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Multi-stage stochastic optimization framework for power generation system planning integrating hybrid uncertainty modelling

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ABSTRACT

In this paper, a multi-stage stochastic optimization (MSO) method is proposed for determining the medium to long term power generation mix under uncertain energy demand, fuel prices (coal, natural gas and oil) and, capital cost of renewable energy technologies. The uncertainty of future demand and capital cost reduction is modelled by means of a scenario tree configuration, whereas the uncertainty of fuel prices is approached through Monte Carlo simulation. Global environmental concerns have rendered essential not only the satisfaction of the energy demand at the least cost but also the mitigation of the environmental impact of the power generation system. As such, renewable energy penetration, $CO_{2,eq}$ mitigation targets, and fuel diversity are imposed through a set of constraints to align the power generation mix in accordance to the sustainability targets. The model is, then, applied to the Indonesian power generation system context and results are derived for three cases: Least Cost option, Policy Compliance option and Green Energy Policy option. The resulting optimum power generation mixes, discounted total cost, carbon emissions and renewable share are discussed for the planning horizon between 2016 and 2030.

1. Introduction

World total electricity generation is expected to grow by 69% from 2012 to 2040 and make up almost a quarter of total energy consumption by 2040 (EIA, 2016). On the other hand, resource depletion and environmental concerns have forced decision makers to aim not merely to satisfy the increasing demand at the least cost, but also to move towards more sustainable economic development. To this end, many countries have enacted environmental policies to regulate the greenhouse gas (GHG) emissions from power production units using fossil fuels. In 2017, renewable energy sources covered 40% of the increase in primary demand, while net additions of coal-fired plants are expected to reduce by 55% in the following 20-year horizon, in relation to additions taking place from 2000 up to 2017 (OECD/IEA and IEA, 2017).

Although renewable energy technologies can achieve a reduction in total GHG emissions from power production, their ability to satisfy demand largely depends on the renewable resource potential of the region. Intermittent renewables can provide a certain amount of electricity but are not effective as standalone technologies to provide baseload power. Power generation planning seeks to design the optimal power generation mix by optimizing a performance indicator (such as minimizing the energy system cost), while at the same time satisfying a set of conditions related, for example, to the security of supply, the limitation of resources, the energy diversity, the environmental impact as well as the renewable technology capacity factors and the evolution of their costs. It is, hence, a challenging undertaking requiring the examination of numerous, often interrelated, aspects.

Mathematical programming is an appropriate method for determining optimal electric power generation systems that will minimize the overall cost (or other objective functions) while satisfying a set of underlying conditions. Conventional energy planning is performed based on a deterministic projection of demand, capital cost of different generation technologies, fuel prices, etc., assuming that all variables are certain and remain unchanged throughout the planning horizon (Koltsaklis et al., 2014). However, some of the future forecasts, such as demand growth, fuel price and renewable energy cost, are susceptible to change in the future, making the planning solution invalid when those variables deviate from the forecasted values (Thangavelu et al., 2015).

The present work proposes a linear multi-stage stochastic optimization (MSO) model that determines the medium-to-long term optimal electricity generation mix, taking into consideration the uncertainty in electricity demand, capital cost reduction for renewable technologies and fuel prices along the planning horizon. In this work, the uncertainties are modelled through a hybrid method combining the Scenario Tree (ST) and the Monte Carlo Simulation (MCS) approach. The volatility of fuel

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prices (natural gas, oil and coal) was modelled through MCS, while the associated uncertainty in electricity demand growth and capital cost reduction for renewable technologies was addressed by applying a finite number of possible weighted scenarios. Applying the MCS to fuel prices enables the extension of the possibilistic (scenario tree) uncertainty modelling approach to a stochastic one, allowing for certain random variables to be represented through continuous probability density functions, leading to a more realistic representation of fuel price uncertainty, based on collected historical data rather than assigning a degree of belief to possible scenarios. As such, novelty of this work lies in developing the hybrid uncertainty modelling approach within the stochastic optimization framework, as well as in the use of updated input data used to perform the optimization of the Indonesian power generation mix. Furthermore, we present results for a number of Planning Options (POs) outlined in Section 6 to derive useful insights on the response of the system under different sets of constraints.

Data were collected from online databases, official reports, as well as communication with people from the Ministry of Energy and Mineral Resources of Indonesia, with the aim to derive optimal power generation mixes and additional capacity to be built in each period across a timeframe from 2016 to 2030 to satisfy electricity demand while fulfilling environmental concerns, renewable penetration and energy diversity targets in this case study.

The remainder of this paper is structured as follows: Section 2 presents existing literature dealing with the optimization of the energy mix under uncertainty. The optimization problem is defined in Section 3; Section 4 presents the mathematical formulation of the MSO problem outlining its objective function and constraints. Next, in Section 5, the Indonesian energy context is presented, while Section 6 describes the results derived from the application of the MSO method to the baseline case and subsequently to a number of defined POs. Then, in Section 7 results are further discussed and finally, Section 8 draws the main conclusions of this work.

2. Literature review on the optimisation of the energy mix under uncertainty

A number of authors have undertaken studies related to the determination of the optimal energy mix at a national (Thangavelu et al., 2015; Prebeg et al., 2016; Ozcan et al., 2014; Ioannou et al., 2017; Costa et al., 2017; Bakirtzis et al., 2012), regional (Koltsaklis et al., 2014; Cheng et al., 2015; Li et al., 2010; Li et al., 2014; Cabello et al., 2014) or even at building (Cano et al., 2016) level. Most studies use the minimization of the power generation system cost as the objective function, which most frequently includes the investment cost of new generating technology, the fuel price, the fixed and variable operating costs. Other costs considered in literature are: salvage and dismantling costs (Cabello et al., 2014; Aghaei et al., 2013), emissions costs (Ahn et al., 2015; Georgiou, 2016; Hu, 2014; Hu et al., 2013), cost of electricity not supplied (Delgado et al., 2011; Feng and Ryan, 2013; Jeppesen et al., 2016), imports of fuel and electricity (Koltsaklis et al., 2014; Georgiou, 2016; Hu, 2014; Hu et al., 2013), cost of carbon capture and storage units (Jeppesen et al., 2016), cost of transmission (Koltsaklis et al., 2014; Zakerinia and Torabi, 2010) and cost of storage (Zakerinia and Torabi, 2010; Krukanont and Tezuka, 2007).

Many works have been established to develop optimization models that incorporate uncertain inputs in the energy generation planning (Ioannou et al., 2017). The MSO method has been widely used to model the uncertainty of selected variables with specific probabilities by means of a multi-period scenario tree. The fundamental concept of MSO is recourse, allowing corrective actions to be implemented in each stage based on the corresponding uncertainty realized so far (Li et al., 2010). In the first stage, a decision has to be made "here and now" before perceiving uncertainty, then in the next stage the decision is made after realizing the uncertainty values (Feng and Ryan, 2013; Krukanont and Tezuka, 2007). For example, the energy mix for period $t+1$ can be decided only after realizing the energy demand at period t.

Li et al. formulated a multi-stage interval-stochastic energy model using integer linear programming for supporting electric power system planning under uncertainty of power demand (Li and Huang, 2012). Through a multi-stage stochastic non-linear programming model, Thangavelu et al. suggested the inclusion of uncertainty in demand, fuel price and technology cost by assigning scenarios to each variable (Thangavelu et al., 2015). Krukanont and Tezuka considered the uncertainty of energy demand, plant operating availability and carbon tax rate in developing a two-stage stochastic linear programming optimization model to analyze the near-term Japanese energy system planning using real data (Krukanont and Tezuka, 2007). Bakirtzis et al. summarised various planning models which incorporated uncertainties, and performed a scenario-based mixed-integer linear programming model to illustrate the effect of demand, fuel prices and CO_2 prices' uncertainties on planning decisions using real data from the Greek power system (Bakirtzis et al., 2012).

The ST and MCS are two foremost approaches that have been used to represent uncertain parameters in MSO problems. The former approximates continuous distribution into discrete scenarios and performs optimization at each realization of uncertain parameter weighted with the corresponding discrete probability (Betancourt-Torcat and Almansoori, 2015). The latter portrays input uncertainty by generating random scenarios based on continuous distributions, which can be determined from historical data or expert judgement (Vithayasrichareon and MacGill, 2012). ST has been widely used for structuring stochastic programming models in power generation system planning (Thangavelu et al., 2015; Li et al., 2010; Cano et al., 2016; Li and Huang, 2012), due to their ability to discretize the vast number of possible outcomes of the uncertain variables (Cano et al., 2016). The ST-based stochastic programming framework is efficient when the optimization problem is convex and the number of decision stages is small (Shapiro, 2006). Nevertheless, a number of scenario reduction techniques (such as backward reduction or forward selection) are available to deal with the rapidly growing number of scenarios in a multi-stage stochastic programming framework (Conejo et al., 2010).

Some previous studies implemented MCS to model uncertainty of key parameters in the power generation mix (Min and Chung, 2013). Tekiner et al. formulated a mixed integer linear programming method to minimize the total weighted three objective functions (total cost, CO_2 emissions and NO_x emissions) and used the MCS technique to produce 1500 demand scenarios (Tekiner et al., 2010). Betancourt-Torcat and Almansoori used the MCS method to simulate uncertainty associated with natural gas price and developed a multi-period linear model to determine optimal power generation in the United Arab Emirates (Betancourt-Torcat and Almansoori, 2015). Min and Chung also applied the MCS approach to integrate the uncertainty of power demand and fuel prices, and generated a linear model to solve South Korea's long-term power generation mix problem (Min and Chung, 2013). Finally, Piao et al. used the MCS technique to predict power demand and used it as input in a non-linear stochastic optimization model for identifying strategies to improve air quality in Shanghai (Piao et al., 2014).

3. Problem definition

This section outlines the main features of the proposed MSO model for the power generation planning under hybrid uncertainty modelling.

3.1. Problem statement

This study addresses the power generation expansion planning (PGEP) problem of a country or region by determining the optimal combination of power production plants. Ten power generation technologies are considered as alternatives for the new power plants to be built including pulverized coal-fired (PCF), natural gas combined cycle

(NGCC), diesel power, hydro power, geothermal, biomass, wind onshore, wind offshore, solar photovoltaic (PV) and concentrated solar (CSP) power plants. The proposed model and the case study did not consider nuclear energy within the potential power generation technologies because the nuclear energy in Indonesia (which is the case study country) is under continuing debates related to the threats on security in one of the world's most geothermally active nations. The utilization of nuclear energy will be considered only following the optimal utilization of new energy sources (such as hydrogen, coal bed methane, liquefied coal and coal gasification) and renewable energy.

The planning horizon of the problem is divided into a set of time intervals, t (with each interval corresponding to a multi-year period) and there is a number of key problem parameters (i.e. electricity demand increase, capital cost reduction for renewable technologies and fuel prices for conventional technologies) subject to uncertainty under each investigated scenario, s of time interval, t. The corresponding techno economic and air emissions data of above energy sources are also given. The PGEP problem aims to determine the combination of energy sources and technologies to meet future electricity demand for each period of the planning horizon under a number of uncertain key parameters.

3.2. Structure of the model

Fig. 1 illustrates the structure of the mathematical model, summarizing the required input parameters (deterministic and uncertain), the set of constraints, the objective function, the decision variables and the output variables. Symbols are summarised in the Nomenclature found in Section 4. Deterministic input parameters include the energy policy targets, as well as the techno economic, resource and technology details. Techno-economic input data of power plants used in the model include capital cost, fixed operation and maintenance (O&M) cost, non-fuel variable O&M cost, carbon emission rate, capacity factor and technical lifetime of the power plant and were collected both through desktop research and through communication with experts. More in specific, data on existing power generation plants of Indonesia, namely the built year, the installed capacity, the decommission time and the capacity factors were obtained following communication with the Ministry of Energy and Natural Resources.

The uncertain parameters comprise the scenario values and probabilities of future electricity demand, the capital cost reduction for renewable technologies and the fuel prices for coal, natural gas and diesel fuels. The incorporation of uncertainties result in the derivation of stochastic planning solutions for power generation mixes.

