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Optimising Energy Transitions: Assessing Renewable Energy Integrations with Grid Limitations

Xin Hui Cheng[a], Dhana Raj Markandu[b], Bing Shen How[a], Viknesh Andiappan[a,*]

[a] Research Centre for Sustainable Technologies, Faculty of Engineering, Computing and Science, Swinburne University of Technology Sarawak, Jalan Simpang Tiga, 93350 Kuching, Sarawak, Malaysia
[b] Institute of Strategic and International Studies Malaysia, Persiaran Sultan Salahuddin, 50480 Kuala Lumpur, Wilayah Persekutuan Kuala Lumpur, Malaysia
vmurugappan@swinburne.edu.my

Achieving high shares of renewable energy requires not only policy ambition but also adequate grid infrastructure to support the intermittency of variable renewable energy generation. This study presents a multiperiod, multi-node energy planning model to develop data-driven energy transition strategies by examining how varying levels of grid readiness influence the installed capacity mix of the energy system and its implications on the total operational cost required. Applied to a Malaysian case study, this paper evaluates the influence on long-term investment decisions under two scenarios (1) with grid enhancement (grid-enhanced case) and (2) without grid enhancement (grid-constrained case). Results show that without grid enhancement, the national grid will constrain solar capacity expansion between 2046 and 2050. As a result, in the absence of timely grid enhancement, the system will rely more heavily on natural gas, resulting in 1.98 $MtCO_2$ higher emissions and approximately USD 35 B higher operational costs required over 25-year period. These findings underscore the importance of aligning infrastructure investments with renewable energy goals to support a sustainable energy transition.

1. Introduction

As the world strives to transition to cleaner and more sustainable energy sources, renewable energy has emerged as a pivotal strategy for meeting global carbon emissions targets. However, large-scale integration of intermittent renewable energy sources, especially solar and wind, requires greater system flexibility to maintain a constant balance between energy supply and demand. To tackle this issue, numerous energy system models have been introduced to capture the intermittency of variable renewable energy in energy planning. For instance, Gils et al. (2017) introduced the Renewable Energy Mix (REMix) energy system model to assess the capacity expansion and hourly dispatch at different levels of variable renewable energy (vRE) penetration. In the year after, Breyer et al. (2018) developed a multiperiod energy system known as the LUT Energy System Transition model. This model was designed to simulate a global energy transition pathway to achieve 100 % renewables in the energy mix by 2050 at an hourly resolution. Furthermore, Zhao and You (2020) developed a multi-scale bottom-up optimisation framework that utilised machine learning-assisted clustering techniques for the carbon-neutral transition planning of electric power sector. It optimised yearly capacity planning and hourly systems operations simultaneously, addressing the power generation intermittency issue. These studies utilised an hourly temporal resolution to capture short-term events such as rapid changes in load or generation to optimise and enhance system resilience and reliability.

While short-term models are effective in capturing real-time operational constraints, they typically lack the capability to guide long-term infrastructure and investment decisions. Long-term energy system models become critical as these models focus on assessing investment decisions and technology transition over multiple decades to generate optimal deployment and retirement strategies for long-term energy planning. For example, the Open Source energy Modelling SYStem (OSeMOSYS) is a widely used energy supply optimisation model designed for long-term integrated assessment and energy planning (Howells et al., 2011). It was recently applied to Vietnam's power sector to determine the least-cost capacity expansion pathway from 2020 to 2050 (Tan et

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al., 2024). The study explored six different scenarios and incorporated seasonal and daily load profiles to account for variation in energy demand and supply. MARKet Allocation (MARKAL) model is another widely adopted long-term energy system model that was developed in the late 1970s and used for capacity expansion planning and least-cost decarbonisation analysis (Fishbone et al., 1983).

However, many long-term energy planning models tend to overlook the structural limitations of the electricity grid, particularly its ability to accommodate the rising shares of variable renewable energy. This presents a disconnection between the long-term models that are investment-focused and the short-term models that reflect operational realities of renewable energy integration. As highlighted by Fernandez et al. (2024) in a recent study, to accommodate the rising shares of variable renewable energy, strengthening power grid infrastructures and incorporating energy storage systems are necessary to overcome existing technical and structural limitations. Without these investments, achieving high renewable energy uptake becomes challenging, necessitating a different energy system configuration and generation mix that may compromise emissions reduction goals. Therefore, evaluating the return on value (e.g., potential cost savings, emissions reductions, long-term benefits of greater system flexibility) of such investments is essential to inform strategic investment decisions.

