



Mixed-Integer Programming Model for Optimization of Production Scheduling and Distribution of Renewable Energy

M. Safii^{1*}, Husain², Ika Okta Kirana¹

¹ Informatika Department, STIKOM Tunas Bangsa, Pematangsiantar 21127, Indonesia

² Teknologi Informasi Department, Universitas Bumigora, Mataram 83127, Indonesia

Corresponding Author Email: m.safii@amiktunasbangsa.ac.id

Copyright: ©2025 The authors. This article is published by IIETA and is licensed under the CC BY 4.0 license (<http://creativecommons.org/licenses/by/4.0/>).

<https://doi.org/10.18280/mmep.121014>

ABSTRACT

Received: 3 July 2025

Revised: 13 August 2025

Accepted: 18 August 2025

Available online: 31 October 2025

Keywords:

mixed-integer programming, renewable energy, optimization, production, distribution

The need for an efficient and sustainable energy system has become a major challenge in the energy transition in Indonesia, although the country has great potential in renewable energy. The utilization of these resources is not yet optimal due to the lack of cost-effective production and distribution planning that meets regional needs. This research designs a Mixed-Integer Programming (MIP) based optimization model to optimally allocate energy production from various renewable power plants. The model considers generation capacity, regional demand, and technical distribution constraints. Implementation is carried out using LINGO for the main calculations and Python for result validation, ensuring accuracy and efficiency of the algorithm. The results show a global optimal solution with minimum costs and an even distribution of energy at the highest efficiency generation, while high marginal cost generation is automatically eliminated.

1. INTRODUCTION

The global energy transition towards sustainable and low-carbon energy sources has become a pressing strategic issue in the last decade [1]. Climate change, volatility in fossil fuel prices, and international pressures to reduce carbon emissions have prompted many countries, including Indonesia, to adopt and accelerate the integration of renewable energy into their national energy systems [2, 3]. Indonesia has significant and diverse renewable energy potential, such as solar power with potential exceeding 200 GW, widespread wind energy in the eastern regions, biomass from agricultural and forestry waste, as well as hydro and geothermal energy [4, 5]. Despite this potential, Indonesia still lacks an integrated, cost-efficient model for renewable energy production and distribution. The utilization of this potential is still far from optimal, primarily due to limitations in production planning, imbalances in distribution, and weak integrative infrastructure between regions [6].

Optimization of scheduling and distribution of renewable energy is crucial in ensuring the efficiency of energy systems, meeting load demands, and minimizing total system costs [7, 8]. Optimization-based mathematical models such as Mixed-Integer Programming (MIP) have been widely used to solve complex problems in energy system planning, especially for large-scale integration of renewable generation [9-11]. In the context of Indonesia, the application of MIP optimization models that consider the technical characteristics of generation and regional demand is still rarely found in the literature, thereby opening up research opportunities to make a tangible contribution to national energy policy.

Previous studies have demonstrated the effectiveness of the MIP approach in the energy sector. For example, developing an MIP model for power system expansion planning considers the integration of renewable energy [12]. The research [13] applied the application of the linear programming method in the construction of a mathematical model of optimization distributed energy, that it is believed that distributed energy can be an effective solution to the problems of conventional energy operations. Meanwhile, the research [14] presented a linear programming approach to the optimization of residential energy systems shows that the scheduling strategy proposed in this paper can save 22.8% of the operating cost under the same conditions. In the evaluation of renewable energy efficiency, a new scenario is constructed, and the result is still ideal. Although various studies have shown the success of applying MIP in energy systems, most of this research still focuses on global or regional contexts outside Indonesia. Research that integrates renewable energy scheduling and distribution aspects simultaneously on a national scale in Indonesia is still limited [5, 15]. Moreover, most previous studies have not considered cross-validation between optimization software and Python-based programming to ensure the accuracy of the model results. Thus, there is a gap in the literature regarding the development of applicable and verified optimization models for Indonesia's complex and dispersed geographical context.

This study develops an MIP-based optimization model for Indonesia's renewable energy generation and distribution, considering plant capacity limits, regional demand, and cost efficiency. The model tested in LINGO and validated in Python, aims to minimize total costs while ensuring equitable

supply. The main contributions are:

- (1) a national-scale, multi-generator optimization model tailored to Indonesia's geography;
- (2) dual-platform validation to enhance result reliability;
- (3) a practical framework to support the national renewable energy mix target of 23% by 2025 [16]. Furthermore, this quantitative approach is expected to serve as a reference for data-driven decision making by the government and energy stakeholders in formulating more efficient and sustainable electricity system planning policies.

2. METHODOLOGY

This study uses a quantitative approach with a MIP based mathematical optimization method to develop a production scheduling model and distribution of renewable energy in Indonesia. The research process is conducted systematically through three main stages: Initial Stage, Modeling, and Final Stage, as shown in Figure 1.

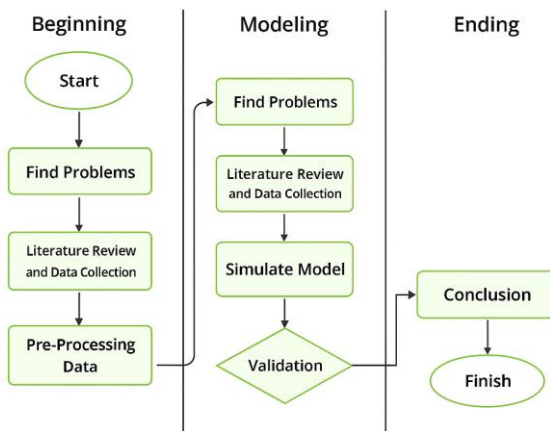


Figure 1. Research flow

The research methodology is structured into three main stages, namely the Initial Stage, the Modeling Process, and the Final Stage, as shown in Figure 1. Each stage is carried out systematically to produce a valid and reliable optimization model for production scheduling and distribution of renewable energy in Indonesia.

2.1 Research design

This research is a quantitative study with an experimental numerical design approach through optimization simulation [17, 18]. The main focus is on the development of a mathematical model to minimize the total cost of renewable energy systems while considering capacity constraints and demand in various regions of Indonesia [19]. The model is formulated using a linear programming approach with the possibility of expanding to MIP for binary distribution control (active/inactive) [20, 21].