The constraints that need to be satisfied include the following: (1) meet the future electricity demand at the least cost, both in terms of required installed capacity and net power generation, (2) attain the required renewable penetration targets, (3) restrain $CO_{2,eq}$ emissions within the target set by government regulations, (4) consider annual construction limits for the installation of renewable energy new capacity, (5) the resource potential of the region, and (6) the fuel diversity to manage risk associated with dependency on certain fuel sources or technologies.

Decision variables represent the types and the capacities of the new power plants installed (i.e. the capacity expansion planning) per each time period and scenario. The optimization model, at each time period and scenario, determines the: energy system cost, the existing power generation capacities, the renewable sources contribution to the power generation mix, the power generation cost structure breakdown (capital cost, fixed cost, variable cost, fuel cost and carbon cost) at present value, the decommissioned power plant facilities that have reached their end of life (decommissioning plan), the required capital cost for the capacity expansion projects, the fuel consumption required by power generation facilities in one year, the annual electricity production from each type of power generation technology, and the GHG emissions

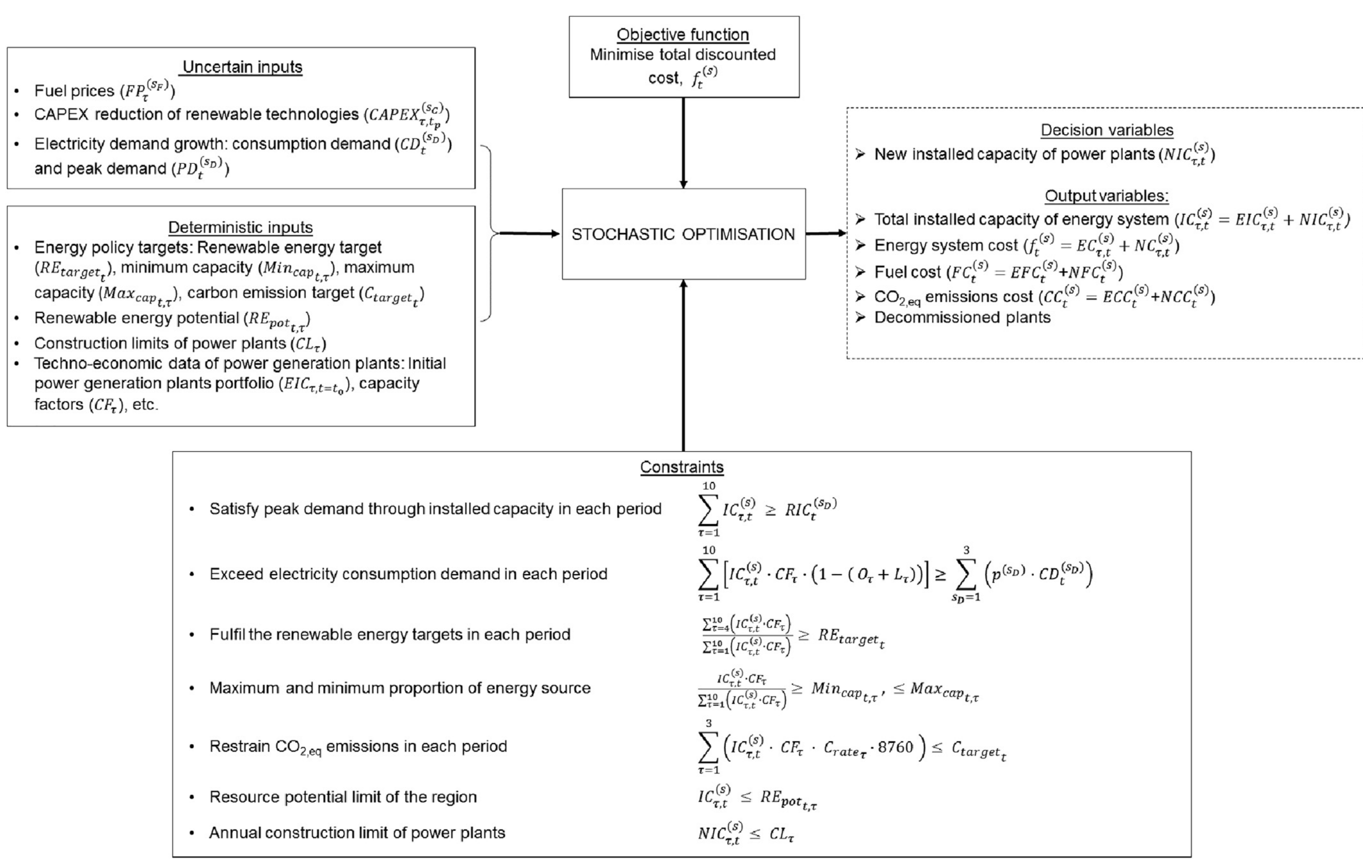

Fig. 1. Schematic representation of the model.

from the power generation system. The mathematical formulation of the optimization problem is presented in Section 4.

3.3. Assumptions of the model

To understand the specifics of the programming approach the following well-informed assumptions were considered:

1. Learning curve effects are only applied to the onshore wind and solar PV power plants, whose capital cost is assumed to experience a declining rate through the course of the planning horizon, due to technological development. Capital costs of other technologies were assumed to retain their initial values and future costs were discounted to the present. Furthermore, the capacity factors of all power plant types were assumed to remain constant.
2. The current work integrated the volatility of fuel price into the model for three types of fuels, including coal, natural gas and diesel, while biomass price was assumed to retain a mean value which (similarly to all technologies) is discounted throughout the planning horizon.
3. The PV degradation rate is assumed to remain stable (at 0.8%/year (Jordan and Kurtz, 2012)) throughout the lifetime of the solar PV power plant. Renewable technologies are assumed to have zero emissions; only emissions during the operation of the conventional power plants are considered and not the lifecycle emissions.
4. It is assumed that, if the system requires capacity expansion at the beginning of a particular period,t this expansion project has to be completed by the end of the previous period, denoted as t_p.
5. The produced electricity (MWh) from conventional energy power plants (coal, natural gas and petroleum-fired power plants) was calculated through the fuel consumption rate, which equals the amount of fuel consumed to generate 1 MWh of electricity. Table 1 includes the fuel consumption rates used as inputs in the model.
6. The total cost of power generation throughout the planning horizon is discounted to present value with a certain assumption of interest rate.
7. Minimum share of a certain technology can be imposed by setting a minimum contribution of each technology to the energy mix. For example, to manage the risk of intermittency from renewable energy sources policy makers can set the share of coal and gas power at a certain minimum level.
8. The sustainability criteria are fulfilled by means of: the carbon tax, which represents the external cost of environmental impact mitigation; the carbon emission limit, which bounds the amount of $CO_{2,eq}$ emission produced by the power generation sector in one year and the renewable energy penetration target, which represents the minimum share of power generated from renewable energy sources.
9. Fuel diversity is imposed within an acceptable range by means of enforcing a maximum proportion cap for each technology. The maximum proportion cap can also be used as a tool to restrain an undesired technology option.

3.4. Uncertainty modelling

In the proposed model, future projection of uncertain variables is represented as a multi-stage ST that grows with both MCS random generated nodes and ST nodes.

1. Energy demand: The uncertainty of peak demand and power consumption growth are represented by three ST nodes (low, medium and high) with their assigned probability.
2. Capital cost reduction for renewable technologies: Technology innovation is anticipated to gradually reduce the cost of energy of renewables. In this study, wind onshore and solar PV are considered to experience a decreasing rate in their capital cost. The uncertainty of the capital cost reduction rate for wind onshore and solar PV are represented by three ST nodes (low, medium and high) with their assigned probability.
3. Fuel Price: The volatility of fuel prices (coal, natural gas and diesel) is represented by n MCS random generated nodes assumed to follow a normal probability distribution function for each fuel type. Normal distribution has been widely used in many stochastic problems (Betancourt-Torcat and Almansoori, 2015; Al-Qahtani et al., 2008); nevertheless, other probability distribution functions were also tested in order to evaluate the effect of statistical uncertainty.

Sections 3.4.1 and 3.4.2 present the two distinct uncertainty modelling approaches.

3.4.1. Monte Carlo simulation

MCS involves the random sampling of the probability distributions of the model's input parameters with the purpose of producing numerous random output values. The sampling from each parameter's probability distribution is realized in a way that reproduces the shape of the resulting distribution; hence, the distribution of the output values deriving from the application of the method reflects the joint probability distribution of the outcomes (Vose and Analysis, 2008). It is a standard mathematical procedure, where random inputs are sampled and the output values are recorded for later processing through calculation that a desired event is realized in a number of occasions across the total iterations. Basic steps required to perform MCS are as follows:

1. Definition of the parametric model, $y = f(x_1, x_2, \ldots x_q)$, where q is the total number of.
2. Definition of probability distributions for the inputs, number of simulations to accomplish the desired accuracy.
3. Generation of set of random inputs $x_{i1}, x_{i,\,2}, \ldots, x_{i,\,q}$.
4. Execution of the deterministic model with the set of input parameters and recording of output value y_i.
5. Repeat steps 4 and 5 for $i = 1$ to n.
6. Compilation of the joint probability distribution of the outputs y_i.

There are numerous statistical distributions that can be utilized for engineering approximations and random number generations.

In this study the normal probability density distribution is used to model the fuel prices, given by the following equation:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp^{-}(x-\mu)^2/2\sigma^2 \tag{1}$$

The mean values and standard deviations of the three different types of fuels are summarised in Table 2.

Table 1
Fuel consumption rate used in the model (Source: (Ministry of State Owned Enterprises (SOEs), 2017)).

Fuel type	Fuel consumption rate	
Coal	0.53	Ton/MWh
Natural gas	8.9	MMBTU/MWh
Petroleum	1.81	Barrel/MWh

Table 2
Mean values and standard deviations of fuel prices of conventional technologies (Source: (Ministry of State Owned Enterprises (SOEs), 2017)).

	Mean value, μ ($/MWh)	Standard deviation, σ ($/MWh)
Coal price	36	5
Natural gas price	72	10
Oil price	82	10

3.4.2. Scenario tree approach

A ST is an ensemble of scenarios (or else realizations), s of the future. It is defined by a set of nodes, $k \in K$, their successors (called children nodes) B_k and their associated probabilities, $p^{(s_k)}$. A scenario is a path from the root node to a leaf node (having no successors) and the probability of scenario, s (denoted as $p_t^{(s)}$) equals the product of probability of occurrence (joint probability) realized from root node to leaf node $p_t^{(s)} = \prod_{k \epsilon K} p^{(s_k)}$. Each stage of the time horizon, $t \in T$ is associated to a set of nodes (representing the different evolutions of the uncertain parameters) forming a set of scenarios. It is a necessary condition, the sum of all probabilities of each scenario within a specific time period to be equal to one, $\sum_{(s)} p_t^{(s)} = 1$.

In this work, the uncertainty is modelled by means of a three-stage ST as illustrated in Fig. 2. The system covers a time horizon of 3 time periods consisting of 4, 5 and 5 years duration, respectively. The number of nodes and finite scenarios is determined by the three uncertain variables (electricity demand, capital cost reduction and fuel price). During the first time period, both the uncertainty of electricity demand and capital cost reduction are represented by three nodes: “Low”, “Medium” and “High” with assigned probability values p_L, p_M and p_H, respectively (producing $3 \cdot 3 = 3^2$ scenarios within the first time period), while the uncertainty of fuel prices is represented by n nodes, with $1/n$ assigned probability each, sampled by means of a MCS process, leading to a total of $n \cdot 3^2$ scenarios, where n is the set of random MCS samples and t is the number of the stage, as shown in Fig. 2.

After reaching the leaf node of each stage's scenarios, the values of the decision variables (new installed capacities of each plant type) of the n nodes (representing the uncertainty of fuel prices) are averaged to provide the input value for the next node. Hence, in each stage, $n \cdot 3^{2 \cdot t}$ scenarios are generated. The fluctuations in the fuel prices were assumed to follow a normal probability distribution, as it is the standard distribution used for many probability problems (Betancourt-Torcat and Almansoori, 2015). MCS generated a random set of fuel prices based on the mean and standard deviation values given in Table 2. It should be highlighted that increasing the size n of the MCS generated samples can provide more robust results; however, it significantly increases the processing time.