Therefore, this study aims to address the gap by developing a multiperiod, multi-node optimisation model for macro-scale energy planning. The developed model is applied to a Malaysian case study to identify the least-cost energy transition pathways under two scenarios: (1) with grid enhancement (grid-enhanced case) and (2) without grid enhancement (grid-constrained case), where renewable energy penetration is constrained. By comparing these scenarios, this study aims to provide insights into how delayed or inadequate grid investments can potentially hinder renewable energy uptake, escalate system costs, or increase carbon emissions. These findings will then help in providing practical recommendations for developing a robust energy transition strategy under varying grid penetration limits, providing insights into (i) optimal energy system configuration, (ii) time value benefits attributed to grid enhancement, and (iii) resulting carbon emissions intensity of the optimal energy systems. In the next section, the research methodology is demonstrated.

2. Methodology

This paper presents a novel multiperiod multi-node energy system optimisation model to recommend least-cost capacity expansion of electricity generation facilities and their retirement strategy. The energy system model was developed based on the principles of the bottom-up modelling approach. The model equations were formulated based on the Resource-Task Network approach (Pantelides, 1994), which illustrates the conversion and transportation of resources within the system. Figure 1 shows the generic network superstructures for (a) resource conversion and (b) resource transportation.

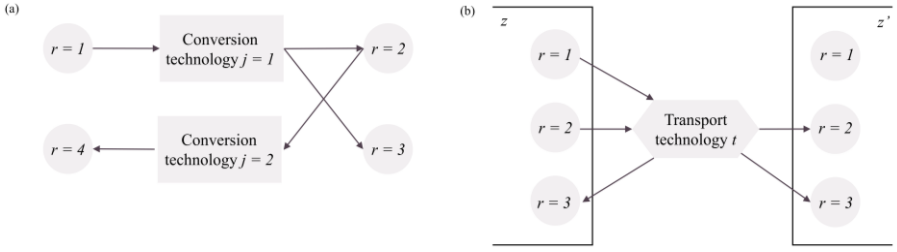

Figure 1: Generic network superstructure developed for (a) resource conversion and (b) resource transportation

Eq(1) computes the mass balance of all resources *r* in each period *y*.

$$\sum_{j=1}^{\mathrm{J}} P_{r,j,z,y} + FT_{r,z,y} = \mathrm{D}_{r,z,y}^{\mathrm{Comp}} \qquad \forall r \forall z \forall y \tag{1}$$

The variable $P_{r,j,z,y}$ represents the net generation of resources *r* in zone *z* in each planning period *y* using conversion technology *j* while variable $FT_{r,z,y}$ denotes the net transfer of resources *r* into or out of zone *z*. Eq(1) is used to ensure that the demand of resource *r* in zone *z* at each planning period *y* is met by the summation of net resource generation in zone *z* and net resource transportation into zone *z*.

$$P_{r,j,z,y} = x_{j,z,y} \times \mathrm{cf}_j \times \phi_{r,j} \qquad \forall r \forall j \forall z \forall y \tag{2}$$

As presented in Eq(2), the variable $x_{j,z,y}$ represents the operational capacity of technology *j* while the parameter cf_j denotes the capacity factor of conversion technology *j*. Capacity factor is defined as the ratio of actual generation output to nominal output of a power generation facility based on its installed capacity. Then, parameter $\phi_{r,j}$ refers to the conversion factor of technology *j*, which is the net output of resources per unit

resource input. A positive value of variable $P_{r,j,z,y}$ indicates net generation while a negative value indicates net consumption of resources *r.*

The total number of technologies ($N^{\mathrm{C}}_{j,z,y}$) required is then determined based on the required operating capacity of each technology ($x_{j,z,y}$) defined in Eq(2). This was achieved by imposing a constraint to limit the operational capacity of each technology based on its minimum available capacity ($x_j^{\min}$) and maximum available capacity ($x_j^{\min}$) .

