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A system dynamics model for energy transition: Substituting fossil fuels with renewable energy

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ABSTRACT

This study develops a system dynamics model to examine Indonesia's transition from conventional energy to renewable energy. The risk of transition planning fails when the reciprocal relationship between market profitability and investor behavior is poorly considered. The model is built on Powersim Studio 10, representing conventional and renewable energy as stocks connected by bidirectional and interacting substitution flows. The probability of substitution is determined by the relative willingness to invest, which is influenced by a leveled energy and electricity purchase agreement. Although these parameters are hypothetical, they are based on relevant literature and developed in the context of Indonesian energy. The simulation results show that the transition follows three phases: initial acceleration, stabilization, and dynamic equilibrium. Sensitivity analysis showed that the elasticity of substitution alone did not determine the speed of the transition. The rapid shift only occurs when renewables become more economically attractive than conventional energy. High elasticity is not enough when fossil energy remains economically dominant. The model is intended to provide a conceptual framework for understanding how economic competitiveness, policy signals, and investor behavior together shape the dynamics of the energy transition. Its structure can help identify the policy conditions needed to strengthen the adoption of renewable energy.

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1. INTRODUCTION

The energy transition from fossil fuels to renewable energy has become crucial as communities are increasingly concerned about climate change, resource constraints on fossil fuels, and the need for sustainable development [1]. Although coal and natural gas reserves remain relatively large, the Indonesian government has set a national policy direction to increase the renewable energy mix by 23% by 2025 and 31% by 2050 [2]. However, the direction toward renewable energy faces multiple challenges, i.e, technology availability, energy generation costs, as measured by the Levelized Cost of Energy (LCOE), electricity purchase contracts under Power Purchase Agreements (PPAs), and price competitiveness. The main problem is the risk of policy failures and stagnant investments. At the project level, the economic attractiveness of renewable energy investments is also influenced by cost-of-energy measures and long-term financial indicators, including net present value, internal rate of return, benefit-cost ratio, and discounted payback period [3]. This transition could fail because the market system is too rigid or because the price of green energy is less competitive with massively subsidized fossil fuels. This is dangerous because it could threaten national energy stocks and undermine our commitment to tackling climate change. Addressing the transition challenge, previous studies have focused more on optimization modeling and spreadsheet-based static analysis to evaluate the energy mix [4]. However, this approach cannot capture the long-term dynamic and feedback behaviour of the system. Therefore, in this study, the system dynamic (SD) model was used, as it is known to evaluate long-term changes and implications for the system structure as a whole [5].

The complexity of the energy system requires an approach capable of capturing the interactions among multiple factors. SD is relevant to map nonlinear cause-and-effect relationships, causal feedback loops, and system delays [6]. In addition, SD allows researchers to trace causal mechanisms over time. SD has been widely used in studies of energy transitions across various countries, as it is effective in formulating the interaction among policy designs, technological changes, and market behaviour in the renewable energy system [7]. Similarly, a study demonstrates that system dynamics is valuable for examining long-term environmental consequences and supporting adaptive policy design in systems involving emissions, cleaner technologies, and regulatory interventions [8]. The study of energy diversification in Finland found that policy feedback can strengthen or even contain policy impacts [9]. Another study using SD on energy transition highlights the importance of a balance between the demand and supply sides in the sustainability of the energy system [10].

Previous studies on SD-based energy substitution still use a unidirectional approach. The energy transition is assumed to involve only a shift from fossil sources to renewable energy. These assumptions do not fully represent the dynamics of energy systems, which are generally reversible. This is due to changes in fuel prices, policies, and market conditions. Moreover, there are some forms of renewable energy that can be substituted with conventional energy. The model shows only one type of substitution direction without considering the backflow in the system when the economic competitiveness of fossil energy is improved [11] , [12]. This paper introduces an SD model to address these gaps. The offered model serves as a framework to ensure that policies are aligned with the behavior of its system. The model used in this study includes some main variables: Qconv (conventional energy production), Qren (renewable energy production), substitution factors, probability of substitution, and economic factors including LCOE, PPA, and Willingness to Invest (WTI). The proposed model in this study introduces a new perspective in the application of technical and behavioral methods in energy substitution. In this study, for instance, the price is not the only factor that determines the investment allocation; the expectations of the investors about the future profits also play an important role in this regard [13]. Another important gap lies in the treatment of the elasticity and probability parameters of substitution, which, in many studies, are still treated as exogenous and static. In fact, the flexibility of energy systems is greatly influenced by market sensitivity to changes in incentives and technological costs. In addition, it is important to assess the effects of policies on the sensitivity of market parameters and on the potential instability of the energy system [10] , [14].

