sources. The corresponding costs were calculated by multiplying the quantity of each energy source by its corresponding LCOE and summing the results.

3.3.3. GMOT algorithm

Fig. 6 depicts the workflow of the GMOT Algorithm. The following sections detail the steps involved in the GMOT algorithm.

3.3.3.1. Initialization and chromosome generation. The process begins by randomly generating a set of potential gene solutions, all of which adhere to the energy demand constraints. The energy demand constraints were devised based on an annual growth rate [53]. Provided that the initialization only generates one chromosome initially, a second chromosome is similarly generated for reference. Hence, two random chromosomes are generated concurrently. Once the comparator is set, the algorithm moves into the objective evaluation where we compare each chromosome's fitness with its predecessor.

3.3.3.2. Fitness evaluation. For evaluating the fitness of the objective functions for both chromosomes, a challenge arises due to the different units and scales of each fitness function. Directly comparing functions that possess varying measures and scales is not feasible. Normalization cannot resolve this problem because the values of GHG emissions and LCOE can vary significantly based on the predictions of the ANNs, making it unknown what the maximum and minimum values could be. To overcome this challenge, an average percentage of improvement has been developed where the percentage of improvement (in this particular case the percentage of decrease in the three objective functions for each chromosome) is compared to the one from the previous iteration/generation as in Eqs. (23)–25. Where F_1, F_2, and F_3 are the first, second, and third fitness of objective function for each chromosome c. i is the current iteration in the GMOT process.

$$\textit{Percent improvement of } F_{1(c)} = \frac{F_{1(i)} - F_{1(i-1)}}{F_1(i-1)} * 100\% \tag{23}$$

$$\textit{Percent improvement of } F_{2(c)} = \frac{F_{2(i)} - F_{2(i-1)}}{F_2(i-1)} * 100\% \tag{24}$$

$$\textit{Percent improvement of } F_{3(c)} = \frac{F_{3(i)} - F_{3(i-1)}}{F_3(i-1)} * 100\% \tag{25}$$

Then the average improvement of the three objective functions $F_{1(c)}$, $F_{2(c)}$ and $F_{3(c)}$ for each chromosome c is then calculated as in Eq. (26).

$$\textit{Total Percent improvement for chromosome } (c) = \frac{F_{1(c)} + F_{2(c)} + F_{3(c)}}{3} \tag{26}$$

3.3.3.3. Gene comparison. In the subsequent phase, the dissimilarity between each pair of genes is computed as a percentage. This computational step is essential for quantifying the disparity or dissimilarity between genes rigorously. The resulting percentage differences serve as informative measures that will be utilized in the forthcoming stages to facilitate direct comparison and comprehensive evaluation of gene variations. These measures will play a crucial role in guiding gene modification strategies.

As depicted in the preceding steps, the initialization process generates two random chromosomes. Moving forward, each iteration introduces a newly modified chromosome, which exhibits the potential to possess comparable or superior fitness compared to its predecessor. During the gene comparison step, the calculation of a percentage, as described in Eq. (27), is performed for every pair of genes between the two chromosomes (the current chromosome c and the previous chromosome $c-1$). It is important to note that this equation is executed for all genes (g) (form $g = 1$ *to* 9), resulting in nine percentage values that can fall anywhere between -100 % to 100 %.

$$\textit{Percentage difference in Gene pair}_g = \frac{Gene_g(c) - Gene_g(c-1)}{Gene_g(c-1)} * 100\% \tag{27}$$

3.3.3.4. Gene modification process. After calculating the 9 gene pairs' difference, the algorithm will perform a gene modification technique based on the fitness of the very last chromosome. The algorithm will either perform a positive gene modification process if the fitness of chromosomes (c) is better than ($c-1$) or a negative gene modification process if the fitness of chromosomes (c) is worse than ($c-1$). If the two chromosomes have similar fitness below a defined threshold, a counter will be initiated. If the fitness does not improve for 15 consecutive chromosomes (iterations) beyond the threshold, the process will be

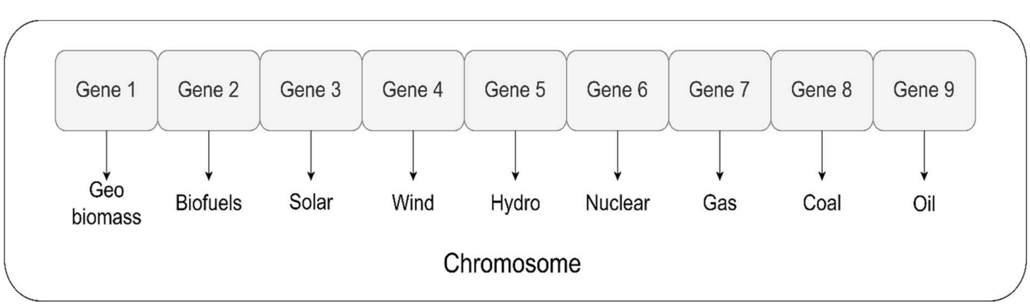


Fig. 5. Representation of gene sequence in the optimization process.

