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How does the interplay between resource availability, intersectoral competition and reliability affect a low-carbon power generation mix in Brazil for 2050?

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ABSTRACT

Increasing penetration of solar and wind energy can reduce the reliability of power generation systems. This can be mitigated by e.g.; low-carbon dispatchable hydropower and baseload biomass power plants. However, long-term supply potential for those sources is often uncertain, and biomass can also be used for biofuel production. The purpose of this study is to assess the interplay between uncertain supply potential of biomass and hydropower, intersectoral competition and reliability on a low carbon power system for 2050, with Brazil as case study, using a soft-link between an energy model and a power system model. Hydropower acts as a balancing agent for solar and wind energy, even under lower hydropower supply potential. When less biomass is available, low carbon transportation is met more with electric cars instead of ethanol cars, leading to an increase in electric load for charging their batteries. The charging strategy determines whether peak load increases substantially; after commuting, or lowers; in off-peak hours. This shows the importance of using a soft-link between the high temporal resolution power system model to assess the reliability, and a least cost-optimization model to assess the interplay between resource availability and intersectoral competition of low-carbon power systems.

1. Introduction

To limit global warming to less than 2 °C, many countries have pledged to reduce carbon dioxide emissions in accordance with the Paris Agreement [1]. A key challenge is to provide electricity with a low carbon intensity, in a reliable and cost-effective way. The largest share of the new electricity generation capacity with a low carbon intensity is expected to come from solar and wind energy [2]. However, these sources are all variable renewable energy (VRE) sources that can cause problems related to the reliability of the power grid because of intermittency. Biomass [3] is seen as low-carbon alternatives that can provide dispatchable power generation that can balance power systems with high shares of VRE. Furthermore, hydropower can be used to match electricity supply and demand due to its fast ramp rate [4]. However, there are concerns related to the supply potential for hydropower and biomass. Hydropower relies on rainfall and in the future, climate change is expected to have a negative impact on the amount of rainfall [5]. For biomass, it is recognized that there is large uncertainty in the future supply potential due to land use change emissions [6]. Furthermore, impacts on biodiversity and soil quality can also result in lower biomass supply potential [7].

A reliable and affordable power system, which is capable of matching supply and demand, is seen as very important for modern economies as stable supply of electricity is one of the back-bones of their development [8]. In power systems with high shares of VRE, it becomes more difficult to match the supply and demand for electricity, which can lead to more blackouts [9]. In low-carbon power systems with high shares of VRE it is therefore required to balance between the intermittent supply of VRE and the demand. Biomass, hydropower, or storage options like e.g. batteries in electric vehicles (EVs) [10] are seen as promising cost-effective options to provide more balance to the grid in low-carbon power systems. However, the interplay between VRE, hydropower and biomass in low-carbon power systems is rarely studied [11].

Biomass can be used in various sectors of the energy and

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electricity generation system, either directly as a solid fuel or converted to liquid fuel. In the case when there is limited supply of biomass to fulfil demand for energy in a low carbon energy system, the question rises in what sector biomass should be utilized best. This depends on the competition (on costs, greenhouse gas emissions (GHGs) and conversion efficiency) among low carbon energy alternatives per sector [12]. The demand for low-carbon transportation can for instance, be met with different energy carriers. Biofuels and low-carbon electricity are seen as two feasible energy carriers for low carbon transportation [13]. Lower supply potential for biomass can result in a decreasing production of liquid biofuels. On the long term, lower supply of biofuels can increase the demand for alternative low-carbon transportation, e.g., electric cars. EVs can play an important role in balancing demand and supply of electricity [14]. Contrary, the growth in the demand for electricity due to a growing EV fleet can result in higher peak load for electricity when commuters start to recharge their batteries after commuting, as shown by Boβmann and Staffell for Germany and the UK [15].

There is a clear interplay between 1) uncertainty in availability of hydropower and biomass and 2) intersectoral competition between sources of low-carbon energy, which affects the reliability of low-carbon power systems. While the influence of single elements on the reliability of a power system is well studied, no specific scientific literature is found focusing on the interplay of the combined effect on the electricity mix, and its costs. Therefore, assessing low-carbon power systems requires an integrated approach. Least-cost optimization models have the ability to assess intersectoral competition and resource variability, but they are not specifically designed to operate with high temporal resolution that is required to assess the reliability of a power system [16]. Dedicated power system models are specifically designed to assess power systems at a high-temporal resolution [17]. A soft-link between both models enables the assessment of the abovementioned interplay.

The aim of this research is to assess how the interplay between uncertain supply of biomass and hydropower, intersectoral competition for low-carbon energy sources, and reliability affects a mix of low carbon electricity sources, and its costs for 2050. Brazil is chosen as a case study because it has high supply potential for hydropower and biomass [18]. The least-cost optimization model TIMBRA (The Integrated Market allocation Energy flow optimization System-BRAzil) is used to calculate the lowest cost energy system. The PowerPlan model is linked to TIMBRA and uses installed capacity to analyze the match between hourly supply and demand for electricity, and quantifies the reliability as it sums up the number of hours when there is a loss of load. Eight scenarios are created to assess the reliability and the additional costs of the power system influenced by lower supply of biomass and hydropower, and the impact of charging patterns of EVs.

The study intends not to show transition pathways towards low-carbon power systems that are influenced by near term political and socio-economic changes. Instead, the focus of this study is on the long-term, to understand the performance of low-carbon power systems in the future.

2. Methods

The methodological framework consists of two main models: TIMBRA and PowerPlan. The models are described in Section 2.1 and the research steps are detailed in Section 2.3. Fig. 1 gives the main points of each model and shows how they are linked to provide the various results. In step 1 of Fig. 1, the TIMBRA model applies least-cost linear optimization to calculate the lowest cost solution for meeting the energy demand in 2050. Both models include operational and capital costs of power plants as well as the costs for primary energy sources. A carbon budget is applied (in TIMBRA) to assess GHG emissions. In step 2, PowerPlan analyzes the match between hourly electricity supply and demand, using the electricity capacity mix of TIMBRA as input. PowerPlan quantifies the loss-of-load by the number of hours of power failure per year, and compares it with a reliability target. When the target is not met, additional capacity is added until the target is fulfilled in step 3. The same reliability target is set for research step 4. The impact of electricity demand for EVs (an output from the TIMBRA model) on the reliability of the power system is assessed in PowerPlan (research step 4).

