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Capturing features of hourly-resolution energy models in an integrated assessment model: An application to the EU27 region

Gonzalo Parrado-Hernando [a,*], Luka Herc [b], Felipe Feijoo [c], Iñigo Capellán-Pérez [a]

[a] Group of Energy, Economy, and System Dynamics, University of Valladolid, Spain
[b] Department of Energy, Power Engineering and Environment, Faculty of Mechanical Engineering and Naval Architecture, University of Zagreb, Zagreb, Croatia
[c] School of Industrial Engineering, Pontificia Universidad Católica de Valparaíso, Valparaíso, Chile

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ABSTRACT

Hourly resolution is essential to realistically address the matching of supply and demand for fluctuating energy sources like solar and wind. This work introduces a novel method to model energy variability in an Integrated Assessment Model building upon a previous work, where regression analysis was utilized to extract hourly-level information from an energy system model. The enhancements include: (1) improved experimental design and more efficient computing, and (2) modelling the management of variability in an integrated assessment model by (i) incorporating a portfolio of flexibility options, and (ii) offering the ability to regulate system curtailment by limiting the expansion of renewables. The scenarios focus on the electricity sector, mirroring current EU27's policies that aim for higher renewable energy and electrification contributions by 2050. Without any variability control measures, significant curtailment (up to 60 %) is observed, the introduction of flexibility options reducing it to half (30 %). Controlling the capacity expansion of renewables is introduced to avoid this unrealistically high curtailment, allowing the model to achieve a penetration of renewables in electricity of 80 % and a 53 % reduction in greenhouse gas emissions compared to 2015 levels in the electricity system. In conclusion, the methodology employed yields broadly consistent outcomes.

Acronym	Definition
IAM	Integrated assessment model
WILIAM	WIthin Limits IAM
VRES	Variable renewable energy source
PHES	Pumped hydropower energy storage
COP	Coefficient of performance
CF	Capacity factor
CHP	Combined heat and power
GDP	Gross domestic product
PV	Photovoltaic
LUE	Land-use efficiency
CEEP	Critical Excess of Electricity Production

1. Introduction

The 2030 Sustainable Development Agenda was adopted during the 70th session of the United Nations General Assembly in 2015. Goal number 7 was defined as *"by 2030, increase substantially the share of renewable energy in the global energy mix"* (subsections 7.2 in Ref. [1]). Addressing this challenge, the power sector is usually identified as the primary driver for many decarbonization strategies, fostering synergies among various energy sectors [2].

Integrated assessment models (IAMs) play a crucial role in evaluating global mitigation pathways to address anthropogenic climate change. These models emerge from an interdisciplinary field that integrates climate, land and water usage, economy, energy, natural resources, and demography into a shared framework of practical knowledge (chapter 16 [3]).

The challenge of energy variability has been a recurring theme in the evolution of IAMs [4]. It is essential for demand and supply to match in every time step of the simulation. Historically, fast backup plants fuelled by natural gas and oil were commonly used to cover the gap of less flexible units such as hydropower, coal, and nuclear power plants. Nevertheless, the research community and global energy policies are increasingly advocating for alternative pathways that heavily rely on the

* Corresponding author.
E-mail addresses: gonzalo.parrado@uva.es (G. Parrado-Hernando), luka.herc@fsb.hr (L. Herc), felipe.feijoo@pucv.cl (F. Feijoo), inigo.capellan@uva.es (I. Capellán-Pérez).

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exploitation of intermittent energy sources across regions worldwide. Flexibility should include technological and demand-side solutions to effectively manage and leverage this intermittency over time.

There is an increasing concern about technical curtailment, which refers to the dispatch-down of renewable energy due to network or system reasons. The bankability of projects and the size and distribution of power plants depend on this key cost indicator. The International Energy Agency recently published actual data on curtailment (figure included in page 81 [5]). In 2023, the curtailment rate for variable renewable energy sources surpassed 5 % in all countries mentioned in the report, with the exception of China and Italy. The report predicts that these rates will rise to over 10 % by 2028.

Energy modelling provides valuable insights on this topic. However, there is a discrepancy regarding the appropriate temporal resolution for the analysis in global models, with many operating at an annual scale [6]. IAMs typically use time slices representing typical days (e.g., summer weekdays, winter holidays) or the residual load duration curve approach (RLDC) to determine the generation mix, and requirements of supply capacity [6]. The existing literature widely recommends, at least, hourly analysis to avoid inconsistencies. Hancheng et al. [7] utilized data from an hourly power sector model to enhance the representation of curtailment and storage in AIM (Asia-Pacific integrated model), asserting the importance of incorporating hourly fluctuations in IAMs. Research in Spain highlighted issues with managing combined cycles gas turbines due to the hourly dynamics of the electricity market [8]. Conversely, Brouwer et al. [9] proposed establishing a minimum hourly reserve level in contingency plans following surveys made to system operators. A methodological review concluded that an adequate accuracy of at least 8 h is sufficient for assessing the energy mix, costs, emissions, and curtailment [10]. The annual carbon emissions were underestimated by 12.75 % when comparing the 1-h and 8-h temporal resolutions.

Challenges associated with modelling VRES (variable renewable energy sources) in large models have been pointed out [11]. Firstly, using a too coarse time-step may lead to inaccurate system operation estimates, such as overestimating the among of demand met by fluctuating renewables and their financial attractiveness (section 3.2 in Ref. [11]). Secondly, the computational costs can become prohibitive when extending detailed simulations up to 2050. Thirdly, the complexity arises from the interconnection between different sectors (electricity, heating/cooling, industry, transportation) to increase the share of renewables in primary energy. Ringkjøb et al. [12] suggest addressing these issues by either linking a short-term operational model with a long-term holistic model or by directly integrating capabilities within a single model. A fourth challenge highlighted in Ref. [11] pertains to the transparency and uncertainty surrounding model parameters and policy decisions. Lastly, capturing the human dimension (public acceptance, human behaviour, etc.) poses another significant challenge to address.

The first and third challenges have been fixed through the integration of MESSAGEix (Model for Energy Supply Strategy Alternatives and their General Environmental Impact) and GLOBIOM (Global Biosphere Management model). Together, these models represent the only IAM currently capable of considering hourly production profiles of variable renewable energy sources. Regarding technologies that introduce flexibility into the power system balance, IAMs vary in the number of options they incorporate. For example, GCAM (Global Change Analysis Model) includes backup technologies, while POLES (Prospective Outlook on Long-term Energy Systems) offers a broader range, including demand-side management, vehicle-to-grid connections, power-to-heat/hydrogen, storage, and grid batteries ([6], table A.2).

A compelling solution that balances the trade-off between accuracy and computational cost (first and second challenges) was proposed by Welsch et al. [13]. They suggest that the outcomes of operational hourly models (such as PLEXOS, an energy modelling software) can be replicated in lower-resolution energy models (OSeMOSYS, Open Source energy MOdelling SYStem, monthly model) by incorporating operational constraints (e.g., maximum instantaneous wind generation share) derived from data analysis on PLEXOS results. This approach mirrors the concept outlined in the current work.

To enhance global policy assessment on climate change and energy transitions, the H2020 Locomotion project has been initiated to develop a new integrated assessment model following the legacy of MEDEAS (Modelling the Energy Development under Environmental And Socioeconomic constraints [14]). The new model, named Within Limits Integrated Assessment Model (WILIAM [15]). This model is available in Python, open source [16]. A synthesis and scenario assessment of WILIAM can be found in Ref. [17]), is a system dynamics simulation tool that captures complex feedback loops and nonlinear relationships among energy, economic, material, social, and environmental factors. WILIAM expands on the interactions between the Earth and human systems by incorporating eight modules: society, demographics, economy, finance, energy, materials, land and water, and climate. Through a combination of top-down and bottom-up modelling approaches, WILIAM enables the exploration of long-term socio-ecological transition pathways while considering the planetary boundaries and socio-economic constraints.

In a previous work [6], we successfully developed a statistical approach to reduce the computational complexity and efforts needed for estimating annual indicators in the energy module of IAMs through a concise set of analytical equations. However, certain methodological limitations were identified. Firstly, the use of machine learning and artificial intelligence was not possible due to the constraints of the IAM being developed, WILIAM. The software used to develop this model, Vensim, does not contain a machine learning toolkit. From a conceptual standpoint, system dynamics emphasizes transparency to ensure clear information tracing, whereas some machine learning methods, like neural networks, employ "black-box approaches", which can be seen as a drawback in terms of ethical practices [18]. Secondly, the exponential growth of combinations poses a challenge. As the number of inputs increases, the number of simulations required to capture the information grows exponentially according to the formula x^n, where x represents the number of values per input, and n represents the number of predictors. To address these issues, the current work incorporates the first two conclusions of [6] namely, the implementation of parallel processing and machine learning algorithms for the feature selection step, and introduces a new strategy for generating statistical data to avoid the exponential increase in computational burden.

In this article, we have devised an approach utilizing regression analysis to endogenously estimate the capacity factors of variable renewables in WILIAM depending on the state of the energy system, including the capacity mix of power and heat generation plants, availability of flexibility options, and the structure of final energy demands. By integrating this approach with other modules, the IAM is able to establish a standardized method capable of incorporating hourly impacts throughout the energy transformation processes, crucial in deep decarbonization scenarios. Additionally, this study examines and confirms the reliability of regression analysis when applied to the 27 countries forming the current European Union (EU27 hereafter) within a global modelling framework developed using the system dynamics methodology.

Research question: does integrating regression models that exact hourly information from an energy model into an IAM provide consistent results?

The article is structured as follows. Section 2 explains the novelties, logic, and scope of the updated model. Section 3 details the results of scenarios developed for this study. Lastly, section 4 outlines the conclusions and suggests new ways for further research.

2. Materials and methods

Fig. 1 illustrates graphically the workflow implemented to represent energy variability in the IAM. Four main steps.

1. Initially, the user defines the inputs and outputs of the hourly energy model that depicts the issue of curtailment. This task includes a range per input for the uniform distributions applied during the randomization of simulations (first two boxes in Fig. 1).
2. Then, a procedure automatically generates all the input files for the energy model, runs the model as many times as input files exist through a parallel processing approach, and creates the database including the valuable information for the next step.
3. Following this, the procedure conducts multiple logistic regression analysis with the content of the database. From the selection of inputs (features) to estimating the weights of the analytic equations that relate them with the outputs (regression models).
4. Finally, the integrated assessment model has been modified to successfully incorporate the analytic equations. So the user only needs to introduce the weights as part of the inputs for the IAM.

It is essential to note that while the method can be replicated in other models, it has been tailored for EnergyPLAN (an hourly energy system model) and WILIAM (an integrated assessment model). Additionally, there are interconnections between the steps. For instance, limitations on the number of simulations impact the experimental design. The interaction of the IAM with the analytical equations illustrates a feedback loop between regression analysis and the IAM's methodology (system dynamics). Several information loops were necessary to determine the optimal parameters.

2.1. Regression analysis

This section comprises selecting inputs and outputs of EnergyPLAN, defining the range of values for these inputs, creating and simulating files with EnergyPLAN, and organizing the results for computing logistic regression models.

2.1.1. Design of the experiment

The IAM used in this study aims to evaluate energy transitions towards 100 % renewable energy systems. The experiment is designed to estimate potential energy curtailment based on the state of the energy system, including the capacity mix of power and heat generation plants, availability of flexibility options (storage, power-to-X, etc.), and the structure of final energy demands. The final energy demand is divided into four economic sectors: electricity, heat, transport, and industry. All decarbonization measures, based on renewables and flexibility options, are focused on the power system. To simplify the analysis, certain assumptions were made. The heating sector is represented as a regional district network with interconnected entities, including total heat demand, contributions from combined heat and power units (CHP), and two power-to-heat flexibilities (heat pumps and electric boilers). Transport flexibility is achieved through vehicles with smart charge-discharge technology for power exchange between the grid and batteries. Industries are assumed to rely on synthetic fuels based on hydrogen, with considerations for demand and electrolyser capacity to enable flexible fuel production instead curtailment.

