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Optimal Energy Resource and Storage Planning for Decarbonisation

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Renewable energy sources and carbon dioxide reduction technologies play a crucial role in mitigating emissions and promoting cleaner energy. However, the challenges posed by the intermittent nature of renewable generation, energy-intensive nature of carbon dioxide reduction technologies, and their high costs threaten the energy security. This project aims to develop an energy planning model to facilitate the development of clean and sustainable energy strategies. A case study focusing on residential energy system is presented, where the model proposes an optimal configuration, which is later assessed for its energy mix and potential impacts from decarbonisation efforts. In the absence of emissions reduction targets, the optimal system yields an emissions factor of 0.10 $kgCO_2/kWh$ and an electricity cost of 1.70 cent/kWh. However, when the emissions reduction levels are mandated for decarbonisation, the optimal system shifts towards cleaner energy sources and, with stricter emissions targets, adopt carbon dioxide removal technologies. Under 25 % and 50 % emissions reduction scenarios, the emissions factor decreases to 0.08 $kgCO_2/kWh$ and 0.05 $kgCO_2/kWh$ respectively, whereas the cost of electricity climbs from 1.79 cent/kWh to 1.88 cent/kWh.

1. Introduction

The energy sector is responsible for roughly 34 % of global greenhouse gas emissions, primarily due to fossil fuels combustion (IPCC, 2023). Despite the ongoing warming climate, the growth of clean energy is being outpaced by economic development, causing overall emissions to continue rising. Renewable energy plays a critical role in reducing greenhouse gas emissions while meeting energy demands (Owusu and Asumadu-Sarkodie, 2016). However, renewable energy systems face challenges such as high costs and intermittent energy production. Alternatively, Carbon Dioxide Removal (CDR) technologies offer a vital solution for removing atmospheric emissions and offsetting residual emissions, contributing to climate change mitigation efforts (Javadi et al., 2024). While CDR technologies can effectively reduce emissions, they are energy-intensive and expensive. These challenges threaten the capability of the power sector to provide adequate, affordable, and clean energy. Given the urgency to decarbonise the power sector, energy planning tools are essential in shaping strategies for developing sustainable and clean energy generation in the future. Energy planning models are computational tools used to optimise energy systems and assess different energy scenarios (Akpahou et al., 2024). They play a key role in identifying cost-effective and sustainable strategies while providing insights into the outcomes of various policy measures. As such, EnergyPLAN allows decision-makers to assess various energy scenarios and generation strategies while accounting factors like energy demand growth, resource availability, technology costs, environmental constraints and policy objectives (Lund et al., 2021). Besides, Hybrid Optimisation Model for Electric Renewables, which enables users to design, simulate and evaluate different hybrid power systems configurations (Chisale et al., 2023). Furthermore, Suhail et al., (2022) developed an energy planning model designed to identify optimal decarbonisation strategies while incorporating various energy sources, alternative feedstocks and carbon capture systems. Lastly, the open source energy modelling system focuses on detailed power representations and multi-resource systems, incorporating materials, financial flows and energy dynamics (Howells et al., 2011). Based on past studies, there is limited storage

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options considered to mitigate the intermittency of renewable energy system. Most previous models also focus on employing low carbon energy generation technologies to minimise carbon emissions without considering the potential of incorporating carbon dioxide removal technologies as a pragmatic solution for emissions mitigation. In response, this work presents an energy planning model that can provide optimal energy planning solutions, while incorporating storage and carbon dioxide removal technologies simultaneously.

