Senior Research

Topic: Optimizing energy mixed used in electricity generation with Variable Renewable Energy (VRE) integration: a case study from Germany

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Introduction

The energy mix in electricity generation refers to the combination of various energy sources used to produce electricity within a region or country. Achieving an optimal energy mix is vital for supporting economic development, as electricity underpins modern production processes and serves as a foundation for daily life. Furthermore, a well-balanced energy mix is crucial for national energy security by reducing dependence on specific energy sources, lowering supply risks, and mitigating blackouts. The determination of an optimal energy mix of a country depends on multiple factors, including the current stage of technological advancements, economic conditions, geographical characteristics, natural resource endowments, and environmental objectives. Therefore, it is in our best interest to fully utilize the natural resource endowments to minimize the cost of electricity production. At the same time, environmental goals have become increasingly significant, as concerns over climate change, air pollution, and exploitation of natural resources have placed greater pressure on the energy sector to reduce greenhouse gas emissions and transition toward cleaner sources of electricity. Pursuing the lowest-cost energy mix does not always align with environmental objectives, as fossil fuel-based technologies are often more economical but contribute more to environmental damage. Furthermore, variable renewable energy sources such as photovoltaic systems and wind turbines also pose significant challenges for grid integration. By using the data from Germany's electrical system, this study seeks to address the following research question: What is the optimal electricity generation mix that minimizes both production costs and CO_2 emissions while adhering to technical and operational constraints?

The structure of this paper is organized as follows. The first section presents a literature review, which is divided into four parts: electricity generation cost structures, CO_2 emissions associated with different technologies, technical and feasibility constraints affecting system design, and multi-objective optimization algorithms used in energy mix optimization problems. The second section outlines the methodology, detailing the system configuration and the optimization techniques used to identify the optimal generation mix. The third section presents the results of optimization, highlighting the trade-offs between cost and emissions. Finally, the fourth section provides a discussion of the findings, with particular emphasis on their implications and adaptability within the context of Thailand's energy sector.

1. Literature Review

The determination of energy mix in electricity generation is a critical challenge in energy planning, as policymakers seek to keep balances between the economic, environmental, social, and technical feasibility goals. Multi-objective optimization (MOO) methods have been widely applied to address this challenge by presenting conflicts and tradeoffs between contradicting objectives. This review explores the key objectives used in electricity generation planning literature and multi-objective optimization methods.

Metrics used for cost of electricity generation

Cost optimization is a fundamental objective in energy mix planning, as it directly influences the economic feasibility of electricity generation and the affordability of power for consumers. The Levelized Cost of Electricity (LCOE) is a commonly used indicator that measures the average cost to produce one unit of electricity (Euro/kWh). The methodology involves calculating the present value of capital investment, fuel costs, and operation and maintenance (O&M) expenses over the expected lifetime of the power plant (IRENA, 2013; Ramirez-Meyers et al., 2021; Short, Packey, & Holt, 1995). While LCOE is a comprehensive tool that facilitates cross-comparison between different electricity generation technologies, it fails to capture key economic and operational differences between dispatchable and intermittent generation sources. As LCOE treats all electricity from all sources as homogenous products, the metric ignores the variation in cost due to the disparities of generation profile between dispatchable (e.g., natural gas, coal, and nuclear) and intermittent (e.g., wind and solar) technologies (Joskow, 2011). To overcome the shortcomings, system LCOE has been introduced as an alternative metric. The system LCOE is defined as the sum of LCOE and the integration cost, an additional expense incurred when incorporating wind and solar (Grubb, 1991; Sims et al., 2011). The integration cost can be categorized into three primary components: balancing costs, grid infrastructure costs, and adequacy costs. Balancing costs refer to the expenses incurred to maintain intraday stability of power supply due to the variability of renewable energy (Hirth, Ueckerdt and Edenhofer, 2015; Holttinen et al., 2012; IEA, 2011). Grid costs cover the transmission and distribution investment to accommodate when variable renewable energy (VRE) supply is geographically dispersed from load centers (ENTSO-E, 2018; IEA, 2011). Adequacy costs refer to expenses associated with ensuring sufficient generation capacity to meet peak electricity demand (Holttinen et al., 2011;

IEA, 2011; IEA, 2017). Ueckerdt et al. (2013) propose a methodology to calculate integration costs by using benchmark technology. The concept is that a benchmark technology would generate the same amount of electricity renewable technologies could generate without the challenges of variability and uncertainty, thereby avoiding any integration costs. By comparing the system costs with and without VRE, it becomes possible to isolate and quantify the additional expenses specifically caused by integrating VRE into the power system.