2.2 Subject and object of research

The subject of the research is the production and distribution system of renewable energy in Indonesia, which involves various types of power plants: Geothermal Power Plant (PLTP), Hydropower Plant (PLTA), Micro hydro Power

Plant (PLTMH), Solar Power Plant (PLTS), Wind Power Plant (PLTB), and biomass-based or non-fossil thermal power plants (PLTU). The object of the research is a mathematical optimization model for scheduling the distribution of energy from the power plants to consumption areas based on cost efficiency [22, 23].

2.3 Data collection procedure

Data collection was carried out through two main stages. First, a literature study and problem identification were conducted to obtain secondary data from various authoritative sources, including official reports from the Ministry of Energy and Mineral Resources (ESDM) [4] and PT PLN (Persero) [24]. The main parameters collected include:

- (1) maximum power plant capacity (in MWh) based on the type of plant (solar, wind, hydro, geothermal, biomass),
- (2) regional energy demand (in MWh) referring to the latest national electricity load projections,

(3) production and distribution cost coefficients sourced from ESDM cost references, PLN operational data, and estimates from literature related to transmission lines and types of plants. Second, data compilation and pre-processing are carried out to ensure the compatibility of the optimization model input format. This process includes cleaning the data from missing or inconsistent values, standardizing units (MWh for energy and rupiah for costs), normalizing cost data to the same reference year, cross-verifying generation capacity from various sources, and compiling cost and distribution distance matrices between regions. The optimization model was first implemented and solved using LINGO software to obtain a basic optimal solution. The same formulation, parameters, and dataset were then replicated in Python using the equivalent MIP solver, PuLP. The validation process was carried out by comparing the objective function values (total costs) on both platforms, verifying the similarity of the decision variable values (energy allocation from each generator to each region), and conducting sensitivity tests to ensure the model's consistent responses to changes in input parameters. The validation of these two platforms ensures that the developed model has high robustness, repeatability, and computational accuracy.

2.4 Modeling and simulation procedures

The modeling steps in this research were carried out systematically as shown in Figure 1, namely:

A. Identify the Problem

The main problem in this study is how to optimally allocate the production and distribution of energy from various renewable generation sources to meet energy demands in various regions at minimum total cost. This issue is formulated into an MIP approach focused on a deterministic scenario based on historical data and system parameters [25, 26].

B. Model Construction

The developed mathematical model consists of an objective function and several constraints that are expressed linearly [27]. The model can be formulated as follows:

(1) Objective function:

Minimization of total production and distribution costs of energy [28]:

$$\text{Min } Z = \sum_{i \in P} \sum_{j \in W} (C_i^P + C_{i,j}^d) x_{i,j} \quad (1)$$

with $x_{i,j}$ = the amount of energy distributed from power plant i to area j (in MWh). C_i^P = production cost per unit of energy from the power plant i . $C_{i,j}^d$ = energy distribution cost from generator i to area j .

(2) Constraints of power plant capacity:

$$\sum_{j \in W} x_{i,j} \leq K_i, \forall i \in P \quad (2)$$

with K_i being the maximum capacity of generator i .

(3) Constraints of regional demand limitations:

$$\sum_{i \in P} x_{i,j} \geq D_j, \forall j \in W \quad (3)$$

with D_j being the energy demand of region j .

(4) Constraints of binary distribution:

$$x_{i,j} \leq M \cdot y_{i,j}, \forall i,j \quad (4)$$

$$y_{i,j} \in \{0,1\}, \quad x_{i,j} \geq 0 \quad (5)$$

The binary variable $y_{i,j}$ represents the decision of energy distribution from generator i to region j where $y_{i,j} = 1$ if the distribution is active and $y_{i,j} = 0$ if it is not. The relationship between $y_{i,j}$ and the continuous variable $x_{i,j}$ is governed by the constraint $x_{i,j} \leq M \cdot y_{i,j}$, where M is a large constant that limits the maximum distribution capacity. This MIP formulation combines discrete decisions (activation of distribution paths) and continuous decisions (volume of energy), allowing for the elimination of high-cost paths and efficient allocation of energy according to regional demand.

2.5 Simulation and model optimization

The model is implemented and optimized using LINGO software with linear programming methods. As a validation and comparison step, the same model is also rebuilt using Python with the Pulp library, in order to verify the accuracy of the objective values, the consistency of the constraints, and the stability of the solutions.

2.6 Model validation

Validation is carried out through a comparison between the results of LINGO and Python, including the objective function value (total cost), the energy distribution allocation pattern ($x_{i,j}$) and the slack and dual values of the capacity and demand constraints. This validation is important to ensure that the model is free from formulation errors and that the solver operates as expected in achieving the global optimal solution [29, 30].

2.7 Analysis and interpretation of results

The optimization results show the allocation of energy from the power plants to the regions in an optimal manner, demonstrating that power plants with lower marginal costs are prioritized. Information from the slack values and shadow prices provides insights related to the utilization of power plants as well as the marginal value of energy for each region. These findings can be utilized as a basis for strategic decision-

making in national energy.

3. RESULTS AND DISCUSSION

The results of the optimization process carried out using a Linear Programming model for energy generation system planning. An analysis was conducted on the objective function value, decision variables, and interpretation of dual parameters such as reduced cost, slack/surplus, and dual price. The results were obtained from a computational process using LINGO software, which efficiently produced a global optimal solution while satisfying all model constraints. The objective function value reflects the minimum total cost of the system, while the distribution of decision variable values indicates the optimal allocation of energy generation from each source. Next, the dual results are used to evaluate the sensitivity and efficiency of each power plant's contribution to the total costs. The discussion in this section focuses on the interpretation of these results to support strategic decision-making in sustainable and economical energy management. The results of this model testing can be seen in Figure 2:

```
Global optimal solution found.
Objective value:                0.6353439E+14
Infeasibilities:                0.000000
Total solver iterations:        0
Elapsed runtime seconds:        0.13

Model Class:                    LP

Total variables:                44
Nonlinear variables:            0
Integer variables:              0

Total constraints:              109
Nonlinear constraints:          0

Total nonzeros:                171
Nonlinear nonzeros:            0
```

Figure 2. Results of the LINGO model testing

The results of the optimization model testing show that the global optimal solution has been successfully found with an objective function value of $63,534.39 \times 10^{13}$ which represents the total minimum cost of the combination of energy production and distribution according to the linear programming model formulation. An infeasibility value of 0.000000 indicates that all model constraints are satisfied without violation. The solution process was carried out efficiently, with a total solver iteration of 0 and a computation time of only 0.13 seconds. The model used is purely linear, with a total of 44 decision variables, no nonlinear variables, and no integer variables. The number of constraints in the model reaches 109, with a total of 171 non-zero coefficients, all of which are linear. This result confirms that the model has a simple mathematical structure but is capable of providing optimal solutions quickly, making it relevant for efficient planning of renewable energy production and distribution.

