Adequacy assessment of an electric power system resulting from a Belgian TIMES model run

Sebastian Gonzato

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Abstract

This report outlines a framework for analysing the resource adequacy of an electric power system resulting from a TIMES model run as well as the results of the analysis. This analysis is done using unidirectional soft-linking of the TIMES BE energy system planning model and the GEPPR power systems operation model. This means the installed capacities from TIMES are used as inputs to the GEPPR model and wherever possible assumptions on other input data are aligned. Several increasingly detailed and complex adequacy assessments are proposed in order to identify the drivers of (in)adequacy within the TIMES BE model. The analysis results in unacceptably low levels of adequacy for all planning years, which for the final planning year (2050) could even eclipse the total energy system costs. These results are mostly likely due to modeling assumptions and should not be interpreted as implying that the power system proposed by TIMES will be unacceptably inadequate. Nonetheless, this exercise highlights the increased sensitivity of resource adequacy to the flexibility of the power system and Variable Renewable Energy Sources (VRES) generation profiles as the penetration of VRES in the power system increases.

Contents

Acronyms

Abbreviations

CEP Capacity Expansion Planning

CHP Co-Heat and Power

EENS Expected Energy Not Served

ESOM Energy System Optimisation Model

GEPPR The Generic Electricity Planning with Probabilistic operating Reserves Model

HVAC Heating, Ventilation and Air Conditioning

OCGT Open Cycle Gas Turbine

VOLL Value Of Lost Load

VRES Variable Renewable Energy Sources

1 Introduction and motivation

2 Literature review of research on adequacy aware Capacity Expansion Planning models

This section briefly discusses methods proposed in the literature to make power system Capacity Expansion Planning (CEP) models adequacy aware along with comments on how easily they may be adapted to a whole Energy System Optimisation Model (ESOM) such as TIMES. These can be broadly categorised into 3 types: capacity constraints, model decomposition and the inclusion of extreme events based on an initial model run.

2.1 Capacity constraints

This method involves the inclusion of an explicit capacity constraint (often called a reserve margin constraint) within the CEP model. This method is analysed in Mertens et al. (1) where it is shown how such constraints bias capacity mixes towards peaking technologies such as Open Cycle Gas Turbine (OCGT) since they are the least cost option to satisfy such constraints. Mertens et al. (2) also discusses the issues associated with crediting the adequacy contribution of VRES (i.e. estimating their capacity credit) in such constraints while the issues associated with crediting storage technologies are addressed in Mertens et al. (3). Stephen and Kirschen (4) presents a novel method of endogeneously treating thermal generator outages and a stochastic peak demand to avoid the issue of incorrectly defining the reserve margin within a capacity constraint.

While it is fairly straightforward to include a capacity constraint in TIMES, the references in the previous paragraph highlight that such a constraint is likely to be biased towards certain technologies and so is undesirable.

2.2 Model decomposition

An adequacy aware power system CEP would ideally include as many time series of (VRES) generator availabilities and load. In this way, the CEP model could make an economically efficient trade-off between installing new capacity and shedding load or alternatively explicit constraints on an adequacy indicator, such as the Expected Energy Not Served (EENS), could be made. This comes at a significant computational cost however, an issue which can be addressed using model decomposition techniques. For example, progressive hedging is used in Munoz and Mills (5), Benders decomposition and Stochastic Dual Dynamic Programming in da Costa et al. (6) and a Julia package for Dantzig-Wolfe decomposition is presented in Downward et al. (7).

Implementing decomposition algorithms for CEP models is a complex undertaking and typically requires access to the source code of a computational model. For this reason such algorithms cannot be easily applied to models such as TIMES.

2.3 Inclusion of extreme events based on an initial Capacity Expansion Planning model run

Hilbers et al. were the first to propose using the results of a CEP model run to select extreme periods for a second, adequacy aware model run. Similar ideas or variations thereof have also been proposed by Sun et al. (9), Teichgraeber et al. (10), Hilbers et al. (11), Teichgraeber et al. (12), Mertens et al. (2). Nuances aside, all of the methods proposed by the aforementioned authors rely on at least one initial model run to correctly identify extreme events and all outperform other time series aggregation or a priori extreme event inclusion methods. The initial model run is critical to identify extreme periods for systems with significant penetration of VRES since such periods are typically associated with a high residual load instead of simply high load.

This method is ideally suited for making an ESOM such as TIMES adequacy aware since it does not require additional constraints or changing the solution method. All that is required is to use an initial model run to inform the representative periods included in the final model run.

3 Literature review of soft-linking models

The adequacy assessments described in this report assess the adequacy of an electric power system produced from a TIMES model run. Academic literature refers to such an interaction as 'unidirectional soft-linking' of two models and similar examples of such an exercise exist. Pavičević et al. (13) links the JRC-EU-TIMES planning model with the Dispa-SET unit commitment model to investigate the effect of assuming different levels of flexibility and sector coupling in Dispa-SET on the results. They find that sector coupling could decrease total costs by 25%. Deane et al. (14) links an Irish TIMES planning model to the PLEXOS power systems operational model and finds that TIMES potentially undervalues flexible resources, underestimates wind curtailment and overestimates the use of baseload power plants. Younis, Ahmed and Benders, René and Ramírez, Jezabel and de Wolf, Merlijn and Faaij, André (15) uses a similar soft-linking approach for a mid-century deep decarbonisation scenario of Columbia, finding that the planning model underestimates 2-5% of the annual energy cost.

It is also worth highlighting approaches to energy transition assessments which go beyong the typical techno-economic analysis. For example, Trutnevyte et al. (16) uses a 'landscape of models' to analyse a qualitative storyline. These models include a broader environmental and socio-behavioural analysis. Gardumi et al. (17) adopts a similar approach, though a hierarchy of models and (bi-directional) soft-links are proposed which is more reminiscent of what was done as part of the EPOC project. Such assessments may be considered holistic in that they go beyond the techno-economic dimension to consider issues related to e.g. vulnerability of consumers or unintended environmental and health impacts of proposed transition pathways (17).

These studies highlight the utility of such soft-linking, which can reveal the blind spots of planning models such as TIMES due to coarse temporal, spatial and technological detail as well as address non-techno-economic issues.

4 Methodology

4.1 Increasingly detailed and complex assessments

Several increasingly detailed and complex adequacy assessments are proposed in order to identify the drivers of (in)adequacy within the TIMES BE model. These assessments are carried out using The Generic Electricity Planning with Probabilistic operating Reserves Model (GEPPR) (18), a versatile power system optimisation model written in the Julia programming language. These model runs or assessments are summarised in Table 1 and explained in further detail in the following sections. Note that "TIMES results" refers to the power system proposed by a TIMES model run.

Model ID		10	20	30	40	45	50	60	70	80	90	100
Description		Validation	Resolution	Storage dispatch effect	Foresight effect	Sensitivity to representative days	Availability factors vs outage draws	Potential flexibility issues	Climate sensitivity	EV sensitivity	HVAC sensitivity	Import sensitivity
Model parameter	Sampling time (1 hour if true)	FALSE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
	Ordered year of representative days	FALSE	FALSE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
	Rolling horizon	FALSE	FALSE	FALSE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
	RES availability factors from full year	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
	Forced outage draws	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
	Clustered unit commitment	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	TRUE	TRUE	TRUE
	Weather years	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
	Electric vehicle demand random draws	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE
	Detailed HVAC demand	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE
	Maximum import capacity?	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE

Figure 1: Increasingly detailed and complex model runs.

4.1.1 10. Validation

In a first instance, an economic dispatch model is run which should yield the same generator dispatch as TIMES. The level of detail is therefore the same as in TIMES: 10 representative days with a 2 hour sampling time. This is also a check that the input data for both TIMES and GEPPR agree with each other.