This research aims to develop an SD model that captures the transition from fossil fuels to renewable energy sources, accounting for the interactions between economic factors and investment behavior. The performance and assessment of the proposed model are evaluated through three explicit indicators: (1) the substitution probability response curve, (2) the capacity stock trajectory of both energy regimes Qconv and Qren, and (3) the structural sensitivity towards changes in substitution elasticity (σ).The model developed results that the comparison between the WTI of renewable energy and conventional energy is the main determinant of the direction of substitution in a bidirectional and endogenous system [15]. Through simulations of various substitution elasticities, this study found that higher elasticity does not necessarily accelerate the energy transition; rather, it depends on the relative investment returns between technologies. These results confirm that the acceleration of the transition to a sustainable energy system is not only determined by the flexibility of market behavior, but also by the economic advantages of renewable energy, as reflected in the ratio of PPA [16]. This study treats substitution elasticity as a policy lever variable that can be adjusted to assess the level of system adaptivity to technology cost-reduction scenarios and policy changes. In addition, the probability of substitution is modeled endogenously using a logistic function based on the WTI ratio between conventional and renewable energy. Thus, this research fills a gap in the literature by presenting a dynamic, reversible, and adaptive model, which is more representative of the real behavior of the energy transition in Indonesia and expands the application of SD in the context of national energy policy [17].

2. MATERIALS AND METHODS

This study used the SD to model the dynamics of energy substitution from fossil fuels to new and renewable energy in Indonesia. This approach was selected due to its capability to represent complex cause-and-effect relationships, including feedback loops, delays, and path dependences inherent in the national energy system [18]. The main goal of the model is to quantitatively represent the process of two-way substitution between conventional and renewable energy, while integrating economic, policy, and behavioral aspects of investment within a single system framework. This study used Powersim Studio 10 software for the entire modeling, simulation, and visualization process. A comparable modeling procedure has been applied in previous research using Powersim Studio, in which a causal loop diagram was developed to represent feedback relationships, followed by stock-flow formulation, model validation, and scenario simulation [19]. The software supports preparing stock-and-flow diagrams, formulating mathematical equations, and testing policy scenarios [20]. System dynamics has also been applied to represent capacity-demand imbalances and evaluate the effects of alternative intervention scenarios on system performance over time [21]. This study is at the fundamental and exploratory phase; therefore, the data used is hypothetical but rational and highly relevant to Indonesia's energy system. The SD model is not intended to produce empirical predictions, but rather to understand the system's behaviour. The SD model consists of the structure and relationships of variables that produce certain dynamic patterns; therefore, the parameters and variables are logical and relevant to the literature and Indonesian energy system without necessarily matching actual data numerically.

2.1. Model Structure and Feedback Mechanism

The model developed in this article is divided into two sub-systems that interact with each other. The two sub-systems are conventional energy capacity and renewable energy. The two are interconnected through the flow from and to the stock in a reciprocal manner. Subsystems are also connected to economic incentives and market behavior in general. Figure 1 shows a stock and flow diagram of the energy transition framework.

