

Article

Efficiencies of Single-Objective Linear Programming and Multi-Objective Optimization: A Case of Electricity Generation in Thailand

Athikom Bangviwat *, Orathai Chaisinboon and Apinya Puapattanakul 

The Joint Graduate School of Energy and Environment, King Mongkut's University of Technology Thonburi, 126 Pracha Uthit Rd., Bang Mod, Thung Khru, Bangkok 10140, Thailand; orathai.chaisinboon@gmail.com (O.C.); apinya.pua@kmutt.ac.th or apinya_ppp@hotmail.com (A.P.)

* Correspondence: athikom.bangviwat@outlook.com

Abstract

Single-objective linear programming has been employed as an optimization technique for most single-objective problems to obtain the best solutions for further enhancement. Recently, practical problems are required to fulfill more than one objective function. Although repeated application of single-objective linear programming can solve problems with more than one objective function, multi-objective optimization techniques were introduced for the optimization of problems with more than one objective function. It is worthwhile to investigate the efficiencies of single-objective linear programming and multi-objective optimization, applied to the same complex objective functions. Meanwhile, information on electricity generation in Thailand in 2024 is adopted as the case study for comparison for the optimization of three objective functions: minimum unit cost, minimum greenhouse gas emission, and maximum employment. The results show that the total time required to run the three objective functions with the linear programming technique is shorter than the runtime required by multi-objective optimization. There are no significant differences in the memory used by both techniques. Both optimization techniques clearly indicate optimized combinations of power sources. Single-objective linear programming shows a possible saving as much as 69,538.44 million Baht in generation costs in 2024, 14.782 million tons of CO₂eq greenhouse gas emissions, and 638 more jobs.

Keywords: linear programming; efficiency; multi-objective optimization; electricity generation; Thailand



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1. Introduction

1.1. Background

Optimization is commonly used as a technique to determine the best solutions or situations of given functions or situations. Linear Programming is employed as a single-objective optimization method to solve single-objective functions, such as minimizing weight for structural design, the shortest distance for traveling from a starting point to a destination, or the least cost for the energy mixture for electricity generation, while other parameters are considered constraints. Uchi et.al. presented a linear programming model for optimizing power generation in energy systems with the objective of minimizing total generation costs while meeting demand and operational constraints. The results validated the effectiveness of LP as a computationally efficient and reliable approach for optimal power flow and cost minimization in modern grid operations, with potential extensions

to renewable integration and smart grid applications [1]. When there is more than one objective function to optimize, the objective functions can be treated one at a time. Doing so may encounter relationships between objective functions and limitations of resources and inputs. Currently, many internationally promoted programs encourage minimizing the use of scarce resources and reducing impact on the environment and society. The best-known programs are the Sustainable Development Goals (SDGs) and the Just Transition.

According to UNDP [2], the concept of “just transition” was used by the US trade unions since the 1980s to protect workers affected by new water and air pollution regulations. The concept has been referenced in meeting climate goals by ensuring all stakeholders’ involvement and benefits toward a net-zero future.

Goal 7 of the SDG program recommends “Ensure access to affordable, reliable, sustainable and modern energy for all”, while Goal 12 calls for “Ensure sustainable consumption and production patterns” [3]. These clearly imply that energy cost is not the only objective; other objectives, such as environmental and social impacts, need to be considered as well. So, multi-objective optimization for electricity generation is required rather than single-objective optimization. Thus, this study aims to compare the efficiencies of the single-objective linear programming method with the multi-objective genetic algorithm by applying them to the electricity generation system in Thailand. In 2013, Projiraprawat K. and Limmeechohchai B. presented a hybrid framework of multi-objective optimization and multi-criteria decision making to solve power generation expansion problems in Thailand [4]. The study resulted in an optimum cost-related CO₂ mitigation plan as well as external cost reduction of around 500 billion US dollars over the planning horizon.

During the recent hearing for the revision of the Power Development Plan (PDP) conducted on 8 September 2026, three main objectives, which are security, ecology, and economy, were announced to promote decentralization and a just energy transition [5]. Saiful I. et.al. [6] introduced a unique adaptive multi-objective optimization approach that employs weighted optimization techniques for real-time microgrid systems to effectively balance various factors including fuel consumption, load mismatch, power quality, battery degradation, and the utilization of renewable energy sources. They found that the technique successfully maximizes photovoltaic production by minimizing power mismatch and stabilizing battery state of charge.

1.2. Efficiency of Single-Objective and Multi-Objective Optimization Algorithms

Single-objective linear programming optimizes a single objective function at a time, while multi-objective optimization can analyze more than one objective function at the same time. Moreover, the result derived by single-objective linear programming satisfies only the objective function in question and ignores other objective functions. Linear programming as a single-objective optimization is simple and requires shorter runtime for a well-defined problem; it, however, lacks flexibility, can oversimplify complex problems, and returns conflicting solutions. While multi-objective optimization can handle several complex objective functions simultaneously, including conflicting functions (e.g., minimizing cost, environmental impacts, and maximizing social benefits, and avoiding premature convergence to local peaks, the method involves complex algorithms, high computation time, and more computation space. The advantages and limitations of linear programming can be summarized as follows:

1.2.1. Advantages and Limitations of Single-Objective Linear Programming

A linear programming model is simple, easy to understand and construct, where the relationships between variables, or constraints, can be easily accessible and visualized, and applicable across a broad range of problems, including engineering, transportation, finance,

and agriculture, and various types of problems, such as resource allocation, production scheduling, and planning. The linear programming technique facilitates quantitative problem-solving, enables more reliable numerical analyses, and permits efficient allocation of limited resources. It also supports the optimal exploitation of resources, i.e., capital, energy, and labor, to maximize profit or minimize costs, even to enhance environmental goals, such as waste reduction and greenhouse gas (GHG) mitigation.

Despite the strengths of the linear programming technique, there are also limitations that can impact its applicability and effectiveness. All known variables are required to be linearly related, which may not reflect real-world complexities. Quadratic, exponential, or other nonlinear functions are not accepted by the linear programming technique. Inaccurate data used for linear programming may result in infeasible or suboptimal solutions. Therefore, the collected data to be optimized needs to be validated. As linear programming is designed to handle linear problems efficiently, extending to nonlinear or integer programming significantly increases computational complexity, which can lead to longer solution times or require searching methods for large problems [7,8].

For realistic problems in the present world, which include conflicting objectives and are subject to constraints, multi-objective optimization is used to find optimized solutions. Many multi-objective optimization techniques have been developed; each technique has its own characteristics that differ from others. This involves search techniques, selection methods, preferences made by the decision makers, an optimization framework, fitness evaluation, mutation or crossover methods, the nature of the problem and constraints, and the degree of complexity. Moreover, classifying problems as static or dynamic further attempts to balance criteria such as diversity, coverage, and convergence.

1.2.2. Advantages and Limitations of Multi-Objective Optimization

Multi-objective optimization (MOO) simultaneously optimizes two or more conflicting objective functions, such as minimizing cost while maximizing performance. The algorithms used (such as genetic algorithms) can be mathematically complex and challenging to configure and scale. A set of solutions forming a Pareto front is obtained rather than a single solution to find optimal solutions for all objective functions. The major advantages of multi-objective optimization (MOO) include a holistic analysis, which is provided with a complete set of solutions to help decision makers to avoid biases and premature selections, and better flexibility for the stakeholders to adapt dynamically, choosing exactly which constraints and balances fit real-world shifting needs [9].