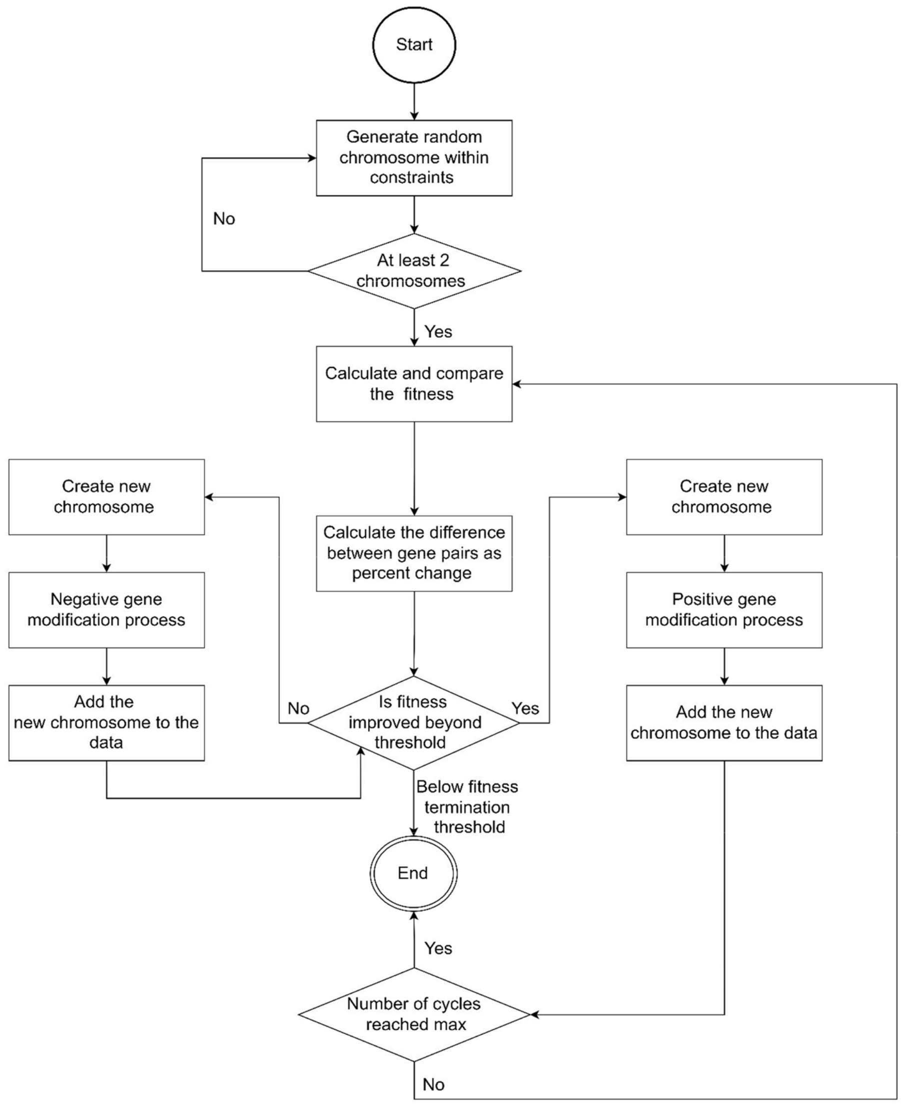


Fig. 6. Neural network-enhanced gene modification optimization algorithm workflow.

terminated indicating the best gene combination for the problem at hand.

Positive gene modification process:

If the fitness of chromosome c is superior to that of the previous chromosome (i.e. $c - 1$), the positive gene modification process will start by creating a new empty chromosome with nine genes. Then the percentages calculated in Eq. (27) are multiplied by their corresponding gene value (of chromosome c). The resulting value is then added to the gene value as shown in Eq. (28).

$$Modified\ Gene_g = \left(Percentage\ difference\ in\ Gene\ pair_g * Gene_g\right) + \ Gene_g \tag{28}$$

This process is executed for all gene pairs, resulting in nine modified genes where those newly modified genes are added to the newly created chromosome.

Negative gene modification process:

If the fitness of chromosome c is not superior (worse) to that of chromosome $c - 1$, a negative gene modification process will start by creating a new empty chromosome with nine genes. Then the percentages calculated in Eq. (27) are multiplied by a hyperparameter (hp) and their corresponding gene value (of chromosome c). The resulting value is then subtracted from the gene value as shown in Eq. (29).

$$Modified\ Gene_g = \left(Percentage\ difference\ in\ Gene\ pair_g * hp * Gene_g\right) - \ Gene_g \tag{29}$$

Hyperparameter selection is based on a progressive adjustment approach. If introducing a new chromosome results in diminished fitness, the algorithm makes a conservative 0.6-step backtrack, rather than retracing a full step to the prior iteration. This method refines the optimization process and fine-tunes the optimal chromosome. This procedure is applied to each gene pair, generating nine modified genes that are incorporated into the new chromosome.

3.3.3.5. Constraints. The optimization problem has constraints, the sum of all genes, signifying energy growth from all sources. Moreover, each individual gene (corresponding to an energy source) must adhere to specific upper and lower bounds. As modified genes might take a value that violates these constraints, the gene modification process is designed to ensure that the sum of all genes will always be equal to the specified value (annual energy consumption in this particular case).

The gene modification process guarantees the fulfillment of the optimization problem constraints through two distinct processes. First, the determination of the percentage difference between each pair of genes -as computed by Eq. (27)- confines the resulting percentage difference within the range of -100 % to 100 %. It is worth noting that the sum of all these percentage differences consistently converges to zero, thereby upholding the imposed constraints and preserving the total sum of all genes in each chromosome. Second, gene modifications that result in values exceeding the upper boundary invoke an adjustment mechanism; in which the gene value is instantaneously set to the maximum permissible value as defined by the upper boundary. The surplus value that would have been allocated to this gene is allocated to the gene with the lowest value. Conversely, if a gene's value falls below the lower boundary following modification, the gene value is reset to the minimum acceptable value specified by the lower boundary for that gene. The excess value that would have been assigned to this gene is subtracted from genes with higher values. The aforementioned mutation-like containment process serves two important purposes: it both expands the exploration of solution space and mitigates the risk of genes becoming confined to their maximum or minimum values. By incorporating these two control mechanisms, the problem at hand maintains its structural integrity while simultaneously enabling a dynamic exploration of solution possibilities.

Upon completion of the gene modification process, one full iteration is completed. At this point, the algorithm proceeds in one of two ways: either terminating the algorithm if the number of iterations surpasses a pre-established limit (i.e. 1000 chromosomal iterations) or repeating the process until 15 consecutive gene modifications yield a below-threshold fitness. This adaptive approach ensures efficient convergence towards optimal results while accommodating different termination conditions.

3.3.3.6. Performance metrics. At each generation, the fitness of the functions is calculated. To ensure fair comparison and aggregation of the fitness values, a crucial step is employed to ensure the normalization of the fitness scores. Since each of the three fitness functions exhibits different units and scales, normalization becomes imperative to establish a consistent and comparable metric among generated chromosomal generations (i.e. iterations). In this work, the min-max normalization technique was applied as described in Eqs. (30)–32. Note that this normalization process takes place after the termination of the algorithm when all the values are known.

$$NF_1 = \frac{F_{1c} - \min(F_1)}{\max(F_1) - \min(F_1)} \tag{30}$$

$$NF_2 = \frac{F_{2c} - \min(F_2)}{\max(F_2) - \min(F_2)} \tag{31}$$

$$NF_3 = \frac{F_{3c} - \min(F_3)}{\max(F_3) - \min(F_3)} \tag{32}$$

Where NF_1, NF_2, and NF_3 are the normalized values of the fitness function F_1, F_2, and F_3 respectively for $c = 1$, till the last chromosome.

Next, the average of all normalized fitness values for the three separate functions is computed as in Eq. (33). This average value serves as a comprehensive performance measure, encapsulating the collective efficacy of the three functions. Ideally, an average value of 0 denotes optimal performance as the aim is to minimize the fitness functions. Conversely, a value of 1 signifies suboptimal outcomes from the fitness functions.

$$Avgerage\ Fitness = Average(NF_1, NF_2, NF_3) \tag{33}$$

In this study, two well-established distance metrics, Euclidean Distance and Normalized Euclidean Distance, were employed to assess and contrast their effectiveness in the optimization process when compared to GMOT. Euclidean Distance quantifies the direct spatial separation between two data points in a multi-dimensional space, with a specific focus on measuring the distance between fitness values and the origin point (0,0,0) [54]. Euclidean Distance is calculated as in 34:

$$Euclidean\ Distance = \sqrt{{F_1}^2 + {F_2}^2 + {F_3}^2} \tag{34}$$

Normalized Euclidean Distance holds particular significance due to its consideration of the normalized values associated with each fitness function, offering a standardized metric to gauge dissimilarity within a multi-dimensional space [55]. Normalized Euclidean Distance is calculated as in 35:

$$Normalized\ Euclidean\ Distance = \sqrt{{NF_1}^2 + {NF_2}^2 + {NF_3}^2} \tag{35}$$

4. Results and discussion

To predict GHG emissions, optimal parameters were identified through a grid search (see Table 2). The ANN was designed with two hidden layers of five nodes each, using the ReLU activation function and a learning rate of 0.001, achieving an r-squared value of 0.97. For energy import predictions, similar parameters were used, with two hidden layers of four nodes each, resulting in an r-squared value of 0.85.