The relationship between the system's state and immediate consequences is quantified through regression analysis. This method aims to discuss whether logistic models better capture potential curtailment effects than our previous work, where wind and solar power generations where found critical technologies of the problem [6]. EnergyPLAN[1] calculates the critical excess of electricity production (CEEP, potential curtailment). In this model, the last option to manage CEEP is curtailment in solar and wind power plants, resulting in reduced capacity factors due to insufficient system flexibility. Decreasing capacity factors of solar and wind power plants occur when there is high installed capacity of these technologies but limited flexibility options.

In order to provide data for regression analysis, the method requires data generation. To precisely depict curtailment on an hourly basis, the following process was implemented.

1. Identify the most influencing demands and technologies for determining curtailment.
2. Verify EnergyPLAN includes sufficient inputs to represent the variables identified in the previous step.
3. Group the inputs logically to ensure coherent changes based on hypotheses. For example, the heat demand and infrastructure (such as large heat pumps and boilers) in district heating networks are interrelated.
4. Assign numerical values (ranges and constants) to all inputs. These values are determined based on data collection and expertise in energy modelling.

The concept of selecting a generalized case study for the experiment has facilitated the design's independence from the specific region. In this approach, a constant legacy electricity demand. In this work, it is named "legacy" electricity demand the one originated from the historical year and its projection, in such a way that total electricity demand is the same plus new demands coming from flexible electricity demand (daily, weekly and monthly) [6]. Legacy demand serves as the basis for all inputs and outputs, in a way that the inputs and outputs are rescaled according to this reference in the IAM. However, hourly distributions, specific to each region, are assumed as constant in all simulations. So, simulations would need to be repeated if these distributions would change. The values ranging from almost zero to very high numbers encompass and validate regressions across a wide scenario space. Zero values are excluded from the ranges to prevent an abundance of NaN values during regression analysis.

A relevant methodological novelty respected to the previous publication [6] involves the strategy for creating the files intended to be executed with EnergyPLAN. After defining the numerical inputs, uniform probability distributions are utilized to introduce stochastic variability among independent cases, thereby preventing of biased criteria. In this study, we utilized 13 clusters of input data combined to generate 12,800 simulations within a reasonable time frame (approximately 6 h on our machine[2]). To address this challenge, we organized inputs by identifying a representative one of them and then establishing proportional or constant relation with the others. These groupings, called *clusters*, along with the corresponding equations and values used for this process are detailed in table A. 1.

2.1.2. Simulations with the energy model

Building upon the methods outlined in the previous article [6], significant enhancements have been made to the code. The complete updated script is now open and accessible through an at a Gitlab repository.[3] To optimize the execution and minimize the runtime, parallel

[1] It is an energy module, open-access in the use, and very disseminated across literature (read the introduction section of [6]). The documentation of EnergyPLAN is available at [58], and reference studies are [19,59].

[2] AMD Ryzen 7 4800H CPU @ 2.9 GHz (8 cores). RAM: 16 GB.

[3] https://urldefense.com/v3/__https://github.com/lherc7/LOCOMOTION__;!!D9dNQwwGXtA!RtVm4Fwq2MkXjOQ4QVrQPp8KQYmseF0Zz2HrE93bdu1KerAUG6_ZmAJQ8RE2265UDtiF0hbjSRaGRmKF0LkCMEo$.

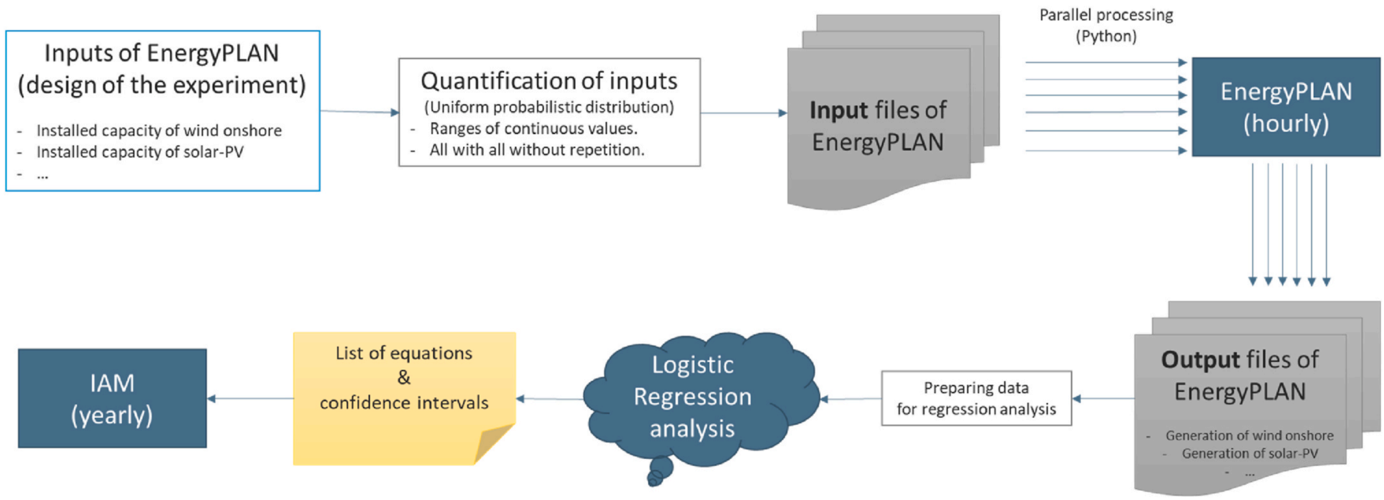

Fig. 1. The methodology overview in this work begins with selecting EnergyPLAN inputs and concludes with modelling in the IAM.

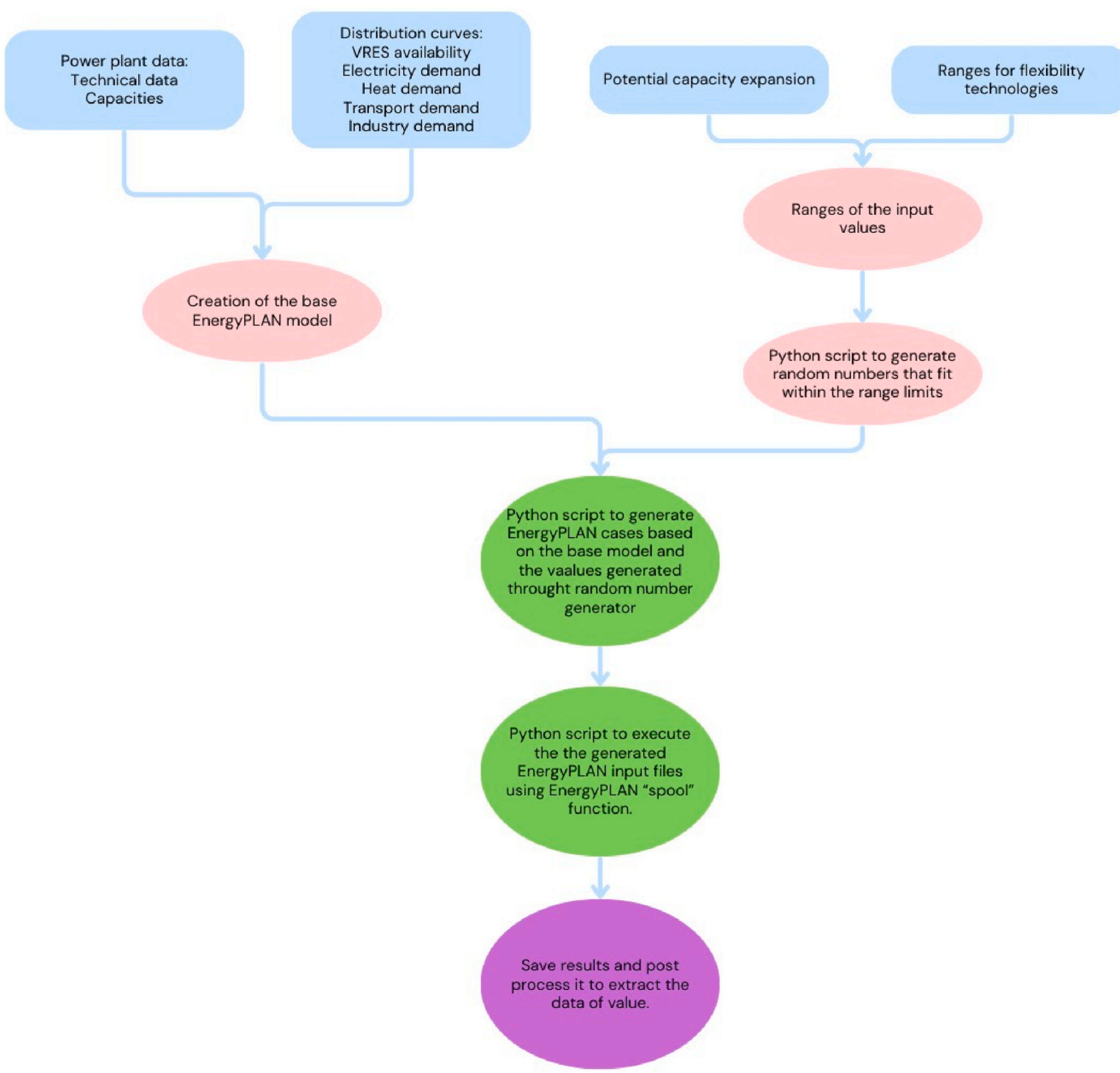

Fig. 2. Flow chart of the process to generate the input files for EnergyPLAN, simulate all the cases, and save the results of interest in an orderly manner.

Table 1
Pseudocode for the process in Python and EnergyPLAN.

The modeller creates the base input file for EnergyPLAN that will be used in simulations.
The modeller creates the table that contains the lower and upper values for the considered technologies.
Python script reads the table containing the data on the lower and upper bounds.
Load a default EnergyPLAN model case of input file.
Creation of the predetermined number of EnergyPLAN input files based on the base EnergyPLAN file and randomly generated values from a given range.
Create the list of input files.
Load subsequent lists with the names of the files into spool function.
Run the function.
Save the results.
From results data, perform postprocessing to extract only parts of the data of value to the further process.
Delete the rest of the data to save on space.

processing of EnergyPLAN [19] simulations has been implemented, leveraging 16 cores simultaneously. The simulations are executed using a modified *spool* function via the command terminal. While the clusters remain unchanged in the previous approach, uniform probability distributions are now employed to determine their values for every simulation, being them limited by a lower and upper bound. This process is illustrated in Fig. 2 (pseudocode provided in Table 8). The boundaries of the parameter values are established in a manner similar to the data utilized in prior research [6]. The distributions are presented in table A1. In many instances, the ranges are broader, particularly on the lower end, as this approach allows for the evaluation of scenarios with limited or no definitive options. For certain cases, such as the generation capacity for wind and solar energy, the upper limits were expanded through an iterative process. This adjustment was necessary to consider unprecedented additions of capacities to exploit renewable energy sources that may be assumed in *green* scenarios.

The EnergyPLAN inputs were parametrized similarly to previous work [6]. The base case scenario file was created, and then the possible changes in the values for some variables were defined. These changes include 13 clusters of values that change in unison within each cluster. These clusters are related to the capacities of solar PV, wind, dispatchable non-fossil fuel generators such as nuclear, geothermal, and hydro. Additionally, the static storage has its own cluster with values for storage capacity, input, and output capacity.

The following cluster pertains to heat demand and is presented by a single value for the total heat demand in district heating. Subsequently, the cluster related to the capacities in cogeneration power plants is defined. This cluster provides information on the capacities of thermal power plants in operation mode when supplying heat to the district heating network, in operation mode when supplying only electricity, as well as the thermal capacity.

Heat pump cluster specifies the capacities of heat pumps in district heating and the size of the heat storage. Similarly, the capacity of the electric boiler and associated thermal storage is defined.

The electric vehicles cluster outlines the demand for charging electric vehicles in the smart charge mode, including factors such as charging capacity, storage capacity and demand for other transport technologies such as internal combustion engines. The vehicle-to-grid (V2G) capacity is defined separately.

The hydrogen demand and supply are specified in two different clusters.