4.1.2 20. Sampling time set to one hour

The sampling time of GEPPR is changed from 2 to 1 hours. The original availabilities of VRES are available in a 1 hour sampling time and hence these are used. For the load time series the value was repeated twice.

4.1.3 30. Representative periods are ordered throughout the year

The 10 representative days used in TIMES are ordered throughout the year so as to obtain a 365 day long time series. This ordering process is described in Gonzato et al. (19) and the figure explaining it is reproduced below. Additionally this process is described in the RepresentativePeriodsFinder.jl package. The re-ordering was done so as to best approximate the full year VRES availability time series.

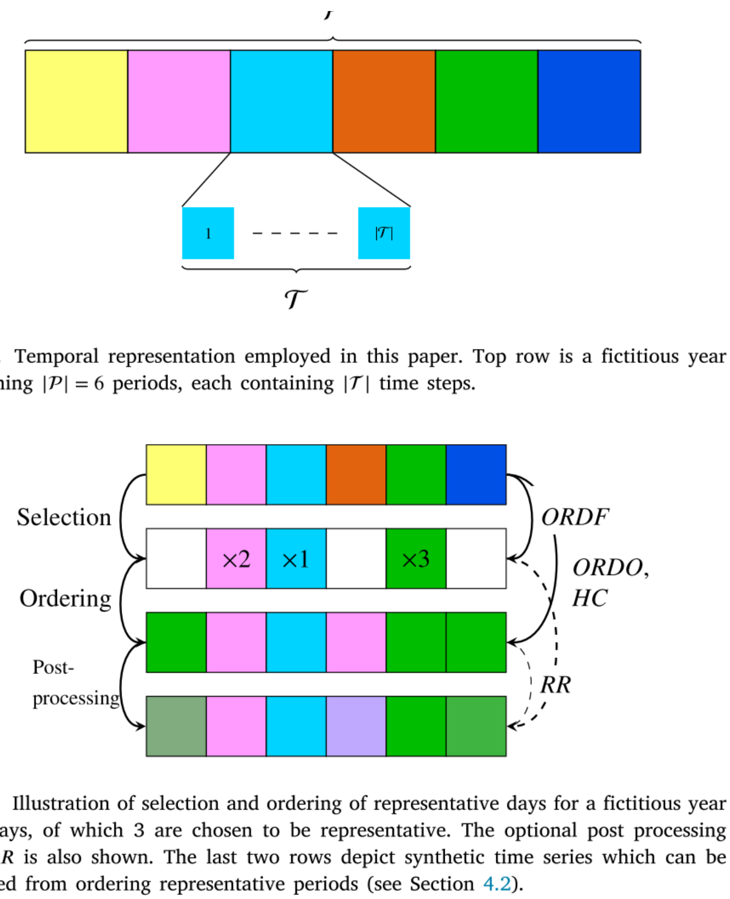


Figure 2: Illustration of the process of ordering representative periods, reproduced from Gonzato et al. (19). Here, the post processing step was also used such that linear combinations of representative periods could be used.

No new information is used in this step. Any differences in adequacy indicators are purely due to the different chronology representation and hence the differing storage dispatch.

4.1.4 40. Rolling horizon

Instead of a one-shot optimisation, a rolling horizon based approach is used, as is typical of industrial adequacy assessments (see e.g. Elia (20)). A lookahead horizon of one week was used which is the same horizon as in Elia (20). This assesses the effect of forecast errors, though it should be noted that a one week lookahead horizon is quite large and not in line with the capabilities of meteorological forecasting tools.

4.1.5 45. Full year Variable Renewable Energy Sources availaiblity factors

The full year availability factor time series is used instead of that coming from the (ordered) 10 representative periods. This tests the sensitivity of the TIMES results to the representative periods chosen. It should be noted however that industrial adequacy assessments in the EU use 200 weather years instead of a single one (20, 21).

4.1.6 50. Forced outage draws

Until this point it is assumed that thermal generators were 100% available[1]. From this point onwards a thermal generator availability time series is created by assuming a forced outage rate, repair rate and typical unit size. This tests the sensitivity of the TIMES results to using annual availability factors (sometimes known as annual load factors) to represent the limited availability of thermal generators instead of actual outage draws (which are non-trivial to represent in an investment model (4)).

4.1.7 60. Clustered unit commitment formulation

To test the sensitivity of the TIMES results to the approximations taken regarding generator flexibility, at this stage a clustered unit commitment formulation is used.

4.1.8 70. Increasing the number of weather years

Due to data availability and time constraints, the adequacy assessments past this point were not conducted and therefore do not appear in the results.

[1] The exception is during the validation stage, where maximum annual load factors were used in the same way as in TIMES

Industrial adequacy assessments run economic dispatch models for many Monte Carlo years which are correlated combinations of VRES availability, load and forced outage time series. Unsurprisingly the sensitivity of power system adequacy to weather increases with increasing penetrations of VRES as highlighted by the increasing interest in "Dunkelflaute" events (periods with little to no solar or wind) (22). This assessment therefore tests the sensitivity of the TIMES results to only including a single weather year when selecting 10 representative days.

4.1.9 80. Electric vehicle transport demand draws

Electric mobility is increasingly being touted as an important solution for decarbonising the transport sector (23). Indeed, in the TIMES results 57.8 GWof car battery capacity is present by 2050. This puts additional strain on the power system which may not be captured by the 10 representative days included in TIMES, hence this assessment tests the sensitivity of the results to including transport demand draws.

To do this, transport demand data from TML is converted into demand for electrical energy. This electrical energy must come from a single battery in the model. The transport demand normalised by the number of electric vehicles is assumed to be 1 minus the availability of the battery (i.e. if a car is driving it cannot be charged). The transport demand is sampled in a similar way to thermal generator outage draws.

4.1.10 90. Detailed Heating, Ventilation and Air Conditioning demand

In a similar spirit to the previous section, this assessment uses synthesied electricity demand required for Heating, Ventilation and Air Conditioning (HVAC) so as to test the sensitivity of the TIMES results to only using 10 representative days of HVAC demand. This demand is synthesised using building models developed by the building task within EPOC which takes outside weather conditions and typical user preferences as inputs. These time series can be generated for several typical buildings and users and then scaled up to the total building stock of Belgium.

4.1.11 100. Import capacity

Given the limited scope of the time series data used here, as a first approximation the import / export flows were fixed for the 10 representative days. As a highly interconnected system, Belgium's ability to import electricity from abroad can have significant impacts on the adequacy of its' power system as evidenced by the influence of assumed nuclear availability (20). As a crude test of the sensitivity of the assumption of import / export flows on the results, this assessment caps the import capacity of the TIMES results by a percentage of the maximum capacity.

4.2 Input data and assumptions

4.2.1 Input data: a summary of the TIMES results

Tables (3), (4), (5) and (6) summarise the installed capacities of the power system and the demand and supply for each period or planning year. The difference between supply and demand is due to losses in the transmission network.