3.1 Distribution decision

The selection of generators in an optimal solution is greatly influenced by the structure of marginal costs. The model tends to choose generation units with low costs and high efficiency, while avoiding the use of units with high costs, even though those units are available in the system, as shown in Figure 3:

Variable	Value	Reduced Cost
X_PLTP1_SUMUT	0.000000	0.1065072E+08
X_PLTP2_LAMPUNG	12497.96	0.000000
X_PLTP3_JABAR	3835.960	0.000000
X_PLTP4_NTT	9237.280	0.000000
X_PLTA1_SUMUT	0.000000	0.2450846E+08
X_PLTA2_SUMBAR	1024.720	0.000000
X_PLTA3_RIAU	9830.770	0.000000
X_PLTA4_SUMSEL	6303.620	0.000000
X_PLTA5_BENGKULU	2396.300	0.000000
X_PLTA6_LAMPUNG	1181.090	0.000000
X_PLTA7_JABAR	1635.930	0.000000
X_PLTA8_JATENG	5787.030	0.000000
X_PLTA9_KALBAR	3333.710	0.000000
X_PLTA10_SULUT	5550.070	0.000000
X_PLTA11_SULTENG	3718.990	0.000000
X_PLTA12_SULSEL	1856.200	0.000000
X_PLTA13_PAPUA	5092.040	0.000000
X_PLTS1_KEPRI	4465.640	0.000000
X_PLTS2_BABEL	2120.500	0.000000
X_PLTS3_SUMSEL	1628.040	0.000000
X_PLTS4_NTB	767.3400	0.000000
X_PLTS5_SULUT	10444.44	0.000000
X_PLTS6_GORONTALO	8583.150	0.000000
X_PLTMH1_ACEH	1368.070	0.000000
X_PLTMH2_SUMUT	0.000000	1787037.
X_PLTMH3_SUMBAR	1677.200	0.000000
X_PLTMH4_BENGKULU	658.6800	0.000000
X_PLTMH5_NTB	1043.640	0.000000
X_PLTMH6_NTT	2035.500	0.000000
X_PLTMH7_KALBAR	1367.510	0.000000
X_PLTMH8_SULUT	693.1000	0.000000
X_PLTMH9_SULTENG	6379.650	0.000000
X_PLTMH10_SULBAR	2597.720	0.000000
X_PLTMH11_PAPUA BARAT	1358.370	0.000000
X_PLTB1_BALI	3234.910	0.000000
X_PLTB2_SULSEL	92050.56	0.000000
X_PLTBIO1_SUMBAR	41911.42	0.000000
X_PLTBIO2_RIAU	32021.10	0.000000
X_PLTBIO3_KEPRI	28456.87	0.000000
X_PLTBIO4_BABEL	3589.350	0.000000
X_PLTBIO5_SUMSEL	58589.43	0.000000
X_PLTBIO6_BENGKULU	26996.52	0.000000
X_PLTBIO1_LAMPUNG	37017.47	0.000000
X_PLTBIO1_KALBAR	1367.510	0.000000

Figure 3. Distribution decision

Based on the results of the linear programming model optimization in the Figure 3, the value of the variables represents the optimal production or distribution amount from each power plant to specific regions to achieve minimum total cost. The X_PLTP2_LAMPUNG plant produces 12,497.96 units, while X_PLTP1_SUMUT and X_PLTA1_SUMUT have a value of zero, indicating that these plants are not used in the optimal solution. The high reduced costs at X_PLTP1_SUMUT (1.065072×10^8) and X_PLTA1_SUMUT (2.450846×10^8) indicate that the use of these units will significantly increase costs, so they are not selected in the optimal solution. Variables with a reduced cost value of zero indicate that the power plants directly contribute to achieving minimum costs or are at their optimal limit.

3.2 Analysis of system constraints and sensitivity

Identification of active and inactive constraints is important to determine further optimization strategies, such as relaxing capacity limits or strengthening generation components that have a significant contribution to overall system cost efficiency. This analysis can be seen in Figure 4.

Based on Figure 4, the optimal value of the Objective Function is achieved at $63,534.39 \times 10^{12}$ with zero infeasibility, indicating that all constraints are satisfied without violations. This model consists of 44 variables and 109 constraints, all of which are linear without any non-linear variables or constraints. The Dual Price column represents the change in the Objective Function value if one more unit of resource is added to that constraint. A positive value indicates that increasing the resource at that constraint will raise the Objective Function value (profit), while a negative value indicates that adding resources will actually decrease the

objective value. Row 2 has a dual price of 1.033204×10^{11} , which means that each additional unit of resource added to that constraint will increase the profit by that amount. Conversely, Row 45 with a dual price of 1.465178×10^{11} indicates that additional resources will decrease the objective value by that amount. Thus, the results of this dual analysis provide strategic guidance for optimizing production, distribution, or resource utilization policies more effectively.