Within the hydrogen supply cluster, electrolyser capacity and hydrogen storage are defined.

The last cluster pertains to flexible demand, where the total sum of flexible demand is inputted along with the flexible capacity that can be utilized.

The process commences with establishing the fundamental parameters of the energy system, setting them as constant assumptions for consistency throughout the regional case study. These constants include the CEEP strategy, the hourly distribution profiles of electricity, heating, and transport and demands, and the variable energy generation distribution profiles. These values do not change across iterations, leading to the development of a foundational or reference simulation that serves as the basis for subsequent steps.

The upgraded version of the spool function executes all the cases using EnergyPLAN. Initially, the list of cases is divided into a set of instances, with each instance determining the simultaneous runs activated on the machine. Additionally, the total number of cases to be executed is specified by the user.

In each instance, the option to load 10, 50 or 100 cases simultaneously per core in the parallel spool functions is available. After the runs in each spool function are completed, post-processing of the results takes place. The relevant data is saved to the designated folder, while any excess data is removed.

The more files per run, the greater the memory demand and processing time. Thus, the number of files represents a trade-off between time efficiency and hardware resources.

Considering the possibility of having a combination count that is not divisible by an even number of multiprocessing cores, the final instance adapts by the remaining number of cases.

Values updated according to recent studies.

- The average annual distance driven with an electric vehicle (EV) has been increased to 150,000 km [20].
- The average autonomy of an EV has been reduced to 250 km [21].

A second round of simulations was necessary to examine the impacts of low-flexibility configurations on the outputs, particularly focusing on the decrease in the capacity factor of solar and wind power plants. In this study, utilizing a probability distribution approach proved beneficial, leading to a reduction in the number of cases run from the 3,188,646 in the previous experiment to just 12,800.

Hourly profiles were tailored to accurately depict the variable renewables technologies and demands specific to the analyzed region, encompassing the 27 countries forming the current European Union (EU27). These profiles are visually accessible in appendix B.

2.1.3. Fitting multiple logistic regression models

In comparison to the previous study, separate logistic regressions (equation (1)) were developed for the capacity factors of wind and solar technologies. This approach was chosen because these variables are constrained to values between 0 and 1, constraining the regression training.

The regression process begins with co-linearity and correlation analysis on the covariates. Subsequently, univariate models are constructed for each of the technologies (wind and solar capacity factors), to evaluate the individual statistical significance of the corresponding covariates. A significant threshold of 5 % (p-value) is set for this assessment. Upon identifying statistically significant covariates, logistic regression models are developed with a polynomial factor of two for covariates to explore non-linear associations, along with the inclusion of two-way interactions.

The coefficients (sign) of each final covariates and interaction in the model are evaluated to confirm their impact on reducing capacity factors as outlined in the literature. Logistic regression proved superiority over alternative regression approaches such as linear regression when

Table 2
Comparison between the multiple logistic regression and multiple linear regression models. MSE: mean squared error.

	Solar		Wind	
	R2	MSE	R2	MSE
Logistic model	0.927	0.000721343	0.938	0.001429833
Linear model	0.882	0.001008413	0.882	0.002371267

evaluated based on prediction accuracy. The model validation was conducted using metrics such as R-squared, Mean Squared Error (MSE), and assessment of residual normality.

Table 2 summarizes this comparison between multiple linear and logistic regression models based on the same predictors. Both were trained with the same inputs and data. The logistic shape enhances the accuracy, as the higher R-squared statistic and lower mean squared error show. Consequently, only the significant coefficients of the logistic regression models were finally integrated into the IAM called WILIAM.

$$p(x) = \frac{1}{1 + e^{-\left(\beta_0 + \sum_{i=1}^{n} \beta_i \bullet x_i\right)}} \tag{1}$$

Providing a more detailed explanation of the performance of the logistic models necessitates further analysis. Each point in Figs. 3 and 5 points out the coordinates of two values: the output from EnergyPLAN (y-axis) and the output from the logistic regression model (x-axis). A perfect accuracy is indicated by a straight red line extending from 0 to 1. A uniform cloud of points around the red line is observed, showing no specific preference or non-linear trend. The goodness is further evidenced by the histogram of residuals in Figs. 4 and 6, where the majority of cases centre around zero (this was not the case for linear regression models). Specifically, Table 4 and Table 6 present a summary of the numerical residuals, with median values of −0.02452 for solar, and 0.07593 for wind power plants (see Table 5).

Table 3 displays the coefficients used to calculate the reduction in the capacity factor of solar power plants. The absence of significance (considered at a p-value of 5 %) for stationary storage is unexpected. Following tests conducted with EnergyPLAN, it was deduced that this lack of significance stems from the low priority given to this technology in the merit order curve for hourly electricity supply. Consequently, EnergyPLAN underestimates the impact of stationary storage, including hydropower and utility grid batteries. Similarly, electrolysers (HYDROGEN_SUPPLY) did not exhibit significance in the fitting process as a main effect. However, the interaction between HYDROGEN_SUPPLY and Solar appears as significant.

2.2. *Regression models in an integrated assessment model*

The following section overviews the energy module of WILIAM before delving into the necessary modifications to integrate the regression models and their effects.

2.2.1. *The energy module of the integrated assessment model*

Ensuring an accurate representation of energy is crucial for evaluating future sustainability pathways. The main objective of the developed energy module is to calculate the primary energy requirements and associated greenhouse gas (GHG) emissions needed to meet economic demand. Fig. 7 illustrates the submodules that make up the energy module of WILIAM, highlighting the principal interrelationships across modules.

This module is structured into seven sub-modules.

(1) **End-use:** Translates the economic demand into final (marketed) energy demand using a hybrid approach that combines bottom-up analysis with sectoral energy intensities for different sectors. The following energy carriers are considered: electricity, gas, heat, hydrogen, liquid, solid bioenergy, and solid fossil.
(2) **Energy transformation:** Maps the entire energy conversion chain from final to primary energy, including intermediary energy commodities and an allocation function for power plant utilization.
(3) **Energy capacity:** Models power plant capacity stock, decommissioning of expired capacities, and the build-up of new capacities, with the latter driven by an allocation function. The allocation of new capacities of process transformation (CHP plants, power plants and heat plants) is determined by a one-to-many allocation function ALLOCATE_AVAILABLE from Vensim software (Vensim DSS [20]) which is governed by exogenous priorities that range from 0 (less priority) to 1 (maximum priority).

Table 3
Statistics of the output representing the reduction in the capacity factor of solar power plants (logistic regression model).

SOLAR_CF_REDUCTION (logistic)	Coefficient	Std.Error	z-value	Pr(>|z|)	
(Intercept)	−9.22E+00	1.25E+00	−7.409	1.28E-13	***
SOLAR	1.80E-04	2.34E-05	7.66E+00	1.83E-14	***
SOLAR^2	−1.02E-09	1.43E-10	−7.15E+00	8.43E-13	***
WIND	2.73E-05	1.17E-05	2.33E+00	0.01957	*
WIND^2	−1.69E-10	6.92E-11	−2.45E+00	0.01443	*
HEAT_DEMAND	−1.48E-03	1.14E-03	−1.29E+00	0.19706	
HEAT_DEMAND^2	3.38E-07	8.61E-07	3.93E-01	0.69468	
ZERO_GHG_SEMIFLEX	2.75E-04	6.35E-05	4.33E+00	1.51E-05	***
ZERO_GHG_SEMIFLEX^2	−1.77E-09	1.94E-09	−9.11E-01	0.3623	
HYDROGEN_DEMAND	−5.12E-02	1.29E-02	−3.98E+00	6.86E-05	***
HYDROGEN_DEMAND^2	2.06E-05	1.09E-04	1.89E-01	0.84993	
FLEXIBLE_DEMAND	−3.04E-02	9.43E-03	−3.22E+00	0.00129	**
FLEXIBLE_DEMAND^2	−6.01E-05	5.87E-05	−1.03E+00	0.30553	
V2G	−1.90E-05	3.75E-06	−5.06E+00	4.20E-07	***
V2G^2	−3.77E-12	9.02E-12	−4.18E-01	0.67618	
HYDROGEN_SUPPLY	−3.21E-05	7.88E-05	−0.407	0.68375	
HYDROGEN_SUPPLY^2	5.62E-10	4.18E-09	0.135	0.89296	
SOLAR · WIND	4.57E-11	1.06E-10	0.433	0.66533	
SOLAR · HEAT_DEMAND	5.97E-09	1.14E-08	0.525	0.59947	
SOLAR · ZERO_GHG_SEMIFLEX	−1.63E-09	5.89E-10	−2.767	0.00566	**
SOLAR · HYDROGEN_DEMAND	3.56E-07	1.37E-07	2.597	0.0094	**
SOLAR · FLEX_DEMAND	1.46E-10	7.80E-10	0.187	0.85157	
SOLAR · V2G	1.37E-10	4.18E-11	3.29	0.001	**
SOLAR · HYDROGEN_SUPPLY	2.45E-07	1.01E-07	2.425	0.01531	*

Significance codes: 0 '***'; 0.001 '**'; 0.01 '*'; 0.05 '.'; 0.1 '' 1

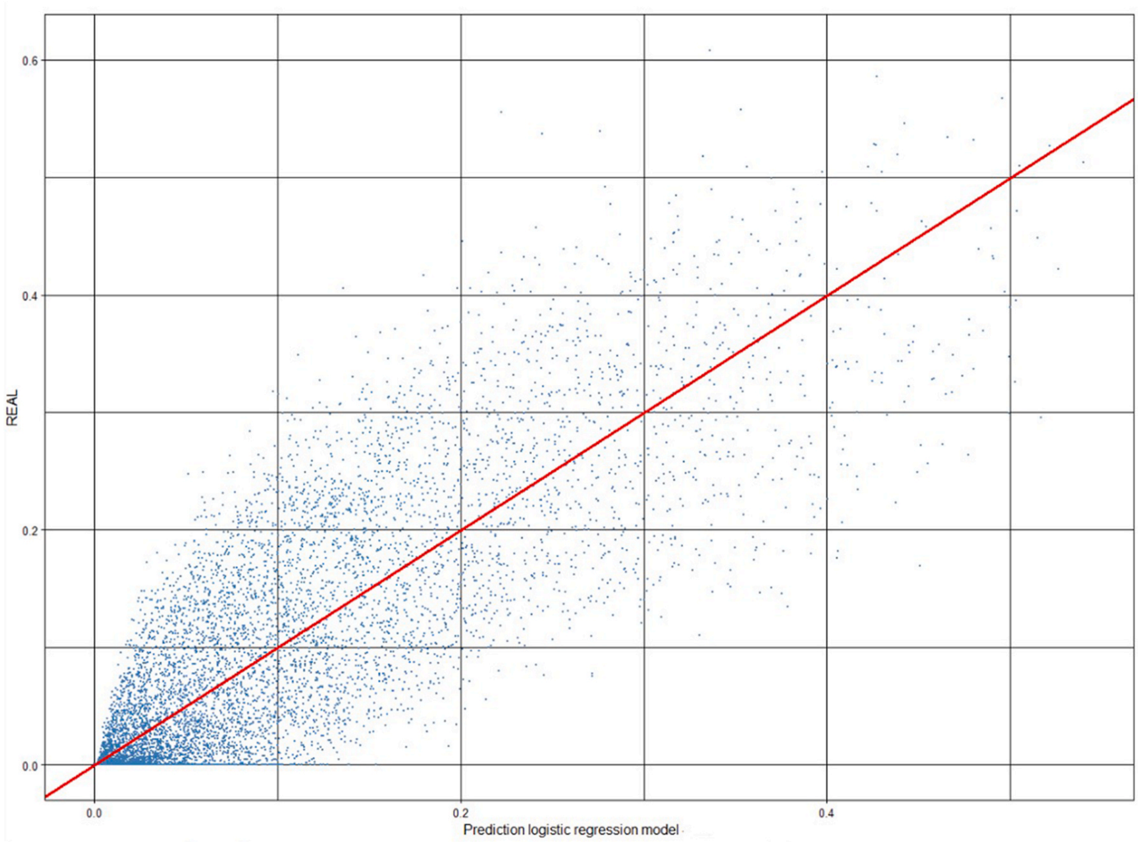

Fig. 3. Output (reduction of the capacity factor in solar power generation) delivered by the logistic regression model (X axis) in comparison to the real value calculated in EnergyPLAN (Y axis). The output fitted a binomial probability distribution.