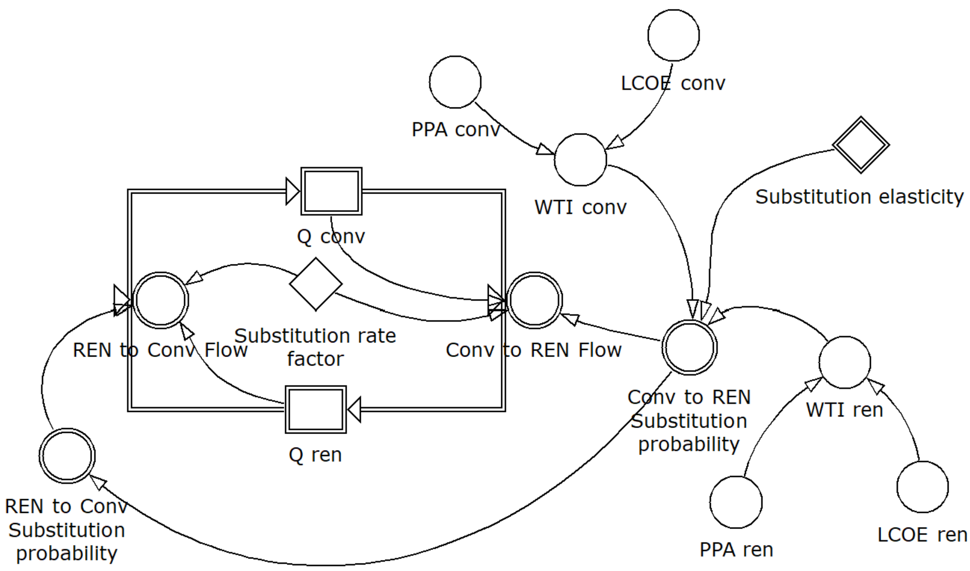


Figure 1. Base scenario simulation of energy substitution dynamics

The main driver of system behavior in this model is the WTI, which is an indicator that shows how much investors want to fund projects. WTI itself is determined by the Levelized Cost of Energy (LCOE) which represents the aspect of the cost of capital and the Power Purchase Agreement (PPA) which represents potential revenue. The dynamics that occur between variables are not linear, so they are formulated endogenously using the following logistic function.

$$Psub = 1/\left(1 + e^{(-\beta\cdot(WTIren/WTIconv-1))}\right) \tag{1}$$

where β represent the parameters of market sensitivity, WTI_{ren} is the willingness to invest in renewable energy, and WTI_{conv} is the willingness to invest in conventional energy.

The LCOE of conventional energy is assumed to be 1,000 (relative units), while the LCOE of renewable energy is 1,300; the conventional PPA is set at 1,200, and the renewable energy PPA is 1,500. All values are expressed in a relative scale to maintain model flexibility in testing scenarios. Other parameters, such as the substitution velocity factor (0.05) and the elasticity of substitution (0.8), were calibrated empirically based on Ref. [22] and adjusted to the Indonesian context. Eqs. 2 and 3 depict the formula of transition flow from conventional energy (*conv*) to renewable energy (*ren*), and vice versa.

$$\text{Flow}_{conv\rightarrow ren} = \text{Prob}_{conv\rightarrow \text{ren}} \times Q_{conv} \times \text{Substitution speed factor} \tag{2}$$

$$\text{Flow}_{\text{ren}\rightarrow conv} = \text{Prob}_{\text{ren}\rightarrow conv} \times Q_{ren} \times \text{Substitution speed factor} \tag{3}$$

Moreover, the probability is endogenously determined based on the ratio between the WTI of the energy sources through the logistic function, as illustrated in Eqs 4 and 5. The WTI is defined as the ratio between the revenue from the PPA and the LCOE. This enables the substitution opportunities to automatically respond to changes in the system's economic conditions through (Eq. 6).

$$\text{Prob}_{conv\rightarrow ren} = \frac{(\frac{WTI_{ren}}{WTI_{conv}})^{\sigma}}{(\frac{WTI_{ren}}{WTI_{conv}})^{\sigma} + 1} \tag{4}$$

$$\text{Prob}_{ren\rightarrow conv} = 1 - \text{Prob}_{conv\rightarrow ren} \tag{5}$$

$$WTI = \frac{PPA}{LCOE} \tag{6}$$

2.2. Parameters and Contextual Justification

The parameters used in the simulation were collected from various sources such as national energy planning documents, Institute reports and other relevant academic literature. Table 1 presents the main parameters of the model. The initial capacity is set to show that conventional energy dominates the system at the beginning of the simulation. Conventional energy capacity is set at 65.5 GW, while renewable energy capacity is set at 10.5 GW. The elasticity of substitution ranges from 0.5 to 1.2. A value close to 0.5 represents a relatively rigid substitution behavior. A value close to 1.2 indicates a more flexible substitution behavior. The average lifetime of an asset is set at 30 years. This assumption reflects the long operating life of coal and gas-based power plants. These parameters define the initial conditions and structural limits for performing scenario and sensitivity analysis.

