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Incorporating grid development in capacity expansion optimisation - a case study for Indonesia

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HIGHLIGHTS

- We develop SELARU—a spatially explicit capacity expansion optimisation model.
- SELARU incorporates economy of scale consideration in generating model results.
- Grid expansion spatial representation changes technology selection in model output.
- Findings from power sector example also apply to multiple energy carrier systems.
- Computing demand requires trade-off between spatial and temporal resolution.

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ABSTRACT

Capacity expansion optimisation is a widely used techno-economic analysis particularly on topics related to climate change mitigation and renewable energy transition. Using optimisation models to investigate capacity expansion in regions that potentially require significant grid infrastructure development requires incorporation of grid expansion problem within the optimisation. This study presents the development of SELARU, a spatially explicit optimisation model that incorporates the economies of scale of grid expansion using contextualized geographical feature to form the model's high-resolution spatial units. The model is used to investigate the case study of Indonesia using various spatial treatments to demonstrate the impact of detailed spatial depiction of grid expansion. Results reveal significant difference in renewable energy deployment trajectory (up to 2272 % increase in new generation capacity) between high-resolution spatial depiction of grid expansion vis-à-vis non spatially explicit energy system optimisation. Due to its high-resolution, SELARU also generates detailed information on the geographical extent of grid expansion requirement, which provides more realistic insights on governance challenges of renewable energy transition. Careful consideration of spatial representation is crucial when optimisation model is used to evaluate scenarios that concern technology selection such as renewable energy deployment or climate change mitigation.

1. Renewable energy transition and grid expansion challenges

Geographical spread of resources and intermittence of power generation are among the main challenges of scaling up renewable energy. Renewable energy sources such as solar radiation, wind power, geothermal power, or hydropower require on-site conversion to electricity or other carriers to allow transport of energy to demand locations elsewhere [1]. For instance, hydropower electricity is available in regions where there are substantial water stream or catchment area and considerable slope and length for head racing the water down to the powerhouse, which is then transmitted to demand locations via electricity grid. In contrast, fuel-firing power generation can virtually be deployed everywhere constrained mainly just by the supply of feedstock fuels (e.g. coal, gas, oil, biomass). Before entering the combustion

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chamber, fuels start their journey from primary energy extraction to processing and storage [2]. These journeys include significant amount of movement that is made available at relatively low-cost by the extent of accumulated logistics infrastructure of various fossil fuel commodities.

The intermittence of renewables for generating electricity is also dependent on their location. For instance, wind and solar energy potentials depends on local weather conditions and solar radiation. Periods of intense solar radiation or high winds—during which solar or wind power plants can maximize their output—vary from one location to another. The time-varying and uncertain production of intermittent renewable electricity require the addressing of potential risks towards stability and reliability of the power grid [1]. This limitation is not true for all type of renewables. For example, hydropower or geothermal power can provide sufficient firm and operating reserves capacities to ensure service reliability and stability of the power grid.

Expanding the geographical coverage of power grid is usually required to reach remote renewable energy resources. Under certain load conditions, such an expansion will also improve grid connectivity that can help address the intermittence issue of renewables by allowing electricity to flow from surplus regions to demanding regions. However, access to low-cost renewable resources may require substantial extension and upgrade to the power grid [3,4], which require significant investment and sufficient load flows to make economic sense. In addition, the expectation of costs and benefits may differ across regions depending on natural conditions, level and pace of societal development, and regulatory regime of the region. This leads to the case where building extensive power grid infrastructure in some regions may become less financially viable compared to deploying smaller distributed systems or vice-versa. Therefore, incorporating grid expansion into broader power generation expansion planning is challenging. In an intermeshed network, the exact location, size of power line extensions and the costs required to connect inter-region transfer capacities are specific to the particular context of resource, supply, and demand in various location within a certain time horizon. Moreover, power grid technical components may also include different configuration of voltage classes, types of electricity current, and grid topology.

2. Spatial representation in optimisation models

In the field of energy modelling, optimisation models are commonly used to evaluate system-wide parameters related to the production, conversion, distribution, storage, and use of energy in a simplified depiction. These models incorporate detailed, bottom-up information, and typically utilises linear programming techniques to solve the optimal configuration of energy technologies that minimises the total cost of the entire depicted system [5–7]. They have been widely used for assessing different scenarios of capacity expansion [8], unit commitment [9], grid control and planning [10], market design and pricing [11,12], social and environmental impacts of energy system [13], and assessing decisions under future uncertainties [14]. Modelling and analysis of the energy system provide the integrating framework that assists policy and industrial decision makers at different levels (i.e. global, regional, and local) in assessing different strategies and possible outcomes [15].

Optimisation models typically employ linear programming approaches, their main component is an objective function that details cost implications of energy technology application as decision variables. The objective function is minimised against numerous constraints such as fulfilment of demand, grid reliability and stability, and emission reduction requirements. Moreover, the models are informed by systems-wide information such as energy demand and resource availability, as well as detailed techno-economic information such as costs of primary energy, construction, operation and maintenance, as well as conversion efficiency, capacity factor and emissions factor.

The construct of an energy system is highly influenced by its spatial detail. Among others, location of primary energy resources vis-à-vis energy demand will have huge implication towards the selection of energy technologies, ranging from conversion to transport of energy carriers. Accordingly, how spatial information is depicted in an optimisation model could determine its sensitivity towards certain parameters and its behaviour in generating optimal configuration of modelled system scenarios. There are different ways in how optimisation models depict spatial information. For the purpose of this study, spatial depiction in optimisation models can be classified into 1) no spatial representation, 2) low-resolution spatial representation and 3) high-resolution spatial representation. Optimisation models that concern singular region, usually based on administrative boundaries, effectively has no spatial representation [16–21]. Models with spatial representation ultimately intend to incorporate transport of energy across multiple regions within the depicted system. This is achieved through simplifying regions with certain geographical boundaries into nodes allowing interconnections between them [22]. Optimisation models with no spatial representation are essentially single-node models. This type of models uses simplified exogenous assumptions to approximate parameters that require spatial representation such as transmission and distribution losses and costs of upgrading the electricity grid for the whole region. In contrast, optimisation models with spatial representation, either with low- or high-resolution, are multi-node models that incorporate distance and accessibility between nodes to better represent different geographic zones, incidence of distributed energy, interconnection distances, and transmission bottlenecks [23–32]. In modelling electricity systems, this information can be further enriched with description of voltage and current physical properties to determine load flows [33,34].

The majority of studies using optimisation models fall into the category of low-resolution spatial representation with their use of administrative regions, or their aggregation, to represent multi-node systems [23,24,27,35–38]. In global studies, energy system optimisation models are part of integrated assessment modelling of the broader human energy-economy-environment systems. Under this setup, the majority of global models depict the world as 5 to ∼40 regions with a small number of models representing up to 100 regions [39]. These regions represent regional costs disparities of implementing policies, technological solutions, and the potential trade between regions. National and regional applications of optimisation models vary in spatial detailing [23,25,37,40–44]. Some studies employ different spatial resolutions for different scopes of analysis, for instance: using limited amount of nodes for long-term planning of infrastructure, and increase the number of nodes (e.g. China: from 8 nodes to 80 nodes [37], Europe: from 28 to 224 [3]) for short-term planning of operation that feeds back transmission infrastructure costs information into the long-term model. In both multi-node applications, the optimisation process is done at relatively coarse resolution (8–224 nodes). High-resolution spatial representation is characterized by geographical features that are more contextualized compared to rather high-level administrative boundaries in determining spatial units within the depicted system. This is done in a limited number of studies using geographic grid with resolutions ranging between 0.25 and 0.50° (756–3025 km^2 at the equator) [45–48].

3. Indonesia's power sector

Indonesia has a geographically diverse and complex energy system. The archipelagic nation consists of more than 17,000 islands that stretch over 5000 km along the equator. In 2020, the country consumed 8.s5 EJ of primary energy with majority of the supplies coming from fossil fuels (86 %) and the remaining from renewables (14.4 %) [49]. By the end of 2020, Indonesia had a total installed electricity generation capacity of 70 GW connected to the grid and 2.75 GW of total installed off-grid generation [50]. More than 60 % of all generation capacity is situated in the Java-Bali electricity system (> 40 GW), while the rest is distributed in other islands of Indonesia. Coal-fired power plants accounted for half of total installed capacity in 2020. Renewables, in contrast, accounted for 12 % of the total, with half of it coming from hydropower.