The method can be extended to incorporate other uncertainties; nevertheless, the ones chosen have been widely cited in literature as among the most impactful (Thangavelu et al., 2015; Li et al., 2010; Vespucci et al., 2016; Ji et al., 2015; Vespucci et al., 2014; Kim et al., 2012).

4. Model formulation

The mathematical formulation of the optimization model is presented in this section, starting with the electricity system costs, followed by the constraints and the objective function formulation of the problem.

Nomenclature

The notations of the sets, parameters and variables, along with their measurement units are defined in order to introduce the mathematical model:

Sets

$p^{(s_D)} = \{0.3, 0.5, 0.2\}$ Probability of energy demand scenario
$p^{(s_C)} = \{0.3, 0.5, 0.2\}$ Probability of capital cost reduction scenario
$p^{(s_F)} = \{\frac{1}{n}, \ldots, \frac{1}{n}\}$ Probability of fuel cost volatility scenario
$p^{(s)} = p^{(s_D)} \cdot p^{(s_C)} \cdot p^{(s_F)}$ Probability of occurrence of scenarios s
$s_C = \{1, 2, \ldots, 10\}$ Capital cost reduction scenario of new onshore wind and solar power plants
$s_D = \{1, 2, 3\}$ Energy demand scenario
$s_F = \{1, 2, 3\}$ Coal, gas and oil fuel price scenario
$s = \{s_C, s_D, s_F\}$ Combination of scenarios/realizations s_C, s_D, s_F
$t = \{1, 2, 3\}$ Time period
t_p Previous time period (years)
$\tau = \{1, 2, \ldots, 10\}$ Power generation plant: coal: 1, natural gas: 2, oil: 3, hydro: 4, geothermal: 5, biomass: 6, onshore wind: 7, offshore wind: 8, solar PV: 9 and solar CSP: 10
n Number of MCS samples
dv Set of decision variables

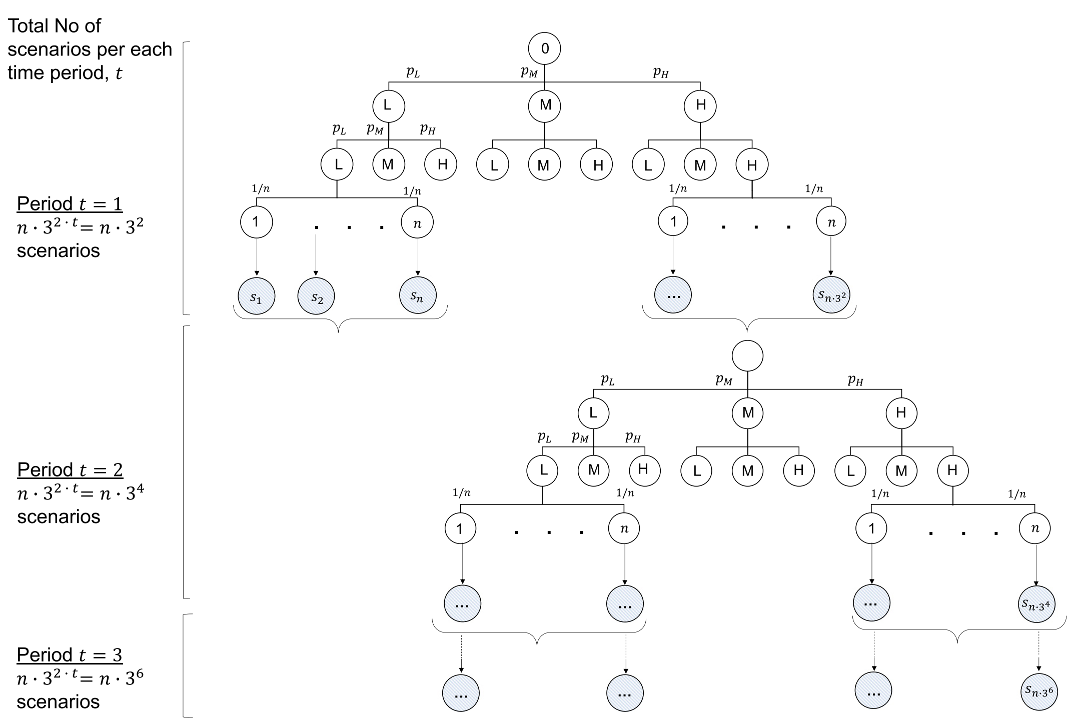

Fig. 2. Hybrid uncertainty modelling approach based on scenario tree and Monte Carlo simulation.

$k \in K$ Set of nodes comprising a scenario

Parameters

$C_{rate\tau}$ $CO_{2,eq}$ emission rate of power generation plant, τ (tons of CO_2/MWh)
CF_τ Capacity factor of power generation plant, τ (%)
CL_τ Annual construction limit for each technology, τ (MW/year)
C_{tax_t} Carbon tax (\$/ton of $CO_{2,eq}$)
Lf_τ Operating life of power generation plant, τ (years)
L_τ Transmission and distribution losses of power generation plant, τ (%)
$Max_{capt,\tau}$ Maximum proportion of power generation plant, τ in energy mix (%) during time period, t
$Min_{capt,\tau}$ Minimum proportion of power generation plant, τ in energy mix during time period, t (%)
O_τ Own power use of power generation plant, τ (%)
$RE_{pott,\tau}$ Renewable energy potential limit of power generation plant, τ during time period, t (in MW)
$RE_{targett}$ Renewable energy penetration target of power generation plant, τ in energy mix (in %)
VOM_τ Non-fuel variable O&M cost of power generation plant, τ (\$/MWh)
FOM_τ Fixed O&M cost of power generation plant, τ (\$/kW)
RM Supply reserve margin (%)
r Interest rate (%)

Variables

$Cemitt^{(s)}$ $CO_{2,eq}$ emitted per year during time period, t under scenario $s \in [s_C, s_D, s_F]$ (ton of $CO_{2,eq}$/year)
$CD_t^{(s_D)}$ Power consumption demand power generation plant, τ under scenario s_D (MWh)
$ECAPEX_{\tau,t_p}^{(s_C)}$ Capital factor of existing power generation plant, τ installed during the previous time period, t_p under scenario s_C (\$/kW)
$EC_t^{(s)}$ Power generation cost of existing power generation plant, τ during time period, t (\$/year)
$EIC_{\tau,t}^{(s)}$ Installed capacity of existing power generation plant, τ during time period, t under scenarios $s \in [s_C, s_D, s_F]$ (MW)
$EACP_t^{(s)}$ Annualized capital cost of existing power plants during time period, t and under scenario $s \in [s_C, s_D, s_F]$ (\$/year)
$ECC_t^{(s)}$ Carbon cost of existing power generation plant, τ during time period, t and under scenario s (\$/year)
$EFC_t^{(s)}$ Fuel cost of existing power generation plant, τ and under scenario s (\$/year)
$EFOM_t^{(s)}$ Fixed O&M cost of existing power generation technology, τ and under scenario s (\$/year)
$EVOM_t^{(s)}$ Non-fuel variable O&M cost of existing power generation technology, τ and under scenario s (\$/year)
$f_t^{(s)}$ Total power generation cost discounted to present value during time period, t and under scenario s (\$)
$FP_\tau^{(s_F)}$ Fuel price of power generation technology, τ and under scenario s_f (\$/MWh)
$NACP_t^{(s)}$ Annualized capital cost of new power generation plants, τ and under scenario s (\$/year)
$NCAPEX_{\tau,t_p}^{(s_C)}$ Capital factor of new power plants, τ during time period, t and under scenario s_C (\$/kW)
$NC_t^{(s)}$ Power generation cost of new power plants, τ and under scenario s (\$/year)
$NIC_{\tau,t}^{(s)}$ Installed capacity of new power generation plants, τ during time period, t and under scenario s (MW)
$PD_t^{(S_D)}$ Peak demand (MW)
$RIC_t^{(S_D)}$ Required installed capacity of power generation plant, τ under scenario s_D (MW)
$NCC_t^{(s)}$ Carbon cost of new power plants of new power generation plant, τ under scenario s (\$/year)
$NFC_t^{(s)}$ Fuel cost of new power plants of new power generation plant, τ under scenario s (\$/year)
$NFOM_t^{(s)}$ Fixed O&M cost of new power generation plant, τ under scenario s (\$/year)
$NVOM_t^{(s)}$ Non-fuel variable O&M cost of new power generation plant, τ under scenario s (\$/year)

Abbreviations

PGEP Power generation expansion planning
PCF Pulverized coal-fired
NGCC Natural gas combined cycle
PV Photovoltaic
CSP Concentrated solar power
MCS Monte Carlo Simulation
ST Scenario Tree

4.1. Generating costs

The total electricity system cost consists of the annualized capital cost, the annual fixed and variable operating (O&M) costs, as well as the fuel and carbon costs of existing and newly installed power plants.

The total capital cost is annualized over the lifetime of the power generation plant, while the rest of the costs are measured on a yearly basis. Fixed O&M cost represents the operation and maintenance costs that are not dependent on the power output of the plant, while non-fuel variable O&M cost, fuel cost and carbon emission cost vary according to the energy production of the plant. Solar PV and wind onshore technologies are subject to capital cost reduction over the planning horizon due to assumed technological advancements.

The annualized capital cost of the existing power generation capacity is calculated based on the discount rate (r) and the operating life of the power production plant (Lf_τ), by means of the following formula:

$$EACP_t^{(s)} = \left[\sum_{\tau\in(7,9)}\sum_{s_C=1}^{3}\left(EIC_{\tau,t}^{(s_C)}\cdot ECAPEX_{\tau,t_p}^{(s_C)}\cdot p^{(s_C)}\right) + \sum_{\tau\notin(7,9)}\left(EIC_{\tau,t}^{(s)}\cdot ECAPEX_{\tau,t_p}\right)\right] \cdot \frac{r}{1-(1+r)^{-Lf_\tau}} \quad (2)$$
$$\forall t = 1:3 \text{ and } s\in[s_D, s_C, s_F]$$

where, τ denotes the type of technology, with $\tau = 1:3$ representing the conventional technologies and $\tau = 4:10$ the renewable energy technologies, $EIC_{\tau,t}^{(s)}$ stands for the technology's τ total installed capacity (MW) during the time period t, $ECAPEX_{\tau,t_p}^{(s_C)}$ is the capital cost in the previous period t_p and the term $\frac{r}{1-(1+r)^{-Lf_\tau}}$ is the amortization factor (Papapetrou et al., 2017), converting the overnight capital expenditure into annual equivalents throughout the power plant's operating life. Accordingly, the fixed O&M cost is calculated as:

$$EFOM_t^{(s)} = \sum_{\tau=1}^{10}\left(EIC_{\tau,t}^{(s)}\cdot FOM_\tau\right) \quad (3)$$
$$\forall t = 1:3 \text{ and } s\in[s_D, s_C, s_F]$$

where, $EFOM_t^{(s)}$ is the fixed O&M cost of installed capacity of existing power plants per year calculated for each scenario and time period. The non-fuel variable O&M cost per year of existing power plants ($EVOM_t^{(s)}$) is estimated by the following equation:

$$EVOM_t^{(s)} = \sum_{\tau=1}^{10}\left(EIC_{\tau,t}^{(s)}\cdot CF_\tau\cdot VOM_\tau\cdot 8760\right) \quad (4)$$
$$\forall t = 1:3 \text{ and } s\in[s_D, s_C, s_F]$$

where, CF_τ is the capacity factor of the power generation technologies, VOM_τ is the unit cost of non-fuel variable O&M cost to generate one MWh of power generated technology (τ) while the term 8760 represents the number of hours per year. The fuel cost of existing fuel-powered energy plants ($EFC_t^{(s)}$) is calculated as:

$$EFC_t^{(s)} = \sum_{\tau=1}^{3}\sum_{s_F=1}^{n}\left(EIC_{\tau,t}^{(s_F)}\cdot CF_\tau\cdot FP_\tau^{(s_F)}\cdot p^{(s_F)}\cdot 8760\right),\ \ \forall t=1:3 \tag{5}$$

where, $FP_\tau^{(s_F)}$ denotes the fuel price under scenario s_F. Finally, the annual carbon cost of existing power plants, $ECC_t^{(s)}$ is estimated as follows:

$$ECC_t^{(s)} = C_{emit}{}_t^{(s)}\cdot C_{tax_t},\ \ \forall t=1:3 \text{ and } s\in[s_D,s_C,s_F] \tag{6}$$

where, the mass of $CO_{2,eq}$ emitted per year ($C_{emit}{}_t^{(s)}$) is calculated as a function of the $CO_{2,eq}$ emission rate of power plant technology ($C_{rate\tau}$) estimated by the following formula:

$$C_{emit}{}_t^{(s)} = \sum_{\tau=1}^{3}\left(EIC_{\tau,t}^{(s)}\cdot CF_\tau\cdot C_{rate\tau}\cdot 8760\right),\ \ \forall t=1:3 \text{ and } s\in[s_D,s_C,s_F] \tag{7}$$