Using 2021 data, the GMOT algorithm was tested on actual energy consumption, LCOE, GHG emissions, and energy imports. Comparing the algorithm's optimal recommendations with the actual 2021 data highlighted the potential benefits of the algorithm's suggestions, including reduced LCOE, energy imports, and GHG emissions.

4.1. Key findings

The results for energy consumption values tested by the GMOT for each energy source (gene) over multiple generations/iterations are presented in Fig. 7. The graph shows four key indicators: the initial random value, the maximum tested value, the minimum tested value, and the optimum value. The optimization process was constrained to produce feasible and realistic results; the total energy increase was limited to 824 TWh, equivalent to the annual energy consumption increase in 2021. Each energy source was allowed to vary between 0 and 824 TWh, providing flexibility in allocation.

A key observation from Fig. 7 is that the optimized values differ significantly from the initial random energy source distribution. This indicates that the optimization process significantly restructured the energy portfolio to achieve the desired objectives.

The results of the algorithm's suggestions indicate significant variations and optimizations across different energy sources. For geo biomass, the tested values increased from an initial random value of 20.89 TWh to 122.71 TWh, with a wide range tested from roughly 15 TWh to 202 TWh, indicating the flexibility and potential of this energy source. Biofuels changed from about 69.73 TWh to 38.35 TWh, with a wide range of values tested (from 37.46 TWh to 212.89 TWh), suggesting the optimization algorithm determined that biofuels, while beneficial, may not be as cost-effective or impactful for GHG reduction compared to other sources. Solar energy values shifted from approximately 23.62 TWh to 180.73 TWh, reflecting the push towards renewable, low-GHG emitting energy sources. For wind energy, the tested values varied from an initial random value of 126.49 TWh to an optimized value of 93.11 TWh, with a range of values tested from 19.49 TWh to 212.06 TWh. Hydro energy changed from 57.18 TWh to 113.67 TWh, indicating an increased reliance on this renewable source. Nuclear energy fluctuated significantly with values ranging from 54.73 TWh to a maximum of 331.32 TWh, finally settling at 22.89 TWh. Gas varied from 142.35 TWh to a maximum of 277.60 TWh, with an optimized value of 234.60 TWh. Coal reduced from 48.13 TWh to 9 TWh, with the maximum value tested being 274.72 TWh, and oil values shifted from 280.88 TWh to 9 TWh, with a maximum tested value of 291.57 TWh.

In this work, the GMOT's termination for the optimal value was achieved at the 28th generation. This indicates that one of the predefined termination criteria was fulfilled in this generation (i.e. 15 consecutive generations where the overall improvement rate was less than the pre-set termination threshold). This assures that a plateau was reached for the generational optimization progression. The optimized

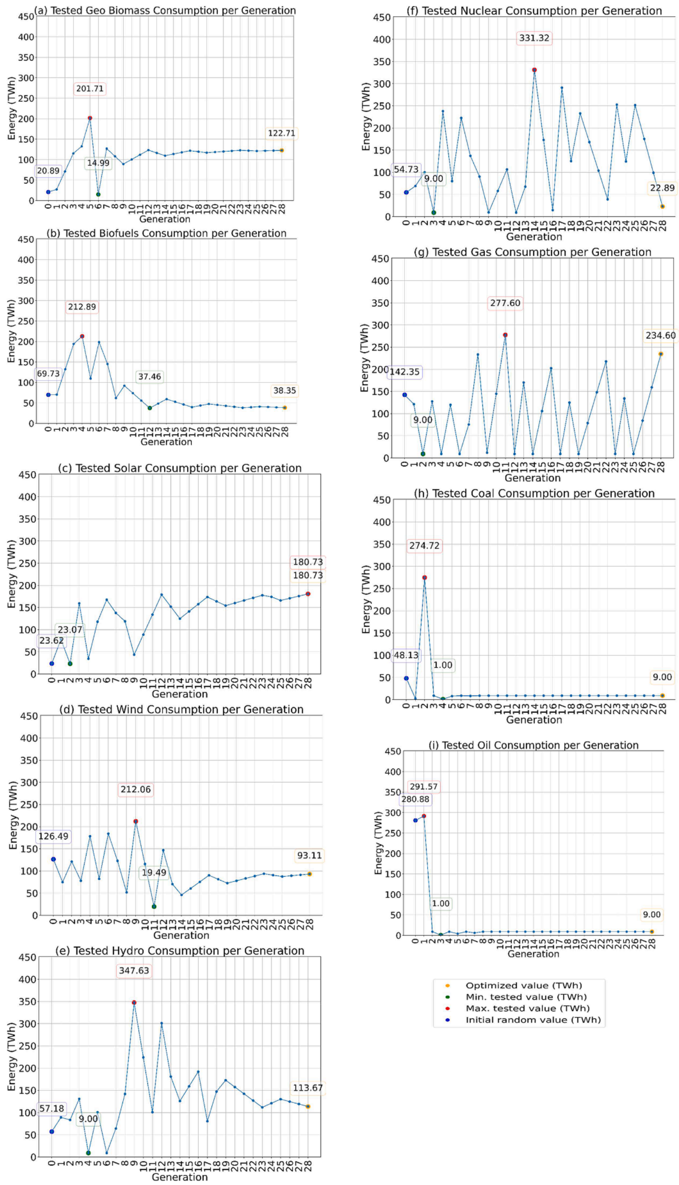


Fig. 7. Energy consumption trends per generation for different energy sources using gene modification optimization technique.

solution generated by the GMOT yielded a 0.26 average fitness (Eq. (33)). In the context of the multi-objective genetic algorithm used in this study, this result suggests proximity to the theoretical optimum. This underlines the effectiveness of the algorithm, as the derived solution is in the vicinity of the optimal resolution in the multi-objective trade-off landscape.

Fig. 8 illustrates the actual versus optimized total energy consumption for the EU energy sources as of 2021. The actual consumption data shows that the highest energy consumption comes from oil (5922 TWh), followed by gas (3966 TWh), coal (1871 TWh), nuclear (1838 TWh), wind (1019 TWh), hydro (901 TWh), solar (420 TWh), biofuels (189 TWh), and geo biomass (180 TWh). The optimized consumption, as per the Gene Modification Optimization Technique, recommends increases of 62.6 % for geo biomass, 18.2 % for biofuels, 32.5 % for solar, 11.5 % for wind, 12.7 % for hydro, and 1.8 % for gas energy sources. Conversely, GMOT suggests decreases of 5 % for nuclear, 10.9 % for coal, and 4.9 % for oil, indicating a strategic shift towards more sustainable and renewable energy sources while reducing reliance on fossil fuels.

The optimization results presented in Fig. 8 highlight the efficacy of the GMOT in reshaping the energy landscape. By recommending substantial increases in geo biomass, solar, wind, and hydro, GMOT emphasizes the importance of enhancing locally generated renewable energy sources. This strategic shift not only aligns with environmental sustainability goals by reducing greenhouse gas emissions but also decreases the EU's reliance on energy imports, bolstering energy security. The reduction in traditional fossil fuels -coal, oil, and nuclear energy- further underscores GMOT's role in minimizing the environmental footprint of the EU's energy consumption. The modest 1.8 % increase in gas consumption indicates its transitional role in the energy mix.