2. Methodology

The model incorporates a set of technologies *n* ∊ *j*, *j'*, *s*, representing conversion technology *j* ∊ *J*, carbon dioxide removal (CDR) *j'* ∊ *J'* and storage *s* ∊ *S*. Feed *i* ∊ *I* with flow rate *F* is sent to technology *j* to produce output *k* ∊ *K* (e.g., electricity (or *k*=1) and emissions (or *k*=2)) at time period *t* ∊ *T*. Output *k* can be dispatched to meet the demand ($\mathrm{F}_t^{\mathrm{Demand}}$), sent to CDR *j'* for emissions reduction, or stored in storage *s*. The model is formulated in mixed-integer linear programming to minimise the total annualized cost of the optimal energy system (see Eq(1)), which comprises three terms: (i) cost of feed entering technology *j*, scaled by fraction of occurrences α_t, the proportion of each time period t to account for its duration, (ii) capital expenditures of technology *n*, proportional to F_{nk}^{Max}, and (iii) operating expenditures of technology *n*, based on F_{knt}, scaled by α_t. The capital expenditures are subjected to an annualised cost factor (ACF) of 0.0433, assuming a 3 % discount rate (BNM, 2025) and 40 year system lifespan. Eq(2) determines the maximum flow rate of output *k* (F_{nk}^{Max}), by comparing each flow rates of output *k* in or out of technology *n* across all the time periods (F_{nkt}) for the highest value. On the other hand, Eq(3) and Eq(4) ensure the assigned electricity demands ($\mathrm{F}_t^{\mathrm{Demand}}$) and the emissions constraints ($\mathrm{Emission}^{\mathrm{Limit}}$) are satisfied.

$$\min\left(Cost^{\mathrm{Total}} = \sum_{n=1}^{N}\sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\Big(\big(F_{ijt}\times \mathrm{D}_{it}\times \alpha_t\big) + \big(\mathrm{ACF}\times F_{nk}^{\mathrm{Max}}\times \mathrm{C}_{nk}\big) + \big(F_{nkt}\times \mathrm{O}_{nk}\times \alpha_t\big)\Big)\right) \tag{1}$$

$$F_{nk}^{\mathrm{Max}} \geq F_{nkt} \quad \forall n \quad \forall k \quad \forall t \tag{2}$$

$$\mathrm{F}_t^{\mathrm{Demand}} \leq F_{k=1t} \quad \forall t \tag{3}$$

$$\sum_{t=1}^{T} F_{k=2t} \leq \mathrm{Emission}^{\mathrm{Limit}} \tag{4}$$

Eq(5) represents the balance between the available feed flow rate (F_{it}) and the total feed flow rate distributed to technology *j* (F_{ijt}) at period *t*. Thereafter, the production rate of output *k* from technology *j* at period *t* (F_{jkt}) is determined using Eq(6), where the respective conversion rate is defined as X_{ijk}. Subsequently, the outlet flow of output *k* (F_{jkt}) is subjected to transmission efficiency (E_{jk}), which refers to the fraction of output *k* successfully delivered by technology *j* after accounting for the transmission losses. Then, F_{jkt} is either dispatched to meet the demand (F_{jkt}^{Out}), distributed across all CDR technology *j'* ($F_{jkj't}$) for emissions reduction, or across all technology *s* for storage (F_{jkst}^{Store}), as outlined in Eq(7).

$$\mathrm{F}_{it} \geq \sum_{j=1}^{J} F_{ijt} \quad \forall i \quad \forall t \tag{5}$$

$$F_{jkt} = \sum_{i=1}^{I} F_{ijt}\times \mathrm{X}_{ijk} \quad \forall j \quad \forall k \quad \forall t \tag{6}$$

$$F_{jkt}\times E_{jk} = F_{jkt}^{\mathrm{Out}} + \sum_{j=1}^{J}\left(\sum_{j'=1}^{J'} F_{jkj't} + \sum_{s=1}^{S} F_{jkst}^{Store}\right) \forall j \quad \forall k \quad \forall t \tag{7}$$

Eq(8) dictates the amount of electricity flowing into CDR technology *j'* at period *t* ($F_{k1j't}$). CDR technology *j'* consumes electricity to capture emissions based on ratio $\mathrm{N}_{j'}$, which is the unit flow of emissions ($F_{k2j't}$) per electricity into CDR technology *j'* ($F_{k1j't}$). Afterward, Eq(9) determines the remaining emissions flow from CDR technology *j'* at period *t* ($F_{k2j't}^{\mathrm{Remain}}$) by subjecting the inlet flow of emissions ($F_{k2j't}$) with the remaining fraction of removal efficiency ($\mathrm{E}_{j'}$). $\mathrm{E}_{j'}$ refers to the efficiency of CDR technology *j'* in capturing emission. Full consumption of electricity by CDR technology *j'* ($F_{k1j't}^{\mathrm{Consume}}$) is assumed.

