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LEGO: The open-source Low-carbon Expansion Generation Optimization model

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ABSTRACT

This paper introduces the open-source Low-carbon Expansion Generation Optimization (LEGO) model. It is a multi-purpose tool to carry out numerous techno-economic analyses of the energy sector, ranging from short-term unit commitment to long-term generation and transmission expansion planning. Its highly flexible temporal structure permits both chronological and representative periods. LEGO is composed of thematic blocks that can be combined freely via data options: unit commitment constraints; DC- or AC-OPF formulations; battery degradation; rate of change of frequency inertia constraints; demand-side management; or Power-to-X in the form of the hydrogen sector. This unique feature allows to incorporate highly technical aspects into long-term investment analyses. To our knowledge there is no open-source model that offers this flexibility, which we hereby make freely available to the scientific community.

Code metadata

Current code version	2021.12.03
Permanent link to code/repository used for this code version	https://github.com/ElsevierSoftwareX/SOFTX-D-22-00021
Permanent link to Reproducible Capsule	N/A
Legal Code License	MIT License (MIT)
Code versioning system used	git
Software code languages, tools, and services used	GAMS, Microsoft Excel
Compilation requirements, operating environments & dependencies	GAMS, Microsoft Excel, MIQCP solver (CPLEX or Gurobi)
If available Link to developer documentation/manual	https://www.tugraz.at/institute/iee/lego/
Support email for questions	Sonja Wogrin wogrin@tugraz.at

1. Motivation and significance

To mitigate climate change, we as a society have embarked on the journey towards net-zero energy systems [1,2]. Ahead of us there lie massive regulatory, social, economic and technical challenges such as the effective coupling of the electric power and other sectors (Power-to-X), as well as the electrification of transport, the large-scale integration of short- and long-term storage technologies, active demand-side management (DSM), and many more. Transparent, realistic, open-source energy system models (ESMs) are necessary to support the energy transition through more informed and better decision making. For an overview of non-open-source ESMs the reader is referred to [3]. There are many open-source ESMs available such as: GenX [4,5], EMMA [6], ANTARES [7], NEMO [8], EMPIRE [9], openTEPES [10], PyPSA [11], SpineOpt [12] and Switch [13] just to name a few.

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Most of these models are very complex, but were designed with one specific purpose in mind, e.g. assessing short-term operation such as the unit commitment (UC) problem or carrying out long-term expansion planning. This makes them inflexible to adapt to potential structural changes of future energy systems and to the temporal scope of study. We identify two main reasons for this inflexibility.

First, the temporal structure of the model itself. Depending on the scope, most existing ESMs either have a structure with chronological time periods (e.g. hours), or use some kind of time slices/blocks, or have representative periods (typically days or weeks)[1]. Chronological periods allow for exact modeling of technical constraints, but lead to computationally intractable models if the overall time horizon is too long. Time slices allow for temporal aggregation and improve tractability, but have difficulties in incorporating technical constraints that require chronology (e.g. storage state of charge or UC start-up decisions). Representative periods combine both advantages, but mostly fail to capture time dynamics that exceed the representative period. Among the other ESMs mentioned, SpineOpt [12] has the most flexible temporal structure and even allows for multiple investment periods. It does, however, not currently support an AC-OPF framework.

Second, we discuss the inflexibility with respect to thematic blocks. Some ESMs consider (or not) UC constraints, a single-node or a network problem (transport problem/DC- or AC- optimal power flow (OPF)), DSM, rate of change of frequency (RoCoF) requirements, storage degradation, other sectors such as gas/hydrogen, policy constraints etc. However, there is usually no easy way for the software users to combine these thematic blocks at will – depending on the scope of the study – without requiring programming skills and in-depth knowledge of the software itself. For those two main reasons, most ESMs are inflexible with respect to analyzing different aspects of power systems with one single model.