Despite the advantages of multi-objective optimization (MOO), there is an increased computational cost, more time-consuming, and more resources required for the exploration of a multi-dimensional search space than single-objective approaches. In addition, outputs provided by multi-objective optimization (MOO) are a range of non-dominated options; therefore, human intervention is ultimately required to select a single “preferred” solution from the Pareto front.

1.2.3. Performance Parameters

Different optimization algorithms have their limitations. Single-objective optimization is employed to obtain the best solution for an objective function at a time, while multi-objective optimization provides a solution satisfying more than one objective function at the same time. The main differences are the computational speed and holistic solutions.

There have been many studies focusing on the performance and efficiency of different optimization methods. Metaheuristic algorithms are compared by considering both solution quality (effectiveness) and computational speed (efficiency) [6]. Beiranvand V. et.al. [5] gathered a brief historical overview of optimization benchmarking of several studies

together with their conclusions. Finally, three performance categories were presented as efficiency, reliability, and quality of solution. Efficiency, as one of the performance categories, can be determined based on (1) number of fundamental evaluations, (2) running time, and (3) memory usage.

2. Case Study: Power Generation Optimization in Thailand

2.1. Power Business in Thailand

The National Energy Committee (NEC) and the Ministry of Energy (MoE)/Energy Policy and Planning Office (EPPO) establish the Power Development Plan (PDP) for the country. The Energy Regulatory Commission (ERC) regulates the system in accordance with the PDP. The Electricity Generating Authority of Thailand (EGAT), the Metropolitan Electricity Authority (MEA), and the Provincial Electricity Authority (PEA) are the main governmental bodies responsible for generation, transmission, and distribution [10]. EGAT acts as the main generator, while MEA and PEA are the distributors for Bangkok and its vicinity areas, and provincial areas, respectively. EGAT is also designated as the enhanced single buyer (ESB) to purchase electricity from private producers, namely independent power producers (IPPs), small power producers (SPPs), and very small power producers (VSPPs), as depicted in Figure 1 and Table 1. Currently, a portion of electricity supplied to the grid is generated by EGAT, while the rest is supplied by IPPs, SPPs, VSPPs, and importation from neighboring countries under different power purchase agreements (PPAs). The dispatch orders are required to comply with the power purchase agreements (PPAs), which may not be optimized. It is, therefore, worthwhile to learn whether the system can be improved and how.

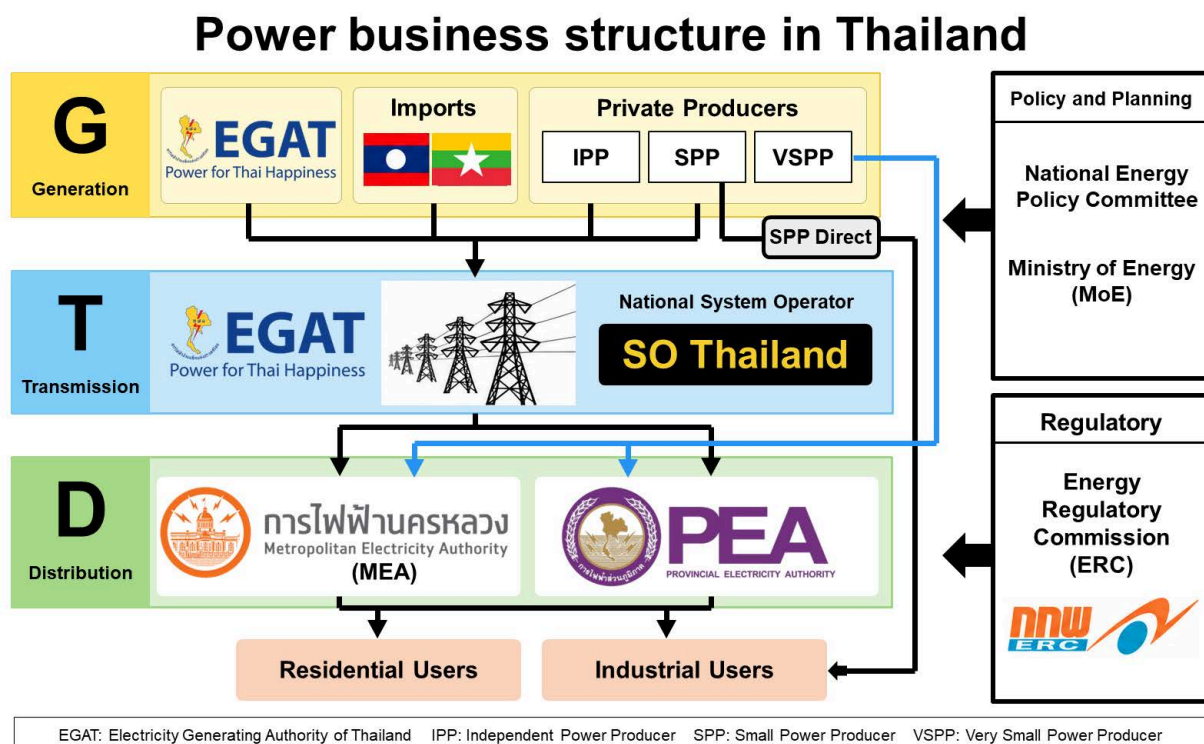


Figure 1. Power business structure in Thailand. Source: Energy Regulatory Commission [10].

Table 1. Net Energy Generation and Purchase in 2024 and 2025.

Power Plants	2025		2024	
	GW	%	GW	%
EGAT's Power Plants				
Natural gas	38,679.44	18.18	44,421.21	20.14
Coal (Lignite)	15,347.39	7.21	15,471.86	7.01
Fuel oil	87.43	0.04	33.92	0.02
Diesel oil	28.93	0.01	225.67	0.10
Renewable energy				
Small hydropower	154.87	0.07	160.26	0.07
Large hydropower	7059.25	3.32	5898.53	2.67
Geothermal	1.27	0.00	1.15	0.00
Wind power	72.25	0.03	60.65	0.03
Solar power	130.55	0.07	136.36	0.06
Other (pumped storage)	381.45	0.18	335.75	0.15
EGAT's total generation	61,951.83	29.21	66,745.36	30.26
Purchase from IPPs				
Natural gas	42,697.53	20.07	49,609.72	22.49
Coal (Lignite)	16,223.34	7.63	14,888.10	6.75
Diesel oil	33.18	0.02	88.51	0.04
IPP's total generation	58,954.05	27.71	64,586.33	29.28
Purchase from SPPs				
Natural gas	41,082.57	19.31	41,250.89	18.70
Coal (Lignite)	113.92	0.05	983.66	0.45
Hydropower	38.79	0.02	35.18	0.02
Biomass	4797.01	2.26	5165.46	2.34
Solar power	1780.84	0.84	1006.56	0.46
Wind power	3284.48	1.54	3248.25	1.47
Black rubber oil	205.05	0.10	194.94	0.09
Waste	1335.68	0.63	1364.37	0.62
Waste gas	36.33	0.02	24.40	0.01
SPP's total generation	52,674.67	24.76	53,273.71	24.15
Purchase from Lao PDR	39,026.32	18.35	35,832.32	16.24
Purchase from Malaysia	109.56	0.05	152.73	0.07
Total purchase from neighboring countries	39,135.88	18.40	35,985.05	16.31
Grand Total	212,716.43	100.00	220,590.45	100.00

Source: EGAT's Annual Report 2025.