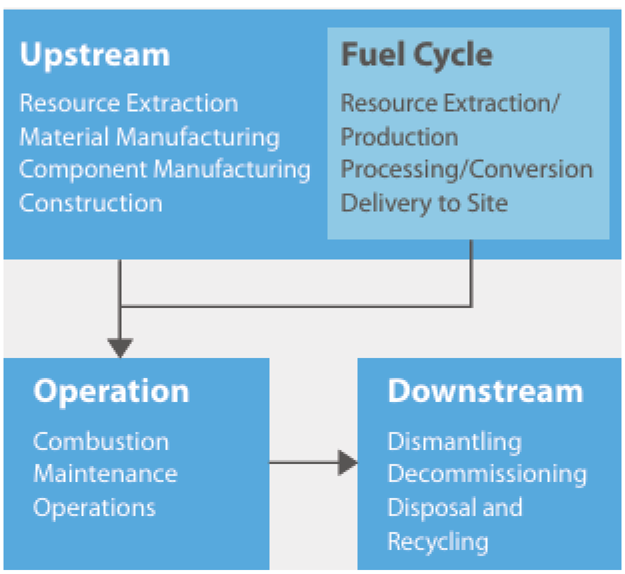
Table 1. Metrics for cost objectives

Metric	Formula	Variables	Description
LCOE	$LCOE = \frac{\sum(C_t + O_t + F_t)/(1+r)^t}{\sum E_t/(1+r)^t}$	- C_t = Capital cost in year t - O_t = Operation & maintenance cost in year t - F_t = Fuel cost in year t - E_t = Electricity generated in year t - r = Discount rate - t = Year of analysis	LCOE measures the cost per unit of electricity generated over a power plant's lifetime.
System LCOE	$sLCOE = LCOE + C_{int}$ Where $C_{int} = (C_{resid} - C_{BM,resid})$ $C_{int} = C_{resid} - \frac{E_{resid}}{E_{total}} C_{total}(0)$	- C_{resid} = Cost of the residual system - $C_{BM,resid}$ = Cost of residual system of benchmark technology - E_{resid} = Electricity generated from the residual system - E_{total} = total Electricity generated - $C_{tot}(0)$ = Cost of total generation in case of no renewable energy	System LCOE extends LCOE framework by incorporating additional system integration costs, such as grid expansion, balancing, and adequacy costs.

Metrics used for environmental goals

Net emission minimization is another crucial goal alongside cost minimization. Thailand's Power Development Plan (PDP 2018 Revision 1) outlines the country's commitment to achieve carbon neutrality by 2050 and net-zero greenhouse gas emissions by 2065. This paper will primarily focus on CO_2 emissions as a representative metric for environmental damage. Sathaye et al. (2011) detailed the methodology for calculating life-cycle greenhouse gas (GHG) emissions using a life-cycle assessment (LCA) approach. Emissions across all phases of energy production, including fuel extraction, processing, transportation, plant operation, and decommissioning, are evaluated into CO_2 emissions per unit of electricity generation (see Figure 1). Life-cycle greenhouse gas (GHG) emissions refer to the total emissions produced throughout the entire lifespan of an energy generation system (Thurber & Verheijen, 2022; UNECE, 2022). This method expresses emissions in tons of CO_2 per megawatt-hour (tCO_2/MWh), enabling a direct comparison between different technologies. The share of renewable energy is frequently used as a key decision-making criterion in multi-objective optimization problems (Abokersh, Cabeza, & Tulus, 2019; Atabaki & Aryanpur, 2018; Fischer, Elfgren, & Toffolo, 2020).

Figure 1. Generalized life cycle stages for energy technologies



Source: Satheye et al. (2011)

Table 2. Metrics for environmental objectives

Metric	Formula	Variables	Description
Total Emissions (TE)	$TE = \sum (EI_i \times E_i)$	- EI_i = CO_2 emission per unit of generation of technology i (tCO_2/MWh) - E_i = Electricity generated from technology i	Measures the overall greenhouse gas (GHG) emissions from all energy sources in the system.
Renewable Energy Share (RES%)	$RES\% = \frac{E_{renewable}}{E_{total}} \times 100$	- $E_{renewable}$ = Electricity generated from renewable sources (MWh) - E_{total} = Total electricity generated (MWh)	Represents the percentage of total energy consumption derived from renewable sources.

Feasibility and operational constraint in electricity generation

The feasibility of the electrical grid system must also be considered to ensure that the model reflects the actual operation and can consistently meet demand in real time. Ignoring feasibility constraints may distort the optimal solution sets by favoring generation mixes that appear cost-effective and low emission on paper but fail to meet essential operational requirements, thereby undermining the validity of the study's findings.