(4) Energy Return on Energy Investment (**EROI**): Computes the indicator of specific renewable technologies as well as for the whole system [22].
(5) **Variability and storage:** Tracks sub-annual effects on annual energy balances based on the current power system setup, including demand-side management, storage, and sector coupling (the main topic of this paper).
(6) **Techno-sustainable potentials:** Considers geographical, resource and EROI constraints of Renewable Energy Storage (RES).
(7) **Emissions:** Calculates (direct) GHG emissions associated to the combustion of fossil fuels in the energy module.

For a comprehensive overview of the energy module of WILIAM, cf [16,23]. An explanation of the capacity expansion and transformative processes of electricity is provided here to enhance understanding of the components and outcomes of the model developed in this work.

In essence, the expansion of traditional power plants follows a cycle of influences. The process begins with the capacity stock, which serves to calculate the available electricity production by technology, taking into account maximum full load hours (subject to constraints). Following this, the shortfall between the available electricity and the electricity demanded by the economy triggers the need for new installations.

The distribution of the energy shortfall among various technologies is determined by two factors. Firstly, each technology sets a maximum expansion limit for its supply, depending on factors like current installed capacity, land, capacity factors, and biomass available. Secondly, the allocation process is modelled throughout a dedicated function within the Vensim DSS software, which emulates a market with access priorities. This functionality present in the software utilized for WILIAM's development (Vensim DSS [24]). This allocation function is designed to promote competitiveness, ensuring that each technology contributes to the supply. Generally, technologies with higher priority receive a larger portion of the shortfall.

Finally, the annual installed capacity involves transforming the energy shortfall (measured in EJ/year) into new capacity (measured in TW/year) through unit conversions and consideration of the full load hours once more.

2.2.2. Integration of the logistic regression models and flexibility options in WILIAM

This implementation of regression models in WILIAM requires three key advances: a) Clearly depicting the energy demands and technologies using regression models within the IAM; b) Establishing equivalence between the inputs and outputs in the IAM and EnergyPLAN; c) Incorporating feedback loops from the outcomes of the regression models (outputs) back to the root causes of the issue (inputs) within the IAM, along with addressing any secondary effects on other components.

New implementations were necessary in WILIAM to incorporate the flexibility options utilized in the regression models. These include hydrogen and synthetic fuels supply, stationary storage (PHES and electric batteries), power-to-heat (heat pumps and electric boilers), as well as the vehicle-to-grid capacity (V2G) and demand management. The stock of installed capacities is governed by the differential equation (2), which considers the equilibrium between the expansion capacity (*EC*) and the decommission capacity ratio (stock divided by the facility's lifetime).

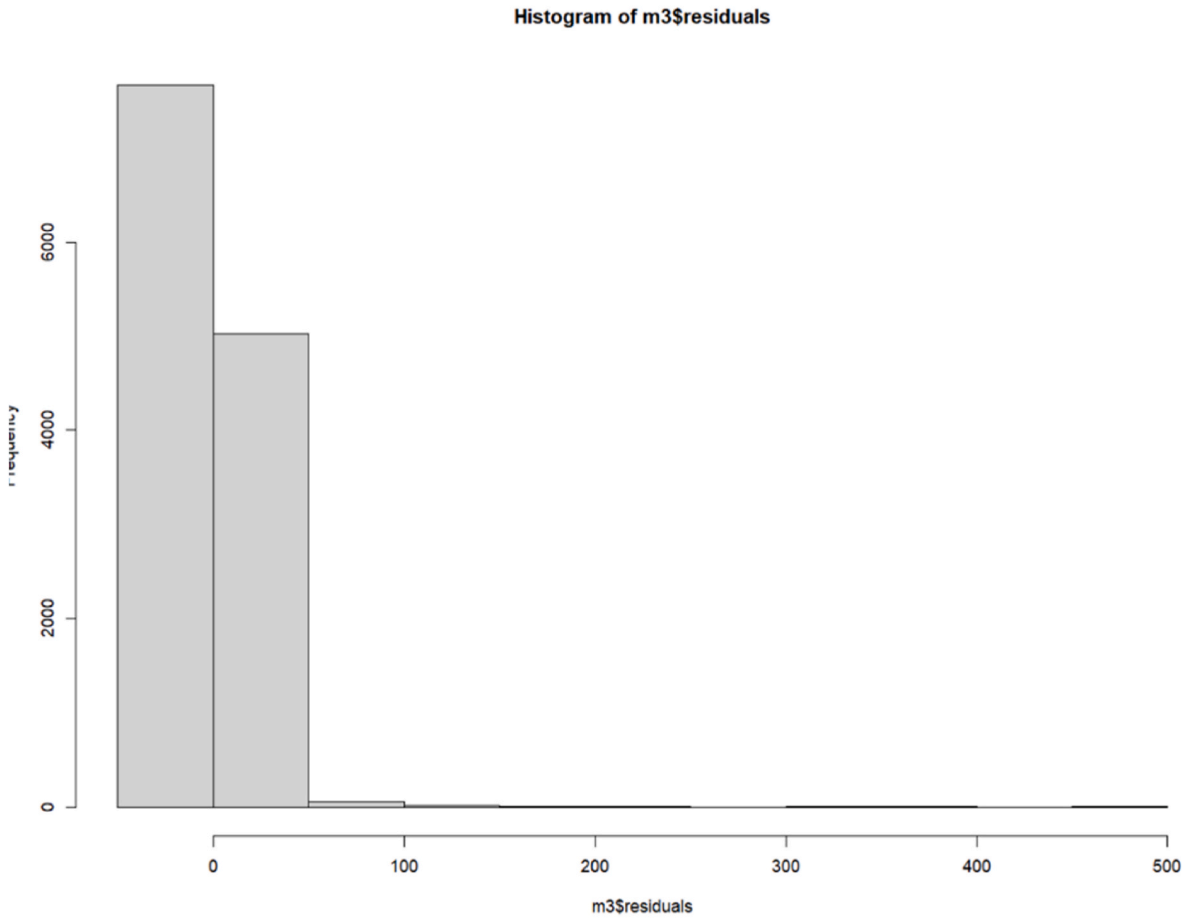

Fig. 4. Histogram of residuals residuals for the logistic regression model depicting the decrease in the capacity factor of solar power plants.

$$\frac{d}{dt}stock_i = EC - \frac{stock_i}{lifetime_i} \tag{2}$$

The expansion is based on both an exogenous policy assumption over time and an endogenous mechanism for installing new flexibilities (explained later). This expansion is constrained by regional potentials, such as the maximum hydropower capacity (PHES) or the final heat demand (power-to-heat technologies). The expansion of heat storage is directly linked to the installed capacity of heat pumps.

Electrolysers are categorized into stationary and flexible units to model varying trends in capacity factor, lifetime and profitability. The hydrogen generated is distributed among three fuels: synthetic methane, synthetic methanol, and pure hydrogen. If demand of pure H2 or synthetic fuels rises, any surplus production is met by new stationary plants. Conversely, the capacity of flexible electrolysers is increased in the presence of curtailment in the power system. Alternatively, the modeller can adjust an external policy to expand electrolyser capacity between specific years.

Thus, an exogenous policy assumption was implemented to depict the impact of flexible demand response, the progression of synthetic fuels in the liquid and gas shares of final energy, and the proportion of V2G charging capacity in the electric vehicles fleet. These policies are linearly phased in over time (t), starting from an initial value (Ti) and reaching a final value (Tf), as outlined in equation (3).

$$value_t = \frac{value_{Tf} - value_{Ti}}{Tf - Ti} \tag{3}$$

Fig. 8 illustrates the causal loop diagram integrated into WILIAM to establish feedback between the inputs and outputs of the regression models. It displays three loops addressing the occurrence of curtailment in the power system. In the right loop, a greater volume of curtailed renewable energy (TWh) leads to a reduction in the capacity factor, consequently raising the average expansion capacity (ΔIC, as per equation (4)) needed to fulfill the electricity demand. This excess capacity is met by the installation of new suppliers within the system.

In the left loop, flexibility options respond to curtailment by incorporating new installations. The determination of which technologies to expand is made within a market model structured around the priority-based ALLOCATE AVAILABLE function with the same priority to all flexibility options for the sake of simplicity. Greater curtailment results in a more substantial expansion of flexibility options to counteract electricity losses effectively.

The third loop in the middle introduces a technical assumption regarding the capacity expansion of variable renewables. If curtailment surpasses a specified maximum threshold (MAX_CURTAILMENT_SP in equation (5)), an implemented penalty logistic function (equation (6)) impedes the expansion process.

The structural validation conceptualized in Fig. 8 could not be assessed in the IAM due to two reasons. Firstly, there are not empirical public data of curtailment at EU27 level, so we cannot compare our results with them. Secondly, the levels of VRES simulated in this work have no real experience in the world. Data provided by organisms like the IEA's report [5] are very valuable for this analysis. We hope to find enough data in the future to effectively address and compare models with real measurements in the power system. In general, literature has shown that validation of IAMs is subject to many issues in, e.g., reproducing historical observations [25].

$$\Delta IC = \frac{curtailment\,[TWh]}{8760\,[h]} \tag{4}$$

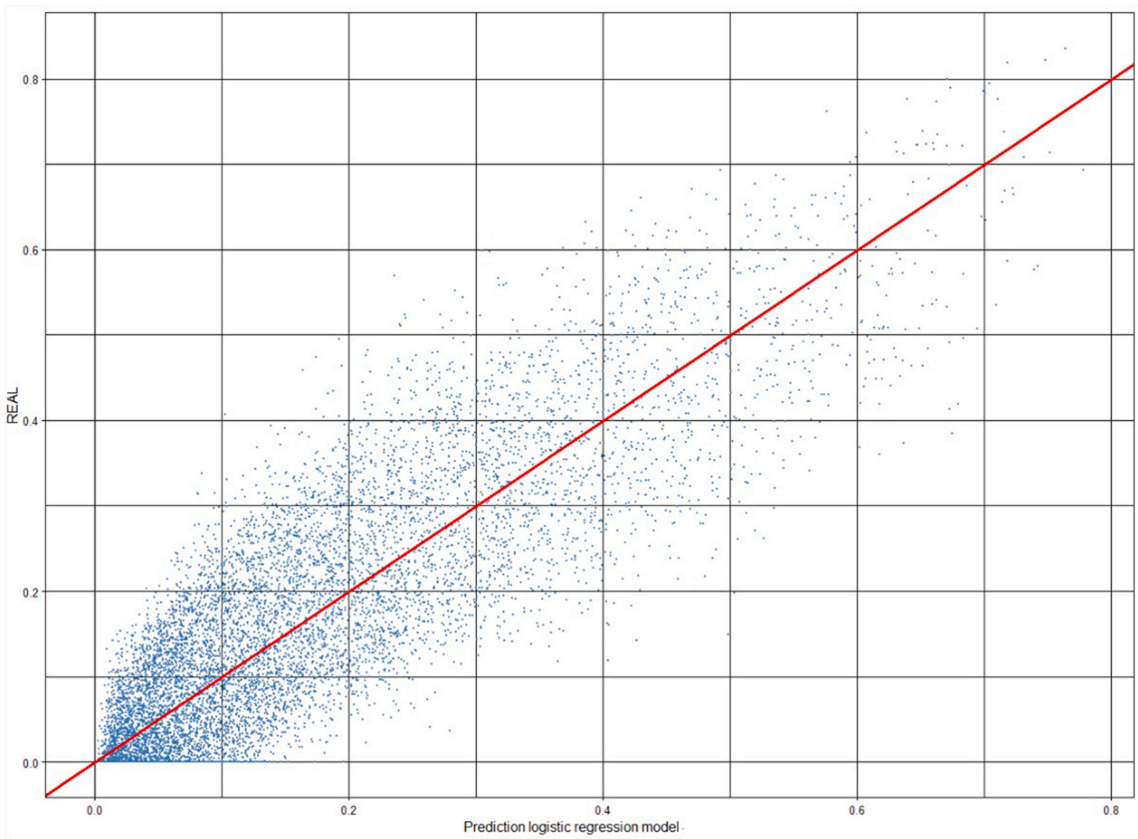

Fig. 5. Output (reduction of the capacity factor in wind power generation) delivered by the logistic regression model (X axis) in comparison to the real value calculated in EnergyPLAN (Y axis). The output fitted a binomial probability distribution.