2.2. Electricity Cost Structure

2.2.1. Costs of Generation of EGAT's Power Plants

The total capacity of power plants installed by EGAT was 15,155.02 MW (as of 2024), including Hydropower plants, coal-fired power plants, natural gas-fired power plants, diesel generators, and renewable energy. The costs of generation by EGAT's power plants reported on EGAT's website are primarily fuel costs [11]. In addition, small power sources, supported by government programs, deliver power to the grid through various purchase agreements in the other category.

2.2.2. Purchase Rates of Power Generated by Others

The power purchase rates for power generated by private power plant projects in Thailand and imported power were required to be approved based on environmental considerations and investment values. The claim can be supported by the government's power purchase rates for different technologies, which ranged from 8.45 Baht/kWh to 1.18 Baht/kWh in 2022, as detailed in Table 2, with an exchange rate of 35.2271 Baht per

USD (as of 15 June 2022). It is not obvious whether the allocation of revenue among different factors is reviewed and incorporated into the permit award process.

Table 2. Power purchase rates of different technologies.

No.	Fuel/Technology	Share (%)	Cost (Bath/kWh)
1	Diesel oil	4.30	8.45
2	Fuel oil	0.60	7.56
3	Natural gas (SPP)	17.77	4.87
4	Mixed fuels and others (SPP)	2.37	4.49
5	Natural gas (Gas pool/IPP/EGAT)	30.81	4.02
6	Imported (Lignite/Laos)	5.48	2.17
7	Coal (IPP/Imported)	7.03	2.14
8	Imported (Hydropower/Laos)	10.99	1.89
9	Hydropower (EGAT)	3.02	1.38
10	Lignite (EGAT)	7.97	1.18
	Renewable		
11	Solar power	2.21	7.73
12	Wind power	1.36	6.81
13	Solid waste	1.08	6.02
14	Small hydro and others	0.89	4.34
15	Biomass	4.12	4.15

Note: A balance of 0.17% is included in mixed fuels and others (SPP). Source: Energy Conservation Technology [12].

2.3. Electricity Sale Price Tariff

It is worth noting that there are a few key factors affecting electricity price components as follows [13]:

2.3.1. Power Generation Costs

Generation and acquisition costs are major factors affecting electricity prices, especially in Thailand, which is a net energy importer and relies on the global market. However, more renewables, such as solar and wind, have been installed, which will reduce dependence on the global market in the long term.

2.3.2. Fuel Adjustment Charge (Ft)

The fuel adjustment charge (Ft), reflecting changes in fuel cost, inflation rate, exchange rate, etc., is reviewed and adjusted every four months by the authorities in response to market changes, which can be the result of the increase in self-produced electricity from rooftop PV, the adjustment in the base tariff, etc., to compensate for the revenue loss of the authorities.

2.3.3. Government Policies

The government periodically adjusts the basic electricity tariffs to balance public affordability with utility solvency. Generally, the tariffs charged to the poor are reduced. The schemes require either government subsidies or an increase in tariffs on higher-income classes to balance the burden borne by authorities. It is obvious that the government's policies can be major factors affecting electricity prices for end users, and it is worthwhile to optimize production costs, which is one of the essential factors determining the basic tariff.

The electricity tariffs, charged to end-users, are classified into eight (8) schedules as follows [14]:

Schedule 1: Residential,

Schedule 2: Small General Service,

Schedule 3: Medium General Service,
 Schedule 4: Large General Service,
 Schedule 5: Specific Business Service,
 Schedule 6: Non-Profit Organization,
 Schedule 7: Agricultural Pumping,
 Schedule 8: Temporary Service.

Monthly charges consist of the following:

1. Base tariff (based on schedules),
2. Service charge,
3. Fuel adjustment charge (Ft),
4. Value added tax (VAT) 7%.

3. Methodology of the Study

In order to compare the efficiency of single-objective linear programming and multi-objective optimization, three (3) main characteristics need to be considered: complexity of the problem, memory required for calculation, and run time. Since both schemes, single-objective linear programming and multi-objective optimization, are applied to the same case study, the power generation system in Thailand, the complexity is the same. As the problem is limited to the power generation of twelve (12) technologies/suppliers, the information accounted for in the calculation is not large, and the memory required for iterations is small. The characteristics of interest for comparison are runtime and memory used for calculation, as illustrated in the graphical scheme below in Figure 2. The actual power generation for the power supply system in Thailand in 2024 has been adopted as the case study for the purpose of self-validation. The actual conditions, unit costs, emission factors, employment factors, and limitations in capacity of the available power plants, as lower and upper limits, are utilized in the optimization models. It has been shown that the results obtained by both LP and MOO are not far off from the actual generations but provide improvements due to the objective functions.

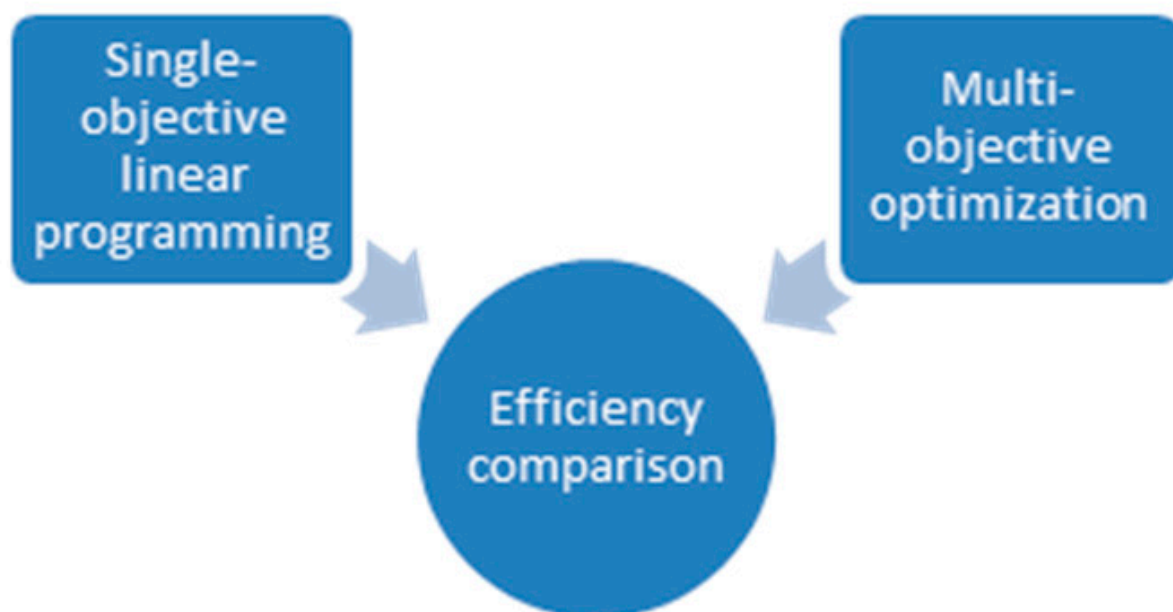


Figure 2. Method of the study.

The set-up objective functions and their constraints are processed by using “linprog” and “gamultiobj” command functions in MATLAB (R2025a) to solve the single-objective

linear programming and multi-objective optimization, respectively. The calculation yields (1) optimized combinations of power generation sources, (2) memory used as calculation space in MB, and (3) run times required for the optimization.