The open-source LEGO (Low-carbon Expansion Generation Optimization) model overcomes these existing short-comings of ESMs. It has been designed to be a user-friendly multi-purpose tool, like a Swiss army knife, that can be employed to study many different aspects of the energy sector. The underlying modeling philosophies are: *modularity* and *flexibility*.

LEGO is *modular* in the sense that – as its namesake – it can be assembled easily with different thematic blocks, shown in Fig. 1, which the user can activate easily via data and without requiring any knowledge of the code. Current modules include: UC decisions or relaxing them by running the model as a relaxed Mixed Integer Program (rMIP)[2]; considering a single-node problem[3] or an electricity network (either via a DC[4]- or a second-order cone programming (SOCP) approximation of the full AC-OPF[5]); degradation for battery energy storage systems (BESS) via cycle aging costs[6]; RoCoF system inertia constraints[7]; DSM via load shifting and load shedding[8]; considering the hydrogen sector[9]; incorporated policy constraints (such as firm capacity requirements[10] [15], and minimum renewable energy penetration[11]) demonstrate how regulatory policy alters cost-optimal operation and investment decisions, which is an important modeling asset on the transition towards climate neutrality. Let us briefly discuss the types of mathematical formulations of each block: UC (MIP); DC-OPF (LP); AC-OPF (QCP); degradation (LP); RoCoF (MIP); DSM (LP); hydrogen (LP); policy constrains (LP). Usually, LPs are the most efficient type of model to solve, then QCPs, MIPs, and finally MIQCPs. In general, it is difficult to predict a-priori exactly which block will have the highest impact on CPU time as this is case-dependent, but in our experience RoCoF is the most computationally expensive, then UC, and then combinations of the AC-OPF with MIP constraints.

LEGO's *flexibility* is currently three-fold: its versatile temporal model structure incorporates all temporal representations: chronological time steps, time slices/blocks, and representative periods — only by adapting the inputs[12]; LEGO can be used as an operation-only model or an investment (GEP, TEP or GEPTEP)[13] model; LEGO runs as a MIP or a mixed integer quadratically[14] constrained problem (MIQCP) and considers discrete decisions (such as lumpy investments and UC) or as a rMIP/rMIQCP[15], where discrete variables are relaxed.

LEGO is based on previous work [16,17] and is now freely available on GitHub: https://github.com/IEE-TUGRAZ/LEGO. To the best of our knowledge, there is no single open-source ESM available that combines LEGO's versatile temporal structure and modularity of thematic blocks. LEGO stands out especially because of its RoCoF and AC-OPF blocks, and its capability of establishing inter-temporal constraints [18] between non-chronological representative periods. The latter allows incorporating both short- and long-term storage in time-aggregated[16] optimization models. There are not many aggregated models that incorporate long-term storage as pointed out in [19]. As a summary, LEGO's strong points and limitations are presented in Fig. 2. The LEGO User manual, available in the GitHub repository contains further details about model flexibility and modularity, as well as the underlying mathematical formulation, inputs and outputs.

The remainder of the paper is organized as follows. Section 2 contains the software description, followed by illustrative examples in Section 3. Section 4 discusses LEGO's impact. Finally, Section 5 concludes the paper.

2. LEGO software description

2.1. LEGO software methods

The LEGO model is a MIQCP coded in GAMS [20]. Within GAMS, LEGO requires solvers that can handle MIPs/MIQCPs. Currently, we use CPLEX [21], but other solvers such as Gurobi [22] can be employed as well. With a free academic license small problem instances, i.e., 1 representative day case, can be solved and analyzed. For solving large-scale instances, a professional GAMS and solver license is required. The MIP tolerance is set to