The government of Indonesia (GoI) has pledged to reduce greenhouse gasses (GHGs) emissions by 29 % relative to baseline emissions in 2030, or by 41 % with conditions of international support, as stated in their nationally determined contribution (NDC) [51]. More recently, GoI announced its intention to enhance the ambition and reach net-zero emissions by 2060, and as early as 2050 with additional international support [52,53]. The country has successfully increased the share of households with access to electricity from 67.15 % in 2010 to 99.2 % in 2020 [54]. Nevertheless, many electrified regions do not receive 24 h of electricity per day nor have access to other modern sources of energy. These are the realities, especially in eastern regions, where dilapidated or non-existent infrastructure impedes the development of public health, education, and the alleviation of poverty, thus resulting in persistent regional inequalities [55].

Indonesia has huge untapped renewable resource potential that can theoretically provide locally available energy to fulfil domestic demand. However, expanding the necessary infrastructure is challenging due to the geographic spread and development inequalities across the archipelago. As a general phenomenon, there is huge location disparity between energy demand (**Fig. 1**) and resource availability of renewables (**Fig. 2**). Indonesia's energy sector is also highly regulated with the State Electricity Company mainly responsible for power generation and grid operation throughout the country. Therefore, the necessity of incorporating grid expansion needs into scenario assessment of high renewable energy deployment is further underlined in order to provide relevant and feasible sustainable energy transition insights.

Modelling based studies on Indonesia's energy system utilise single-node or coarse resolution multi-node models. Single-node models are employed to maintain model tractability for cross-sector analysis that include macro-economic details [60] or studies that address topics with temporal variability [61]. Multi-node model applications on Indonesia [62] [63] [64] [65] describe regional geographical conditions, power grid network, and cross-borders trade to assess scenarios of transitioning to renewables. The highest resolution among these multi-node analyses occurs in a recent study commissioned by the International Renewable Energy Agency (IRENA) and Indonesia's Ministry of Energy and Mineral Energy Resources (MEMR) [65]. The study utilises PLEXOS energy market modelling and simulation software [66] to analyse Southeast Asia in 35 regions, with Indonesia covering 18 of these regions.

4. Knowledge gaps and research objectives

Using optimisation model to explore scenarios of renewable energy capacity expansion can be problematic without the adequate spatial detail representation. Theoretically, solutions of optimum energy technology configuration could be misled by distorted costs of grid infrastructure requirements to connect on-site power generation to demand locations. The optimisation process in single-node models virtually assume equal cost for transmitting different types of electricity generation in the region that the models address [60,61,67–72]. In reality, distances to existing grid infrastructure, and therefore transmission costs, vary between fossil-based power generation and on-site renewable electricity generation. Multi-node models incorporate information on resource disparities among regions and required grid infrastructure for energy transfers among regions [3,23,25,37,41–48,62,73]. However, the use of low-resolution spatial representation may underestimate grid network requirement within each of the nodes. Moreover, the spatial averaging effects might have ruled out the extreme points in designing the system; misidentifying high potential resource locations that are separated in short distances.

Formulation of grid expansion problem in optimisation model also need to consider the economies of scale. In situations where significant grid investments are required, the selection of distributed systems as optimum solution might be favourable instead of expanding the grid to remote areas. This is possible despite its higher unit electricity generation cost, mainly because remote areas typically also have low energy demand. However, combining these areas may result in sufficient demand that justifies the use of lower-cost bulk power generation technologies even after taking grid expansion costs into account. From a

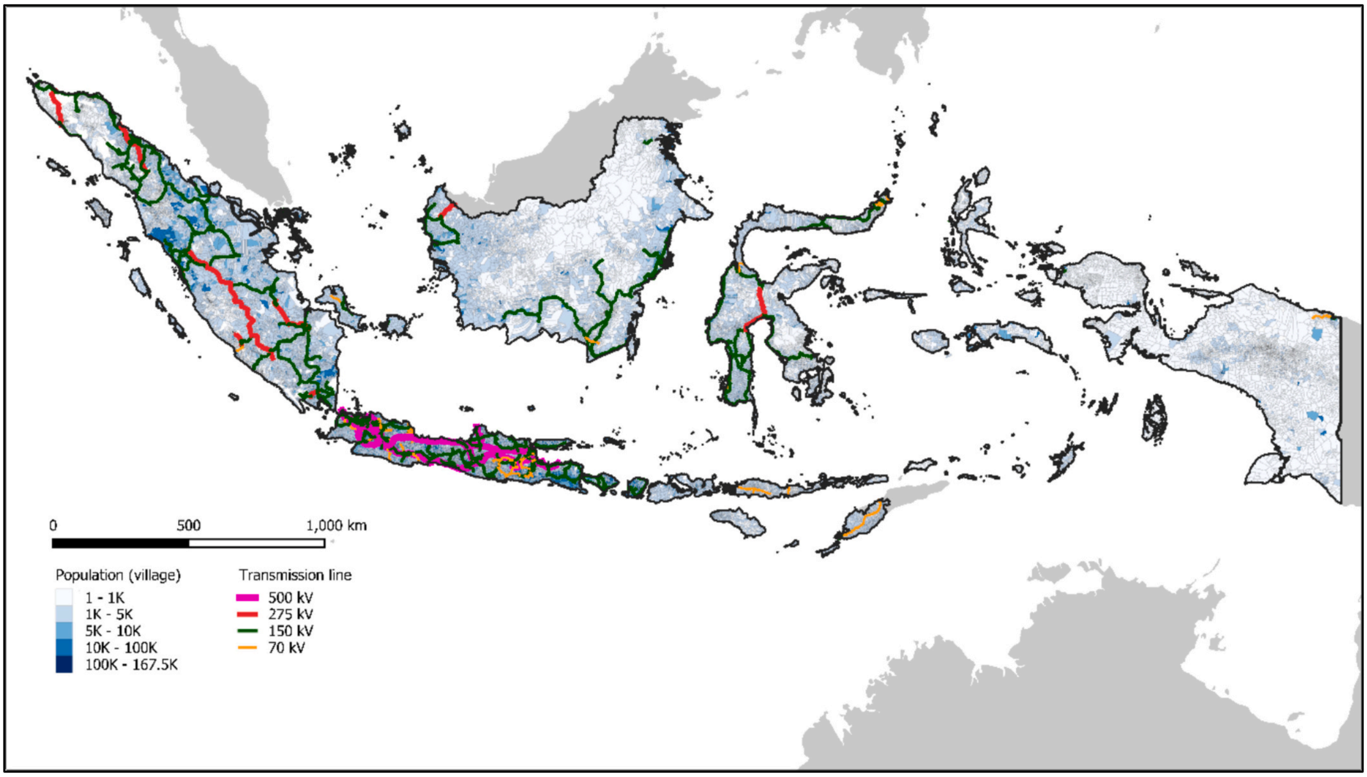

Fig. 1. Map of population distribution for year 2019 as proxy of energy demand and overlay of existing transmission lines.