3.1. Single-Objective Linear Programming

Linear Programming is a mathematical optimization method subject to constraints [15]. Although Euler and Lagrange were mentioned in the early development of the calculus of variations (Euler, 1744), George Dantzig is recognized as the father of linear programming (LP) and the inventor of the simplex method. He is known among mathematicians, including von Neumann, Kantorovich, Leontief, and Koopmans, for significant contributions to the development of extensions of mathematical programming related to linear programming [16]. Linear programming is structured with an objective function, subject to constraints and parameter limits.

Single-objective optimization focuses on an objective function that requires a single best solution. Multi-objective optimization overcomes this restriction by finding a set of optimal solutions for multiple objective functions that may even be conflicting. The non-dominated solutions form the Pareto front, which includes the best solutions where no component can be improved without worsening other objectives. The problem-solving process involves formulating the mathematical model, identifying the feasible region, and finding the optimal point. Methods commonly used for solving linear programming problems include [17]:

- (1) The Graphical Method: The graphical method is normally used for simple problems with only two decision variables.
- (2) The Simplex Method: An iterative algebraic algorithm, such as the simplex method, is used to solve problems with three or more variables.
- (3) Computational Solvers: Advanced computer programs and software (Matlab ver. 25), such as Python, Gurobi optimizer, Excel solver, etc., support real-world problems with hundreds of variables, and specialized software is used.

3.2. Genetic Algorithm-Multi-Objective Optimization

There is increasing awareness among planners and engineers across various fields of design and system operations about maximizing efficiency and benefits. A number of works were conducted on reservoir design and operation for known total irrigation demand and on the optimal allocation of water to ensure its availability to crops on the farm. A comparison of the applications of the two models, a Genetic Algorithm (GA) and Linear Programming (LP), for real-time reservoir operation in an existing Chiller reservoir system in Madhya Pradesh, India, was performed. Their performance was analyzed, and the results indicated that the LP model performed better [18].

Multi-objective evolutionary algorithms (EAs) were introduced to address the computational complexity of objectives simultaneously and to increase the computational speed using the non-dominated sorting concept. Several algorithms were developed under the aforementioned principles, including the Non-dominated Sorting Genetic Algorithm II (NSGA-II), which addresses the limitations of the previous version [19]. Multi-objective optimization methods can be categorized by various criteria and search techniques [9], including classical, metaheuristic, and enumerative algorithms [20]. The optimization procedures can be performed with or without the interference of the presentation of preferences, which can occur prior to, posterior to, or during the iterations. In addition, search methods can combine two or more algorithms, known as hybrid algorithms, to compensate for the limitations of each. The following settings are applied for the MOO process:

‘PopulationSize’ = 100,

'MaxGenerations' = 1000,
'FunctionTolerance' = 0.001

3.3. Efficiency Comparison of Single-Objective Linear Programming and Multi-Objective Optimization: The Case of the Optimization of Electricity Generation in Thailand

The price of electricity charged to end users, especially residential users, has been a persistent issue. Doubts are raised about the electricity business structure, which includes many generators, both state-owned and private companies, with different cost imbursement contracts. Revisions to the price on a minimum-generation-cost basis are requested. It is an opportunity for the authorities to include other objectives, as recommended by the Sustainable Development Goals (SDGs) [3], into the next revision and the future plan. The newly proposed method of planning, justice by design, offers an interdisciplinary framework that integrates energy justice (EJ) with Responsible Research and Innovation (RRI) to ensure the fair distribution of costs, the allocation of benefits, and participation in decision-making, and can be employed to deliver just energy futures [21]. Three (3) objective functions, which are f1: minimum unit production cost, f2: minimum greenhouse gas (GHG) emissions, f3: maximum employment, including twelve (12) sources of generations/supplies, are optimized by using linear programming, one at a time. The specified objective functions are subject to constraints, namely equality and inequality constraints, as well as lower and upper bounds. Each objective function is optimized by using linear programming, one at a time.

The genetic algorithm (GA) multi-objective optimization technique is used to determine the best solution that satisfies all three (3) objective functions: f1, f2, and f3. The optimization process is carried out with the same equality constraints, inequality constraints, lower bounds, and upper bounds, and generation data as employed when the objective functions are optimized by single-objective linear programming. Run times are recorded for further comparison.

3.3.1. Objective Functions

A multi-objective optimization problem deals with optimizing two or more conflicting objectives simultaneously. In this approach, the objective functions, $f_k(x)$ for $k = 1, 2, \dots, n$, are minimized (or maximized), while considering some equality or inequality constraints. The mathematical formula of the objective function with constraints can be expressed as follows [8,22]:

Objective functions: $\min. f_k(x)$, for $k = 1, 2, 3, \dots, n$

The common objectives for energy planners to optimize are, at least, the minimum cost, the least impact on the environment, and the maximum employment. As a case study, past information on power generation using fuels, both fossil and renewable energy, from various sources and different technologies supplying the power grid in Thailand, was used to demonstrate and compare different optimization techniques. The selection of 12 fuel sources/technologies is performed to optimize the objective functions, identified as follows:

- A. To minimize the production cost function: $f1(x_i)$,
- B. To minimize the environmental concern function (emission): $f2(x_i)$,
- C. To satisfy the societal objective function (employment): $f3(x_i)$.

Objective functions:

minimize $f1(x_i)$ (production cost),

minimize $f2(x_i)$ (GHG emission),

maximize $f3(x_i)$ (employment),

where

$i = 1, 2, 3, \dots, 12$

subject to:

$g_i(x) \leq 0$, where $i = 1, 2, \dots, m$, and

$h_j(x) = 0$, where $j = 1, 2, \dots, p$.

in which,

x is the vector of decision variables,

m is the number of inequality constraints, and

p is the number of equality constraints.

As new optimization algorithms have been developed and are available for various applications, it is of interest to learn more about their efficiency, especially in cases with multiple objectives. In the case of power generation, the production cost of electricity generation is not the only decision parameter; the environmental and social impacts caused by the primary energy used for production are also of concern. To design an effective transportation system, cost and time are the essential parameters for optimization. Optimization is applied to determine what to grow, how much to grow, and how to use the harvest to increase farmers' revenue. In addition to returns, risk and transaction costs need to be considered for any investment program.

3.3.2. Information Used for Calculation

In order to elaborate on the efficiencies of the optimization techniques, actual electricity generations and supplies in 2024 are acquired from EGAT's website, https://www.egat.co.th/ft/index_3.html (accessed on 28 July 2026). Information from the website includes:

- (1) Total units generated by EGAT, purchased from IPPs, SPPs, imported from neighboring countries, and others.
- (2) Expenses on fuels, power purchases, and governmental programs.

The acquired information is used to develop coefficients for objective functions, lower bounds, and upper bounds for optimization.

Coefficients for Objective Functions

The objective functions in focus, f_1 , f_2 , f_3 described above, are subject to constraints as:

$$A_1 \times x_1 + A_2 \times x_2 + A_3 \times x_3 + A_4 \times x_4 + A_5 \times x_5 + A_6 \times x_6 + A_7 \times x_7 + A_8 \times x_8 + A_9 \times x_9 + A_{10} \times x_{10} + A_{11} \times x_{11} + A_{12} \times x_{12} = b \quad (1)$$

where

x_i : decision variables,

A_i : coefficient vector,

i : number of decision variables.

Different coefficients, derived from sources described in the notes, are applied for different objective functions, as depicted in Table 3.

Table 3. Coefficients for objective functions.

