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Long-term energy system planning considering short-term operational constraints

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ABSTRACT

The intermittent nature of renewable energy sources (RESs) brings formidable challenges in the operation of power system. Long-term energy system planning models overlook the impact of renewable intermittency on system operations due to the computational burden associated with large model size and long planning horizon. Hence, strategies such as soft-linking multiple models are developed, but they do not assure the convergence and optimality of such incoherent modeling framework. In this context, this paper utilizes unit commitment (UC) extension of TIMES modeling framework to integrate operational constraints directly in a long-term power system planning model. This strategy eliminates the complexity of handling multiple models. Results indicate that incorporation of UC constraints improve the performance of conventional generators in terms of increased capacity utilization, and help to assess flexibility requirements with high RESs. Energy storage provides the balancing and flexibility needs with stringent generator constraints. Sensitivity analysis shows that improved flexibility of thermal generators enables increased renewable penetrations.

1. Introduction

Increased climatic concern calls for escalating penetration of variable renewable energy sources (RES) in the power system to decarbonize the electricity sector. Conventionally, the uncertainty of load dynamics and contingency are major challenges for reliable grid operations [1]. However, RESs are associated with variability and uncertainty due to their intermittent nature. This adds to the complexity of operating power system, increases reserve capacity requirements and inflates the cost of ancillary services [2–5]. Most long-term planning studies often disregard these challenges and consequently, the investments required to operate the electricity grid steadily are underestimated [6].

The need for long-term planning at the regional and national level, increasing concern of climate change and optimal use of energy resources are the reasons that make it essential to develop energy models. These models provide a method for scientific analyses of the impact of future technologies on the energy system and serve as a decision-making tool for policymakers. They may analyze the whole energy system or may be used for a detailed study of a particular energy sector (e.g., electricity, transportation, industry, and so forth). A comprehensive planning study of the electricity sector is referred to as power system planning which is the process of deciding to add new/upgrade existing power system elements to satisfy the foreseen future loads [7]. Power system planning studies are often classified based on the time horizon of the model: long-term and short-term. Long-term planning studies have a large time horizon (5 years to a few decades), and they deal with generation and transmission expansion planning, policy development, and investment decisions. On the contrary, short-term planning studies deal with issues such as unit commitment, economic dispatch, power flow and, day ahead market and have a time horizon of up to 1 year [7,8].

Long-term planning models give an insight into possible energy scenarios and have limited temporal details due to large size and planning horizon [9]. Due to associated computational burdens these models do not consider the short-term operational constraints and may present oversimplified results, which have adverse impacts on planning decisions. They can overestimate RES capacity in the system and underestimate flexible resources [10]. Furthermore, RES generation and electricity demand are time-dependent (seasonal and diurnal variation), and a model with low temporal resolution cannot capture these dynamics. In addition to this, the net-load variations increase with

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increasing RES penetration, and this compels conventional generators to change their outputs in proportion to the variations. This change in output causes frequent cycling of the baseload power plants (mostly coal power plants) which have thermal and mechanical operational constraints and it impairs their efficiency and operational life.

To address the above drawbacks, studies show that integrating unit commitment constraints and increasing the time resolution of a planning model can significantly alter the generation mix [6,11,12]. These impacts spurred many modelers to integrate detailed operational constraints in the planning model. An operational problem such as maintenance scheduling can be simultaneously considered in long-term planning, with reasonable computational efforts [13,14]. However, it is possible only for a medium-sized power system.

An iterative approach may be used to integrate operational constraints in a long-term planning model with high RES penetration [15]. A widespread practice is to soft-link a power system planning model with a dedicated short-term operational model [10,16,17]. The soft-linking technique can be used to study the impact of high RES penetration on power system operation. This technique improves the technical feasibility of planning portfolio as the operational constraints are considered along with long-term targets [10]. TIMES is widely used to generate a long-term energy planning model and soft-linked with other short-term operational models [18–20]. An Open Source Energy model system is compared with a soft-linked model TIMES-PLEXOS but the authors do not make any qualitative statement about the results [21]. Since the basic functioning of two soft-linked models may not coincide, it does not guarantee convergence and an optimal solution [22].

Incorporating temporal and technical details of the generating units within an energy system model can reduce the complexity and additional efforts in building and handling two separate models. These constraints restrict the flexibility of the system to practical conditions and restrain excessive cycling of conventional generators. This necessitates a rise in flexibility resource requirement to integrate RESs. Hence, direct integration of technical constraints can address the operational challenges arising due to RE intermittency and required flexibility by accounting for the physical behavior of generators in long-term planning model.

India has a high solar and wind potential and exploiting these resources is an apparent step to curb its energy deficiency along with meeting its INDC targets [23,24]. Several national-scale long-term energy system planning studies have been undertaken to formulate policies and initiatives for sustainable growth [25–28]. Various modeling techniques have been used to forecast electricity demand, find the optimum energy mix for electrical power supply, analyze the role of renewables for CO_2 emissions reduction pathways for India [29–33]. The modeling frameworks used in these studies are MARKAL, TIMES, LEAP and other macro-economic models. These studies consider spatial granularity at national level and do not account for regional behaviors (e.g. inter-regional energy trade, RES potential variation). Primary focus of these studies is to obtain a least-cost energy system, but often short-term operational aspects of power systems are not considered. They neglect the operational challenges and flexibility requirement of the power system associated with high RES penetration. The models used in these studies usually employ coarse time resolution. Even when temporal resolution is increased, they do not capture the short-term operational dynamics, such as ramping limits, minimum load levels of generators, etc. Due to this inherent limitation, they may not present a realistic future energy scenario [34]. Therefore, since the generation portfolio of India is expected to have a large share of intermittent RES; the system planning methodology also needs to be upgraded to account for the operational challenges.

In this study, TIMES energy system model generator is used to develop a long-term power system planning model with explicit representation of power generating technologies and RES potential. The impacts of short-term operational constraints in a long-term planning model are analyzed using the in-built unit commitment extension of TIMES. This feature helps to overcome the difficulties of soft-linking multiple models. UC parameters such as ramp rates, minimum load level, start-up time & cost, minimum up & downtime, and maximum non-operational time, are considered in this study. Partial load efficiency loss is also modeled and its impact is analyzed. The overall aim of the study is to capture the dynamics of RESs and operations of conventional generators in a long-term planning framework. Section 2 describes the methodology used in developing the model. Section 3 discusses the input data and model settings followed by results and discussion in section 4. Section 5 provides a conclusion to the study.

2. Methodology

A methodology is proposed to depict the impact of short-term operational constraints on the long-term system planning by direct integration of technical constraints in the planning model. This section outlines the overall model structure, selection of time resolution and the method to integrate UC constraints.

2.1. Model structure

The Integrated MARKAL-EFOM System (TIMES) is an energy model generator developed by Energy Technology System Analysis Program (ETSAP) of the International Energy Agency to conduct in-depth energy and environmental analysis [35]. It is a technology-rich, bottom-up model generator, which uses linear-programming to produce a least-cost energy system as shown in Fig. 1. It can be used for the analysis of a large energy sector or detailed study of a single energy sector [36]. TIMES has found its application in the study of long-term policy analysis of the electricity sector and to make cost-effective investments [12]. TIMES based energy system model of electricity and domestic heat supply has been used to analyze electric load management in different scenarios [37]. TIMES based model has been soft-linked to other sectoral models as discussed earlier [38]. Hence, based on applicability of the model and availability of data, we developed a power systems model in TIMES.

The data handling shells, VErsatile Data Analyst (VEDA) family of tools handle the extensive data utilized to build the model and develop scenarios. VEDA-FE (Front End) handles the input data, constraints and scenarios. The TIMES code gets input from VEDA-FE and works in GAMS environment. The text output, produced by TIMES model, is then read by VEDA-BE (Back End).

2.2. Selection of temporal resolution

Bottom-up long-term energy planning models are rich in technology details and a higher temporal resolution would increase the model overhead size. Hence, to avoid associated computational burden, stylized temporal resolution is adopted. In most MARKAL based studies, a year is divided into six timeslices while a few have attempted to consider twenty timeslices [9,39–41]. Studies using OSeMOSYS modeling platform have used 6–16 annual time slices [21,42,43]. Application of ReEDS model has utilized 17 timeslices [44,45].

The stylized representation of timeslices limit the ability of the model to capture the RES variability. TIMES is a successor of MARKAL and supports more flexible timeslice definition. Timeslices in TIMES based studies range from 4 to 48 for whole energy systems and when only power system is considered, higher timeslices are adopted [37,46,47]. Some TIMES based studies have adopted 288 timeslices [12,15]. The authors choose 3 days (24 h each) from four seasons to capture the variation in load and RESs. Further information on time resolutions of long-term models can be found in an extensive survey provided in Refs. [22,48,49].