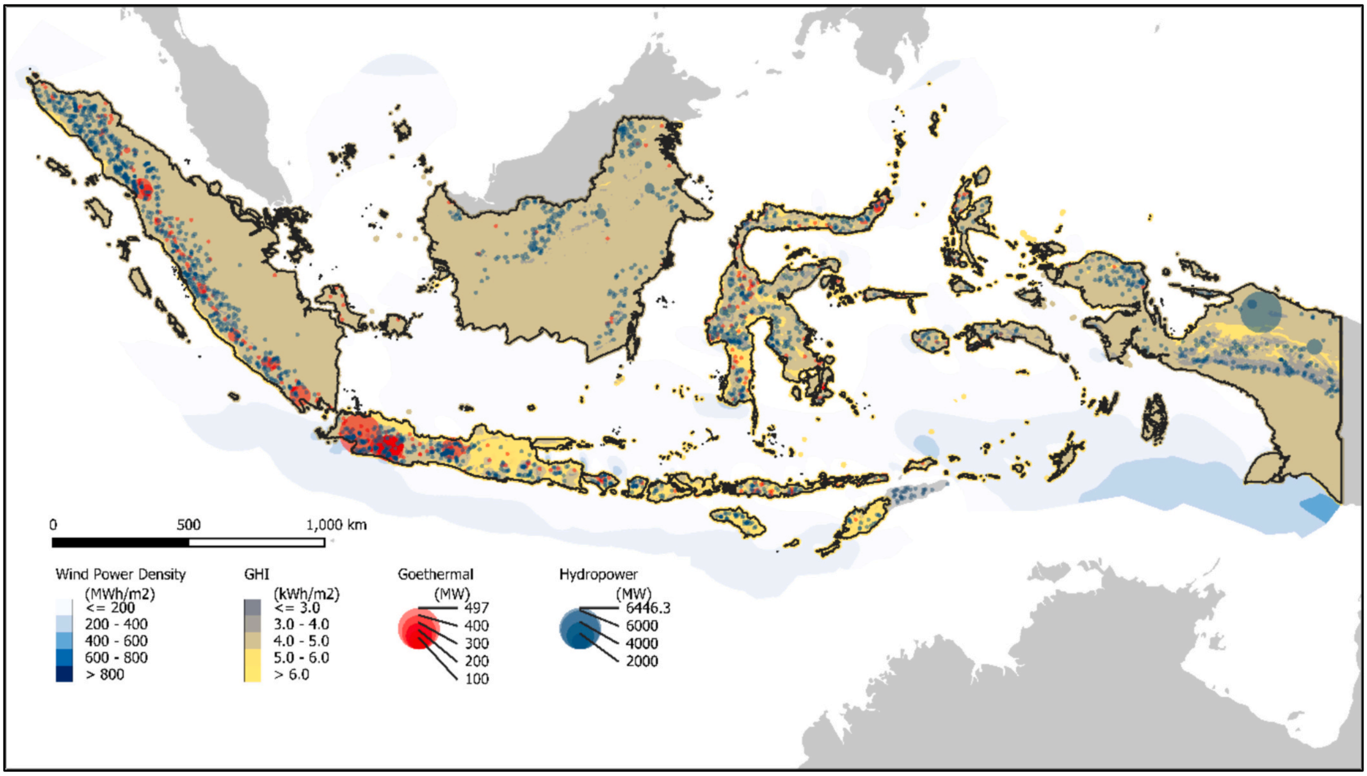

Fig. 2. Distribution of solar in daily average of Global Horizontal Irradiance (GHI) **[56]**, wind in Wind Power Density **[57]**, geothermal **[58]** and hydropower **[59]** resource potential.

long-term perspective, incremental grid expansion can also result in future competitiveness of low-cost bulk power generation technologies due to accumulation of economies of scale over certain fraction of the modelled time horizon. Allowing optimisation models to depict incremental grid expansion and its contribution to accumulation of economies of scale requires explicit formulation for deploying transmission lines and transformer substations.

As previously mentioned, literature review reveals that high-resolution multi-node applications using geographical grid are rather limited. Moreover, both high-resolution as well as low-resolution multi-node analyses only address grid expansion in terms of capacity increase and not the geographical extent [3,23,25,37,40–44,74]. To address this research gap, this study aims to develop high-resolution spatially explicit optimisation model that addresses economies of scale of geographical grid expansion into power system optimisation. The study also explores the impact of such an addressing of the grid expansion problem, especially in regions that potentially require significant geographical expansion of grid infrastructure due to e.g. sparse distribution of available resources, or having development trajectories that indicate significant shift of future energy demand locations regardless of the presence of new grid development plans.

We present the development of spatially explicit optimisation model that is applied to Indonesia's power sector at varying spatial resolutions to address the aforementioned research objectives. The methodology for model development and other key elements to the modelling framework are first presented. We then summarize results and discuss key insights from model application for Indonesia's energy system with non-spatial treatment, as well as coarse- and high-resolution spatially explicit application. Finally, we conclude by evaluating the usefulness of the approach and deriving recommendations for future studies.

5. Methodology

We develop a spatially explicit optimisation model called SELARU. The model has the unique feature of high-resolution multi-nodes spatial representation with the capability of incorporating the economies of scale of geographical grid expansion into its optimisation process. We employ SELARU to investigate the case study of Indonesia's electricity sector in accordance with our earlier hypothesis that high-resolution spatially explicit optimisation model is particularly relevant to assess geographically diverse systems with a developing trajectory for future energy demand in new locations. The model is used in various spatial treatments to demonstrate the impact of different spatial depictions of grid expansion.

5.1. SELARU modelling framework

We limit the application of SELARU to the electricity sector for this study in anticipation of the high computational demand due to the sheer size of the optimisation problem (see Table 1). In this study, SELARU generates optimal configuration of technology application for power generation, transmission lines and substations that minimises cumulative total system cost throughout the planning horizon, while meeting

Table 1
| GAMS execution summary of Non-Spatial, Low-Res and High-Res SELARU applications. The solver is set to return best found solution when total solve time exceeds 100,000 s or processed over 1 million nodes in CPLEX's Branch and Cut algorithm.

	Non-Spatial	Low-Res	High-Res
MILP Solve (total system cost) in billion US$ (constant 2020)	398.4	359.8	359.19
Theoretical best solution	398.2	350.36	348.56
Gap	0.05 %	2.62 %	2.96 %
Average run time (hh:mm:ss)	0:00:01	0:00:18	7:37:18
Number of rows	31,930	1,090,108	13,197,680
Number of columns	29,326	993,986	12,183,266
Number of non-zeroes	76,279	2,354,638	28,757,565
Number of integers	135	5405	69,380

demand and other technical constraints (illustrated in Fig. 3).

SELARU is based on Mixed Integer Linear Programming (MILP) and developed using the General Algebraic Modelling System (GAMS) [75]. Varying SELARU applications in this study were executed in GAMS using CPLEX solver [76]. SELARU endogenously determines the capacity expansion decisions for all 20-year timesteps from 2020 to 2100. Model outputs, i.e. generation, voltage transformations, and transmission flows, are solved to ensure annual balance of energy supply and demand at each node for all the timesteps.

Existing and planned infrastructure are taken into account in the modelling horizon of this study. The data is obtained from the ESDM One Map developed by MEMR [58] and General Electricity Supply Plan by PLN [77], which includes electricity generation facilities, transmission lines, and transformer substations. As the aim of the study is to investigate the impact of detailed spatial representation, climate mitigation scenarios are not considered. This approach is adopted to avoid potential effect of scenario interventions that might influence the model's solution beyond the formulated objective function and energy system constraints.

Further details of MILP formulation and input data used in this study are available in the supplementary information. The study can also be reproduced using information in the GitHub repository mentioned in Data availability.

5.2. Spatial representation

As in other optimisation models, SELARU uses nodes and lines to represent the spatial context of energy systems. The nodes represent geographic areas within which selection of technologies for power generations, storages, transmission lines and substations will be solved as decision variables. The nodes also contain information such as potential of renewables, energy demand, and area of exclusion zones originating from spatial aggregation within the regions that the nodes represent. The lines connecting different nodes represent eligible connections or transmission corridors along which electricity can be transported.

For this study, SELARU is applied in three spatial resolutions. We apply SELARU first as a single-node model (henceforth “Non-Spatial” application) and as low resolution multi-node model (henceforth “Low-Res” application) to represent existing approaches summarised in previous sections. The Low-Res application uses 34 nodes based on administrative boundaries of Indonesian provinces. These 34 nodes are connected with 90 lines representing possible inter-province connections (many of the provinces comprise of islands that are separated by ocean). Note that the number of nodes in the Low-Res application is about twice the number of nodes of the IRENA-MEMR study [65] which has the highest spatial resolution to date.

Finally, we apply the default mode of SELARU Indonesia application with 516 nodes and 1624 lines that connect the nodes (henceforth “High-Res” application, see Fig. 4). The nodes in High-Res application are generated through clustering villages as the lowest administrative unit in Indonesia. This selection assumes that village map is a suitable proximation for the geographic distribution of socio-economic activities. In contrast, higher level administrative boundaries, for example province or sub-province level administrative maps, are highly influenced with geographic conditions or political justification instead. 83,458 villages are aggregated to 500 clusters using k-Clusters algorithm [78] performed in QGIS software [79]. Under the algorithm, mean coordinates of villages that belong to a unique cluster—weighted using their population density and distances to neighbouring villages—are used as the basis for Voronoi Tessellation [80] to generate polygons describing the clusters' bounding area. Clustered zones that include different islands or separated by water body are further divided, resulting in 516 nodes that represent areas ranging from 0.15 to 11,634 ha, with an average of 3782 ha which is comparable to 0.55° geographic grid resolution. International electricity trade with neighbouring countries is not considered in all three applications (i.e. Non-Spatial, Low-Res and High-Res).