Generated Energy from Power Plant	MWh	A1, A2, A3, . . . , A12		
		Cost (Baht/MWh) (1),(2)	Emission Factors (kgCO ₂ e/MWh) (3),(4),(5)	Employment Factors (Jobs/MWh) (6),(7),(8),(9)
EGAT's Hydropower plants	X1	1706.9	24	2.85948×10^{-5}
EGAT's NG power plants	X2	2438.3	490	1.90632×10^{-5}
EGAT's Coal power plants	X3	2925.9	820	2.99564×10^{-5}
EGAT's oil power plants	X4	18,222.2	600	2.99564×10^{-5}

Table 3. Cont.

Generated Energy from Power Plant	MWh	A1, A2, A3, . . . , A12		
		Cost (Baht/MWh) (1),(2)	Emission Factors (kgCO ₂ e/MWh) (3),(4),(5)	Employment Factors (Jobs/MWh) (6),(7),(8),(9)
IPP's NG power plants	X5	3384.8	490	1.90632×10^{-5}
IPP's Coal power plant	X6	2406.3	820	2.99564×10^{-5}
SPP's NG power plants (firm)	X7	3913.8	490	1.90632×10^{-5}
SPP's NG power plants (non-firm)	X8	3146.3	490	1.90632×10^{-5}
Import from Lao's hydropower plants	X9	2306.1	0	0
Import from Lao's coal power plants	X10	2128.0	0	0
Import from Malaysia	X11	6930.0	0	0
Others sources	X12	3052.0	38	2.85948×10^{-5}

Notes: (1) Cost (Baht/MWh): unit cost of energy in terms of Thai Baht for 1000 units of electricity (Thai currency: approx. 33 Thai Baht per 1 US Dollar). (2) Cost per Unit of Electric Energy for Bhumibol Hydro Plant Electricity Generating Authority of Thailand, by Chaisri Phoothiwut, University of Chiang Mai, Thailand [23]. (3) Emission factors (kgCO₂e/MWh): emissions of greenhouse gas equivalent to an amount of CO₂ (Carbon dioxide) in kilograms from the generation of 1000 units of electricity (1000 kWh). (4) Technology-specific Cost and Performance Parameters, AN-NEX III, IPCC [24]. (5) Emission Factor from Electricity Generation/Consumption for Greenhouse Gas Mitigation Projects and Activities, Carbon Credit Certification Office, Thailand Greenhouse Gas Management Organization [25]. (6) Employment factors (jobs/MWh): employment required for the generation of 1000 units of electricity (1000 kWh). (7) Updated employment factors and occupational shares for the energy transition [26]. (8) World Energy Employment 2025, International Energy Agency [27]. (9) The Australian Electricity Workforce for the 2024 Integrated System Plan: Projections to 2050. Prepared for RACE for 2030 [28].

Constraints

Actual power generations and supplies in 2024 are employed as constraints for the optimization, as provided in Table 4.

Table 4. Power generations/supplies in 2024.

Month	Generation (MWh)
January 2024	16,115,140
February 2024	15,905,250
March 2024	19,696,900
April 2024	18,501,740
May 2024	19,647,910
June 2024	18,853,440
July 2024	18,574,900
August 2024	18,491,650
September 2024	16,947,370
October 2024	17,199,470
November 2024	16,523,980
December 2024	15,562,620
Total	212,020,370

Source: www.egat.co.th.

Power Plant Information as Boundaries

Optimization of an objective function requires boundaries for optimization. For the case study of the study, lower boundaries of all parameters are set zeros, or non-negative parameters, while upper boundaries are set at actual generation capacities or historical supplies of the technologies as described below.

While the lower bounds of all supply sources are set at zero, the upper bounds of the supply sources are determined by the following information and assumptions:

- The total installed capacity, EGAT-owned, IPPs, SPPs, and imports, from EGAT's website;
- Maximum deliverable energy from hydropower is adopted from the historical information;
- A total of 85% of dispatchable energy from fossil fuel power plants is accounted for.

The derived lower bounds and upper bounds shown in Table 5 are used for the optimization process.

Table 5. Boundaries for optimization.

		Capacity (MW)	LB (MW)	UB (MW)	
$E_{HP,EGAT}$	E1	3038.13	0.00	636,260.00	ub HP EGAT = Max (during Jan–Mar 24)
$E_{NG,EGAT}$	E2	9552.00	0.00	5,845,824.00	ub-NG EGAT = $(9552 \times 30 \times 24 \times 0.85)$
$E_{CP,EGAT}$	E3	2535.00	0.00	1,551,420.00	ub-CP EGAT = $(2535 \times 30 \times 24 \times 0.85)$
$E_{OIL,EGAT}$	E4	4.40	0.00	5610.00	ub Oil EGAT = Max (during Jan–Mar 24)
$E_{NP,IPP}$	E5	16,967.00	0.00	10,383,804.00	ub-NP IPP = $(16,967 \times 30 \times 24 \times 0.85)$
$E_{CP,IPP}$	E6	2006.50	0.00	1,227,978.00	ub-CP IPP = $(2006.5 \times 30 \times 24 \times 0.85)$
$E_{SPP,Firm}$	E7	6445.53	0.00	3,944,664.36	Ub SPP-non firm = $(6445.53 \times 30 \times 24 \times 0.85)$
$E_{SPP,nonFirm}$	E8	2800.35	0.00	1,713,814.20	Ub SPP-non firm = $(2800.35 \times 30 \times 24 \times 0.85)$
$E_{HP,LA}$	E9	4461.00	0.00	1,547,010.00	Ub HP LA = Max (during Jan–Mar 24)
$E_{CP,LA}$	E10	1473.00	0.00	901,476.00	ub-CP LA = $(1473 \times 30 \times 24 \times 0.85)$
E_{ML}	E11	300.00	0.00	216,000.00	ub-DC ML = $(300 \times 30 \times 24)$
E_{OTHERS}	E12	1105.49	0.00	1,355,000.00	Ub Others = Max (during Jan–Mar 24)

Source: EGAT [11].

4. Results and Analysis

This study evaluates the efficiencies of optimization of various objective functions using single-objective linear programming and multi-objective linear programming. A power generation system in Thailand is employed as a case study.

4.1. Comparison of Efficiencies of Optimization Techniques (Single-Objective Optimization and Multi-Objective Optimization)

4.1.1. Optimal Combination of Sources of Generation

The actual power generation and supply in Thailand during January to December 2024 were used as a case study to compare efficiencies of optimization techniques, single-objective linear programming and multi-objective optimization. Figure 3a–d depict the optimized combinations of generation sources and supplies against the actual generation. Each month, linear programming (LP) optimization was employed to determine the generation source combinations for three objective functions, one at a time, and the genetic algorithm (GA) was used to optimize all three objectives with a set of generation sources.

It was found that different combinations of power generation sources satisfy different objective functions, and none of the actual generation/supply combinations is optimized, which presents an opportunity to improve the dispatch of power generation across different sources. Furthermore, it is possible to optimize all three objective functions by a multi-objective optimization algorithm.