Grid frequency is the rate, measured in hertz (Hz), at which the alternating current in a power system changes direction each second. In European countries and Thailand, the standard grid frequency is maintained at 50 hertz, with a frequency deadband allowing small deviations to ensure system stability. As most power plants in large electrical systems use synchronous generators, the rotational speed of the generators is directly linked to grid frequency. Hence, frequency deviation can imply an imbalance between electricity demand and supply. A drop in frequency occurs when electricity demand exceeds generation, causing generators to slow down due to increasing resistance. Conversely, when electricity generation exceeds demand, the reduced load resistance causes generators to accelerate, leading to a rise in grid frequency.

The method of maintaining grid frequency is typically classified into two control strategies: isochronous control mode and droop governor control mode. Isochronous control mode will provide electricity at a constant frequency regardless of the load changes by adjusting the fuel input according to the load demand. However, isochronous control mode is only practical in an isolated system, where only one generator is responsible for supplying the entire system. Having multiple generators in isochronous control mode operating in a large, interconnected grid system can result in a conflict between each generator, as each generator attempts to correct frequency deviations independently, potentially resulting in instability and oscillations in power output. Therefore, the droop governor control mode is utilized in large, interconnected power systems. For this method, each generator is assigned a predefined droop response function, which determines how its power output will change in response to deviations from the nominal grid frequency. With multiple generators having their own response functions, the system can achieve decentralized frequency regulation, where load is shared proportionally among generators. Although the droop control method allows for grid frequency deviations, proportional load sharing among generators helps ensure that these deviations remain within the acceptable deadband.

The load categorization method offers a simplified yet effective framework for addressing the challenge of grid frequency balancing. Load categorization is used by an operator to accurately predict the changes in electricity demand according to the pattern and period of time, enabling them to dispatch appropriate generation technologies that can effectively respond to sudden or significant load variations (Ueckerdt et al., 2013; Ueckerdt & Kempener, 2015). Traditionally, electrical load can be classified into three categories:

- Base load represents the minimum, continuous level of electricity demand that must be met throughout the day. This category is supplied by high efficiency but low flexibility technologies such as coal, nuclear, and hydro power plants.
- Intermediate load corresponds to the moderate variation of demand that lies between base and peak load. Intermediate load is often served by moderately flexible technologies such as combined cycle gas turbine (CCGT), and biomass power plants.
- Peak load covers the most drastic changes in demand over short periods of time. Addressing this type of load requires generation technologies with high ramping capability to respond quickly to sudden fluctuations in demand. It is typically met by open-cycle gas turbines

(OCGT), hydro power plants, diesel generators, and battery energy storage systems (BESS).

One widely used approach in the literature is the application of clustering algorithms, utilizing K-means clustering to classify electricity demand into categories such as base, intermediate, and peak load (Jangid, Mathruria, and Gupta, 2021; Rajabi et al., 2020; Salimi-beni, Farrokhzad, Fotuhi-Firuzabad, & Alemohammad, 2006). Using centroid to identify cluster means and applying them as cutoffs offers an easy and intuitive calculation method for classifying segments of the aggregate load duration curve. However, since the centroids are derived from the aggregate load pattern, rendering them inherently static and unable to capture real-time load dynamics. The Gaussian mixture method and deep learning with load-shape preservation are used to cluster the hourly demand patterns within a day by capturing variability and overlapping load behaviors (Jangid, Mathruria, & Gupta, 2021; Kim et al., 2024; Rajabi et al., 2020). Fits the load data using multiple Gaussian distributions, each representing a distinct load with probabilistic boundaries. On the other hand, the deep learning with load-shape preservation framework employs deep neural networks to learn latent representations of load data while explicitly preserving the shape and dynamics of the original time series. However, these latter two frameworks do not quantify the contribution of each load type, as their primary contribution lies in load forecasting. Although this represents an important area in electrical engineering, it falls outside the scope of this paper. Time series forecasting models such as ARIMA and SARIMA can provide a method for categorizing load by identifying seasonal patterns and utilizing the trends to distinguish normal demand from drastic deviations in load behavior (Minaar, Van Zyl, & Hicks, 2023). Nevertheless, these time series methods are incompatible with residual load forecasting and categorization because the residual load's seasonal components also vary as the level of VRE integration differs. Due to these drawbacks, a new methodology will be introduced for load categorization that dynamically adjusts threshold levels.