5.3. Incorporating grid expansion

Total system cost (Z) in SELARU is formulated as total system costs ($TSC_y^{[\dots]}$) of all deployed generation ($\mathbb{EG}$), transformer-substation ($\mathbb{TS}$), transmissions ($\mathbb{TL}$) infrastructures, of all vintages v, in all nodes ($\mathbb{N}$) or in all corridors connecting two-nodes ($\mathbb{NN}$), in all modelled years (y) along

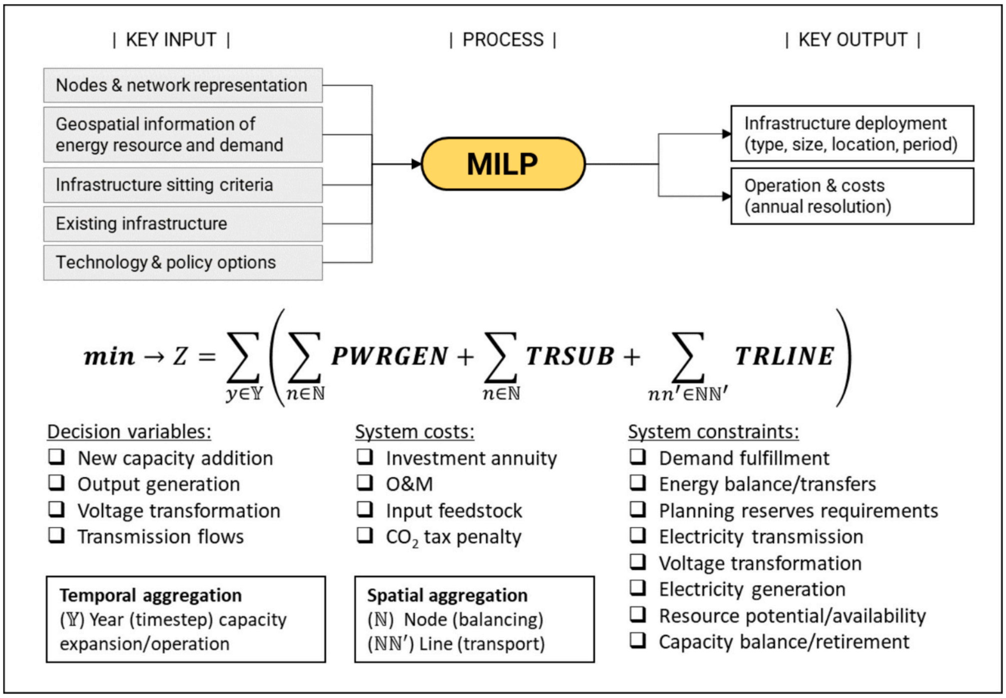

Fig. 3. Schematic overview of SELARU modelling framework used in this study.

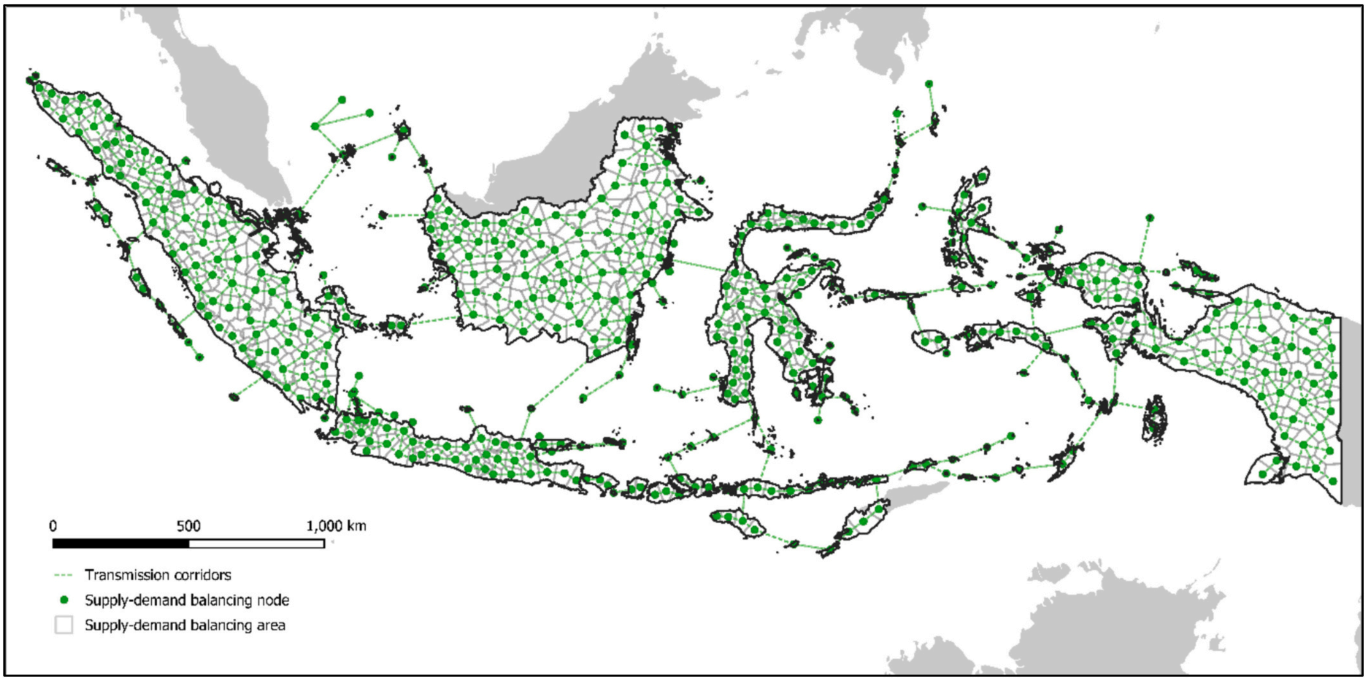

Fig. 4. Spatial representation in High-Res SELARU application comprises 516 nodes of supply-demand balancing regions (green dots with associated bounding area outlined in black) and 1624 possible inter-nodal connections (lines in green).

the planning horizon ($\mathbb{Y}$)..

$$Z = \sum\nolimits_{y\in\mathbb{Y}}\left(\sum_{n\in\mathbb{N},eg\in\mathbb{EG},v\leq y} TSC^{\mathbf{EG}}_{n,eg,v,y} + \sum_{n\in\mathbb{N},ts\in\mathbb{TS}} TSC^{\mathbf{TS}}_{n,ts,y} + \sum_{nn'\in\mathbb{NN}',tl\in\mathbb{TL}} TSC^{\mathbf{TL}}_{nn',tl,y}\right)$$

The *TSC* for each technology class comprises of costs of capacity investment annuities and operational expenses (i.e. operation and maintenance, input feedstock, and emissions penalty), given for each node *n* and planning period *y* (by)

$$\begin{aligned} TSC^{\mathbf{EG}}_{n,eg,v,y} =& CAP_{n,eg,v,y}{}^*\mathrm{CAPEX}_{n,eg,v}{}^*\mathrm{CRF}_{eg} + CAP_{n,eg,v,y}{}^*\mathrm{FOM}_{eg} \\ &+ OUT^{ely}_{n,eg,v,y}{}^*\mathrm{VOM}_{eg} + \sum\nolimits_{f\in\mathbb{F}} FUEL_{n,eg,v,f,y}{}^*\mathrm{P}_{n,f,y} \end{aligned}$$

$$TSC^{\mathbf{TS}}_{n,ts,y} = CAP_{n,ts,y}{}^*\mathrm{CAPEX}_{n,ts,y}{}^*\mathrm{CRF}_{ts}$$

$$TSC^{\mathbf{TL}}_{nn',tl,y} = CAP_{nn',tl,y}{}^*\mathrm{d}_{nn'}{}^*\mathrm{CAPEX}_{nn',tl,y}{}^*\mathrm{CRF}_{tl}$$

The annuity of investment for each technology is computed by the quantity of deployed capacities *CAP*, their overnight-capital costs per unit of capacity (CAPEX), their capital recovery factor (CRF), and their length of connection between node *n* and n' ($\mathrm{d}_{nn'}$). Technology-specific interest rates and economic lifetime determines the CRF for each technology. The fixed operation and maintenance costs are based on a factor FOM of installed capacity (*CAP*). Variable operation and maintenance costs are based on a factor VOM of output production (*OUT*). For fuel-firing power generation technologies, input feedstock costs are determined by the sum of all fuels $\mathbb{F}$ multiplied by the price of that fuel *f* available at node *n* in year *y* ($\mathrm{P}_{n,f,y}$). For this study, price of feedstock fuels changes along the planning horizon and adjusted with applicable spatial cost correction to account for logistic costs to different nodes and annual price changes along the planning horizon.