These results affirm GMOT's capability to support the EU's objectives of energy efficiency and sustainability, demonstrating its potential for broad application in optimizing energy resource management globally. The technique's ability to integrate and balance multiple objectives, including cost reduction, emission control, and import minimization, marks a significant advancement in energy optimization methodologies.

Fig. 9 highlights the behavior of energy imports as a percentage of total energy consumption throughout the generations of the GMOT algorithm. The initial generations exhibit significant fluctuations, with energy imports peaking at 60.50 %. However, as the optimization process progresses, the algorithm converges towards a more stable value. The optimum energy import value is identified at 58.45 %, reflecting a slight increase of 2 % compared to the baseline. This marginal increase suggests that, while some objectives such as cost and GHG emissions see significant improvements, the optimized energy mix necessitates a modest rise in imports. This trade-off could be attributed to the need to balance domestic renewable energy sources with reliable, possibly imported, low-GHG energy sources to ensure a stable supply.

Fig. 10 presents the cost trajectory, measured in terms of Levelized Cost of Energy (LCOE), for each generation in the GMOT optimization process. The highest cost is recorded at approximately $142,129,141, reflecting the initial random values. As the generations advance, the GMOT algorithm effectively reduces the LCOE, achieving an optimum cost of $77,916,061 by the 28th generation. This represents a substantial reduction of around 46 % compared to the actual cost. The significant cost savings underscore the potential for GMOT to enhance the economic feasibility of energy sources, making them more competitive. The stabilization of cost values in later generations indicates the algorithm's ability to consistently identify cost-effective energy solutions.

Fig. 11 illustrates the progression of GHG emissions, measured in metric tons, across the generations of the GMOT algorithm. Initially, GHG emissions peak at approximately 3.29 billion tons. The optimization process effectively reduces emissions, with the algorithm converging to an optimum value of around 3.08 billion tons by the 28th generation. This reduction signifies a decrease of about 9 % compared to actual emission levels. The steady decline in GHG emissions over successive generations demonstrates the algorithm's efficacy in identifying energy mixes that are environmentally sustainable. This reduction is crucial for meeting EU climate targets and underscores the importance of integrating optimization techniques like GMOT in energy policy planning.

The optimization process suggested a notable shift in the EU energy portfolio for optimal results. Testing indicated an increased emphasis on geo biomass, biofuels, solar, gas, and hydro energies, favoring GHG reduction. Conversely, the GMOT advised minimizing the use of, coal, and oil. This is in line with other research in the field where similarly found optimization models favoring renewable energy sources such as in [56] which emphasize the importance of transitioning to renewable and low-carbon grid electricity generation to achieve sustainable energy goals.

Despite being a fossil fuel, increasing the utilization of natural gas was recommended, likely due to its lower GHG emissions compared to coal and oil [57]. Furthermore, the GMOT proposed significant improvements in energy costs. Specifically, a dramatic decrease of

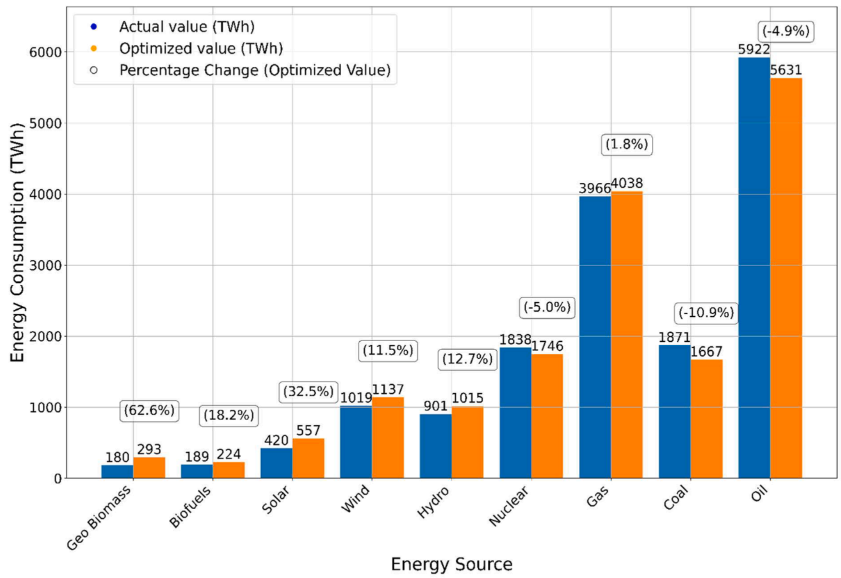


Fig. 8. Comparison of actual and simulated optimized energy consumption by source in the EU for the year 2021.

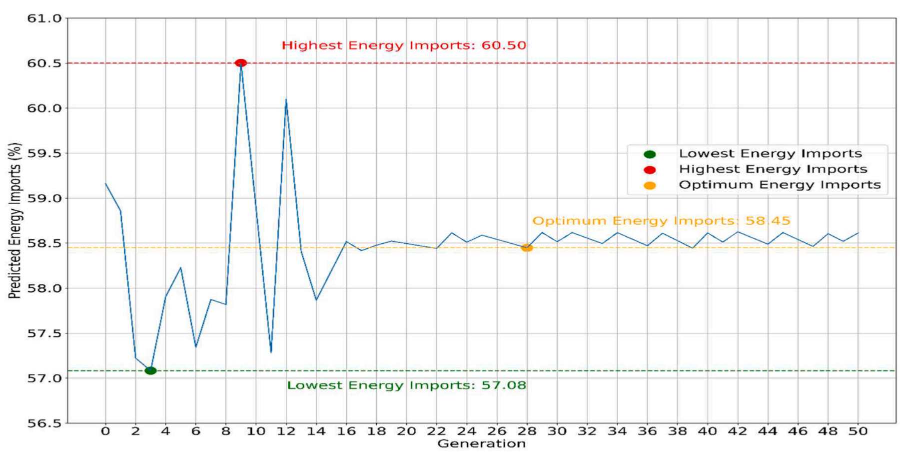


Fig. 9. Energy imports as a percentage of total energy consumption across generations.

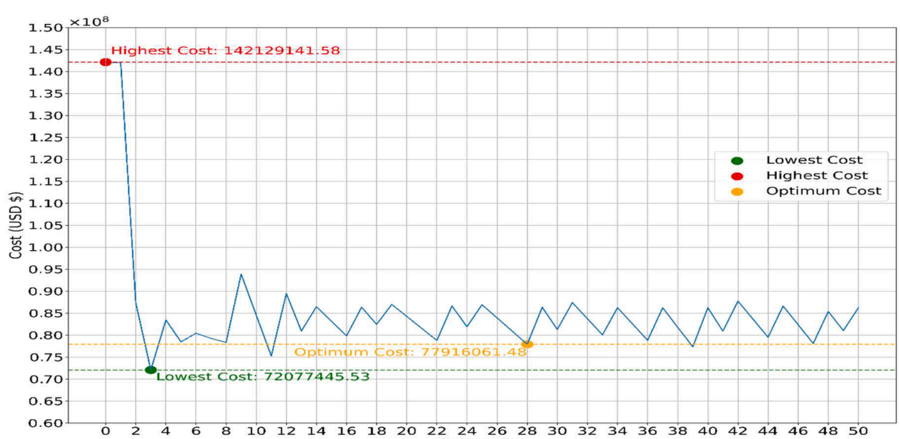


Fig. 10. Cost optimization (LCOE) across generations.

approximately 46 % in LCOE was achieved, which could have significant implications for the affordability and competitive positioning of energy sources. This is in line with other research that also noted energy optimization could result in significant cost savings [58].