$$N^{\mathrm{C}}_{j,z,y} \times x_j^{\min} \le x_{j,z,y} \le N^{\mathrm{C}}_{j,z,y} \times x_j^{\max} \qquad \forall j \forall z \forall y \tag{3}$$

Following this, Eq(4) to Eq(5) calculate the balance of the total number of technologies installed across each period. Notably, the model presented in this paper uses the existing power generation facilities as the foundation for capacity expansion planning, ensuring that future investment decisions are built upon the current energy landscape. Hence, Eq(4) presents the total number of energy facilities available for operation in the initial period ($N^{\mathrm{C}}_{j,z,y=1}$). As shown, $N^{\mathrm{C}}_{j,z,y}$ is made up by the "existing facilities" ($\mathrm{NE}^{\mathrm{C}}_{j,z}$) and total "additional new investments" ($NI^{\mathrm{C}}_{j,z,y}$) that are expected to come online in the initial period. The total number of facilities from this period serves as the existing facility that will be carried forward to the next period ($N^{\mathrm{C}}_{j,z,y-1}$). The total number of facilities in the subsequent period ($N^{\mathrm{C}}_{j,z,y>1}$) is then calculated by summing the existing facilities from the former period ($N^{\mathrm{C}}_{j,z,y-1}$) and additional new investments ($NI^{\mathrm{C}}_{j,z,y}$), while subtracting the retirements of both existing ($NR^{\mathrm{C}}_{j,z,y}$) and additional new investments installed in the former periods ($NR^{\mathrm{CE}}_{j,z,y}$). The same modelling approach is applied for each subsequent period. It should be noted that the variable $NI^{\mathrm{C}}_{j,z,y}$, $N^{\mathrm{C}}_{j,z,y-1}$, $NR^{\mathrm{C}}_{j,z,y}$ and $NR^{\mathrm{CE}}_{j,z,y}$ are all modelled as integer variables.

$$N^{\mathrm{C}}_{j,z,y} = \mathrm{NE}^{\mathrm{C}}_{j,z} + NI^{\mathrm{C}}_{j,z,y} \qquad \forall j \forall z \forall y \epsilon \mathrm{Y}: y = 1 \tag{4}$$

$$N^{\mathrm{C}}_{j,z,y} = N^{\mathrm{C}}_{j,z,y-1} + NI^{\mathrm{C}}_{j,z,y} - NR^{\mathrm{C}}_{j,z,y} - \mathrm{NR}^{\mathrm{CE}}_{j,z,y} \qquad \forall j \forall z \forall y \tag{5}$$

In order to model the grid-constrained scenario, the total number of new technology investments can be limited by applying a constraint using the integer parameter, maximum allowable build rate ($\mathrm{BR}_{j,z,y}$).

$$NI^{\mathrm{C}}_{j,z,y} \le \mathrm{BR}_{j,z,y} \qquad \forall j \forall z \forall y \tag{6}$$

The maximum allowable build rate is a user-defined parameter that can be calculated based on the constraint of the study, which in this case is the maximum allowable capacity of each energy source in each planning period *y*. Eq(7) demonstrates the conversion of maximum allowable capacity to maximum allowable build rate.

$$\mathrm{BR}_{j,z,y} = \frac{\text{Maximum allowable capacity}_{j,z,y}}{\text{Ref unit}_j} \qquad \forall j \forall z \forall y \tag{7}$$

In this study, the parameter maximum allowable capacity refers to the upper limit of capacity that can be integrated into the energy system for each power generation technology. This value may either represent a technical constraint such as land availability or grid readiness, or a policy-driven target, such as the maximum allocated budget or targeted installed capacity. To incorporate this into the model, the maximum allowable capacity is divided by a reference unit size ($\mathrm{Ref\ Unit}_j$), which defines the standard capacity of the technology modelled. Following this, the equations were computed in a commercial optimisation software known as the Advanced Interactive Multidimensional Modeling System (AIMMS) with the objective of minimising total system cost as denoted in Eq(8).

$$minC^{\mathrm{Tot}} = \sum_{y=1}^{\mathrm{Y}} (FA^{\mathrm{C}}_y + Cost^{\mathrm{UR}}_y + VO^{\mathrm{C}}_y + VO^{\mathrm{T}}_y - Revenue_y) \tag{8}$$

The terms represented on the right-hand side are known as the total investment costs (FA^{C}_y), resources purchase cost ($Cost^{\mathrm{UR}}_y$), variable operational costs for operating the conversion technologies (VO^{C}_y) and transportation technologies (VO^{T}_y), as well as the total revenue generated from the sales of energy resources ($Revenue_y$).