Table 1. Simulation parameters and structural boundaries

Parameter	Initial	Unit	Primary Sources & Contextual Justification
Initial Conventional Capacity (Qconv)	65.5	GW	MEMR National Energy Balance [2]
Initial Renewable Capacity (Qren)	10.5	GW	MEMR National Energy Balance [2]
Substitution Elasticity (σ)	0.5 – 1.2	Dimensionless	Adjusted from global literature [15] , [23] with Indonesian contextual justification
Average Asset Lifetime	30	Years	Standard coal/gas power plant lifecycle

Based on these parameter settings, the simulation was carried out in three stages. First, the basic model was simulated under the initial parameters to validate the system's behavior in the absence of policy. Second, a simulation was carried out to validate the substitution elasticity scenario under three parameters: σ = 0.5 (conservative), σ = 0.8 (moderate), and σ = 1.2 (progressive). This represents the ability of the energy transition system to respond to changes in economic conditions. Third, a sensitivity analysis was carried out based on parameters such as LCOE, PPA, and substitution speed factors. This was done to validate the stability of the model. The simulation was carried out over 100 time units to observe changes in substitution models for conventional and renewable energy over time.

2.3. Model Validation and Behavioral Verification

This research is a conceptual/theoretical model. Thus, the validation process does not focus on statistical proof. The focus of validation is to ensure that the model is accurately defined. The first validation is structural verification: the equations in the model are checked to see if they are in accordance with the rules of system dynamics and the substitution model in macroeconomics. Next, the second validation is the extreme condition test: that is, looking at the conditions and reactions of the model under extreme conditions. An example is by setting the renewable PPA rate to zero. The model successfully shows a complete cessation of the growth of renewable energy and a complete switch to conventional energy. The final validation carried out on this model was a behavioral sensitivity analysis: it was done by changing the value of the substitution elasticity (σ) and the rate of LCOE decline simultaneously. With it, the model manages to identify the critical threshold at which the system shifts from a stopped investment flow to an accelerated energy transition. Third, validation shows that the model responds logically to structural changes. Thus, the validation process meets the criteria needed to assess the long-term energy policy scenario in Indonesia.

3. RESULTS

The main objective of the SD model is to represent, in a quantitative and systematic manner, the dynamics of the transition or substitution of energy demand from conventional to renewable energy sources. The model development process consists of identifying key variables, determining relationships, and formulating mathematical equations that describe the interactions and flows between the two main subsystems: conventional energy production (*Qconv*) and renewable energy production (*Qren*).

3.1. Basic Scenario Simulation

The SD model has two stock variables: energy produced from a conventional source (*Qconv*) and energy produced from a renewable source (*Qren*). The initial value of *Qconv* in the base scenario was set to 50,000 relative units, and the initial value of *Qren* was set to 10,000 relative units. This initial value represents that, in the base scenario, the energy system is dominated by fossil fuels. The two stock variables are linked by two opposing flows: a flow from conventional to renewable energy (*conv → ren*), and a flow from renewable to conventional energy (*ren → conv*).

The flow is defined as a function of the substitution probability, available energy capacity in the source stock, and a substitution velocity factor. The substitution probability in the SD model is endogenously defined using Equations 1-5 with respect to the relative WTI between renewable and conventional energy. The probabilities follow a logistic function bounded between 0 and 1, where an increase in the likelihood of shifting toward renewable energy automatically reduces the probability of reverting to fossil energy.

The interaction among the stock variable, the flow variable, and the auxiliary variable forms a causal loop that endogenously drives the system. Auxiliary variables such as LCOE and PPA influence WTI, which, in turn, determine substitution probabilities and the magnitudes of flows between stocks, Qconv, and *Qren*. When renewable energy becomes more attractive from an investment perspective, the flow from conventional to renewable energy will increase, resulting in reducing the stock of *Qconv* and increasing the stock of *Qren*. The transition subsequently feeds back into the system, taking relative competitiveness into account in the subsequent period, thereby developing an endogenous feedback cycle that governs long-term transition dynamics. The model, therefore, does not assume a linear or one-way transition but rather reversible and dynamic adjustment depending on the economic parameters.

Another key parameter in the SD model, i.e, the substitution velocity factor and elasticity parameter, was set at 0.05 and 0.8, respectively. Substitution velocity controls the speed of stock changes, while the elasticity parameter represents the system's sensitivity to changes in WTI. The developed SD model has a modular structure that integrates economic variables (LCOE and PPA), behavioral responses (WTI and substitution probability), and dynamic stock flows to provide a systemic and dynamic representation of energy substitution. The developed structure enables the exploration of policy scenarios and the understanding of the effects of market changes in the energy transition system.