2.1. Models

The linear optimization model TIMBRA is used to calculate the lowest-cost energy system under a set of user-defined restrictions for the period 2010–2050 [19]. The model is adjusted specifically to the Brazilian energy system. This model is used to assess the dynamic interaction between primary energy sources, a list of predefined conversion technologies and end-use demand in the main sectors (industry, transportation, residential & commercial, agriculture and non-energy). Hence, TIMBRA is used to calculate the capacity mix of the Brazilian power system for 2050, which is the main input for the PowerPlan model. The cost assessment is based on capital costs (CAPEX) and operational costs (OPEX) of energy conversion technologies, and on fuel costs [20]. TIMBRA distinguishes three regions.

The GHG emissions are included in TIMBRA by applying a carbon budget. The carbon budget is the volume of GHG emissions that Brazil may emit (for the period: 2010–2050) to limit global warming to two-degree Celsius [36]. The supply of solar, wind and hydropower are allocated to the regions. Therefore location specific characteristics of power plants are included (see Nogueira de Oliveira [21] for more information). The regions interconnecting transmission lines represent the exchange capacity for electricity between these regions (see Appendix E). In TIMBRA time slices are used to represent electricity supply and demand, and represent a user-defined aggregation of a certain time period.

In TIMBRA the model can consider a wide range of different transport modes supplied with different fuels e.g.: fossil fuels, biofuels, electricity and hydrogen [37]. Transformations in the car fleet is endogenous to TIMBRA, and depend on investment costs, resource competition, fuel consumption per kilometer and GHG emissions. Additional demand for electricity from EVs is used as input for analyzing the charging patterns in PowerPlan (research step 4).

PowerPlan is a bottom-up simulation model, which is used to assess the dispatched electricity production and reliability of electricity systems [22]. The model simulates the hourly amount of generated electricity of user-defined power plants and matches this production with the hourly demand for electricity based on the merit-order approach (see Section 2.3.2 for further detail). The model properties of TIMBRA and PowerPlan are further described in Appendix A. The power plants included in this study are listed in Table B2 (Appendix B).

2.1.1. Flexibility measures

In TIMBRA, hydropower and concentrated solar power (CSP) are modelled as static power plants with fixed load factors per time slice. Furthermore, TIMBRA is not designed to deal with demand side management (DSM). PowerPlan is a simulation model that is specifically designed to assess the match between supply and demand of electricity systems. Therefore, the operational performance of dispatch power plants like hydropower and CSP can be modelled with PowerPlan as such. Further, there is the option to

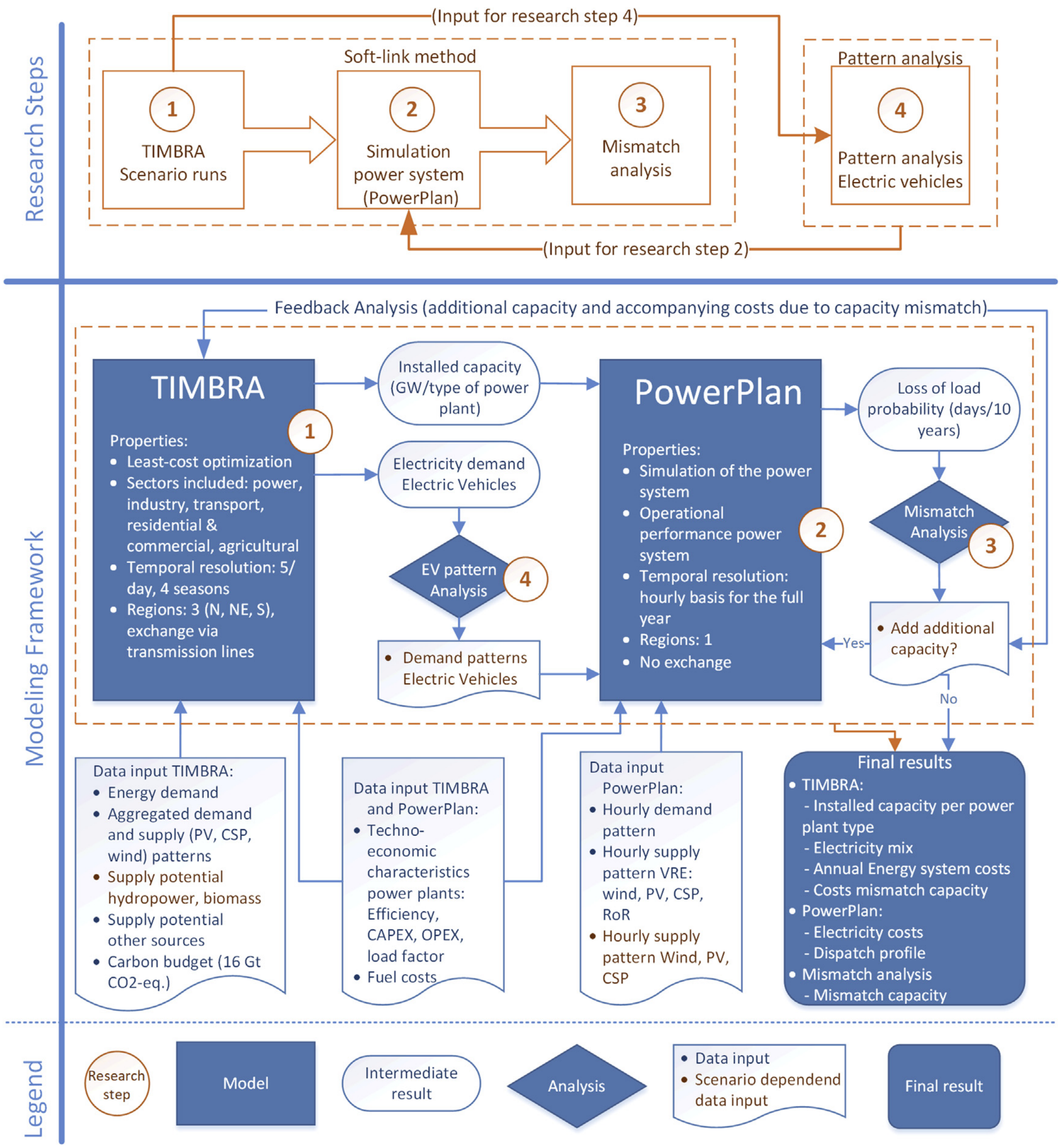

Fig. 1. Schematic overview of the methodological framework.

assess the impact of DSM on the reliability of the power system [10]. PowerPlan can also assess the impact of storage technologies (e.g. pumped hydro storage [PHS], compressed air energy storage [CAES], and batteries) on the reliability of power system. However, due to the large capacity of reservoir based hydropower in Brazil and it's fast ramp rate (the ramp rate is the ability of power plants to increase or decrease the electricity production over a certain unit of time), there is no direct need for additional storage technologies next to reservoir hydropower (as shown in Section 3).