Multi-objective optimization algorithms used in energy mix problems

A wide range of multi-objective optimization algorithms have been employed in the energy mix literature to address the trade-offs between multiple objectives. Among these, two prominent scalarization techniques found in the literature are the epsilon-constrained method and the weighted sum method. The epsilon-constraint method is used to solve multi-objective optimization problems by optimizing one of the objectives while treating others as constraints (Javadi et al., 2019; Jing et al., 2021; Louis et al., 2020; Murray et al., 2018; Si et al., 2019; Vergara-Zambrano et al., 2022; Zhang et al., 2020). The weighted sum method scalarizes a set of objectives into a single objective function by taking a linear combination of all objectives, each pre-multiplied by a predetermined weight that reflects the degree of emphasis placed on a particular goal (Gbadamosi and Nwulu, 2020; Groissböck and Pickl, 2016; Pratama et al., 2017; Purwanto et al., 2015). However, the weighted sum method struggles with non-convex Pareto fronts. There are two prominent metaheuristic algorithms frequently used in the literature to solve multi-objective energy system optimization problems: the Non-dominated Sorting Genetic Algorithm II (NSGA-II) and Particle Swarm Optimization (PSO). NSGA-II uses non-dominated sorting to classify solutions into different pareto fronts based on the dominance ranking (Deb et al., 2002; Li and Qiu, 2016; Prina et al., 2019; Uen et al., 2018; Zidan et al., 2013). The algorithm iteratively selects the most optimal solutions from the current population to generate new candidate solutions. Meanwhile, Particle Swarm Optimization (PSO) leverages collective information about the fitness of each candidate solution, updating each particle's trajectory by combining its own experience with that of the best-performing individuals in the swarm to explore new regions of the solution space (Abdoos and Ghazvini, 2018; Hatamkhani and Moridi, 2019; Kennedy & Eberhart, 1995; Yuan et al., 2021).

2. Methodology

This study utilizes hourly electricity load data for Germany in the year 2023, along with the cost and emission estimates associated with each generation technology to evaluate and optimize the electricity generation mix under multiple objectives. The simulation and optimization process is as follows:

1. Hourly electricity load data for Germany in the year 2023 from European Network of Transmission System Operators for Electricity (ENTSO-E) is used as the baseline for demand profile.
2. The generation from Photovoltaic (PV) system is simulated by using the PVlib python library by Holmgren, Hansen, and Mikofski (2018), which enables accurate modeling of PV output based on location-specific irradiance, temperature, and system configuration

parameters. In this study, the PV system is assumed to be installed in Munich, Germany, with corresponding irradiance data, which measures the amount of solar energy received per unit area (W/m^2), used to simulate hourly generation for the year 2023.

3. The generation from wind turbine is simulated by using the windpowerlib python library by Haas, et al. (2024). The models simulate wind power output based on meteorological conditions and turbine characteristics. In this study, the wind turbine is assumed to be installed in Wilhelmsfeld, Germany, and hourly weather data retrieved from the Meteostat database for wind speed, temperature, and air pressure.
4. Once the generation from renewable sources were simulated, residual load, which is the portion of demand that must be met by dispatchable generation, is calculated by subtracting VRE generation from hourly load data.
5. The residual load then is clustered into 3 different load categories: base, intermediate, and peak load. To address the limitations from the literature review, this study develops a new methodology to dynamically adjust the threshold of each load category. The baseload threshold is defined using a 48-hour rolling 1st quantile, capturing the minimum consistent demand level. The peak load threshold is determined by using a 12-hour bidirectional exponential moving average and a 24-hour rolling 9th quantile, identifying short-duration but high variations in load changes. The remaining load between these two thresholds is classified as intermediate load.
6. LCOE is calculated using the discounted cash flow method, which accounts for the capital expenditure (CAPEX), operational and maintenance (O&M) costs, fuel costs, efficiency, lifetime, and higher heating value (HHV), which reflects the energy conversion from heat to electricity. These characteristics are derived from a literature review and reflect technology-specific assumptions for the context of Germany.

generation type	CAPEX (EUR/kW)	O&M (% of CAPEX)	Fuel (EUR/kg)	lifetime	discount rate	Emission(tonCO2 /kWh)	Efficiency	HHV (kJ/kg)
PV	1235	2	0	25	0.05	3.40E-05	-	-
Wind	2000	3	0	25	0.05	1.20E-05	-	-
Coal	1500	5	0.0727	50	0.07	0.00085	0.46	25000
CCGT	1200	5	0.1668	35	0.07	0.00034	0.64	50000
Gas	700	5	0.1668	30	0.07	0.00052	0.3	50000

7. In this study, the NSGA-II is employed for multi-objective optimization. The algorithm defines total system cost and CO_2 emissions as objective functions, while treats the installed capacities of photovoltaic (PV) and wind generation as the decision variables. The algorithm evaluates each combination of PV and wind capacity across 400 populations over 100 generations, resulting in 40,000 evaluated combinations.