Above equations are also applied for the new power generation plants. The electricity system cost of new power plants was estimated for every scenario and time period as:

$$NC_t^{(s)} = NACP_t^{(s)} + NFOM_t^{(s)} + NVOM_t^{(s)} + NFC_t^{(s)} + NCC_t^{(s)} \tag{8}$$

$$NACP_t^{(s)} = \left[\sum_{\tau\in(7,9)}\sum_{s_C=1}^{3}\left(NIC_{\tau,t}^{(s_C)}\cdot NCAPEX_{\tau,t_p}^{(s_C)}\cdot p^{(s_C)}\right) + \sum_{\tau\notin(7,9)}\left(NIC_{\tau,t}^{(s)}\cdot NCAPEX_{\tau,t_p}\right)\right]\cdot\frac{r}{1-(1+r)^{-Lf_\tau}} \tag{9}$$

$$NFOM_t^{(s)} = \sum_{\tau=1}^{10}\left(NIC_{\tau,t}^{(s)}\cdot FOM_\tau\right) \tag{10}$$

$$NVOM_t^{(s)} = \sum_{\tau=1}^{10}\left(NIC_{\tau,t}^{(s)}\cdot CF_\tau\cdot VOM_\tau\cdot 8760\right) \tag{11}$$

$$NFC_t^{(s)} = \sum_{\tau=1}^{3}\sum_{s_F=1}^{n}\left(NIC_{\tau,t}^{(s_F)}\cdot CF_\tau\cdot FP_\tau^{(s_F)}\cdot p^{(s_F)}\cdot 8760\right) \tag{12}$$

$$NCC_t^{(s)} = \sum_{\tau=1}^{3}\left(NIC_{\tau,t}^{(s)}\cdot CF_\tau\cdot C_{rate\tau}\cdot C_{tax_t}\cdot 8760\right)\quad \forall t=1:3 \text{ and } s\in[s_D,s_C,s_F] \tag{13}$$

4.2. Constraints

The total installed capacity, namely the existing and new power generation capacity must satisfy the peak demand of the country, $PD_t^{(s_D)}$ for all demand scenarios, s_D and time periods, t. Furthermore, a reserve margin is taken into account as a buffer to protect against system breakdowns or sudden upsurges in electricity demand. The reserve margin is defined as the difference between the (required) installed capacity (RIC) and the peak demand divided by the peak demand (Turvey and Anderson, 1977; International Atomic Energy Agency, 1977).

$$RM = \frac{RIC_t^{(s_D)} - PD_t^{(s_D)}}{PD_t^{(s_D)}},\quad \forall t=1:3 \tag{14}$$

Electricity demand is driven by population growth, economic development and various other factors. However, extensive electricity demand estimation is not the focus of the current work. The following constraint ensures that the installed capacity of existing power plants plus the installed capacity of new power plants are sufficient to meet the expected peak demand plus the reserve margin, hence the required installed capacity after reordering Eq. (14) should satisfy the following inequality:

$$\sum_{\tau=1}^{10}\left(EIC_{\tau,t}^{(s)} + NIC_{\tau,t}^{(s)}\right)\geq RIC_t^{(s_D)},\quad \forall t=1:3 \text{ and } s\in[s_D,s_C,s_F] \tag{15}$$

The net electricity produced by the available power generation facilities is estimated after accounting for the plant's own use of electricity (O_τ), the transmission and distribution losses (L_τ). Net electricity must exceed the projected power consumption ($CD_t^{(s_D)}$) across all years between the time periods.

$$\sum_{\tau=1}^{10}\left[\left(EIC_{\tau,t}^{(s)} + NIC_{\tau,t}^{(s)}\right)\cdot CF_\tau\cdot(1-(O_\tau+L_\tau))\right]\geq\sum_{s_D=1}^{3}\left(p^{(s_D)}\cdot CD_t^{(s_D)}\right)\quad \forall t=1:3 \text{ and } s\in[s_D,s_C,s_F] \tag{16}$$

To satisfy the renewable penetration targets, a minimum renewable energy share in the power generation mix is set to boost renewable energy penetration. This constraint can be varied across the different time periods, with targets set at more ambitious levels in the course of time.

$$\frac{\sum_{\tau=4}^{10}\left(EIC_{\tau,t}^{(s)}\cdot CF_\tau\right) + \sum_{\tau=4}^{10}\left(NIC_{\tau,t}^{(s)}\cdot CF_\tau\right)}{\sum_{\tau=1}^{10}\left(EIC_{\tau,t}^{(s)}\cdot CF_\tau\right) + \sum_{\tau=1}^{10}\left(NIC_{\tau,t}^{(s)}\cdot CF_\tau\right)}\geq RE_{targett}\quad \forall t=1:3 \text{ and } s\in[s_D,s_C,s_F] \tag{17}$$

Subsequently, to enhance the diversity and security of the energy mix, minimum and maximum contributions of each technology can be set. For example, to manage the risk of intermittency from renewable energy sources, policy makers can set the share of coal and gas power at a certain minimum level ($Min_{capt,\tau}$). This constraint can be applied across all technologies and time periods:

$$\frac{EIC_{\tau,t}^{(s)}\cdot CF_\tau + NIC_{\tau,t}^{(s)}\cdot CF_\tau}{\sum_{\tau=1}^{10}\left(EIC_{\tau,t}^{(s)}\cdot CF_\tau\right) + \sum_{\tau=1}^{10}\left(NIC_{\tau,t}^{(s)}\cdot CF_\tau\right)}\geq Min_{capt,\tau}\quad \forall t=1:3,\ \tau=1:10 \text{ and } s\in[s_D,s_C,s_F] \tag{18}$$

Imposing a maximum proportion constraint, for example on the most cost efficient power generation technologies, forces the model to introduce other less cost efficient technologies in the power generation mix so as to cover the energy demand, rendering the mix more diverse. Fuel diversity can be enforced by policy makers to confine the dependency on a technology or fuel source under a reasonable level through setting a maximum proportion cap ($Max_{capt,\tau}$) for each technology, τ, and time period, t. Grid stability is another important factor that should be taken into account. The fact that most renewable energy technologies cannot be dispatched when required, as they strongly depend on weather conditions, prevents them from being a reliable base-load solution over a long term period. To this end, the total electricity production from renewable sources can be set not to exceed a maximum proportion.

$$\frac{EIC_{\tau,t}^{(s)}\cdot CF_\tau + NIC_{\tau,t}^{(s)}\cdot CF_\tau}{\sum_{\tau=1}^{10}\left(EIC_{\tau,t}^{(s)}\cdot CF_\tau\right) + \sum_{\tau=1}^{10}\left(NIC_{\tau,t}^{(s)}\cdot CF_\tau\right)}\leq Max_{capt,\tau}\quad \forall t=1:3,\tau=1:10 \text{ and } s\in[s_D,s_C,s_F] \tag{19}$$

The following constraint limits the allowable amount of $CO_{2,eq}$ emissions produced from fossil-fuel generation facilities, by introducing a $CO_{2,eq}$ allowable level, controlling the resulting share of fossil-fuel plants and obliging the inclusion of renewable technologies to the mix so as to satisfy the rest of the demand. Different limits can apply at each planning period.

$$\sum_{\tau=1}^{3}\left(\left(EIC_{\tau,t}^{(s)} + NIC_{\tau,t}^{(s)}\right) \cdot CF_{\tau} \cdot C_{rate\tau} \cdot 8760\right) \le C_{targett} \quad (20)$$
$$\forall t = 1:3 \text{ and } s \in [s_D, s_C, s_F]$$

The renewable potential expresses the theoretical upper limit of the amount of energy that can be produced from renewable sources over a particular geographic region as estimated by surveys undertaken by experts (Ahn et al., 2015). The following constraint is imposed on renewable technologies to make sure the power produced from renewable sources is within the potential capacity of that region or country.

$$EIC_{\tau,t}^{(s)} + NIC_{\tau,t}^{(s)} \le RE_{pott,\tau} \quad (21)$$
$$\forall t = 1:3,\ \ \tau \in [4:10] \text{ and } s \in [s_D, s_C, s_F]$$

In this study, the maximum potential ($RE_{pott,\ \tau}$) for hydro, geothermal, biomass, onshore wind, offshore wind, solar PV and solar CSP are summarised in Table 4.

The annual construction of new renewable energy plants is subject to the availability of labour, manufacturing capacity, area available for construction and social readiness for a particular technology. There is therefore an upper construction limit which remains unchanged across the different time periods.

$$NIC_{\tau,t}^{(s)} \le CL_{\tau} \quad (22)$$
$$\forall t = 1:3, \tau \in [4:10] \text{ and } s \in [s_D, s_C, s_F]$$

Finally, it should be assured that only non-negative new rated capacities can be accepted for every scenario, time period and technology in the solution.

$$\min_{dv} f_t^{(s)} = EC_t^{(s)} + NC_t^{(s)} \quad (1)$$
$$= EACP_t^{(s)} + EFOM_t^{(s)} + EVOM_t^{(s)} + EFC_t^{(s)} + ECC_t^{(s)}$$
$$+ NACP_t^{(s)} + NFOM_t^{(s)} + NVOM_t^{(s)} + NFC_t^{(s)} + NCC_t^{(s)}$$

Subject to

Total installed capacity should satisfy peak demand	(15)
Net electricity production should satisfy electricity consumption demand	(16)
Renewable energy targets should be fulfilled	(17)
Ensure the fuel diversity and energy security of the power generation mix	(18)–(19)
Restrain $CO_{2,eq}$ emissions of the power generation mix	(20)
Satisfy resource potential limit of the region	(21)
Satisfy annual construction limit of the power plants	(22)
Positive new installed capacities	(23)

$$NIC_{\tau,t}^{(s)} \ge 0 \quad (23)$$
$$\forall t, s \in [s_D, s_C, s_F] \text{ and } \tau = 1:10$$

4.3. Objective function

The objective of the optimization problem is to minimize the discounted total cost of the power generation mix (consisting of power plants, τ) for each stage, t and scenario, s (namely, the set of combinations of scenarios s_D, s_C, s_F).The objective cost function ($f_t^{(s)}$) of the optimization model is presented below:

The set of decision variables (dv) of the problem comprises: the types of new power plants to be installed and their corresponding installed capacities ($NIC_{\tau,t}^{(s)}$), while other variables determined per scenario and time period include: the probabilities of all scenarios ($p^{(s)}$), the cost of existing and new energy system (total and per plant type), along with their consisting costs (e.g. annualized CAPEX, fuel cost, fixed O&M cost), the required installed capacities ($RIC_t^{(S_D)}$), the total decommissioned capacities, the existing installed capacities (total and per plant type), the new installed capacities (total and per plant type), the total installed capacities (total and per plant type), the forecasted power consumption, as well as the total $CO_{2,eq}$ emission mass and cost. The proposed optimization model was developed using the constrained solver fmincon of MATLAB R2017a optimization toolbox, based on the interior-point algorithm (Potra and Wright, 2000), while the sequential quadratic programming was also tested (Boggs and Tolle, 1995). The potential of falling into a local minimum in the analysis has been investigated through changing the initial guess of decision variables and comparing the results obtained. The different algorithms and initial guesses yielded consistent results.

Following the derivation of the optimal power generation mixes across all scenarios and time periods, boxplots were produced to illustrate the resulting energy mixes, along with the weighted mean proportions of each power plant type, taking into account the scenarios' probabilities.