Fig. 6. Histogram of residuals residuals for the logistic regression model depicting the decrease in the capacity factor of wind power plants.

Table 4
Statistics of residuals for the logistic regression model for the reduction in the capacity factor of solar power plants.

Min	1Q	Median	3Q	Max
−0.59604	−0.1201	−0.02452	0.03976	0.72008

$$signal\_curtailment_i = \frac{share\_curtailment\_elec}{MAX\_CURTAILMENT\_SP} \quad (5)$$

$$share\_loss_i = \frac{1}{1 + \left(\frac{(1 - signal\_curtailment_i) \bullet 0.5}{signal\_curtailment_i \bullet 0.5}\right)^2} \quad (6)$$

The modelling of power-to-heat technologies requires additions to the energy transformation chain. The integration leads to an increase in electricity usage and a reduction in heat demand for final energy demands. Additionally, the adoption of electrolysers (power-to-hydrogen technology) results in a rise of electricity consumption and a decrease in the need for liquids and gaseous fuels within the system.

The historical storage trend data was sourced from the IRENA database [26] for pumped hydropower storage (PHS), while data for

Table 5
Statistics of the output representing the reduction in the capacity factor of wind power plants (logistic regression model).

WIND_CF_REDUCTION (logistic)	Estimate	Std.Error	z-value	Pr(>|z|)	
(Intercept)	−6.73E+00	6.21E-01	−10.837	<2.0E-16	***
WIND	8.75E-05	1.05E-05	8.302	<2.0E-16	***
WIND^2	−2.07E-10	6.12E-11	−3.379	0.000728	***
SOLAR	7.39E-05	8.62E-06	8.573	<2.0E-16	***
SOLAR^2	−2.11E-10	5.42E-11	−3.882	0.000104	***
HEAT_DEMAND	−1.83E-03	6.48E-04	−2.82	0.004797	**
HEAT_DEMAND^2	1.16E-06	6.40E-07	1.816	0.069443	.
ZERO_GHG_SEMIFLEX	2.39E-04	3.69E-05	6.483	8.97E-11	***
ZERO_GHG_SEMIFLEX^2	−2.16E-09	1.44E-09	−1.503	0.132896	
HYDROGEN_DEMAND	−2.80E-02	7.37E-03	−3.795	0.000147	***
HYDROGEN_DEMAND^2	2.04E-05	8.00E-05	0.255	0.798602	
FLEXIBLE_DEMAND	−2.55E-02	5.23E-03	−4.879	1.07E-06	***
FLEXIBLE_DEMAND^2	1.22E-05	4.27E-05	0.286	0.775044	
V2G	−1.38E-05	2.05E-06	−6.704	2.03E-11	***
V2G^2	−1.43E-12	6.50E-12	−0.22	0.82561	
HYDROGEN_SUPPLY	−1.64E-05	3.65E-05	−0.45	0.652774	
HYDROGEN_SUPPLY^2	4.81E-10	3.09E-09	0.156	0.876365	
SOLAR · WIND	−3.71E-10	6.17E-11	−6.014	1.81E-09	***
WIND · HEAT_DEMAND	−7.66E-09	5.86E-09	−1.307	0.19115	
WIND · ZERO_GHG_SEMIFLEX	−1.26E-09	3.04E-10	−4.124	3.73E-05	***
WIND · HYDROGEN_DEMAND	1.00E-07	6.79E-08	1.476	0.139971	
WIND · FLEX_DEMAND	9.63E-08	4.99E-08	1.929	0.053765	.
WIND · V2G	8.36E-11	2.05E-11	4.074	4.62E-05	***

Significance codes: 0 '***'; 0.001 '**'; 0.01 '*'; 0.05 '.'; 0.1 '' 1.

Table 6
Statistics of residuals for the logistic regression model for the reduction in the capacity factor of wind power plants.

Min	1Q	Median	3Q	Max
−0.73477	−0.18999	−0.07593	0.11181	0.79293

stationary batteries was obtained from the International Energy Agency [27] and a German case study [28]. The lifetime of hydropower storage technologies (80 years) and stationary batteries (20 years) were extracted from Table 2 in Ref. [29].

3. Scenarios

The structure of this article is shown in Fig. 9. The study concentrates on the feedback generated by the regression functions within various segments of the energy module of the integrated assessment model, known as WILIAM. Consequently, a *green growth scenario* has been parametrized to illustrate the impact of this research.

A green growth scenario is envisioned as a form of environmentally sustainable economic growth that aims to attain development and climate objectives through innovations in the supply chain and cleaner production processes [30]. Consistent with Hickel and Kalis [31], these scenarios seek to decouple the growth of economic activities, typically measured by the gross domestic product, from carbon emissions. This decoupling is achieved through extensive utilization of renewable energy sources and the electrification of human activities.

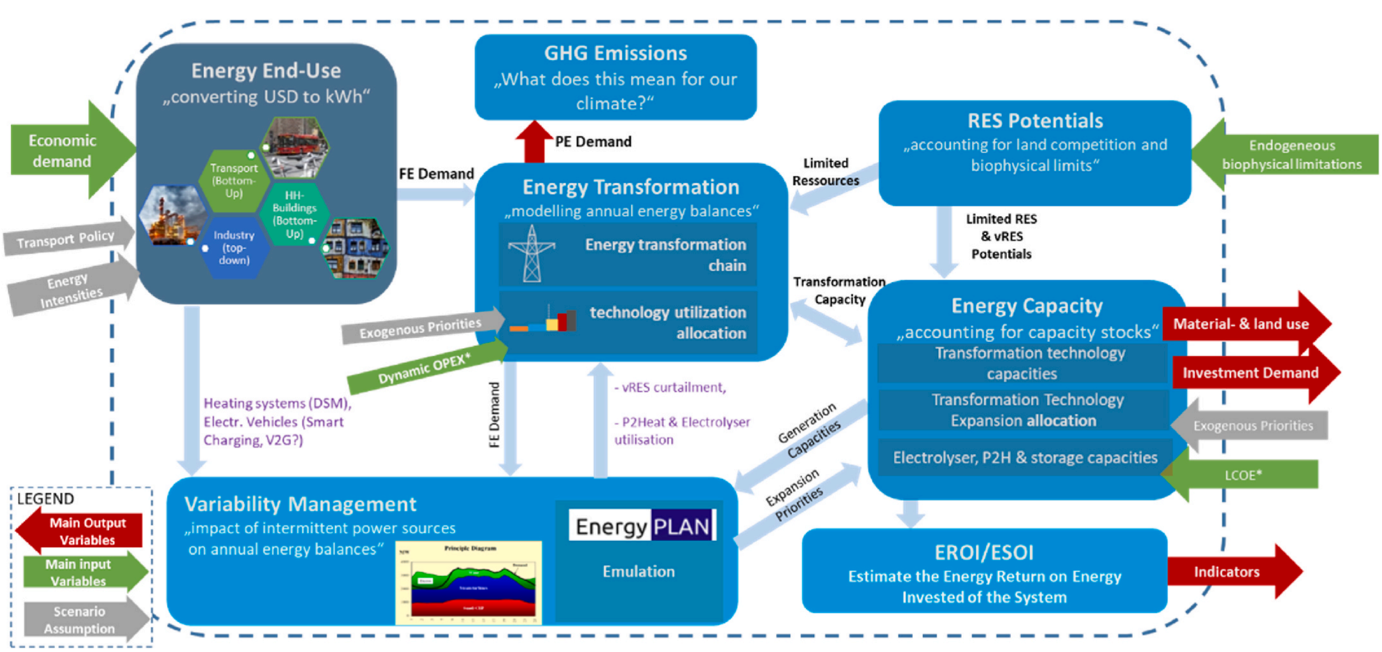

Fig. 7. General overview of the energy module in WILIAM.

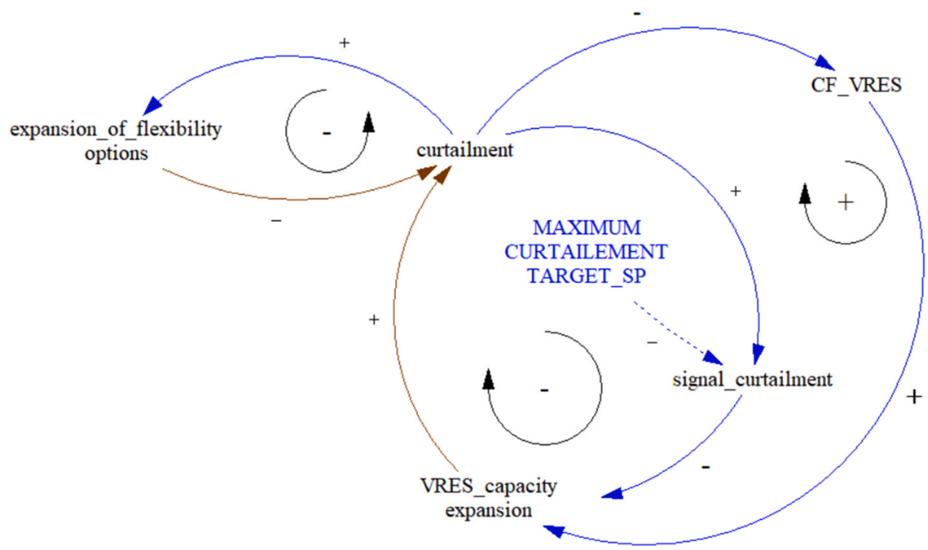

Fig. 8. Causal loop diagram of the factors afecting the management of energy variability in WILIAM.

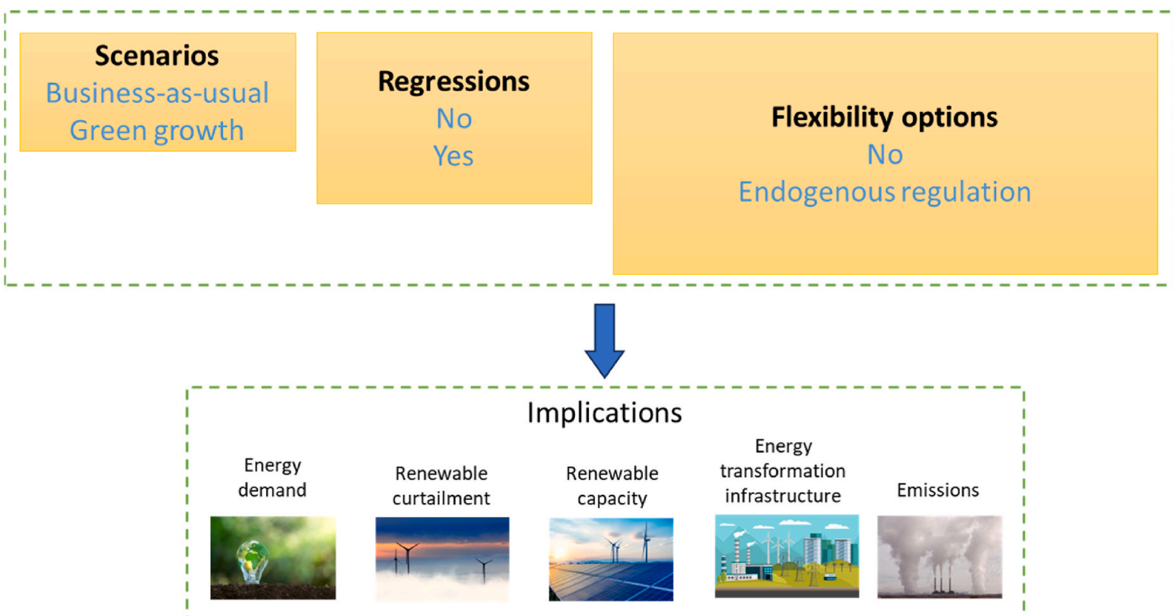

Fig. 9. Framework of this work to study the regression analysis in WILIAM.