3. Case Study

In this paper, the developed energy system optimisation model was applied to a Malaysian case study based in Peninsular Malaysia. In line with its international climate commitments, Malaysia has set an ambitious target to achieve net-zero emissions by 2050 (Economic Planning Unit, 2021). To support this long-term goal, the government launched the National Energy Transition Roadmap (NETR) in 2023, aiming to achieve a 70 %

renewable energy share target by 2050, driven predominantly by large-scale deployment of solar photovoltaic (PV). Nevertheless, given the intermittent nature of solar PV, a stable and resilient grid is essential. This creates a need for grid infrastructure upgrades when solar integration exceeds the current national grid penetration limit of 24 % (Energy Commission Malaysia, 2020).

According to NETR, Malaysia will require between MYR 1.2 T to MYR 1.3 T of investment by 2050 to meet its energy transition goals (Ministry of Economy, 2023). These investments have varying degrees of commercial viability, robust and differentiated policy support remains critical to mobilise financing, especially from private capital markets and public financial institutions. Given the uncertainty in securing these investments, there is a risk that large-scale solar deployment may become infeasible if the necessary funding for grid enhancement cannot be obtained. Therefore, this paper examines two infrastructure readiness scenarios: (1) with grid enhancement and (2) grid constrained, to analyse their impacts on total system costs and installed capacity mix between 2025 to 2050. By quantifying the cost implications under varying levels of grid readiness, the results offer a benchmark for assessing the cost-effectiveness and strategic value of grid upgrades. The results can also provide insights into how the energy system may need to adapt to meet future demand in the absence of grid enhancements. Together, these findings inform more strategic energy planning in supporting Malaysia's energy transition.

3.1 Scenario 1: With grid enhancement (grid-enhanced case)

This scenario assumes that targeted grid enhancements and supporting infrastructure are in place, allowing the system to accommodate higher shares of intermittent solar generation. Under this assumption, the model considers that the solar capacity targets outlined in the Malaysia's NETR are technically achievable. The maximum allowable solar capacity in this scenario is therefore computed based on the targeted solar capacity expansion stated in the NETR. Table 1 (left column) presents the annual targeted solar capacity that were computed as input parameters to the model.

Table 1: Maximum allowable solar capacity under the scenario (1) with grid enhancement (grid-enhanced case) and (2) without grid enhancement (grid-constrained case).

Year	Maximum allowable solar capacity (MW)	
	Scenario 1	Scenario 2
2026 – 2030	4,712.94	4,712.94
2031 – 2035	9,602.94	9,602.94
2036 – 2040	18,202.94	18,202.94
2041 – 2045	28,893.94	28,893.94
2046 - 2050	36,973.06	34,453.06

3.2 Scenario 2: Without grid enhancement (Grid-constrained case)

This scenario assumes a condition in which timely investment for grid enhancement is not secured and grid infrastructure upgrade is not possible. As a result, the national grid retains its current variable renewable energy penetration limit of 24 % of peak demand, limiting solar PV expansion in meeting the electricity demand. To reflect this condition, a maximum allowable solar capacity is imposed as presented in Table 1 (right column). This capacity is further translated into the maximum allowable build rate (integer parameter) using Eq(7), with a solar reference unit of 10 MW.