Explicit formulation of transmission system requires the application of energy balance and transfers constraints. Supply and demand must match at any time, voltage level must be kept within physical limits, and current flows have to stay below the thermal limits of components. In this SELARU version, power generation is solved to ensure annual balance of energy supply and demand, voltage classes are aggregated, and physical limits of transmission components are simplified using line losses and capacity factors. The basic framework of the energy system model is given by the energy balance and transfers at nodes in all times. Nodal supply-demand balance and transfers constraints ensure the fulfilment of demand for electricity and firm capacity at all nodes $\mathbb{N}$ for all voltage classes $\mathbb{kv}$ in all planning periods $\mathbb{Y}$, given by

$$\forall[\mathrm{ely}\mid\mathrm{plrsv}] =, \boldsymbol{n}\in\mathbb{N}, \boldsymbol{kv}\in\mathbb{kv}, \boldsymbol{y}\in\mathbb{Y},$$

$$S^{\mathrm{ely}}_{n,kv,y} \geq \mathrm{D}^{\mathrm{ely}}_{n,kv,y}{}^*\left(1+\mathrm{loss}^{\mathrm{dl}}\right)^*\left(1+\mathrm{ownuse}^{\mathrm{ds}}\right)$$

$$S^{\mathrm{plrsv}}_{n,kv,y} \geq \widehat{\mathrm{D}}^{\mathrm{ely}}_{n,kv,y}{}^*\left(1+\mathrm{margin}^{\mathrm{plrsv}}_{n,y}\right)^*\left(1+\mathrm{loss}^{\mathrm{dl}}\right)^*\left(1+\mathrm{ownuse}^{\mathrm{ds}}\right)$$

$$\begin{aligned} S^{[\dots]}_{n,kv,y} =& \sum_{eg\in(kv,eg),v\leq y} OUT^{[\dots]}_{n,eg,v,y} + \sum_{n'n\in\mathbb{N}'\mathbb{N},kv} FLOW^{[\dots]}_{n'n,kv,y}{}^*\left(1-\mathrm{loss}_{tl\in(kv,tl)}{}^*\mathrm{d}_{n'n}\right) \\ &- \sum_{n'\in\mathbb{NN}',kv} FLOW^{[\dots]}_{nn',kv,y} + \sum_{kv'\leq kv} Vup^{[\dots]}_{n,kv',kv,y}{}^*\left(1-\mathrm{loss}_{ts\in(kv,ts)}\right) \\ &+ \sum_{kv'\geq kv} Vdo^{[\dots]}_{n,kv',kv,y} - \sum_{kv\leq kv'} Vup^{[\dots]}_{n,kv,kv',y}{}^*\left(1-\mathrm{loss}_{ts\in(kv,ts)}\right) \\ &- \sum_{kv\geq kv'} Vdo^{[\dots]}_{n,kv,kv',y} \end{aligned}$$

(With) $OUT^{\mathrm{plrsv}}_{n,eg,v,y} \leq CAP_{n,eg,v,y}{}^*\mathrm{capcred}^{\mathrm{plrsv}}_{eg}$

Planning reserves (plrsv) allow the system to ensure sufficient firm capacity to meet the forecasted demand peak load plus a reserve margin. The supplied firm capacities must exceed the peak demand ($\widehat{\mathrm{D}}^{ely}_{n,kv,y}$) plus a margin for planning reserve ($\mathrm{margin}^{\mathrm{plrsv}}_{n,y}$) at all supply-demand balancing node *n*. At specific node *n*, voltage class *kv*, and planning period *y* electricity demand and firm capacity is supplied ($S^{\mathrm{ely}}_{n,kv,y}$ or $S^{\mathrm{plrsv}}_{n,kv,y}$) with all in-situ the power generated $\left(OUT^{\mathrm{ely}}_{n,eg,v,y}\right)$ and firm capacity reserved ($OUT^{\mathrm{plrsv}}_{n,eg,v,y}$), plus all incoming transmission from all other nodes n' ($FLOW^{[\dots]}_{n'n}$), minus all outgoing transmission to all other nodes n' ($FLOW^{[\dots]}_{nn'}$), and plus the net-change of voltage classes step-up ($Vup^{[\dots]}_{n,kv,kv'>kv}$) and step-down ($Vdo^{[\dots]}_{n,kv,kv'<kv}$) to and from other voltage

classes kv'.The efficiency of the power grid is mainly influenced by the rate of transmissions line losses ($loss_{tl}$) and distance ($\mathrm{d}_{n'n}$). Fulfilment of demand and firm capacity requirements are factored to include distribution line losses ($\mathrm{loss}^{\mathrm{dl}}$) and substation own use ($\mathrm{ownuse}^{\mathrm{ds}}$). Reservation of firm capacity from specific generation facility ($OUT^{\mathrm{plrsv}}_{n,eg,v,y}$) is capped by the size of installed capacity ($CAP_{n,eg,v,y}$) and firm capacity credits or effective load-carrying capability ($\mathrm{capcred}^{\mathrm{plrsv}}_{eg}$). $\mathrm{Capcred}^{\mathrm{plrsv}}_{eg}$ reflects the expected availability when power is needed [81], in this case in period of peak demand.

Flows of electricity ($FLOW^{\mathrm{ely}}_{nn',kv,y}$), firm capacities ($FLOW^{\mathrm{plrsv}}_{nn',kv,y}$), and voltage transformations ($Vup^{[\ldots]}_{n,kv',kv,y}$, $Vdo^{[\ldots]}_{n,kv,kv',y}$) in the power grid are capped by installed capacity energy infrastructures (CAP) and maximum and minimum thresholds of capacity factor ($\widehat{\mathrm{CF}}$ and $\check{\mathrm{CF}}$), given by

$$\forall[\mathrm{ely}\mid\mathrm{plrsv}], FLOW^{[\ldots]}_{nn',kv,y} = \sum_{tl\in\mathrm{kvtl}}\left(CAP_{nn',tl,y}+CAP_{n'n,tl,y}\right)*CF^{[\ldots]}_{tl}*\mathrm{hleng}^{[\ldots]}$$

With $\check{\mathrm{CF}}_{tl} \geq CF^{[\ldots]}_{tl} \geq \widehat{\mathrm{CF}}_{tl}$, $\mathrm{hleng}^{\mathrm{ely}} = 8760$, and $\mathrm{hleng}^{\mathrm{plrsv}} = 1$

$$\forall[\mathrm{ely}\mid\mathrm{plrsv}], kv \in \{\mathrm{EHV},\mathrm{HV}\}, \sum_{ts\in(kv,ts)} CAP_{n,ts,y}*\widehat{\mathrm{CF}}_{ts}*\mathrm{hleng}^{[\ldots]}$$
$$\geq \sum_{kv>kv'} Vup^{[\ldots]}_{n,kv',kv,y} \mid \sum_{kv<kv'} Vdo^{[\ldots]}_{n,kv',kv,y}$$

$$\forall kv \in \{\mathrm{MV}\}, CAP_{n,ts\in(kv,ts),y} \geq \sum_{n'} CAP_{nn',tl\in(kv,tl),y} + \sum_{n'} CAP_{n'n,tl\in(kv,tl),y}$$

Transformer-substation maximum capacity limit determines the maximum voltage transformation and reserves for extra high voltage (EHV) and high voltage (HV). Meanwhile, medium voltage (MV) substation capacity must cover all incoming and outgoing transmission lines' capacity. This ensures a must built MV substation for each MV line-connected neighbouring nodes. Decoupling of transmission line and substation deployment decisions enables the analysis of different grid topology, from using mini grids, in case of short-range small-capacity transmission, or extending from the main grids afar, in case of long-range high-capacity transmissions.