However, the prerequisite for detailed modeling of operational constraints is to preserve the temporal chronology with a sufficiently high resolution. Hence, a short-term operational model, in which

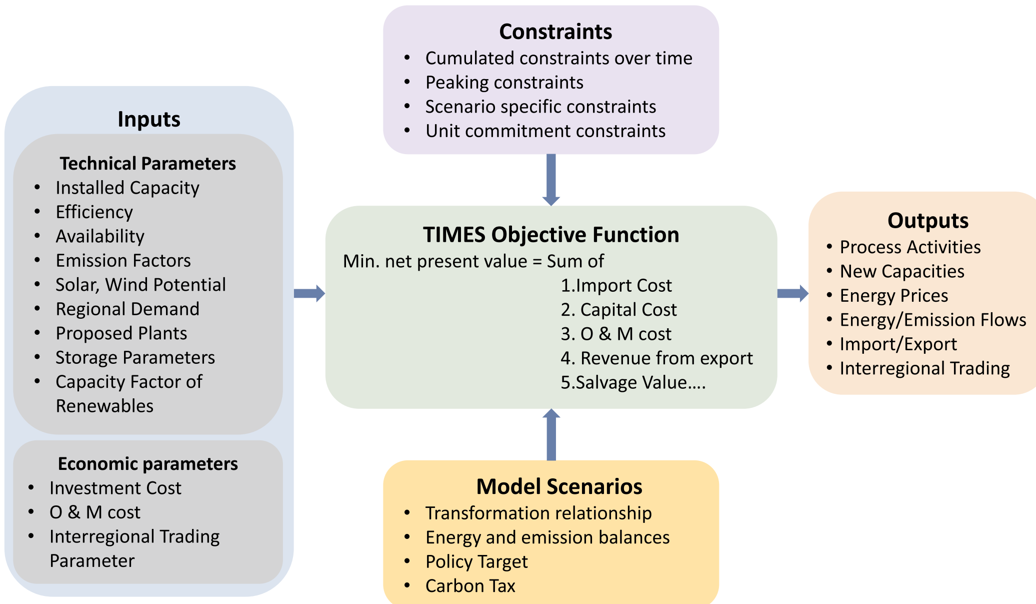


Fig. 1. Structure of TIMES model generator.

temporal chronology is kept intact by running optimization in rolling horizon for complete year with hourly or sub-hourly time resolution, is soft-linked with an energy model. For example, the Irish TIMES model consisting of 12 timeslices is soft-linked to a short-term operational model with a temporal resolution of 30 min [38]. However, soft-linking two complex model is associated with increased computational cost and feedback link issues where convergence cannot be assured [22].

In this study, a typical day for each month (12×24) is chosen, which divides the year into 288 timeslices. This makes the temporal resolution of the model large compared to other long-term planning models. Considering 24 h of a day helps in maintaining the required temporal chronology. The seasonal intermittency of RESs is also encapsulated by taking every month of the year into account.

2.3. Unit commitment extension of TIMES

Long-term models often overestimate RES integration in the system and underestimate the flexibility requirements [50]. Hence, it is important to include the short-term operational constraints in long-term generation planning models to overcome this drawback [50,51]. IEA-ETSAP developed a new extension (dispatching and unit commitment feature) in TIMES energy model generator to improve dispatch of power plants by considering unit commitment constraints. It directly implements operational characteristics of power plants into an energy system modeling framework [52]. The five general short-term constraints considered are start-up time, ramp rates, minimum load level, shut-down time, minimum online and offline time.

This extension in TIMES provides the user the flexibility to implement any, among the three, unit commitment methods namely: basic, advanced and discrete.

The basic unit commitment in TIMES uses linear programming to implement UC in the model. Apart from the above five general UC constraints, basic UC enables modeling of partial load efficiency losses and limit on the number of start-up cycles. The basic UC consists of only two distinct phases (dispatching phase and offline phase, i.e., the online state is equal to the dispatching state). The accuracy in modeling these constraints is low, and hence this feature has the least impact on the model size [52].

The advanced unit commitment feature offers all the constraints included in the basic UC along with differentiated start-up types (hot, warm and cold), start-up times and cost differentiated by start-up types. It considers the operation of the power plant in detail and consists of four distinct phases (offline, start-up, dispatching and shut-down phases). It may lead to overheads in model size and solution time [52].

Discrete unit commitment in TIMES includes all the constraints and phases available in advanced UC and additionally offers the modeling of new units. The entire new capacity can be divided into multiple virtual units. UC is performed on these virtual units. The drawback is that all individual units will have the same operational characteristic, except the online/offline times that are modeled in a discretized way. The discrete unit commitment increases the model size and solution times significantly requiring enhanced computational power [52].

The dispatching and unit commitment extension of TIMES enables the modeling of partial load efficiencies of thermal power plants. These plants usually have higher efficiencies when operated closer to full load. The partial load efficiency loss is modeled using two parameters: Maximum load above which no efficiency loss occurs and below which there is an increase in specific fuel consumption due to a loss in efficiency [52].

The UC extension of TIMES is well suited to improve the dispatch of power plants, such that it is closer to practical operations, and analyze the flexibility of the system along with impacts of high renewable penetration on system operation. Additional sets, parameters, variables, and equations are introduced in TIMES to implement this feature along with relevant changes to the model generator code by IEA-ETSAP [52].

As a case study, this dispatch and unit commitment extension of TIMES is utilized to analyze the impact of adding short-term operational constraints to a long-term power system planning model. The sensitivity analysis of the operational flexibility (minimum load level) of the thermal generators is performed, along with analyzing the partial load efficiency losses. The study is further extended for an energy system with high RE penetration by adding a carbon tax to gain further insights into the model behavior.

3. Model description

This section discusses the development of North Indian multi-regional TIMES (NIMRT) model for the power sector of Northern Region, which is the largest among the five regional grids of India. This region has a heterogeneous blend of electricity sources such as coal, gas,

Table 1
Time periods and milestone years of the model.

Start	End	Milestone Year	Period Length
2012	2012	2012	1
2013	2013	2013	1
2014	2015	2014	2
2016	2018	2017	3
2019	2022	2020	4
2023	2027	2025	5
2028	2032	2030	5
2033	2037	2035	5
2038	2042	2040	5

lignite, hydro, solar and wind. With a massive renewable capacity, the electricity mix is expected to undergo a drastic change in the future due to the implementation of environmental policies. The study of this area is also crucial because it faces regular load shedding, power quality issues, theft and T&C losses, which may affect system operations.

NIMRT model consists of 9 regions including 7 states (Jammu & Kashmir, Himachal Pradesh, Uttarakhand, Punjab, Haryana, Uttar Pradesh and, Rajasthan) and 2 Union Territories (Chandigarh and Delhi). The model is calibrated for actual plant capacity for base years (2012–2017). It spans 28 years. The planning period is divided unequally as shown in Table 1. First few periods of short duration help to calibrate existing power plant capacity whereas longer time spans in later stages are sufficient with increasing data related uncertainties. Mid-year discounting is considered so that the milestone year represents the middle year of the period length.

3.1. RES representation

Long-term planning models do not address intra-regional RES variability at a suitable spatial and temporal scale. Capturing this intra-regional variability is important to quantify optimal capacity and identify suitable investment locations. Region-specific capacity potential and annual capacity factors are the two key parameters that are associated with RES description in TIMES. Usually a single aggregated annual capacity factor of RES is used for a particular region, however, it overlooks the intra-regional variation in RES.

The NIMRT model has a detailed RES representation which captures their short-term intermittency to quantify flexible capacity requirement and for other methodological enhancement reasons. Each region is divided into 1° by 1° geographical grid cells, and these are further classified into ten equal range of solar and wind class based on the annual capacity factor available in that grid cell. The available area and class of technology in a grid cell for solar or wind installation is calculated using a GIS tool (ArcGIS 10.5). Historical wind speed data is taken from Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA V2), and processed in R to calculate the timeslice-wise capacity factor for each grid cell. Fig. 2 shows the steps involved in calculating the wind capacity factor for each grid cell. The mathematical formulation is taken from Ref. [53] and the wind turbine data is taken from Ref. [54]. Grid cell wise, hourly solar generation data is taken from PVWAtts, an online tool developed by NREL. Similar steps are followed to calculate the solar capacity factor. However, statistics and sampling are not considered for solar radiation, and the mean is calculated directly, subsequently calculating the timeslice-wise solar capacity factor for each grid cell.

3.2. Data inputs and scenarios

The NIMRT model is data intensive and focused on the power sector. Techno-economic parameters of the generating units, resource supply and trading, unit commitment parameters, and demand projection are the major inputs for the model.

3.2.1. Techno-economic parameters of power plants

A detailed techno-economic description of power plant units (coal, gas, lignite, nuclear, hydro) is specified. It includes existing, under construction and permitted (proposed), and future power plants. The details of existing power plants such as O&M cost, efficiency, annual capacity factor are taken from IESS-2047 documentation. Under construction and permitted plants are proposed with their expected year of commissioning. Future technologies are specified to meet the future demand as existing plants will retire on completion of technical life. Parameters of coal power plants vary according to the size of the unit. Units of capacity up to 210 MW are small, 210–500 MW are medium and greater than 500 are large. Average size of small hydro unit is 20 MW and that of large hydro unit is greater than 100 MW.

Various techno-economic parameters for new technologies are taken from CERC tariff reports and other international reports. Future power plants that are proposed in the model will be technologically advanced with greater efficiency. New coal power plant technologies include: sub-critical (η = 32.7%), supercritical (η = 40%), ultra-supercritical (η = 46%) and internal combustion combined cycle (η = 49%). New gas power plants, hydropower plants (large and small), new class wise solar and wind technologies, and various storage technologies are specified such as pumped hydro storage (PHS), Lithium-ION battery (Li-ION), Flow battery, Sodium Sulphur (NaS) and Lead (Pb) acid battery. The investment costs, efficiency, annual availability factor and fixed O&M costs for the technologies are specified (Table 2).

3.2.2. Resource supply and trading

The northern region of India imports coal, gas, diesel and nuclear fuel from domestic (other states of India) and foreign sources. The domestic coal import is modeled by accounting for the transportation costs involved. Bi-directional inter-regional trading process is defined in the model based on the existing high voltage transmission lines between the regions as shown in Fig. 3. However, the trading links do not simulate real transmission line operation and crudely represent physical phenomena to enable energy exchange between the regions. It is assumed that regions which are presently not connected via high voltage transmission lines will have no connection in the future as well. However, an increase of capacity of existing lines is possible.