Row	Slack or Surplus	Dual Price
1	0.6353439E+14	-1.000000
2	0.000000	0.1033204E+09
3	0.000000	0.000000
4	0.000000	0.000000
5	8237.680	0.000000
6	0.000000	0.1340876E+09
7	0.000000	0.6734189E+08
8	0.000000	0.000000
9	0.000000	0.8308120E+08
10	0.000000	0.1426885E+09
11	0.000000	6641474.
12	0.000000	0.000000
13	0.000000	0.000000
14	0.000000	0.1642357E+08
15	0.000000	0.000000
16	0.000000	0.3156903E+09
17	0.000000	0.000000
18	0.000000	0.7451053E+08
19	0.000000	5247837.
20	0.000000	0.1663976E+08
21	0.000000	942763.9
22	0.000000	0.000000
23	0.000000	0.000000
24	0.000000	0.000000
25	543.4500	0.000000
26	0.000000	0.1322988E+09
27	0.000000	0.8951217E+08
28	0.000000	0.000000
29	0.000000	0.2052015E+08
30	0.000000	6192803.
31	0.000000	0.3303461E+08
32	0.000000	4754217.
33	0.000000	0.000000
34	0.000000	0.000000
35	0.000000	0.000000
36	0.000000	0.000000
37	0.000000	0.000000
38	0.000000	0.000000
39	0.000000	0.000000
40	0.000000	0.000000
41	0.000000	0.000000
42	0.000000	0.000000
43	0.000000	0.000000
44	0.000000	6192803.
45	0.000000	-0.1465178E+09
46	0.000000	-0.1276521E+08
47	0.000000	-0.2849275E+08
48	0.000000	-0.1380086E+09
49	0.000000	-0.1021256E+09
50	0.000000	-0.2207139E+08
51	0.000000	-0.9184811E+08
52	0.000000	-0.1878183E+08
53	0.000000	-0.1150381E+08
54	0.000000	-0.3563217E+08
55	0.000000	-0.1258560E+08
56	0.000000	-0.3222547E+09
57	0.000000	-0.1967900E+08
58	0.000000	-0.8962288E+08
59	0.000000	-0.1244510E+08
60	0.000000	-3316404.
61	0.000000	-0.2893411E+08
62	0.000000	-4795431.
63	0.000000	-7831383.
64	0.000000	-4835546.
65	0.000000	-0.1362332E+08
66	0.000000	-0.1987374E+09
67	12497.96	0.000000
68	3835.960	0.000000
69	9237.280	0.000000
70	0.000000	0.000000

Figure 4. Analysis of constraints

3.3 Implementation with Python

The results of the energy distribution optimization model test conducted using Python show that an optimal solution has been achieved, as indicated by the model status being optimal. The objective function value obtained is 56405002169769.4, which represents the minimum total cost of energy distribution

to all analyzed areas. The energy distribution from various power plants to the demand areas is presented in Figure 5.

Status: Optimal

Jumlah energi yang didistribusikan:

Dari PLTP 2 ke Lampung: 12497.96

Dari PLTA 2 ke Sumatera Barat: 1024.72

Dari PLTA 3 ke Riau: 9830.77

Dari PLTA 4 ke Sumatera Selatan: 6303.62

Dari PLTA 5 ke Bengkulu: 2396.30

Dari PLTA 6 ke Lampung: 1181.09

Dari PLTA 7 ke Jawa Barat: 1525.08

Dari PLTA 8 ke Jawa Tengah: 5676.18

Dari PLTA 11 ke Sulawesi Tengah: 3608.14

Dari PLTA 12 ke Sulawesi Selatan: 1856.20

Dari PLTA 13 ke Papua: 4981.19

Dari PLTS 1 ke Kepulauan Riau: 4465.64

Dari PLTS 2 ke Kep.Bangka Belitung: 2120.50

Dari PLTS 3 ke Sumatera Selatan: 1628.04

Dari PLTS 4 ke NTB: 767.34

Dari PLTS 6 ke Gorontalo: 8472.30

Dari PLTM/H 1 ke Aceh: 1257.22

Dari PLTM/H 2 ke Sumatera Utara: 432.60

Dari PLTM/H 3 ke Sumatera Barat: 1677.20

Dari PLTM/H 4 ke Bengkulu: 658.68

Dari PLTM/H 5 ke NTB: 165.45

Dari PLTM/H 6 ke NTT: 1924.65

Dari PLTM/H 8 ke Sulawesi Utara: 582.25

Dari PLTM/H 9 ke Sulawesi Tenggara: 6268.80

Dari PLTM/H 10 ke Sulawesi Barat: 2486.87

Dari PLTM/H 11 ke Papua Barat: 1247.52

Dari PLTB 1 ke Bali: 3124.06

Dari PLTB 2 ke Sulawesi Selatan: 90083.51

Dari PLTBio 1 ke Sumatera Barat: 39098.65

Dari PLTBio 2 ke Riau: 22079.48

Dari PLTBio 3 ke Kepulauan Riau: 23880.38

Dari PLTBio 4 ke Kep.Bangka Belitung: 1358.00

Dari PLTBio 5 ke Sumatera Selatan: 50546.92

Dari PLTBio 6 ke Bengkulu: 23830.69

Dari PLTBio 7 ke Lampung: 23227.57

Dari PLTBio 8 ke Kalimantan Barat: 1256.66

Total Biaya Minimum = 56405002169769.4

Figure 5. Energy distribution

Based on the image above, it can be explained that the energy distribution shows that several power plants provide a dominant contribution to meeting energy needs in certain

areas. For example, PLTB 2 distributes a large amount of energy to South Sulawesi totaling 90,083.51 MWh, while PLTBio 5 and PLTBio 7 distribute energy of 50,546.92 MWh to South Sumatra and 23,227.57 MWh to Lampung, respectively. Renewable energy sources such as PLTS and PLTM/H also make significant contributions, such as PLTS 6 to Gorontalo (8,472.30 MWh) and PLTM/H 9 to Southeast Sulawesi (6,268.80 MWh), as can be seen in Figure 6.

The distribution carried out not only reflects cost efficiency but also demonstrates the optimization of utilizing local energy potential, by maximizing generation based on renewable natural resources. This result indicates that the optimization approach based on linear programming is capable of producing economically viable energy allocation scenarios and supports sustainable energy policies, with the total energy visible in Figure 7.

Figure 7 presents a visualization of the total energy allocation (measured in MWh) distributed to each provincial region in Indonesia based on the results of the developed MIP model optimization. It shows that South Sulawesi received the highest energy allocation, nearing 92,000 MWh, followed by South Sumatra and North Sumatra with allocations of approximately 58,000 MWh and 42,000 MWh, respectively. Other regions such as Lampung, Riau, and the Riau Islands also received significant energy distributions, indicating that areas with high demand and/or those near low-cost power generation facilities tend to receive larger energy allocations. Conversely, regions such as North Sulawesi, NTB, and Aceh receive relatively small energy allocations. This distribution reflects the results of the objective function of cost minimization and operational constraints of the model, where the system tends to prioritize supply to regions that are economically and operationally more efficient. This is in line with the principles of optimizing renewable energy systems that consider both the demand side and distribution efficiency.