1 For a comparison of these approaches, please refer to [14].

2 Set option pRMIP (Yes/No) in Parameters sheet.

3 Set option pTransNet to No in Parameters sheet.

4 Set option pTransNet to Yes and pEnableSOCP to No in Parameters sheet.

5 Set option pTransNet to Yes and pEnableSOCP to Yes in Parameters sheet.

6 Set option pEnableCDSF to Yes in Parameters sheet.

7 Set option pEnableRoCoF to Yes in Parameters sheet.

8 Set option pDSM to Yes in Parameters sheet.

9 Set option pEnableH2 to Yes in Parameters sheet.

10 Set a value for pMinFirmCap in Parameters sheet.

11 Set a value for pMinGreenProd in Parameters sheet.

12 In particular, by setting indices p, rp, k and corresponding parameters in sheets *Hindex*, which specify how actual hours p are related to representative periods rp and k, and in sheet *Weights* where the duration of in hours of rp and k are set.

13 Setting parameters EnableInvest [0,1] to 0 renders generators as non-candidates for investment, which means an operation only model. Setting them to 1 allows each generator to serve as a candidate for investment. This parameter exists for thermal, renewable, storage and FACTS units. We consider candidate investments in both generation expansion planning (GEP) and transmission expansion planning (TEP).

14 It is only quadratic if the SOCP formulation of the AC-OPF is solved, otherwise the model is a mixed-integer linear program (MIP).

15 Integrality is relaxed with option pRMIP in Parameters sheet.

16 Such as representative periods or time slices or blocks.

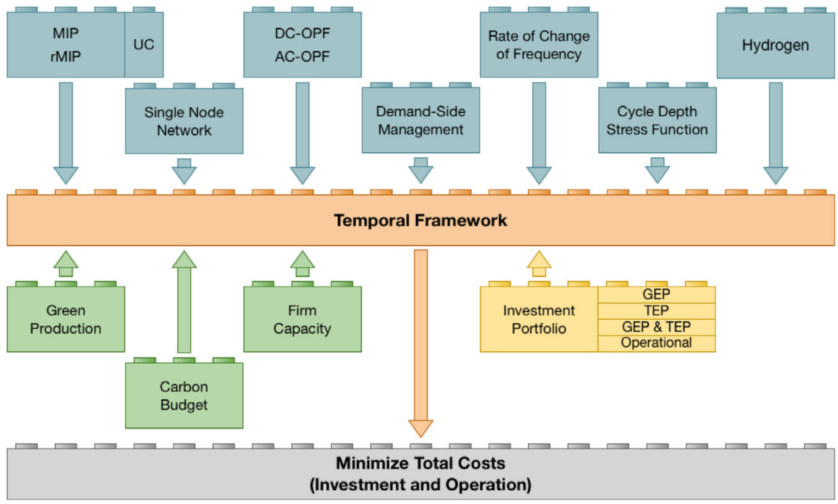

Fig. 1. LEGO's thematic blocks.

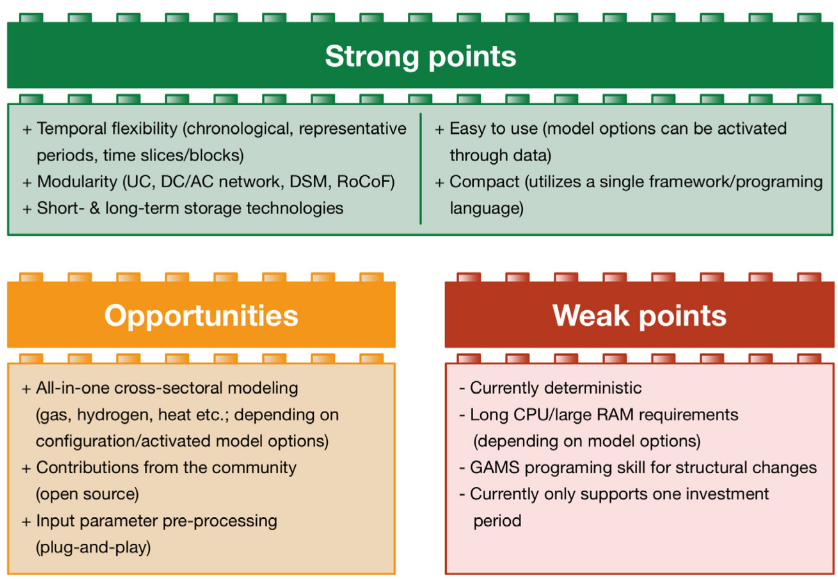

Fig. 2. Overview of LEGO's strong points and limitations.