$$F_{k2j't} = F_{k1j't} \times N_{j'} \quad \forall j' \quad \forall t \tag{8}$$

$$F_{k2j't}^{\mathrm{Remain}} = F_{k2j't}(1 - \mathrm{E}_{j'}) \quad \forall j' \quad \forall t \tag{9}$$

On the other hand, the inventory of electricity in storage *s* at period *t* (S_{k1st}) is calculated using Eq(10). Storage *s* can either store the distributed output at period *t* (F_{k1st}^{Store}), or discharge the output stored at the previous period (*t*–1) as $F_{k1st}^{\mathrm{Withdraw}}$. The inventory of electricity in storage *s* at the previous period *t*–1 ($S_{k1s(t-1)}$) is projected to loss through self-discharge. Thus, $S_{k1s(t-1)}$ is subjected to the remaining fraction of E_s, the electricity losses of storage *s* over time through self-discharge. The flow rate of electricity into and out of storage *s* is also subjected to its charging efficiency $\mathrm{E}_{ks}^{\mathrm{Store}}$ and discharging efficiency $\mathrm{E}_{ks}^{\mathrm{Withdraw}}$. $\mathrm{E}_{k1s}^{\mathrm{Store}}$ refers to the efficiency of charging electricity into storage *s* whereas $\mathrm{E}_{ks}^{\mathrm{Withdraw}}$ refers to the efficiency of discharging electricity from storage *s*.

$$S_{k1st} = S_{k1s(t-1)}(1 - \mathrm{E}_s) + \left(F_{k1st}^{Store} \times \mathrm{E}_{ks}^{\mathrm{Store}}\right) - \left(\frac{F_{k1st}^{\mathrm{Withdraw}}}{\mathrm{E}_{ks}^{\mathrm{Withdraw}}}\right) \quad \forall s \quad \forall t \tag{10}$$

Eq(11) stated that the total flow of output *k* at time *t* (F_{kt}) is determined by summing the flow rate of output *k* dispatched directly from technology *j* (F_{jkt}^{Out}), the remaining flowrate of output *k* after employing CDR technology *j' t* ($F_{kj't}^{\mathrm{Remain}}$) and the stored output *k* withdraw from storage *s* ($F_{kst}^{\mathrm{Withdraw}}$) at each time period.

$$F_{kt} = \sum_{j=1}^{J} F_{jkt}^{\mathrm{Out}} + \sum_{j'=1}^{J'} F_{kj't}^{\mathrm{Remain}} + \sum_{s=1}^{S} F_{kst}^{\mathrm{Withdraw}} \quad \forall k \quad \forall t \tag{11}$$

The flow rate of output *k* into or out of technology *n* at time period *t* (F_{knt}) is constrained by its lower ($\mathrm{F}_{knt}^{\mathrm{Lower}}$) and upper bound ($\mathrm{F}_{knt}^{\mathrm{Upper}}$), as shown in Eq(12). The binary variable A_{nt} is responsible for the selection of technology *n* at period *t*.

$$\mathrm{F}_{knt}^{\mathrm{Upper}} \times A_{nt} \geq F_{knt} \geq \mathrm{F}_{knt}^{\mathrm{Lower}} \times A_{nt} \quad \forall n \quad \forall t \tag{12}$$

3. Case Study

A residential case study is conducted to evaluate the model's performance in addressing short-term optimisation challenges by meeting the electricity demands of the population. Figure 1(a) presents the hourly electricity consumption of 123.7 k households in the urban area of Kuala Lumpur, Malaysia.