With regard to GHG emissions, the optimization process identified a significant potential for reduction, with a proposed decrease of around 9

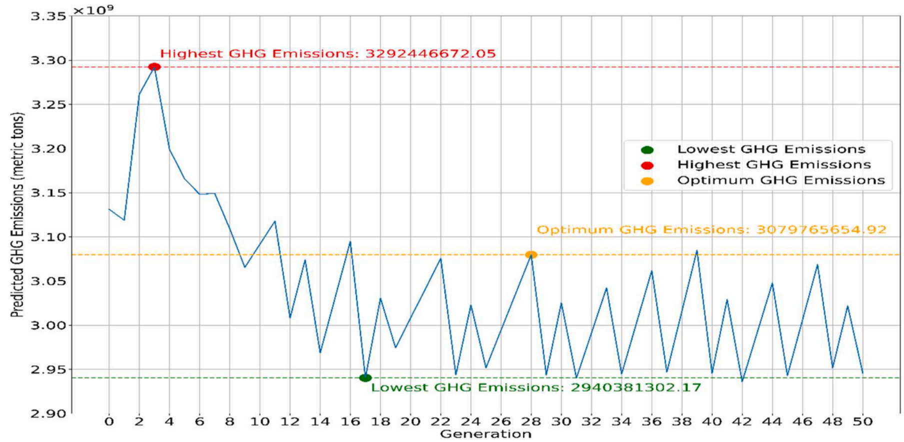


Fig. 11. Greenhouse gas (GHG) emissions optimization across generations.

% compared to current emission levels. This decrease could play a vital role in the EU's efforts to mitigate climate change. The slight increase in energy imports suggested by our model echoes other research that noted energy imports could play a role in optimized energy systems, especially if the imported energy is from sustainable and low-GHG emitting sources [56]. This highlights the potential need for international cooperation in achieving energy optimization goals.

4.2. Technical analysis

In Fig. 12, the optimal point is identified through the proposed GMOT method, presenting a visual representation of the optimization process. Initially, during the early generations, a wide dispersion of points is exhibited by the scatter plot. These initial solutions are characterized by elevated values for each fitness, indicating their suboptimal performance in terms of cost, GHG emissions, and energy import. As the optimization process advances through subsequent generations, a noticeable trend is observed. The points gradually cluster together, signifying an enhancement in the quality of solutions as they shift towards lower values for the three fitness functions. This convergence pattern clearly demonstrates that enhanced solutions are being generated over time by the optimization process, ultimately reaching the optimal point at generation 28 (Gen. 28).

To validate the efficacy of the GMOT method, comparative testing was conducted against two other Pareto optimization distances, employing Euclidean distance and Normalized Euclidean distance as objective space metrics. These comparisons, presented in Figs. 13 and 14, aim to provide quantitative insights into the optimization process, its outcomes, and the associated trade-offs.

In Fig. 13, Euclidean distance served as the distance metric to assess the optimization process. As a result of this approach, the optimization process successfully identified an optimal solution at generation 17 (Gen. 17), represented as the point closest to the origin. However, it is essential to note that Euclidean distance does not inherently consider variations in the scales of different objectives. Consequently, it may tend to prioritize solutions excelling in one objective while potentially neglecting trade-offs with other objectives. This characteristic of Euclidean distance is vital to our discussion as has the potential to

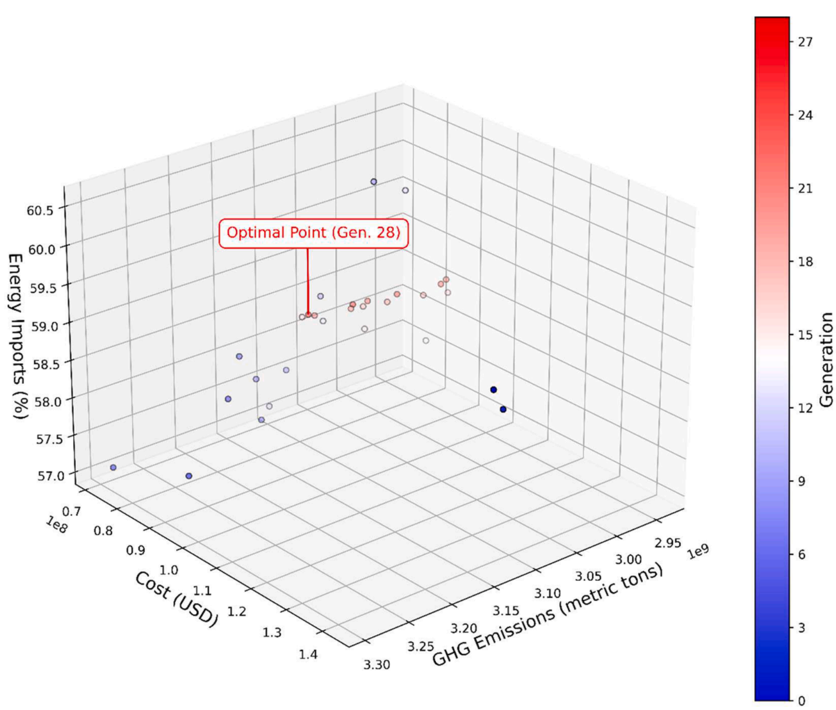


Fig. 12. Visualization of neural network-enhanced gene modification technique convergence and optimal point across generations.

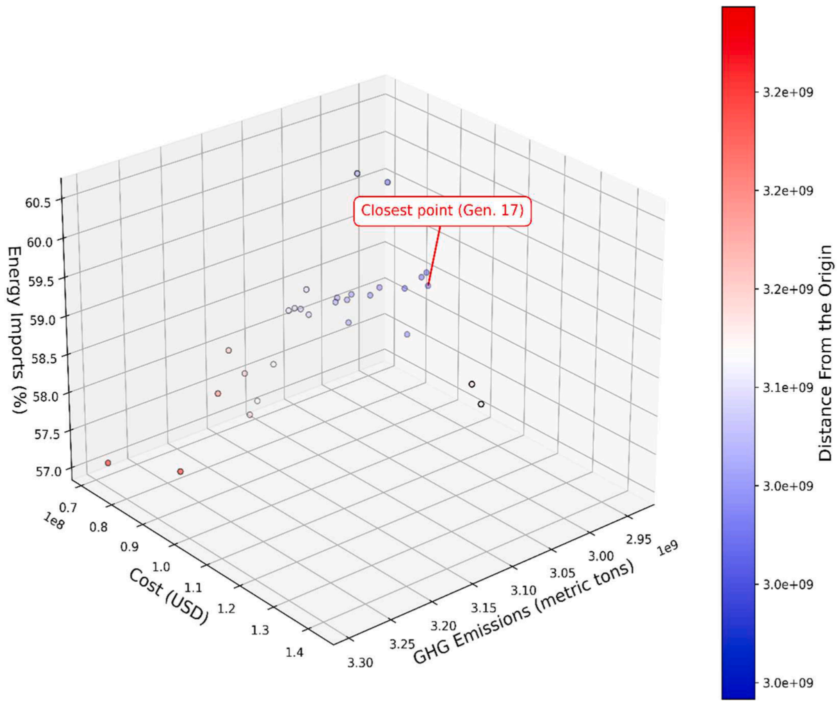


Fig. 13. Visualization of Euclidean distance technique convergence and optimal point across generations.