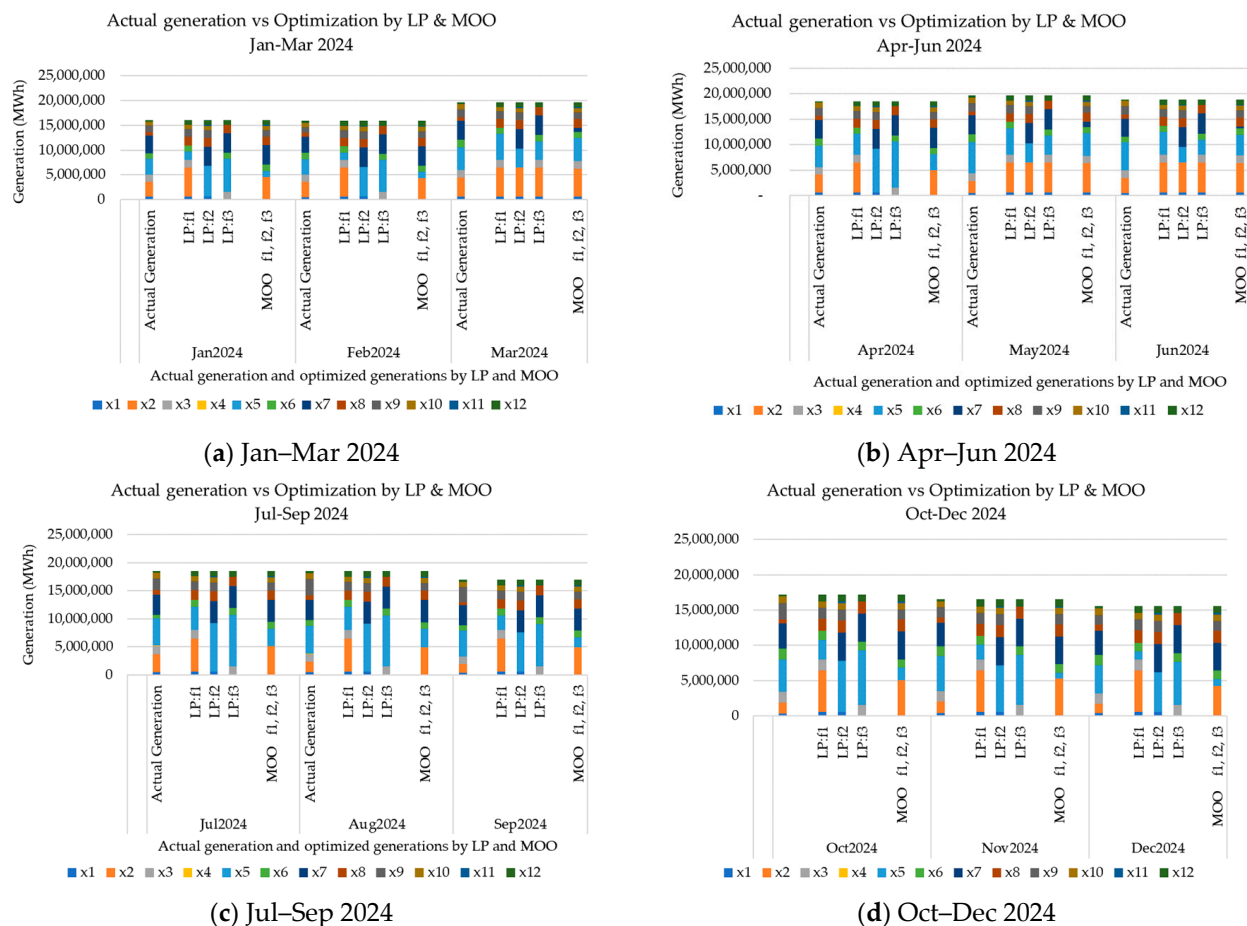


Figure 3. Actual generations vs. optimized generations (by LP and MOO).

4.1.2. Efficiencies (Run Time and Memory Used) of Single-Objective Linear Programming (LP) and Multi-Objective Optimization (MOO)

The same set of objective functions is optimized by single-objective linear programming and multi-objective optimization algorithms. Those are: (1) minimum cost of generation, (2) minimum GHG emissions, and (3) maximum employment. Both optimization methods can be considered as subject to the same complexity.

The average run time required for a run of a single-objective linear programming is 0.175–0.210 s. Three runs are processed for three objective functions. The average run time for three objective functions is 0.574 s, while the average run time for genetic algorithm multiple-objective optimization is 3.984 s, much longer than the time required for three linear programming runs, as indicated in Table 6.

Memory used for calculation is another parameter to determine the efficiency of the optimization method. The approximate average memory used for optimization by single-objective linear programming and genetic algorithm multi-objective optimization ranges from approximately 3500 to 3800 MB, as shown in Table 7. There have not been significant differences in the memory used by both optimization methods.

Table 6. Run times required by LP and MOO.

Month	LP:f1 (s)	LP:f2 (s)	LP:f3 (s)	LP:All (s)	MOO f1, f2, f3 (s)
January 2024	0.119	0.173	0.255	0.547	3.491
February 2024	0.265	0.170	0.248	0.683	3.787
March 2024	0.169	0.171	0.248	0.683	3.787
April 2024	0.331	0.171	0.192	0.532	4.197
May 2024	0.169	0.169	0.164	0.502	3.468
June 2024	0.178	0.256	0.169	0.603	4.147
July 2024	0.170	0.258	0.164	0.592	3.614
August 2024	0.114	0.263	0.162	0.539	3.948
September 2024	0.123	0.269	0.164	0.556	3.944
October 2024	0.118	0.265	0.161	0.544	3.531
November 2024	0.175	0.173	0.173	0.521	3.969
December 2024	0.169	0.176	0.164	0.509	3.179
Average	0.175	0.210	0.189	0.574	3.984

Source: Calculated by authors.

Table 7. Memory used for calculation by LP and MOO.

Month	LP:f1 (MB)	LP:f2 (MB)	LP:f3 (MB)	LP:All (MB)	MOO f1, f2, f3 (MB)
January 2024	3415.93	3433.73	3501.69	3450.45	3950.39
February 2024	3480.94	3435.25	3499.12	3471.77	3955.25
March 2024	3485.32	3436.62	3500.23	3474.06	3966.51
April 2024	3931.89	3498.42	3495.62	3641.98	3034.33
May 2024	3488.83	3485.70	3503.91	3492.81	3776.19
June 2024	3490.56	3490.68	3501.31	3494.18	3803.16
July 2024	3933.66	3499.67	3501.27	3644.87	3821.50
August 2024	3416.59	3491.67	3495.15	3467.80	3824.62
September 2024	3429.79	3492.58	3504.39	3475.59	3833.13
October 2024	3420.57	3500.58	3495.32	3472.16	3867.21
November 2024	3420.58	3492.58	3506.04	3473.07	3880.37
December 2024	3424.62	3501.69	3504.96	3477.09	3877.90
Average	3528.27	3479.93	3500.75	3502.98	3799.21

Source: Calculated by authors.

4.2. Optimized Unit Costs, Emission Factors, and Employment in the Power Generation System in Thailand

To elaborate on the optimization of the power source combination, the objective function values are calculated and compared with actual generation. Values of the objective functions of the economic, environmental, and societal aspects, which are f1: unit cost minimization, f2: GHG emission minimization, and f3: employment maximization, are presented in Table 8 and shown in Figures 4–6. It is noted that when single-objective linear programming (LP) is used as the means of optimization, it is required to optimize an objective function at a time. For three (3) objective functions, as provided in the case study, it needs to repeat the process three times. The multi-objective optimization technique processes three (3) objective functions at the same time and provides optimized solutions for all objective functions.

Table 8. Unit cost, emission factor, and employment were calculated using LP and MOO.