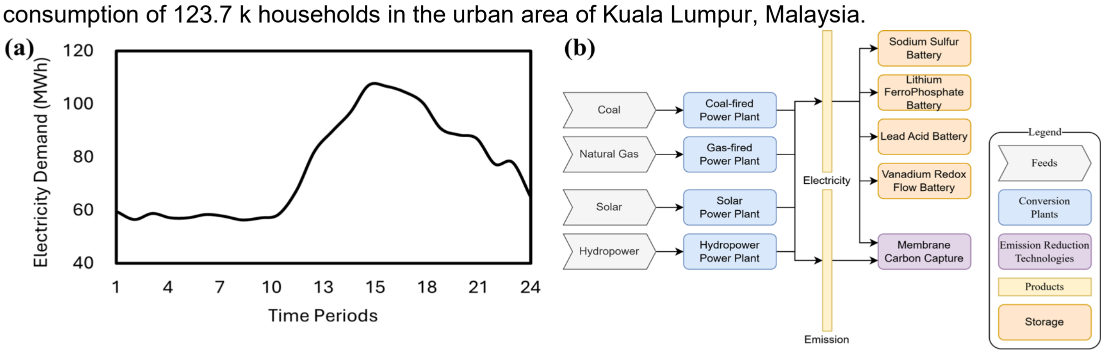

Figure 1: (a) Hourly electricity demand (Aqilah et al.*, 2021); (b) Case study superstructure*

The households are grouped into three categories: high-income; medium-income; and low-income, based on their respective income range (KRI, 2018). High-income households make up the largest portion, accounting for 49 % of the population, followed by medium-income households at 45 %, with the remainder filled with low-income households. Each household category is projected to have varying electricity consumption patterns, influenced by differences in lifestyle, number of occupants and income levels (Aqilah *et al.*, 2021). Accordingly, electricity consumption is categorised based on these household groups, determined by multiplying the number of households in each category by their respective consumption rates. Figure 1(b) shows the superstructure developed for the case study. The superstructure comprises of energy sources, energy conversion plants, energy storage and emissions reduction technologies. The energy sources that are widely available, along with their conversion plants are included in the superstructure to generate electricity for the population. Energy storage, includes a variety option of well-established battery energy storage systems, are included to store electricity. Emissions reduction or Carbon Dioxide Removal (CDR) technology is included as a viable option for addressing tightening emissions constraints. The optimal energy system is then assessed for its energy mix, cost implications and potential impacts from decarbonisation. Table 1 summarises the technical and economic data of the technologies illustrated in the superstructure.

4. Results and Discussions

Figure 2 presents the energy mix of the optimal energy system alongside its associated storage condition. The Total Annualised Cost Factor (TACF) encapsulates the summation of all annual capital, operational and fuel expenditures associated with the electricity production across an energy plant. As seen in Figure 2(a), the optimal system employs a mix of hydropower, solar photovoltaic (PV) and natural gas energy plants to address the electricity demand. Among the generation sources, solar PV offers a lower TACF at 10.97 USD/MWh, compared to natural gas (14.16 USD/MWh) and coal-fired plants (23.73 USD/MWh). However, their reliance on sunlight confines their operational availability to daylight hours (7am to 5pm) only, corresponding to time periods t24 to t10 (numerical values after “t” refers to the time periods shown in Figure 1(a)). As a result, solar energy contributes only 6.7 % to the total electricity demand across all time periods, necessitating other power sources (i.e., hydropower and natural gas) to ensure uninterrupted supply, especially at the periods of high demand. Hydropower, with the lowest TACF at 9.83 USD/MWh, emerges as the main electricity contributor, covering 62.1 % of total demand. Despite its cost advantage, its capacity is capped at 50 MW, restricting its ability to solely meet surging demand, notably the higher demand of 67.5 MW at t11. In response, natural gas power plant with a capacity of 39.5 MW, bridge the shortfall while accounting for 26.9 % of the total demand. Nonetheless, the combined capacity of hydropower and natural gas (89.5 MW) fall shorts when the demand peaks to 107.1 MW at t15, necessitating storage technologies for peak-shaving. Figure 2(b) depicts that surplus electricity stored during off-peak periods, mainly generated from hydropower (54.2 MWh), owing to its lower operating cost (3.60 USD/MWh) compared to 3.70 USD/MWh for natural gas. Meanwhile, natural gas generates an additional 21.4 MWh of electricity for storage, while solar, limited by its restricted availability, supplies 18.0 MWh only. This surplus is stored across a mix of battery technologies, including sodium sulfur (NAS), lithium ferrophosphate (LFP) and lead-acid (Pb-A) batteries, later discharged during high-demand periods (t13 to t19) to reduce peak loads. Although LFP are the most economical, with a TACF of 10.18 USD/MWh, followed by Pb-A at 12.05 USD/MWh, both have limited capacities (i.e., Pb-A: 40 MWh; LFP: 40 MWh). Thus, NAS batteries, the third most economical option at a TACF of 16.77 USD/MWh, are deployed to ensure adequate electricity stored for peak-shaving, mitigating the necessity for coal-fired power generation and its associated costs.