3. Results

To test for the validity of the results, convergence indicators are monitored through the epsilon indicator (eps) and the hypervolume indicator. The epsilon indicator measures the relative distance between the prior Pareto front and a new one. As shown in the log (Figure 2), the epsilon indicator consistently decreases and stabilizes at 0.0013 from generation 20 onward, signifying that the Pareto front converges. The hypervolume can be interpreted as a Riemann sum of the volumes between each point on the Pareto front and a predefined reference point in the objective space. Based on figure 3, the hypervolume stabilizes after the 20th generation, indicating that the solution set has converged and is no longer expanding in the objective space.

Figure 2. Optimization log

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==========================================================
n_gen  |  n_eval  | n_nds  |      eps       |  indicator
==========================================================
     1 |      400 |    141 |              - |            -
     2 |      800 |    204 |  0.0043976941 |        ideal
     3 |     1200 |    300 |  0.0071832546 |        ideal
     4 |     1600 |    400 |  0.0054078425 |        ideal
     5 |     2000 |    400 |  0.0006857713 |            f
     6 |     2400 |    400 |  0.0013128119 |            f
     7 |     2800 |    400 |  0.0017822170 |            f
     8 |     3200 |    400 |  0.0060883540 |        ideal
     9 |     3600 |    400 |  0.0004518385 |            f
    10 |     4000 |    400 |  0.0007092499 |            f
    11 |     4400 |    400 |  0.0009110868 |            f
    12 |     4800 |    400 |  0.0072392366 |        ideal
    13 |     5200 |    400 |  0.0004250005 |            f
    14 |     5600 |    400 |  0.0006208929 |            f
    15 |     6000 |    400 |  0.0008237177 |            f
    16 |     6400 |    400 |  0.0009322235 |            f
    17 |     6800 |    400 |  0.0010492657 |            f
    18 |     7200 |    400 |  0.0011169265 |            f
    19 |     7600 |    400 |  0.0011758532 |            f
    20 |     8000 |    400 |  0.0011966137 |            f
    21 |     8400 |    400 |  0.0012109280 |            f
    22 |     8800 |    400 |  0.0039460472 |        nadir
...
    97 |    38800 |    400 |  0.0013254081 |            f
    98 |    39200 |    400 |  0.0012896626 |            f
    99 |    39600 |    400 |  0.0012471093 |            f
   100 |    40000 |    400 |  0.0012623462 |            f
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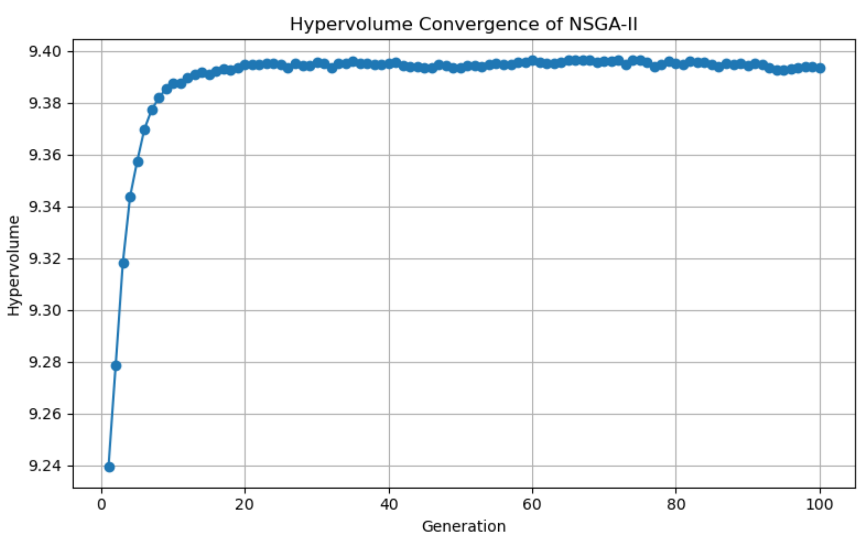
Figure 3. Hypervolume



After the algorithm is finished, the final Pareto front is obtained (Figure 4), representing the set of most efficient trade-off solutions in which cost, and emissions cannot be improved without causing a deterioration in the other. From the Pareto frontier, the cost-emission trade-off can be described as having a linear relationship. The Ordinary Least Squares (OLS) regression shows a statistically significant negative slope, with a coefficient of –0.0117, indicating that a reduction of 0.0117 tons of CO2 equivalent per megawatt-hour of electricity generation can be achieved by increasing the system cost by 1 Euro per megawatt-hour (Figure 5).