1e-3 and relaxation induced neighborhood search frequency is set to *1000*. Otherwise, we use solver default settings.

The input data are contained in an Excel file[17]. Data sheets are color-coded depending on whether they stem from the electricity sector (green) or the hydrogen sector (blue). Model options and thematic blocks are activated via data and without having to alter the GAMS model code. Model results (primal and dual) and other outputs are written directly to an Excel file, which can be (if desired) loaded into (salmon-colored) result sheets of the data Excel file via the Menu sheet. GAMS communicates directly with Excel via GDX (GAMS Data Exchange) files for inputs and outputs.

LEGO comprises a detailed representation of an electric power system that consists of an electric grid made up by buses and power lines, as well as generators (whether thermal, renewable or storage technologies). The objective function of LEGO is total system cost minimization, subject to the selected technical and policy constraints. It is also possible to connect the power sector to the hydrogen sector via electrolizers. If candidate generation and/or transmission investments are enabled, this renders LEGO an investment model. If candidate investments are not specified (in generator and network data sheets), then LEGO runs an operation-only problem with existing generator and line data. For a detailed description of each model parameter, the reader is referred to the LEGO user manual available at the GitHub repository.

2.2. LEGO software architecture

Fig. 3 contains an overview of the LEGO software architecture. The input data is contained in the color-coded sheets of an Excel file, which we refer to as 'LEGO-Case.xlsm' here. The main body of the code is contained in the GAMS model 'LEGO.gms'. To run the model, the user simply has to type 'user1=LEGO-Case' in the GAMS command line. Via GDX, the data is incorporated into GAMS automatically, the model is solved, and the outputs are written into a separate Excel file 'tmp_LEGO-Case.xlsm', which is generated automatically. Via the 'Load' button in the Menu sheet, the outputs from the temporary Excel file can be incorporated into 'LEGO-Case.xlsm' if the user wants to save inputs and outputs together. Moreover, the GAMS code itself consists

17 We have chosen Excel to store the model data, instead of a professional data base, because it is easy-to-use and does not require a user with further knowledge about how to handle a data base.

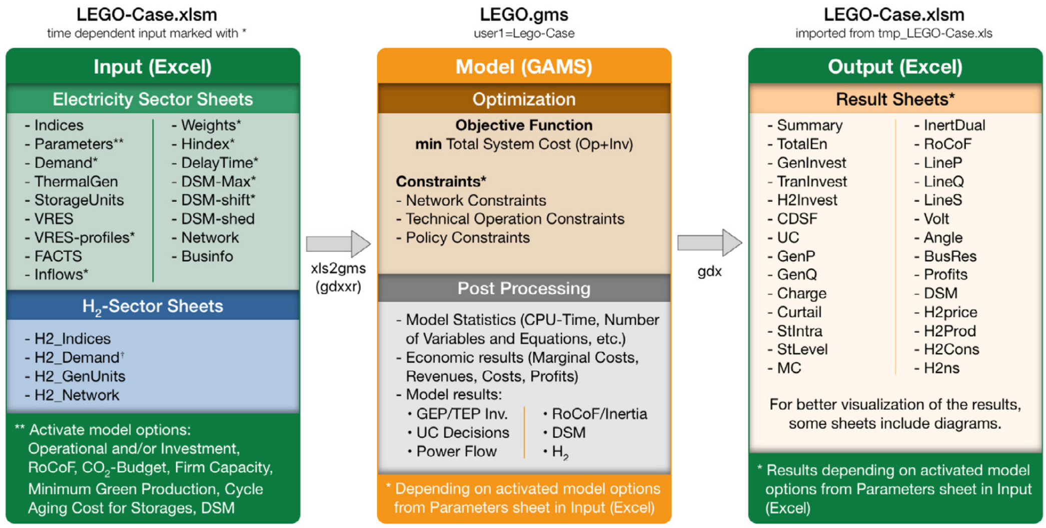

Fig. 3. LEGO software architecture overview.

of two parts: the optimization model (reading inputs, model formulation, solving the model); and, post processing including economic results.