5. Application to the Indonesian power generation system

In this study, Indonesia's power system's portfolio is used as input for the proposed model. Indonesia's prominence is highlighted by its population of 255 million people (fourth largest in the world) in 2016 (PWC, 2017) and its considerable potential of fossil-fuel and renewable resources. Globally, Indonesia is the largest coal exporter and fourth largest coal producer. The country has an estimated 28 billion tons of coal reserves (accounting for 3.1% of total global reserves (British Petroleum (BP), 2016)). It is the world's tenth largest producer of natural gas and the seventh largest exporter of liquefied natural gas (LNG) (International Energy Agency, 2015).

Indonesia is the largest economy in Southeast Asia and has achieved steady, high growth rates over the last 15 years. Its energy consumption is predicted to grow rapidly as a result of population growth, rapid urbanisation and rising living standards (International Energy Agency, 2015). Therefore, satisfying demand growth and ensuring the sustainability of energy supplies is one of key pillars of Indonesia's economy. In 2016, Indonesia had approximately 59.6 GW installed power plant capacity, generating 290 TWh of electricity (PWC, 2017). Electricity peak load was estimated to reach 32,204 MW in 2017 (Ministry Of Energy and Mineral Resources Republic of Indonesia, 2017). Energy mix is currently comprised by coal (54.69%), gas (25.89%), oil (6.97%) and renewables (12.45%) (Direktorat Jenderal Ketenagalistrikan Kementerian Energy Dan Sumber Daya Mineral, 2017). The Indonesian government seeks to reduce the dependency on fossil fuel by increasing the renewable energy contribution to the power sector by at least 25% by 2030 (Directorate General for Electricity and Energy Utilization, 2015). Additionally, according to the 2014 National Energy Policy (the "2014 NEP") of Indonesia, renewable energy should reach at least the 23% of the power generation mix by 2025, while in 2050 the target is to increase renewables share to at least 31% (Government of Indonesia, 2014). As a contingency to the high share of renewable energy in the country's mix, PLN (the company responsible for the majority of Indonesia's energy production) will be required to use another 5.1 GW of gas-fired power plants to meet the resilience requirements of the power generation system (Ministry of Energy and Mineral Resources, 2017). The forecasted power demand growth and base fuel price assumption data were obtained from the National Electricity General Plan (RUKN) draft in 2015. RUKN also specifically sets the minimum reserve margin target (set to 35%), as well as the assumption on own use and transmission losses of the power system in Indonesia (9.48% according to (Ministry Of Energy and Mineral Resources Republic of Indonesia, 2017)). The carbon emission reduction target was set to 26% from the Business As Usual (BAU) value in 2030, as specified in Presidential Decree No. 61 of 2011 on the National Action

Table 3
Indonesia's power generation portfolio in 2015 (Source: (Directorate General for Electricity and Energy Utilization, 2016)).

Generation technology	Capacity (in MW)
Coal-fired	25697
Natural gas-fired	17964
Diesel power	6394
Hydropower	5342
Geothermal	1435
Biomass	86
Wind Onshore	1
Solar PV	11
Total	56932

Plan for Reducing Emissions of Greenhouse Gases in efforts to enforce environmental impact mitigation (Government of Indonesia, 2011). The summary of Indonesia's 2015 initial fleet capacity by generation technology can be found in Table 3.

Furthermore, the detailed techno-economic data used as input in the present case study and their references are shown in Table 4. Each technology is characterized by a capacity factor. The capacity factor is defined as the ratio of the actual electricity output during a certain amount of time to the maximum potential electrical output during this period.

Nuclear energy was not considered as an option due to the current lack of political will from the government and the limited support from the public due to safety issues (Hariyadi, 2016). Furthermore, according to the National Energy Plan of Indonesia (2017), nuclear energy will be considered as the last option, if despite the optimal utilization of new energy and renewable energy sources, the renewable energy target of 23% in total energy consumption is not reached by 2025 (Directorate General for Electricity and Energy Utilization, 2015). As carbon tax has not been implemented in Indonesia yet, the baseline case does not include it in the cost of electricity generation, while the imports and exports of electricity are not taken into account in this case study as the amount of power exchange with neighbouring countries is not significant. The annual construction limits of the renewable energy generation technologies were estimated on the basis of historic annual installed capacities of each technology as well as the renewable energy potential (summarised in Table 4). Under the business-as-usual (BAU) scenario, carbon emissions from the power sector are projected to reach 750 million tons in 2020, 1000 million tons in 2025 and 1250 million tons in 2030 (Asian Development Bank, 2016). Data on costs of power plants differ considerably across literature. To this end, the final values considered in the model were derived after retrieving a number of recent references (such as the NREL Annual Technology Baseline database (National Renewable Energy Laboratory, 2018)) and calculating their average values.

In addition, the MCS sample size was determined through a convergence study, according to which the optimization problem was run with different MCS samples (i.e. for 20, 50, 100, 150, 200 and 500 iterations) and subsequently the resulting total weighted new installed capacities, estimated for each time period, were compared. The minimum number of MCS samples required for the results of the case study to converge was determined 150, i.e. further increase in the sample did not change the solution noticeably but it had an impact on the computational time. The uncertainty of electricity demand and capital cost reduction are represented by three nodes: “Low”, “Medium” and “High” with assigned probability values 0.3, 0.5 and 0.2, respectively adopting the approach of (Thangavelu et al., 2015). For the electricity demand scenario, the three possible nodes correspond to demand increase of 5% (low), 8% (medium) and 11% (high) per annum; while the nodes referring to the future values of capital cost for onshore wind and solar PV power plants were retrieved from the National Renewable Energy Laboratory (NREL) Annual Technology Baseline (ATB) 2018 database (National Renewable Energy Laboratory, 2018), which provide trajectories of costs for energy technologies. The time series values used as input to the model are summarised in Appendix A.

As shown in Fig. 2, the number of optimization scenarios for $n = 150$ were amounted to 1350, 12,150 and 109,350, derived through the combination of scenarios s_C, s_D, s_F during the first, second and third time periods, respectively. For each optimization scenario, there are 10 decision variables, standing for the new installed capacities ($NIC_{\tau,t}^{(s)}$) of the power plant technologies and 44 constraints.

6. Results

The case study performed capacity expansion planning with 2016 as the base year and three planning stages at years 2020, 2025 and 2035. The stochastic optimization model minimizes the total expected cost of the power generation mix for all three planning stages by considering all possible input scenarios. The proposed model was initially applied to determine the optimal power generation mix under a baseline case. Accordingly, the model was applied under three representative cases calling for: Least Cost option, Policy Compliance option and Green Energy Policy option, which aim to determine the stochastic power generation mix under a set of different policy priorities, modelled in the proposed methodology through adjusting the corresponding constraints' limits.

6.1. Baseline case

Under the baseline case, existing targets for renewable energy contribution were considered as input to the model (minimum increase of 16% by 2020, 23% by 2025, and 31% in 2050), the maximum $CO_{2,eq}$ emissions limit was set according to the BAU scenario for each planning

Table 4
Techno-economic data of power plants[a].

Technology	Capacity factor	Life time	Capital cost	Fixed O&M cost	Variable O&M cost	$CO_{2,eq}$ emission rate	Annual construction limit	Renewable potential
	%	years	\$/kW	\$/kW/year	\$/MWh	$tCO_{2,eq}$/MWh	MW/year	MW
Coal (PCF)	70	30	3600	33	5	1.09	–	–
Gas (NGCC)	70	30	882	18	6	0.6	–	–
Diesel	70	30	700	11	6	0.8	–	–
Hydro	61	40	4600	75	–	0	1600	75,670
Geothermal	80	30	5200	152	–	0	1000	28,910
Biomass	56	20	4000	58	5	0	1300	32,654
Wind Onshore	35	30	1615	51	–	0	1000	60,600
Wind Offshore	42	25	6100	132	–	0	50	
Solar PV	16	25	2600	18	–	0	8500	207,800
Solar CSP	53	20	7872	67	4.1	0	30	

[a] Techno-economic data derived from the average value of various sources: (Thangavelu et al., 2015; Betancourt-Torcat and Almansoori, 2015; Ministry of State Owned Enterprises (SOEs), 2017; PWC, 2017; National Renewable Energy Laboratory, 2018; Directorate General of New Energy Renewable Energy and Energy Conservation, 2014).

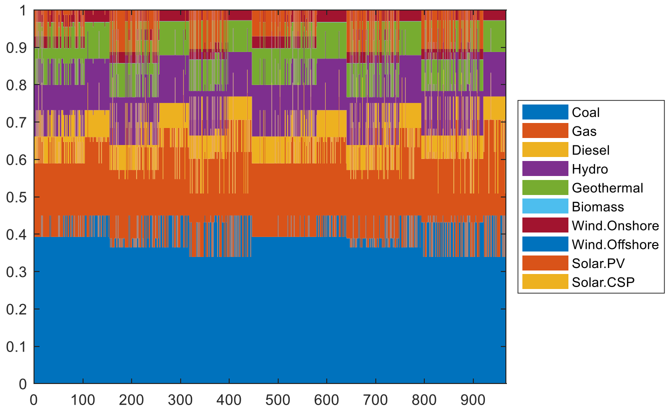

Fig. 3. Power generation mix across different scenarios (for year 2025).

period (presented in Section 6.1), while the allowable contribution of each technology was set to 45% for all technologies. This limit was picked on the basis that coal should not exceed the 2015 quotas, as well as to impose some degree of technology diversity within the resulting energy mix.

The optimised stochastic power generation mix for all leaf nodes (namely, all combinations of s_D, s_C and s_F scenarios) run for planning period 2025 is shown in Fig. 3 and it includes coal 17.6–45.0%, natural gas 9.9–45.0%, oil 3.8–8.0%, hydro 8.1–17.5%, geothermal 4.0–12.6%, biomass 0.0–4.7% and onshore wind 2.3–5.2%, offshore wind 0.0–0.12%, solar PV 0.0–14.4% and solar CSV 0.0–0.1%.

It has to be noted that results shown in Fig. 3 do not account for the likelihood of occurrence of each scenario, but rather present the resulting energy technology mixes under all possible realizations of uncertain energy demand, capital cost and fuel prices. Probabilities of each scenario and time period are calculated separately as the product of probability of occurrence realized from the root node to the leaf node. As such, in order to identify the most representative technology proportion values in the energy mix, the associated probabilities of all scenarios were incorporated through the estimation of their weighted mean values. To identify the weighted mean proportion of power generation produced from each technology, τ during time period, t the output of each scenario, s is multiplied by the probability of its occurrence $p^{(s)}$ and the products are, then, summed up. For instance, during a specific time period t, the weighted mean proportion (denoted as $\bar{x}_{t,\tau_1}$) of power generation derived from technology τ_1 is calculated as:

$$\bar{x}_{t,\tau_1} = \sum\nolimits_{(s)} \left(p^{(s)} \cdot x^{(s)}_{t,\tau_1} \right) \tag{24}$$

In Fig. 4, the optimised stochastic power generation mix across the whole simulation period is illustrated. Outliers have been removed from the box plot representation, while the weighted mean proportions of the different technologies, $\overline{x_\tau}$ in the power generation mix are denoted by a red asterisk. The central red line in the whisker charts represents the median, while the bottom and top edges of the blue boxes indicate the 25th and 75th percentiles, respectively. The black whiskers cover the non-outliers that represent the most extreme data points. It should be highlighted that the illustration with the boxplots can demonstrate the range of potential output values; however, the likelihood of occurrence of each realization can be only found through the weighted average output value (asterisk symbol), which indicates the expected value of the results (here the power production proportion of each technology in the mix), taking into account all scenarios and their probabilities. Under the baseline scenario, power generation from coal appears to decrease throughout the planning horizon from 40% to 34%, NG power generation experiences a slight decrease from 21% to 19%, which is covered by the increasing share of hydro, geothermal, onshore wind and solar PV.

