INTEGRATED GRID PLANNING MODEL UNDER UNCERTAINTY: TOWARDS SUSTAINABLE FUTURE GRIDS

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Abstract

The installed capacity of distributed solar PV in the distribution network has been growing over the past years resulting from the implementation of renewable policies and technological development. However, the current approach for transmission and generation expansion planning does not account for distribution network constraints. Also, the risk of uncertainty caused by economic, regulatory and technology development are often not considered in a deterministic least cost optimization grid planning model. As a consequence, we do not know the impact of distribution network constraints on grid expansion planning and how uncertainty may influence the transmission and distribution level investment decisions. This paper presents a novel stochastic integrated grid planning approach considering distribution network constraints, combining a two-stage optimization grid expansion model with a distribution network hosting capacity (HC) assessment for a stylized representation of the Malaysian grid. Our result shows that omitting distribution constraints and ignoring uncertainty in grid investment planning has a significant impact on the optimal solution and quantifiable economic consequences. We also evaluate the benefit of hosting capacity (HC) enhancement, which, as we show can lead to potential savings of 0.86% ($2.37billion) of the expected cost. Finally, our proposed model is more generally applicable for transition planning to reinforce current grids and integrate sustainable generation capacity.

1 Introduction

Renewable generation capacity is growing significantly as a result of technology advancement and policies that aim to reduce the CO_2 emissions, including carbon prices and renewable targets. Solar photovoltaic (PV) generation capacity has increased particularly quickly, and in many places it is now among the cheapest forms of electricity generation. Solar PV capacity comes in different forms. Large solar photovaltaic (LPV) plants may be connected to transmission networks, as other types of renewable capacity, including wind, tends to be. However, in most markets, a large fraction of solar PV capacity is connected to distribution networks (distributed solar photovoltaic, DPV), beyond the transmission system operator's control.

This presents a challenge to grid planners, operators, and investors in other types of generation capacity, which will only increase as the amount of DPV grows. Electrical infrastructure will need to be expanded or rearranged to accomodate variable renewable generation. However, the current approach for transmission and generation expansion planning does not generally account for distribution network constraints. Also, separately, risk and uncertainty are not always properly accounted for, as many planning models are deterministic. As a consequence, we do not know the impact of distribution network constraints on grid expansion planning and how uncertainty may influence transmission and distribution level investment decisions. Energy storage presents a similar challenge. Storage can play a vital role in accommodating variable renewable generation into the electricity system, but, like solar PV, a large amount of storage capacity is connected to distribution networks, and therefore invisible to transmission system opeartors.

In light of these issues, a new modeling framework for optimizing system expansion is needed, that must satisfy several requirements. First, it should be able to jointly model transmission and distribution networks; in the latter, detailed distribution grid operating constraints should be included to accurately model distribution network issues resulting from DPV and storage installations. Second, it should properly account for long-run uncertainties. Third, it should account for the fact that expansion decisions can de delayed to future periods in which more information on, among others, PV costs, are available.

This is a significant challenge. Distribution network constrains are nonlinear, so the framework proposed above would be a large-scale multi-stage stochastic optimization problem. In this paper, we present a first attempt to formulate and solve such a framework. We combine a two-stage stochastic optimization transmission and generation expansion model with a detailed distribution network hosting capacity (HC) assessment, solving these two models iteratively to heuristically find a fixed point. We apply this model to a stylized representation of the Malaysian grid, which is expected to have to integrate a large amount of DPV capacity over the coming decade

We find that, first of all, distribution network constraints are important and including them changes optimal transmission and generation capacities, not just in distribution networks but also at the transmission level. Distribution network hosting capacity (HC) enhancement techniques, using distribution connected storage, could significantly reduce the overall costs of meeting a renewable target, and increase distributed solar PV (DPV) penetration in the distribution network. However, the correct mix of distribution-connected and transmission-connected storage is crucial. Moreover, investing in battery storage after grid investment has been finalized is more economical if this is an option. Finally, this paper demonstrates that combined transmission and distribution network modelling is possible practical to assist with transition planning for future grids.

2 Methodology

2.1 Notation

2.1.1 Set and indices

L	Corridors l
L^D	Corridors, l connected to distribution node, N^D
N	Nodes, n
K	Generator types, k
E	Model stages e
T	Years, t
P	Intra-annual ime blocks, p
S	Scenarios, s
N^D	Distribution nodes, n
K^C	Conventional generator types, k
K^S	Solar PV generators, k
K^{DS}	Distributed solar PV generator, k
B	Energy storage (ESS) facilities, b

2.1.2 Parameters

CY_{esk}	Capital cost of new generation k, $e = 1, 2$ (\$/MW), scenario s
CX_{es}	Transmission investment cost $e = 1, 2$ (\$/MW/km), scenario s
CV_{esk}	Generation cost type k, stage $e = 1, 2$ (USD/MWH), scenario s
CZ_{esb}	Capital cost of new ESS b, $e = 1, 2$ (\$/MW), scenario s
CD_{esb}	ESS discharge cost type b, stage $e = 1, 2$ (USD/MWH), scenario s
E_{sk}	Carbon emission by plant type k (t/MWH), scenario s
CP_{es}	Carbon price per year stage $e = 2, 3$ scenario s \$/t)
i	Discount rate per year (1/yr)
N	Sample size (hours)
Q_{senp}	Electricity demand at node n, stage $e = 2, 3$ (MW), scenario s
γ_{esl}	Susceptance of corridor l
X_l	Initial transmission capacity (MW)
Y_{nk}	Initial generators at node n (MW)
Z_{nb}	Initial battery storage at node n (MW)
LF_k	Load (demand) factor for each generator type k
SP_p	Hourly solar pattern (per unit)
RE_{se}	Renewable target (%) stage $e = 1, 2$, scenario s
SM_n	Allowed DPV penetration level at node $n = N^D$
SB_n	Allowed ESS level at node $n = N^D$
V_n	Voltage limits at distribution node $n = N^D$
RL_k	Ramping limit by plant technology k (MW/hour)
RT_b	Roundtrip efficiency of battery storage type b
H_b	Energy capacity of battery storage b measured in hour at full capacity
ρ_s	Probability of scenario s

2.1.3 Variables

tc_{se}	Total cost at stage e (\$)
x_{sel}	New transmission investment $e = 1, 2$ (MW)
y_{senk}	Capacity of new plant stage $e = 1, 2$ (MW)
z_{esnb}	Capacity of new ESS stage $e = 1, 2$ (MW)
g_{esnpk}	Generation of plant stage $e = 2, 3$, period p (MW)
g^S_{esnpk}	Generation of Solar plant stage $e = 2, 3$, period p (MW)
r^d_{esnpb}	Discharging of ESS stage $e = 2, 3$ at bus n, period p (MWH)
r^c_{esnpb}	Charging of ESS stage $e = 2, 3$ at bus n, period p (MWH)
f_{selp}	Reactive power flow stage $e = 2, 3$ (MW)
θ_{snp}	Voltage angle between nodes (radian)
nse_{senp}	Not supplied energy node n at period e (MW)
$spill_{senpk}$	Solar energy spillage (MW)

2.2 Model Overview

The model combines a stochastic two-stage optimization-based grid expansion model with a distribution network hosting (HC) capacity assessment. We develop six scenarios which generally represent economic, regulatory and technology uncertainty. Together, they capture different anticipated relationships among model parameters such as capital costs, operational cost, demand growth, renewable targets and carbon tax. First, the transmission and generation expansion model calculates an optimal solution considering only