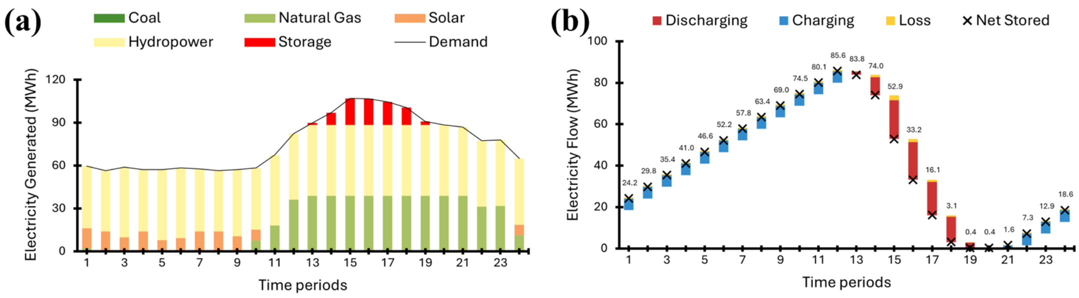

Figure 2: (a) Energy mix of optimal energy system and (b) its storage condition

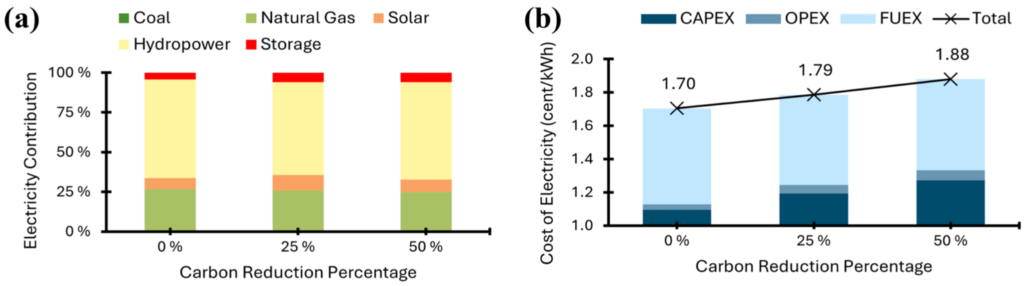

Figure 3: Effects of emissions constraints on (a) energy mix; (b) cost of electricity

Table 1: Technical and economic data of technologies

Technology	Conversion	Efficiency	Capital cost factor	Operating cost factor	Capacity	Reference
Coal power plant	0.43 kWh_e/kWh_{In} 0.35 kg_{CO2}/kWh_{In}	1.2 $\%_{Loss\ to\ Transmission}$	2,481.81 USD/kW_e	11.48 $USD/MWh_e.y$	50 MW_e	(Bellotti et al., 2019)
Natural gas power plant	0.43 kWh_e/kWh_{In} 0.35 kg_{CO2}/kWh_{In}		2,119.44 USD/kW_e	3.70 $USD/MWh_e.y$	40 MW_e	(Oh et al., 2021)
Solar power plant	0.15 kWh_e/kWh_{In}		706.82 USD/kW_e	2.59 $USD/MWh_e.y$	40 MW_e	(IRENA, 2023)
Hydropower plant	0.72 kWh_e/kWh_{In}		1,261.42 USD/kW_e	3.60 $USD/MWh_e.y$	50 MW_e	
Sodium sulfur battery	-	90 $\%_{Charge}$ 90 $\%_{Discharge}$ 1 $\%_{Daily\ Loss}$	2,916.52 USD/kW_e	2.37 $USD/kWh_e.y$	40 MWh_e	(Borerwe and Longe, 2025)
Lead acid battery		90 $\%_{Charge}$ 89 $\%_{Discharge}$ 5 $\%_{Daily\ Loss}$	1,999.16 USD/kW_e	2.18 $USD/kWh_e.y$	40 MWh_e	
Lithium ferrophosphate battery		95 $\%_{Charge}$ 95 $\%_{Discharge}$ 2 $\%_{Daily\ Loss}$	1,585.56 USD/kW_e	2.35 $USD/kWh_e.y$	40 MWh_e	
Vanadium redox flow battery		90 $\%_{Charge}$ 89 $\%_{Discharge}$ 1 $\%_{Daily\ Loss}$	3,005.83 USD/kW_e	2.47 $USD/kWh_e.y$	40 MWh_e	
Membrane carbon capture system	7.20 kg_{CO2}/kWh_e	99.8 $\%_{Capture}$	2,937.03 $USD/(kg_{CO2}/h)$	1.19 $USD/kg_{CO2}.y$	25 t_{CO2}/h	(Adhikari et al., 2023)