5.4. *Resource constraints*

The potential deployable capacity and geolocation of geothermal and hydropower resources are obtained from ESDM One Map [58] and World Bank Indonesia Hydropower Study [59]. Both geothermal and hydropower potential generation are capped by nation-wide technology specific maximum capacity factor. Deployment of utility scale photovoltaic (PV), concentrated solar power (CSP) and wind power generation facilities are limited to available land with less than 16 degree incline slope [82], excluding protection areas [83] as well as water body and settlement areas [84]. PV, CSP, and wind farms are assumed to have density of 41–77 [85], 31–49 [86], and 6–8 MW km^{-2} [85]. In addition, distributed small-scale PV systems can be built over 5 % of the buffered settlement areas. Deployment of large-scale (≥10 MW) fossil-based power generation facilities are only allowed in nodes representing areas larger than 100 km^2. The maximum-built capacity of power generation is limited by the technical potential to deploy different group of power generation facilities (greg) aggregated at node n ($\mathrm{pot}^{CAP}_{n,\mathrm{greg}}$), given by

$$\sum\nolimits_{eg\in\mathrm{greg},v\leq y} CAP_{n,eg,v,y} \leq \mathrm{potential}^{CAP}_{n,\mathrm{greg}}$$

Wind and hydropower power generation $\mathbb{EG}^{\mathrm{WIND|HYDRO}}$ is capped by the annual average capacity factor ($\overline{\mathrm{CF}}^{[\ldots]}_{n,eg}$) that are geographically distributed and classified based on resource-technology groups obtained from Global Wind Atlas [57] and World Bank Indonesia Hydropower Study [59]. The availability of wind and hydropower resources are given by,

$$\forall eg \in \mathbb{EG}^{\mathrm{WIND|HYDRO}}, OUT^{\mathrm{ely}}_{n,eg,v,y} \leq CAP_{n,eg,v,y}*\overline{\mathrm{CF}}^{[\ldots]}_{n,eg}$$

For photovoltaic-based electricity generation $\mathbb{EG}^{\mathrm{PV}}$, solar resource potential is calculated based on zonal daily average of global horizontal irradiance (GHI); and for concentrating solar power $\mathbb{EG}^{\mathrm{CSP}}$, direct normal irradiance (DNI) obtained from Global Solar Atlas [56]. The availability of solar resources are given by,

$$\forall eg \in \mathbb{EG}^{\mathrm{PV}}, INPUT_{n,eg,v,y} \leq CAP_{n,eg,v,y}*\mathrm{surface}^{\mathrm{PV}}_{eg}*\overline{\mathrm{GHI}}_n*365.25$$

$$\forall eg \in \mathbb{EG}^{\mathrm{CSP}}, INPUT_{n,eg,v,y} \leq CAP_{n,eg,v,y}*\mathrm{surface}^{\mathrm{CSP}}_{eg}*\overline{\mathrm{DNI}}_n*365.25$$

5.5. *Exogenous demand*

Spatially explicit projections of electricity demand are exogenous input to the model. Demand information is obtained from national demand projection and its downscaling to take into account regional disparities in accordance with the spatial resolution of the analysis. Non-Spatial application uses national electricity demand that is projected using linear regression throughout the modelling time horizon with dependent variables including historical data for electricity consumption [50], population [87], gross domestic product (GDP) [88], and population projection from the Shared Socioeconomic Pathways “Middle of the road” scenario (SSP2) [89].

For Low-Res application, the same projection method is applied, but substituting national-level data with province-level data, except for the SSP2 population projection. The results are then harmonized with national electricity demand projection to ensure comparability. For High-Res application, province-level electricity demand are first downscaled according to district-level GDP data (the most detailed breakdown of publicly available data). The resulting district-level electricity demand is further downscaled according to village level population. This downscaling process results in village electricity demands that are then aggregated to 516 nodes of the High-Res application.

6. Results and discussion

Three SELARU applications for Indonesia were provided with the same input data, except for different levels of spatial aggregation of resource availability and demand. As expected, high spatial resolution increased solving complexity exponentially (Table 1). Use of personal computer, with Intel Core i7-6800K processor (3.4 GHz, 4 cores, 8 threads) and 16 GB of installed memory, was sufficient for solving Non-Spatial and Low-Res applications. However, the hardware failed to generate feasible solutions for High-Res application. High-Res application was solved using a server with four Intel Xeon 5217 processors (3.0 GHz, 16 cores, 32 threads) and a total of 767 GB of installed memory. It is important to note, however, that actual utilization of computing resources cannot be determined as the server was shared with other users via randomized access. Applying high spatial resolution greatly increases computational requirement due to the dramatically increased number of variables considered in the model.

High-Res application resulted in the lowest total system cost for all timesteps (∼359.19 Billion US\$) with differences of 9.84 % and 0.17 % lower compared to total system costs in Non-Spatial and Low-Res applications respectively. A significant proportion of these differences is mainly caused by the execution parameter of the CPLEX solver, where a solution is returned after the Branch and Cut algorithm reaches a certain complexity threshold (> 1 million nodes). However, looking into optimum technology selection gives a different story. For power generation, High-Res application generated 466 GW of newly installed capacity with 28 % coming from renewables—compared to 521 GW with 8 % renewables and 524 GW with 1 % renewables from Non-Spatial application and Low-Res application respectively. The majority of additional newly installed capacity occurred due to the selection of renewable power generation technologies, increasing the contribution of renewables to the national electricity generation mix to more than doubled (204 %) and over one-third (138 %) compared to Non-Spatial and Low-Res applications respectively. However, generated electricity outputs are relatively similar among all three applications with 3764 TWh generated in Non-Spatial, 3629 TWh generated in Low-Res and 3664 TWh generated in High-Res applications respectively. This reflects that the spatially explicit optimisation makes it possible for renewable electricity generation in remote areas to still be the most cost-effective despite their intermittent property. Fig. 5 shows further details of these patterns.

6.1. Influence of grid expansion requirement towards optimum solution

Without adequate representation of the energy system's spatial features, optimum configuration of power generation technologies is mainly driven by their unit generation costs. As a common approach in single-node modelling exercises, Non-Spatial application generates transmission and distribution costs (Fig. 5**a**) ex-post by applying a general assumption of unit grid expansion requirement to generation capacity addition from the optimisation. Note that the costs exert no influence towards the selection of power generation technologies within the optimisation process, despite resulting in higher grid infrastructure costs compared to spatially explicit approach in Low-Res and High-Res applications. Similarly, if the assumption is changed to generating lower grid infrastructure costs, the model result will remain unchanged.

On the other hand, grid expansion requirement influences optimisation result greatly in High-Res application as demonstrated by Fig. 5**c**. Power generation technologies for solar and wind power could outcompete fossil-based power generation without the application of any climate change mitigation measures (i.e. no carbon price and no emission reduction targets), and despite their low-capacity factor as they require less grid expansion. However, it is also important to note that such a selection only took place beyond certain amount of power generation (Fig. 5**d**). This indicates that the High-Res application internalises non-linear trade-off dynamic between unit generation cost-efficiency of e.g., large-scale thermal power plants vis-à-vis flexible deployment of smaller scale renewable generation. As high-resolution spatial representation of grid expansion led to increased renewable energy contribution, cumulative carbon dioxide (CO_2) emissions of the energy system is also lower (2.7 $GtCO_2$ in High-Res versus 2.84 $GtCO_2$ in Non-Spatial or by 5.2 % less for all timesteps). These behaviours are further confirmed by sensitivity analysis results (Fig. 6**b and** 6**c**) that demonstrate the sensitivity of power generation technology selection and the resulting CO_2 emissions as key model outputs towards incremental changes in key model input of unit grid expansion cost.