For the two scenarios involving flexibility options, all policies start in 2025. The flexible demand increases from zero to 10 % by 2030. The percentage of liquids and gases replaced by hydrogen-based synthetic fuels rises from zero to 10 % by 2040. Lastly, the proportion of vehicle-to-grid electricity exchange during smart charging mode escalates from zero to 50 % of the total electric vehicle capacity by 2050.

The reference scenario is employed to understand the impacts of the green growth scenario on the model without curtailment effects or flexibility options (as it is defined as a low RES penetration scenario). After that, the green growth scenario is simulated in three distinct manners. First, curtailment is applied without expanding flexibility options. Second, curtailment is applied along with expanding flexibility options. Third, the latter includes a policy to restrict electricity curtailment to a maximum of 5 %. This 5 % limit is recommended by some authors for economic reasons [32] or as an ad-hoc assumption [33]. A brief description of these scenarios is presented in Table 7, while the names and meaning of the simulations are outlined in Table 8.

When implemented, the policy of flexible demand is iniciated in 2020. It gradually increases from 0 to a portion of the existing legacy electricity demand by 2030 (reaching 5 % in the scenario with flexibility options), after which it remains constant until the conclusion of the simulation.

The scenarios outlined here are not intended to mirror a realistic or probable future. Instead, their aim is to depict rather extreme situations to showcase the model's mechanics and explore the potential and limitations of the approach. Therefore, the scenarios tested aim to replicate current EU27 policies promoting the increase in renewable energy share and electfrification process. It is important to note that these scenarios should not be viewed as recommendations from the authors. Rather, the results illustrate the behaviour of the logistic functions generated by the regression analysis and the endougenous expansion of flexibility options (assigning equal priority to all technologies).

4. Results

To reduce complexity in figures, the 40 technologies of the energy

Table 7
Description of key inputs and assumptions for the green growth narrative in this article (EU27).

	Reference (REF)	Green Growth (GG)
Substitution between of final energies	Continuation of future trends in consumption of goods and services, along with sectoral final energy intensities.	Electrification of the economy. Promotion of substitution of fuels by electricity.
Capacity expansion of energy facilities	Historical values remain constant for the future. High values of power plants fuelled by gases (0.8) and onshore wind (0.7).	Increase the exploitation of renewable energy sources. Low values (0.2) for fossil fuels and high values for renewables (0.9).
Hydrogen	No promotion of synthetic fuels	Implications of transitioning from fossil fuels to hydrogen generated by electrolysers for industrial use (as feedstock). To decarbonize, an additional 1400 TWh of electricity (equivalent to ~0.16 TW of electrolysers in operation) will be needed by 2050. This shift impacts the production of ammonia and methanol in the chemical industry, liquids refinery, and steel production. These numbers are taken from Ref. [34].
Total transport passenger demand	There is no reduction in transport demand by mode and type of powertrain compared to past trends (passenger-km).	
Load factor and fuel efficiency in transport	The historical trend is assumed to continue, with no change in the intensity of people per vehicle (mode and type of powertrain).	
Passenger transport demand by mode	Passenger transport demand includes modal share, transport mode, and powertrain use. From 2025 to 2030, the policy assumes a broad transition to electric vehicles. Percentages vary by region. For example, in 2030, electric vehicles are projected to reach 32 % in Lithuania, 13 % in Malta, 21 % in Spain, 25 % in Sweden, and 26 % in Germany.	
Priorities for the allocation of capacity expansion of process transformation technologies	High values are assigned to renewables (0.7 for VRES) and lower values to fossil fuels (0–0.2).	Higher values are assigned to renewables (0.7 for VRES) while lower values are designated for fossil fuels (0–0.2).
Solar rooftop technologies	The available space on urban building roofs is divided equally, with 50 % allocated for solar PV pannels and 50 % for solar thermal systems.	
Improvement of solar-PV efficiency	An annual efficiency increase of 0.0015 is assumed from 2022 (20.5 %) to 2050 (24.7 %).	
RES potentials	RES potential modelling is documented in the wiki github [35]. Solar and bioenergy potentials are endogenosuly determined with the interaction with the land-use module. For more details about the modelling of the land availability for solar PV on ground cf [36]. For solar and wind the selected EROImin (standard) is 8:1. The rest of renewables are limited as follows: • Onshore wind: 3.3 EJ/year • Offshore wind (fixed): 2.9 EJ/year • Geothermal: 0.14 EJ/year • Dammed hydropower: 1.33 EJ/year • Run-of-fiver hydropower: 0.43 EJ/year • Oceanic: 0 EJ/year	
Storage potentials	• Pumped hydropower storage (0.057 TW) • Utility-scale batteries (0.2 TW)	

Table 8
Structure of simulations using the WILIAM integrated assessment model.

Acronym	Name	Simulation
A	REF	Business as usual without the effect of hourly resolution in the power system.
B	GG	Green growth without hourly resolution impact in the power system.
C	GG_VarEffects	Green growth with hourly resolution impact (through regression analysis) in the power system.
D	GG_VarEffects + FlexOpts	Green growth with hourly resolution impact (through regression analysis) in the power system and the active mechanism for capacity expansion of flexibility options.
E	GG_VarEffects + FlexOpts + MAXcurtailment	Green growth with hourly resolution impact (through regression analysis) in the power system, the active mechanism for capacity expansion of flexibility options, and limitation of electricity curtailment (5 %).

transformation submodule of WILIAM are aggregated and mapped under the following acronyms.

- "WIND": offshore and onshore wind.
- "SOLAR": open-space photovoltaic, urban photovoltaic, and concentrated solar power.
- "BEECS": bioenergy in combined heat and power units (CHP) and power plants (PP) with carbon capture and storage.
- "Fossil_CCS": fossil plants equipped with carbon capture and storage technologies.
- "NUC": nuclear power plants.
- "RoRES": rest of renewables. Geothermal, waste, biofuels (liquids, solids, and gases), oceanic.

However, additional feedback mechanisms need to be considered to accurately capture the economic impacts of the energy transition. This includes endogenizing the energy transformation chain, investments dynamics, changes in economic structure, and more, which are areas of ongoing research.

The gross domestic product shows a consistent growth of the EU27 economy, increasing from around 13.5 billion dollars in 2015 to around 27.3 billion dollars in the reference scenario, and to 31.6–32.5 billion dollars in the GG scenarios. In the current version of WILIAM (v1.2), the only feedback loop from energy to the economy is done through fossil fuel prices. In the GG scenarios, where there is a shift from fossil fuels to renewables, prices are expected to decrease due to decreased supply-demand tension and the utilization of resources of higher quality grade leading to lower extraction costs. However, additional feedbacks mechanisms need to be considered to accurately capture the economic impacts of the energy transition. This includes endogenizing the energy transformation chain, investments dynamics, changes in economic structure, and more, which are areas of ongoing research.

Furthermore, the trend towards electrification in the energy sector is evident in Fig. 10. The reference scenario indicates a modest growth in final energy consumption to approximately 3600 TWh. In contrast, the GG scenario projects consumption exceeding 8000 TWh by 2050, despite the annual energy savings achieved through reduced energy intensities across all sectors.

The electricity demand is met by utilizing various energy sources (see Fig. 11). EU27 is increasingly embracing renewables for the future. In the proposed reference scenario, this green transition is moderate, with the installation of ~1000 GW (37 % of the mix). This leads to a ten-point rise in the share of renewable electricity, illustrated in Fig. 12.

Conversely, the GG scenarios presents a significant challenge due to the extensive electrification of the economy. The deployment of

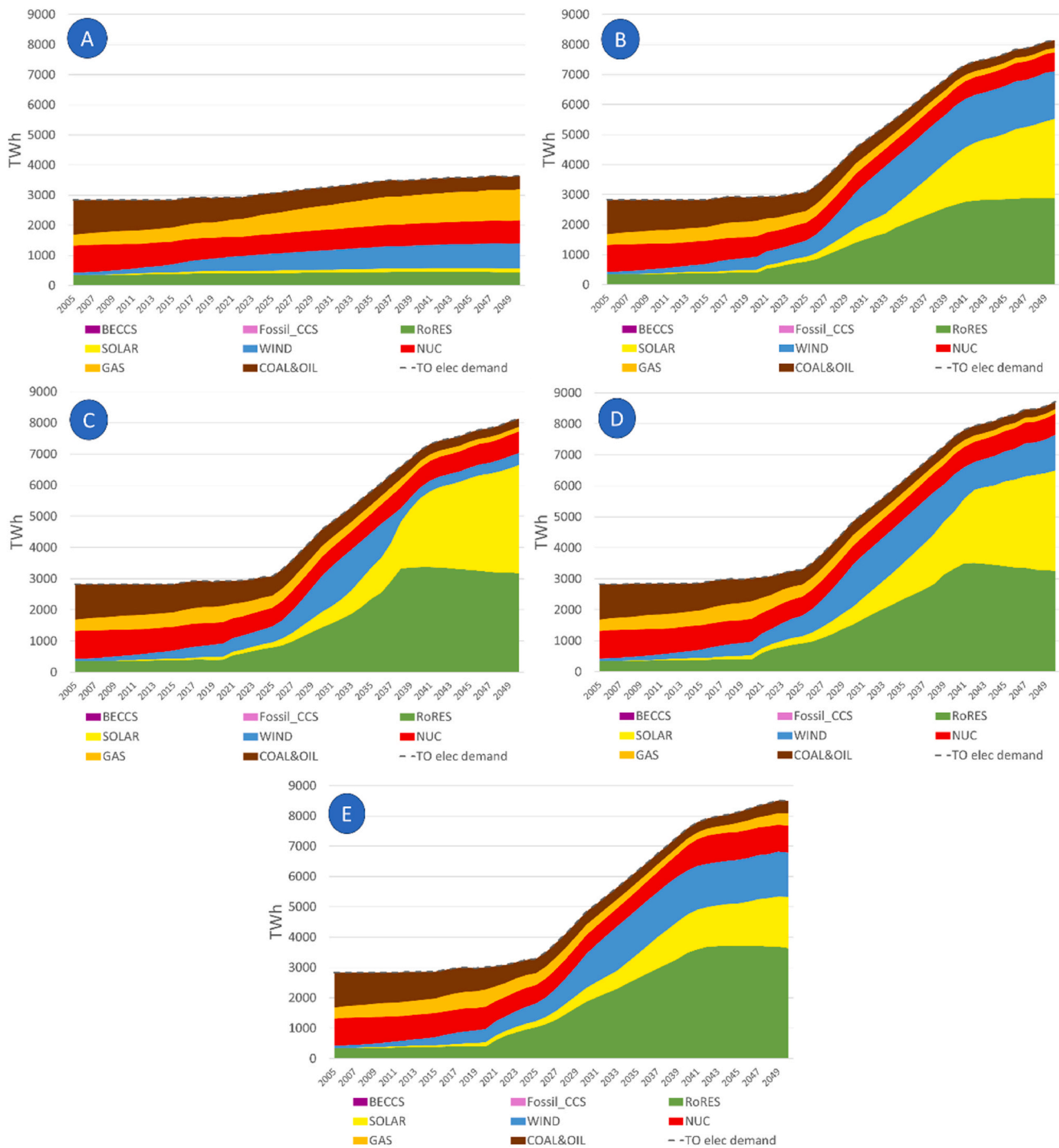

Fig. 10. Electricity mix over time in EU27 (TWh). A) REF; B) GG; C) GG_VarEffects; D) GG_VarEffects + FlexOpts; E) GG_VarEffects + FlexOpts + MAXcurtailment. CCS: carbon capture and storage. BECCS: bioenergy with CCS. RoRES: rest of renewables. NUC: nuclear.