2.2. Scenarios

Eight different scenarios are used in this study: one base scenario, three supply constraint scenarios and four demand constraint scenarios (Table 1). The base scenario is based on the SSP1 scenario from Lap et al. [12]. All scenarios aim to fulfill the total energy demand with the lowest possible costs, while being constrained to emit 16 Gt CO_2-equivalents over the period 2010–2050. The difference in the final electricity demand can fluctuate between the scenarios due to switches in fuel (e.g. biofuels) and transport mode. All economic values are harmonized to US$$_{2010}$.

The supply constraint scenarios are run with low hydropower and biomass supplies. The low hydropower (LH) scenario is adopted in this study because there are several concerns that due to climate change the amount of precipitation in the northern part of Brazil is expected to decrease [23]. As Brazil is highly dependent on hydropower and the majority of the unexploited hydropower capacity is situated in the north of Brazil [24], a decrease in precipitation is expected to decrease the reliability of the Brazilian power system [25]. The low biomass scenarios (LB and LHB) are run with a lower supply potential than the base scenario, because there is still large variability on how much sustainable biomass is expected to be available for energy [26]. The availability of biomass in this study relates not to the annual supply potential due to fluctuating climatic conditions, but rather to the long-term supply potential, as a

Table 1
Overview of the scenarios used in this study.

Scenario								
Parameters[a]	Base	Supply constraint Scenarios			Electric Vehicle demand scenarios			
Acronym[b]	B	LH	LB	LHB	EV-HB	EV-SB	EV-HL	EV-SL
Costs[a]	Annual costs of supply of energy[e] for the entire energy system (2050) + Electricity price ($/MWh)							
GHG emissions	Carbon budget: 16 Gt CO_2-eq. emissions in the period 2010–2050							
Hydropower supply potential (TWh)	765	715	765	715	765	765	715	715
Biomass supply potential (EJ)[c,d]	15.9	15.9	12.7	12.7	15.9	15.9	12.7	12.7
Electric vehicles charging pattern[f]	–				Home charge	Smart charge	Home charge	Smart charge
Models	TIMBRA + Powerplan				Powerplan			

[a] The costs of the entire energy system is the unit to be optimized (the mathematical optimization) and is therefore the only parameter that is flexible. The other parameters are modelled as a constraint (either in TIMBRA and/or PowerPlan).
[b] B: base; LH: low hydro; LB: low biomass; LHB: low hydro and biomass; EV-HB: Electric Vehicles, Home charging, Base scenario; charging pattern for EVs focusing on charging at home using the same premises as the base scenario; EV-SB: Electric Vehicles, Smart charging, Base scenario; charging pattern for EVs focusing at off-peak times, using the same premises as the base scenario. EV-HL: Electric Vehicles, Home charging, LHB scenario; charging pattern for EVs focusing on charging at home using the same premises as the LHB scenario; EV-SL: Electric Vehicles, Smart charging, LHB scenario; charging pattern for EVs focusing at off-peak times, using the same premises as the LHB scenario.
[c] Data related to the availability of biomass is based on scientific and governmental literature and is presented in Appendix B.
[d] In TWh, the supply potential for biomass ranges between 3500 and 4400 TWh. This emphasizes the high supply potential of biomass in relation to hydropower.
[e] The costs of energy supply encompass the costs for primary energy carriers and the costs of converting the primary energy into energy carriers for final energy consumption in the selected sectors. Therefore, costs for the conversion of final energy to useful energy (for instance, the conversion of gasoline to kinetic energy in a car) are excluded. When costs are mentioned with relation to the results of this study, this means the annual costs of energy supply.
[f] In all scenarios the electricity demand patterns are analyzed as described in Section 2.3.2.

result of agricultural land that becomes available because of agricultural yield increases. The availability of land is assumed to be the most important factor that causes differences in supply potential of bioenergy [27].

The EV demand scenarios are used to explore the impact of electricity demand for EVs on the power system, by analyzing the charging patterns of EVs. The charging pattern of EVs is important, as it can ensure a strong peak in electricity demand when commuters begin to recharge their batteries after commuting, as shown by Boβmann and Staffell for Germany and the UK [15]. By using demand-side management consumers can be encouraged to charge their vehicles during off-peak times by financial incentives and/or by stimulating charging at work (day-time). Ideally, they can be charged in off-peak times or when intermittent electricity production by VRE is high, lowering the burden on the grid during peak hours [28].

2.2. Research steps

An overview of the research steps is shown in Fig. 1.

2.2.1. Step 1: Scenario runs least-cost optimization model

The base scenario, and three supply-constraint scenarios are modelled in TIMBRA to analyze the low carbon electricity mix for 2050. Outcomes from step 1 are:

- Electricity generation mix in 2050 (TWh per power plant type)
- Capacity expansion of the power system (installed capacity per power plant type)
- Additional electricity demand for EVs (endogenous in TIMBRA)
- Costs of energy supply (billion US$/year)

The base scenario is run in TIMBRA with variation for nine parameters. The sensitivity of these parameters is shown in relation to the power generation mix and the annual costs of energy supply (see Appendix G). The impact of the uncertainty of the future capital expenditures of VRE power plants is discussed in Appendix G.

2.2.2. Step 2: Simulation runs power system model

The installed capacity per type of power plant (from TIMBRA, research step 1) are simulated in PowerPlan to analyze the dispatched power production and loss-of-load of the power system on an hourly basis. The techno-economic input data of the power plants is equal for both models, based on reported data [12] (see Appendix B).