Compare Unit Costs (Baht/MWh)	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Avg.
Actual gen	2982.99	2957.15	2964.41	2961.77	3036.38	3014.48	3098.29	3098.25	3007.07	3010.41	3053.47	3039.71	3012.12
Opt by LP	2622.72	2612.84	2758.78	2731.40	2757.26	2731.40	2721.80	2718.88	2659.46	2669.89	2641.23	2596.14	2684.14
Opt by MOO	3003.83	3012.54	2851.73	3024.92	2855.36	2801.89	3018.96	3036.10	3002.77	2994.98	2962.56	3007.26	2964.41
Compare Specific Emissions (kgCO_{2e}/MWh)	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Avg.
Actual gen	445.20	458.37	449.71	453.36	449.67	443.19	425.89	407.36	411.80	439.11	460.78	458.23	442.72
Opt by LP	362.54	360.85	385.71	378.98	385.45	381.05	379.41	378.92	368.79	370.57	365.69	358.01	373.00
Opt by MOO	412.95	411.92	437.43	420.31	437.85	432.96	421.29	422.29	417.03	415.11	411.99	409.11	420.91
Compare Employment (Jobs)	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Avg.
Actual gen	3582.79	3546.59	4298.91	4035.85	4256.56	4014.57	3823.20	3650.09	3346.03	3576.86	3638.25	3432.16	3766.82
Opt by LP	4050.56	4002.54	4869.91	4596.52	4858.70	4676.97	4607.06	4594.21	4240.93	4298.60	4144.08	3924.15	4405.35
Opt by MOO	3289.69	3241.78	4308.15	3813.83	4303.48	4096.04	3836.01	3834.28	3482.00	3516.36	3360.71	3155.18	3696.46

Source: Calculated by authors.

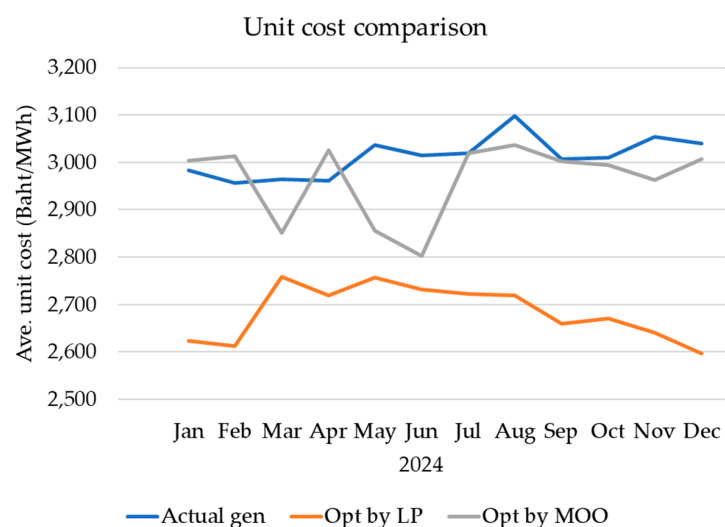


Figure 4. Comparison of power unit costs, calculated from combinations of power sources; actual, LP, and MOO.

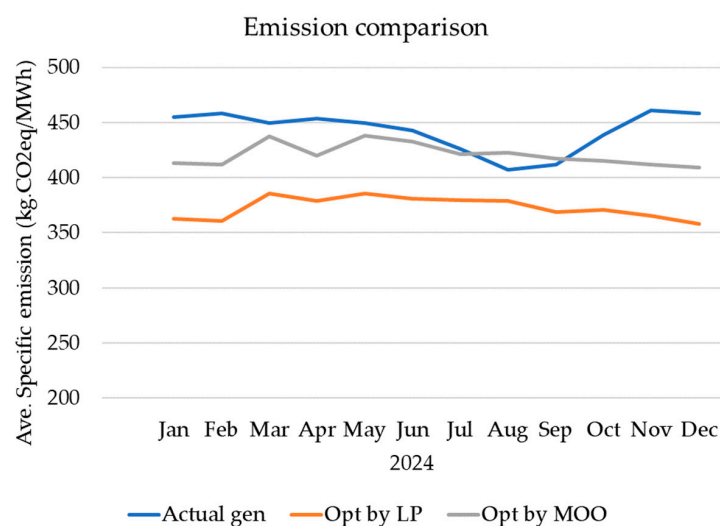


Figure 5. Comparison of GHG emissions, calculated from combinations of power sources; actual, LP, and MOO.

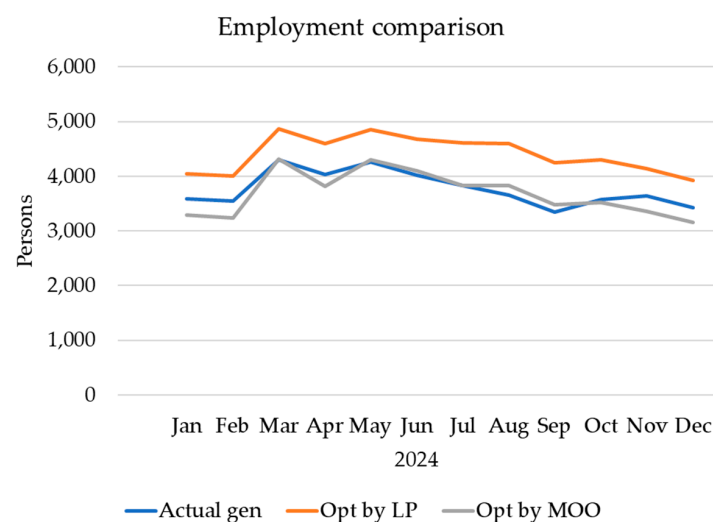


Figure 6. Comparison of maximum employments, calculated from combinations of power sources; actual, LP, and MOO.

4.2.1. Minimum Unit Cost

One of the major objectives of power generation is the minimum unit cost of generation. Different power sources have different generation costs. Various combinations of power sources to meet the demand for power result in different unit costs. It is noted that the optimized values by either linear programming or a genetic algorithm are lower than the actual generation throughout the year 2024. If cost is the only objective of optimization, single-objective linear programming (LP) provides the lowest unit cost, where yearly averages are: actual generation: 3012.12 Baht/MWh, optimized by LP: 2684.14 Baht/MWh, optimized by MOO: 2964.41 Baht/MWh.

4.2.2. Minimum GHG Emission

GHG emissions from the actually selected power source of generation are much higher than the optimized combination of generation sources. Throughout the year 2024, the calculated GHG emissions from the actual power generation sources are between 400 and 500 kg-CO₂eq for 1000 units (MWh) of generated electricity. The combination of power sources can be optimized by single-objective linear programming (LP) and genetic algorithm (GA) multi-objective optimization, resulting in lower GHG emission, which is in the range of 350 to 450 kg-CO₂eq/MWh during the same period of the year 2024, where yearly averages are: actual emission: 442.72 kg-CO₂eq/MWh, optimized by LP: 373.00 kg-CO₂eq/MWh, optimized by MOO: 420.91 kg-CO₂eq/MWh.

4.2.3. Maximum Employment

It is not customary to specify the number of jobs for the unit generation of electricity. Generally, the number of workers is specified by the size of the power plant, for example, “100 workers are required for the construction of 100 MW (million watts capacity), and 50 operators and 20 maintenance engineers are needed during the operation phrase of the power plant.” However, for optimization purposes, the number of workers are defined in terms of jobs/MWh (jobs per 1000 units of electricity generated). The possible maximum employment, which is society’s concern, is also explored, and it is found that the calculated maximum employment from the actual power sources employed during the year 2024 is between 3200 and 4200 persons, while the maximum employment calculated from the optimized combination of power sources (by linear programming) increases significantly in the range of 4000 to 5000 persons, as shown in Figure 6. The difference in the average possible maximum employment is approximately 700 more jobs (4405.35–3766.82 jobs).