The LEGO model has a plethora of input data of both technical and economic nature. The open-source data sets are based on the StarNet Lite demo version for long-term planning developed by Prof. Andres Ramos at IIT-Comillas (https://pascua.iit.comillas.edu/aramos/starnet.htm), but that data can be changed depending on the users system data. A more detailed description of the input data can be found in Fig. 4 as well as the LEGO user manual. Model results do not only include technical information obtained by primal variables such as: (active/reactive) power production of each generator, (active/reactive) power flow and voltages, generation and transmission investments, battery degradation, storage state of charge etc., but also information obtained by Lagrange multipliers such as spot/reserve prices (through marginal costs (MCs)), firm capacity/renewable quota payments, and subsequently revenues, costs and profits of generators. This information provides a detailed techno-economic analysis of the entire power system.

In particular, LEGO's temporal structure is defined by temporal indices (p, rp, k) in the Indices sheet, and the corresponding linkage and weights presented in sheets Weights and hIndex. Since some input data, marked with an '*' in Fig. 3, is time-dependent (such as demand, renewable profiles, hydro inflows, DSM profiles), the structure of these data sheets must be shaped accordingly. We illustrate this structure with one concrete example. Let us assume that we have original time series that represent one year's worth of data, that would correspond to hourly time periods $p = 1, \ldots, 8760$. Let us now illustrate two different options to represent this year within LEGO using indices rp and k: (a) as chronological hourly data, and (b) using representative days.

In case (a) the representative period is the year itself, so the cardinality of rp is one, and the chronological time periods k within the representative period are the individual hours themselves, i.e., $k = 1, \ldots, 8760$. The weight of each k is therefore one, and so is the weight of the representative period. The set hIndex relates the original periods p to the chronological periods k within rp. In this case, as both p and k represent the same chronological hours, they are the same. Time-dependent data using indices rp and k correspond to the exact hourly time series and are represented by a 8760x1 matrices/vectors in case (a).

In case (b), let us assume that we approximate the year using 7 representative days, in which case $rp = 1, \ldots, 7$. This would be the result of a clustering procedure on the original time series, which would also yield the weight of each representative day within the year and the relation between the original period p and its representative (rp, k). Since we have clustered days, index $k = 1, \ldots, 24$, represents the chronological hours within the representative day. Time-dependent data are the centroids stemming from the clustering procedure, and are represented by 24×7 (k, rp) matrices in case (b).

3. Illustrative examples

In Section 3.1, we present an illustrative example that shows the importance of accounting for technical characteristics in power system planning, and in Section 3.2 real-world results of the Austrian power system. All case studies have been carried out on a standard PC (Intel Core i7 11th Gen with 2.80 GHz and 32 GB of RAM) using GAMS version 37.1.0 with the CPLEX solver.

3.1. Transmission expansion planning DC versus AC

This section shows the results of a MIP version of LEGO for a 9-bus test system and 7 representative days available on GitHub, enforcing a 100% renewable penetration and enabling GEPTEP under two paradigms: a DC- and an AC-OPF setting.

While the candidate line 4–5 is built under both settings, generation investments, production decisions and power flow results differ significantly as shown in Fig. 5. In the DC setting, the power flow through line 4–5 is at maximum capacity most of the time. In 3 out of 7 representative days, the line is at maximum capacity for all 24 h of the day. The flow direction is mostly from bus 5, where the wind resources are located, to the rest of the system via bus 4.