Hourly production of VRE sources is calculated using supply patterns for solar and wind energy. These patterns are created following a simulation tool described in Staffel & Pfenninger [29] (see Appendix D for detailed information). The supply pattern for run-of-river (RoR) hydropower in PowerPlan is based on the weekly inflow pattern of the current operating plants in the North. For future RoR power plants, the ratio between the inflow of water and the capacity is assumed to be the same as for the existing RoR power plants (see Appendix C for more details). The supply pattern for bagasse is based on the monthly sugarcane harvest reports (see Appendix D). The bagasse supply pattern is included separately because the electricity production fluctuates over time (dependent on the sugarcane harvesting). While the sugarcane harvest period falls within the dry period, bagasse is seen as complementary to hydropower in terms of electricity production [30]. This can result in a more reliable low carbon power system [31].

The VRE supply patterns are normalized for 8760 h per year. The data of the supply patterns is normalized as normalized data can be linked to different capacities. The normalization shows the hourly production for a 1 MW power plant. The pattern exists of 8760 data points representing the load factor of that specific hour (Equation (1)). The sum of all data points is therefore the total power output given a certain capacity for a total year. The generic conversion from the pattern to generated power is calculated using Equation (1). The sum of the electricity production of all hours is the annual electricity production per power plant. A detailed explanation of the VRE patterns is found in Appendix D.

$$P_{h,u} = C_u \times VRE_h \tag{1}$$

P = Power generated at hour h for VRE power plant u in GWh, C = Installed capacity of VRE power plant u in MW, VRE = variable generation pattern normalized at hour *h*.

Besides the hourly supply pattern, an hourly electricity demand pattern is created. The demand pattern for 2050 is converted from the 2015 demand pattern to the 2050 pattern, by multiplying the maximum hourly demand [32] to the growth in electricity demand (taken from TIMBRA, step 1). The demand at each hour in 2050 is calculated using Equation (2), and the sum of each hour is the total electricity demand for 2050.

$$D_h = MD_{2050}\ x\ P_h \tag{2}$$

D = Demand at hour *h* in GWh, MD = Maximum hourly demand (GWh) for 2050, P = variable electricity demand pattern normalized between 0 and 1 at hour *h*.

The LOLP is calculated by subtracting the generated electricity of all power plants from the demand at each specific hour. If the returned value is negative, this means there is a loss of load. The model sums up all loss of load hours to give the yearly hours of loss of load.

The results from step 2 are:

- Hourly dispatch profiles of the power system for the modelled scenario
- LOL (number of days/year)
- Electricity generation costs ($/MWh)

The electricity generation costs are calculated by PowerPlan and are based on levelized costs of electricity generation, using the capacity for each power plant type (TIMBRA output) as input. The methods used to calculate the levelized costs are found in IEA 2010 [33] and encompass fuel, capital, and operational costs. Reservoir hydropower data as used in PowerPlan is based on the mean monthly inflow of water to the current hydropower reservoirs and the maximum storage capacity of the reservoirs for the four main regions (see Appendix C and D for more details).

2.2.3. Step 3: Mismatch analysis

The aggregated patterns of both supply and demand are used as input for PowerPlan to identify the difference between aggregated and hourly patterns. The model run is made in PowerPlan to analyze the match between electricity supply and demand in Brazil for 2050. The installed capacity of power plants derived from TIMBRA is used as input, however, here the hourly demand and supply patterns (see step 2, Section 2.3.2) are used as input.

The result of run 2 in PowerPlan is aligned to an international reliability target. In this study the reliability should be a LOLP of 3 days per 10 years for all scenarios. The LOLP in Europe ranges between 1 and 3.3 [34], while in developing countries the LOLP may be much higher [35]. Therefore, a LOLP of 3 is considered to be realistic for Brazil. When the LOLP is > 3, the power system is perceived as not being sufficiently reliable, and additional capacity is needed to fulfil demand for electricity in a reliable way. Next, additional capacity is added in PowerPlan (step 3; Fig. 1), until the LOLP target is reached.

For the additional capacity it is assumed that this will be fulfilled with flexible operating natural gas fired combined cycle (NGCC) power plants. The additional costs of the additional required capacity to overcome the mismatch between electricity demand and supply per scenarios are assessed by linking this additional capacity back to TIMBRA. The total annual costs of energy supply, as assessed in this study, therefore includes the additional capacity of the NGCC power plants required to fulfill the target for a reliable power grid. The methodological steps of the soft-link approach are shown in Fig. 1. The mismatch analysis is also carried out for step 4 (see below), and the results of all the scenarios are shown in Section 3.4.

2.2.3. Step 4: The impact of charging patterns of electric vehicles

The demand for electricity consumed by EVs is simplified in TIMBRA considering the temporal resolution. The electricity demand of EVs is an output of TIMBRA (Step 1), where it is assumed that this demand is the same for every hour of the year (flat line EV demand). However, charging of EVs depends on user preferences [36], and access to charging facilities [37]. By using batteries of EVs the flexibility of the power system can be influenced, i.e., DSM.

Four hourly charging patterns are created to assess the impact of EV electricity demand on the reliability of the power system (based on Boβmann & Staffell [15] and Gnann et al. [38]). The patterns are used as input for PowerPlan: a conventional charging pattern where commuters charge their cars right after the trip (at work and at home), and a smart charging pattern where charging is done during off-peak time to lower the burden on the grid. The patterns are created by taking the total demand for EVs from the base and the LHB scenario (step 1).

The EV charging patterns are added to the electricity demand pattern from step 2 (minus the flat line EV demand). The conventional charging pattern is adjusted from the flat line EV demand from TIMBRA by increasing the demand when commuters arrive at their work (between 9 a.m. and 2 p.m., Monday to Friday), or at home (between 5pm and 11pm for the whole week), while decreasing it during other hours of the week. The sum of the patterns should be the same as this represents the total demand for charging EVs. The demand pattern for smart charging of EVs has increased demand during off-peak times. The patterns are visualized in Appendix B. The installed capacity of the power plant types of the base scenario (from TIMBRA; step 1) is used as input for PowerPlan. Eventually, the mismatch analysis is carried out for both scenarios (step 3) showing the mismatch capacity and the influence on the costs of the energy system.

3. Results

The results of the research steps are described below.