Figure 4. Final pareto-front

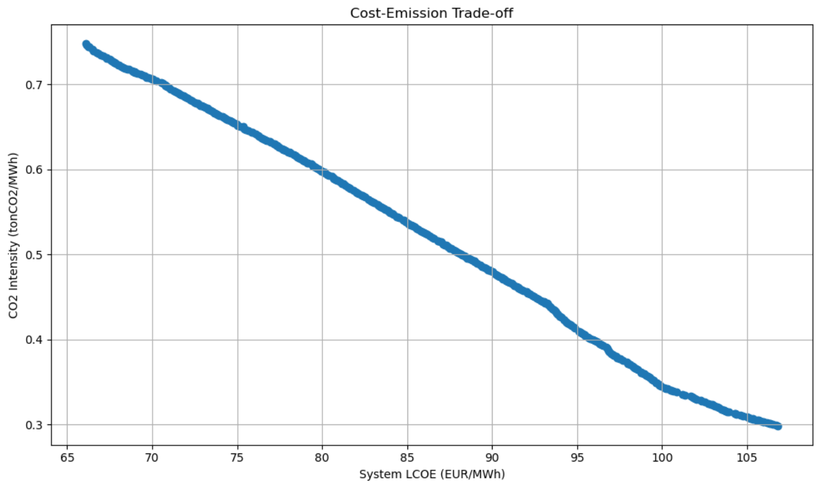


Figure 5. OLS regression results estimating the trade-off between cost and emissions along the pareto frontier