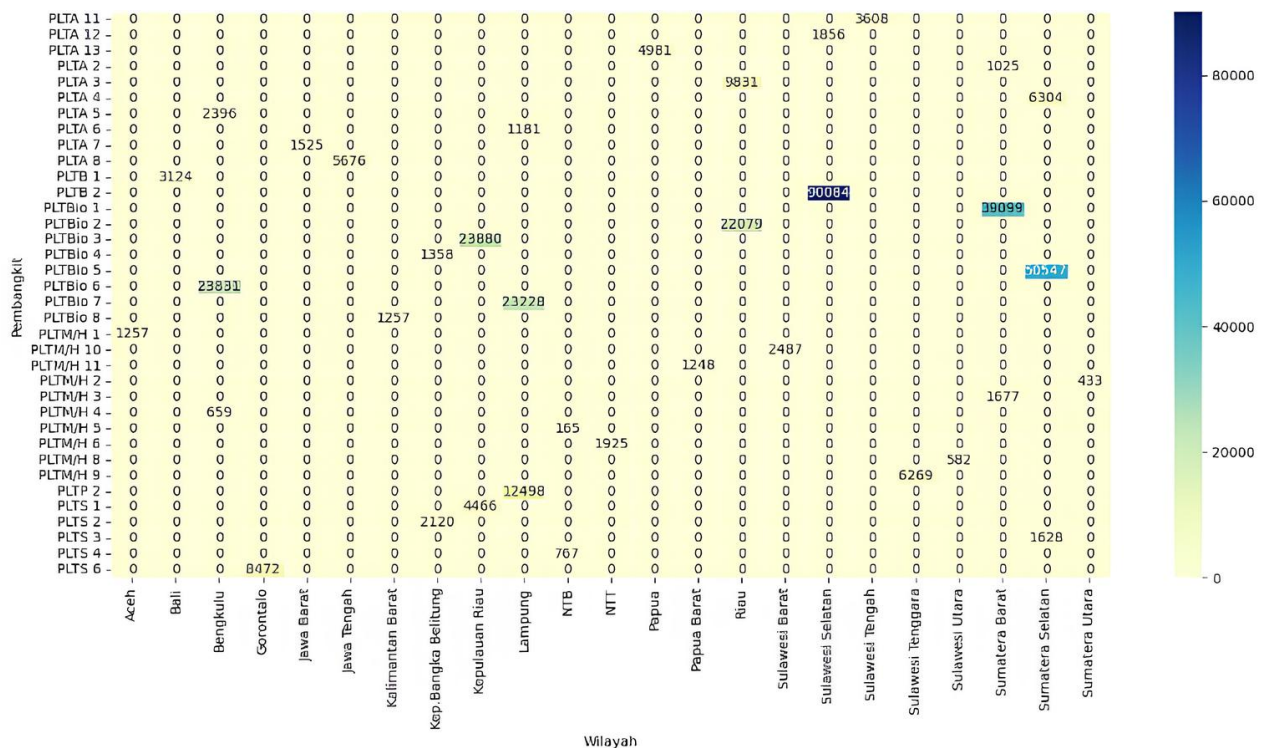


Figure 6. Optimal energy distribution graph

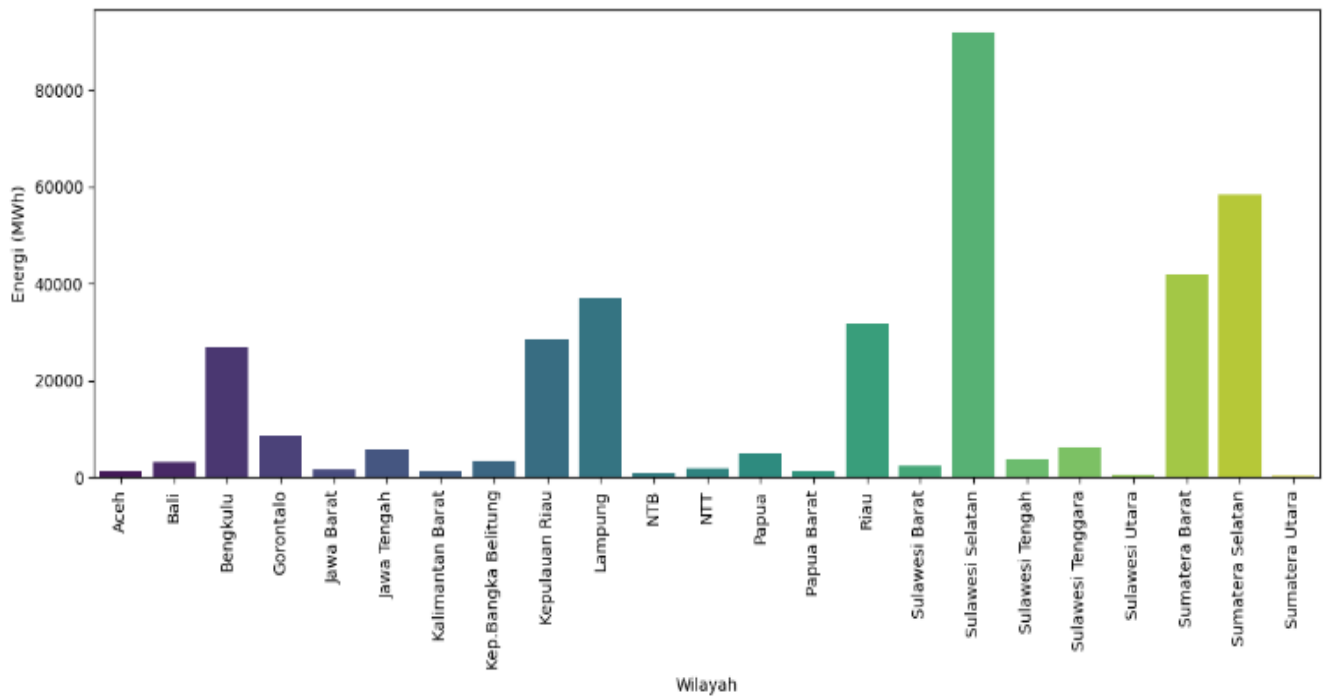


Figure 7. Total energy allocation

Table 1. Comparative table

Comparative Aspects	LINGO Results (1)	Python Results (2)	Analysis of Differences
Total Energy Distribution Cost	6.353439×10^{13}	5.6405×10^{13}	Python results show cost efficiency due to more optimal supply sources.
Energy Distribution Pattern	The distribution of supply is more random, with some regions supplied from distant power plants.	More centralized distribution, regions are supplied from the nearest power plant.	This difference indicates an improvement in the strategy for utilizing local power generation capacity.
Utilization of Power Plant Capacity	Not fully optimized for low-cost generators	Maximizing low-cost power generation	Direct effect on reducing total costs.
Relevance to the Target Budget	Exceeding the target	Closer to the target or below the target	The second scenario is more suitable for practical implementation.