3.2.3. Unit commitment parameters

Activation of this extension requires specification of some TIMES attributes associated with UC. For this study, we used the discrete unit commitment feature and enabled it by specifying the NCAP_SEMI attribute in addition to other UC parameters. Table 3 summarizes all the attributes used in this study and the values associated with them. The attribute NCAP_SEMI enables the model to divide the whole new plant capacity internally into many virtual units having the capacity specified by this attribute. The operational constraints of all the virtual units will be the same. The transition time of power plants to the next standby condition (hot to warm, warm to cold) is defined by maximum non-operational time. There are no operational constraints specified for biomass power plants as the generation output level depends highly on fuel availability and quality.

3.2.4. Demand projection and load curve

Electricity demand projection for the years 2016–17 to 2026–27, and 2031–32 and 2036–37 for all the states of India are available in the Electric Power Survey Report by Central Electricity Authority (CEA) India [55]. As the study horizon extends beyond 2037, the future energy demand is projected using multiple linear regression method in R, using GDP and population as exploratory variables shown in Fig. 4. The training data for the regression model is constructed using population estimates and projections from World Bank (1990–2017), GDP (2010 USD PPP) from OECD GDP long term forecast from (1990–2017), and per capita power consumption time series from World Bank (1990–2014) [56–58].

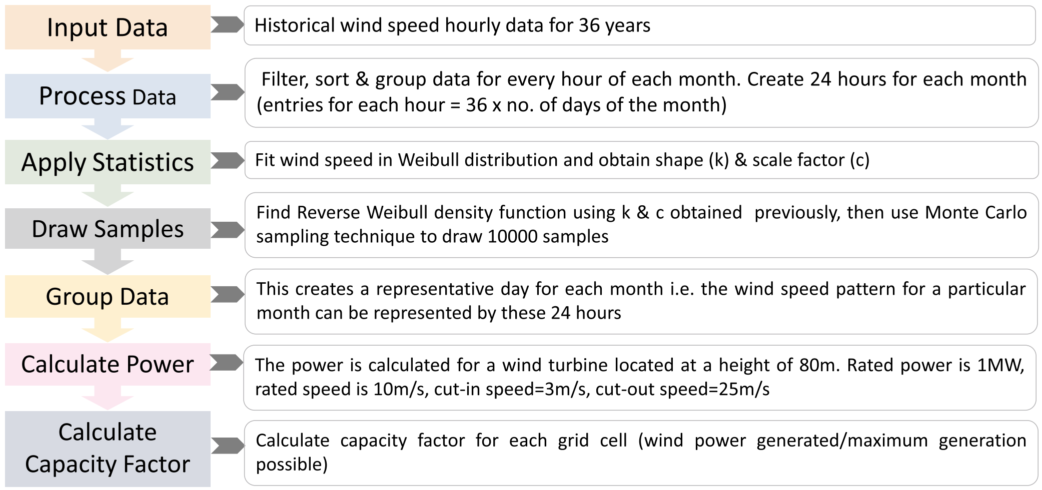


Fig. 2. Steps for calculating wind capacity factor.

Table 2
Parameter description of technologies.

Technology	No. of Units in Base years	Investment Cost for new technology (MINR/GW)			Fixed O&M Cost (MINR/GW/year)	
		Unit Type	2017	2037	2017	2037
Coal	Small- 55	Subcritical	49700	59700	1490	1790
	Medium- 56	Supercritical	54900	65900	1650	1980
	Large- 43	Ultra-Supercritical	63500	76100	1900	2280
Gas	46		37800	45500	1510	1820
Hydro	Small- 268	Small	95000	94260	3100	3100
	Large- 103	Large	135300	108070	4440	3760
Nuclear	16		81410	75210	2000	1880
Storage	PHS- 4	Li-Ion	168750	67500	3300	1300
		Flow	168750	70000	3300	1400
		NaS	255000	54000	5100	1000
		PHS	82500	82500	1650	1650
		Pb Acid	82500	25000	1650	500
Solar	NA[a]		53000	24000	700	700
Wind	NA[b]		62000	49000	1100	1100

[a] Solar capacity in 2017 in all regions is 2.35 GW.
[b] Wind capacity is in 2017 in all regions 1.31 GW.

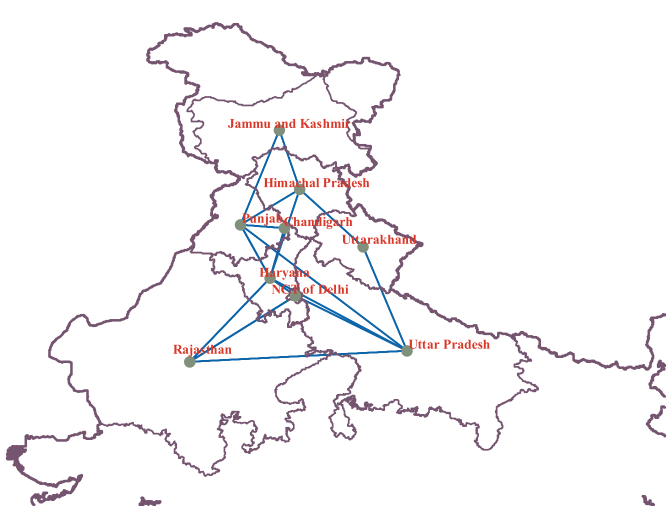


Fig. 3. Interregional trading links.

In TIMES modeling framework, the load curve is specified as fractions of demand for each timeslice. Due to unavailability of region-specific data, we consider the national load curve pattern for the years 2010 and 2011 for all the regions as shown in Fig. 5.

3.2.5. Scenarios

The model is analyzed for two scenarios: Reference and high RE. Reference scenario presents the model behavior in business as usual case. While high RE scenario refers to the model behavior with high RES penetration, which is obtained by adding a carbon tax to the system. These scenarios further consist of several cases, and each case is given a unique name to differentiate and appreciate the results. In the reference scenario, the base case is obtained by simulating the model for business as usual case without any operational constraints or environmental factor. The UC case is obtained by adding the constraints described in Table 3, to the base case. The sensitivity of the model concerning minimum load level is analyzed and the load levels considered are described in Table 4. The partial load efficiencies are modeled, and the data is shown in Table 5. The case is named UC-PLE.

In the high RE scenario, the case names have been updated with suffix ct hence base case is now base-ct, UC case is UC-ct. The overhead model size increased significantly after integrating the unit commitment constraints. A 32 GB ram and 16-core system was used for simulations. The total simulation time was above 24 h for some model cases.

3.3. Other settings

The energy flow within the model is tracked in Peta Joules (PJ), and all the power plant capacities are monitored in Gigawatt (GW). The system discount rate is set to 6% and the discounting year is 2017. The currency unit in the model is million Indian rupees (MINR). Assumed aggregate technical and commercial losses are 15% in 2012 and expected to decrease to 5% in 2040 gradually. The model calculates the emissions generated from the burning of fossil fuels to produce electricity. The carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O) emissions tracked are in kilotonne (kt).

4. Results & discussions

The results are presented for two scenarios namely, reference and high RE as mentioned previously. The reference scenario is a comparison of the base-case and UC-case with no environmental factor. The results are grouped in themes to analyze the sensitivity of the model to parameter variations. The themes considered are power generation & dispatch of technologies, technology capacity mix, RE curtailment &

Table 3
Unit commitment parameters.

Constraints	TIMES Attribute	Unit	Typical Values			
			Coal	Gas	Hydro	Nuclear
Ramp Rates	ACT_UPS	% of online capacity	40%	100%	100%	30%
Start-up Time	ACT_SDTIME	Hours	8–12	1–4	15 min	24
Min. Load level	ACT_MINLD	% of installed capacity	55%	50%	20%	50%
Min. up & downtime	ACT_TIME	Hours	8–12	6	None	24
Start-up Cost	ACT_CSTSD	Currency units per unit of started-up capacity (MINR/GW)	3000	5000	2000	11,000
Min. level of semi-continuous unit size	NCAP_SEMI	Capacity unit (GW)	0.6	0.1	0.075	0.2
Maximum non-operational time	ACT_MAXNON	Hours	12	4	15 min	24

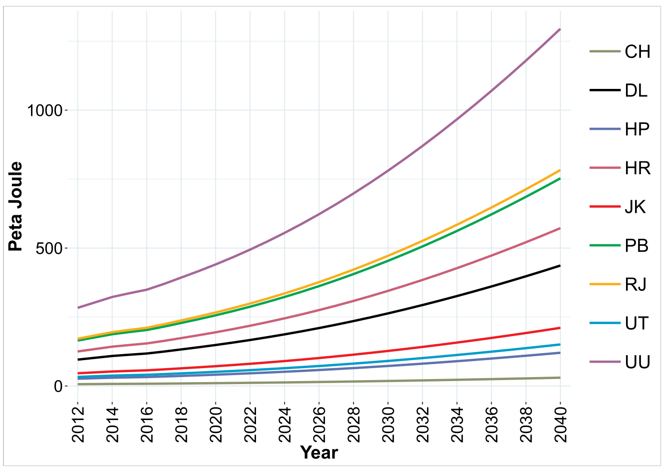


Fig. 4. North India state-wise demand projection.

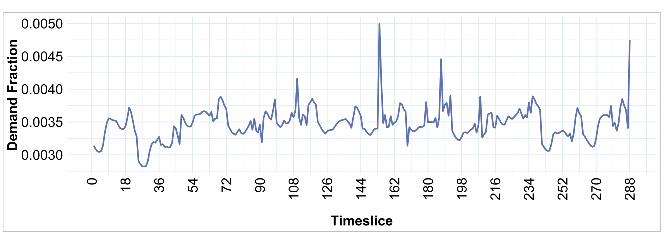


Fig. 5. Timeslice-wise demand fraction.