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                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.998
Model:                            OLS   Adj. R-squared:                  0.998
Method:                 Least Squares   F-statistic:                 1.685e+05
Date:                อ., 22 เม.ย. 2025   Prob (F-statistic):               0.00
Time:                        04:56:35   Log-Likelihood:                 1389.6
No. Observations:                 382   AIC:                            -2775.
Df Residuals:                     380   BIC:                            -2767.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          1.5252      0.002    620.199      0.000       1.520       1.530
x1            -0.0117   2.84e-05   -410.440      0.000      -0.012      -0.012
==============================================================================
Omnibus:                        6.146   Durbin-Watson:                   0.015
Prob(Omnibus):                  0.046   Jarque-Bera (JB):                6.288
Skew:                          -0.309   Prob(JB):                       0.0431
Kurtosis:                       2.890   Cond. No.                         652.
==============================================================================
```

To predict the energy mix, a polynomial regression model is adopted to the observations on the Pareto front in order to estimate the corresponding generation shares, emissions, and system cost for any given level of VRE integration along the trade-off curve. The selection of the most appropriate polynomial degree model for each technology was validated by the Bayesian Information Criterion (BIC). Figure 6 demonstrates the generation share of each technology within the Pareto front depending on the level of VRE integration in the system.

Figure 6. Polynomial Regression Fits for Generation Shares

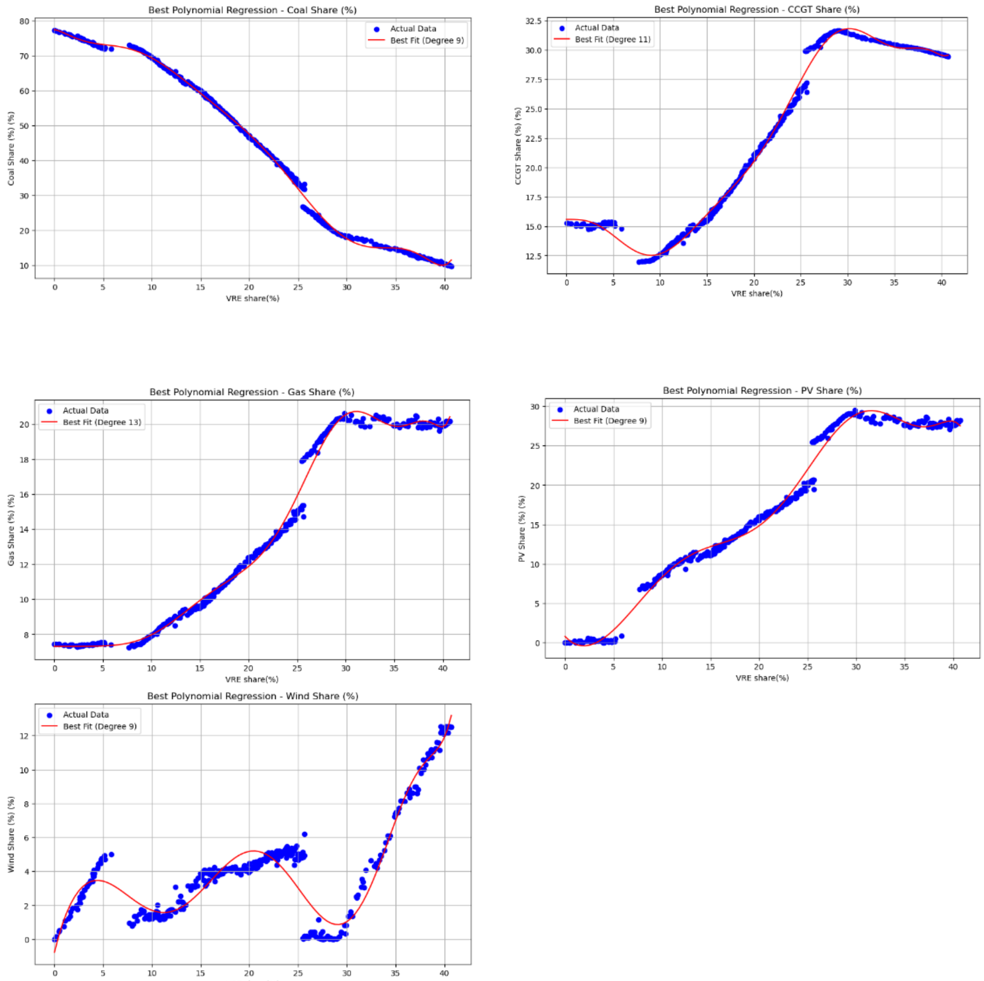
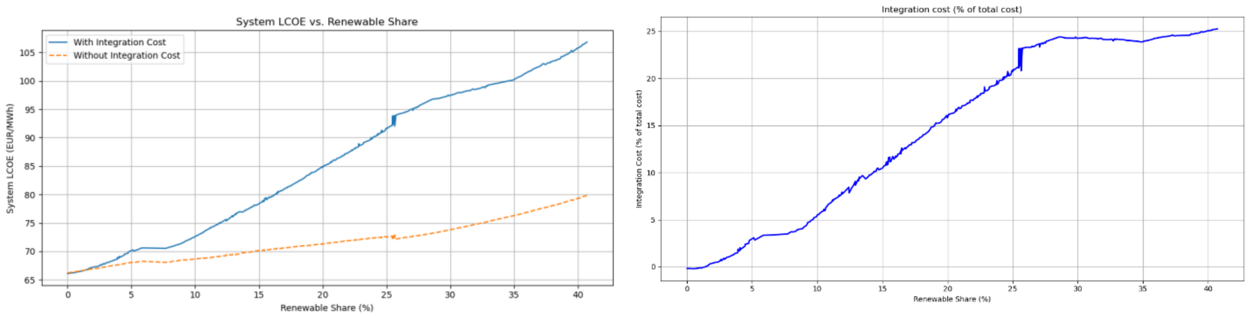


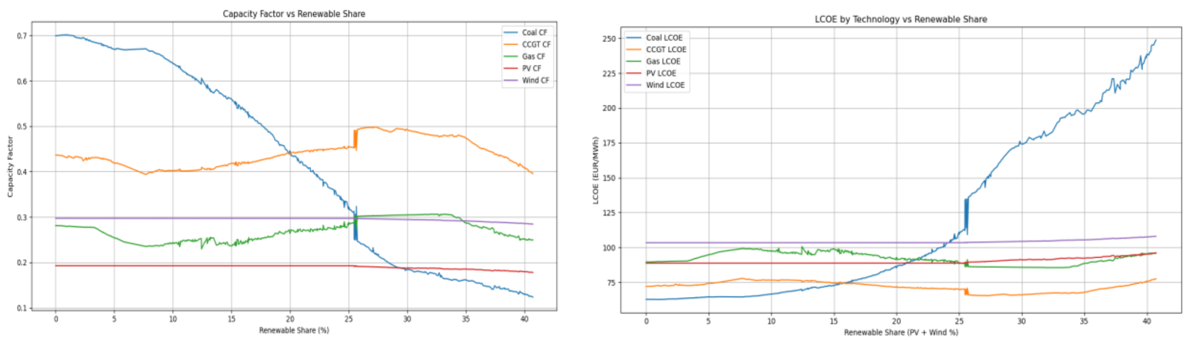
Figure 7 illustrates the significance of incorporating integration cost into the calculation of energy generation when there is an increasing share of renewable energy in the system. Without taking integration cost into consideration, the cost of electricity generation can be misleading and may result in distorted assessments of system affordability. According to figure 7, the integration cost can approach up upto 25 percent of the total system cost at 40 percent renewable energy integration. A significant increase in integration costs can be observed at 25 percent of VRE integration in the system due to VRE generation becoming extremely prominent during periods of resource availability but unable to supply during resource-scarce periods. As a result, the system must increasingly rely on flexible generation technologies to ensure reliability. Consequently, a decrease in coal share and an increase in CCGT and gas turbine share can be observed in figure 6.

Figure 7. Magnitude of integration cost depending on renewable energy share



Another important implication derived from this study is that the cost profile of each generation technology evolves in response to the increasing share of VRE in the system. Capacity factors, which are the ratio of actual output to potential output, are important to the economic viability of a generation technology. According to figure 8 on the left panel, the capacity factor, especially for less flexible generation types like coal generation, becomes significantly less economical as VRE share increases. This reduction occurs because coal-fired plants, which are designed for steady baseload operation, are increasingly displaced during periods of high solar and wind output, forcing them to operate below optimal load levels or remain idle for extended durations. Nevertheless, the cost of generation from CCGT and gas turbines, which are more flexible to load changes, is less impacted. This also implies that future energy policy should incorporate these dynamics into transitional mechanisms such as carbon taxation and carbon credit schemes, as the cost of certain technologies can increase significantly with higher VRE integration. By utilizing operational constraints, the cost of higher-emissions technologies can become less economical as their limited flexibility leads to reduced utilization under increasing shares of variable renewable energy.