3.4 Slack and dual price results

The analysis results on slack and dual price from capacity and demand constraints in the optimization model show the differing contributions of each generator and region to the objective function value. In the generator capacity constraints, it was found that most generators are not operating at their maximum operational limits, as indicated by positive slack values and a dual price of zero. This indicates that the actual generation capacity is still below the allowed limit, so these constraints do not directly affect the total system cost value as can be seen in Appendix.

It can be explained that several power plants have zero slack and negative dual prices, indicating that these power plants are operating at maximum capacity and are binding. For example, Geothermal Power Plant 2, Hydroelectric Power Plants 2 to 6, Hydroelectric Power Plant 12, Solar Power Plants 1 to 4, as well as Mini Hydro Power Plants 3 and 4 show significant negative dual price values, indicating that increasing the capacity of these plants could potentially reduce the total system costs substantially. In contrast, other plants like Bio Power Plant and Mini Hydro Power Plant mostly still have quite a large reserve capacity, as indicated by high positive slack. In the section of demand, all regions show a slack value of zero or close to zero with a positive dual price, which means that the entire energy demand in each region is optimally met

and is active in the model (binding constraints). Regions with high dual prices such as South Sulawesi (Rp322,254,700/MWh), South Sumatra (Rp198,737,350/MWh), and Hydro Power Plant 12 in South Sulawesi (Rp315,690,250/MWh) indicate that increasing the supply to these regions can significantly reduce the total system costs. This finding emphasizes that the capacity expansion strategy for power generation needs to be directed towards plants and regions with high dual prices in order to achieve optimal cost efficiency.

The results of the implementation carried out using LINGO for the main calculations and Python for validating the results to ensure the accuracy and efficiency of the algorithm can be seen in Table 1.

4. CONCLUSIONS

Based on the results of the MIP modeling obtained, this model is capable of determining the allocation of energy distribution from various types of power plants to each region in Indonesia. Python results show cost efficiency due to more optimal supply sources. The difference in results shows an improvement in the strategy for utilizing local power generation capacity. This optimization demonstrates the great potential of using MIP as a supporting tool for national energy

policies, especially in designing efficient and equitable energy distribution. Through proper allocation management, the government can reduce disparities in energy access between regions, maximize the utilization of existing power generation resources, and minimize overall operational costs. The strategic implications of this result are that the MIP approach can serve as a foundation for long-term energy planning, assist in the transition towards renewable energy systems, and strengthen regional energy equity in Indonesia. Although the results obtained are already optimal within the framework of the model used, there are several limitations that need to be acknowledged. The current model is deterministic with the assumption of static energy demand, thus not accounting for the dynamics of demand fluctuations, supply uncertainties, or system disturbances. Furthermore, energy delivery is assumed to occur without real-time constraints, and does not accommodate energy storage technologies such as batteries or pumped storage that could enhance the system's flexibility. For future research, it is recommended that the model be expanded to consider uncertainty modeling (for example, through a stochastic optimization approach), dynamic demand and supply scenarios, as well as the integration of energy storage technology. The use of this approach will not only improve the robustness of optimization results but also bring the model closer to real operational conditions in the field. Furthermore, the addition of real-time dispatch aspects and multi-objective optimization considering carbon emissions will make a significant contribution towards achieving Indonesia's decarbonization targets.

ACKNOWLEDGMENT

Researchers express their gratitude to the Ministry of Higher Education, Science, and Technology of the Republic of Indonesia and the leadership of the Muhammad Nasir Foundation AMIK and STIKOM Tunas Bangsa as well as the Rector of Bumigiora Mataram University.