Table 4
Minimum load level considered in model cases.

Technology	UC-Case	UC-Case 1	UC-Case 2
Coal	55%	30%	70%
Gas	50%	20%	55%
Lignite	55%	35%	70%

Table 5
Partial load efficiency loss data.

Technology	Max. load	Increase in fuel (Hot state)
Coal & lignite	70%	1.3 times
Gas & diesel	60%	1.2 times

role of storage technologies, and interregional energy exchange. The regional variations in the above themes are also presented. Some of these themes are further subdivided into two categories: impact of minimum load level and impact of partial load efficiency loss.

The high RE scenario is a comparison of base-case and UC-case when a carbon tax is added to the system. To avoid repetition in results, only the themes that represent significant impact are shown in high RE scenario. The high RE system is analyzed for different minimum load levels as in Table 4 to assess the impact of operational flexibility of thermal power plants. In this scenario, themes considered are power generation and dispatch of technologies and technology capacity mix.

4.1. Reference scenario

The base-case is obtained by considering the supply and demand data, techno-economic parameters of power plants, new technologies, timeslice-wise availability factor of renewables and their region-wise potential along with spatial, temporal and other settings. UC-case is obtained by incorporating the unit commitment constraints in the base-case.

4.1.1. Power generation and dispatch of technologies

The temporal and spatial resolution of the model permits a detailed analysis of power generated and timeslice-wise dispatch of technologies. Fig. 6 compares the generation mix in the base-case and UC-case. In base-case, coal-based generation dominates with continuous contribution of more than 50% in the generation mix till 2035. Its contribution decreases to 46.6% in 2040 due to a steady increase in solar-based generation. Solar penetration is higher (25.2%) than wind (7.8%) in 2040 attributable to the greater cost reduction potential of solar power plants. The total RES penetration increases from 5% in 2017 to 33% in 2040.

Incorporation of operational constraints (Table 3) led to significant changes in the generation mix and dispatch of technologies when compared to the base-case. The share of coal-based generation in this case is 54% (7.4% higher than base-case) while that of solar is 24% (1.2% lower than base-case). The discharge of storage is higher in the UC-case while the wind and gas-based generations decrease in this case compared to the base-case. The cause behind change in generation mix is the thermal and mechanical constraints imposed on the power plants. In UC-case, constraints on coal power plants are stringent compared to other technologies. These constraints restrict frequent cycling (on-off and up-down ramping) of coal power plants and force them to operate at the prescribed minimum load level. Thereby, the share of coal plants increases while RES penetration decreases in UC-case. Solar and wind-based RES generation is intermittent and requires greater operational flexibility. Storage works as a flexible resource to accommodate these RESs without affecting operational stability and security. Thus, increasing the share of storage in UC-case compared to base-case.

The power dispatch of technologies in base-case and UC-case is shown in Fig. 7. Dispatch of coal and solar generators are complementary to each other in both cases. Hydro and wind generators provide the necessary balance to the system. Coal units maintain a minimum load level, and therefore solar penetration is lower in UC-case. The share of hydropower plants is higher in this case because they are flexible and hence play a vital role in the generation mix when the operational constraints are added in the model.

Fig. 8 compares the generation output of single units of different technologies for a single day (24 timeslices). The incorporation of UC

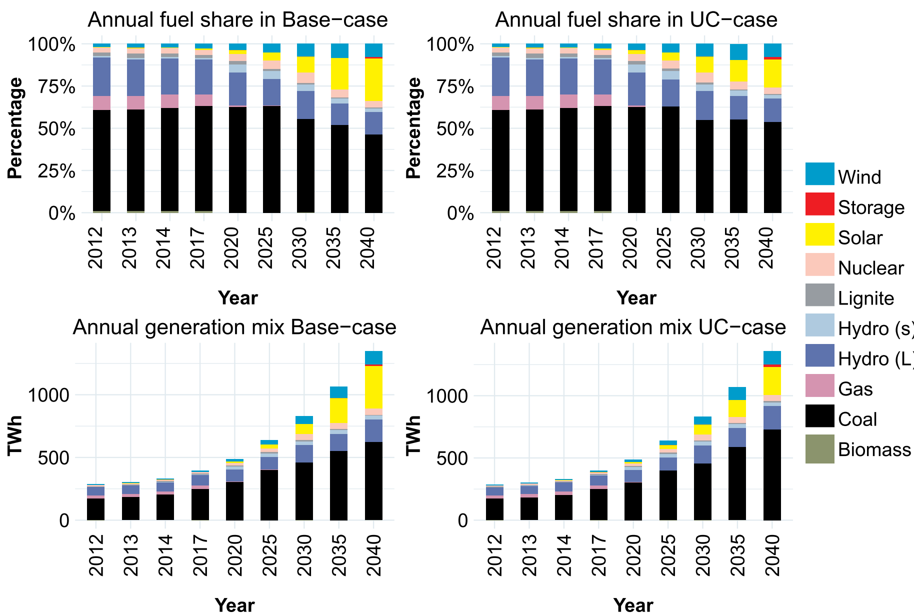


Fig. 6. Comparison of fuel penetration and annual generation mix.

constraints changes the dispatch of conventional generators. Their addition to the model prevents coal and gas units from excessive cycling and extreme ramping and forces the units to maintain a minimum load level. Hydropower plants are considered highly flexible such that their output can be fluctuated to meet the demand and maintain balance as depicted in Fig. 8, however, the minimum load level was maintained during the process. The absence of unit commitment constraints led to excessive cycling of biomass power plants.

Fig. 9 depicts the region-wise variation in technology generation. In all regions except RJ (where necessary balancing is provided by storage), the share of solar is reduced and coal is increased. This increases the electricity production of the PB, RJ and UU where coal plants are in high capacity.

4.1.1.1. Impact of minimum load level. The impact of varying minimum load level (Table 4) of generating units on the generation mix is depicted in Fig. 10. Reducing the minimum load level increases the operational flexibility of the system. Coal-based generation reduces in UC-Case 1 while it is almost constant in UC-Case 2 compared to UC-case. The lower level of minimum load level requirement (UC-Case 1) allows the generating units to produce lesser amount of electricity whereas, higher minimum load level (UC-Case 2) forces the units to operate at higher levels, thereby increasing the coal-based generation. Solar generation increases in UC-aCse 1 as the system is flexible (low minimum load-level) and reduces in UC-Case 2 due to lower flexibility (high minimum load-level) compared to UC-case. However, when compared to UC-case, the coal-based generation is slightly less in UC-Case 2 because some old generating units shut down instead of operating at a higher load level. This decrease in coal-based generation led to an increase in wind penetration. Hydro penetration increases in UC-Case 2 since they are highly flexible and their requirement is higher when system flexibility is lower, whereas, it decreases in UC-Case 1.

Fig. 11 depicts the dispatch of generators in UC-Case 1 and UC-Case 2. It is observed that coal power plants cycle more in UC-Case 1 and less in UC-Case 2 allows when compared to UC-case (Fig. 7). Varying the minimum load level changes the dispatch and cycling of the conventional generators significantly. Hence, the minimum load level is an indicator of system flexibility.

Fig. 12 compares the generation output of different technologies for a single day (24 timeslices) in the three cases. Higher minimum load-level (UC-Case 2) prevents cycling (constant output) of coal and gas

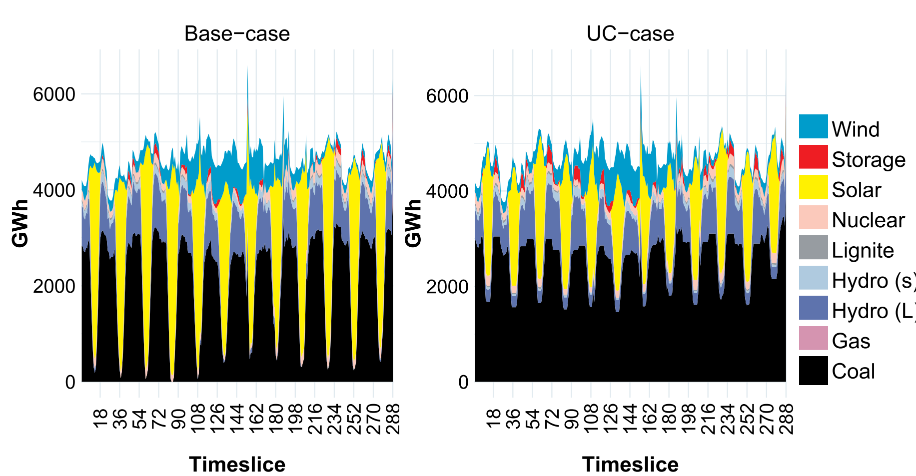


Fig. 7. Annual dispatch pattern comparison for 2040.