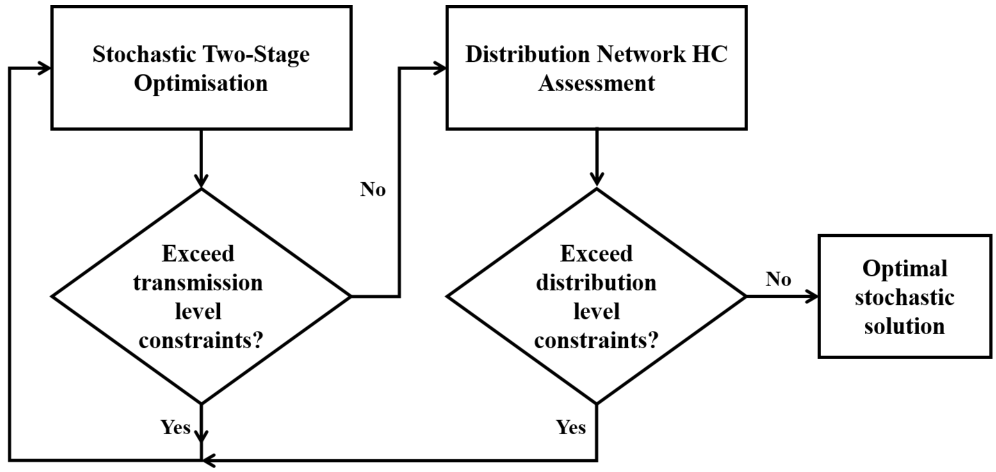

Figure 1: Stochastic integrated grid planning model flowchart

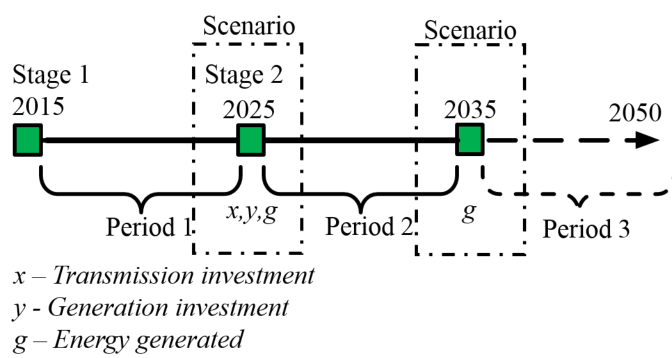

Figure 2: Model timeline on decision stages

transmission grid constraints. Then, at the distribution level, the proposed capacity of distributed solar PV (DPV) energy mix is assessed subject to distribution network hosting capacity (HC) limits that consider reverse power flow and voltage constraints. This cycle iterates until the proposed optimal solution satisfies the transmission level constraints and distribution network constraints as depicted in figure 1.

The optimization model is established based on linearized DC power flows, while the distribution network hosting capacity is assessed using non-linear steady state power flow analysis. To evaluate the effects of distributed solar PV (DPV) in lower level network, we introduce a distribution corridor that connects the transmission and distribution nodes. Also, we consider two distinct types of solar PV in the case study; dispatchable large-scale solar (LPV), which is connected to the transmission network, non-distpatchable distributed solar (DPV) which is connected to the distribution network. In addition, we include three battery storage types in this model; grid scale, controllable Distribution Service Operator (DSO) operated storage, and uncontrollable distribution-connected domestic storage. We conduct a sensitivity analysis for different configurations of battery types in the network.

2.3 Timeline and Model Objective

There are two decision points for investment and three periods of energy market operations as depicted in figure 2. In 2015, the planner decides on transmission investment and the generators commit to building new plants which are assumed to be fully commissioned starting 2025. The second point of investment decisions occur in the year 2025 and the built assets will come into operation in year 2035. Note that, after the second stage decision in 2025, only dispatch decisions are made for the next 25 years until 2050, so the model has combined planning horizon of 35 years.

The model minimizes the total expected cost of grid investment and operations taking into account grid network constraints, build constraints, resource limitations, and solar generation target. The total expected cost includes capital expenses for new transmission, generation, and battery storage investment and also grid operation cost including generation margin, battery discharge cost and carbon tax. The overall model objective function is formulated in (1) consist of total cost for each stage, e, defined in (2), (3) and (4).

$$min \left\{ tc_1 + \sum_s \rho_s \left[\left(\frac{1}{1+i} \right)^{10} tc_{2s} + \left(\frac{1}{1+i} \right)^{10} tc_{3s} \right] \right\} \tag{1}$$

$$tc_1 = \sum CX_1 x_1 + \sum_{nk} CY_{1k} y_{1nk} + \sum_{nb} CZ_{1b} z_{1nb} \tag{2}$$

$$\begin{aligned} tc_2 = {} & \sum CX_{2s} x_{2s} + \sum_{nk} CY_{2sk} x_{2snk} + \sum_{nb} CZ_{2sb} z_{1snb} \\ & + \frac{8760}{N} \sum_{t=1}^{10} \left(\frac{1}{1+i} \right)^{t-1} \sum_{npk} (CV_{2sk} + E_{sk} CP_{2s}) g_{2snpk} + \sum_{nkp} CD_{2sb} r^d_{2snpb} \end{aligned} \tag{3}$$

$$tc_3 = \frac{8760}{N} \sum_{t=1}^{15} \left(\frac{1}{1+i} \right)^{t-1} \sum_{npk} (CV_{3sk} + E_{sk} CP_{3s}) g_{3npk} + \sum_{nkp} CD_{3sb} r^d_{3snpb} \tag{4}$$

2.4 Model constraints

2.4.1 Transmission network and generation

The transmission nodes are connected in mesh and each transmission line is represented by a single bidirectional corridor l, where the active power flow is limited to the total available capacity at each period. Using a linearized DC approximation of power flows, Kirchoff's current law (KCL) and Kirchoff's voltage law (KVL) are defined in (5) and (6). The reference or slack node angle is set to 0, and transmission and generation investments are non-negative.

$$\begin{aligned} & \sum_{k \notin K^s} g_{esnpk} + \sum_{k \in K^s} (g_{esnpk} - spill_{esnpk}) + \sum_{b \in B} r^d_{esnpb} \\ & \qquad - \sum_l f_{esp} - Q_{enp} - \sum_{b \in B} r^c_{esnpb} + nse_{esnp} = 0 \end{aligned} \tag{5}$$

$$f_{espl} - \gamma_{esl} (\theta_{esnp} - \theta_{esmp}) = 0 \tag{6}$$

$$-(X_l + x_{1l}) \leq f_{2slp} \leq (X_l + x_{1l})\forall l, p \tag{7}$$

$$-(X_l + x_{1l} + x_{2slp}) \leq f_{3slp} \leq (X_l + x_{1l} + x_{2slp})\forall l, p \tag{8}$$

The electricity output generated by non-solar generators are limited by the available plant capacities at each stage taking into account the generators' efficiency or load factor, LF in (9) and (10).

$$0 \leq g_{2snpk} \leq (Y_{nk} + y_{1nk})LF_k\forall n, p, k \in K^C \tag{9}$$

$$0 \leq g_{3snpk} \leq (Y_{nk} + y_{1nk} + y_{2snk})LF_k\forall n, p, k \in K^C \tag{10}$$

We include a security or reserve margin in equation (11) and equation (12) to ensure enough reserve capacitiy is installed; this is a common approximation of more detailed security constraints which would complicate the model unnecessarily.

$$\sum_{nk}(Y_{nk} + y_{1nf}) \geq \sum Q_{2snp}(1 + RM)\forall s, p = peak \tag{11}$$

$$\sum_{nk}(Y_{nk} + y_{1nf} + y_{2nf}) \geq \sum Q_{3snp=peak}(1 + RM)\forall s, p = peak \tag{12}$$

In addition, to evaluate the effect of the intermittent energy generated by solar PV generators, ramping limits (13), (14), energy spillage (15) and load shedding (16) are also considered.

$$g_{esnpk} - g_{esn,p-1,k} \leq RL_k\forall e, s, p, n, k \tag{13}$$

$$g_{esn,p-1k} - g_{esn,p-1,k} \leq RL_k\forall e, s, p, n, k \tag{14}$$

$$0 \leq spill_{esnpk} \leq g_{esnpk}\forall e, s, p, n, k \in K^s \tag{15}$$

$$0 \leq nse_{esnp} \leq Q_{esnp}\forall e, s, n, p \tag{16}$$

Finally, constraint (17) defines a solar generation target at every stage e.

$$\sum_{npk} g_{esnpk} \geq RE_{es}\sum_{np} Q_{esnp}\forall e, k \in K^s \tag{17}$$

For all types of generators including solar PV and battery storage, those technologies are limited to the availability of resources, siting and built constraints.