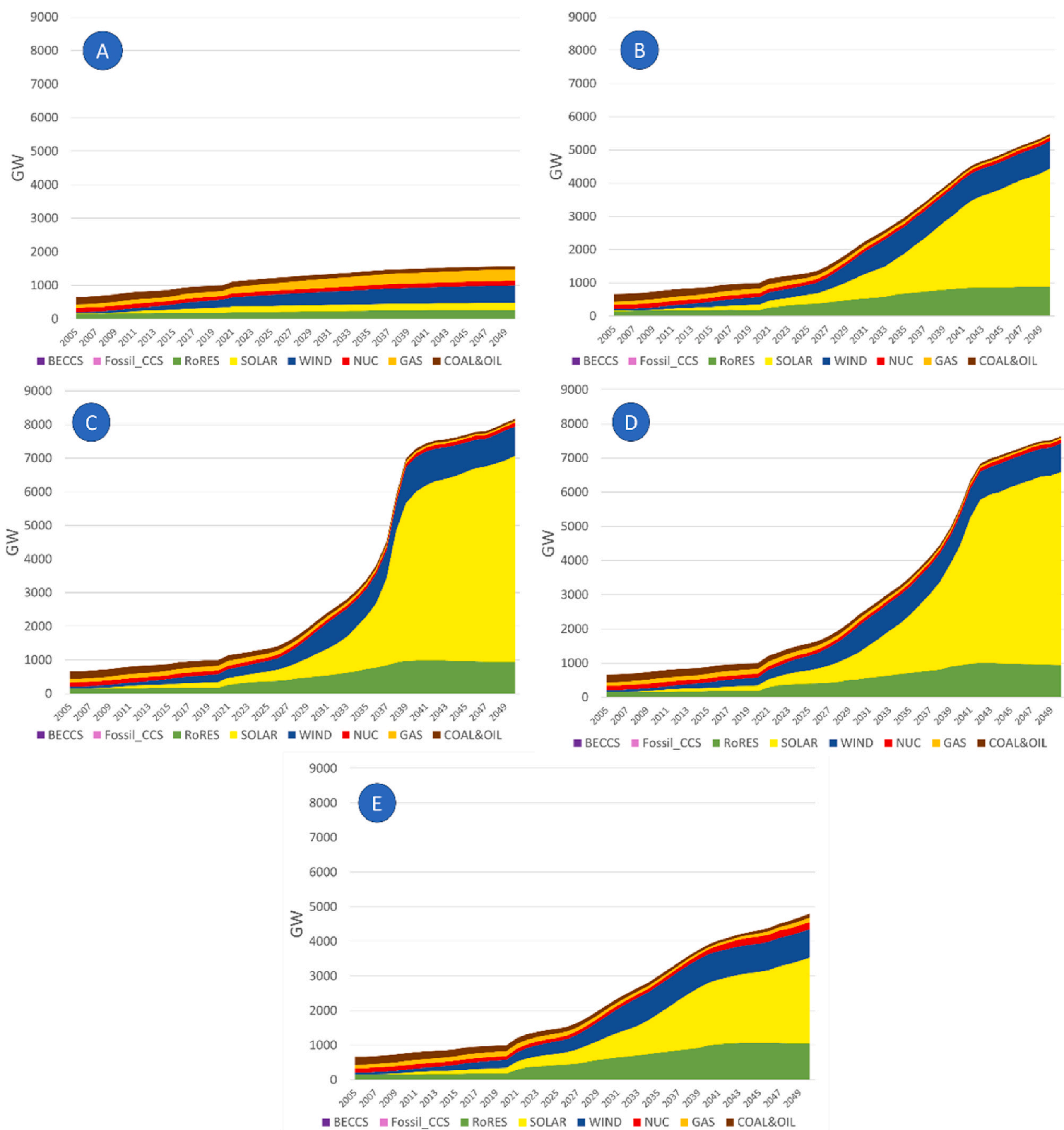

Fig. 11. Installed capacities in the power sector of EU27 over time (GW). A) REF; B) GG; C) GG_VarEffects; D) GG_VarEffects + FlexOpts; E) GG_VarEffects + FlexOpts + MAXcurtailment. CCS: carbon capture and storage. BECCS: bioenergy with CCS. RoRES: rest of renewables. NUC: nuclear.

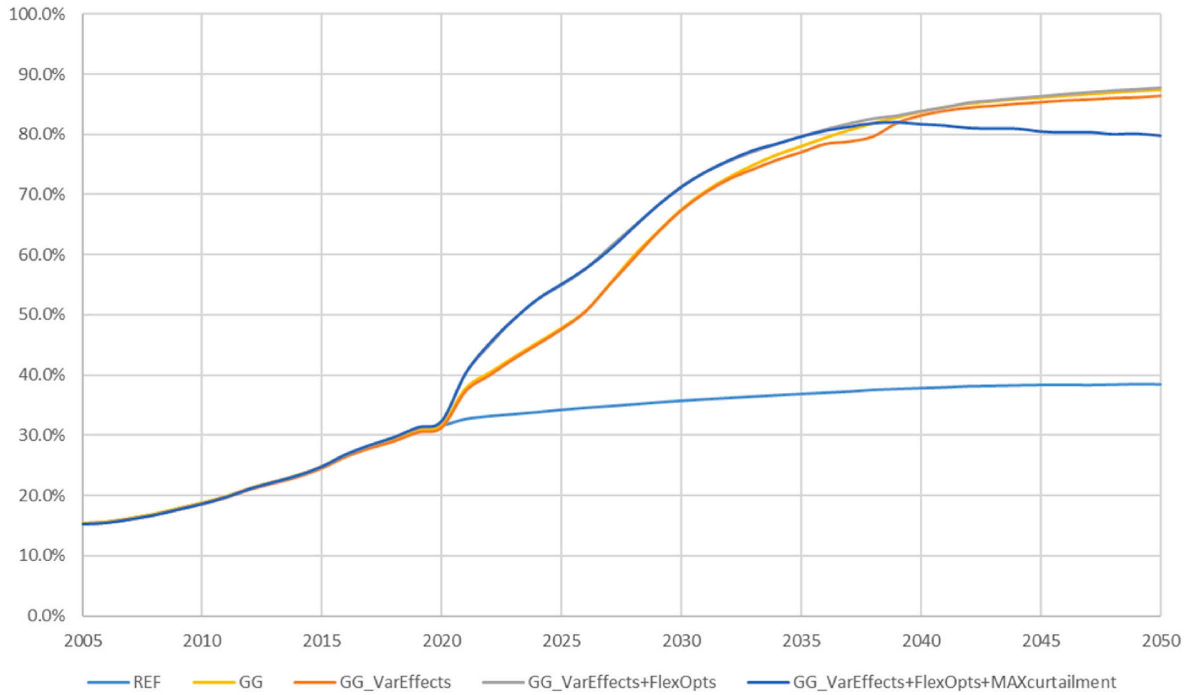

Fig. 12. Percentage of renewable electricity in the power system.

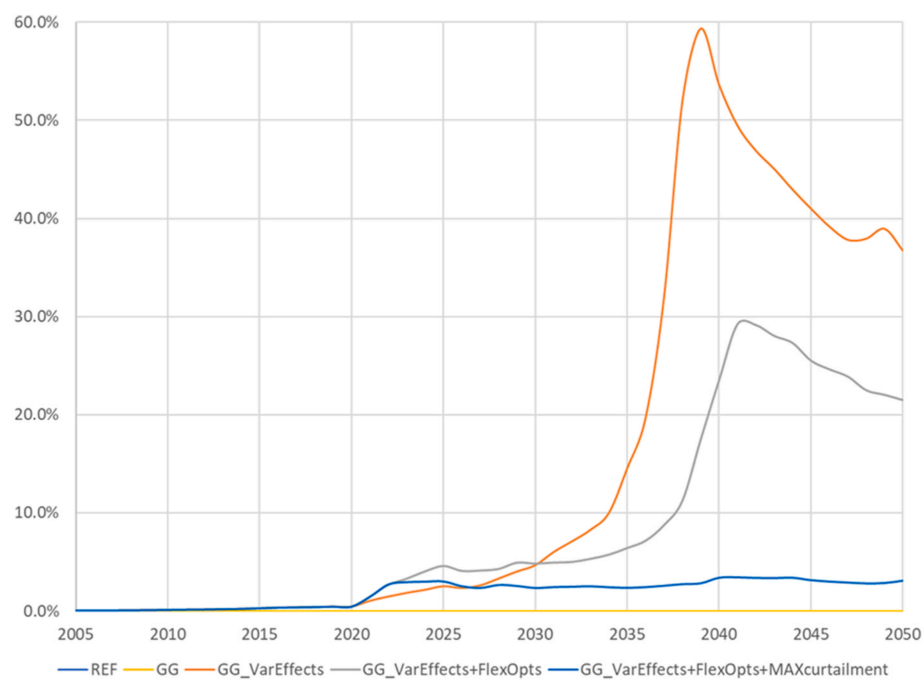

Fig. 13. Percentage of curtailment in the power system (REF and GG overlap in 0% by scenario design).

renewables surges to ~4300–5300 GW (91–96 % of the mix) to achieve a penetration exceeding 80 % in the electricity mix across all GG scenarios.

The wind capacity reaches saturation in all scenarios due to a significant constraint related to the biophysical regional potential of the resource. This potential is endogenously calculated considering factors such as available land use and the minimum (standard) energy-return-on-energy-invested (EROI) threshold of 8:1. For a detailed explanation of this method these the documentation of WILIAM (cf. section 2.4 of deliverable 8.4 of the H2020 Locomotion project [37]).

Activating the curtailment feedback in the model (see Fig. 13) reduces the full load hours of variable renewables. As GG scenarios specifically promote these technologies, exogenous priorities were higher for variable renewables than other suppliers to balance the annual electricity demand. This increased expansion results in a higher level of curtailment. This creates a form of backsliding, forming a positive feedback loop. Scenario C, compared to B, features a higher installed capacity for harnessing solar energy in Fig. 11 due to this loop. In

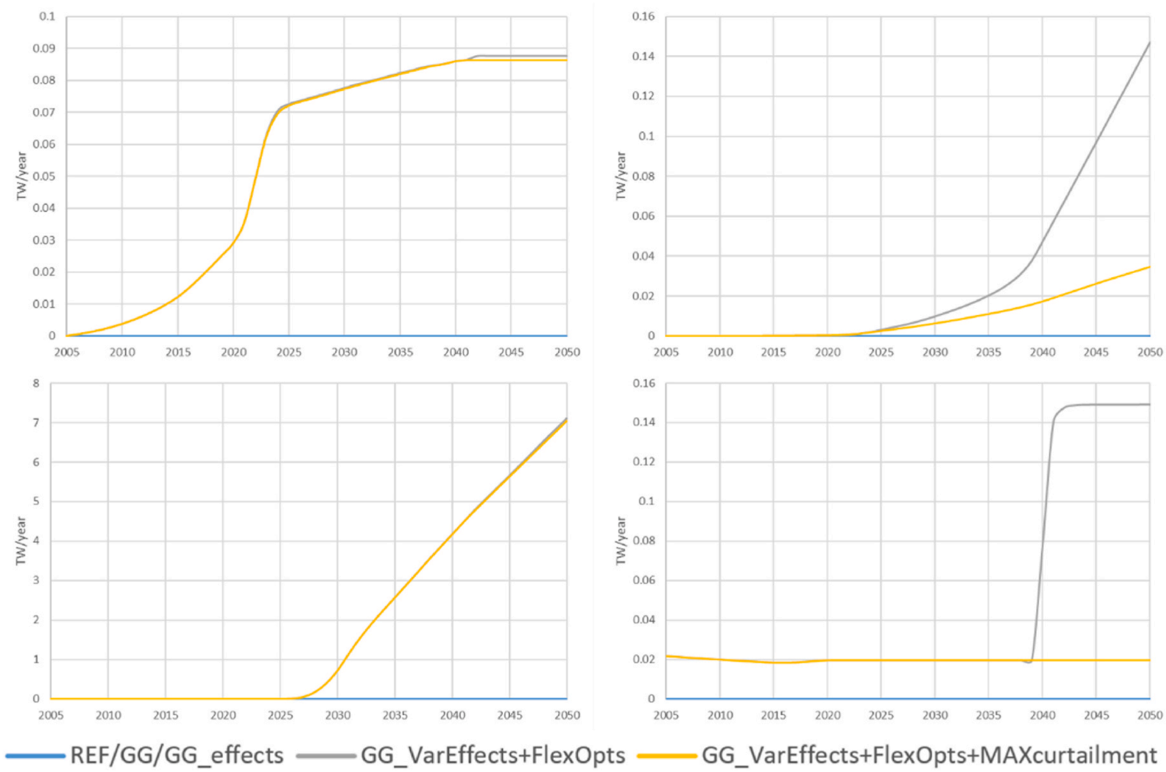

Fig. 14. Endogenous capacity expansion of flexibility options in WILIAM. Units: TW/year. P2H: power-to-heat (electric boilers and heat pumps). ELT: flexible electrolysers. V2G: vehicle-to-grid capacity. STO: stationary storage (utility-scale grid batteries and pumped hydropower storage).