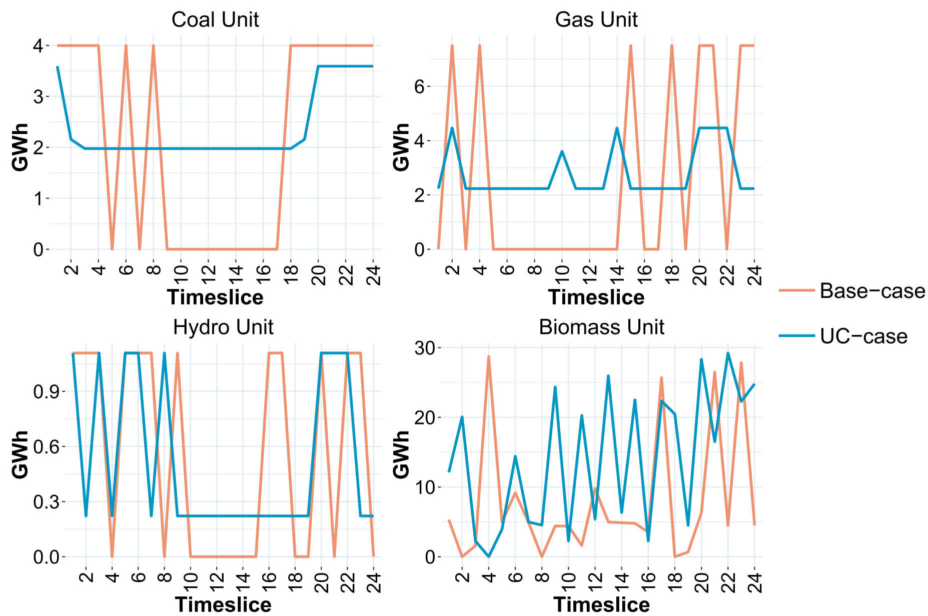


Fig. 8. Output comparison of a single unit of technologies.

plants, whereas, when it is decreased (UC-Case 1), the plants can cycle more. The behavior of hydropower plants remains the same (flexible) and generation output of solar increases in UC-Case 1 and decreases in UC-Case 2 as discussed earlier.

The variation in regional generation mix is depicted in Fig. 13. Coal-based generation is higher in UC-Case 2 in UU region while hydro-based generation is higher in UT region. UC-Case 2 is a system with less flexible power plants, hence hydro penetration is greater to increase flexibility to accommodate renewables. Solar-based generation is higher in UC-Case 1 in UU and HR regions since these areas have flexible coal power plants.

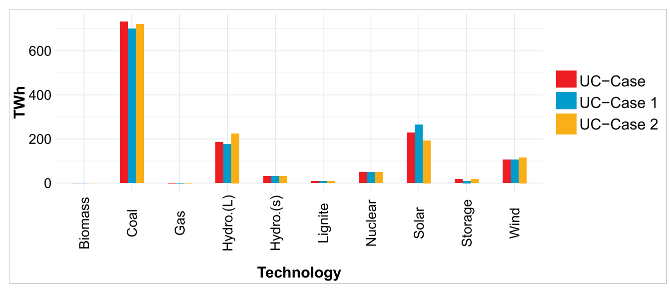


Fig. 10. Technology-wise generation output comparison for 2040.

4.1.1.2. Impact of partial load efficiency loss. The partial load efficiency losses feature of TIMES is utilized to portray a realistic operation of thermal power plants. This led to noticeable changes in the generation mix as shown in Fig. 14. This reduces coal-based generation by 16 TWh, while increases hydro generation by 17 TWh compared to UC-case. Coal units operating at lower load levels are shut down to prevent additional costs associated with loss in efficiency. In UC-PLE, penetration of hydro, wind and storage technologies increases to meet the demand, which was earlier fulfilled by coal. Solar technology is cheaper than wind in our study, however, the model prefers wind due to unavailability of appropriate solar technology in the timeslice when coal output decreases, which can be seen in Fig. 15, and hence solar generation decreases.

4.1.2. Technology capacity mix

A major outcome of a power system planning study is the new capacity and storage requirements of the energy system. Fig. 16 outlines the year wise required capacity of generating technologies along with regional distribution in 2040 for base-case and UC-case. In both cases, there is a steady increase in coal and solar capacity. Lower flexibility of coal power plants in UC-case reduces the share of RES; solar capacity reduces from 302 GW in base-case to 203 GW in 2040. Also, wind capacity in the UC-case (43 GW) is lower by 5 GW compared to the base-

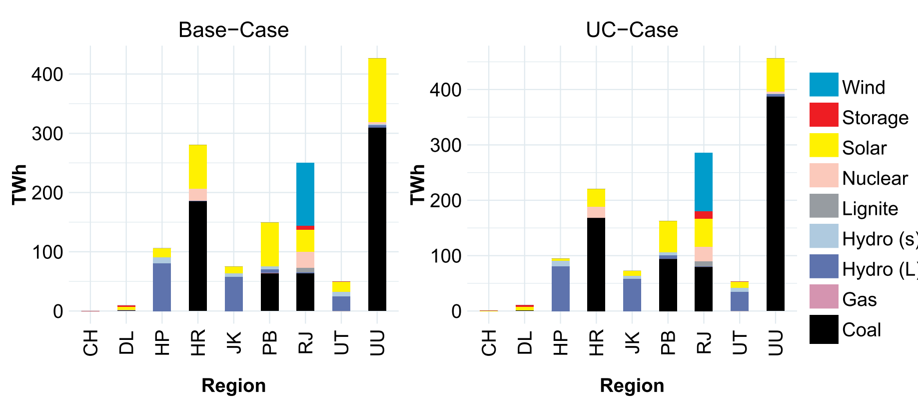


Fig. 9. Region-wise variation of technology generation.

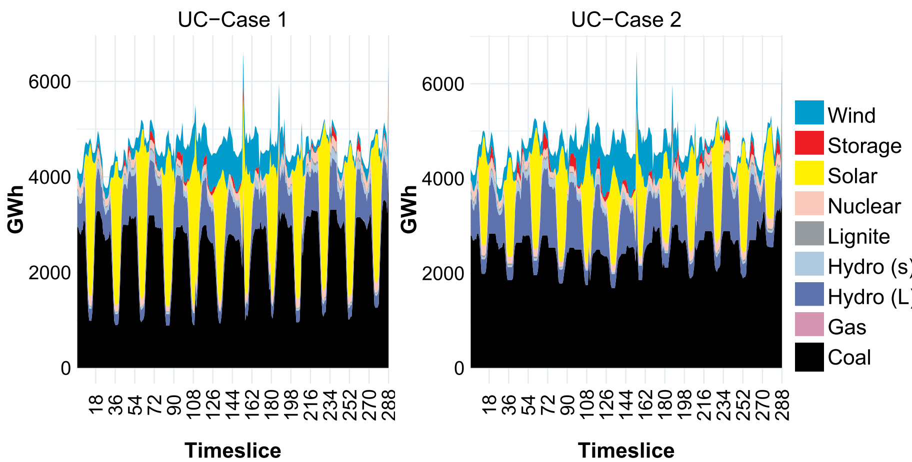


Fig. 11. Dispatch pattern comparison for 2040.

case (48 GW). To provide the necessary flexibility, capacity of battery storage (NaS) rises from 14 GW in base-case to 22 GW in UC-case and new pumped hydro storage of 1 GW capacity is added in UC-case only.

To increase system flexibility in UC-case, 17 GW hydro capacity is added in UC-case compared to only 11 GW in base-case. In the base case, 1 GW of new supercritical coal power plant and 99 GW of ultra-supercritical coal power plant is added in the system in 2040 making the total capacity 143 GW. While in UC-case, 106 GW of ultra-super-critical coal power plant is added in the system, increasing the capacity of new coal plants by 6 GW and making a total capacity of 149 GW. Reduction in solar capacity is significant compared to increment in coal power plants due to better CUF of coal power plants in UC-case. Change in capacity mix reflects the operational needs of the future power system with high renewable generation.

The regional capacity distribution differs significantly in the two cases. Solar capacity reduces in all regions except for RJ because the gas capacity in this region reduces in the UC-case. Storage capacity is higher in RJ and DL in the UC-case. The overall system capacity is lower by almost 100 GW in the UC-case as compared to base-case, but still, the supply-demand balance is maintained as the existing capacities operate at higher load levels and are adequate to balance the system.

The performance of renewable power plants is usually denominated by a metric called capacity utilization factor (CUF). It is defined as the ratio of actual power produced to the maximum generation possible. The annual CUF is outlined in Table 6. The CUF of most technologies increases with the application of unit commitment constraints that restrict the repetitive cycling of conventional generating units and force them to operate at a defined minimum load level. Incorporation of operational constraints led to better utilization of technologies and avoid excessive capacity addition.

4.1.2.1. Impact of minimum load level. Changing the minimum load level of technologies affects technology capacity. Fig. 17a depicts the capacity comparison for UC-case, UC-Case 1 and UC-Case 2. Coal capacity is higher in UC-Case 1 (153 GW) and is lower in UC-Case 2 (141 GW) as compared to UC-Case (149 GW). When coal power plant units operate at lower load levels (UC-Case 1), they produce less electricity and hence require greater generating capacity. Whereas, when the minimum load level is increased (UC-Case 2) the generating units are forced to generate more electricity thereby reducing the capacity requirement.

Solar penetration is higher when system flexibility is higher (UC-

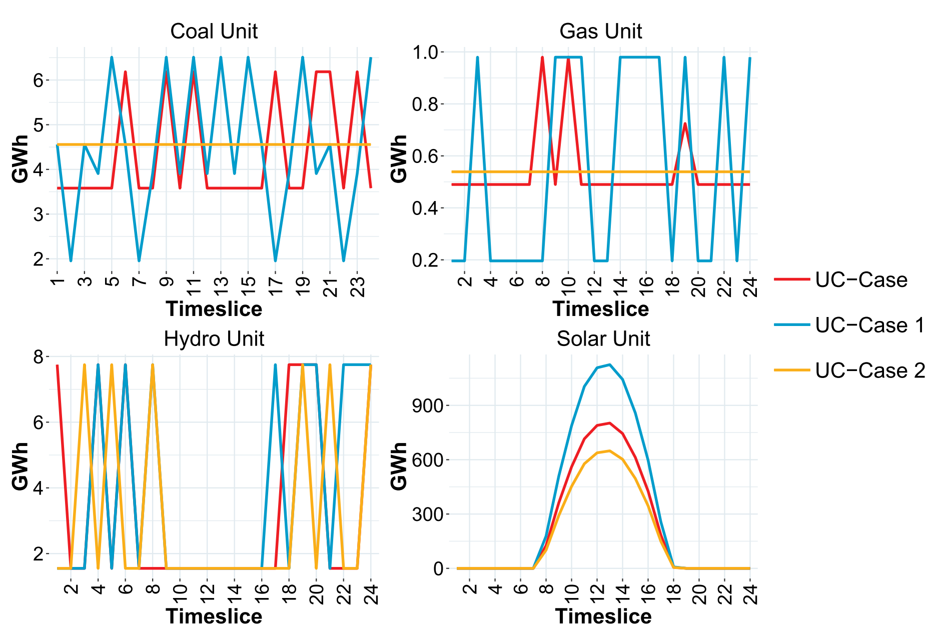


Fig. 12. Output comparison of technologies.