2.4.2 Solar photovaltaic (PV)

We consider two types of solar PV; dispatchable large solar PV (LPV) and non-dispatchable distributed solar PV (DPV). The grid operator has the ability to control the energy generated by the LPV but the energy generated from DPV will flow into the distribution network without any control. These distinct characteristics of the two solar PV technologies are reflected in (18), (19), (20) and (21). In this model, LPV is connected to the transmission grid and DPV is installed only in the distribution network.

$$0 \leq g^S_{2npk} \leq (Y_{nk} + y_{1nk})SP_{ep} \forall n, p, k \in K^s \tag{18}$$

$$0 \leq g^S_{3npk} \leq (Y_{nk} + y_{1nk} + y_{2nk})SP_{esp} \forall n, p, k \in K^s \tag{19}$$

$$0 \leq g^S_{2npk} = (Y_{nk} + y_{1nk})SP_{ep} \forall n, p, k \in K^s \tag{20}$$

$$0 \leq g^S_{3npk} = (Y_{nk} + y_{1nk} + y_{2nk})SP_{ep} \forall n, p, k \in K^s \tag{21}$$

2.4.3 Battery storage

Next, we add battery storage modeling components and for practical reasons, we consider only Li-Ion battery storage which is one of the most commonly used technology. There are three battery storage types used in this model to represent grid scale battery storage, which is fully dispatchable in a similar way as transmission-connected generation capacity; controllable Distribution Service Operator (DSO) operated storage, which is dispatchable by the DSO but connected to the distribution network, and uncontrollable distribution-connected domestic storage. We use a generic representation of an ESS, with the energy capacity (MWh stored) and power conversion (MW input/output) components decoupled [10, 4, 6]. In general, ESS can provide intra-day energy arbitrage services to improve load factors, discharging during peak periods to minimize the utilization of expensive peaker generators, and charging during high renewable resoure periods, provide inter-seasonal storage, and provide a number of ancillary services, among a number of other uses[5, 1]. For the purpose of this study, all types of battery are only utilized for peak shaving and load shifting while minimizing costs. The characteristic of ESS are modeled in 22, 24, 25, 26, 27. Please note that battery storage is not constrained by ramp rates, as it is sufficiently flexible at our temporal resolution.

$$r_{esnpb} = r^d_{esnpb} - r^c_{esnpb} \tag{22}$$

$$-(Z_{nb} + z_{1nb}) \leq r_{2snpb} \leq Z_{nb} + z_{1nb} \tag{23}$$

$$-(Z_{nb} + z_{1nb} + z_{2snb}) \leq r_{3snpb} \leq Z_{nb} + z_{1nb} + z_{2snb} \tag{24}$$

$$r^s_{esnpb} = r^s_{esnp-1b} - r^d_{esnpb} + RT_b r^c_{esnpb} \tag{25}$$

$$r^s_{2snpb} \leq (Z_{nb} + z_{1nb})H_b \tag{26}$$

$$r^s_{3snpb} \leq (Z_{nb} + z_{1nb} + z_{2snb})H_b \tag{27}$$

2.4.4 Distribution network hosting capacity (HC) assessment

As depicted in figure 1, the proposed DPV capacity at each distribution node from the high-level grid planning model is further analyzed using a distribution network hosting capacity (HC) assessment. Reactive power flow and voltage at each bus within the network is evaluated using a steady state AC power flow analysis. The hosting capacity is measured using the solar penetration level, SM_n and home storage level SB_n subject to reverse power flow constraints and voltage limits in the distribution network.

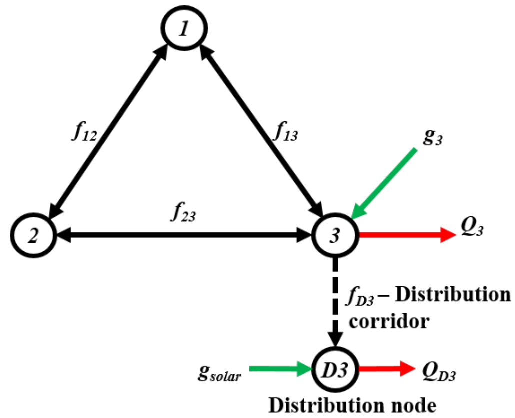

Figure 3: Mathematical representation of grid network

To evaluate the firm level effect of DPV and small scale storage, we introduce an additional corridor that connect the transmission and distribution nodes as shown in figure 3. The negative effects caused by high levels of distribution-connected solar generation includes voltage violations and back-feed to the transmission source, which could create instability within the systems. Thus, we set zero reverse flows to the transmission node in equation (28) and impose low voltage limits are set at 0.95 pu and maximum limits set at 1.05 pu (29); these are common regulatory constraints in current distribution networks.

$$f_{eslp} \leq 0, l \in L^D \tag{28}$$

$$0.95pu \leq V_{n=N^D} \leq 1.05pu \tag{29}$$

The allowable home storage and distributed solar penetration in distribution nodes is specified in (30). Relevant assumptions and parameters applied for the established distribution network are detailed in the next section.

$$\sum_{npk} g_{esnpk} \geq SM_n \sum_{np} Q_{enp} \forall e, n \in N^D, k \in K^{DS} \tag{30}$$

$$\sum_{npb} r^d_{esnpb} \geq SB_n \sum_{np} Q_{enp} \forall e, n \in N^D, k \in K^{DS} \tag{31}$$

In our model, hosting capacity assessment is done iteratively until the DPV and home storage levels satisfy distribution network constraints (i.e., reverse power flow and voltage limits). If the proposed DPV and home storage level exceed the constraints, the model will successively reduce DPV and home storage level which will set a new limit for both distributed PV and home storage in the upper level optimization model as shown in figure 4.

2.5 Model Outputs

The above model has calculate the optimal stochastic solution by minimizing the total cost of transmission and generation investment and usage. Using this model, we will first establish how including a distribution system HC analysis affects the optimal solution. Then, the effect of uncertainty is analyzed based on two economic metrics: expected value of perfect information (EVPI) and expected cost of ignoring uncertainty

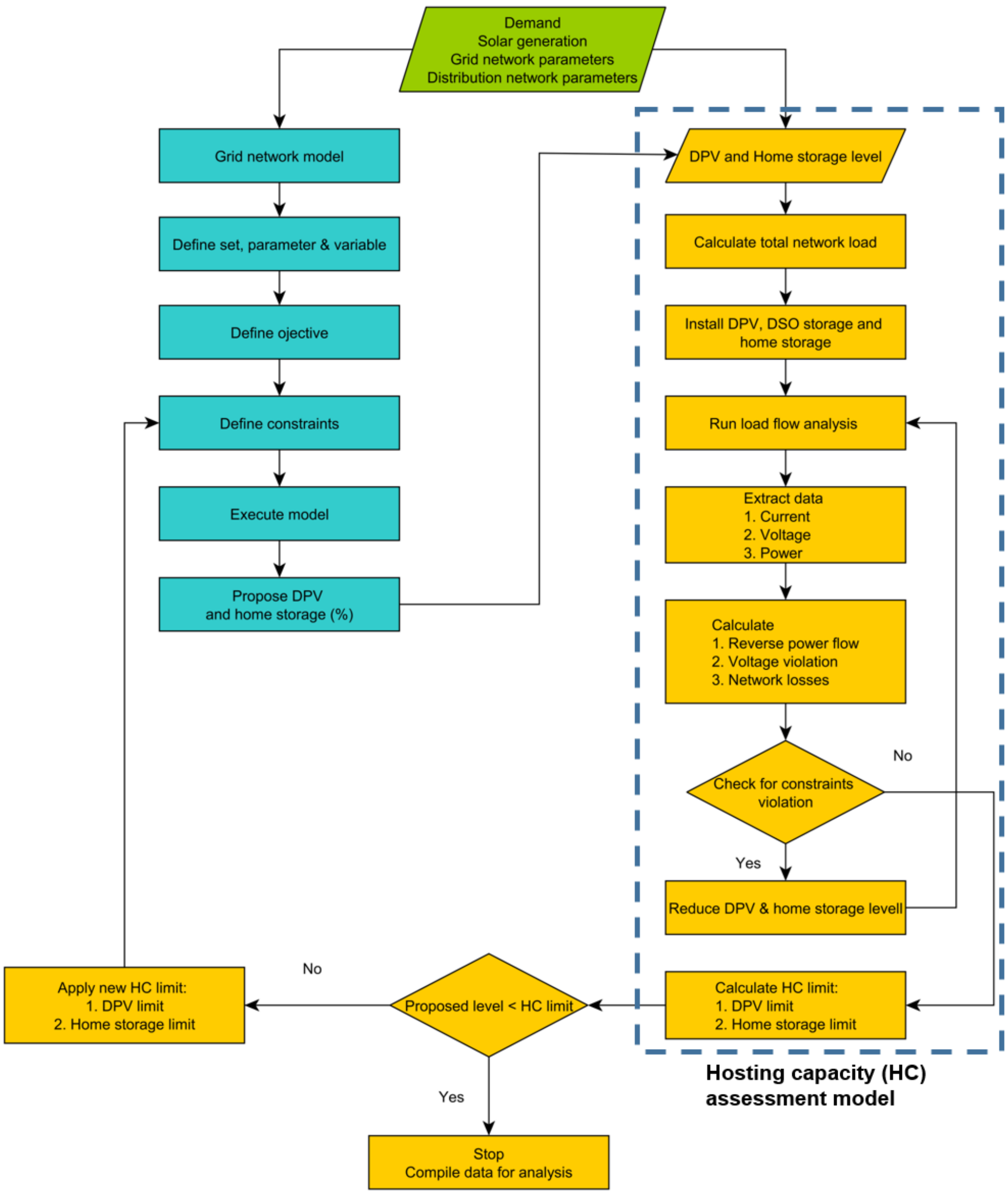

Figure 4: Hosting capacity assessment model

(ECIU). Finally, we examine a case where battery storage investment is sequential to grid investment and takes place after the uncertainty is resolved.