It is worth noting that LP concentrates on one objective function at a time, while MOO provides a set of solutions with trade-offs to satisfy all objective functions simultaneously. As shown in Figures 4–6, the optimized values by MOO, including unit cost, specific emission, and possible employment, are found to be close to the actual values and quite different from the optimized values by LP. This is obvious by comparing the average values of actual generation, optimized by LP, and optimized by MOO, as indicated in Table 8.

5. Conclusions and Policy Recommendations

The objectives of the study are to compare the efficiencies of LP and MOO, with an application of power generation in Thailand in 2024 as the case study. Three (3) objective functions are included for the optimization. They are (1) cost minimization, (2) greenhouse gas emission minimization, and (3) maximum employment. Comparison of the efficiencies of LP and MOO is concluded in Section 5.1. Sections 5.2–5.4 describe the findings and opportunities for improvement, while Section 5.5 presents the possible cost savings, GHG emission mitigation, and employment increase. Toward the end, Section 5.6 recommends future work.

5.1. Efficiency and Practicality

The average summation of run times by single-objective optimization for all three objective functions is slightly more than 0.6 s, which is much lower than that required for running a multiple-objective optimization for the same set of three objective functions of about 4 s, as depicted in Table 6, while both techniques occupy about the same amount of memory, approximately 3500–3800 MB, as shown in Table 7. In addition to the efficiency comparison, the optimized combination of the power supply sources analyzed by the genetic algorithm multiple-objective function satisfies all three objective functions at the same time [29]. Linear programming yields the combination of the power supply sources optimizing an objective function at a time. Therefore, in linear programming, different sets of supply-source combinations are required to satisfy different objective functions.

5.2. Multi-Objective Optimization as a Holistic Solution for Decision Makers

Currently, optimization techniques are effective and versatile tools for selecting daily products and designing programs for public needs. For example, the generated power needed to be delivered to the grid has to be low-cost, low-emission, and maximize employment (to serve the community's requirements). The best vehicle should meet energy consumption performance (liters/km or kms/battery charge) and the initial cost of the vehicle. Most of the current programs require multiple objectives to be optimized. A holistic solution is more appropriate for multiple-objective optimization for policymakers who plan programs that satisfy economic, environmental, and social constraints.

5.3. Different Techniques for Different Purposes

The linear programming technique yields the lower unit cost and GHG emissions for all cases compared with the actual operation and those calculated by the genetic algorithm multiple-objective optimization. That is probably because the single-objective linear programming technique optimizes an objective function at a time, while the genetic algorithm multiple-objective optimization technique optimizes more than one objective function. The combination of power supply sources derived by the genetic algorithm multiple-objective optimization technique satisfies a broader scope.

5.4. Optimized Values as an Opportunity for Improvement

It is obvious that the optimized values of unit costs of generation, derived from both optimization techniques, single-objective linear programming (LP) and multiple-objective optimization (MOO), are lower than the current supply, which clearly indicates an opportunity for improvement. In other words, the decision maker can reduce the electricity base tariffs charged to the end users by altering the combination of generation sources, as illustrated in Figure 3. The optimized costs are 2684.14 Baht/MWh and 2964.41 Baht/MWh, determined by the LP technique and the MOO technique, respectively, which are 89.11% and 98.42% of the actual yearly average cost of 3012.12 Baht/MWh.

Similarly, the combinations of power supply sources can be optimized to satisfy GHG emission minimization and employment maximization. The right combination of power sources can be determined to yield as low GHG emissions as 373.00 and 420.91 kg-CO₂eq/MWh, by LP and MOO, compared with the actual yearly average emission of 442.72 kg-CO₂eq/MWh, as provided in Table 8. Combinations of power sources can also be determined to satisfy the maximum employment requirement of as many as 4405.35 persons, compared with the employment calculated from the actual combinations of power sources of 3766.82 persons, as shown in Figure 5.

5.5. Potentials of Cost Saving, GHG Emission Mitigation, and Employment

If the suggested optimized combinations of power sources are followed, the potentials for cost savings, GHG emission mitigation, and an increase in employment can be achieved. Instead of generation by the power sources as used in 2024, the average unit cost of generation by the optimized power sources suggested by LP can be reduced from 3012.12 Baht/MWh to 2684.14 Baht/MWh. The potential saving could be 69,538.44 million Baht $[(3012.12 - 2684.14) \text{ Baht/MWh} \times 212,020,370 \text{ MWh}/1,000,000]$ for the year 2024. In the same manner, the average GHG emissions can be reduced from 442.72 kg-CO₂e/MWh to 373.00 kg-CO₂e/MWh (optimized by LP). The potential reduction in GHG emissions could be 14.782 million tons.CO₂e $[(442.72 - 373.00) \text{ kg-CO}_2\text{e/MWh} \times 212,020,370 \text{ MWh}/(1000 \times 1,000,000)]$. The potential for more employment resulted from the suggested optimized power sources by using single-objective linear programming. An increase in employment can be estimated from 3767 jobs to 4405 jobs.

5.6. Recommendations for Future Plans

As elaborated in Section 4, there are areas for improvement for all objectives, including least cost, minimum GHG emission, and possible maximum employment. Although all three objectives can be optimized simultaneously by a multi-objective optimization (MOO) technique, single-objective linear programming (LP) can also optimize the objectives one at a time to emphasize the most required objective. Recommendations for future plans can be described as follows:

5.6.1. Plan for Future Demand Expansion and Decrease in Burdens

It is evident from the above analysis that the future capacity expansion to cope with the increasing demand should be those of low costs or less GHG emission, such as rooftop PV and wind turbines. In addition, ownership of the systems is also considered to minimize their production and administration costs. Community-owned renewable energy power plants can be the answer to the requirements.

5.6.2. Plan for Future Business Opportunity

Promotion of self-production and community-owned renewable energy power plants may jeopardize the present authorities of EGAT, PEA, and MEA. New businesses for the authorities, such as engineering, installation, and maintenance services, can be offered to households and communities for their convenience. New businesses can compensate for the losses of income as the power generator and distributors.

5.6.3. Plan for Global GHG Mitigation Compliance

Discouraging fossil fuel power plants, including natural gas-fired and coal-fired power plants, will expedite the reduction of GHG emissions toward the net-zero emission target of the country. The current power development plan (PDP) can be revised to replace fossil fuel power plants with renewable energy sources.

5.6.4. Plan for “Just Transition” in Energy Supply Structure

The recent trend of power transition is not limited to economic and environmental concerns; the societal objective is also included as a major objective in “Just transition”. This means that shutting down fossil fuel power plants without remedial measures may not be adequate for the transition. Shutting down or buying back fossil fuel power plants, especially coal-fired power plants, has to be carefully planned with proper steps to avoid disruption, which can adversely affect workers and their families.

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Abbreviations

LP	Linear programming
MOO	Multi-objective optimization
GA	Genetic algorithm
kgsCO ₂ e	kilograms of carbon dioxide equivalent
tonsCO ₂ e	tons of carbon dioxide equivalent
EGAT	Electricity Generation Authority of Thailand
PEA	Provincial Electricity Authority
MEA	Metropolitan Electricity Authority
ERC	Energy Regulatory Commission
EPPO	Energy Policy and Planning Office
Baht	Thai Baht (currency)
kWh	kilo-watt hour
MWh	mega-watt hour or 1000 kWh
UNDP	United Nations Development Programme

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