Total mean weighted installed power capacity was calculated 81.6 GW in the 2020 baseline case, increasing to 210 GW in 2030 due to the growing energy demand. Constraints imposing the renewable technologies penetration, as well as lower carbon emission levels appear to slow down the increase in the installed capacity of coal, as opposed to the NG and renewable energy capacity which appear to increase at a rapid pace over the planning horizon (as shown in Fig. 5). In fact, coal installed capacity is predicted to increase by 93.5% from 2020 to 2030 time periods, while NG, hydro, geothermal, onshore wind and solar PV are projected to grow by 118.5%, 131.6%, 164.6%, 250% and 319.4%, respectively. Furthermore, new total weighted installed capacity was estimated 33.8 GW in 2020, 70 GW in 2025 and 92.4 GW in 2030, weighted RES share was 37.6% in year 2030, $CO_{2,eq}$ emissions were 526 million tons and total discounted cost was calculated $ 531 billion. The model failed to find an optimum solution for around 5% of the total uncertainty scenarios, meaning that not all constraints could be satisfied under

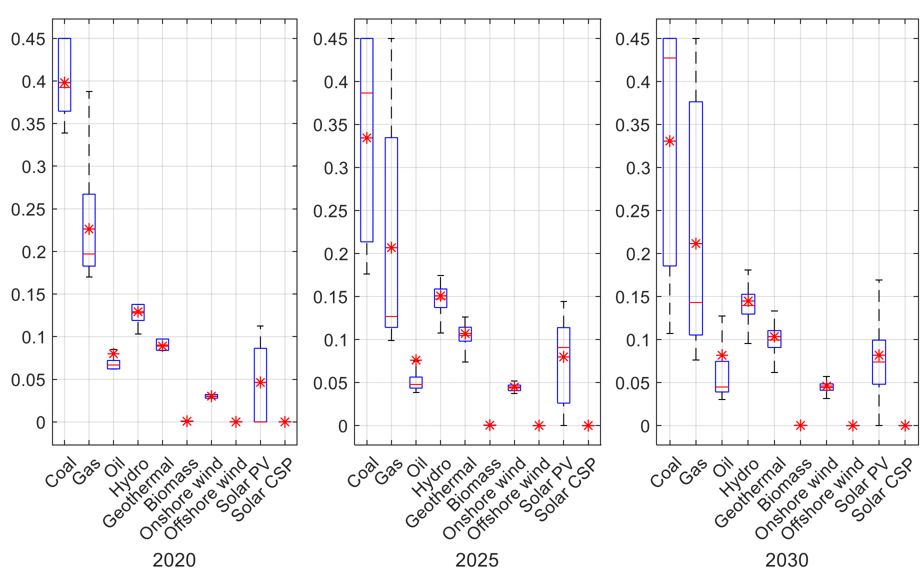

Fig. 4. Optimised power generation mix throughout the simulation period under the Baseline Case.

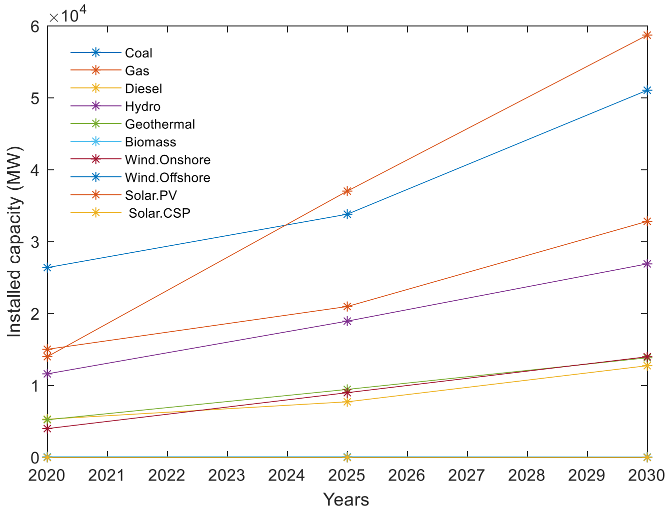

Fig. 5. Weighted average installed capacity under the baseline case.

these scenarios. Results illustrated here were, thus, cleansed and their probabilities were readjusted to sum up to one.

6.2. Sensitivity analysis

Above results were derived under the assumption that the MCS sample of fuel prices follows a normal distribution. In Fig. 6, stochastic power generation mixes for the 2025 planning period, under the assumption of uniform, PERT and Weibull probability distributions, are shown. The equivalent PERT, Weibull and uniform distributions were based on fitting the baseline normal distribution. In general, results appeared not to deviate largely in relation to normal distribution, with deviations observed for uniform distribution predicting 12.5% less coal, 30% more NG and 20% more oil share in relation to the baseline case.

Applying the ST approach to all three uncertain parameters, including the fuel prices, requires the definition of three discrete nodes corresponding to the fuel prices values (assuming the same number of nodes as in the case of capital costs and energy demand uncertainty) with their assigned probabilities. To test how results would differ in such a case, we ran the model taking the values summarised in Table 5 and assigning probabilities similar to the other uncertain

Table 5
Values of the discrete nodes assumed for the application of the 3-stage ST.

Fuel price ($/MWh)	Low price scenario	Medium price scenario	High price scenario
Coal	31	36	41
Gas	62	72	82
Oil	72	82	92

parameters (low: 0.3, medium: 0.5, high: 0.2). The resulting boxplots are illustrated in Fig. 7.

Comparing Fig. 7 with Fig. 4, it can be shown that the weighted average results demonstrate significant differences. Furthermore, the length of the box plots resulting from the ST approach is smaller than the one derived from the hybrid uncertainty modelling. This outcome is reasonable as if we apply the ST approach to model uncertainty in the fuel prices by means of three nodes (following the same pattern as the other two uncertain parameters), the number of scenarios would amount to: $3^3 = 9$, $3^6 = 729$ and $3^9 = 19{,}683$ for 2020, 2025 and 2030 time periods, respectively (hence less than the number of scenarios under the hybrid uncertainty modelling: 1350, 12,150, 109,350 for 2020, 2025 and 2030 time periods, respectively).

The benefit of employing the MCS lies in the fact that it allows for a continuous distribution to be assigned on the selected parameter based on collected historical data rather than assigning a degree of belief to possible scenarios.

It has to be noted that one of the key assumptions allowing for the combination of the ST and MCS methods is the averaging of the MCS outputs (i.e. the new installed capacity of the power plants which are, subsequently, used as input in the next time period) by the end of each time period to reduce the dimensionality of the problem and make it computationally feasible. If the averaging did not take place, the number of scenarios would amount to: $150 \cdot 3^3 = 1350$, $150^2 \cdot 3^6 = 1.8 \cdot 10^6$ and $150^3 \cdot 3^9 = 2.5 \cdot 10^9$ for 2020, 2025 and 2030 time periods, respectively, creating nodes originating from the tails of the probability distributions, leading to scenarios that may be infeasible to solve (i.e. due to too high fuel prices) and requiring very high computational effort to deal with. This would also increase the number of outliers and potentially the length of the boxplots to incorporate the outputs with lower probabilities. Nevertheless, the weighted mean proportion ($\overline{x_\tau}$) of power generation accounting for the probabilities of all scenarios is not expected to deviate substantially. Taking the above into consideration, it can, therefore, be deduced that the boxplots (for example the ones shown in Fig. 4) directly incorporate the fuel price uncertainty occurring on the

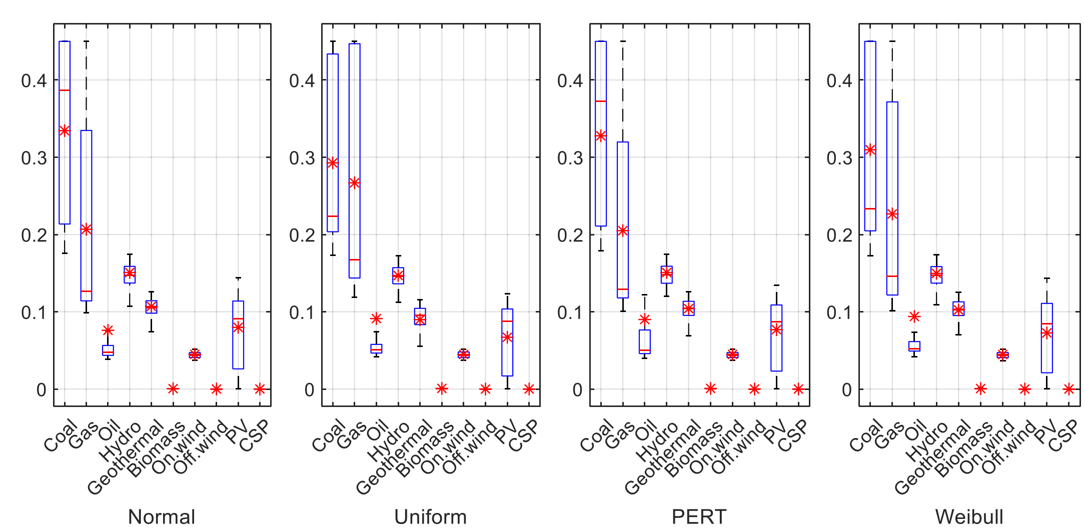

Fig. 6. Optimal power generation mix under the 3 different probability distributions for 2025.

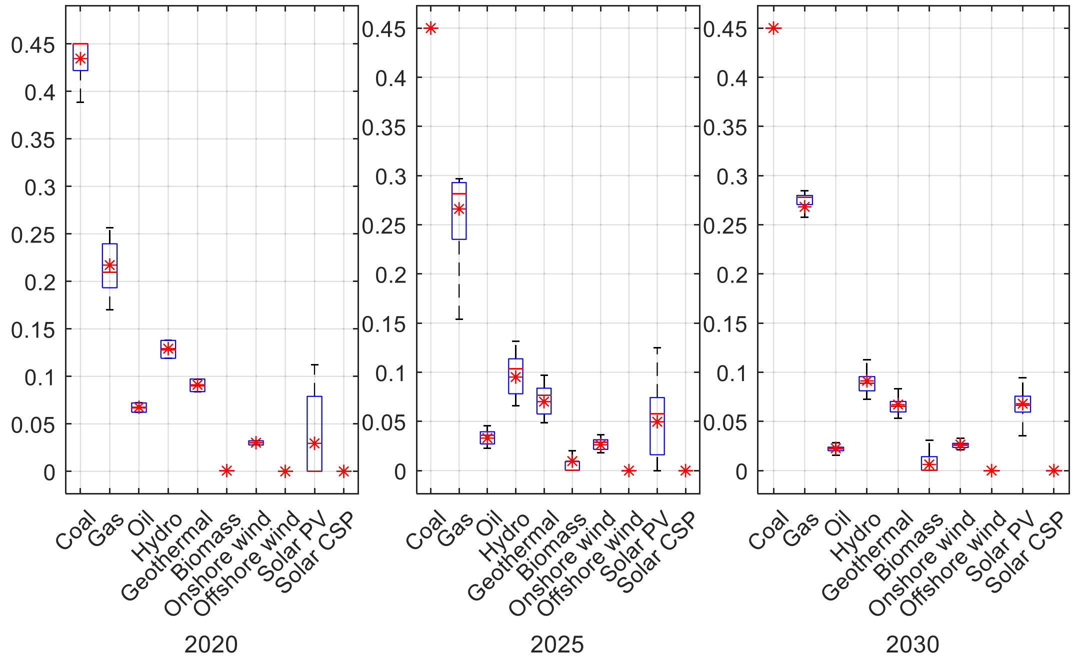

Fig. 7. Optimal power generation mix when developing a three-stage ST.

current time period being examined (by means of the n random values of the MCS), but they indirectly incorporate the fuel price uncertainty of the previous time periods through deriving the most expected output values of these periods resulting from the averaging of the new power plant installed capacities.

6.3. Modelling of planning options (POs)

The proposed model was, then, applied to determine the optimal power generation mix for three Planning Options (POs): Least cost, Policy Compliance and Green Energy Policy option. Different sets of constraints were imposed for each option and are summarised in Table 6.

The Least Cost PO focuses only on minimizing the cost of the power generation system, while no carbon emissions limit, renewable contribution and fuel diversity targets are in place. The Policy Compliance option imposes the renewable energy penetration targets, $CO_{2,eq}$ emission limits and required coal and natural gas quotas prescribed by the Indonesian's National Energy Policy (NEP). The Green Energy option enforces stricter renewable energy penetration targets and $CO_{2,eq}$ emission limits. It should be noted that the power generation mix is based on the total power generation of the installed technologies.