2.5.1 Impact of hosting capacity (HC) constraints on grid investment

We have previously shown that in a deterministic integrated planning model, distribution network constraints have a significant impact on the overall investment. The current model combines a stochastic two-stage planning model and distribution hosting capacity (HC) assessment. Depending on the problem, HC enhancement techniques varies from, active network management (ANM), network reinforcement, application of on load tap changer (OLTC), energy storage and harmonics mitigation. In this paper, we apply hosting capacity (HC) enhancement techniques by connecting small scale Li-Ion battery storage in the distribution network; controllable Distribution Service Operator (DSO) owned storage, and uncontrollable distribution-connected domestic storage. In this way, distribution network HC limits will increase to allow higher penetrations of distributed solar PV (DPV). The model is used to evaluate HC enhancement techniques on grid investments under uncertainty.

2.5.2 Expected Value of Perfect Information

In decision theory, the EVPI is the price that one would be willing to pay for perfect information, and therefore the upper bound to the value of an improved forecast [13]. It also demonstrates the economic impact caused by uncertainty. The EVPI is calculated by comparing the total cost of the stochastic model to a model where both transmission system operators (TSOs) and generators have perfect information. After solving the stochastic model, a perfect foresight deterministic model is used to obtain a minimum cost for each scenario independently. The EVPI is then calculated as the difference between the total expected cost from stochastic solution and the probability weighted average of the scenarios' deterministic cost. In addition, we calculate EVPI without considering the distribution network constraint to determine the value of detailed information about distribution network, which is managed by the distribution service operator (DSO).

2.5.3 Expected Cost of Ignoring Uncertainty

The expected cost of uncertainty (ECIU) is calculated by comparing the optimal solution from a naive first stage decision and the stochastic solution. Before calculating the ECIU, one selected naive scenario is solved using the deterministic model to obtain the first stage transmission investment. Then, the first stage transmission investment is imposed as a constraint in a full stochastic model to obtain the optimal solution. This represents a situation in which planners decide in the first stage based on only one specific scenario even though there are other possible scenarios that could occur. In the second stage, the expansion plan is made according to the scenario that has occurred. In this paper, similar approach to the previous literature, we consider the average of the expected for each naive scenario as the overall ECIU. The ECIU is calculated as the expected cost increase when the first stage stochastic model is constrained to adhere the first stage naive decision. This metric critically depends on the selection of the naive scenario. If the ECIU is zero, a deterministic model can be used but if the value of ECIU is significant, the two stage stochastic model is expected to save costs.

2.5.4 Co-optimized and sequential approach

We consider two different approaches for battery storage investment planning [4]. First, a co-optimized approach where battery storage investment is planned together with grid investment planning in the first stage and similar lead time is assumed. In the second case, battery storage is planned and constructed during the operational period, after grid investment is finalized, and we refer this as a sequential approach. This could potentially reduce the expected cost because the decision to invest in battery storage is made after the uncertainty is resolved. In this case, the the total cost formulation and battery storage investment constraints are given in 32, 33, 34, 35, and 36.

$$tc_3 = \sum_{nb} CZ_{2sb} z_{1snb} + \frac{8760}{N} \sum_{t=1}^{15} \left(\frac{1}{1+i} \right)^{t-1} \sum_{npk} (CV_{3sk} + E_{sk} CP_{3s}) g_{3npk} + \sum_{nkp} CD_{3sb} r^{d}_{3snpb} \quad (32)$$

$$-(Z_{nb} + z_{2snb}) \leq r_{2snpb} \leq Z_{nb} + z_{2snb} \quad (33)$$

$$-(Z_{nb} + z_{2snb} + z_{3snb}) \leq r_{3snpb} \leq Z_{nb} + z_{2snb} + z_{3snb} \quad (34)$$

$$r^{s}_{2snpb} \leq (Z_{nb} + z_{2snb}) H_b \quad (35)$$

$$r^{s}_{3snpb} \leq (Z_{nb} + z_{2snb} + z_{3snb}) H_b \quad (36)$$

Note that one significant difference between both cases is the assumed lead time. In the co-optimized case, a 10 years lead time is assumed, which is similar to transmission line and generator lead time. In the sequential approach the lead time for battery storage is less than a year.

3 Assumptions and Data

3.1 Transmission and generation characteristics

The transmission network in Malaysia is operated at 132kV, 275kV and 500kV, but for simplicity we formulate a high level network model based on the 275kV and 500kV network. 13 transmission nodes are modeled; these represent the main cities in Malaysia. The same representation is commonly used by the Malaysian regulators and utilities [7, 9, 8]. Transmission line losses and the effect of aggregating the transmission lines and generators are not considered in this paper. To demonstrate the interactions between transmission and distribution network, we establish a corridor that connects a distribution node to each transmission node. This corridor represent the lines or cables connecting distribution substations and transmission main intake. However, as congestion on these lines is unlikely, detailed parameters of both connecting points are not considered and unlike the transmission corridor, the distribution corridor is not subject to thermal constraints.

All generators are allocated to the nearest nodes, using data on actual generation capacities. The distance between the nodes are calculated based on the location of the main cities in Figure 5. In reality, tramission corridors may not be straight lines, but this is unlikely to affect the intended objective of this paper. Generator efficiency, technical and cost parameters are obtained from [2, 13] and own assumptions which are listed in 1. Zero carbon emissions are assumed for all hydro and solar generators. Capital costs of new transmission and generation capacity are overnight investment costs; i.e. net present values of construction costs and other fixed costs. Only solar, hydro and biomass plants are considered to be renewable and both types of solar PV can count towards the solar target. As hydro capacity in Malaysia is largely controlable, instead of run of river, and the amount of wind generation is negligible, the only source of intermittency is solar PV capacity.

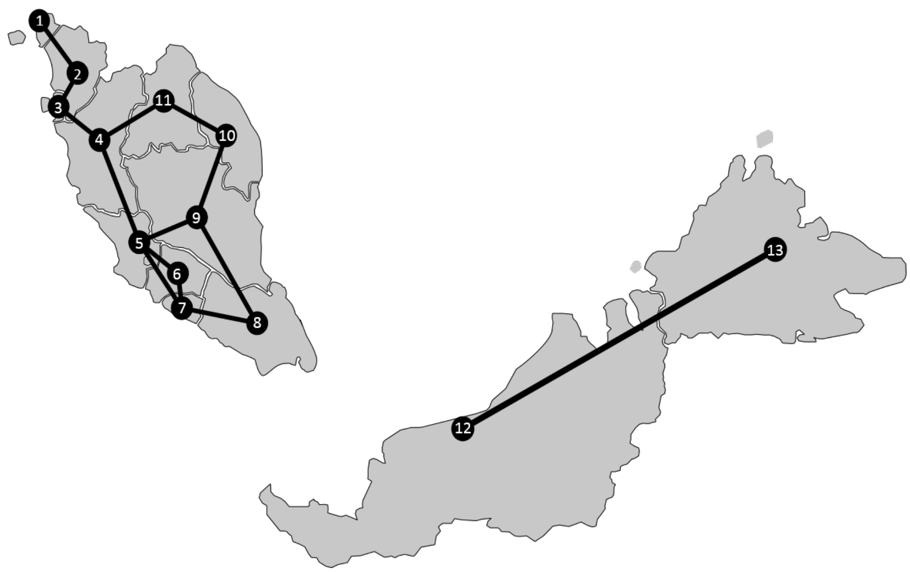

Figure 5: Malaysia Grid Network Model

Plant Type	Load Factor (%)	CO_2 Emission (tonne/MWh)	Operation Cost (USD/MWH)	Capital Cost ($/MW)	Ramping Rate (MW/hr)
Biomass	38	0.093	4.2	4060000	240
CCGT	59	0.353	2.97	1014000	960
Coal	46	0.748	4.15	2264000	240
Diesel	55	0.8	7	1139000	420
Hydro	64	0	2.46	2493000	9000
OCGT	32	0.53	4.17	699000	3000
LPV	17	0	1	1436000	N/A
DPV	17	0	0	2297000	N/A

Table 1: Power plant cost and technical characteristic - 2015

Node	Installed Capacity (MW)							
	Bio	CCGT	Coal	Diesel	Hydro	OCGT	LPV	DPV
1		650						
2								5.41
3								3.95
4	14.13	660	3080					9.77
5	14.39	1943	1486		900	820		54.02
6	23.4	1584	1400		2.2	436.4		34.41
7		1411				434		15.57
8	17.85	1042	2100			210		10.4
9	16.83	275						7.31
10					6.38			20.89
11		1029			650			5.62
12	44.3		480	171.96	614.8	867.6		0.3
13	54.19	1034.2		332.8	97.86			18.14

Table 2: Generator installed capacity

The list of existing generators taken from [8] and [9] is summarised in table 2. As a result of the current Malaysian Feed in Tariff (FiT), most solar capacity is scattered throughout distribution networks, and in many cases, consists of rooftop solar installed in residential areas, at the point of final electricity consumption. To represent solar output variability in the upper level optimization model, we use MERRA2 solar generation data extracted from [11] for all major cities in Malaysia and normalised to a per unit value. Solar generation starts after 7.30 am and reaches its peak between 12pm to 3pm, which is similar to solar generation patterns used in previous research in [12][14]. To assess the impact of different levels of solar penetration on the distribution network, the lower-level model uses the built-in Open Distribution Simulation Software (OpenDSS) solar PV module to represent a cluster of solar PV connected within distribution network. Because Malaysian weather patterns are very stable and only vary from the dry to the rainy season, we use two 24-hour solar and demand patterns that capture the highest weekly average and the lowest weekly average in a year.