3.1. Installed capacity and electricity mix

The results show that around 1500 TWh of electricity will be produced in 2050, compared to 630 TWh in 2010. At first glance, the electricity production for 2050 from the base, and the supply constraint scenarios appear very similar. Hydropower delivers 47–52% of all electricity and is the largest producing source, followed by wind (21–22%, Fig. 2B). The total installed capacity ranges from 346 to 380 GW (Fig. 2A). The main difference is the installed capacity of concentrated solar power, which is 55 GW in the base scenario and 77 GW in the LHB scenario. Although the supply potential for biomass is high (see Table 1), the use of biomass for electricity production is limited. This is because biomass is mainly consumed in both the transport and industrial sector. In those sectors, biomass is seen as the major low-cost renewable alternative for fossil fuels [12].

In comparison to the base scenario, the LB scenario shows a decrease in electricity production from biomass power plants (−27%). A mix of power plants (mainly CSP but also nuclear and coal with carbon capture and storage [CCS]) substitutes this decrease in biomass. The lower supply of biomass mostly affects the delivery of baseload power, which explains why nuclear and coal come into play because they also deliver baseload power. However, CSP with 12 h of thermal storage capacity, is also capable of delivering power with a high load factor (47%).

The LH scenario shows a decrease, mainly in hydropower from RoR (−20%) and slightly in reservoir-based hydropower (−4%). This is because the reservoir-based hydropower capacity is small in the

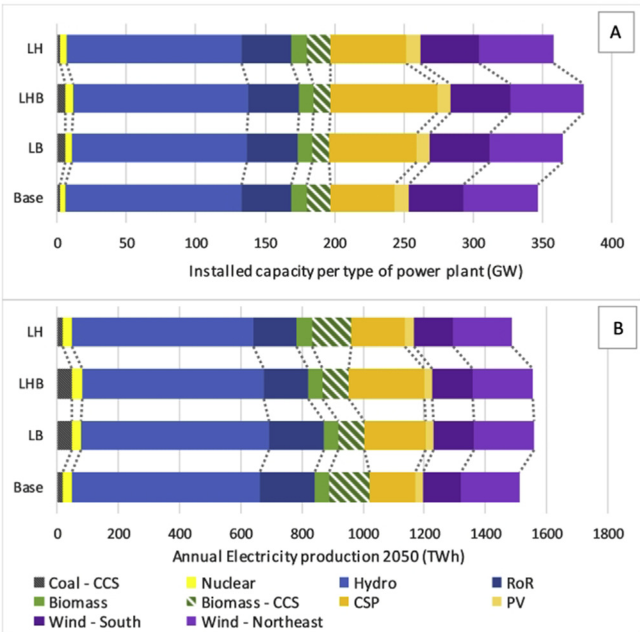

Fig. 2. A Projected installed capacity in Brazil per power plant type in 2050 for the base, and the three supply constraint scenarios as modelled in TIMBRA. 2 B:Projected annual electricity production in Brazil in 2050, for the base, and the three supply constraint scenarios as modelled in TIMBRA in this study.

northern region (the region that is expected to be affected by a decrease in precipitation). The loss of hydropower is substituted by wind energy and CSP. In the LHB scenario, the loss of power is substituted by CSP, wind, and coal with CCS. Power generation from biomass with CCS remains important in all the scenarios. The combination of baseload power generation from biomass with CCS (causing a net decrease of atmospheric CO_2 emissions) is present in all scenarios, even given a lower biomass supply.

Furthermore it is noticed that the overall electricity production is larger (+3%) in both low biomass scenarios, due to increasing electricity demand for an increasing number of electric cars. As the supply potential of biomass is lower, less biofuels are produced.

While there is still demand for low-carbon transportation, in these scenarios this demand is met by EVs, resulting in a higher demand for electricity. In the base scenario the total energy demand for private transportation met by electric cars is 195 TWh, compared to 263 TWh for both low biomass scenarios.

3.2. Dispatch profiles

Simulations of the base scenario, and the three supply constraint scenarios in PowerPlan show a large difference in power production between the seasons for the different sources (Fig. 3). In general, power production during summer is dominated by hydropower while production from VRE and bagasse is low. Conversely, during wintertime electricity production from VRE and bagasse is higher and during some hours they produce approximately 75% of the hourly production (Fig. 3). However, where nowadays hydropower is mainly used to deliver baseload power [40], in these scenarios hydropower provides a balancing service to maintain grid stability, i.e., when VRE production is high, hydropower production is low and vice-versa.

3.3. The impact of charging electric vehicles

The charging strategy of EVs has a large impact on the LOLP. When recharging happens after commuting trips (EV-HB) the peak load reaches over 250 GW in summer, while in the case of smart charging the load will be balanced out with peak demand close to 220 GW (see Fig. 4). Conventional charging therefore can lead to a LOLP of nearly 13 days per year (EV-HB scenario) while the LOLP of a power system with smart charging of EVs is one day per year (EV-SB). The high LOLP in the EV-HB scenario arises because, during peak times there is not enough capacity to fulfill demand, especially when VRE production is low. In the EV-SB scenario, the demand for EVs is shifted to off-peak times. The load curve is flattened out and therefore the combined capacity of hydro, baseload and VRE is better able to meet the total demand in comparison to the EV-HB scenario. The result of the mismatch analysis is shown in Section3.4.

3.4. Summarized results of the soft-link approach

The total capacity needed for a reliable power system ranges between 357 and 437 GW, dependent on the scenarios (Fig. 5). The need for additional capacity to reach the LOLP target differs per scenario and ranges between 10 and 57 GW. Scenarios with lower biomass availability and home charging of EVs require additional capacity.

In both low biomass scenarios the loss of baseload power generation from biomass is partly compensated by more variable sources (e.g. wind), and the overall electricity generation increased (see Fig. 3). The combination of both changes leads to a mismatch between supply and demand. An important reason for this mismatch is the difference between hourly and aggregated patterns. In the aggregated wind supply patterns from TIMBRA the minimum load factor is 12% (Fig. B2, Appendix B) and the difference in peak load is approximately 13% (Fig. B1, Appendix B). In the modeling structure of TIMBRA, this minimum load factor of wind energy is model-wise regarded as baseload power production. However, in comparison to the hourly data, there are several hours with no wind production. The combination of low to no wind energy and peak demand therefore requires back-up capacity of approximately 50 GW (additional to hydropower) to secure a reliable production. This can also be observed in Fig. 3 where hydropower has reached its maximum capacity, and VRE production is low (e.g. hours 382 and 405 for the summer profiles of the LHB scenario; Fig. 3).