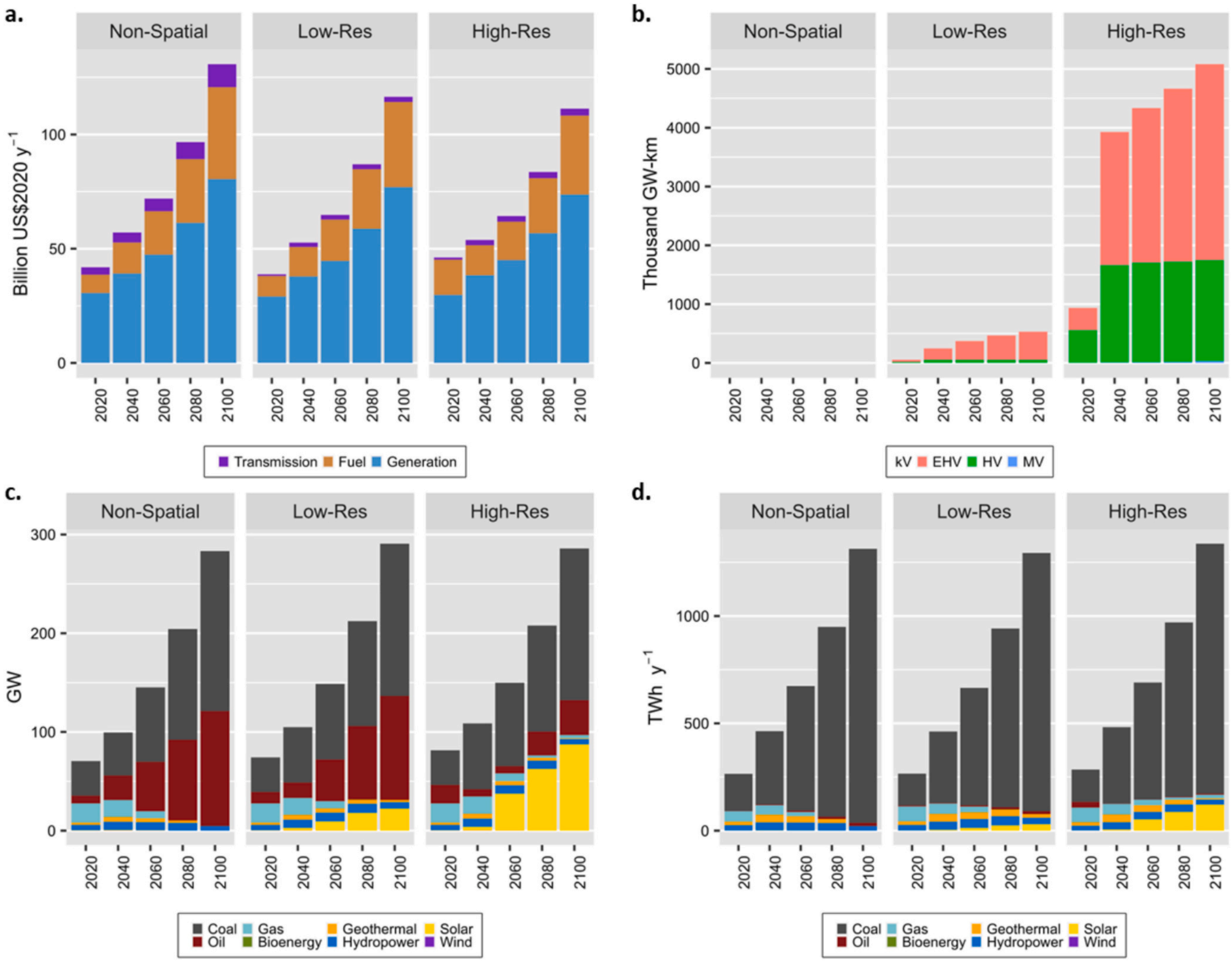

Fig. 5. Summary of execution of Non-Spatial, Low-Res and High-Res SELARU applications results for a) Total system cost in 2020 value for each timestep, b) length of newly installed transmission line, c) newly installed power generation capacity, and d) annual electricity output. Note that zero km of installed transmission line in Non-Spatial application is due to non-existence of transmission line as modelling result. The very low length of installed transmission line in Low-Res application reflects how coarse spatial resolution underestimates grid expansion requirement by not considering grid expansion within each province.

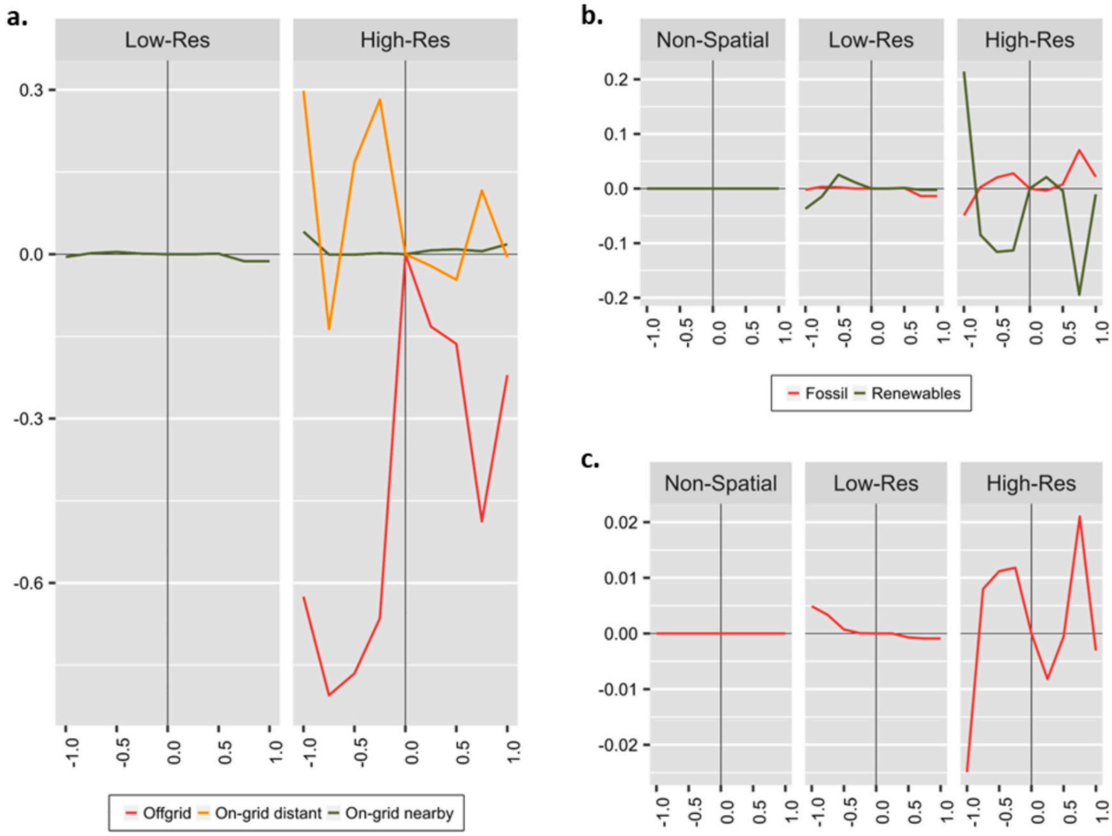

Fig. 6. Sensitivity analysis graphs showing the impact of incremental change of input unit grid expansion cost (x-axis) towards relative changes in models outputs (y-axis): a) newly installed generation capacity by connection and proximity to existing grid; b) newly installed generation capacity by type of primary energy; and c) cumulative CO_2 emissions.