3.2. Results of Elasticity Scenario Simulation

This model is simulated using three different substitution elasticity values, namely 0.5 (conservative/rigid), 0.8 (moderate), and 1.2 (progressive/flexible). The results of the simulation of these three scenarios can be seen in Table 2. It shows that a higher elasticity (σ = 1.2) appears to be able to accelerate the initial phase of the transition. This elasticity also allows Qren to reach 23,790 units in the 20th unit of time. In contrast, in a rigid scenario (σ = 0.5), Qren only reached 20,880 units in the same period. However, at the 100th unit of time, the variation in total capacity in all three scenarios narrows to less than 1.8% (a difference of only 540 units relative between σ = 0.5 and σ = 1.2).

Table 2. Comparison of numerical capacities across different elasticity scenarios

Time Units	Rigid Scenario (σ = 0.5) Qconv / Qren	Moderate Scenario (σ = 0.8) Qconv / Qren	Flexible Scenarios (σ = 1.2) Qconv / Qren
0	50,000 / 10,000	50,000 / 10,000	50,000 / 10,000
20	39,120 / 20,880	37,560 / 22,440	36,210 / 23,790
40	34,150 / 25,850	32,840 / 27,160	31,450 / 28,550
60	32,010 / 27,990	31,210 / 28,790	30,880 / 29,120
100	30,950 / 29,050	30,550 / 29,450	30,410 / 29,590

4. DISCUSSION

4.1. Interpretation of Transition Phases and Feedback Loops

The SD model developed in this study shows that the substitution process between conventional and renewable energy occurs endogenously. This dynamic is driven by a causal feedback loop between two main subsystems: conventional energy stocks (*Qconv*) and renewable energy stocks (*Qren*). This model does not show a linear one. Energy transitions evolve through three distinct behavioral phases: the take-off phase (0–20 units of time), the stabilization phase (20–60 units of time), and the dynamic equilibrium phase (60–100 units of time). The simulation illustrates that the energy transition does not occur linearly but rather through three main phases: the take-off phase, the stabilization phase, and the dynamic equilibrium phase. These three phases produce an S-curved pattern commonly found in systems with limited growth. The curve shows a substitution that occurs quickly at first, then slows and eventually reaches a new equilibrium point.

As seen in Figure 2, in the initial phase of the simulation, renewable energy capacity increases rapidly as conventional energy capacity declines. This condition is triggered by a difference in the WTI between the two energy sources. When the electricity selling rate from renewable energy (PPA) increases, or the LCOE decreases, the WTI of renewable energy becomes greater than the WTI of conventional energy. This increase in investment attractiveness raises the probability of substituting conventional for renewable energy, thereby increasing the flow of energy from *Qconv* to *Qren*. As a result, fossil energy stocks are decreasing rapidly while renewable energy stocks are growing exponentially. This phase illustrates the prevalence of reinforcing feedback loops, whereby the higher the penetration of renewable energy sources, the more attractive their investment potential becomes, and vice versa. This situation illustrates the typical acceleration of substitution that takes place during the initial stages of the energy transition, where the positive effects of incentives and policies start to materialize.

The second phase of the system is the stable transition phase, in which the system reduces the acceleration of substitution. The difference in capacity between conventional and renewable energy sources is gradually decreasing. This system is very close to the point of temporary equilibrium, where the rate of conv to ren is almost equal to the rate of rate of ren to conv. Such condition describes the internal dynamics of the system that occur when obstacles begin to affect the system. Constraints such as infrastructure capacity, investment readiness, and technological efficiency. This phase can also be seen as the process of stabilizing the energy market from an economic perspective. Capacity growth in renewable energy sources is constrained by the system structure and investors' conservative attitude to market risk rather than driven by acceleration factors.

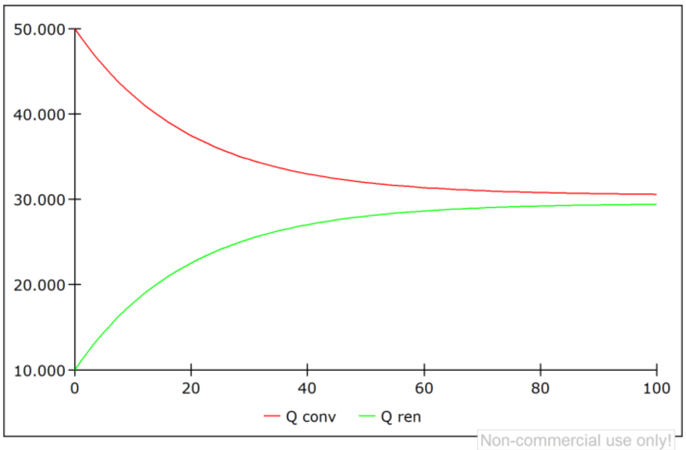


Figure 2. Simulated transition trajectories of conventional and renewable energy capacities under the base scenario.