The second reason for a higher need for additional capacity (Fig. 5B) is conventional charging of EVs. High peak demand from commuters charging the batteries of their EVs after commuting results in 19 GW of additional capacity in comparison to the base scenario (EV-HB scenario). In the EV-HL scenario, even more additional capacity is required, i.e., an additional 34 GW compared to the base case. The combination of lower biomass and hydropower availability does already lead to higher required additional capacity. This, in combination with conventional charging, amplifies the need for additional capacity to 68 GW (+18%) to secure a reliable power grid.

The scenarios with smart charging have lower additional capacity requirements. In comparison to the base scenario the EV-SB requires 13 GW less in additional capacity. The EV-SL scenario requires 18 GW less than the LHB scenario.

Biomass supply potential and additional capacity are the two main factors that influence the difference of the total costs of energy supply when all scenarios are compared (Table 2). When biomass supply is lower, the costs increase with 17 (LB scenario) to 25 (LHB scenario) billion dollars per year compared to the base

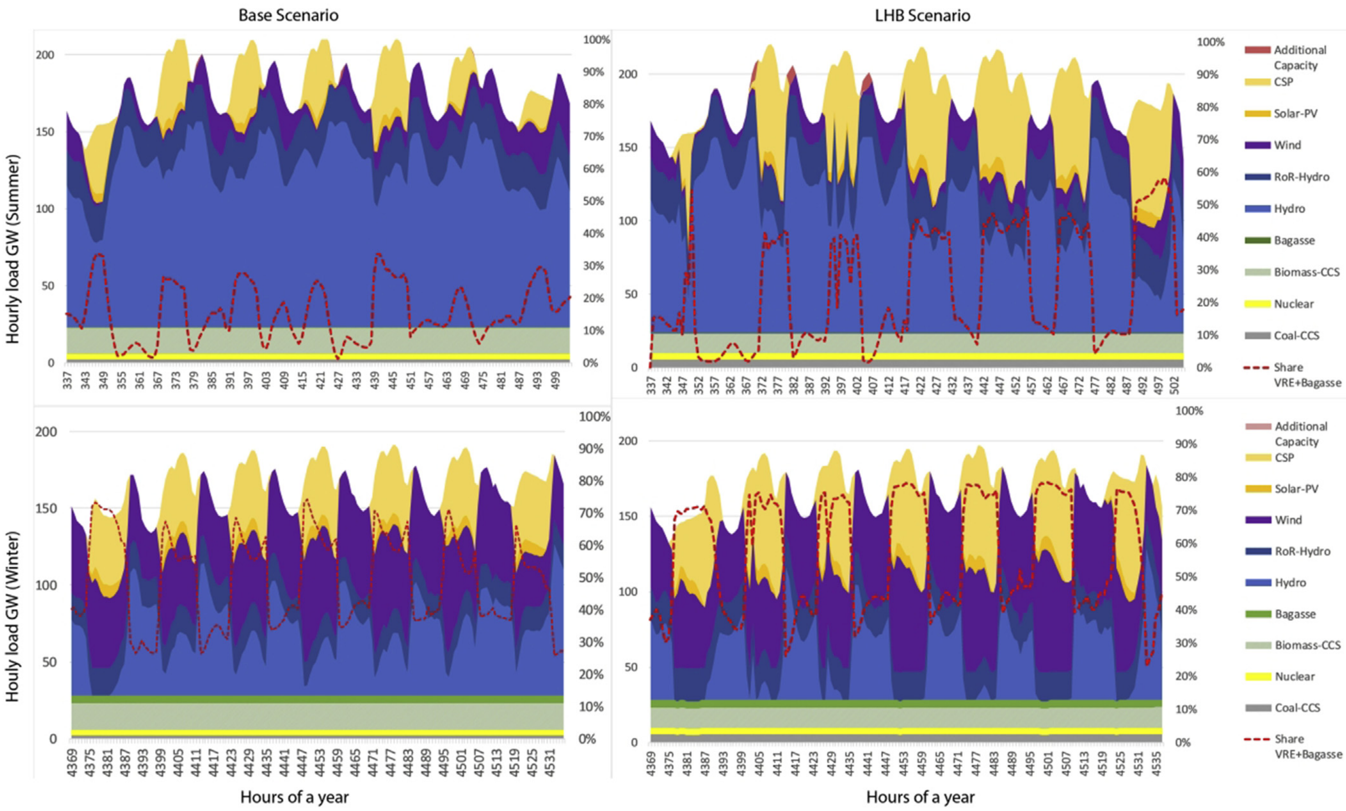

Fig. 3. Dispatch profiles of the base and the LHB scenario as modelled in PowerPlan for this study. The dispatch profiles are shown for the 3rd (summer) and the 27th (winter) week of the year. The secondary axis shows the share of the load of VRE and bagasse as the percentage of the total load.

scenario. The higher costs are explained by biomass, which affects the entire energy system. Biomass is a relatively low-cost renewable alternative in both the industry and transport sector. Because of the restrictions on GHG emissions due to the carbon budget, more expensive low-carbon alternatives, or more expensive biomass conversion technologies with higher efficiencies (e.g. biomass gasification for hydrogen production), are required in these sectors when biomass supply is low. The costs of the additional capacity are proportional to the required additional capacity to fulfill the reliability target.

4. Discussion

The difference between aggregated (TIMBRA) and hourly (PowerPlan) supply and demand patterns in energy scenario modeling, results in a mismatch capacity of 10–57 GW for a low-carbon power system in Brazil in 2050. On average, this is approximately 7% of the total required capacity. Poncelet et al. [39] shows that the mismatch due to differences in temporal resolution (also hourly versus aggregated patterns) for the Belgium case is 10% of the total capacity. The share of solar and wind energy is very similar to this study (i.e., just over 50% of the total capacity). The higher mismatch reported by Poncelet et al. [39] can likely be explained by the number of time slices used in the Belgium model, which is lower than in the TIMBRA model.