Sum of GW	Period					
ProcessSet	2018	2020	2030	2040	2050	**Total Result**
PWR_PLANT_BFG	0.315	0.309894622205066	0.2257075398	0.089534934	0.019251349	**0.959388445**
PWR_PLANT_BIO	0.295484946935239	0.24876015577176	0.169788677749	0.042052312		**0.756086093**
PWR_PLANT_CHP	4.47008517205892	7.7720991759964	7.034736877179	6.708985299	5.895166901	**31.88107342**
PWR_PLANT_DIESEL	0.00524861878453039	0.00441865902127502	0.003015910126	0.000746964		**0.013430152**
PWR_PLANT_GAS	3.98696939657864	3.35651321137356	2.290953461731	0.567410567		**10.20184664**
PWR_PLANT_H2				0.000108385	0.524551518	**0.524659903**
PWR_PLANT_HYD	0.110752523	0.110752523	0.110752523	0.110752523	0.110752523	**0.553762615**
PWR_PLANT_NUC	6.018	6.018	2.077			**14.113**
PWR_PLANT_OIL	0.359066298342541	0.302287440475458	0.206323173658	0.051100972		**0.918777885**
PWR_PLANT_SOLAR	3.996176115	5.69216974900747	16.02879077806	34.26235364	85.86701086	**145.8465011**
PWR_PLANT_STG				0.060333291	13.84457661	**13.9049099**
PWR_PLANT_WIND_OF	1.177	1.67652365706154	4.6	5	8	**20.45352366**
PWR_PLANT_WIND_ON	2.0925534	2.327710052443	6.848124983095	13.9736879	17.99092078	**43.23299711**
PWR_PLANT_WST	0.268497822178905	0.560938509867747	0.618110634191	0.675891467	0.67515874	**2.798597173**
Total Result	**23.0948342928788**	**28.3800677562233**	**40.21330455859**	**61.54295825**	**132.9273893**	**286.1585541**

Figure 3: Summary of installed capacities in GWcoming from the TIMES results.

Sum of GW	Period					
Type	2018	2020	2030	2040	2050	**Total Result**
Car Battery		0.04530801	45.1375223	55.3693692	57.8710031	**158.423203**
Hydrogen Tank				4.97020863	23.0805639	**28.0507725**
Li-Ion Battery				0.06033329	13.8445766	**13.9049099**
Pumped Hydro	0.02031					**0.02031**
Total Result	**0.02031**	**0.04530801**	**45.1375223**	**60.3999111**	**94.7961436**	**200.399195**

Figure 4: Summary of installed storage capacities in GWcoming from the TIMES results.

Sum of TWh	Period					
ProcessSet	2018	2020	2030	2040	2050	**Total Result**
FD-AGR-APPLIANCES	1.077307050453	1.07730705	1.07730705	1.07730705	1.0773070505	**5.3865352523**
FD-AGR-GREEHNHOUSE				1.207347341	1.317780164	**2.5251275051**
FD-AGR-LOW ENTHAPLY				0.183723447	0.1837234474	**0.3674468947**
FD-AGR-OFFROAD		0.030474658	1.199413597	1.332274601	1.3322746009	**3.8944374563**
FD-COM-CHARGERS		0.014299032	2.227874574	3.578974056	3.6551857986	**9.4763334606**
FD-COM-COOKING	2.677339572612	2.320360963	0.535467915	4.241885603	4.6116139729	**14.386668026**
FD-COM-LIGHTING	5.232469415082	4.711830576	5.659565048	6.458389291	7.3699642785	**29.432218609**
FD-COM-OTHER EL	2.614255427803	2.377816938	2.856128519	3.259259269	3.7192902603	**14.826750415**
FD-COM-OTHER IT	1.754467056077	1.595789547	1.916791811	2.187339062	2.4960729408	**9.9504604161**
FD-COM-REFRIGERATION	2.872795363996	2.6667879	1.834631605	1.906351129	1.9490949001	**11.229660898**
FD-COM-SPACE COOLING	2.794567136167	2.590231948	3.118592554	3.531394433	3.9724442354	**16.007230306**
FD-COM-SPACE HEATING	1.457063883317	0.078230555	0.452898554	5.979184601	7.4818041933	**15.449181786**
FD-COM-WATER HEATING	2.036830570714	0.019911497	0.248908061	1.382943162	2.1234793838	**5.8120726743**
FD-IND-CH-AMMONIA	0.081309367111	0.08114694				**0.1624563072**
FD-IND-CH-CHLORINE	2.94813	2.94813	2.94813	2.94813	2.94813	**14.74065**
FD-IND-CH-ETHOXIDE	0.42918	0.42918	0.42918	0.498523052	0.4436452179	**2.2297082697**
FD-IND-CH-HVC	0.553379111111	0.553379111	0.553379111	0.612431214	1.060431214	**3.3329997614**
FD-IND-CH-OTHER	10.97604883844	10.8191016	10.8191016	19.7774196	27.810088621	**80.201760257**
FD-IND-FOOD	6.346010302189	5.008145258	4.743219317	4.930326008	6.9331901515	**27.960891036**
FD-IND-NFM	2.119064027778	2.11909421	2.11924512	2.834628412	2.7970340984	**11.989065868**
FD-IND-NM-CEMENT	0.824340136986	0.857442673	1.003778588	1.11215853	1.197	**4.9947199278**
FD-IND-NM-GLASS	0.533059294442	0.879042428	2.038927017	3.223344939	1.0590500465	**7.7334237253**
FD-IND-NM-LIME	0.347188920304	0.326073807	0.085116135	0.08325	0.08325	**0.9248788616**
FD-IND-NMM-OTHER	0.754862716929			1.230566187	2.0882110437	**4.0736399479**
FD-IND-OTHER	6.918779888889	6.819328786	6.834996417	10.01930877	9.631071524	**40.223485383**
FD-IND-PAPER	1.854777777778	2.05978994	3.570100911	5.080411881	10.313922471	**22.87900298**
FD-IND-STEEL	4.395088408212	4.395088408	4.402572742	9.049711811	21.145675474	**43.388136844**
FD-IND-WOOD	0.172361111111	0.195739821	0.217058603	0.254148867	2.5140245098	**3.353332912**
FD-RSD-CHARGERS		0.167922048	9.769367076	10.87597788	11.290229865	**32.103496868**
FD-RSD-COOKING	1.319597618097	1.143651269	0.263919524	0.707410461	0.7984729087	**4.2330517805**
FD-RSD-LIGHTING	1.018490335948	0.766891472	0.805564283	0.836883888	0.8549672182	**4.2827971976**
FD-RSD-OTHER ELECTR	5.179472304709	5.247494378	5.504456792	5.71451929	5.8350369334	**27.480979698**
FD-RSD-REFRIGERATION	1.838653377515	1.834422234	1.81382993	1.883647985	1.9237589463	**9.2943124728**
FD-RSD-SPACE HEATING	5.71781757514	3.183573311	2.015103242	3.505092539	4.0040275483	**18.425614215**
FD-RSD-WATER HEATING	3.397046508904	1.309887313	0.85020488	4.310283897	5.6231917834	**15.490614383**
FD-TRA-RA-FREIGHT	0.384242728435	0.432471515	0.535011299	0.620022295	0.7169551706	**2.6887030077**
FD-TRA-RA-PASSENGER	1.21826161184	1.243205345	1.360281518	1.486255311	1.5350307142	**6.8430345005**
FD-TRA-RO-BUS	0.000327102125	0.004872837	0.004356153	0.360563851	0.5579370586	**0.9280570018**
FD-TRA-RO-CAR					-3.52052E-08	**-3.52052E-08**
FD-TRA-RO-HEAVYDUTY				4.66387817	7.6662527869	**12.330130957**
FD-TRA-RO-LIGHTDUTY	0.000252415776	0.006881932	0.00623559	1.589044335	2.5320434603	**4.1344577324**
FD-TRA-RO-MOTO	0.002922206536	0.005307371	0.023732486	0.073103869	0.0923665841	**0.1974325169**
Total Result	**81.84775916253**	**70.32030467**	**83.84444762**	**134.6074161**	**174.74503054**	**545.36495808**

Figure 5: Summary of demand for electricity in $\mathrm{GW\,yr^{-1}}$ coming from the TIMES results, broken down by process set.