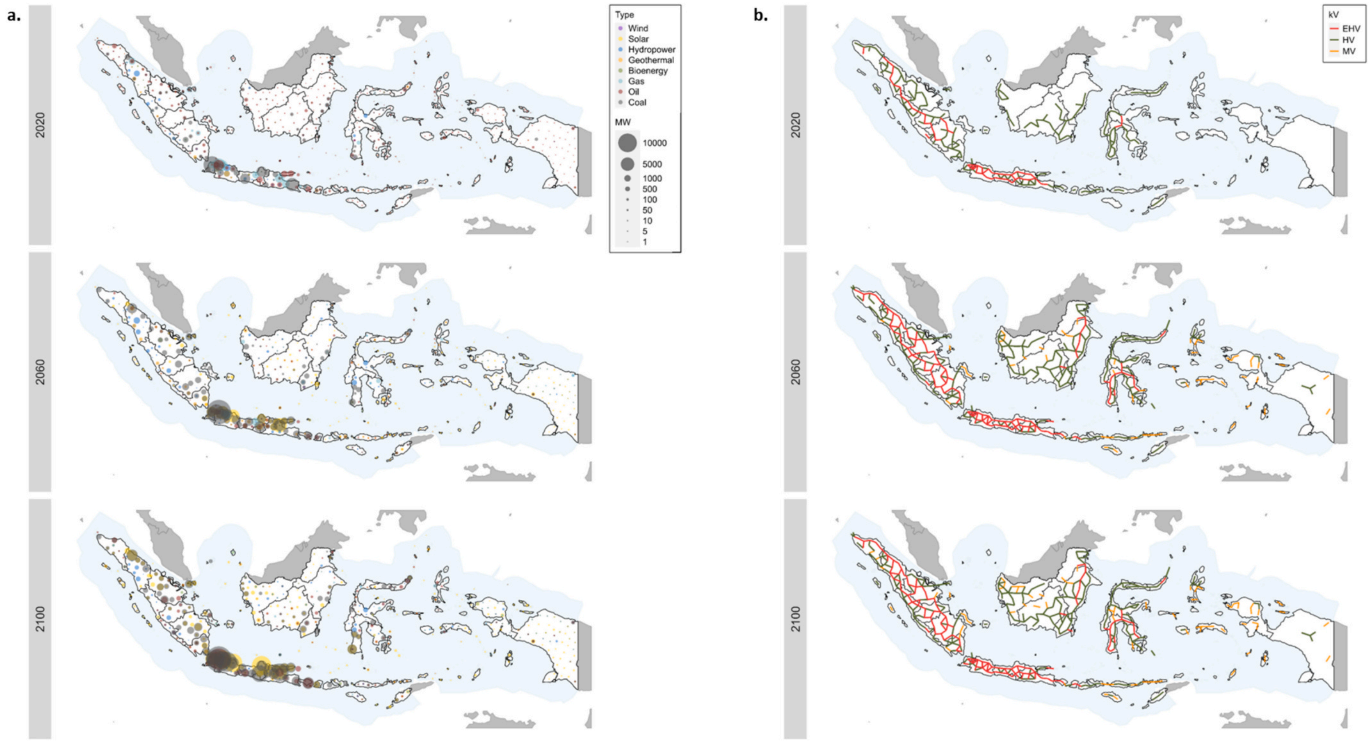

Fig. 7. Map visualisation of High-Res application result for a) installed power generation capacities and b) transmission lines for year 2020, 2060, and 2100.

6.2. Economies of scale and grid expansion

Cost-competitiveness of different power generation technologies is also influenced by regional disparity for demand, energy resource potential and accessibility. Building a low-cost generation option near existing grid infrastructure to meet demand within the proximity of the power plant will result in most cost-competitiveness. Conversely, building multiple distributed system with higher unit cost of power generation in area with sparsely distributed demand may be more cost-efficient compared to building a large-scale power plant as the latter requires grid expansion. However, it should also be possible that the most cost-efficient solution is obtained from connecting multiple regions with independent grid infrastructure (i.e. enhancing the economies of scale) to allow the use of low-cost generation option. As previously mentioned, building the ability to examine all these illustrative scenarios in generating the solution for optimum energy technology configuration is a key research gap that SELARU development aims to tackle.

The ability to address the issue of economies of scale is demonstrated by results from the High-Res application, which is the default spatial resolution for SELARU. Fig. 7 demonstrates that flexible internal combustion engines (least location-bound technology) is the main type of selected new generation capacity prior to grid expansion (i.e. the first time-step). Overtime, power generation technologies which are more location-bound (i.e. renewables or large-scale fossil-firing power plants) became selected in locations that match their requirements towards grid connectivity.

To further evaluate SELARU's ability to address grid expansion economies of scale issue, we also conducted sensitivity analysis towards the selection of new installed capacity based on their connection (on-grid versus off-grid) and proximity to existing grid (nearby versus distant). The result (Fig. 6**a**) demonstrates a trend of decreasing selection of on-grid generation capacity expansion that are far away from existing grid instead of off-grid generation capacity expansion as unit cost of grid expansion cost increases. This confirms SELARU's effective addressing of grid expansion economies of scale, as distant on-grid selection will instead be substituted by multiple off-grid options under increased unit cost of grid expansion cost if the economies of scale are not considered.

6.3. Limitations and further development opportunities

The optimisation approach in energy system modelling allowed the depiction of a ‘perfectly executed’ system where investment and operation decisions follow a singular centralized logic. While this provides normative insights that are useful for policy recommendations [5], optimization comes with hefty computational requirement especially when a big number of decision variables are involved. As shown in Table 1, the use of high-resolution spatial representation dramatically increases computing requirement due to the sheer number of decision variables. Such a barrier can be highly problematic if we consider the need for numerous model runs involved in scenario analysis, dealing with uncertainties, sensitivity analysis etc.

Hence, the use of high-resolution spatial representation may require trade-off from simplification of other elements of the investigated system. It is therefore important to ensure that the benefits of using high-resolution spatially explicit representation outweigh the consequential disadvantages from simplification elsewhere. This consideration will be dependent on the research objectives and the context of the investigated system. As previously mentioned, this study limits the scope of the energy system into the electricity sector. Moreover, the temporal resolution over the 80 years of the modelling period is 20-year timesteps in which generation, voltage transformations, and transmission flows, are solved to ensure annual balance of energy supply and demand. These simplifications follow practical adequacy principle, as they still provide methodological robustness in investigating the implication of different spatial representations in an optimisation based assessment that involves geographical grid expansion. Clearly, these simplifications can be problematic for different research objectives such as examining the impact of electrification in the transport sector. In considering the trade-offs that eventually led to the scope and spatio-temporal resolution of SELARU modelling framework in the investigation, the study benefits from guiding principles for ESOM-based analysis [5], particularly in allowing the tool to be driven by the problem and to make the analysis as simple as possible while as complex as necessary.

SELARU modelling framework shares the advantage of optimisation models in that they have flexible formulations that are capable of addressing a wide range of energy and environmental topics. Therefore, future developments of SELARU modelling framework could include modular expansion to address topics that require enhancement in areas that are currently simplified such as sector coupling and higher temporal resolution.

7. Conclusions and recommendations

Through the development of SELARU and its application in three spatial resolutions for Indonesia, we demonstrated how handling of spatial representation influences results of power sector capacity expansion optimisation. Optimisation models that use single-node (Non-Spatial), multi-node with coarse resolution (Low-Res) and multi-node with high resolution (High-Res) for spatial representation could generate different results for energy technology selection. However, incremental improvement to coarse resolution may not deliver significantly different results compared to single-node modelling approach.

Careful consideration of spatial representation is crucial when optimisation models are used to evaluate scenarios that concern technology selection such as renewable energy deployment or climate change mitigation. Moreover, the spatial context of the energy system is also an important consideration. Indonesia's energy system is characterized by vast amount and diverse location of fossil and renewable energy resources, with sparsely located demands and limited reach of existing grid infrastructure. The fact that Indonesia is an archipelago further highlights the need for optimisation-based analysis that allows the possibility of selecting multiple independent grid networks in its solving for optimum energy technology selection. The need for high-resolution spatial representation is understandably more relevant compared to relatively more homogenous systems such as those with highly connected grid infrastructure or limited geographic spread of renewable resources.

Applying high-resolution spatial representation increases computing requirement for optimisation greatly. Hence, trade-off between enhancing spatial resolution versus temporal resolution may be necessary. For issues of intermittent or uncertain rate of production of renewable energy generations, enhancing spatial resolution may be a necessary prerequisite to make high temporal resolution representation meaningful.

Finally, potential insights that can be derived from modelling results is also an area where the use of high-spatial resolution optimisation models needs to be considered carefully. For example, result on length of newly installed transmission line is a good indicator of the implementation complexity of the scenario that is being evaluated. Moreover, the spatially explicit addressing of energy demand and supply balancing also opens the opportunity to address multiple objectives, particularly under the context of sustainable development goals. For example, SELARU approach could allow the evaluation of intervention scenarios that incorporate protection of areas with high conservation values or the addressing of regional inequality.

Code availability

Datasets and GAMS codes required to reproduce the study results can be accessed at https://doi.org/10.5281/zenodo.14045250.

CRediT authorship contribution statement

Bintang Yuwono: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Lukas Kranzl:** Writing – review & editing, Investigation. **Reinhard Haas:** Writing – review & editing, Investigation. **Retno Gumilang Dewi:** Writing – review & editing, Investigation. **Ucok Welo Risma Siagian:** Writing – review & editing, Investigation. **Florian Kraxner:** Writing – review & editing, Investigation, Funding acquisition. **Ping Yowargana:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Author contributions

BY and PY conceived the idea and developed the concept for the study. BY performed input data collection and processing. BY performed model formalisation and execution. BY and PY led the writing and analysis. All authors discussed the idea and contributed to the manuscript. PY supervised the study.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2024.124837.

Data availability

All datasets that are used for the calculation are available from the cited references. Compilation of these datasets can be accessed through https://doi.org/10.5281/zenodo.14045250. Summary of input data and calculation results can be found in the Supplementary Information. Complete results of model runs can be reproduced using information in https://doi.org/10.5281/zenodo.14045250.

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