However, the DC model does not account for voltage limits nor reactive power. In order to be within the established voltage limits (between 0.9 and 1.1 p.u.), the actual active power flow on line 4–5 is, in reality, closer to 85% of maximum capacity (instead of the 100% predicted by the DC-OPF). This causes significant distortions in power flow and subsequently in optimal investment results. Moreover, in the DC setting under 100% renewable penetration, a-priori, no generator provides reactive power, rendering an AC-infeasible power system. When allowing for the ex-post investment of additional FACTS devices, the DC system can be made AC-feasible at an additional system cost of 85 M€. However,

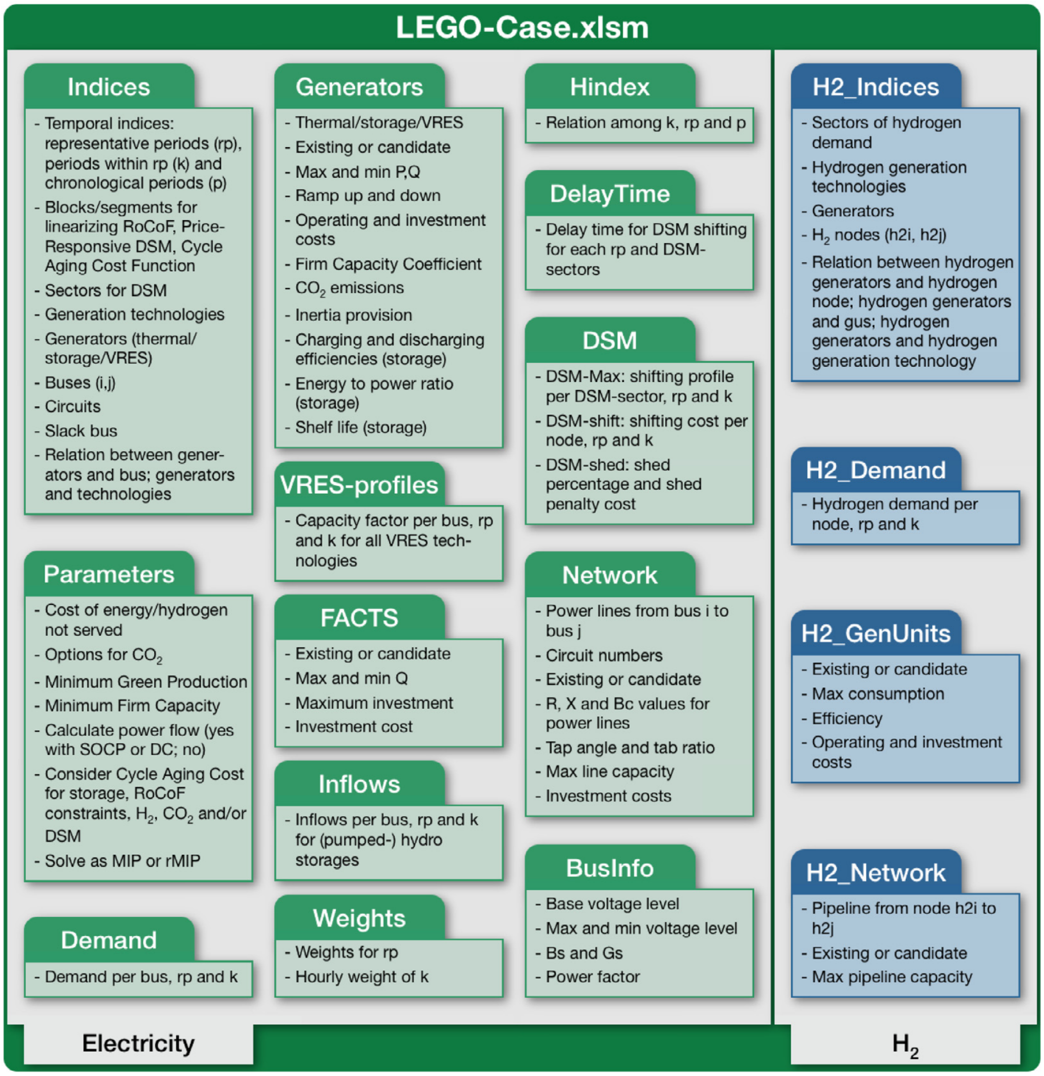

Fig. 4. LEGO input file sheets and contained data.