4. Results and Discussions

Figure 1 illustrates the optimal capacity expansion pathways computed for Peninsular Malaysia's power system from 2025 to 2050 at five-year intervals, in both scenarios. In general, the results indicate a consistent reduced reliance on coal-fired power generation under both scenarios. This is presented by the gradual reduction of coal installed capacity from the current 43.1 % to 8.1 % by 2045, followed by a complete phase-out from the energy system by 2050. To compensate for the reduction in coal capacity, solar power installations are projected to increase from the current 1,912 MW to 34,453 MW in 2050, with an absolute increase of 32,540 MW over 25 y. This substantial increase in solar PV capacity is expected to be met predominantly by ground-mounted solar. Throughout the transition period, the installed capacity of hydropower is expected to grow from the current 1,515 MW to 9,300 MW in 2050, corresponding to an absolute increase of 7,785 MW over 25 y. This growth is mainly driven by the planned commissioning of the 300 MW in 2027, complemented by hydro dams of 100 MW capacity. Together, the expansion of solar and hydropower capacity achieves a renewable energy share of 69.4 % in 2050, close to the national renewable energy targets of 70 %. It is important to highlight that the results presented above reflect the optimal installed capacity mix for Peninsular Malaysia's energy system under the

scenario of “with grid enhancement (grid-enhanced case)”, where grid infrastructure enhancements are assumed to be successfully implemented with financial support from capital markets and domestic financial institutions. Nevertheless, in the “without grid enhancement (grid-constrained case), the expansion pathway diverges notably in the final planning period. As shown in Figure 1, between 2046 to 2050, the optimal installed capacity mix is to be met by substituting 2,520 MW of solar PV capacities with 600 MW of natural gas power generators in meeting the demand to ensure the energy system stays within the 24 % solar penetration limit set by the Energy Commission. Due to differences in capacity factors (cf_j), meeting the same generation demand would require only 600 MW of gas capacity compared to 2,520 MW of solar capacity. This is because natural gas power generators have a relatively higher capacity factor of 0.84 while solar power has a lower capacity factor of 0.2. This shift toward fossil-based power generation technology causes the emissions released from the energy system to increase from approximately 57.98 $MtCO_2$ between 2046 to 2050 to 59.69 $MtCO_2$.

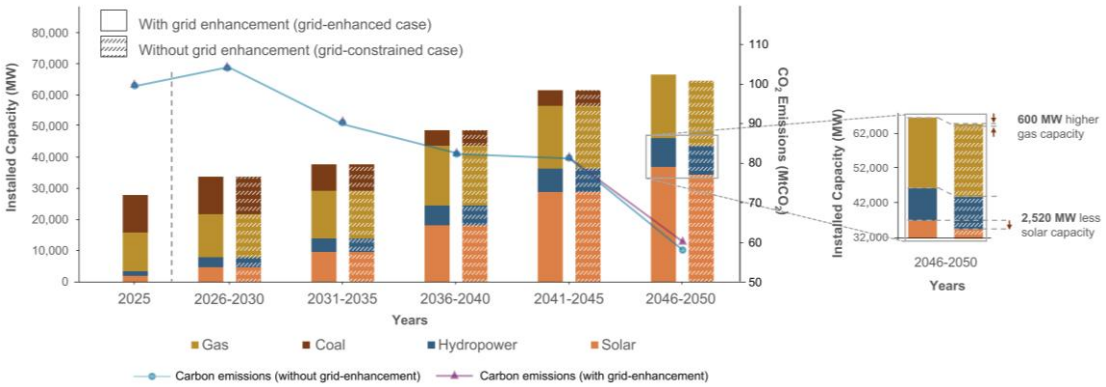

Figure 2: Comparison of capacity expansion pathway from 2025 to 2050 with and without grid enhancement

Aside from this, the readiness of grid infrastructure to accommodate higher penetration of intermittent renewable energy sources also has substantial implications on the overall system cost. Figure 2 presents a comparison of the annual and cumulative operational costs under the scenarios with (left bars) and without (right, striped bars) grid enhancements over the period from 2025 to 2050. The results show relatively similar annual cost requirements between 2025 and 2045 in both scenarios, with a notable cost divergence emerging from 2046 to 2050. It can be noticed that between 2046 to 2050, the scenario with grid enhancements is projected to be approximately USD 280 M cheaper. On top of that, the cumulative operational costs under the grid-constrained case incur an estimated operational cost of USD 256.2 B, relative to the USD 221.2 B under the scenario “with grid enhancement (gird-enhanced case)”, demonstrating a total cost saving of approximately USD 34.98 B over 25 y. It is worth noting that when grid enhancement allows greater penetration of more cost-effective renewable energy sources, it not only delivers substantial economic savings but also reduces the system’s reliance on emissions-intensive power generation. These findings underscore the critical role of timely grid infrastructure upgrades to support the penetration of more cost-effective renewable energy and reducing reliance on emissions-intensive power generation technologies.