In Gouvello et al. [25] the reduction of hydropower in Brazil in the low hydropower scenario (for 2030) in terms of generated power is 5.2% in comparison to the reference scenario, which is slightly lower, but comparable to the 7.2% reduction found in this study. Similar trends can be observed in Lucena et al. [18], showing a reduction between 0.3% (RCP4.5 low impact scenario) and 11.9% (no policy high impact) in terms of generated power in comparison to the reference scenario. Besides the impacts of climate change on hydropower, it can also influence the supply potential of bioenergy [40]. To assess the impact of climate change on the energy system, a combination of global circulation models, crop growth models and energy system models are required.

As a potential solution to lower this risk, the international energy agency (IEA) proposes lowering the hydropower demand during the dry season, because this can be complementary with a larger production of solar and wind energy and electricity generation from bagasse during the same season [41]. This solution is confirmed in this study, where electricity production from wind, solar, and bagasse is responsible for on average 43–50% of the power generation in the period May–November compared to 31–37% during the other months, dependent on the scenarios.

In general, this study shows that the flexible operational nature of hydropower is successful in securing grid stability. However, backup capacity is required in a limited number of hours. PHS or vehicle-to-grid (V2G) are two options that can deliver peak demand services. Although, storage services are unnecessary if there is approximately 50 GW of baseload capacity (see Section 3.4), as possible surpluses of VRE can be compensated by lowering the production from hydropower. Biomass is a feasible option (see Section 3.1) to deliver low-carbon baseload power generation. Furthermore CSP, in combination with short term storage is demonstrated as an excellent technology to provide flexible power generation during peak demand, as also shown by Soria et al. [42].

Boβmann & Staffell [15] show for Germany and the UK that the load with conventional charging of EVs can increase the normal electricity load by 8–15%, which is similar to this study. The average demand for electricity for transportation is on average 13% [15],

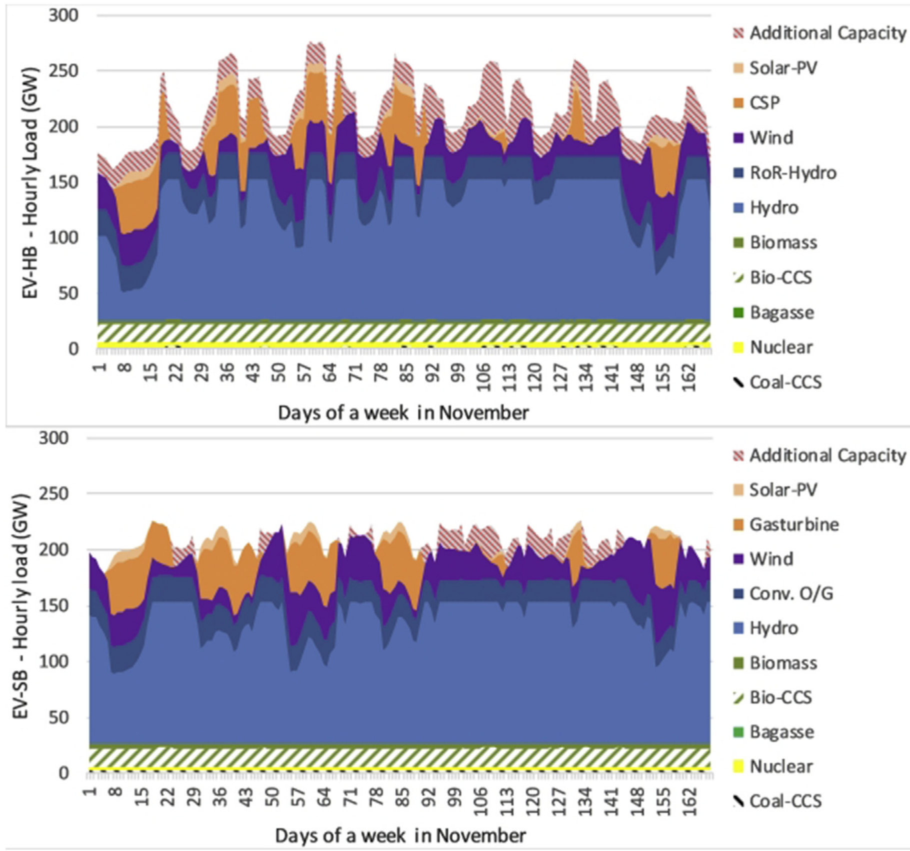

Fig. 4. Dispatch profiles of the EV-HB and EV-SB scenarios as modelled in PowerPlan for this study. It shows the additional capacity required to bring the LOLP from 13 days per year (upper graph) to one day per year (lower graph). The dispatch profiles show are shown for a typical week (here in November).

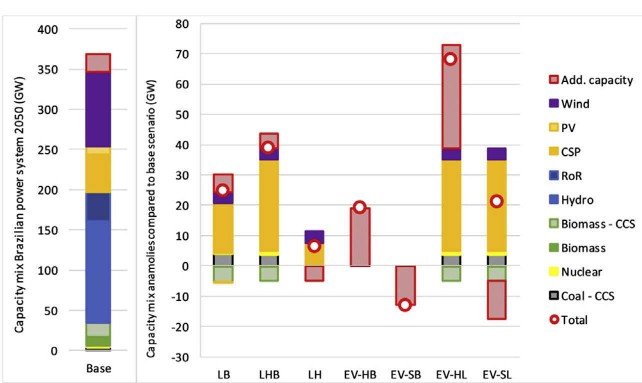

Fig. 5. A) Capacity mix of the base scenario for the Brazilian power system of 2050.5 B: Changes in capacity planning per type of power plant of the Brazilian power system for the modelled scenarios as compared to the base scenario. The red circle represents the total change in capacity in comparison to the base scenario. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

which is also similar to this study (15%). However, the analysis of EV charging in this study is limited because it only considers grid-to-vehicle interaction. Whereas, electric car batteries can also serve as energy storage units which can deliver energy to the grid (V2G) at peak demand, therefore they can provide storage capacity to stabilize the grid [14]. The V2G service however, mainly affects the local electricity distribution network and therefore it cannot be generalized for the whole country. Just like V2G, there are other DSM options to increase the flexibility of the local network, such as peak shaving with electronic appliances [43]. Other methods and system boundaries are required to analyze the impact of V2G and similar flexibility measures.