3.2 11kV Distribution

Using OpenDSS [3], we formulate a ten-bus network model based on typical settings of a 11kV distribution network in Malaysia. Distribution networks in Malaysia are operated at three voltage levels: 33kV, 11kV and 400V (the latter is also referred to as low-voltage). Most Malasyian customers are connected to the distribution network, and a majority of the residential customers are connected to low-voltage network. However, the aggregation and equivalent impedance of the 33kV transformer, 11kV feeders, distribution transformers and low-voltage networks are not required for our purposes. In contrast, time series simulation is required to evaluate the distribution network hosting capacity. Our ten-bus network model based is shown graphically in figure 6.

Characteristic	Quantity
Power Transformer Rating	30MVA
Total Load	17.1MW
Power Factor	0.97
Average Cable Length	1km - 2km

Table 3: Network Characteristic

Generally, there will be two 33/11kV power transformers operating in parallel in most 33kV substations in peninsular Malaysia. For operational reasons, the system planner would plan for peak demand to be capped at 50% to 75% of the network total capacity. The reason for this is to ensure demand is fully or at least partially transferable to another transformer within the same substation in case of a failure in one power transformer. That will ensure fast restorations of supply and contributes to prudent asset management by having a longer lifespan of power transformers. However, for simplicity, and because we do not consider outages here, this typical configuration is omitted in the network model used for this paper. Thus, we assume that only one power transformer is connected to the modeled network.

For the 11kV outgoing feeder, we model a single radial feeder to further simplify the analysis; actual feeders are usually inter-connected in mesh, although connections between feeders are mostly redundant and used during outages or maintenance only. At each 11kV substation, voltages will be stepped down from 11kV to 400V by distribution transformers. The effects of aggregation for each case of reverse power flow, voltage rises and network losses are validated at the preliminary stage of this research, showing minimal and insignificant differences between the simplified model and a more complex, realistic model, giving confidence that our results are not affected by these simplifications.

The network is modeled based on a 11kV distribution network in a highly populated area in Malaysia where the average distance between substations is 1km to 2km. Therefore, it is assumed that all buses are connected by 300mmp Three-Core 11kV Armoured Cables (Aluminium Conductor) and the distance between buses is set to 2km. Due to data limitations, electrical properties of the power transformer and cables are set according to technical specification manuals from major suppliers of those equipment in Malaysia. The final network model in figure 6 is based on the characteristic summarised in table 3.

3.3 Demand

Peak demand for each node is extracted from [9] and disaggregated based on own assumptions to calculate peak demand data for each transmission and distribution node. Then, each node is assigned to a demand pattern based on three typical demand categories identified in Malaysia. Demand aggregations and classifications are established based on the economic and demographic of each state. We then use three sets of actual hourly demand data from a representative day (5^{th}September 2016) extracted from energy meters installed at the major substations in Klang Valley, Malaysia, to generate demand time series for residential, commercial and industrial loads, representing the three typical demand types in Malaysia depicted in figure 7.

The main characteristic of residential demand is the low energy consumption between 7am until 6.30pm during working hours and rush hours. Energy usage starts to increase after 7.00pm and gradually decreases

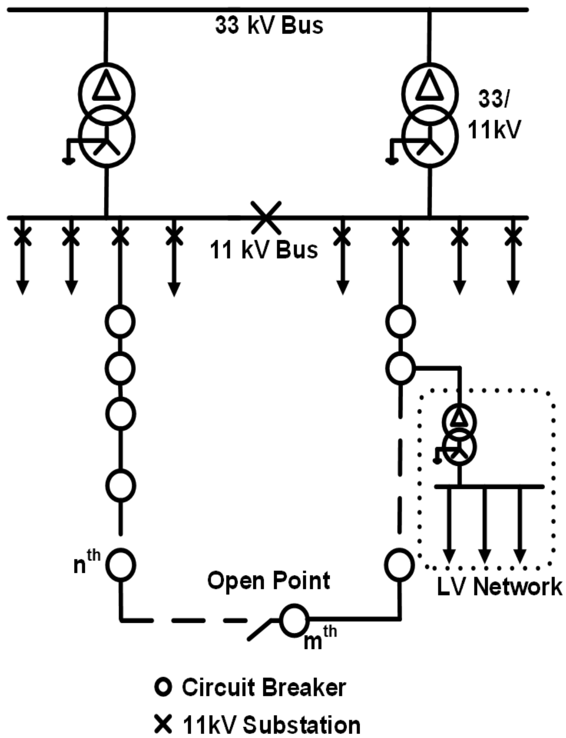

Figure 6: Distribution Network in Peninsular Malaysia

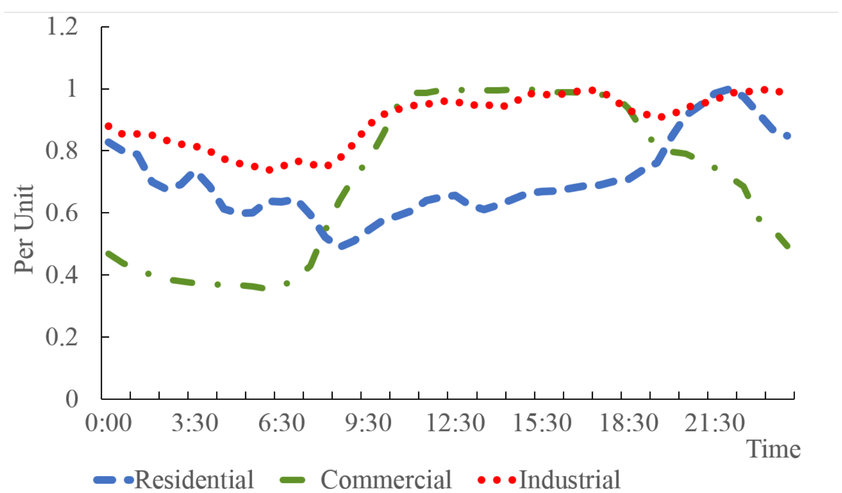

Figure 7: Demand patterns

around 10.30pm. In contrast, commercial demand patterns will reach their peak consistently for a few hours after 10am where most business transactions take place and are subsequently reduced after 6.30pm. On the other hand, industrial demand patterns appear to be flat with minor fluctuations within 0.75 - 1 per unit value; this data was extracted from the main substation which supplies an area of heavy industries that operates 24 hours a day. It is possible that other industrial areas will have different demand patterns, but it is impossible to consider all of those. We therefore focus on this representative case study.

Node	Peak Demand (MW)			Demand Category		Availability							
	Total	Tx Node	Dx Node	Tx Node	Dx Node	Bio	CCGT	Coal	Diesel	Hydro	OCGT	LPV	DPV
1	92.29	4.61	87.67	*I*	*R*		1				1	1	1
2	1033.18	103.32	929.86	*I*	*R*							1	1
3	1633.90	490.17	1143.73	*I*	*R*							1	1
4	1464.51	366.13	1098.38	*I*	*R*	1	1	1		1	1	1	1
5	7291.07	2916.43	4374.64	*C*	*R*	1	1	1			1	1	1
6	769.92	115.49	654.43	*I*	*R*	1	1	1			1	1	1
7	697.09	34.85	662.24	*I*	*R*		1				1	1	1
8	2927.71	731.93	2195.78	*I*	*R*	1	1	1			1	1	1
9	720.41	144.08	576.33	*I*	*R*	1						1	1
10	402.73	60.41	342.32	*I*	*R*		1			1	1	1	1
11	428.20	42.82	385.38	*R*	*R*					1		1	1
12	2288.00	343.20	1944.80	*C*	*R*	1	1	1	1	1	1	1	1
13	914	91.40	822.60	*C*	*R*	1	1		1	1	1	1	1

$Tx - Transmission$
$Dx - Distribution$
$I - Industrial$
$C - Commercial$
$R - Residential$
$1 - Available$
$Blank - Not\ Available$

Table 4: Demand and resource availability

In the distribution network hosting capacity (HC) assessment model, total peak demand is assumed to be evenly distributed at each phase and node, for lack of more detailed information about the distribution of demand over the network. The total demand is set at 17.1 MW or 60% of the total transformer capacity which, as explained above, is a realistic level. Also, residential demand patterns are assigned to all distribution nodes and buses with an average power factor of 0.97, corresponding to the actual demand data mentioned above. Resource availability and demand parameters for each node is are listed in table 4.