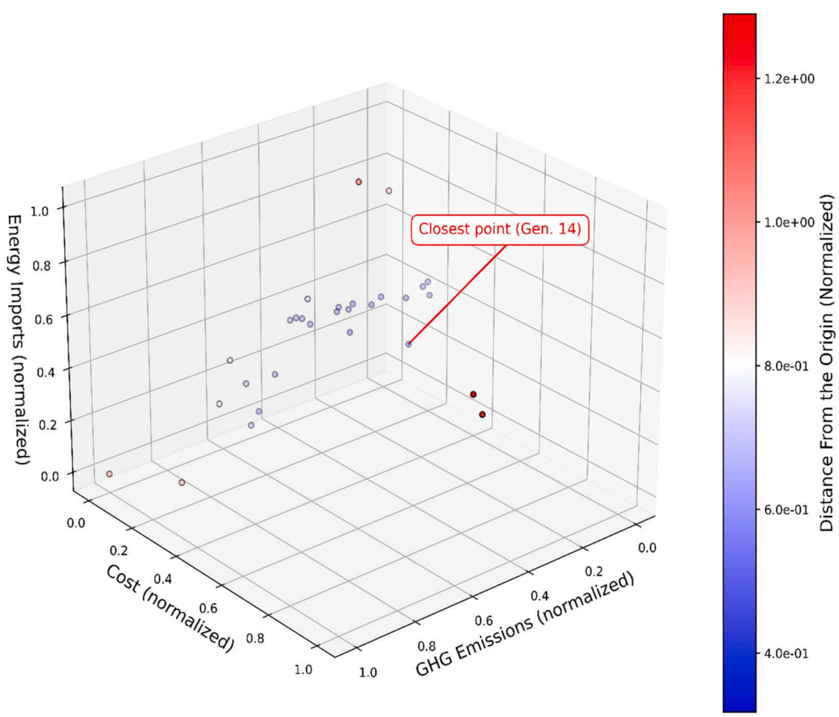


Fig. 14. Visualization of normalized Euclidean distance technique convergence and optimal point across generations.

overemphasize the significance of certain objectives, such as GHG emissions, within the multi-objective context. This relationship is evident in Fig. 13, where points characterized by higher GHG emissions values (the highest scale among the fitness functions) exhibit greater distances from the origin. Consequently, these points are representative of solutions considered less favorable according to this distance method within the optimization process.

In Fig. 14, the normalized Euclidean distance was utilized as the distance metric for assessing the optimization process. The application of this method resulted in the identification of an optimal solution, this time occurring at generation 14 (Gen. 14), represented as the point closest to the origin. It is essential to note that the selection of normalized Euclidean distance was motivated by the need to address the challenge posed by varying scales among objectives, thereby ensuring a more equitable contribution from all objectives in the optimization process. Nevertheless, a limitation associated with normalized Euclidean distance becomes apparent. It may not effectively mitigate the influence exerted by objectives with substantially higher scales. This observation becomes evident in Fig. 14, where the points closest to the origin predominantly correspond to those with lower GHG emissions (the highest scale among the fitness functions).

Fig. 15 provides a visual representation of the percentage change in each fitness function, comparing it to the baseline level for the year 2021 for the EU. This comparison specifically considers the optimal results achieved by GMOT at generation 28, in contrast to generation 17 for the Euclidean Distance method and generation 14 for the Normalized Euclidean Distance method. The results demonstrate that GMOT excels in optimizing fitness functions influenced by dominant high-scale variables. GMOT's superiority becomes obvious when compared to alternative techniques like Euclidean Distance and Normalized Euclidean Distance. GMOT achieves a substantial 46 % reduction in costs, outperforming these alternatives, which achieve a 40 % cost reduction each. This cost reduction by GMOT is not only economically significant but also demonstrates its objective approach to optimization. Additionally, GMOT achieved a 9 % reduction in GHG emissions, a noteworthy achievement considering the intricate nature of high-scale variables. This demonstrates GMOT's robustness in handling complex problems featuring multiple fitness functions in an objective manner, without subjectivity biasing the optimization process.

It is essential to emphasize that while Euclidean Distance and Normalized Euclidean Distance achieve slightly better reductions in GHG emissions at 13 % and 12 %, respectively, they do so at the potential expense of optimizing other critical aspects, such as cost. This subjectivity is primarily driven by the higher scale of GHG emissions compared to the other two variables. However, this subjective prioritization of GHG reduction over cost underscores the critical significance of employing objective methods like GMOT. GMOT's capacity to maintain a balanced and objective approach to optimization, addressing GHG emissions and cost, and energy imports reduction without undue bias, positions it as an invaluable tool for addressing multifaceted challenges across various industries.

The Gene Modification Optimization Technique represents a significant advancement in energy management optimization, transcending the capabilities of traditional algorithms such as ANFIS, grid search, and various multi-objective optimization techniques like genetic algorithms, particle swarm optimization, and simulated annealing. Rather than competing with these established methods, GMOT introduces a novel paradigm that leverages the predictive power of ANNs to navigate the complex landscape of energy system optimization.

A key distinction of GMOT lies in its utilization of ANNs to predict the multifaceted outcomes of diverse energy source combinations on critical parameters such as cost, GHG emissions, and energy imports, while simultaneously adhering to system constraints. This approach fundamentally differs from traditional optimization techniques, which typically operate on direct data or predefined fitness functions. Traditional methods often struggle with the high dimensionality and intricate interdependencies inherent in energy systems. They may optimize based on simplified models or direct data relationships, which can lead to suboptimal solutions when dealing with the complex, non-linear interactions present in real-world energy scenarios. In contrast, GMOT employs ANNs as sophisticated predictive models that can capture and represent these complex relationships more accurately. The integration of ANNs within GMOT's framework allows for a more comprehensive exploration of the solution space. While traditional optimization algorithms might work with a limited set of predefined variables or simplified fitness functions, GMOT's ANN-based approach can consider a vastly wider range of possibilities. This is because the ANNs can learn and represent complex, high-dimensional relationships between energy source configurations and their impacts on cost, emissions, and imports.

This advanced approach enables GMOT to handle the extraordinary complexity of optimizing energy sources based on their actual configurations; a task that is often intractable for conventional methods due to the sheer number of variables and their intricate interdependencies.

By leveraging the predictive capabilities of ANNs, GMOT can effectively navigate this high-dimensional optimization landscape, offering solutions that are more robust and adaptable to the complexities of real-world energy systems. GMOT does not merely compete with existing optimization techniques but introduces a more sophisticated framework that is particularly well-suited to the challenges of modern energy system optimization. Its ability to harness the predictive power of ANNs in evaluating complex fitness landscapes positions GMOT as a cutting-edge tool for addressing the multifaceted challenges in energy management and optimization.