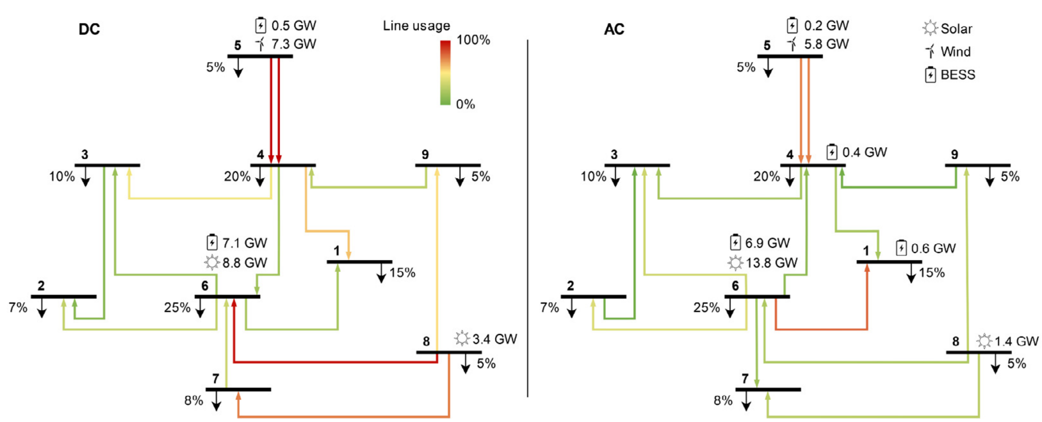

Fig. 5. Comparison of LEGO results under a DC (left) and AC (right) power flow setting: GEP investments (indicated in GW), nodal demand (%), and line usage (indicated by color range).

such an approach leads to a sub-optimal generation mix. Using the RoCoF functionality, a similar analysis [16] can be carried out regarding system inertia requirements. In the literature, there are few works that analyze GEPTEP accounting for an AC power flow. However, some examples with similar findings are [23–26].

3.2. Techno-economic analysis of the Austrian power system

Austria recently launched the legal framework for the transition towards a 100% renewable power system by 2030 (Renewable Expansion Act – EAG [27]). In order to meet the expected