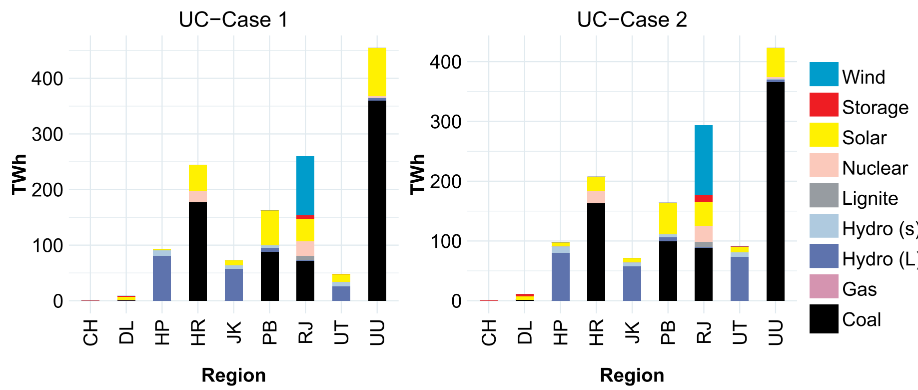


Fig. 13. Region-wise generation in 2040.

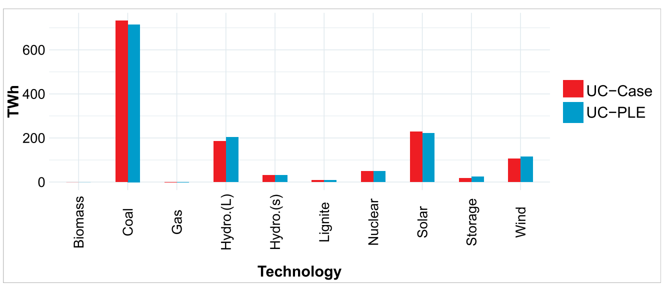


Fig. 14. Technology-wise generation output comparison for 2040.

Case 1). Hydro capacity increases when constraints on conventional generators are made stringent (UC-Case 2) due to their flexible nature. The capacity of storage decreases in both cases when compared to UC-case. In UC-Case 1, the conventional generators are flexible, and hence the role of storage is limited while, in UC-Case 2, storage capacity decreases due to a reduction in solar capacity. Wind capacity increases in both cases to maintain supply-demand balance.

4.1.2.2. Impact of partial load efficiency loss. Addition of partial load efficiency led to changes in the capacity mix as shown in Fig. 17b. The capacity of coal decreases by 3 GW since the generating units operate at a higher load level to avoid partial load efficiency losses. Large hydro and wind capacity increases by 5 GW and 8 GW respectively as their contribution to generation mix increases. Solar capacity decreases by 11 GW due to operation of thermal plants at higher load levels. The capacity of storage decreases by 2 GW considering decrement in solar penetration.

4.1.3. RE curtailment and role of storage

Renewable curtailment is the main issue that reduces the economic feasibility of RE power plants. Fig. 18 shows the solar and wind curtailment in base-case and UC-case. RE curtailment is higher in UC-case compared to base-case despite higher storage capacity in the former case. Conventional generators are not allowed to adjust their load level as per the RES generation due to restrictions on frequent cycling and extreme ramping in the UC-case. The model curtails extra electricity generated by the RES that remains after full charging of the storage technologies. It is also observed that wind curtailment reduces abruptly between 2035 and 2040. The increment of demand between 2035 and 2040 is high whereas the increase in capacity of conventional generators is not at the same proportion. Therefore wind curtailment reduces to fulfil the demand.

Region wise solar curtailment is shown in Fig. 19. In the base-case, there is high solar curtailment in RJ while, it is absent in the UC-case due to high storage capacity in RJ. Curtailment in HR, PB and UU is

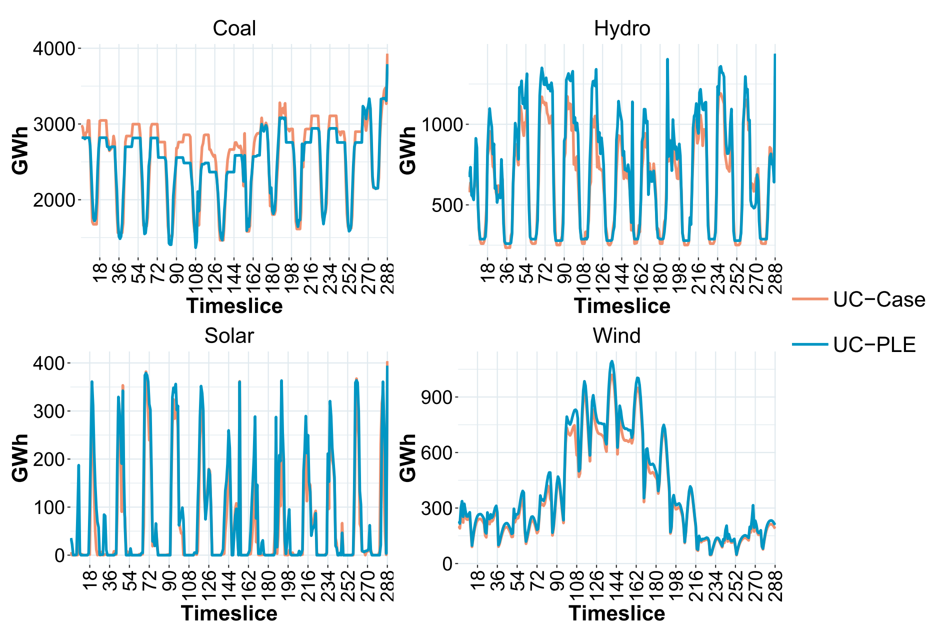


Fig. 15. Output comparison of technologies.

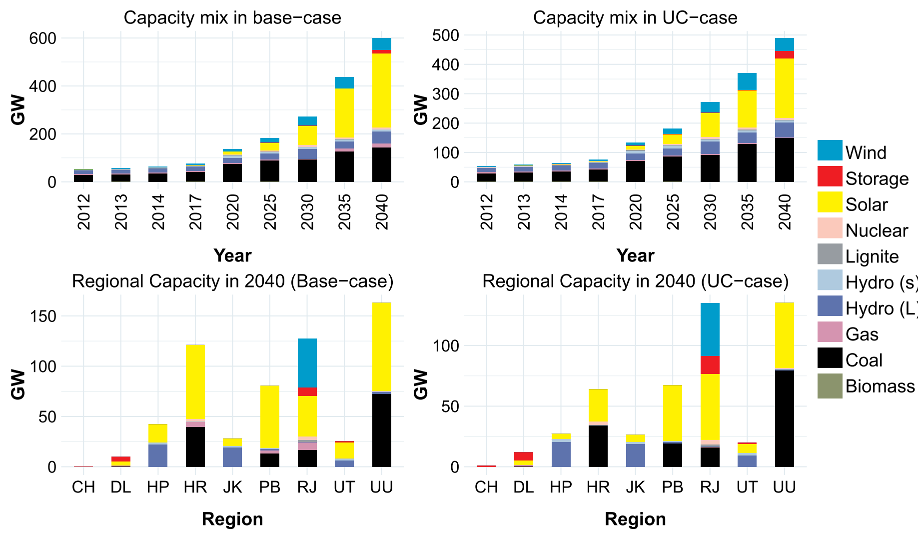
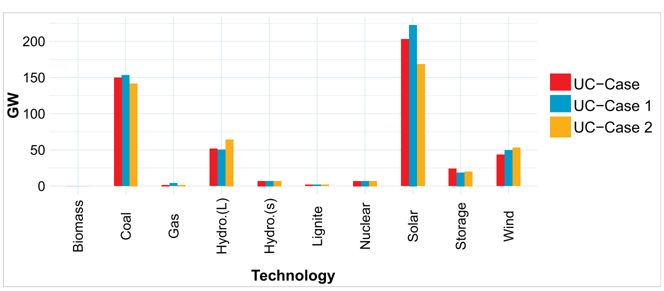


Fig. 16. Annual and regional capacity mix in 2040 in base-case and UC-case.

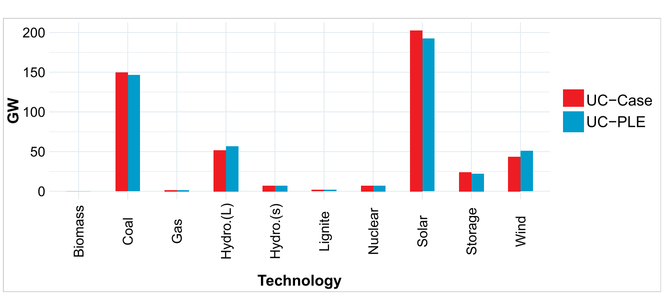
Table 6
Capacity utilization factor comparison for 2040 (in %).