Figure 8. Capacity Factors and LCOE across level of VRE integration



4. Discussions

Since this study uses data from Germany as a case study for energy mix optimization, certain adjustments are necessary to apply the methodology to the context of Thailand. The specification of each technology must be conducted in the context of Thailand, as differences in technological advancements, resource endowments, and infrastructure can influence the cost of that technology in a specific country. Moreover, calculating system costs by decomposing each component of the cost is highly encouraged rather than using fixed LCOE assumptions from external sources. As demonstrated by this study, LCOE is not a fixed metric; it is highly sensitive to variations in capacity factor, which can fluctuate significantly depending on system conditions, resource availability, and the level of renewable energy integration. Using a static cost structure will diminish the interpretation regarding the cost dynamic.

One important point to note is that while the Pareto front derived from this study identifies the optimal energy mixes that achieve the most efficient trade-offs between cost and emissions, it does not demonstrate a transitional pathway. A practical transitional plan needs to account for existing infrastructure, sunk costs, and the irreversibility of past capital investments. Based on this limitation, future studies are recommended to incorporate constraints regarding capital investments such that a sequence of investment and operational decisions will be internalized in the model.

5. Conclusion

This study developed an integrated framework to determine the optimal electricity generation mix that minimizes both cost and emissions under operational constraints, using the German power system as a case study. The new methodology for dynamic load categorization has also been introduced to overcome the limitations of the static load categorization method. Using the NSGA-II multi-objective optimization algorithm, the research identifies the Pareto-efficient front that highlights the best trade-offs between total system cost and CO_2 emissions. The results show that integration costs have a significant impact on overall generation costs, especially as the level of VRE penetration increases. The integration costs can account for up to 25 percent of total electricity generation costs at 40 percent VRE shares, highlighting the importance of incorporating these costs into the traditional LCOE metric.

The most efficient energy mix highlights a trade-off between cost and emissions that follows a nearly linear pattern, with approximately 6 kilograms of CO_2 per megawatt-hour reduced for every 1 Euro increase in system cost.

Key insights from this study include the observation that the cost of electricity generation cannot be calculated by using static LCOE because the cost of each technology dynamically shifts with changes in renewable penetration. Technologies with low operational flexibility, such as coal, become increasingly uneconomical due to declining capacity factors when displaced by solar and wind generation. In contrast, more flexible technologies like combined cycle gas turbines (CCGT) and open-cycle gas turbines (OCGT) could maintain their economic viability.

Furthermore, this study demonstrated the usefulness of calculating LCOE through decomposed cost components rather than applying constant LCOE assumptions. This approach captures the cost dynamics resulting from fluctuating utilization levels, providing a more accurate picture of electricity generation costs under different energy mixes.

In conclusion, this study contributes to the literature on energy mix optimization by incorporating integration costs and operational constraints. These findings can inform policymakers and energy planners in designing more robust, cost-effective, and environmentally aligned electricity systems.

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