The incorporation of EVs in the passenger transport fleet is not only influenced by economics and GHG performance. For instance, range anxiety, presence of charging facilities and reduction of local air pollution can influence sales either positively or negatively [44]. These factors are not considered in this study and to assess this in combination with economics and GHG performance, a different method like e.g. agent based modeling (ABM) is required [45]. ABM is also a suitable method to assess short-to medium term transitions in the energy system, to reflect on uncertainties like political landscape, and provide business perspectives. Addressing range anxiety, user preferences on charging strategies (to overcome unloaded batteries at all time), and charging speeds is key for the transition from fossil to electric vehicles. In the Netherlands there are currently multiple pilot projects (ongoing or planned) [46], showing that overcoming these issues is possible in the near future.

There is a mismatch in peak demand due to different representation of the temporal resolution in both models, leading to a LOLP that is too large. To reach the LOLP target additional capacity is added. NGCC is chosen as power plants that delivers the additional capacity because it can deliver power during peak demand. Although NGCC power plants emit CO_2, because the number of operating hours is very limited, the CO_2 emissions from NGCC power plants are negligible in comparison to the total CO_2 emissions of the energy system. However, there are options to produce flexible low-carbon electricity that can also serve as additional capacity. For example, PHS can deliver 15 GW with a reservoir capacity of 29 TWh [47] and batteries from EVs can be used to temporarily

Table 2
Results of the soft-link approach for the analyzed scenarios of the power system of Brazil in 2050.

Scenario	B	LB	LHB	LH	EV-HB	EV-SB	EV-HL	EV-SL
Total Capacity[a]	369	394	408	376	388	356	437	391
Total costs[b]	207	224	232	212	211	205	237	229
Cost difference[c]	–	7.9%	11.7%	2.3%	1.6%	−1.1%	14.1%	10.3%
Mismatch capacity	23	29	28	18	42	10	57	11
Mismatch costs[d]	4	5	5	3	7	2	10	2
Electricity costs[e]	62.90	65.80	69.30	63.80	63.80	62.30	70.80	68.50

[a] In GW, including the mismatch capacity.
[b] Total costs of supply of energy (in billion US$/y), including the costs for the additional capacity
[c] Difference of total costs of supply of energy, relative to the base scenario
[d] In billion US$/y, considering the additional capacity is met with NGCC-CCS power plant
[e] In US$/MWh

deliver electricity. The selection of the power plant for the additional capacity is a drawback of the soft-link approach as ideally this choice is made endogenously within TIMBRA, because of the least-cost optimization methodology. However, due to the soft-link approach this is not possible. Furthermore, baseload power plants (e.g., nuclear, fossil with CCS, or biomass [with CCS]) are interesting options to deliver the additional capacity, because this alleviates the power system to use hydropower resources for baseload power production. Water is expected to become a scarcer resource in the future in Brazil as there will be large demand for tap and irrigation water [48].

5. Conclusion

The aim of this study is to assess how the interplay between variable supplies of biomass and hydropower, intersectoral competition for low-carbon energy carriers and reliability affects a low-carbon electricity generation mix for 2050 in Brazil.

The variable supply of power by solar and wind energy does not result in electricity overproduction because it is well balanced with hydropower from reservoirs due to its fast ramping time, and also due to the thermal storage of concentrated solar power. Another positive factor considering the reliability is the seasonal balance between hydropower on the one hand, and variable renewable energy and co-generation from bagasse on the other hand. Hydropower is dominating power production in the summer season, while electricity production from variable renewable energy and bagasse is dominating the power system in the dry season. However, the capacity of hydropower is insufficient to fulfill demand in specific conditions when wind and solar power production is near zero, and peak demand for electricity is high. Although hydropower and VRE contribute an average of 85% of the total installed capacity, 15% (i.e., 60 GW on average) is required in the form of baseload and additional capacity, for a reliable Brazilian power grid.

When the biomass supply potential is low, the effect of intersectoral competition becomes visible. In the transport sector low-carbon transportation using ethanol cars is decreasing and substituted by electric cars. Subsequently, the total demand for electricity increases with approximately 70 TWh in comparison to the base scenario. Furthermore, the capacity of baseload biomass fired power plants with carbon capture technology decreases by 5 GW. The low hydropower scenario shows a decrease of nearly 60 TWh of electricity from hydropower and no changes in EVs compared to the baseload scenario. In both scenarios, the electricity decrease is compensated for, by increasing the capacity of concentrated solar power. This is an interesting alternative as it can provide flexible electricity generation due to its 12-h thermal storage unit. The low biomass scenario also compensates for the decrease of baseload electricity (from biomass), by increasing the capacity of coal-fired power plants (with carbon capture), and nuclear energy.

Another effect of the interplay between the supply potential of biomass and reliability, is the impact of charging patterns of EVs. When conventional charging is applied (EV-HB scenario) peak load increases by approximately 40 GW, resulting in the need for large additional capacity (+45 GW compared to the base scenario) and costs (+8% compared to the base scenario). However, when smart charging is applied (EV-SB scenario), less additional capacity is required (-3 GW) with lower costs (-0,5%), compared to the base scenario. When less biomass is available and demand for electricity increases further due to the electrifying transport fleet (EV-HL and EV-SL scenario), the effect of EVs on the electricity system amplifies.

The annual costs of energy supply range from 207 to 237 billion dollars per year for the assessed scenarios. The additional costs (to fulfill the reliability target) range from −2 to 30 billion dollar per year in comparison to the base scenario. The highest costs are observed in the two low biomass scenarios and the EV-home scenarios. The higher costs due to low biomass availability are because they affect the entire energy system, and subsequently more expensive alternatives are required. The impact of climate change on hydropower can be overcome at relative low costs (+1.7% compared to the base case).

Assessing the interplay between resource availability, intersectoral competition and reliability of a Brazilian low-carbon power system, shows that lower biomass supply leads to multiple changes in the electricity mix. While a shift away from biobased electricity to variable renewable energy is observed, this leads to a relativly small loss in installed capacity (5 GW). However, due to a shift from cars fueled with ethanol to electricity, more variable renewable energy capacity is required (22 GW). This shift results in changes of the reliability of the power system because of the charging strategy of electric vehicles. Overall, the combination of lower biomass supply and a conventional charging strategy, requires 68 GW of additional capacity for a reliable power system. However, when charged smart, only 10 GW of additional capacity is required to ensure a reliable power system with a reduced biomass supply.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.energy.2020.116948.

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