Figure 3 illustrates how different emissions reduction targets affect the optimal energy system, specifically reducing its emissions by 25 % and 50 %. In the absence of emissions reduction requirement (0 %), the baseline system achieves an emissions factor of 0.10 kg_{CO2}/kWh and delivers an electricity at a cost of 1.70 cent/kWh. When a 25 % emissions reduction is mandated, the energy mix transitions towards cleaner sources. Solar power sees a significant boost, contributing 9.7 % of total electricity generation, as shown in Figure 3(a). This increment not only curbs emission, but also reduces the reliance on fossil fuel energy, particularly natural gas which drops to 26.0 %. Simultaneously, the share of storage rises to 5.9 % to support more usage of solar energy outside sunlight hours (i.e., t24 to t10), consequently reduce hydropower's share to 58.4 %. However, the limited capacity and operational availability restrict the capability of green energy plants (i.e., solar and hydropower) to meet further emissions reduction on their own. In response, the system adopts membrane-based carbon capture technologies to further mitigate the carbon footprint. At a 25 % reduction target, the capture system sequesters 35 t of CO_2, consuming 4.9 MWh of electricity and reducing the emissions factor to 0.08 kg_{CO2}/kWh. A more stringent 50 % reduction target necessitates higher capture efforts, with 83 t of CO_2 captured at an energy consumption of 11.6 MWh, further reducing emissions to 0.05 kg_{CO2}/kWh. However, solar plants lack the sufficient operational availability to power the energy-intensive capture technology while addressing the higher demands. Therefore, the optimal system increases the electricity generation from hydropower, raising its share to 61.2 % whereas solar drops to 7.9 %. Storage experiences a slight increase to 6.0 % while the natural gas usage falls to 25.0 %. Meanwhile, these shifts and reliance on carbon capture system increase the cost of electricity, which refers to the total expenses associated in generating electricity. The total expenses encompass capital expenditures (CAPEX), operating expenditures (OPEX) and fuel expenditures (FUEX). Figure 3(b) depicts that the cost of electricity climbs from 1.79 cent/kWh at 25 % reduction target to 1.88 cent/kWh at a 50 % reduction target.

5. Conclusions

This work presents an energy planning model developed to support the transition towards sustainable and low-carbon energy future, demonstrated through a residential case study. After evaluating the availability, capacity, and costs of all technologies within its superstructure, the model identifies cost-effective energy generation options that ensures adequate and affordable electricity supply. Additionally, surplus electricity is stored in cost-efficient storage options during off-peak hours and dispatched during peak hours, employing peak-shaving strategy to reduces the need for costly additional generation capacity. When emissions reduction targets are enforced, the model prioritises a shift towards greener energy sources. Under more stringent emissions targets, carbon dioxide removal technology, powered by excess electricity, is introduced to offset emissions further. Overall, the model demonstrates strong potential to facilitate the development of cleaner and cost-efficient energy systems under tight environmental constraints. Future research could extend this work by integrating emissions removal policies, such as carbon pricing, financial subsidies and grants, tax incentives and exemptions, to assess their influence on decarbonisation strategies.

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