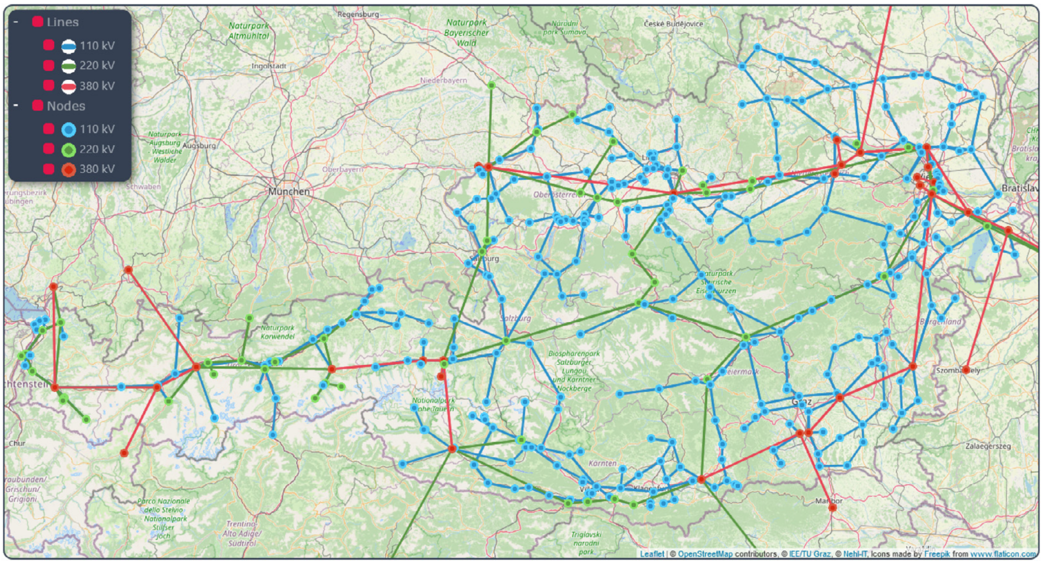

Fig. 6. Current infrastructure of the Austrian power system used in LEGO.

annual power demand of 82 TWh, the EAG specifies the following targets for additional annual generation per technology: 11 TWh of solar PV; 10 TWh of wind; 5 TWh of hydro; and, 1 TWh of biomass. Given these top-down targets, we utilize LEGO to derive cost-optimal expansion plans for Austria's electricity infrastructure until 2030. Other studies [28,29] regarding the decarbonization of Austria's power and energy system report similar findings.

Fig. 6 depicts the current infrastructure of the Austrian power system used in LEGO (1,304 generators; 468 nodes; and 1,097 power lines, 110, 220, and 380 kV). For this study, that has a temporal resolution of seven representative days, LEGO generates approximately 900,000 variables, and solves 800,000 equations. The solution time depends on the modeling options and the thematic blocks, and ranges from 20 min to 5 h. First results [30] indicate that under 2030 EAG targets, power imports/exports as well as power consumption of pumped hydro storage (PHS) is 150% higher than in 2020. Without allowing imports/exports, power consumption of national PHS increases to 180%.

This study is conducted as part of the START2030 research project [31], which aims to provide comprehensive analyses of the economic incidence and social impacts induced by transitioning to a 100% renewable power system in Austria by 2030.

4. Impact

So far, the LEGO model has led to the following scientific publications [16,17,32] and several contributions at international conferences [30,33–36], which have demonstrated LEGO's potential for assessing novel research questions in transitioning towards low-carbon power systems. It is actively used in two publicly-funded research projects: the aforementioned project START2030 [31] and InfraTrans2040 [37], which comprises the comprehensive elaboration and evaluation of three expansion scenarios for the energy infrastructure of the energy carriers electricity, gas, and heat to enable a sustainable, climate-neutral economic and energy system in Austria by 2040.

5. Conclusions and extensions

LEGO comprises an open-source user-friendly multi-purpose tool for techno-economic analyses of transitioning energy systems. Its unique flexible temporal structure and modularity allow users to carry out a wide spectrum of studies — making it an ideal companion throughout the energy transition.

In ongoing/future work, we are planning to extend the hydrogen sector to including the full gas infrastructure, as well as including the heating sector, to allow for full sector-coupling analyses. Moreover, we want to develop an additional software module between input data and the model, which uses only raw input data (such as hourly time series) and transforms them, e.g. through clustering procedures, into the temporal format desired by the user, thereby facilitating data preparation and corresponding input sheets. In the future, we are planning to extend LEGO to be a stochastic model[18], and to support multiple investment periods, as well as adding new sectors[19], such as gas and heat.

Declaration of competing interest

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

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[18] This extension is straight-forward in terms of the code, however, it requires careful collection of additional scenario-dependent data and making sure that the communication between Excel and GAMS still works efficiently. Moreover, it most likely requires having to solve LEGO using decomposition techniques.

[19] The software structure was specifically designed with this in mind, however, to do so the user requires further knowledge of GAMS and has to be careful when formulating intersections between sectors.

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