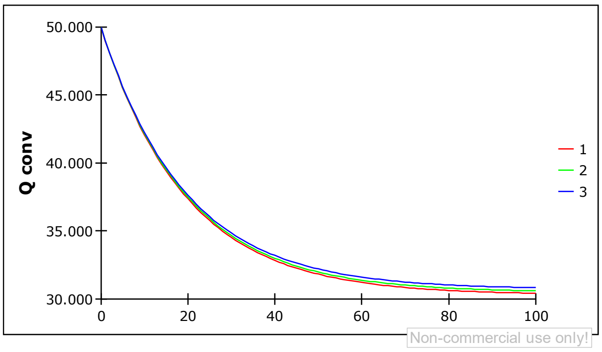
The last phase is the dynamic equilibrium phase. This phase is characterized by the convergence of conventional and renewable energy capacities at a similar rate. There has been no further change in the level of energy stocks, as the two substitution flow lines have reached equilibrium. The system is in a state of equilibrium. Fossil energy and renewables coexist in the national energy mix in such a way that neither completely dominates the other. This means that the policy is effective in balancing energy needs with sustainability demands. The results of this simulation are consistent with the energy transition behavior in several countries. Penetration of renewable energy was rapid at first, but was later followed by a stabilization phase due to the limitations of infrastructure and the carrying capacity of the system. During the take-off phase, the exponential growth of renewable energy was strongly driven by the reinforcement of the feedback loop (R1). This is because the relatively early WTI prefers green technology due to policy incentives or competitive PPA levels. However, when the capacity gap narrows during the stabilization phase, the counterweight feedback loop (B1) begins to dominate and then this slows the acceleration. This structural shift reflects the existence of market saturation constraints and the adoption of renewable energy networks in national grid integration [10], [11].

4.2. The Role of Market Elasticity and Reversibility

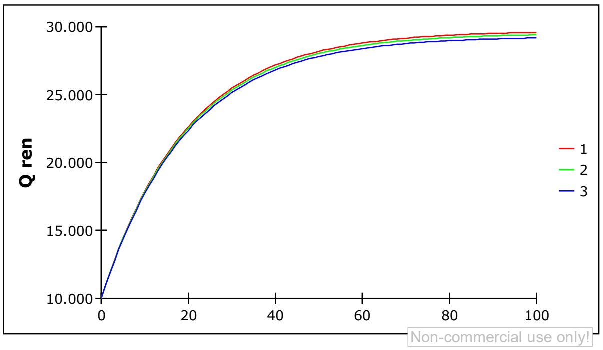
The structure of this model also shows two main feedback mechanisms operating simultaneously. The first mechanism is a positive feedback loop or booster loop that speeds up the energy substitution process. Along with the *increase in Qren*, the attractiveness of investment in the renewable energy sector has also increased along with the increase in renewable energy WTI, thus strengthening the substitution from conventional energy to renewable energy. The second mechanism is the negative feedback loop, or counterbalancing loop, which stabilizes the system as the difference in capacity between energy sources decreases. If *Qconv* decreases too quickly, then the probability of substitution also decreases automatically due to the reduced conventional energy stock. The combined effect of these two loops describes the behavior of the self-regulating nature of the system.

The contribution of this SD model lies in its ability to depict the reversibility of energy systems. In practice, it is often noted that the energy transition process does not always indicate a one-way path from fossil fuels to renewable energy. Sometimes, some of the renewable energy capacity is also replaced by fossil fuels due to price fluctuations, subsidies, or geopolitical factors. This model captures the phenomenon through a backflow (ren-to-conv *flow),* which allows energy to change direction in response to changes in the WTI ratio between the two energy sources. When the cost of generating renewable energy increases or the price of fossil fuels decreases, the possibility of replacing renewable energy increases, so that part of the demand returns to fossil fuels. This two-way mechanism makes the model more realistic than the one-way substitution model widely used in the previous literature [12], [24].