Sum of TWh	Period				
ProcessSet	2018	2020	2030	2040	2050
PWR_EXPORT	-4.021164021164	-25.08832655	-18.99022869	-0.32176882	-5.423621977
PWR_IMPORT	18.70163763217	1.5701165952	11.289053818	58.159607421	57.980792249
PWR_PLANT_BFG	0.734189923315	0.7962765815	0.6514138827	0.018371796	
PWR_PLANT_BIO	1.796302920549	0.1520624616	0.0111157865	0.0172815366	
PWR_PLANT_CHP	18.10634724184	34.403155625	38.589865029	16.472220183	11.102681314
PWR_PLANT_DIESEL	0.00137447389			0.0002302254	
PWR_PLANT_GAS	8.801992956425	10.102815234	1.114902506	0.3130816186	
PWR_PLANT_H2				0.0002522523	1.3836878972
PWR_PLANT_HYD	0.3098345974	0.2910576304	0.2910576304	0.2910576304	0.2910576304
PWR_PLANT_NUC	30.60500476105	33.7393152	13.175374937		
PWR_PLANT_OIL		0.5947329105	0.0194839717	0.0077031749	
PWR_PLANT_SOLAR	4.054038865158	5.7745896929	15.948393731	31.863441725	75.664570926
PWR_PLANT_WIND_OF	3.527477713477	5.0245538117	13.786234054	14.985037016	23.976059225
PWR_PLANT_WIND_ON	2.398098597521	2.6675917624	7.9036452311	15.972066774	20.281508866
PWR_PLANT_WST	0.728909409553	2.6403360453	3.4106775452	3.4157041569	3.5583333333
STG-BAT				-0.003264881	-1.317014024
STG-ELECTROLYZERS				-1.813506363	-6.86719262
Total Result	**85.74404507118**	**72.668277005**	**87.200989437**	**139.37751545**	**180.63086282**

Figure 6: Summary of the supply of electricity in $\mathrm{GW\,h\,yr^{-1}}$ coming from the TIMES results, broken down by technology.

4.2.2 Assumptions

Due to the different scopes of TIMES and GEPPR (energy and electric power system respectively) and formulations, a number of assumptions had to be made for validation to be possible. These are listed below.

Losses The TIMES model captured losses between different voltage networks whereas GEPPR was not written so as to accomodate voltage networks. To overcome this, the losses from TIMES were fixed for all adequacy assessments and added to the load time series input to GEPPR. This approximation should lead to the same dispatch for the validation stage.

Co-Heat and Power (CHP) units Since these are optimised by TIMES to satisfy heating and not electricity demand the dispatch of these units was presumed fixed and subtracted from the load time series input to GEPPR.

Imports and exports The TIMES model used import-export curves to represent trade opportunities. While this would have been possible to also implement in GEPPR, it would have increased the implementation complexity. Instead, the import-export flows were fixed and subtracted and added respectively to GEPPR's load time series.

Annual availability factors The TIMES model uses annual availability factors to account for limited availability of thermal generation units. This is non-trivial to implement in a rolling horizon approach and hence it was dropped for assessments which used this solution approach.

Nuclear For the validation stage, the dispatch of legacy nuclear power plants (not Small Modular Reactors) was constrained to be between bounds provided by the TIMES modelling team, as was done in the TIMES model run. For assessments which used the ordered year of representative days this was not done.

Electrolysers The electricity consumption of electrolysers was added to GEPPR's load time series. This is done because GEPPR's scope is limited to the power system, and so it is unable to model the process of electrolysis to produce hydrogen which is then burned in gas power plants.

Hydrogen Since some power plants in 2050 use hydrogen which is endogeneously produced within the TIMES optimisation, the fuel cost of this was set to the import cost of hydrogen.

4.3 Clustered unit commitment and economic dispatch model

The below is reproduced largely unedited from Gonzato et al. (24).

Typically in adequacy assessments an economic dispatch model is solved for many Monte Carlo years $y \in \mathcal{Y}$ to obtain a load net of power injection[2] profile ϕ_{yt} where $t \in \mathcal{T}$ is the set of timesteps (here hours) of operation. A Monte Carlo year is a combination of a weather profile and forced outage draw which

[2] The load minus the generation and storage charge and discharge.

determines the availability AF_{ryt} of resources $r \in \mathcal{R}$ and load profile D_{yt}. An economic dispatch problem for year y can be written as:

$$
\begin{aligned}
\min & \sum_{g\in\mathcal{G},t\in\mathcal{T}} C_g \cdot q_{gyt} + \sum_{t\in\mathcal{T}} ls_{yt} \cdot VOLL \\
& \text{s.t.} \\
& \sum_{g\in\mathcal{G}} q_{gyt} + \sum_{h\in\mathcal{H}} (d_{hyt} - c_{hyt}) = D_{yt} + ls_{yt} \quad t \in \mathcal{T} \\
& e_{hyt+1} = e_{hyt} + 1/\sqrt{\eta_h} \cdot c_{hyt} - \sqrt{\eta_h} \cdot d_{hyt} \quad h \in \mathcal{H},\ t \in \mathcal{T} \\
& 0 \leq q_{gyt} \leq AF_{gyt} \cdot K_g \quad g \in \mathcal{G},\ t \in \mathcal{T} \\
& 0 \leq c_{hyt} \leq AF_{hyt} \cdot K_h \quad h \in \mathcal{H},\ t \in \mathcal{T} \\
& 0 \leq d_{hyt} \leq AF_{hyt} \cdot K_h \quad h \in \mathcal{H},\ t \in \mathcal{T} \\
& 0 \leq e_{hyt} \leq AF_{hyt} \cdot K_h / E2P_h \quad h \in \mathcal{H},\ t \in \mathcal{T}
\end{aligned}
\tag{1}
$$

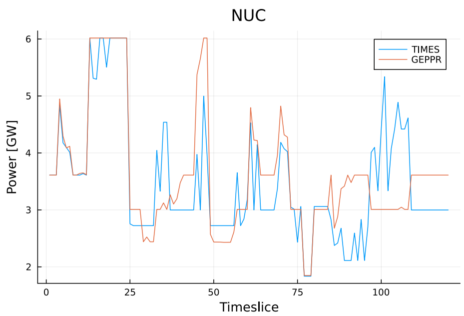
where the variables ls, q, c, d and e are load shedding, generation, storage charge, discharge and energy content. $VOLL$, C_g, K, $E2P$ are the Value Of Lost Load, cost of generation, capacity (in MW) and energy to power ratio (in hours).

The clustered unit commitment formulation builds on the above model. Describing it in detail is beyond the scope of this report, however a description can be found at (25).

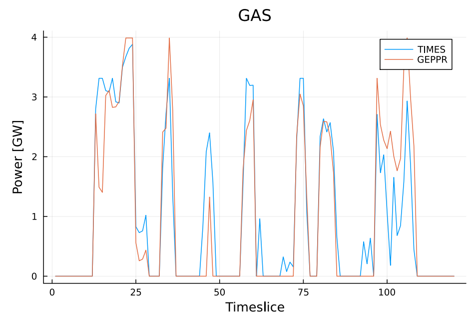
5 Results

5.1 10. Validation

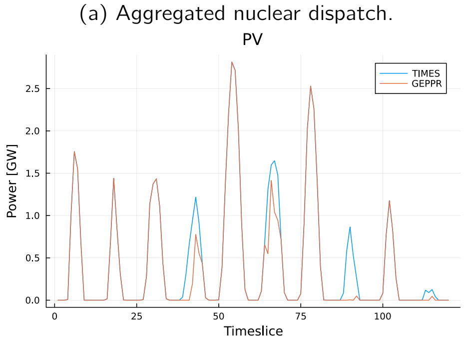
A first step investigates the results of a GEPPR model run which should yield the same dispatch as the TIMES model run. This was not achieved within the allotted time for unknown reasons. Figure 7 plots the aggregated dispatch of nuclear, gas, solar PV and onshore wind power plants for all timeslices in 2018. The dispatch in GEPPR of solar PV and onshore wind almost exactly matches that of TIMES, as does that of gas though to a lesser degree. The nuclear dispatch displays more of an error. Removing a constraint which bounds the nuclear dispatch so as to give a more realistic profile reduces the dispatch of VRES technologies to zero but at the cost of an increased error in the nuclear dispatch. This is evident from Figure 8.