5. Conclusions

This study introduces the Neural Network-Enhanced Gene Modification Optimization Technique for multi-objective energy resource management, demonstrating significant advancements in optimizing energy consumption. This innovative approach integrates artificial intelligence with energy management by utilizing neural network models as fitness functions to project the impacts of various energy combinations on greenhouse gas emissions, energy costs, and imports. A key strength of this method lies in its automated parameter settings, which effectively reduce human bias and enhance the objectivity of results. In simulations using data from the European Union, the technique achieved remarkable outcomes over 28 generations of optimization: a 46 % reduction in the levelized cost of energy and a 9 % decrease in

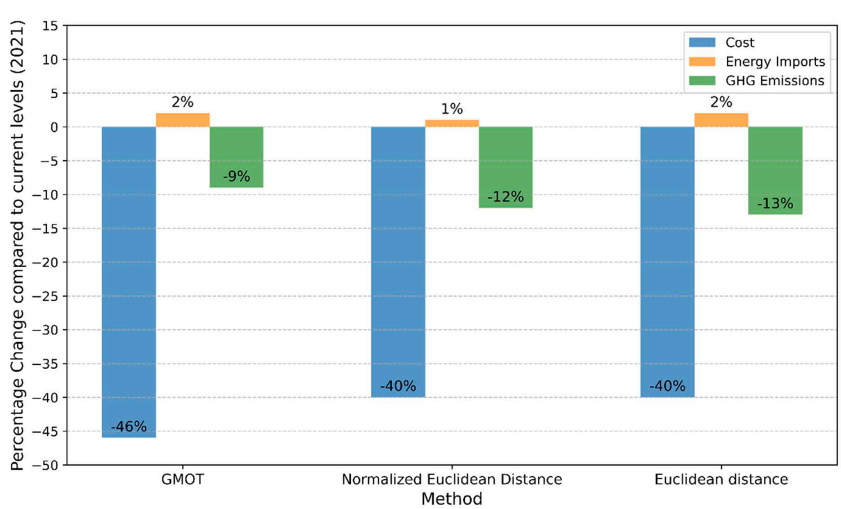


Fig. 15. Performance comparison of optimization methods on cost, imports, and GHG emissions in the EU (2021 Baseline).

greenhouse gas emissions, while maintaining balanced energy imports. These results underscore the method's proficiency in addressing complex, multi-dimensional optimization challenges. To validate its efficacy, the technique was benchmarked against traditional methods, such as Euclidean Distance, confirming its superior performance and transparency. Additionally, the ability to visualize chromosomes and gene values added a layer of clarity to the optimization process, facilitating easier interpretation and application of results. The technique's use of neural network prediction models to project the impacts of different energy configurations is a crucial innovation. This approach effectively addresses the variability inherent in greenhouse gas emissions, costs, and imports, ensuring that the optimization process is grounded in accurate, data-driven projections. Consequently, it significantly enhances decision-making accuracy in energy management. By minimizing human intervention through automated parameter settings, the method not only reduces bias but also bolsters the reliability of optimization outcomes. This comprehensive approach represents a significant advancement in energy resource management, offering potential applications beyond the energy sector and paving the way for more efficient and sustainable energy systems.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT and Bing in order to improve readability and language. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Funding

Open Access funding provided by Hungarian Electronic Information Services National Programme (EISZ) - Corvinus University of Budapest.

CRediT authorship contribution statement

Mutaz AlShafeey: Writing – original draft, Software, Resources, Methodology, Investigation, Formal analysis, Conceptualization. **Omar Rashdan:** Writing – review & editing, Writing – original draft, Validation, Formal analysis, Data curation, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

References

[1] IPCC I. Summary for policymakers" in global warming of 1.5 °C. An IPCC special report on the impacts of global warming of 1.5 °C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty. Sustainable Development, and Efforts to Eradicate Poverty Geneva, Switzerland: World Meteorological Organization. 2018;32.
[2] Bhowmik C, Bhowmik S, Ray A. Optimal green energy source selection: an eclectic decision. Energy Environ 2020;31:842–59.
[3] AlShafeey M, Csaki C. Tech mining analysis: renewable energy forecasting using artificial intelligence technologies. In: IEEE Nigeria 4th international conference on disruptive technologies for sustainable development (NIGERCON): IEEE; 2022; 2022. p. 1–5.
[4] Esily RR, Chi Y, Ibrahiem DM, Chen Y. Hydrogen strategy in decarbonization era: egypt as a case study. Int J Hydrogen Energy 2022;47:18629–47.
[5] Welsby D, Price J, Pye S, Ekins P. Unextractable fossil fuels in a 1.5 °C world. Nature 2021;597:230–4.
[6] Bazilian M, Bradshaw M, Goldthau A, Westphal K. Model and manage the changing geopolitics of energy. Nature 2019;569:29–31.
[7] Parsons J, Buongiorno J, Corradini M, Petti D. A fresh look at nuclear energy. American Association for the Advancement of Science; 2019. p. 105.
[8] Buongiorno J., Parsons J.E., Petti D.A., Parsons J. The future of nuclear energy in a carbon-constrained world. 2019.
[9] Gernaat DE, de Boer HS, Daioglou V, Yalew SG, Müller C, van Vuuren DP. Climate change impacts on renewable energy supply. Nat Clim Chang 2021;11:119–25.
[10] Guerra OJ. Beyond short-duration energy storage. Nat Energy 2021;6:460–1.
[11] Bjørnskov J, Mortensen LK, Filonenko K, Shaker HR, Jradi M, Veje C. Optimization of district heating production with thermal storage using mixed-integer nonlinear programming with a new initialization approach. Energy Inform 2021;4:1–17.
[12] Long W, Wu T, Liang X, Xu S. Solving high-dimensional global optimization problems using an improved sine cosine algorithm. Expert Syst Appl 2019;123: 108–26.
[13] Manna S, Loeffler TD, Batra R, Banik S, Chan H, Varughese B, et al. Learning in continuous action space for developing high dimensional potential energy models. Nat Commun 2022;13:368.
[14] Bre F, Fachinotti VD. A computational multi-objective optimization method to improve energy efficiency and thermal comfort in dwellings. Energy Build 2017; 154:283–94.
[15] Cui Y, Geng Z, Zhu Q, Han Y. Multi-objective optimization methods and application in energy saving. Energy 2017;125:681–704.
[16] Von Homeyer I, Oberthür S, Jordan AJ. EU climate and energy governance in times of crisis: towards a new agenda. Taylor & Francis; 2021. p. 959–79.
[17] Kuzemko C., Hadfield A. Defining and projecting EU energy policy. EU leadership in energy and environmental governance: global and local challenges and responses. 2016:21–50.
[18] Blanco H, Nijs W, Ruf J, Faaij A. Potential for hydrogen and Power-to-Liquid in a low-carbon EU energy system using cost optimization. Appl Energy 2018;232: 617–39.
[19] Spielhofer R, Schwaab J, Grêt-Regamey A. How spatial policies can leverage energy transitions− finding Pareto-optimal solutions for wind turbine locations with evolutionary multi-objective optimization. Environ Sci Policy 2023;142: 220–32.
[20] Bazgan C, Ruzika S, Thielen C, Vanderpooten D. The power of the weighted sum scalarization for approximating multiobjective optimization problems. Theory Comput Syst 2022:1–21.
[21] Del Ser J, Osaba E, Molina D, Yang X-S, Salcedo-Sanz S, Camacho D, et al. Bio-inspired computation: where we stand and what's next. Swarm Evol Comput 2019; 48:220–50.
[22] Merk T, Peterson V, Köhler R, Haufe S, Richardson RM, Neumann W-J. Machine learning based brain signal decoding for intelligent adaptive deep brain stimulation. Exp Neurol 2022;351:113993.
[23] Roald LA, Pozo D, Papavasiliou A, Molzahn DK, Kazempour J, Conejo A. Power systems optimization under uncertainty: a review of methods and applications. Electr Power Syst Res 2023;214:108725.
[24] Gunantara N. A review of multi-objective optimization: methods and its applications. Cogent Eng 2018;5:1502242.
[25] Kasem MM. Multiobjective design optimization of parabolic trough collectors. Sci Rep 2022;12:19964.
[26] Antunes CH. Multiobjective optimization in the energy sector: selected problems and challenges. New Perspectives in Multiple Criteria Decision Making: Innovative Applications and Case Studies; 2019. p. 357–70.
[27] Miettinen K. Nonlinear multiobjective optimization. Springer Science & Business Media; 1999.
[28] Kim IY, De Weck OL. Adaptive weighted-sum method for bi-objective optimization: pareto front generation. Struct Multidiscip Optim 2005;29:149–58.
[29] Odu G, Charles-Owaba O. Review of multi-criteria optimization methods–theory and applications. IOSR J Eng 2013;3:01–14.
[30] Saini N, Saha S. Multi-objective optimization techniques: a survey of the state-of-the-art and applications: multi-objective optimization techniques. Eur Phys J Spec Top 2021;230:2319–35.
[31] Krzywanski J, Skrobek D, Zylka A, Grabowska K, Kulakowska A, Sosnowski M, et al. Heat and mass transfer prediction in fluidized beds of cooling and desalination systems by AI approach. Appl Therm Eng 2023;225:120200.
[32] Ashraf WM, Uddin GM, Arafat SM, Krzywanski J, Xiaonan W. Strategic-level performance enhancement of a 660 MWe supercritical power plant and emissions reduction by AI approach. Energy Convers Manag 2021;250:114913.
[33] Krzywanski J, Grabowska K, Sosnowski M, Żyłka A, Sztekler K, Kalawa W, et al. In: Modeling of a re-heat two-stage adsorption chiller by AI approach. MATEC Web of Conferences. EDP Sciences; 2018. p. 05014.
[34] Li Y, Yan Z. Improved shuffled frog leaping algorithm on system reliability analysis. Brain Inform 2019;6:1–7.
[35] Chen B, Liu Q, Chen H, Wang L, Deng T, Zhang L, et al. Multiobjective optimization of building energy consumption based on BIM-DB and LSSVM-NSGA-II. J Clean Prod 2021;294:126153.
[36] Jiang M, An H, Gao X, Liu D, Jia N, Xi X. Consumption-based multi-objective optimization model for minimizing energy consumption: a case study of China. Energy 2020;208:118384.
[37] Shboul B, Zayed ME, Tariq R, Ashraf WM, Odat A-S, Rehman S, et al. New hybrid photovoltaic-fuel cell system for green hydrogen and power production: performance optimization assisted with Gaussian process regression method. Int J Hydrogen Energy 2024;59:1214–29.