The system sensitivity test to market behavior was carried out by conducting simulations using three parameter values: 0.5 (conservative), 0.8 (moderate), and 1.2 (progressive). These three scenarios represent the level of flexibility of the system to economic, technological, and policy changes. The simulation results in Figure 3 show that all three scenarios produce similar system behavior. Convergence towards equilibrium occurs within the system but has differences in terms of speed and time to reach a stable point. Low elasticity ($\sigma = 0.5$) describes a rigid system with slow transitions, while moderate elasticity ($\sigma = 0.8$) is more realistic for developing countries such as Indonesia.



(a) Dynamics of conventional energy demand (Q conv) under three elasticity scenarios (σ = 0.5, 0.8, and 1.2).



(b) Dynamics of renewable energy demand (Q ren) under the same scenarios

Figure 3. Elasticity scenario simulation results

On the other hand, the scenario with high elasticity ($\sigma = 1.2$) shows a highly responsive system to changes in economic competitiveness, but it can lead to a slowdown if the relative gains from renewable energy have not exceeded those from conventional energy. As an empirical basis for determining elasticity values, references to international studies examining energy substitution in the electricity and industrial sectors are used. The range of elasticity values obtained from the literature is shown in Table 3.

Table 3. Range of elasticity values

Source	Research Context / Location	Methods/Models	Value σ	Main Description
[25]	Global studies 1800–2012	Long-term macroeconomic models	≈ 4.33	Demonstrate a high long-term substitution elasticity between fossil and renewable energy, which signifies the flexibility of the global energy system.
[26]	Transition to carbon neutrality in China	Computable General Equilibrium (CGE) model — electrical and non-electrical substitution	0.8 – 1.2	Moderate substitution; Elasticity increases in line with decarbonization policies.
[27]	Intermittent vs fossil renewable energy	Dynamic models with non-constant elasticity	0.5 – 1.5 (non-constant)	The elasticity of substitution is not constant; it increases with declines in renewable energy prices and greater supply stability.
[23]	OECD and non-OECD countries	Macro analysis of clean–dirty energy substitution	0.3 – 0.8	Low elasticity; limitations to clean energy substitution for fossil fuels, especially in developing countries.

Source	Research Context / Location	Methods/Models	Value σ	Main Description
[28]	Global studies 1800–2012	Long-term macroeconomic models	0.3 – 0.6	Low elasticity; Energy systems have historically struggled to adapt to price changes due to technological and infrastructure limitations.

One of the interesting results that can be derived from this simulation is that the elasticity of substitution is not always an accelerator but is dependent on the economic conditions of the system. If the ratio of renewable to conventional WTI is less than 1, the rise in elasticity will slow down the substitution process, as the system will become more responsive to the gap between investment and benefits. However, if the policies are successful in reducing the cost of renewable energy or raising the PPA so that the ratio of renewable energy to conventional WTI is greater than the conventional WTI, then the rise in elasticity will accelerate the process and enhance the growth effect of renewable energy. These results support the argument that the solution to the long-term stability of the energy system is embedded in how market flexibility can be combined with existing policy frameworks [29]. Hence, elasticity should be considered an adaptive policy variable that will allow the system to react proportionally to changes in the economic environment.

The results also indicate that the differences in elasticity cause only a minor variation in the final yield of the system, with only a one to two percent difference in total capacity at the end of the simulation period. However, this difference is behaviorally relevant because it influences the rate at which the system achieves balance. The system with high elasticity achieves equilibrium at a slower rate because of its sensitivity to WTI inequality, while the system with moderate elasticity stabilizes faster without extreme fluctuations in the transition curve. The above condition suggests that the impact of the substitution velocity factor (0.05) and the initial WTI ratio is more important in defining the shape of the transition curve than the difference in elasticity itself. In other words, the acceleration of energy substitution in the system can be achieved more effectively through structural policies that reduce the cost of renewable energy sources rather than increasing flexibility in the markets [30], [31].

The simulation results show that the success of the energy transition depends on the balance between economic competitiveness and the adaptive behavior of the system. Systems will naturally move towards greater renewable energy penetration when renewable energy cost gains have been achieved through LCOE reductions [32]. However, if there is still a large economic gap between renewables and fossil fuels, changes in behavioral parameters will not significantly accelerate the transition. This condition shows that economic factors remain the main drivers. Meanwhile, behavioral variables serve as reinforcers that determine the sensitivity of the system to changes in market and policy incentives [33].