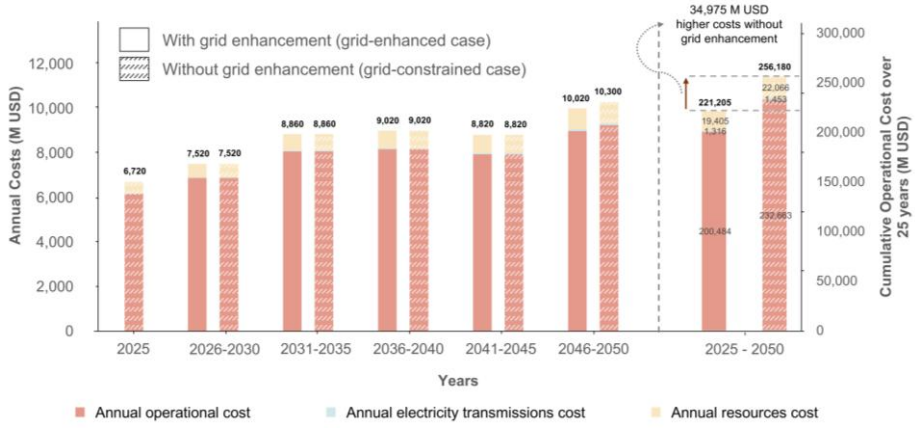

Figure 3: Comparison of the total annual and cumulative operational cost with and without grid enhancement

Conclusions

To conclude, this paper presents a macro-scale energy planning model to evaluate the implications of varying grid readiness on the installed capacity mix and total system costs. The results indicate that without grid enhancement, the energy system becomes increasingly reliant on natural gas power generation, with an estimated 600 MW of additional gas-fired capacity required in meeting the energy demand. This contributes to a rise in cumulative emissions from 57.98 $MtCO_2$ to 59.69 $MtCO_2$ between 2046 and 2050. Additionally, the results also highlighted that grid enhancement can help in reducing the total operational costs, resource costs and transmission costs of approximately MYR 34.98 B over 25 y. These findings highlight the critical importance of timely grid infrastructure upgrades in facilitating greater integration of variable renewable energy and supporting long-term decarbonisation objectives. Looking ahead, with the rapid rise of data centres in Malaysia, the power system will face mounting pressure to integrate even higher shares of renewable energy. Therefore, future work should explore the grid capacity requirements to accommodate this growing demand and assess the implications if grid enhancement remains constrained. This will be essential to inform infrastructure investment planning and ensuring a resilient and sustainable energy transition.

Nomenclature

$P_{r,j,z,y}$ – Net generation of resources
$FT_{r,z,y}$ – Net transfer of resources
$\mathrm{D}_{r,z,y}^{\mathrm{Comp}}$ – Total energy demand required
$x_{j,z,y}$ – Operational capacity of technology
cf_j – Capacity factor
$\phi_{r,j}$ – Conversion factor of technology
$x_j^{\min}$ – Minimum available capacity
$x_j^{\max}$ – Maximum available capacity
$N_{j,z,y}^{\mathrm{C}}$ – Total number of technologies
$NI_{j,z,y}^{\mathrm{C}}$ – Total additional new investments
$\mathrm{NE}_{j,z}^{\mathrm{C}}$ – Existing energy facilities
$NR_{j,z,y}^{\mathrm{C}}$ – Retirement of existing technology
$NR_{j,z,y}^{\mathrm{CE}}$ – Retirement of additional new investments
$\mathrm{BR}_{j,z,y}$ – Maximum allowable build rate
$\mathrm{Maximum\ Allowable\ Capacity}_{j,z,y}$ – Maximum allowable capacity
$\mathrm{Ref\ Unit}_j$ – Reference Unit
FA_y^{C}– Total investment costs
$Cost_y^{\mathrm{UR}}$ – Resources cost
VO_y^{C} – Variable operational cost for conversion technologies
VO_y^{T} – Variable operational costs for transport technologies
$Revenue_y$– Revenue

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