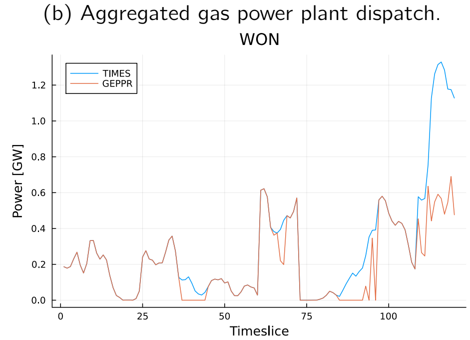
(a) Aggregated nuclear dispatch.



(b) Aggregated gas power plant dispatch.

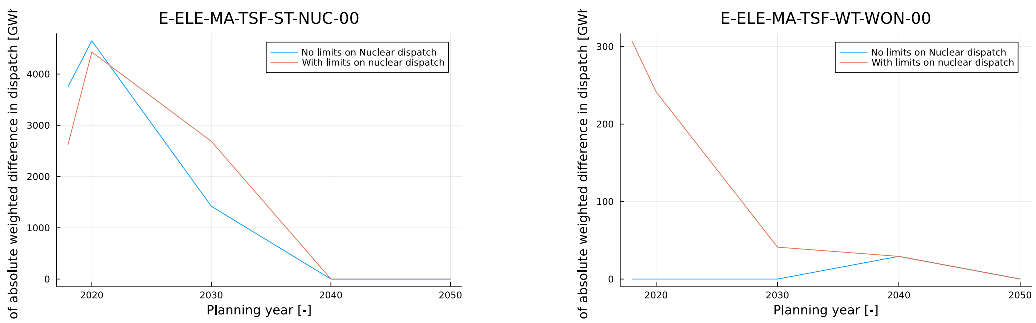


(c) Aggregated solar PV dispatch.



(d) Aggregated onshore wind dispatch.

Figure 7: Validation of dispatch from GEPPR and TIMES model runs for 2018.



(a) Nuclear

(b) Onshore wind

Figure 8: Evolution of the annual absolute difference in dispatch between GEPPR and TIMES model as a function of the planning year. The decrease could be explained by retiring of old power plants.

In the TIMES results, there is no load shedding and therefore EENS at all. However, Figure 9 shows that the GEPPR model run does have approximately 40 $\mathrm{GW\,h\,yr^{-1}}$ of EENS. This is of minor importance as this error goes to zero for 2020 and it is the later results which are of greater interest.

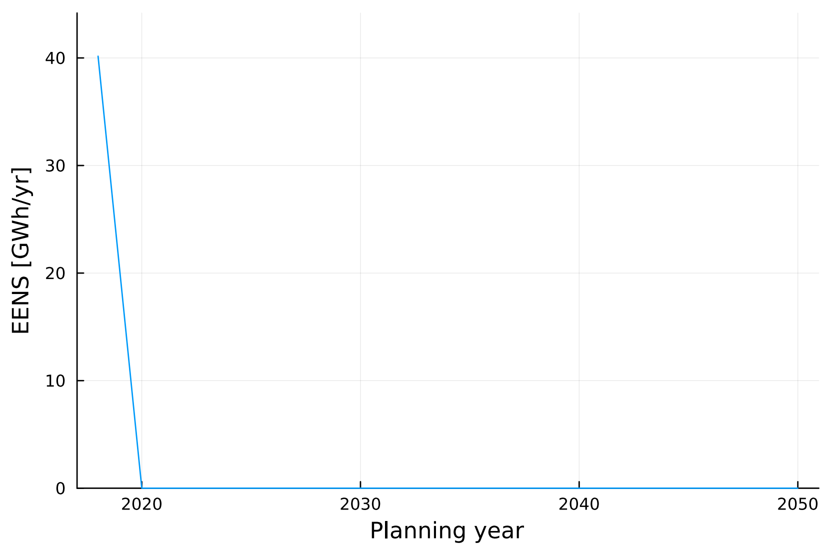


Figure 9: Evolution of the EENS resulting from the GEPPR validation model run as a function of the planning year. Contrary to the TIMES results, the EENS is non-zero for the year 2018.

5.2 Increasingly detailed adequacy assessments

This section investigates the adequacy of the TIMES results for progressively more complex input data and models. Figure 20b teases the results of this analysis which Section 5.3 covers in greater detail. It shows the EENS normalised by the total load, which reaches approximately 0.02% of the total load by 2040. By comparison, the Australian reliability standard requires that EENS does not exceed 0.0006% of the total load (26, Section 6). While most of the increases in complexity result in greater levels of EENS, model runs 30 to 45 do not, most likely because they relax constraints related to storage dispatch. This highlights the importance of storage technologies (and perhaps flexiblity providers more generally) in the highly decarbonised power system described by the TIMES results.

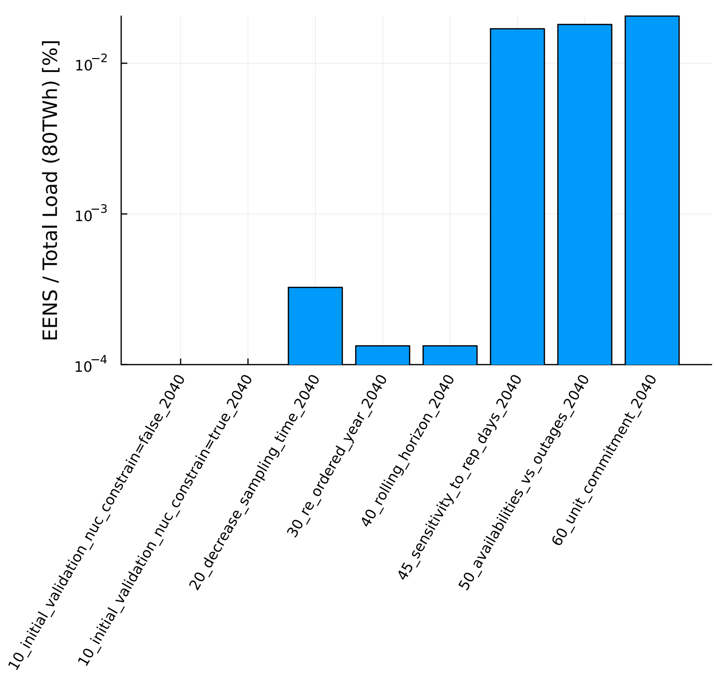


Figure 10: Comparison of the EENS (approximately normalised by the total load, assumed to be 80 TWh, and expressed as a percentage) resulting from increasingly complex GEPPR model runs for the year 2040.

5.2.1 20. Sampling time set to one hour

Figure 11 shows the evolution of EENS as a function of the planning year. Reducing the sampling time from two to one hour[3] is enough to incur 100 $\mathrm{GW\,h\,yr^{-1}}$of EENS in 2040, highlighting the sensitivity of the adequacy of high VRES systems to the output of these resources. Later results further strengthen this observation.