The model in this study provides an overview of the behavior of adaptive energy systems. Substitution occurs gradually towards a stable equilibrium. The model also emphasizes the importance of understanding the energy transition as an adaptive, nonlinear, and dynamic process. The interaction between economic variables (PPA, LCOE, WTI) and behavioral factors (elasticity, probability of substitution) results in a transition pattern consistent with the empirical patterns observed in developing countries. The model shows that the energy transition is very dynamic and can move forward or backward. This happens because the system depends on changing economic conditions and policymaking.

4.3. Limitation and policy applicability

This model serves as a conceptual framework that uses many assumptions. Its quality relies heavily on verified and validated parameters rather than empirical historical data. Therefore, all policy interpretations must be applied with caution. There are four main limitations in this study, which directly affect how the application of this model for when will be used to support policy in the real world. First, this model uses a renewable energy mix in aggregate. This causes the model to be unable to distinguish between intermittent sources such as solar and wind and baseload sources such as geothermal and hydro. Meanwhile, high elasticity applied to intermittent sources can lead to severe system instability. This behavior is not currently captured by this model. Second, the model uses static economic parameters. An example is the assumption of LCOE and PPA parameters that ignore market volatility. In practice, investment behavior is very dynamic and sensitive to changes such as fuel prices and inflation. Third, this model excludes institutional barriers. This limitation is important because the development of low-carbon technology ecosystems also depends on technological infrastructure, financial support, regulatory responsibility, stakeholder partnerships, and institutional readiness [34]. Things like social opposition, delayed land acquisition, and institutional bureaucracy are not included in the model. As a result, the simulation presents more optimistic results than what should have happened contextually in Indonesia. Fourth, this model does not have variables that represent the technology learning curve. As such, the model cannot simulate the reduction in endogenous technology costs that occur over time. This approach may underestimate the acceleration of renewable energy driven by natural markets in the long run. In addition, this model is not a point prediction. Thus, Indonesian policymakers should not use this model at all to estimate the right capacity. Instead, the model should be used as a tool to support strategic decisions. Policy interventions should prioritize structural cost reductions to establish favorable WTI ratios. This can be achieved through mechanisms that are currently popular such as feed-in tariffs or carbon taxes.

5. CONCLUSION

The present research has been carried out to construct a model of conventional and renewable energy substitution dynamics. The researcher researched the Indonesian shift from fossil fuels to renewable energy. The simulation confirms that the energy transfer is non-linear and follows an S-curve. The process is characterised by three different behavioural phases: initial acceleration, stabilisation and dynamic equilibrium. High substitution elasticity does not accelerate the energy transition in Indonesia. The effect is particularly sensitive to investors' WTI in the renewable energy sector. A quick shift occurs only when renewables become more economically appealing than traditional fossil fuels.

The results also suggest structural constraints in the system. This model assumes the overall renewable energy mix. Also, economic characteristics are static and do not take institutional impediments into account. This restricts the model to be able to produce accurate quantitative predictions (point predictions). Therefore, results may only be regarded as structural behavioural tendencies under particular assumptions. Policy proposals should consider these Limitations. Policy makers can design a competitive renewable tariff framework without actually implementing it in a real system.

Future research could be carried out to fill this gap. First, researchers can go into the renewable sector to get more granular with certain technologies. This allows the model to reproduce the intermittency of solar and wind generation. Secondly, future models need to consider the dynamics of the learning curve. This addition will mimic declines in the costs of endogenous technologies over time. Third, the researcher has to incorporate institutional limits. This includes tracking social opposition and land acquisition delays, for example. Such developments will provide sharper analytical insights for national energy transition planning.

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DECLARATION OF AI-TOOL USAGE

During the writing and editing of this publication, the authors employed ChatGPT, developed by OpenAI, as an interactive conversation and brainstorming tool. The tool was used to facilitate conceptual alternatives discovery, model assumptions and structure discussion, simulation results interpretation, language modification and consistency checking . The system dynamics model, equations, parameter settings and simulations were created and implemented by the authors using Powersim Studio . All ideas and AI-assisted outputs were rigorously evaluated and independently confirmed and updated by the authors . The authors made all final methodological, analytical, and interpretive decisions and take full responsibility for the accuracy, originality, and integrity of the manuscript.