3.4 Scenarios

We establish six scenarios s, defined by the cost parameters, demand growth, renewable targets and carbon prices to represent regulatory, technological, and economic uncertainty. In the 'Status Quo' scenario, there are no major changes in any parameter that influences transmission and generation planning. The gas price is expected to increase resulting in moderate escalation of thermal generation costs and capital costs. In this scenario, demand growth is set at its current rate of 40 - 50%, solar targets are unambitious and carbon prices are not enforced.

In the 'Off-grid' scenario, system-level demand is expected to reduce due to the increased amount of self-consumption in the distribution network. The capital and operational costs for distributed generation and battery storage are low, making them more attractive. Transmission investment is assumed uneconomical in this scenario and ambitious renewable objectives are implemented.

The third scenario, 'Decarbonization', favours renewable generation, with conventional generation costs increasing significantly while the cost of renewable generation reduces as a result of government subsidies and decarbonization policies. Ambitious renewable targets and high carbon prices are will eventually remove thermal generators like coal plant from the merit order altogether. However, there is a residual need for flexible generators, which is reflected in a moderate cost increase for this technology.

In the fourth scenario, 'No storage', investment in any type of energy storage system (ESS) is uneconomical due to the absence of supporting policies or regulation to encourage the development of battery storage which could potentially drive down costs. Unlike ESS technology, conditions for renewable generators are favorable as a result of simultaneous reduction in prices, implementation of renewable targets and high carbon prices, similar to the 'Decarbonization' scenario.

The 'Technology' scenario emphasizes on cost decreases resulting from technological advancement and industrialization, which also translate into higher demand growth (50 - 70%). Consequently, the projected cost for all generating plants and transmission investments are significantly reduced. However, as compared to the conventional generators, this scenario favors of new technologies including biomass, solar PV and battery storage.

Finally, the 'Low cost conventional' scenario also features a higher demand growth. In term of cost, this scenario simulates a favorable environment for conventional generators, with a simultaneous decrease in gas prices and thermal plant capital costs. However, high carbon prices are imposed by the regulator, but with low renewable targets and an unchanged cost for renewable technologies.

4 Result and discussion

4.1 Hosting capacity assessment

First, we consider the added value of including a distribution network HC assessment in a high-level transmission and generation expansion model. Table 7 summarizes the total cots of transmission and generation expansion planning over the modeled time horizon for the upper-level model only (without HC), for the combined model (with HC), and the combined model where DSOs actively manage their network using energy storage. As this table shows, accounting for distribution network constraints has increased the total discounted system cost by 0.91% or $2.47 billion. Note for the first two cases, only grid size battery storage is considered.

Scenario	Operating Cost	Capital Cost	Transmission investment cost	Demand growth	Carbon Price (USD/tonne)	RE Target (% of total electricity production)
Status Quo	Conv +20%	Conv +20%		40%	None	10%
Off-grid	Conv +20%, RE -25% LPV -25%, DPV -40% LBS -25%, DBS -40% Home -40%	Conv +15%, RE -25% LPV -25%, DPV -50% LBS -25%, DBS -50% Home -50%	N/A	40%	15	30%
Decarbonization	Conv +20%, RE -25% LPV -25%, DPV -25% LBS -25%, DBS -25%	Conv -15%, RE -25% LPV -25%, DPV -25% LBS -25%, DBS -25% Home -25%	5%	40%	30	40%
No-ESS	Conv +20%, RE -25% LPV -25%, DPV -25%	Conv -15%, RE -25% LPV -25%, DPV -25%	5%	40%	30	40%
Technology	Conv & Hydro -15% Bio -30%, LPV -30% DPV -30%, LBS -30% DBS -30%	Conv & Hydro -10% Bio -20%, LPV -20% DPV -30%, LBS -20% DBS -30%, Home -35%	-30%	50%	15	20%
Low cost conventional	Conv & Hydro -15%	Conv & Hydro -10%	5%	50%	30	10%

Conv - conventional plant
RE - renewable plant
LPV - Large PV
DPV - Distributed PV
LBS - Grid size battery storage
DBS - DSO owned battery storage
Home - Domestic battery storage

Table 5: Stage 1 scenarios (change from 2015)

Scenario	Operating Cost	Capital Cost	Transmission investment cost	Demand growth	Carbon Price (/tonne)	RE Target (% of total electricity production)
Status Quo	Conv +25%	Conv +15%		50%	None	20%
Off-grid	Conv +25%, RE -30% LPV -30%, DPV -60% LBS -30%, DBS -60% Home -60%	Conv +15%, RE -25% LPV -30%, DPV -70% LBS -30%, DBS -70% Home -70%	N/A	50%	30	60%
Decarbonization	Conv +25%, RE -30% LPV -30%, DPV -30% LBS -30%, DBS -30%	Conv +15%, RE -30% LPV -30%, DPV -30% LBS -30%, DBS -30% Home -30%	7%	50%	60	80%
No-ESS	Conv +25%RE -30% LPV -30%DPV -30%	Conv +15%RE -30% LPV -30%DPV -30%	5%	60%	60	80%
Technology	Conv & Hydro -20% Bio -35%, LPV -35% DPV -40%, LBS -35% DBS -40%	Conv & Hydro -15% Bio -25%, LPV -30%, DPV -50%, LBS -30% DBS -50%, Home -55%	-50%	70%	30	40%
Low cost conventional	Conv & Hydro -20%	Conv & Hydro -15%	7%	70%	60	20%

Conv - conventional plant
RE - renewable plant
LPV - Large PV
DPV - Distributed PV
LBS - Grid size battery storage
DBS - DSO owned battery storage
Home - Domestic battery storage

Table 6: Stage 2 scenarios (change from 2015)

	Without HC	With HC	HC Enhanced
Stage 1 Line Investment (GW)	9.19	6.05	6.98
Stage 1 Cost ($ bil)	148.57	149.79	150.25
Expected cost ($ bil)	271.62	274.09	271.72

Table 7: First stage investment and expected cost

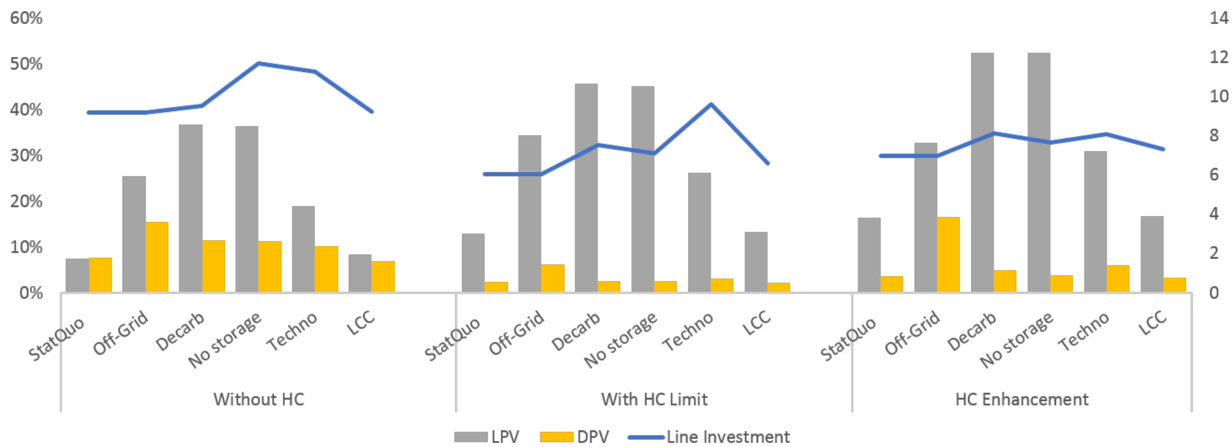

Figure 8: Solar generation mix

Without considering distribution network constraints, the model proposes a significant amount of transmission line investment in the first stage decision to fully utilize the cheaper energy generated by both large solar PV (LPV) and distributed solar PV (DPV) in the second period of operation after the year 2025. As figure 8 shows, higher DPV investment is proposed to reduce the net demand at the distribution level so the energy generated from LPV can be utilized within the transmission network. When HC constraints are imposed, the overall amount of DPV is significantly reduced at some distribution nodes where, in otherwise HC limits would be exceeded. However, due to the fixed solar target, some of this DPV investment is shifted to other distribution nodes, including those with lower solar resources. Also, due to the non-dispatchable characteristic of DPV and in the absence of small scale battery storage to mitigate this problem, larger LPV capacity is required, which is more expensive than DPV. Therefore, investing more in transmission reinforcement is not economical.