Figure 12 shows the dispatch for day two of year 2040 (load shedding occurs only occurs in day two and one). The timing of the load shedding event is unusual. Typically load shedding in countries such as Belgium would occur during the evening peak in demand at around 18. However, for this high VRES system, the hours with the highest demand occur during the day to better match the output of solar PV. Load shedding therefore occurs just before and after this peak, at 9 and 16, respectively.

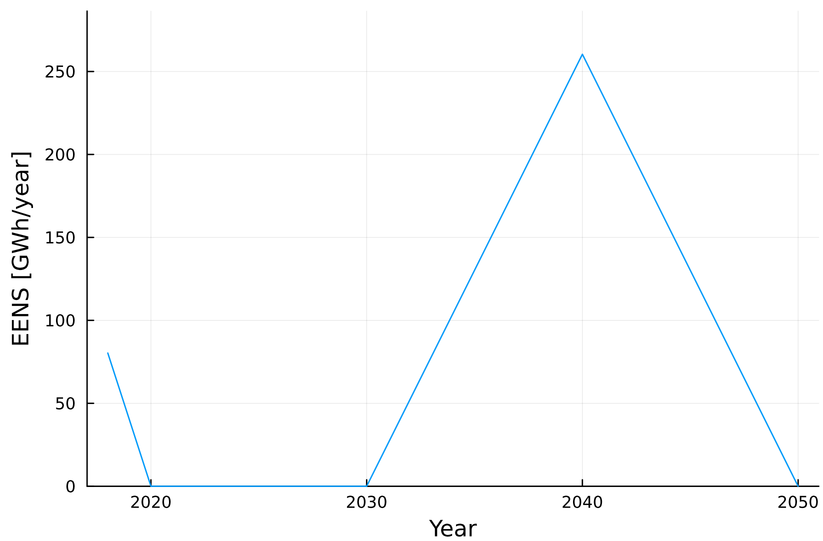


Figure 11: EENS as a function of the planning year for model run 20 (the sampling time for VRES reduced from 2 to 1 hours, see Table 1 and Section 4.1).

[3]This only affects the VRES timeseries. The load is repeated for two consecutive hours as can be seen in Figure 12

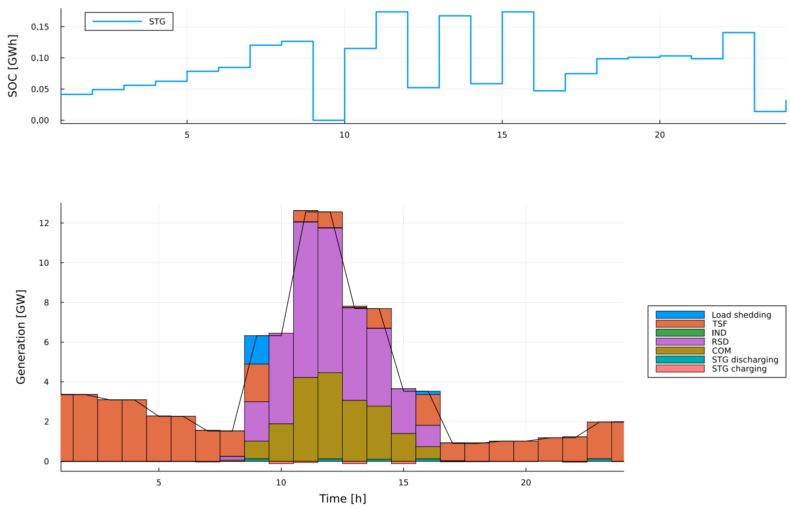


Figure 12: Dispatch of GEPPR model run 20 (the sampling time for VRES reduced from two to one hour, see Table 1 and Section 4.1) for day two and year 2040. Generation is aggregated by sector, COM = Commercial, RSD = Residential, IND = Industry, TSF = unknown.

5.2.2 30. Representative periods are ordered throughout the year

Figure 13 shows the evolution of EENS as a function of the planning year. In comparison with Figure 11, the EENS of years 2018 and 2040 decreases. This is likely due to the correlation between the load and VRES generation changing between these two model runs due to the ordering of the representative days. In this case, this change in correlation favours less EENS.

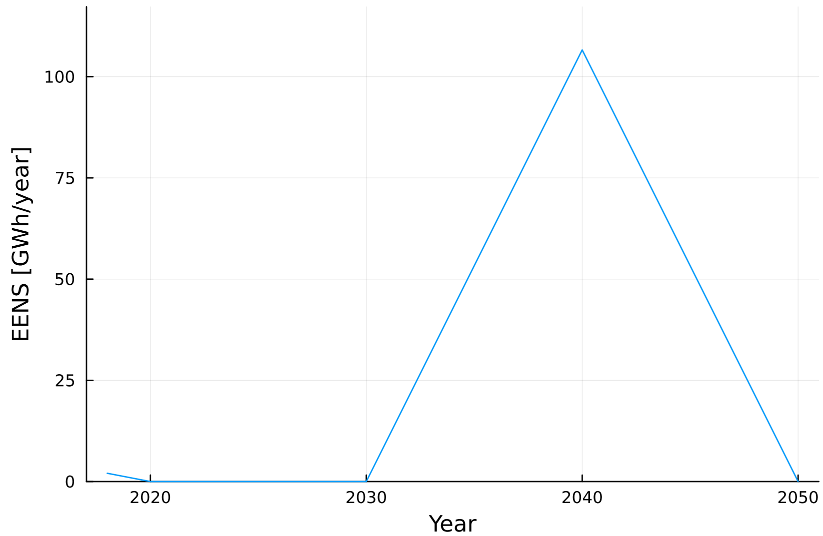
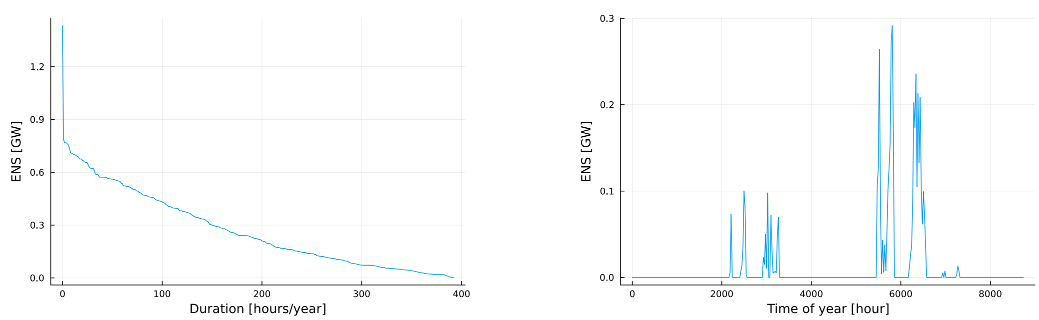


Figure 13: EENS as a function of the planning year for model run 30 (representative days ordered throughout the year, see Table 1 and Section 4.1).

Figure 14a shows the load shedding duration curve for the year 2040. Though there are many hours of the year in which load shedding occurs (approximately 400), most of the load shedding is less than 0.6 GW. Figure 14b plots the mean daily load shedding, illustrating how load shedding events are clustered around particular days.



(a) Duration curve

(b) Timeseries

Figure 14: Additional load shedding or energy not served figures for model run 30 (representative days ordered throughout the year, see Table 1 and Section 4.1) and year 2040.

5.2.3 40. Rolling horizon

Figure 15 shows the evolution of EENS as a function of the planning year. Little difference can be seen with respect to Figure 13.