REFERENCES

- [1] Tian, J., Yu, L., Xue, R., Zhuang, S., Shan, Y. (2022). Global low-carbon energy transition in the post-COVID-19 era. *Applied Energy*, 307: 118205. <https://doi.org/10.1016/j.apenergy.2021.118205>
- [2] Mauludin, M.S., Khairudin, M., Asnawi, R., Prasetyo, S.D., Trisnoaji, Y., Rizkita, M.A., Arifin, Z., Rosli, M.A.M. (2025). Sustainable energy solutions in urban management: Carbon emissions and economic assessment of photovoltaic systems at electric vehicle stations in hybrid buildings. *Challenges in Sustainability*, 13(3): 377-397. <https://doi.org/10.56578/cis130305>
- [3] Erdiwansyah, Gani, A., Mamat, R., Bahagia, Nizar, M., Yana, S., Mat Yasin, M.H., Muhibbuddin, Rosdi, S.M. (2024). Prospects for renewable energy sources from biomass waste in Indonesia. *Case Studies in Chemical and Environmental Engineering*, 10: 100880. <https://doi.org/10.1016/j.cscee.2024.100880>
- [4] Kementerian ESDM. (2022). *Handbook of Energy & Economic Statistics of Indonesia*. Jakarta: Kementerian ESDM Indonesia. <https://web.pln.co.id/statics/uploads/2024/08/Statistik-PLN-2023-29.7.24-1.pdf>
- [5] Langer, J., Quist, J., Blok, K. (2021). Review of renewable energy potentials in Indonesia and their contribution to a 100% renewable electricity system. *Energies*, 14(21): 7033. <https://doi.org/10.3390/en14217033>
- [6] Husain, Triwijoyo, B.K., Taufik, M., Mawengkang, H. (2024). Optimization model of multi criteria decision analysis for smart and sustainable sport tourism planning development problem. *Mathematical Modelling of Engineering Problems*, 11(11): 3035-3046. <https://doi.org/10.18280/mmep.111116>
- [7] Albogamy, F.R., Paracha, M.Y.I., Hafeez, G., Khan, I., et al. (2022). Real-time scheduling for optimal energy optimization in smart grid integrated with renewable energy sources. *IEEE Access*, 10: 35498-35520. <https://doi.org/10.1109/ACCESS.2022.3161845>
- [8] Ammari, C., Belatrache, D., Touhami, B., Makhouloufi, S. (2022). Sizing, optimization, control and energy management of hybrid renewable energy system—A review. *Energy and Built Environment*, 3(4): 399-411. <https://doi.org/10.1016/j.enbenv.2021.04.002>
- [9] Olabi, A.G., Abdelkareem, M.A. (2022). Renewable energy and climate change. *Renewable and Sustainable Energy Reviews*, 158: 112111. <https://doi.org/10.1016/j.rser.2022.112111>
- [10] Riedmüller, S., Buchholz, A., Zittel, J. (2025). Enhancing multi-energy modeling: The role of mixed-integer optimization decisions. *arXiv*. <https://doi.org/10.48550/arXiv.2505.14492>
- [11] Klemm, C., Vennemann, P. (2021). Modeling and optimization of multi-energy systems in mixed-use districts: A review of existing methods and approaches. *Renewable and Sustainable Energy Reviews*, 135: 110206. <https://doi.org/10.1016/j.rser.2020.110206>
- [12] MacRae, C., Ozlen, M., Ernst, A. (2014). Transmission expansion planning considering energy storage. In 2014 IEEE International Autumn Meeting on Power, Electronics and Computing (ROPEC), Ixtapa, Mexico, pp. 1-5. <https://doi.org/10.1109/ROPEC.2014.7036327>
- [13] Rabe, M., Widera, K., Vasa, L. (2022). Application of the linear programming method in the construction of a mathematical model of optimization distributed energy. *Energies*, 15(5): 1872. <https://doi.org/10.3390/en15051872>
- [14] Guo, M., Wang, W., Chen, R. (2022). Renewable hybrid energy system scheduling strategy considering demand response. *Sustainable Energy Technologies and Assessments*, 52: 102247. <https://doi.org/10.1016/j.seta.2022.102247>
- [15] Apribowo, C.H.B., Hadi, S.P., Wijaya, F.D., Setyonegoro, M.I.B. (2024). Optimal sizing and placement of battery energy storage system for maximum variable renewable energy penetration considering demand response flexibility: A case in Lombok power system, Indonesia. *Energy Conversion and Management*, 23: 100620. <https://doi.org/10.1016/j.ecmx.2024.100620>
- [16] Purba, E.N.N., Irianto, C.G. (2025). Regulatory analysis of renewable energy use strategies in Indonesia: A review. *G-Tech: Jurnal Teknologi Terapan*, 9(1): 109-120. <https://doi.org/10.70609/gtech.v9i1.5910>
- [17] Arinkoola, A.O., Onuh, H.M., Ogbe, D.O. (2016). Quantifying uncertainty in infill well placement using numerical simulation and experimental design: Case

- study. *Journal of Petroleum Exploration and Production Technology*, 6(2): 201-215. <https://doi.org/10.1007/s13202-015-0180-z>
- [18] Jankovic, A., Chaudhary, G., Goia, F. (2021). Designing the design of experiments (DOE)-An investigation on the influence of different factorial designs on the characterization of complex systems. *Energy and Buildings*, 250: 111298. <https://doi.org/10.1016/j.enbuild.2021.111298>
- [19] Potrč, S., Čuček, L., Martin, M., Kravanja, Z. (2021). Sustainable renewable energy supply networks optimization-The gradual transition to a renewable energy system within the European Union by 2050. *Renewable and Sustainable Energy Reviews*, 146: 111186. <https://doi.org/10.1016/j.rser.2021.111186>
- [20] Wang, D., Wu, H., Zheng, W., Zhao, Y., Tian, G., Wang, W., Chen, D. (2025). A mixed-integer linear programming model for addressing efficient flexible flow shop scheduling problem with automatic guided vehicles consideration. *Applied Sciences*, 15(6): 3133. <https://doi.org/10.3390/app15063133>
- [21] Safii, M., Efendi, S., Zarlis, M., Mawengkang, H. (2022). Intelligent evacuation model in disaster mitigation. *Bulletin of Electrical Engineering and Informatics*, 11(4): 2204-2214. <https://doi.org/10.11591/eei.v11i4.3805>
- [22] Gómez Sánchez, M., Masip Macía, Y., Fernández Gil, A., Castro, C., González, S., Pedrera Yanes, J. (2020). A mathematical model for the optimization of renewable energy systems. *Mathematics*, 9(1): 39. <https://doi.org/10.3390/math9010039>
- [23] Kim, J.K., Park, H., Kim, S., Lee, J., Song, Y., Yi, S.C. (2023). Optimization models for the cost-effective design and operation of renewable-integrated energy systems. *Renewable and Sustainable Energy Reviews*, 183: 113429. <https://doi.org/10.1016/j.rser.2023.113429>
- [24] PT PLN (Persero). (2024). Statistik PLN 2023. <https://web.pln.co.id/statics/uploads/2024/08/Statistik-PLN-2023-29.7.24-1.pdf>
- [25] Qin, J., Jiang, R., Mo, H., Dong, D. (2024). A data-driven mixed integer programming approach for joint chance-constrained optimal power flow under uncertainty. *International Journal of Machine Learning and Cybernetics*, 16(2): 1111-1127. <https://doi.org/10.1007/s13042-024-02325-x>
- [26] Das, T., Goerlandt, F., Pelot, R. (2024). A mixed integer programming approach to improve oil spill response resource allocation in the Canadian arctic. *Multimodal Transportation*, 3(1): 100110. <https://doi.org/10.1016/j.multra.2023.100110>
- [27] Akulker, H., Aydin, E. (2023). Optimal design and operation of a multi-energy microgrid using mixed-integer nonlinear programming: Impact of carbon cap and trade system and taxing on equipment selections. *Applied Energy*, 330: 120313. <https://doi.org/10.1016/j.apenergy.2022.120313>
- [28] Agajie, E.F., Agajie, T.F., Amoussou, I., Fopah-Lele, A., et al. (2024). Optimization of off-grid hybrid renewable energy systems for cost-effective and reliable power supply in Gaita Selassie Ethiopia. *Scientific Reports*, 14(1): 10929. <https://doi.org/10.1038/s41598-024-61783-z>
- [29] Ereiz, S., Duvnjak, I., Jiménez-Alonso, J.F. (2022). Review of finite element model updating methods for structural applications. *Structures*, 41: 684-723. <https://doi.org/10.1016/j.istruc.2022.05.041>
- [30] Swaminathan, S., Tantri, B.R. (2024). Confusion matrix-based performance evaluation metrics. *African Journal of Biomedical Research*, 27(4S): 4023-4031. <https://doi.org/10.53555/AJBR.v27i4S.4345>