Technology	Base-Case	UC-Case
Biomass	0	0
Coal	44.38	49.65
Gas	0.23	0.6
Hydro (L)	34.72	36.21
Hydro (s)	44.88	44.88
Lignite	42.42	47.39
Nuclear	70.08	70.08
Solar	11.07	11.21
Storage	6.1	7.5
Wind	21.82	24.24



(a) Impact of minimum load level

Fig. 17. Technology-wise capacity comparison for 2040.



(b) Impact of Partial Load Efficiency Loss

Fig. 17. (*continued*)

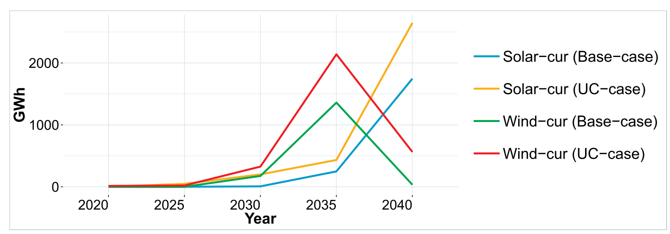


Fig. 18. Annual solar and wind curtailment comparison.

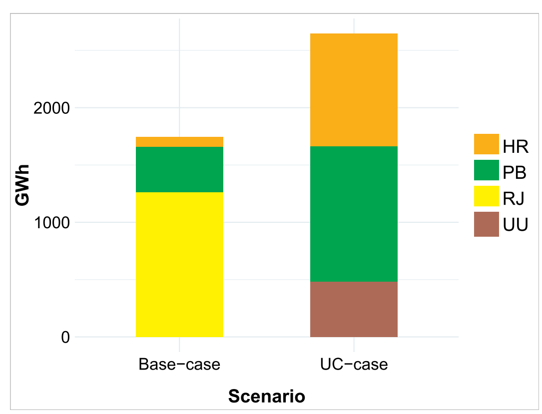


Fig. 19. Region-wise solar curtailment in 2040.

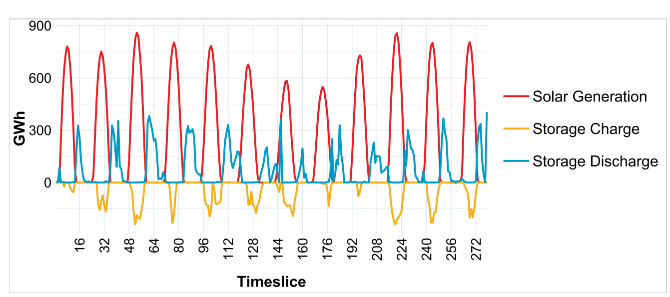
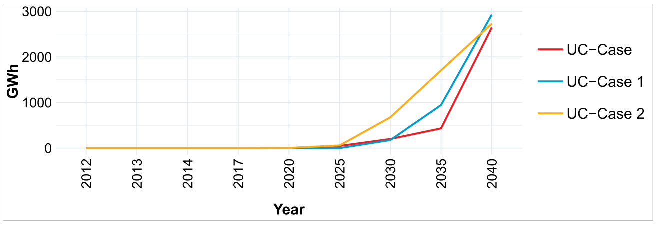
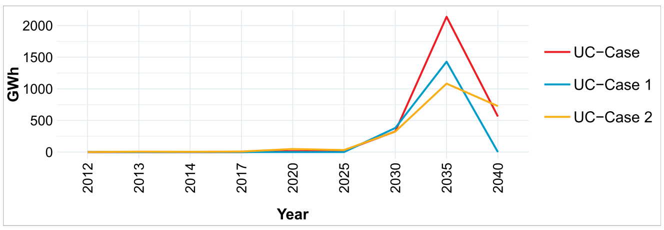


Fig. 20. Storage charging/discharging process in 2040.



(a) Solar curtailment

Fig. 21. Solar and wind curtailment comparison.



(b) Wind curtailment

Fig. 21. (*continued*)

higher in the UC-case due to the absence of storage technologies and high coal capacities in these regions.

Fig. 20 shows the charging and discharging process of the storage technologies in UC-case in comparison with solar generation. Charge and discharge cycle of storage technologies is highly concurrent with solar generation in the model. Charging process takes place in the same timeslices as that of solar generation while discharging takes place in its absence. This behavior of storage facilitates the smooth integration of solar and helps to maintain supply-demand balance.

4.1.3.1. Impact of minimum load level. The minimum load level affects the operating levels of conventional generators. Varying this parameter changes the RE penetration in the system which subsequently affects the RE curtailment as well. Solar curtailment is higher in UC-Case 1 and UC-Case 2 compared to UC-case as seen in Fig. 21 due to lower storage capacity in both cases. However, curtailment in UC-Case 1 is lower than UC-Case 2, since the former represents a system with high flexibility. On the other side, wind curtailment is lower when system flexibility is lower. It can be inferred that wind plays a role in maintaining the demand-supply balance in the system.

4.1.4. Interregional energy exchange

This section discusses the import and export of electricity between the regions. Net import-export of electricity in all regions is shown in Fig. 22. There is no change in net electricity imported in regions having a less generating capacity such as CH and DL. Exports of HP and HR decrease due to decreased solar-based generation in the absence of required storage flexibility (Fig. 9). With a high capacity of coal in UU and hydro in UT, these regions produce more electricity in UC-case

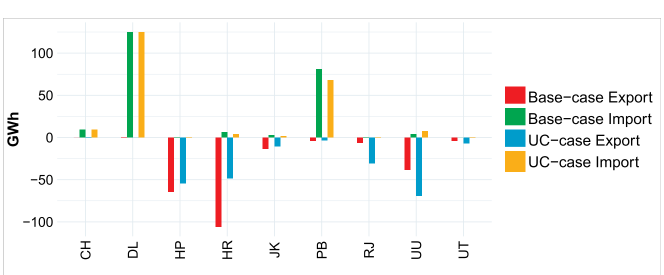


Fig. 22. Net trade of electricity in each region for 2040.

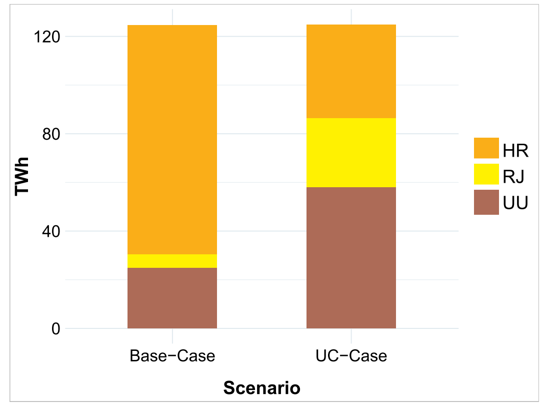


Fig. 23. Import of DL from other regions in 2040.

while production in RJ is high since it is a coal-rich region and has storage support to integrate high solar penetration. DL has direct interregional trade link only with HR, UU, RJ as shown in Fig. 3. With high solar-based generation, HR exports mostly to DL in base-case. However, in UC-case, DL imports major from RJ and UU as depicted in Fig. 23. With UC constraints, due to a reduction in solar penetration, import of DL shifts from solar-based generation to coal-based generation.

4.2. High RE scenario

Policymakers are always observant about the effects of climate change and its impact on long-term planning decisions [59]. Hence, we introduce a carbon tax in the model to study the evolution of the energy system under climate change constraints in the same framework. Introducing a carbon tax ensures high RE penetration in the system to produce emission-free electricity. This helps to assess the model behavior with UC constraints and large share of RESs. Fig. 24 shows the carbon tax in MINR/kilotonne [60]. The base-ct case consists of all the data considered in base-case along with a carbon tax. UC-ct is obtained by adding a carbon tax to UC-case.

4.2.1. Power generation and dispatch of technologies

Fig. 25 shows the fuel mix and generation mix in base-ct and UC-ct. The share of renewables is significant in both cases. The share of coal in the generation mix is 30% in the base-ct case while it is 26% in UC-ct in 2040. The coal-based generation is lower in UC-ct because the operational constraints force the coal units to produce some fixed amount of electricity and carbon emissions. Some coal units are shut down to obtain a least-cost energy system and avoid carbon tax. Gas based generation increases by 1.12 TWh in UC-ct since the carbon emissions of these plants are lower compared to coal power plants. Hydro based generation remains constant in both cases.

Wind penetration is higher in UC-ct to compensate for the decrease in coal generation as shown in Fig. 26. It can be seen that the timeslices during which coal generation decreases, wind generation increases, thereby maintaining the supply-demand balance in the system. Solar generation is 337.5 TWh in UC-ct and 427.7 TWh in base-ct and activity

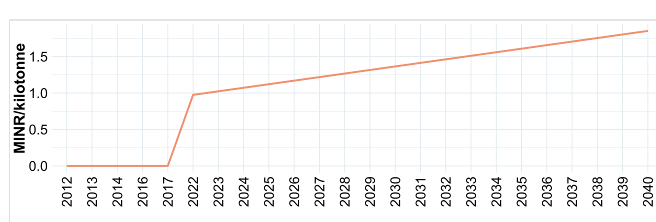


Fig. 24. Carbon tax variation over the years.