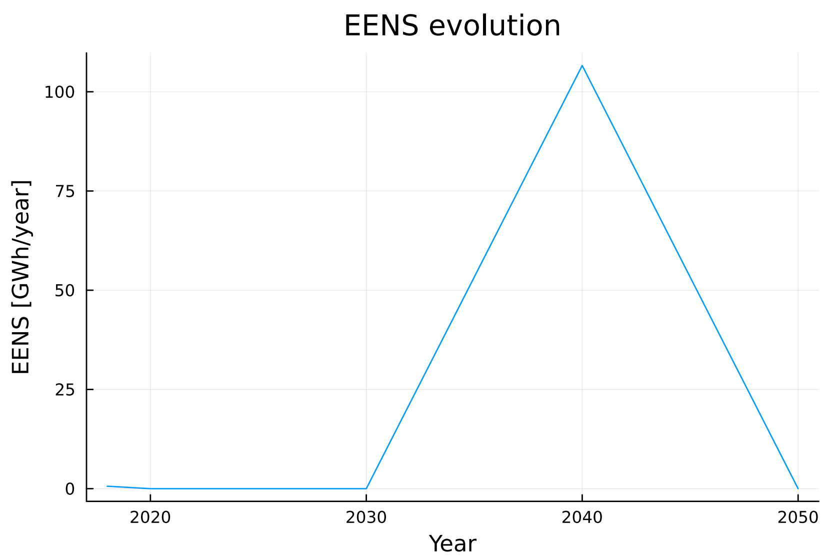


Figure 15: EENS as a function of the planning year for model run 40 (rolling horizon instead of single shot optimisation, see Table 1 and Section 4.1).

5.2.4 45. Full year of Variable Renewable Energy Sources availability factors

Figure 16 shows the evolution of EENS as a function of the planning year. The EENS is 2 orders of magnitude greater than that observed in Figure 15. This highlights the sensitivity of the EENS to VRES output, particularly since it increases dramatically in later planning years where there is higher VRES capacity (see Table 3). This is in line with results found in the literature[4]. Such high volumes of EENS are unlikely to be acceptable in Belgium (see Section 5.3 for a discussion of the economic costs of this.).

[4](20) note the correlation of temperature and VRES output on scarcity events. (27) illustrate how the inter-annual variability of total costs increases with increasing VRES. (28) and (29) both investigate the increased sensitivity of expansion planning results on VRES generation profiles.

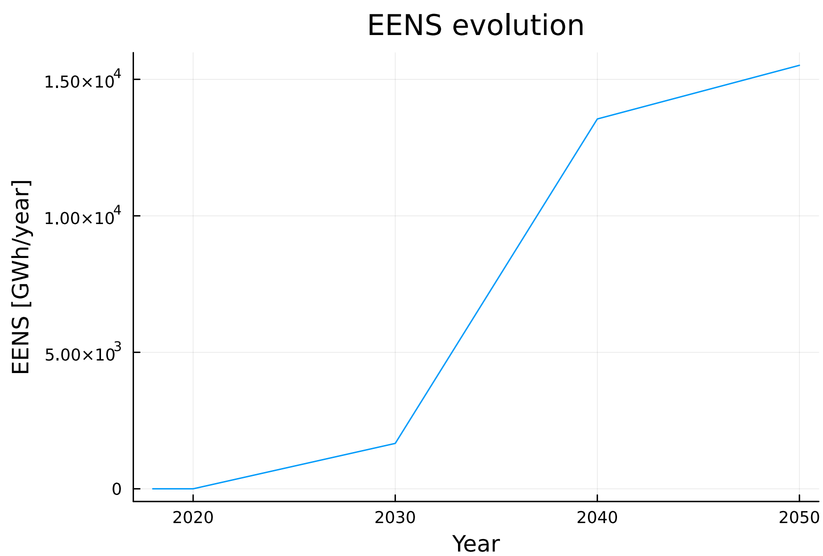
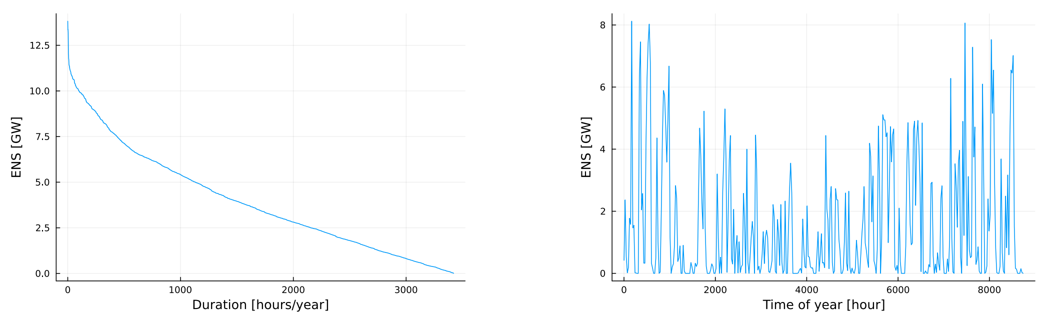


Figure 16: EENS as a function of the planning year for model run 45 (full year of VRES availability factors instead of those from the representative days, see Table 1 and Section 4.1).

Figure 17a highlights the severity of the load shedding events for the year 2040, with load shedding occurring for more than one-third of the year at values greater than a GW. Figure 17b illustrates how these events are evenly distributed throughout the year.



(a) Duration curve

(b) Timeseries

Figure 17: Additional load shedding or energy not served figures for model run 45 (full year of VRES availability factors instead of those from the representative days, see Table 1 and Section 4.1) and year 2040.

5.2.5 50. Forced outage draws

Figure 18 shows the evolution of EENS as a function of the planning year. The inclusion of forced outages of conventional generators increases the EENS, particularly for the year 2030 in which conventional generation is still dominant. This increase is less dramatic than that which occurred when introducing variability in VRES generation however (see Figure 16 and Figure 10).

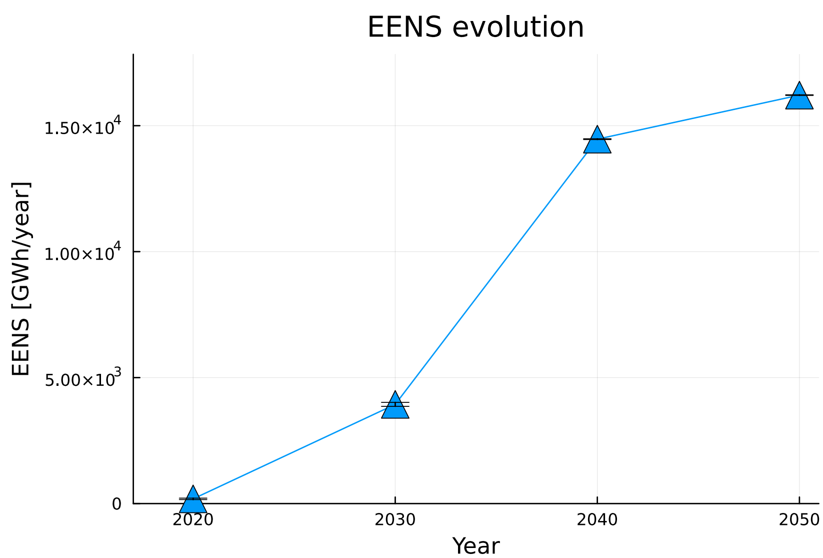


Figure 18: EENS as a function of the planning year for model run 50 (forced outage draws for conventional generators, see Table 1 and Section 4.1). Error bars indicate 95% confidence intervals.

5.2.6 60. Clustered unit commitment

Figure 19 shows the evolution of EENS as a function of the planning year. The inclusion of unit commitment constraints further increases the EENS, though again less than the introduction of increased variability in VRES generation (moving from model run 40 to 45, see Figure 10). This highlights the possibility of load shedding occurring due to inflexible generation and not just due to insufficient resource capacity in a particular hour. Similar results can be found in the literature[5].