6.3.1. Least Cost option

The Least cost option seeks to find the optimum power generation mix under no renewable energy penetration targets, $CO_{2,eq}$ emissions targets, or fuel diversity goals; rather, this PO intents to determine the least expensive power generation mix which satisfies the peak and consumption demand, and takes into account the renewable energy potential and annual construction limit of the region. Hence, in the mathematical model, in the inequality (17), $RE_{targett}$ is set to zero throughout the whole planning horizon, the minimum and maximum proportions of technologies expressed in inequalities (18) and (19) are set to 0% and 100%, respectively, while the carbon emissions level target $C_{targett}$ in (20) has been set to a very high number so as not to favour inclusion of greener energy technologies in the optimum mix.

The power generation mix of the Least Cost option is dominated by coal power, since there is no imposed carbon emission restriction or renewable penetration target. Even though the renewable penetration in

Table 6
Set of constraints for each PO.

Constraint	Baseline case	Least Cost	Policy Compliance[a]	Green Energy Policy
Peak demand	√	√	√	√
Consumption demand	√	√	√	√
Renewable potential limit	√	√	√	√
Annual construction limit	√	√	√	√
Minimum proportion	x	x	Coal: 30% in 2025 29% in 2030 NG: 22% in 2025	x
Maximum proportion	45% for each technology	x	Oil: 25% in 2025 24% in 2030 Rest of technologies: 45%	45% for each technology
Renewable penetration target	16% in 2020 23% in 2025 25% in 2030	x	16% in 2020 23% in 2025 25% in 2030	24% in 2020 35% in 2025 38% in 2030
$CO_{2,eq}$ emission limit	750 m ton in 2020 1000 m ton in 2025 1250 m ton in 2030 of $CO_{2,eq}$/year	x	26% $CO_{2,eq}$ reduction in relation to 2020, 2025 and 2030 BAU	30% reduction in relation to 2020, 2025 and 2030 Baseline case
Carbon pricing	x	x	x	$ 30/metric ton of $CO_{2,eq}$

[a] Source: (PWC, 2017; Directorate General for Electricity and Energy Utilization, 2015).

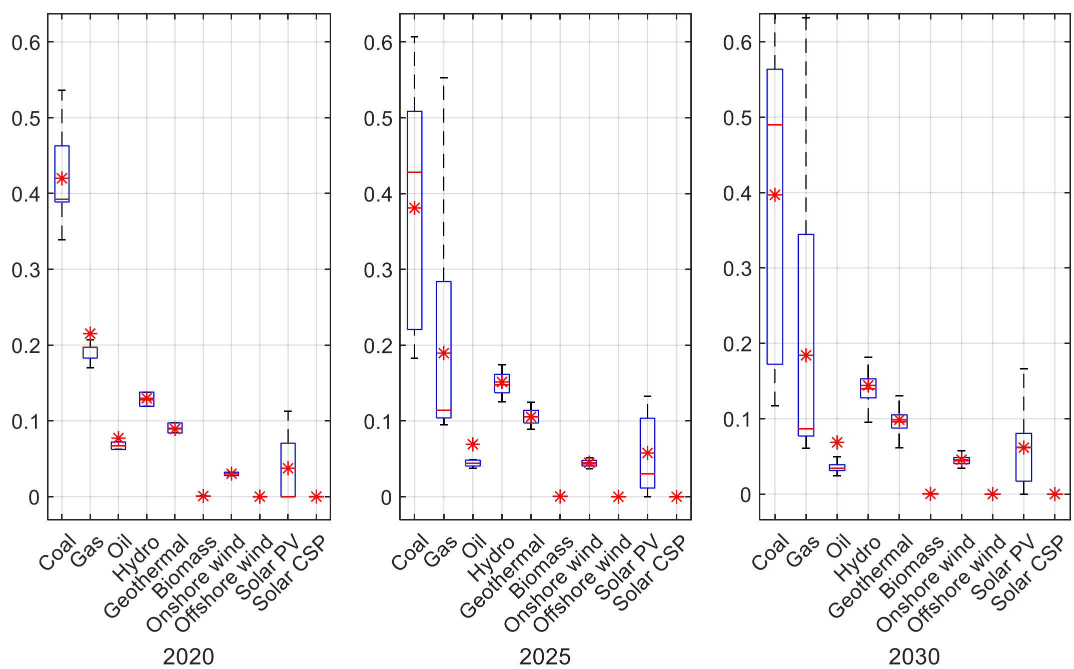

Fig. 8. Optimised power generation mix throughout the simulation period under the Least Cost option.

this option is not as high and varied as in other options, it can still fulfil the 25% renewable penetration target for 2030, due to the high contribution of the relatively low cost hydropower, as well as the contribution of geothermal, onshore wind and solar PV power plants. According to the results, overall power generation in 2030 will rely heavily on the three most cost efficient technologies: coal (40%), natural gas (18%), hydropower (14%) and geothermal (10%). The rest of the power generation originates from oil (7%), onshore wind (5%), and solar PV (6%). Cost efficiency accounts both for the total cost of the technology integrating the capital, fixed operational, variable operational and fuel cost, as well as for the total lifetime duration and the capacity factor of each technology. As can be seen from Fig. 8, to satisfy the increasing energy demand at the least cost, the (weighted average) share of coal of the total power production is projected to remain more or less stable until 2030 comprising the dominant energy source of the power generation mix (42% and 40% in 2020 and 2030, respectively) throughout the planning horizon. Natural gas is predicted to undergo a decrease of 14% in its share between 2020 and 2030, while the diesel consumption is projected to experience a 12% decrease between the same timeframe; their reducing contribution is slowly superseded by hydropower

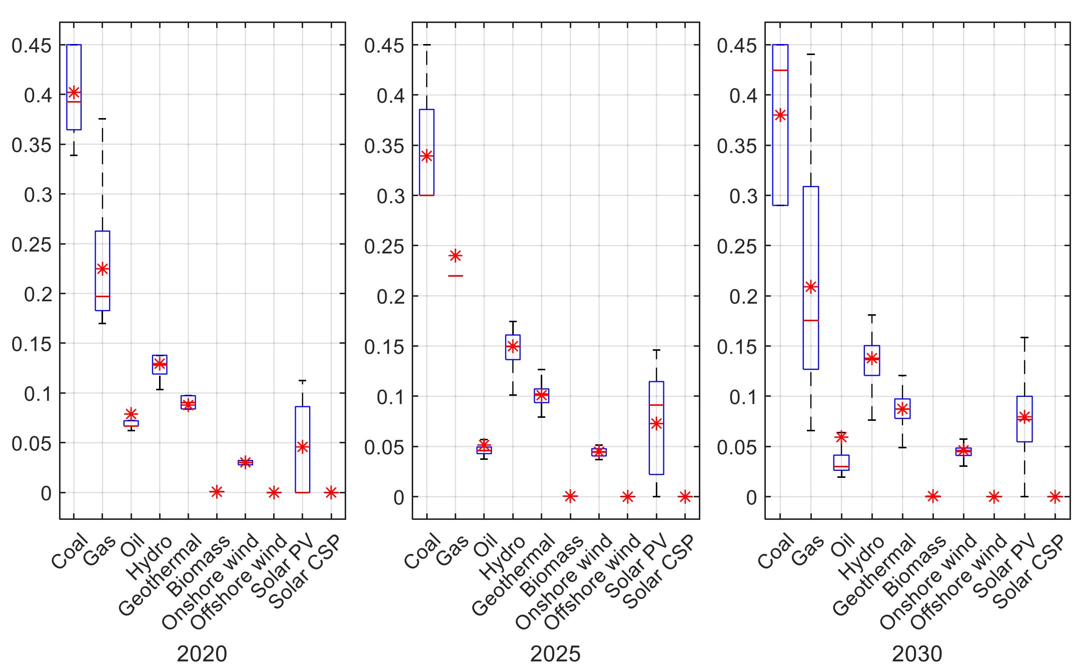

Fig. 9. Optimised power generation mix throughout the simulation period under the Policy Compliance option.

(12% increase from 2020 to 2030), and with small additions in onshore wind and solar PV mainly due to the decreasing trajectories of their future capital costs.

6.3.2. Policy Compliance option

This option encompasses the stochastic power generation mix optimization, based on the Indonesian government's policy targets for the power generation sector, as detailed in Table 6. The set of constraints (18)–(19) (Section 4) for this option imposes a minimum natural gas utilization of $Min_{cap2,\ 2}$=22% (in 2025) to promote the domestic use of natural gas. Coal share is also set a minimum limit of $Min_{cap1,\ 2}$=30% by 2025, which in 2030 is reduced to 29%. Furthermore, oil share is set to reach a maximum percentage of $Max_{cap3,\ 2}$=25% by 2025, which should decrease to 24% by 2030. A maximum 45% share is imposed to the rest of the technologies to ensure the diversity of the energy mix. As far as the environmental constraints are concerned, the $RE_{targett}$ throughout the whole planning horizon are adjusted in the model (through inequality (17)) to fulfil the Government's targets and the same applies with the $CO_{2,eq}$ emission limit. As carbon tax has not been implemented in Indonesia yet, C_{tax_t}=0 $/ton under the Policy Compliance option.

Fig. 9 shows that the power generation system will be dominated by coal, hydro and natural gas-fired power plants, while other renewable energy technologies such as solar PV and onshore wind are expected to increase their share in the final mix. Coal power growth is limited up to a certain level that satisfies the $CO_{2,eq}$ reduction and RES penetration targets, reaching a weighted average power generation share of 38% by 2030. The installation of natural gas-fired power plant capacity is driven by the minimum proportion limit imposed by the policy as well as by the low carbon emissions of the technology.

Furthermore, according to the model output, hydro, geothermal, onshore wind and solar PV will be employed to fill the gap in 2030 to satisfy the increasing power demand. In fact, as the capital cost for onshore wind and solar PV is expected to decrease over the planning horizon, the weighted average new installed capacities until 2030 of onshore wind and solar PV power plants are estimated to reach 14GW and 62.7GW, according to the model.

6.3.3. Green Energy Policy option

The Green Energy Policy option aims to investigate the effect of enforcing progressively stricter targets for the RE penetration (increasing the RES penetration targets by approximately 50%) and mitigation of environmental impact on the power generation mix, throughout the planning period. To this end, a hypothetical carbon pricing was also introduced as a policy for reducing emissions and drive investments into cleaner power generation technologies. Since, no carbon pricing policy is currently in effect in Indonesia, this study assumes an average price of C_{tax_t}=$30/metric ton of $CO_{2,eq}$ (across all time periods), which is comparable to other studies in literature (Kim et al., 2012; Tran and Smith, 2018; Heck et al., 2016). No constraints on the minimum proportions of power generation technologies in the mix were taken.

As shown in Fig. 10, the 2020 power generation mix is again most likely to be dominated by coal due to the existing high installed capacity of the technology, while the gas-fired power generation technology appears to be the second most preferred solution under this set of constraints. However, from 2025 onwards, coal plants are projected to fall sharply (dropping to the level of 14.8% in 2030) with natural gas fired power plants becoming the main electricity producer in the country (25% of power production in 2025 and 32% by 2030). The green energy targets and carbon reduction policies also increase the share of other low carbon technologies. Hydro, geothermal and solar PV power plants are the preferred solutions for covering the largest part of the RES penetration target, while an increasing biomass and onshore wind capacity addition can be observed.