APPENDIX

A. Distribution of slack and dual price

Kapasitas_PLTP_1	Slack: 3483.42	Dual Price: 0.00
Kapasitas_PLTP_2	Slack: 0.00	Dual Price: -103320410.00
Kapasitas_PLTP_3	Slack: 3835.96	Dual Price: 0.00
Kapasitas_PLTP_4	Slack: 9237.28	Dual Price: 0.00
Kapasitas_PLTA_1	Slack: 8237.68	Dual Price: 0.00
Kapasitas_PLTA_2	Slack: -0.00	Dual Price: -134087650.00
Kapasitas_PLTA_3	Slack: -0.00	Dual Price: -67341890.00
Kapasitas_PLTA_4	Slack: -0.00	Dual Price: -176665960.00
Kapasitas_PLTA_5	Slack: -0.00	Dual Price: -83081204.00
Kapasitas_PLTA_6	Slack: -0.00	Dual Price: -142688520.00
Kapasitas_PLTA_7	Slack: 110.85	Dual Price: 0.00
Kapasitas_PLTA_8	Slack: 110.85	Dual Price: 0.00
Kapasitas_PLTA_9	Slack: 3333.71	Dual Price: 0.00
Kapasitas_PLTA_10	Slack: 5550.07	Dual Price: 0.00
Kapasitas_PLTA_11	Slack: 110.85	Dual Price: 0.00
Kapasitas_PLTA_12	Slack: -0.00	Dual Price: -315690250.00
Kapasitas_PLTA_13	Slack: 110.85	Dual Price: 0.00
Kapasitas_PLTS_1	Slack: -0.00	Dual Price: -74510535.00
Kapasitas_PLTS_2	Slack: -0.00	Dual Price: -5247837.30
Kapasitas_PLTS_3	Slack: -0.00	Dual Price: -193305730.00
Kapasitas_PLTS_4	Slack: -0.00	Dual Price: -942763.89
Kapasitas_PLTS_5	Slack: 10444.44	Dual Price: 0.00
Kapasitas_PLTS_6	Slack: 110.85	Dual Price: 0.00
Kapasitas_PLTM/H_1	Slack: 110.85	Dual Price: 0.00
Kapasitas_PLTM/H_2	Slack: 110.85	Dual Price: 0.00
Kapasitas_PLTM/H_3	Slack: -0.00	Dual Price: -132298840.00
Kapasitas_PLTM/H_4	Slack: -0.00	Dual Price: -89512170.00
Kapasitas_PLTM/H_5	Slack: 878.19	Dual Price: 0.00
Kapasitas_PLTM/H_6	Slack: 110.85	Dual Price: 0.00
Kapasitas_PLTM/H_7	Slack: 1367.51	Dual Price: 0.00
Kapasitas_PLTM/H_8	Slack: 110.85	Dual Price: 0.00
Kapasitas_PLTM/H_9	Slack: 110.85	Dual Price: 0.00
Kapasitas_PLTM/H_10	Slack: 110.85	Dual Price: 0.00
Kapasitas_PLTM/H_11	Slack: 110.85	Dual Price: 0.00
Kapasitas_PLTB_1	Slack: 110.85	Dual Price: 0.00
Kapasitas_PLTB_2	Slack: 1967.05	Dual Price: 0.00
Kapasitas_PLTBio_1	Slack: 2812.77	Dual Price: 0.00
Kapasitas_PLTBio_2	Slack: 9941.62	Dual Price: 0.00
Kapasitas_PLTBio_3	Slack: 4576.49	Dual Price: 0.00
Kapasitas_PLTBio_4	Slack: 2231.35	Dual Price: 0.00
Kapasitas_PLTBio_5	Slack: 8042.51	Dual Price: 0.00
Kapasitas_PLTBio_6	Slack: 3165.83	Dual Price: 0.00
Kapasitas_PLTBio_7	Slack: 13789.90	Dual Price: 0.00
Kapasitas_PLTBio_8	Slack: 110.85	Dual Price: 0.00
Permintaan_Sumatera_Utara	Slack: -0.00	Dual Price: 1787037.10
Permintaan_Lampung	Slack: -0.00	Dual Price: 146517780.00
Permintaan_Jawa_Barat	Slack: -0.00	Dual Price: 6123733.30
Permintaan_NTT	Slack: -0.00	Dual Price: 7972597.50
Permintaan_Sumatera_Barat	Slack: -0.00	Dual Price: 138008620.00
Permintaan_Riau	Slack: -0.00	Dual Price: 102125650.00
Permintaan_Sumatera_Selatan	Slack: -0.00	Dual Price: 198737350.00
Permintaan_Bengkulu	Slack: 0.00	Dual Price: 91848108.00
Permintaan_Jawa_Tengah	Slack: -0.00	Dual Price: 18781829.00
Permintaan_Kalimantan_Barat	Slack: -0.00	Dual Price: 5311009.10
Permintaan_Sulawesi_Utara	Slack: -0.00	Dual Price: 2597563.60
Permintaan_Sulawesi_Tengah	Slack: -0.00	Dual Price: 12585599.00
Permintaan_Sulawesi_Selatan	Slack: -0.00	Dual Price: 322254700.00
Permintaan_Papua	Slack: 0.00	Dual Price: 19679005.00
Permintaan_Kepulauan_Riau	Slack: -0.00	Dual Price: 89622878.00
Permintaan_Kep.Bangka_Belitung	Slack: -0.00	Dual Price: 12445099.00
Permintaan_NTB	Slack: -0.00	Dual Price: 3316404.20
Permintaan_Gorontalo	Slack: 0.00	Dual Price: 28934114.00
Permintaan_Aceh	Slack: -0.00	Dual Price: 4795430.70
Permintaan_Sulawesi_Tenggara	Slack: -0.00	Dual Price: 25347411.00
Permintaan_Sulawesi_Barat	Slack: -0.00	Dual Price: 7831382.60
Permintaan_Papua_Barat	Slack: -0.00	Dual Price: 4835454.50
Permintaan_Bali	Slack: -0.00	Dual Price: 13623316.00