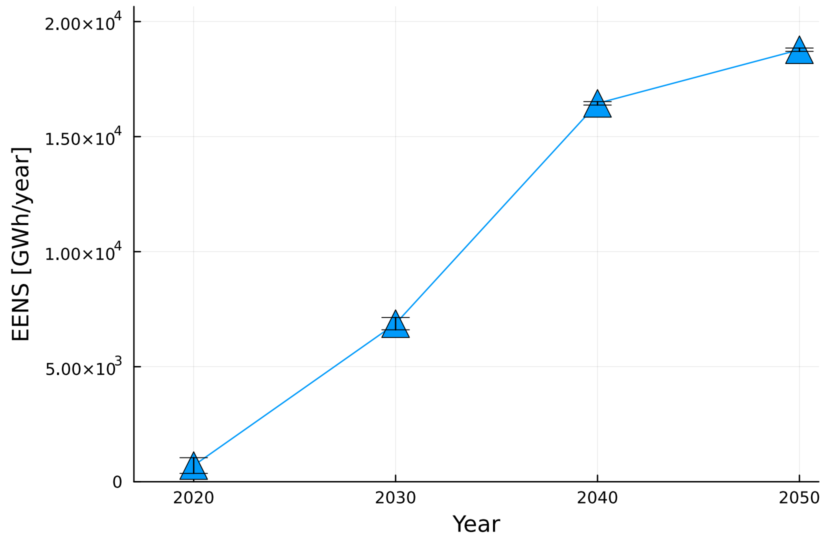


Figure 19: EENS as a function of the planning year for model run 60 (forced outages of conventional generators, see Table 1 and Section 4.1).

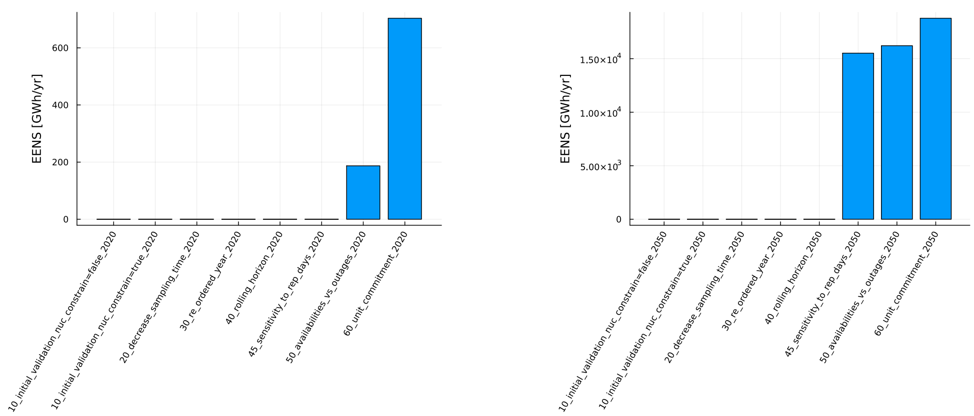
5.3 Overview of results

Figure 20 plots the EENS for increasingly complex GEPPR model for the years 2020 and 2050. The EENS is non-zero starting from model run 50 for the year 2020 and model run 45 for 2050 (see Table 1 and Section 4.1), highlighting the sensitivity of high VRES systems to the output of these generators compared to low VRES systems which are more sensitive to generator outages. Such levels of load shedding are unlikely to be acceptable in Belgium. In addition, if model runs 70 to 100 were carried it is almost certain that the EENS would further increase since these model runs would increase the variability of the load net of generation.

However, these results should be interpreted with extreme caution and not be interpreted as the EENS which would result if the power system proposed

[5]For example, (30) find that the ignoring unit commitment constraints in a planning model can overestimate the capacity credit of VRES and energy storage. In an operational model, this would translate to unit commitment constraints increasing shed load.

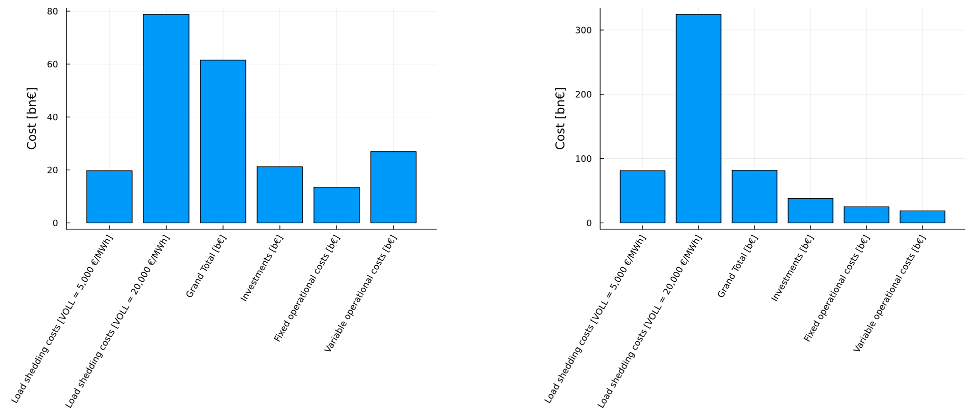
by TIMES was implemented. For now, it's worth considering that the power system proposed by TIMES in 2020 is essentially the Belgian power system at the time of writing which has not experienced any blackouts at all, let alone 600 GW hworth. This suggests that this large volume of EENS are due to the assumptions made and discussed in Section 4.1. More specifically, fixing the import and export flows may be causing this. The annual load factors used by TIMES means that the availability factors of thermal generators is 'optimised' to account for these flows, which may further exacerbate. The caveats associated with these results are further discussed in Section 6.



(a) 2020 (b) 2050

Figure 20: Comparison of the EENS resulting from increasingly complex GEPPR model runs. Note the difference in y-axis scales for the two figures.

Figure 21 compares load shedding costs for model run 50 (see Table 1 and Section 4.1) with other costs coming from TIMES for the years 2030 and 2050. These figures serve to highlight just how great the EENS is for this model run.



(a) 2030

(b) 2050

Figure 21: Comparison of load shedding costs with other (undiscounted) costs from the TIMES model run for model run 50 (forced outage draws for conventional generators, see Table 1 and Section 4.1). Load shedding costs are of the same order of magnitude for both 2030 and 2050.

6 Concluding remarks

The adequacy assessment of the TIMES results revealed unacceptable levels of inadequacy. That this was found also for the year 2020 (though to a lesser degree than for 2050) suggests that this is largely due to the assumptions taken in order to carry out this exercise. The most important of these include adding import and export flows to the load; fixing CHP dispatch; fixing electrolyser dispatch; and adding power system losses to the load.

Avoiding the need for such assumptions in the future would require the following:

- A European-wide power system model This would allow for a better representation of import and export flows. Achieving this requires, among other elements: projections for the future European capacity mix; several (ideally 30 or more) years worth of VRES generation and load time-series data;

- An energy system model instead of power system model This would allow for a representation of hydrogen and other energy carrier flows which is more closely aligned with TIMES. Indeed this modelling capability features in ENTSO-E's roadmap for the European Resource Adequacy Framework (21).

Even with these improvements, it is still possible that an overestimation of adequacy issues would occur if the electrical load, such as that coming from household and industrial use, was assumed to be inflexible or inelastic. Such an assumption appears unlikely for high VRES systems.

This exercise was nonetheless fruitful in illustrating the concept of increasing the model complexity can reveal insights into what is causing adequacy issues. In particular, the increasing sensitivity of adequacy to VRES generation and the need for increased flexibility were highlighted in line with other work (see Sections (5.2.4) and (5.2.6)). Including scarcity days in TIMES using methods similar to the ones described in Section 2.3 as well as ramping constraints could be computationally efficient additions to resolving this issue.

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