[38] Bischl B, Binder M, Lang M, Pielok T, Richter J, Coors S, et al. Hyperparameter optimization: foundations, algorithms, best practices and open challenges. 2021. arXiv. arXiv preprint arXiv:210705847.
[39] Arnold C, Biedebach L, Küpfer A, Neunhoeffer M. The role of hyperparameters in machine learning models and how to tune them. Political Sci Res Methods 2023: 1–8.
[40] Joo H, Bao C, Sen I, Huang F, Battle L. Guided hyperparameter tuning through visualization and inference. 2021. arXiv preprint arXiv:210511516.
[41] Deb K. Multi-objective optimization using evolutionary algorithms. John Wiley & Sons; 2001.
[42] Treanţă S, Jha S, Khan MB, Saeed T. On some constrained optimization problems. Mathematics 2022;10:818.
[43] Adihou Y, Mabrouk MT, Haurant P, Lacarrièere B. A multi-objective optimization model for the operation of decentralized multi-energy systems. In: Journal of Physics: Conference Series. IOP Publishing; 2019, 012104.
[44] Eichfelder G, Quintana E, Rocktäschel S. A vectorization scheme for nonconvex set optimization problems. SIAM J. Optim 2022;32:1184–209.
[45] Rudin C, Chen C, Chen Z, Huang H, Semenova L, Zhong C. Interpretable machine learning: fundamental principles and 10 grand challenges. Stat Surv 2022;16:1–85.
[46] Anon, IEA. Outlook for biogas and biomethane: prospects for organic growth. IEA Paris, France; 2020. p. 1–93.
[47] Brown C., Foley B. Achieving a cost-competitive offshore wind power industry: what is the most effective policy framework? 2015.
[48] AlShafeey M, Rashdan O. Quantifying the impact of energy consumption sources on GHG emissions in major economies: a machine learning approach. Energy Strategy Rev 2023;49:101159.
[49] Hagan MT, Menhaj MB. Training feedforward networks with the Marquardt algorithm. IEEE Trans Neural Netw 1994;5:989–93.
[50] Artacho FA, Dontchev AL, Gaydu M, Geoffroy MH, Veliov VM. Metric regularity of Newton's iteration. SIAM J Control Optim 2011;49:339–62.
[51] Damadi S, Moharrer G, Cham M, Shen J. The backpropagation algorithm for a math student. In: 2023 International Joint Conference on Neural Networks (IJCNN): IEEE; 2023. p. 01–9.
[52] Tian Y, Zhu W, Zhang X, Jin Y. A practical tutorial on solving optimization problems via PlatEMO. Neurocomputing 2023;518:190–205.
[53] Van Ruijven BJ, De Cian E, Sue Wing I. Amplification of future energy demand growth due to climate change. Nat Commun 2019;10:2762.
[54] Sayed M, Gharghory SM, Kamal HA. Euclidean distance-based multi-objective particle swarm optimization for optimal power plant set points. Energy Syst 2016; 7:569–83.
[55] He L, Ishibuchi H, Trivedi A, Wang H, Nan Y, Srinivasan D. A survey of normalization methods in multiobjective evolutionary algorithms. IEEE Trans Evol Comput 2021;25:1028–48.
[56] Kabeyi MJB, Olanrewaju OA. Sustainable energy transition for renewable and low carbon grid electricity generation and supply. Front Energy Res 2022;9:1032.
[57] Wang Q, Guo J, Li R, Jiang X-t. Exploring the role of nuclear energy in the energy transition: a comparative perspective of the effects of coal, oil, natural gas, renewable energy, and nuclear power on economic growth and carbon emissions. Environ Res 2023;221:115290.
[58] Carvalho MM, Fleury A, Lopes AP. An overview of the literature on technology roadmapping (TRM): contributions and trends. Technol Forecast Soc Change 2013; 80:1418–37.