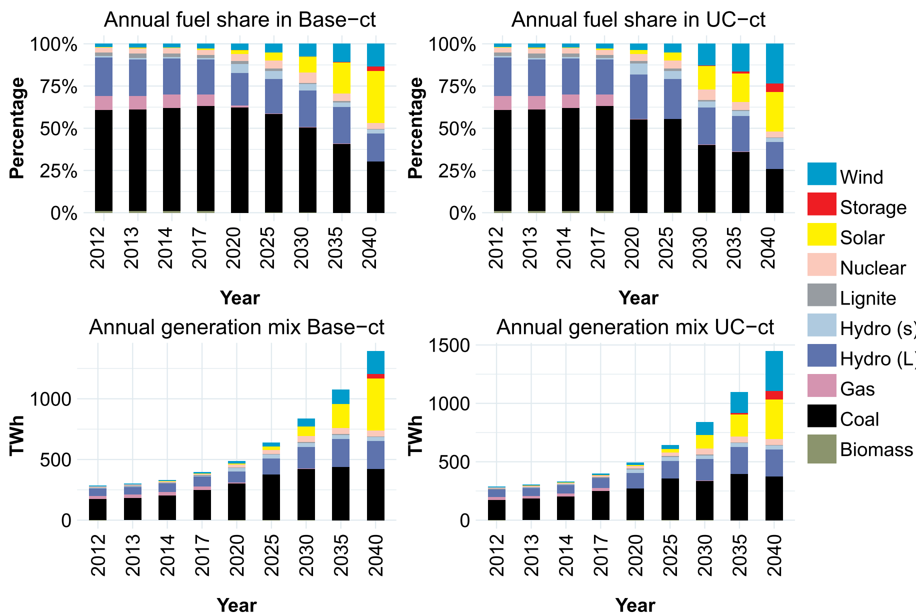


Fig. 25. Annual generation mix in base-ct and UC-ct cases.

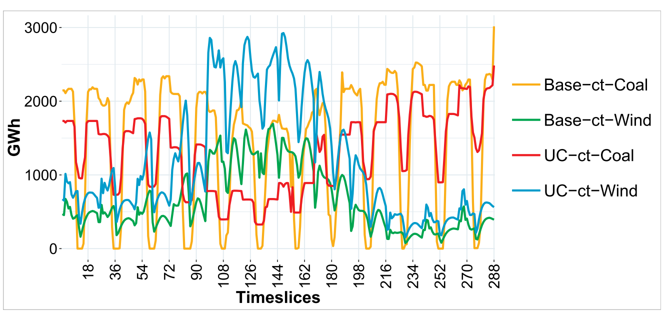


Fig. 26. Coal and wind generation pattern in 2040.

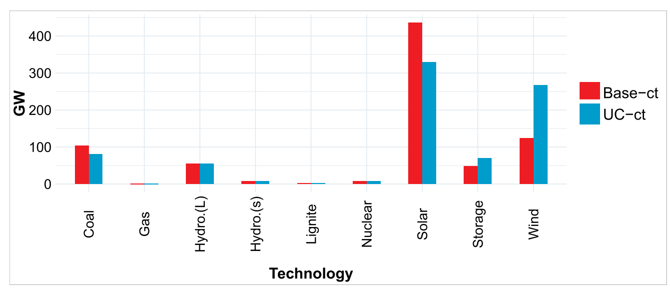


Fig. 27. Comparison of Technology capacity in 2040.

Table 7
Technology wise generation comparison in 2040.

Technology	UC-ct	UC-ct-Case 1	UC-ct-Case 2
Coal	374.64	431.94	365.24
Gas	1.16	0.76	1.25
Hydro (L)	231.81	231.81	231.81
Hydro (s)	31.67	31.67	31.67
Lignite	6.8	6.92	7.05
Nuclear	49.10	49.10	49.10
Solar	337.50	351.90	335.70
Storage	72.61	56.29	77.21
Wind	340.58	260.01	354.22

of storage is 72.6 TWh in UC-ct and 40 TWh in base-ct. When solar availability is high, the additional electricity generated by solar is used to charge the storage technologies and is not reflected directly in the generation mix. Hence activity of storage is higher in UC-ct.

4.2.1.1. Impact of minimum load level. The impact of changing the minimum load levels (Table 4) on the generation mix in a high renewable scenario is presented in Table 7. Decreasing the minimum load level (UC-ct-Case 1) increases the contribution of coal in the generation mix. Coal units can now operate at lower load levels and the system flexibility is greater which enables higher renewable penetration. Increasing the load level (UC-ct-Case 2) decreases the share of coal power plants because now the units are forced to produce more electricity thereby increasing the carbon cost and hence, some more coal units are shut down as compared to UC-ct. Solar penetration increases in the generation mix when the minimum load level is decreased due to increased flexibility. The activity of wind and storage decreases in this case. When the minimum load level is high, wind penetration increases to compensate for the decrease in coal-based generation and activity of storage increases to provide flexibility to the system.

4.2.2. Technology capacity mix

The addition of carbon tax changed the capacity significantly. Fig. 27 shows the comparison of capacity of each technology in 2040. Coal capacity reduces in UC-ct as compared to base-ct to avoid carbon tax, and the capacity utilization factor of existing capacity is higher. Solar capacity decreases, whereas, storage and wind capacity increases. Wind and storage capacity is higher in UC-ct to compensate for the

Table 8
Capacity of technology in 2040 (GW).

Technology	UC-ct	UC-ct-Case 1	UC-ct-Case 2
Coal	81	98	78
Gas	1	1	1
Hydro (L)	54	54	54
Hydro (s)	7	7	7
Lignite	2	2	2
Nuclear	7	7	7
Solar	329	324	328
Storage	70	57	74
Wind	267	184	272

decrease in coal (also evident in generation mix).

4.2.2.1. Impact of minimum load level. Capacity mix when the minimum load level is changed is shown in Table 8. It follows a similar trend as the generation mix discussed previously. Imposing a carbon tax on less flexible thermal plants reduces their capacity and brings in more storage capacity to support the integration of renewables. However, share of solar in the generation mix is lower in UC-ct-Case 2 compared to other UC-ct-Case 1, but the capacity of solar is higher in UC-ct-Case 2. To produce emission-free electricity in a system with stringent operational constraint, solar charges the storage and hence its generation is not directly reflected in the generation mix in Uc-ct-Case 2.

5. Conclusion

This study analyzes the impact of short-term operational constraints on long-term system planning by incorporating technical constraints of power plants in the same planning modeling framework. Previous studies adopted soft-linking approach of two different modeling frameworks to couple short-term operations and long-term planning. In this study, the unit commitment constraints are incorporated directly in TIMES model of long-term planning using its in-built UC extension. This methodology not only ensures the convergence of the model to obtain a feasible solution but also reduces the effort involved in building and handling separate models for short-term and long-term power system studies.

The power system model of the Northern regional grid of the Indian power sector is developed in TIMES with a detailed spatial and temporal representation of solar and wind energy. A detailed description of the existing generating units & availability of future technologies, their techno-economic parameters, load profile and demand projections are the inputs to the model.

Results show that long-term models underestimate the CUF of thermal generating units but in practice, they have high CUF. Incorporation of unit-commitment constraints in planning model prevents excessive cycling and extreme ramping of the baseload power plants and changes their dispatch profile. Hence, it leads to better utilization of existing capacities and reduces the requirement of new generation capacity (evident from CUF of technologies). Therefore, overestimation of generation capacity and associated investment can be avoided by incorporating the short-term operational constraints in long-term system planning.

With stringent UC constraints on the conventional generators, they operate at fixed load levels and cannot frequently cycle to accommodate the varying RESs. Hence, the system cannot accept all the renewable energy and this leads to higher wind and solar curtailment in UC-case compared to base-case. Role of storage increases in UC-case to provide the necessary supply and demand balance. This implies that adding UC constraints prevents the model from overestimating RES penetration and enables better quantification of the flexible resources required.

Further, sensitivity analysis on operational constraints by changing the minimum load level of conventional generators show significant changes in the generation and capacity mix of technologies. When conventional generators are flexible, they allow higher RES penetration and require less storage. Conversely, when the flexibility is low, RES penetration is low, and the storage requirement is elevated. The inflexible coal plants decrease the solar penetration in the system resulting in higher curtailment. If the flexibility requirement is not adequately quantified at the planning stage it could result in high RES curtailment during actual system operations, which in turn would cause financial loss for RES stakeholders.

The methodology used in this study can be utilized to assess flexibility requirements in the system under various scenarios. High RE penetration scenario is developed by adding a carbon tax to the system. With the carbon tax constraint, the model prefers to shut down some coal units to obtain a least-cost energy system and increases the share of RES.

However, with unit commitment constraints, the capacity share of coal units decreases further with increased CUF of operating units. Technical constraints force the units to operate at a defined load level and for a minimum time. While the activity of flexible gas power plants and storage increases. It is clear from the results that a high RES based power system would require additional flexibility resources and obligates the conventional generators to be highly flexible for prolonged use.

UC extension of TIMES also permits to portray realistic operating characteristics of the thermal units by incorporating attribute for partial load efficiency. Addition of partial load efficiency loss reduces the coal-based generation, as the unit operating at lower load levels are shut down to avoid further fuel costs associated with a loss in efficiency. Hydro and wind-based generation increases to maintain demand-supply balance. Solar curtailment decreases and the activity of storage increases.

The empirical results reported herein should be considered in light of some limitations. The electricity demand is not modeled in detail due to the unavailability of data. Electricity demand components such as electric transport (electric vehicles) may undergo profound transformations in the long run, and the results of planning study may vary. The accuracy of the model outcome is subject to the quality of data used during model development. Limitations in the accessibility of Indian power sector data for the model may have been directly reflected in the results.

Nevertheless, it can be concluded that the integration of short-term operational constraints in the long-term modeling framework can affect the generation and capacity mix significantly. Hence, consideration of these constraints is highly essential to portray a realistic picture of future energy scenario. Further, incorporation of these constraints in the same planning framework ensures convergence and optimality, and reduces the computational efforts involved.

Acknowledgement

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