In this paper, we consider distribution service operator (DSO) owned storage and home storage to study the effect of distribution network HC enhancement techniques. There are other commonly applied HC enhancement technique such as power quality mitigation, active network management, and distribution network reinforcement to increase DPV penetrations - we do not consider these explicitly, but we would expect very similar results. In our model, HC enhancement leads to cost reductions of nearly $2.37 billion in NPV terms. Anticipating a higher solar penetration and lower generation costs resulting from higher utilization of small scale battery storage (DSO owned and home storage), 6.98GW of line investment is proposed in the first stage.

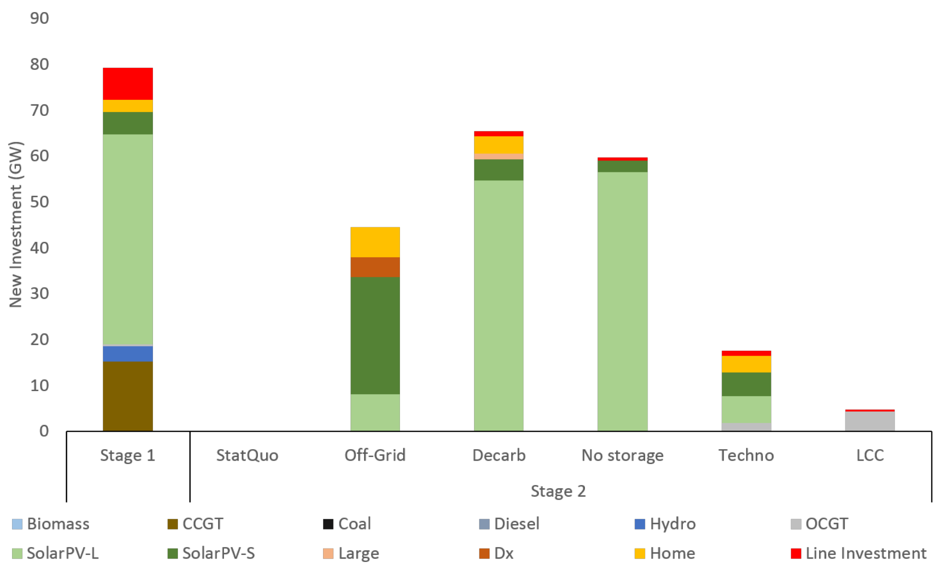

Figure 9: New Investment

4.2 Optimal stochastic solution and scenario analysis

We now present the results of the integrated model in more detail. In the stochastic optimal solution, we observe a significant amount of transmission investment in the first stage that connects generation sources to high demand nodes. Almost half of the total line investment takes place in the first stage. This can be explained in two ways. First, decisions taken in year 2015 will take into account all possible scenario that could occur in year 2025 due to the 10 year lead time of transmission investment. Due to ambitious solar target in three scenarios, the construction of solar generators must start earlier, in the first stage, if these constraints are to be met. Similarly, high demand growth requires new generators to be built in the first stage. Even if it is unlikely that both an ambitious solar target and high demand growth will occur, even a small chance of occurrence will require generators to be built earlier, in the first stage. Hence, transmission investment is chosen to transport the generated power and satisfy all constraints, including in the extreme scenario. This also includes distribution network constraints, which are evaluated using HC assessment. Secondly, it may be optimal to invest earlier, anticipating the needs for future line investment. In this way, the generation cost is be reduced while renewable objectives are met.

Note that in our model, battery storage technology is only used for load shifting and peak shaving. No grid size battery storage and DSO owned battery storage is used in the first stage, because the first-stage solar target is low and can be achieved by integrating LPV, DPV and home storage in the network. In the second stage decision, additional DSO owned storage and home storage is constructed in the 'Off-grid' scenario to allow higher DPV penetrations. As shown in figure 9, grid battery storage only comes in in the 'Decarbonization' scenario.

In all scenarios, CCGT and hydro is utilized for base load as depicted in figure 10 and CCGT dominates in only three scenarios; 'No storage', 'Technology' and 'Low conventional cost'. It is interesting to note that OCGT is not utilized after 2035 in the 'Off-Grid' and 'Decarbonization' scenarios which are designed to favour renewables through ambitious solar targets and higher carbon prices. In both scenarios, DSO owned storage and home storage are used to mitigate the non-dispatchable characteristic of DPV in the

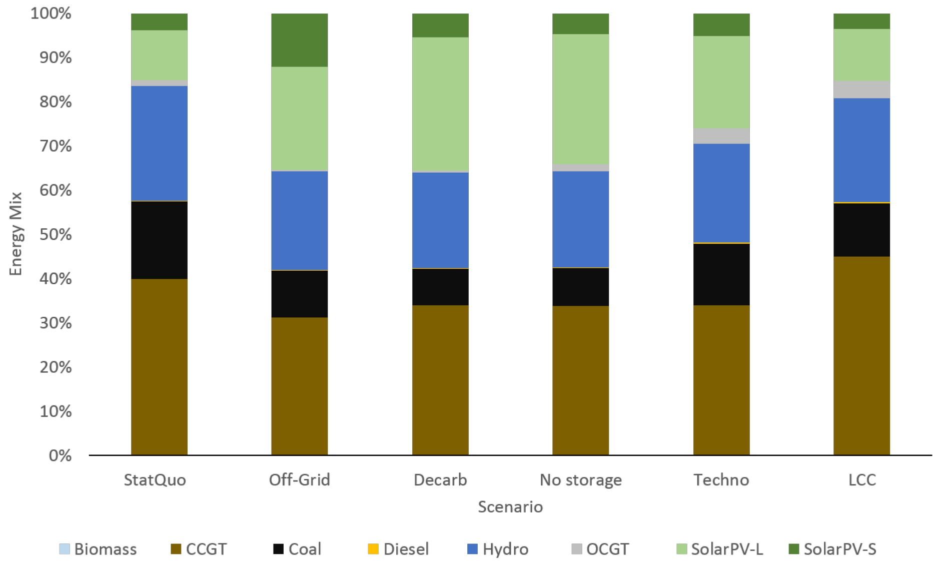

Figure 10: Energy Mix

distribution network. Furthermore, in the 'Decarbonization' scenario, large battery storage facilities are utilized to replace OCGT, as a result of the higher carbon price. For the same reason, the utilization of coal plant is at its minimum in this scenario.

Unsurprisingly, we observe the highest DPV mix in the 'Off-grid' scenario, which increases self-consumption and reduces dependency on larger generation facilities.This approach could reduce the overall cost of electricity generation, but that is not necessarily the case due to price and technology uncertainty. Despite this, the first stage investment decision provides an indicative transition plan to be implemented accounting for future uncertainty. We observe a higher utilization rate of some technologies in the third operational period (2035), which means that investments made in the first stage are being used only after 2035 as in 8.

Table 8show how the average capacity factor varies for each scenario. In StatusQuo, thermal and hydro are used as base load plant. In Off-grid, capacity factors decrease significantly, except for DPV and home storage. In the Decarbonisation scenario, coal utilisation drops even lower because of the high carbon price; the No Storage scenario is similar. In the Technology and Low Cost conventional scenarios capacity factors are higher, particularly for coal.

4.3 Uncertainty

4.3.1 Expected value of perfect information (EVPI)

We now calculate transmission-generation EVPIs. Table 9 list the costs of each scenario obtained from the deterministic planning model assuming both transmission planners and generators have perfect foresight. The EVPI of 9.13% is calculated as a percentage difference between the expected cost from the stochastic model and a probability weighted average of the total deterministic cost in each scenario. This represent the upper bound to the value of an improved forecast. This EVPI is large, especially compared to previous studies, indicating that uncertainty has a significant effect in our model.