7. Discussion

Fig. 11 integrates the values of renewable energy share, discounted total cost, $CO_{2,eq}$ emissions and total new installed capacity of renewable energy technologies of the power generation mix under the different POs considered. As such, it can be observed that the Least Cost option offers the lowest total discounted cost at the expense of higher $CO_{2,eq}$ emissions, as compared to the other options examined. Indicatively, during the planning period 2030, total weighted discounted

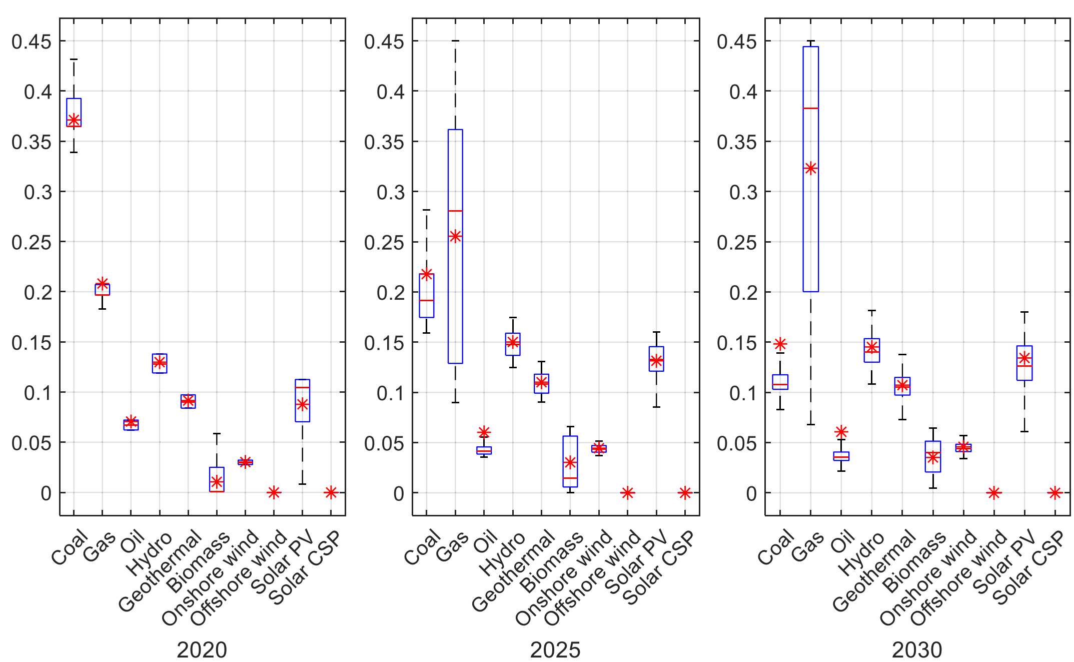

Fig. 10. Optimised power generation mix throughout the simulation period under the Green Energy Policy option.

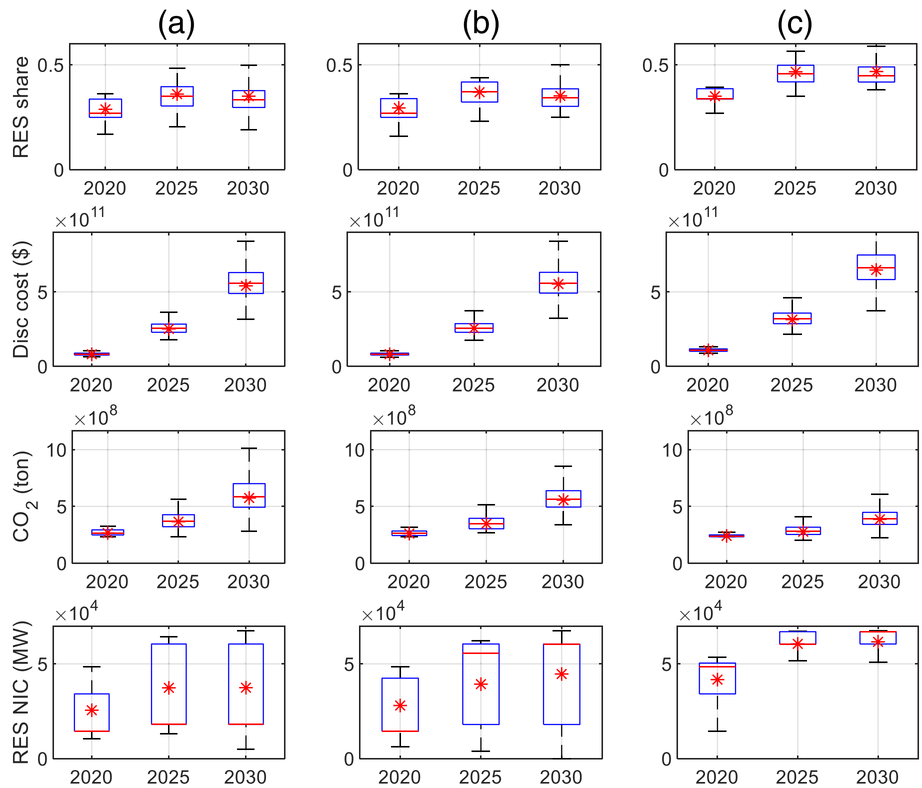

Fig. 11. Renewable energy contribution proportion, total discounted cost, $CO_{2,eq}$ emissions and Renewable energy sources (RES) New Installed Capacity (NIC) of technologies for the: (a) Least Cost option, (b) Policy compliance option and (c) Green Energy Policy option.

cost is projected to amount to $541 billion with 574 million tons $CO_{2,eq}$ emissions under the Least cost PO, while under the Green Energy Policy PO cost is predicted to amount to $648 billion with 386 million tons of $CO_{2,eq}$ emissions from power production. Least Cost PO is also characterized by the lowest weighted new installed capacity and total contribution of renewables in the power generation mix when compared to the rest of the POs examined; nevertheless, by the end of the planning period 2030 power production from RES is projected to reach a 35% share, surpassing the currently existing RES penetration target of 25%. Although this option comes with the lowest cost, the power generation mix appears to be less diverse; with coal being the dominant source of electricity production having weighted average proportions of around 40% across the whole planning horizon, while the rest of energy sources are expected to remain at relatively low levels (below 20%). This can potentially jeopardise the security of the power generation system, since alternative technologies that can provide peak power, such as NG-fired power plants have relatively small shares in the power generation mix. Peaking generation plants, such as the fast start and flexible gas-fired power plants are required to satisfy changes in peak demand and network congestions, which may be caused by the increasing integration of intermittent renewable energy in the network, challenging the power generation system security. Indeed, it is estimated that every 8 MW of wind generation installed, requires approximately 1 MW of new peaking power plant (Qadrdan et al., 2017). However, the present model does not take into account the ability of NG fired power plants at demand tracking. It should also be noted that intermittency only applies to specific renewable energy technologies, i.e. the solar PV and the onshore/offshore wind power plants, while geothermal and biomass technologies, which appear to be present in the Indonesian power generation mix, can be predictable in terms of their output (i.e. dispatchable sources).

As far as the Policy Compliance option is concerned, outcomes related to the RES power production share, discounted total cost and $CO_{2,eq}$ emissions demonstrated deviations of <5% in relation to the Least Cost option, although the energy mix profiles of the two POs are quite different, principally due to the minimum 24% share of gas-fired plants constraint enforced by the policy. With slightly better environmental impact mitigation, this option limits the $CO_{2,eq}$ emissions to 555 million ton of $CO_{2,eq}$ per year and surpassing the 26% $CO_{2,eq}$ reduction target for 2030 (reaching a share of 35.2%).

As mentioned above, the optimal total weighted discounted cost under the Green Energy Policy option is expected to be 30% higher than the Least Cost option, ranking this option as the most expensive, due to the higher amount of new installed capacity of renewables, needed to satisfy the more ambitious environmental impact mitigation targets. Increasing costs were greatly attributed to the introduction of the carbon pricing policy. Additionally, under this option, the weighted RES share equals 46% and the expected new installed capacity of RES equals 62,600 MW per year (38% higher than the Least Cost option) during the 2030 time period. The higher RES penetration targets, the carbon pricing policy and the more ambitious $CO_{2,eq}$ emissions reduction targets resulted in an improved environmental performance of the power generation system, which, however, incurred higher cost to the power generation system.

8. Conclusions

In this paper, a linear multi-stage stochastic optimization model was developed to optimize the future power generation mix of a region or country by minimizing the total discounted cost, while also considering a number of constraints related to the peak and consumption demand, renewable energy potential limit, renewable energy penetration targets, annual construction limit, fuel diversity, $CO_{2,eq}$ emission targets and carbon pricing policy. The model took into account the uncertainty of three parameters, namely the demand of electricity, the future reduction of capital cost of renewable technologies (due to learning curve effects), and the volatility of coal, natural gas and diesel prices. Uncertainty in energy demand and declining capital cost of solar PV and onshore wind was simulated by means of a ST approach, while the volatility of fuel prices was approached through MCS assuming a normal probability distribution.

The aim of this paper is to expand the existing multi-stage scenario tree optimization approach to include at least one variable as stochastic. Compared to the possibilistic approach of assigning empirical values for probabilities of three or more scenarios, assigning a statistical distribution for given variables allows for continuous consideration of uncertainties. Between the three variables considered in our case study, values of fuel prices can be statistically represented based on past data, compared to the other two variables where an empirical degree of belief in different potential outcomes can be assigned based on past trend and expert experience. Further, a trade-off between fidelity of the analysis and computational efficiency should be made in order to define problems that can be solved with reasonable computational effort. In a future stage, advanced methods for stochastic modelling should be investigated in order to allow for more variables to be considered stochastically through reducing dimensionality of the problem, i.e. importance sampling, Latin hypercube sampling etc. As a rule of thumb for future researchers, stochastic modelling should be adopted for variables that can rely on existing datasets and for which, continuous representation of uncertainty is important, while the possibilistic approach is appropriate either when future projections and forecasts are available or when an empirical degree of belief in different potential outcomes can be assigned based on experience and expertise. The clustering algorithm can be used to derive two-stage or three-stage or any stage scenarios by exploiting the numerous forecast/projection data.

Indonesia's power system has been used as a case study to test the applicability of the proposed model by means of a baseline case. The model was, then, applied to determine the optimal power generation mix for three planning options: Least Cost, Policy Compliance and Green Energy Policy option.

Coal appeared to play a dominant role in the development of Indonesia's power generation system under the Baseline, Least Cost and Policy compliance options, as a result of the relatively low construction and operation cost of the technology. The results indicated that to achieve the sustainability target set by the policy, Indonesia needs an expansion in renewable-based power generation capacity to meet the future demand as the conventional fossil-based power generation is capped up to a certain level to meet the $CO_{2,eq}$ reduction target. This will be a significant challenge as the required installed capacity of renewable generation is much higher than the current installed capacity for each renewable technology. On the one hand, enhancing the renewable energy and environmental impact mitigation targets can increase the RES share in the energy mix to the expense of a higher total power generation system cost. On the other hand, a cheaper power generation mix could potentially be achieved (which can potentially also satisfy the RES penetration target); however, imposing no diversity constraints might jeopardise the security of the power generation system. A more secure power generation system can be achieved by diversifying the generation capacities and accommodating fast start and flexible gas-fired power plants. However, the share of power generated from coal, oil and natural gas combined has to be kept below approximately 60% in 2030 to achieve more ambitious environmental impact mitigation targets as the ones assumed under the Green Energy Policy option. This maximum limit can be increased by shifting from coal to natural gas generation at the expense of higher power generation system cost. Gas-fired generation can, thus, be used as a contingency technology, in order to approach the $CO_{2,eq}$ emission targets, while at the same time offer higher protection against the intermittency of renewable-based power generation and hence support the integration of wind and solar technologies.

The developed model could be a useful tool for decision makers to assist in quantitative analysis and to provide a better understanding in power generation system planning, taking into account uncertain inputs changing over the planning horizon. The results generated by the model could be improved by supplying more accurate data, such as comprehensive remaining technical life data of recently installed power generation facilities and annual construction limit for each renewable energy technology that has been assessed further. The methodology developed in this study could also be used in other problems where the optimal solution is highly dependent on the stochasticity of key related variables.

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Appendix A

The capital cost projections of solar PV and onshore wind power plants across the planning horizon used as inputs in the model are summarised in the following Table

Table A-1
Projection of capital costs of solar PV and onshore wind power plants (Source: (National Renewable Energy Laboratory, 2018)).

Capital costs ($/kW)	Scenarios	2020	2025	2030
Solar PV	Low	1248	949	732
	Medium	1612	1350	1111
	High	1916	1752	1490
Onshore wind	Low	1548.68	1246.86	911.84
	Medium	1606.96	1588.03	1576.01
	High	1665.24	1929.2	2240.18

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