Scenario	Biomass	CCGT	Coal	Diesel	Hydro	OCGT	LPV	DPV
Period 2 (2025)								
Status Quo	0	0.38	0.45	0.06	0.64	0.04	0.03	0.17
Off Grid	0	0.28	0.31	0.06	0.58	0.05	0.12	0.17
Decarbonization	0	0.28	0.29	0.06	0.57	0.06	0.17	0.17
No storage	0	0.28	0.29	0.06	0.57	0.06	0.17	0.17
Technology	0	0.33	0.46	0.11	0.64	0.14	0.08	0.17
Low Cost Conventional	0	0.42	0.46	0.11	0.64	0.14	0.03	0.17
Period 3 (2035)								
Status Quo	0	0.33	0.46	0.11	0.64	0.14	0.08	0.17
Off Grid	0	0.29	0.25	0.00	0.54	0.00	0.17	0.15
Decarbonization	0	0.32	0.14	0.09	0.49	0.00	0.17	0.16
No storage	0	0.32	0.15	0.10	0.50	0.16	0.17	0.16
Technology	0	0.34	0.34	0.17	0.58	0.25	0.17	0.16
Low Cost Conventional	0	0.46	0.23	0.21	0.64	0.20	0.09	0.17

Table 8: Average capacity factor (ACF)

Scenario	Total Cost (USD Billion)	Savings from perfect info (USD Million)
Stochastic	271.72	
StatusQuo	159.11	112.61
Off Grid	237.43	34.29
Decarb	312.26	-40.54
No-ESS	318.72	-47.00
Techno	209.60	62.12
LCC	195.69	76.03
EVPI	24.81 (26.71)	
EVPI (% Stochastic cost)	9.13% (9.88%)	

Table 9: Expected Value of Perfect Information

Scenario	Total Cost (USD billion)	Cost of Ignoring Uncertainty (USD billion)
Stochastic	271.72	
StatusQuo	272.80	1.08
Off Grid	271.74	0.02
Decarb	271.74	0.02
No-ESS	271.78	0.06
Techno	271.79	0.07
LCC	272.62	0.90
ECIU	0.36 (0.13%)	

Table 10: Expected Cost of Ignoring Uncertainty

Using the same metric, we calculate the EVPI without accounting for distribution network constraints or hosting capacity (HC) limits to calculate the upper bound value of information related to the distribution network. Then, we calculate the difference between both EPVI; with and without HC limits. The EVPI for both cases differs by nearly \$1.9 billion or 0.75%. This indicates that uncertainty is especially important in a model that considers distribution network constraints.

4.3.2 Expected value of ignoring uncertainty (ECIU)

In this section, we calculate a transmission-only ECIU. Each scenario is solved using deterministic model to determine the native first stage transmission decision. Then, the first stage naive decision is imposed on the stochastic model as an additional first stage constraint. This demonstrates how the naive decision made by the planner in the first stage will impact the decision in the second stage where the uncertainty starts to have an effect The result obtained from this exercise is compared against the expected cost from the stochastic model as in table (10).

From table 10, the resulting ECIU, 0.13% of the stochastic cost indicates the cost of ignoring the uncertainties. However, the scenario-dependent CIU depends to a large extent on the selection of naive scenario. Two scenarios jump out in particular: ’Status Quo’ and ’Low cost conventional’. The cost of ignoring uncertainty are significantly higher for both scenarios due to its low transmission and generation investment in the first stage resulting in a larger investments requirenemt in second stage. Hence, if a deterministic model is used, making sure that this captures future renewable development is crucial.

4.4 Comparison between co-optimized and sequential approach

In this case study, we compare two different battery storage planning approaches; co-optimized and sequential. The former optimizes battery storage investment together with transmission and generation investment while the latter optimizes battery storage later during the operational period after transmission and generation investments are finalized. This is perhaps more consistent with current practice, in which battery storage investment, including home storage investment, takes place as part of distribution network hosting capacity enhancement.

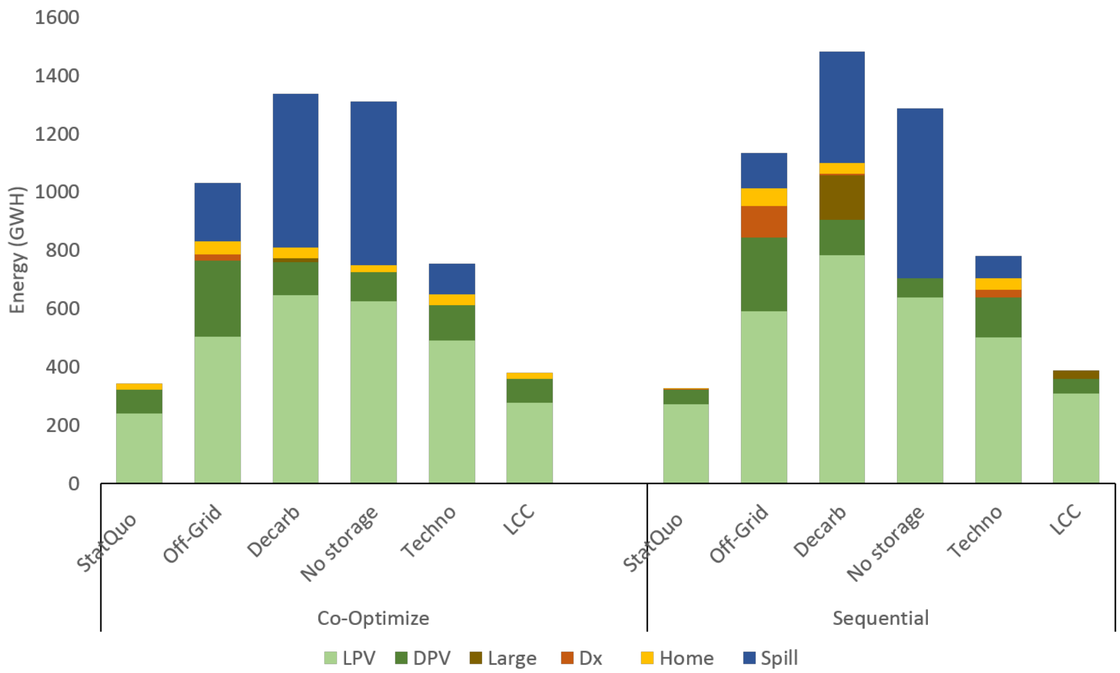

Table 11: Energy mix for co-optimized and sequential approach

The expected cost is reduced by 0.63% ($1.7 billion) in the sequential approach, which can be explained in several ways. First, in the co-optimized approach, a 10 year lead time is assumed for all types of battery storage, similar to generation and transmission project lead times. In the sequential approach, the model assumes that all types of battery storage will be in operation within a year. All other parameters are similar throughout. Second, if battery storage investment is decided in the operational period, this allows planners to decide with a better understanding of which scenario will occur. Notwithstanding the potential cost increase of energy storage with a shorter lead time, which we do not model, the result implies that being able to wait and see which scenario will occur, and being able to plan energy storage with shorter lead times, has significant benefits, and significant impacts on the generation mix.

5 Conclusions

In this paper, we have proposed and demonstrated a stochastic integrated planning model that allows distribution network hosting capacity (HC) constraints to be included long term grid planning under uncertainty. This is important especially in countries where distribution-connected solar PV capacity is expected to play a large role in the energy mix. Current grid planning methods generally do not consider distribution network constraints, and as a result, distribution system operators are facing increasing difficulties managing voltages and reverse power flows. Our model quantifies the effects of these distribution network constraints, their interactions with uncertainty about future demand, costs, and policies, and the value of energy storage in resolving some of them. We apply our model is applied to a stylized representation of of the Malaysian grid, where solar energy is expected to play a particularly large role.

Based on our findings, we conclude that distribution network constraints have a significant impact on the overall planning and in our case study increase the total net present value (NPV) system cost by almost 1%, or close to $2.7 billion. This happens because hosting capacity limits reduce the amount of cheaper distributed solar PV (DPV) in the distribution network, forcing investment in more expensive renewable technologies and/or shifting DPV to locations with lower quality solar resources. Integrating distribution ssystem operator (DSO) operated battery storage and domestic home storage in the distribution network to increase the hosting capacity goes some way to address this problem. The resulting higher DPV investment in high-resource distribution networks results in cost reduction of 0.86% of total discounted system costs, equivalent to $2.37 billion.

We also quantify the effects of uncertainty in our model by calculating the expected value of perfect information (EVPI), including economic, policy, technology and uncertainty. This upper bound to the value of better forecasts is, in our case study, around 10% of the overall system cost and hence, uncertainty has very significant effects. Policy makers should therefore do all they can to minimise uncertainty. We also show how including distribution constraints in the model increases the value of perfect information. We calculate the expected cost of ignoring uncertainty; i.e., the cost of using a deterministic model, to be on the same order of magnitude as the cost of distribution network constraints. Hence, efforts to use models that can accommodate these constraints are at least as important as efforts to move to stochastic planning modelling methods.

Finally, we evaluate the difference between a co-optimized and a sequential approach for battery storage investment. In our case study, a sequential approach, where storage investment is postponed until some uncertainty is resolved and until transmission and generation investments are made, can reduce the overall cost by 0.63%. This demonstrates that there is value in waiting, and in reducing the lead time of energy storage investment.

This paper has been a first attempt to address joint transmission and distribution network modelling for planning purposes. More research on this topic is necessary, but we have demonstrated that our approach is worth further analysis.

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