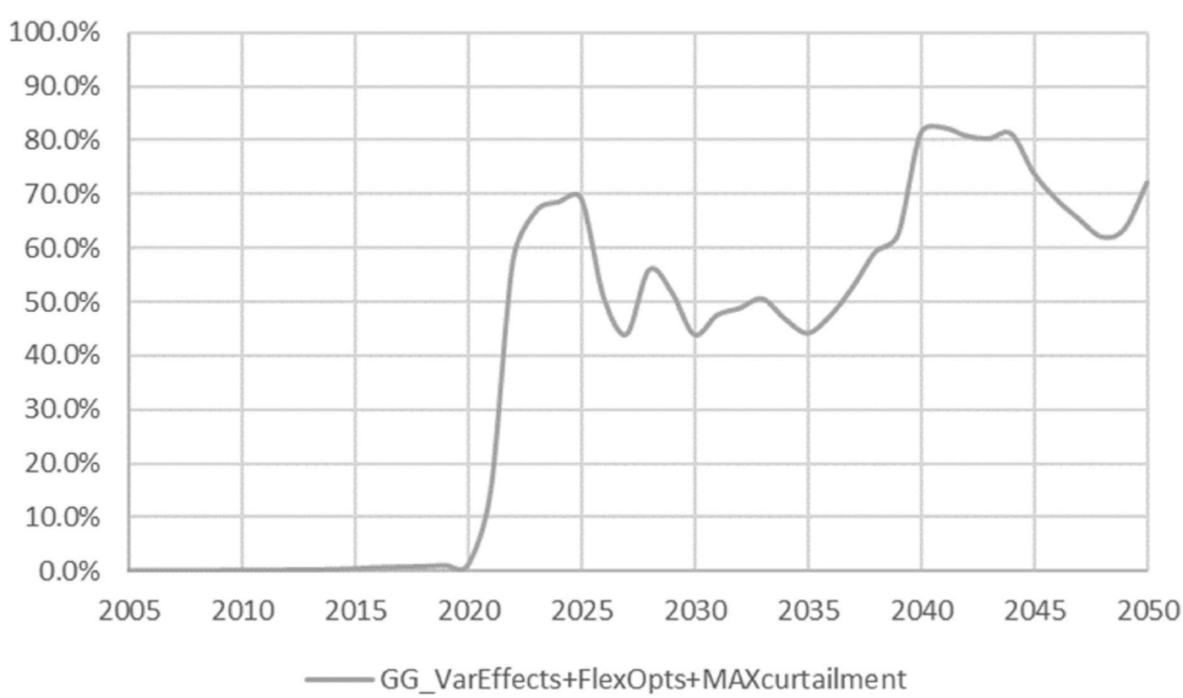

Fig. 15. Stress signal in the power system. This feedback is exclusively activated for the simulation titled "GG_VarEffects + FlexOpts + MAXcurtailment".

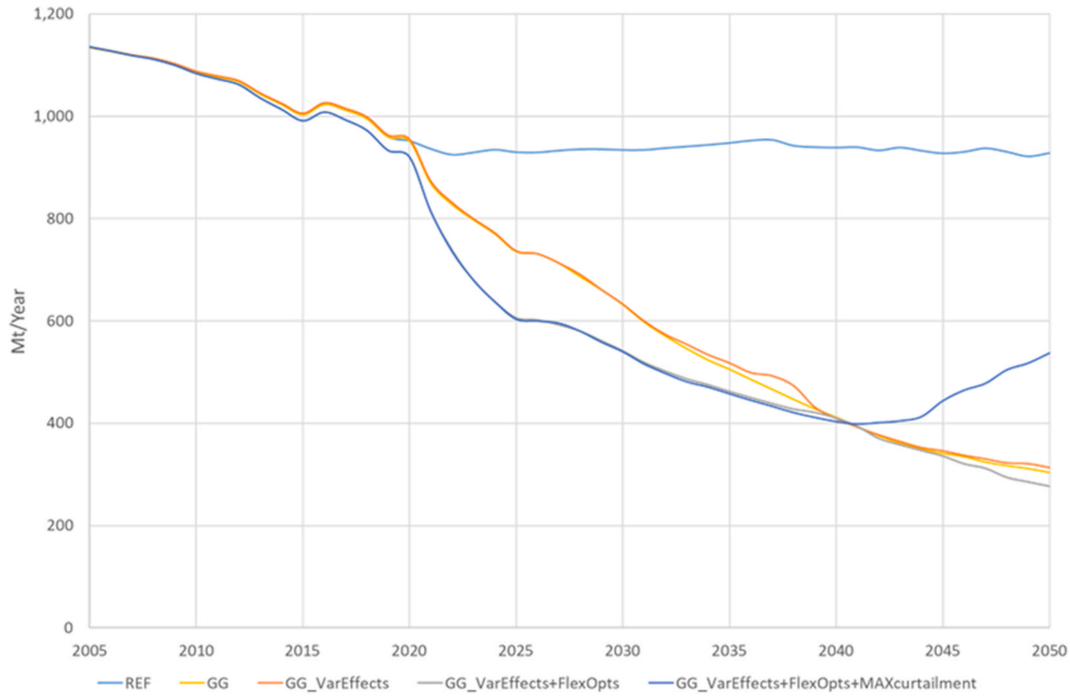

Fig. 16. Total equivalent (direct) carbon emissions along the energy transformation chain.

scenario C, the proportion of electricity curtailed peaks at nearly 60 % in 2039, while scenario B assumes zero curtailment.

The application of flexibility options in scenario D increases operational hours, thereby reducing curtailment peaks by around 30 % 3 years later. However, the endogenous mechanism to address curtailment falls short in ensuring profitability, which was initially set at a maximum of 5 %.

In scenario E, where curtailment is kept below 5 %, the capacity factor of VRES is further enhanced, alleviating the pressure for new installations. This leads to a slight reduction in renewable penetration after 2037. Scenario E proves highly effective as it requires approximately 3 TW less installed capacity than other GG scenarios (C and D) to achieve a similar renewable share in the electricity mix of around 80 %. Scenario E emerges as the most plausible among GG narratives since curtailment is maintained at realistic levels according to actual data from Ref. [5].

The level of curtailment in the system positively correlates with the intensity of flexibility options expansion, as depicted in Fig. 14. Simulations C and D exhibit an exponential response to mitigate the growth of curtailment. The maximum annual expansion is achieved with flexible electrolysers, reaching approximately 150 GW by 2050 in simulation D.

In this scenario and by the final year, stationary storage and flexible electrolysers approach 150 GW, while power-to-heat technologies (electric boilers and heat pumps) collectively reach nearly 90 GW. However, only vehicle-to-grid capacity showed statistical significant during regression analysis, thus playing a significant role in the flexibility of the system.

With an estimated 7 TW from the electrification of the transport sector by 2050 and the exogenous policy assumption of V2G in smart charge mode (set at 50 % by the final year), vehicle-to-grid capacity emerges as a key player in the causal loop with substantial flexibility impact.

The signal used to control the growth of VRES capacities is illustrated in Fig. 15 for the GG scenario E. There is a significant surge in 2020 coinciding with the onset of the energy transition. In this scenario, renewables progress steadily in tandem with the implementation of flexibility measures. The demand for VRES remains consistently high, with annual expansion restrictions exceeding 50 % for the majority of the period.

The environmental impact varies significantly across scenarios, as depicted in the annual carbon emissions from the energy transformation chain in Fig. 16. Initially, the business-*as*-usual scenario (A) reflects a stable trend of emissions over time. In the GG scenarios, there is an overall decreasing trend initially, with scenario E being an exception. The transition to renewable energy is insufficient to curb carbon emissions post-2040, as rising energy demands from the economy lead to increased fossil fuel usage in the absence of adequate renewable contributions (constrained by the stress signal and maximum curtailment). Consequently, the penalty on curtailment control results in higher carbon emissions in the energy sector compared to the other GG scenarios (B, C, and D). Scenario E showcases the fastest decarbonization pathway until 2040 due to the higher share of renewables in this period (cf. Fig 12). However, after this year, the decreasing trend in CO2 emissions is reversed and start to increase due to the reduction in the share of renewables. This behaviour is determined by the trade-off between more installed capacities with lower capacity factors in scenarios C and D, and less installed capacities with higher capacity factors in scenario E.

5. Discussion

Curtailment poses a prevalent challenge in EU27 decarbonization initiatives. Various methods are currently available to illustrate its impacts on different aspects of the power system.

This work contributes to the state-of-the-art in different ways. First, the improved experimental design generates a continuous set of real values in the input files based on uniform probability distributions.

Second, the source code (open-source, Python) has been improved with the integration of parallel processing algorithms. Third, incorporation of multiple non-linear terms and forward and backward stepwise regression to determine the optimal inputs for fitting the desired outputs. Fourth, modelling of flexibility options in the WILIAM model, including hydrogen and synthetic fuels supply, stationary storage in pumped hydropower energy storage (PHES) and electric batteries, power-to-heat (heat pumps and electric boilers), vehicle-to-grid technologies, and the implementation of demand-side management policies. Fifth, assessment of the impacts of hourly statistics in WILIAM.

In the experimental design, employing uniform probabilistic distributions for inputs appears suitable to circumvent the computational cost associated with simulating EnergyPLAN across all cases (6 h with the described method versus 7 days in our previous work [38]).

The use of logistic regression models has improved the accuracy of the estimation of the reduction of the capacity factors for solar and wind technologies depending on the electricity mix configuration with relation to the linear regression. The sign of the coefficients generally make sense, however, critical flexibility options like stationary storage and electrolysers were found not statistically significant. This constrain hinders a comprehensive evaluation of the ideal mix of flexibility options to promote in EU27. Further tests revealed that EnergyPLAN underestimates the importance of stationary storage in the merit order. An indicative symptom is the preference in publications using this model to focus on heating, transport sectors [39–42], and electrolysers [43] for enhancing flexibility, rather than stationary storage. It should be highlighted that EnergyPLAN was selected when starting this line of research for two previous studies ([38,44]) due to its speed given that the combinatorial approach was highly time-consuming, hence model accuracy was traded-off for speed. Moreover, the insufficient number of model simulations (compared to the previous study [6]) may explain the weak correlation with vehicle-to-grid capacity.

Aligned with a comparable study [39], the robustness of the dataset used to construct region-specific hourly profiles may be enhanced by using load time series and several years for all countries in each model region. The impact of climate change on the hourly profiles of renewables can significantly influence the results [45], posing a notable limitation as the regression models rely on the assumption of constant coefficients.

Another key limitation has been identified in using EnergyPLAN for this work. The physical representation of the power grid is missing, i.e., the simplification of the grid into a single node. Hence, the regression models developed do not consider analysis to, e.g., system's stability or power flows, representing another optimistic assumption. This is especially relevant when considering the substantial contribution of non-inertial units in the green growth scenarios (solar and wind technologies). This oversight becomes critical when addressing severe events like blackouts and power quality loss [46]. Previous studies, like [47], have highlighted the value added of modelling the EU27 grid to incorporate network constraints, making simulated electricity production more aligned with official reports from power system operators. This discrepancy is especially noticeable in estimating the requirements of gas-fired power plants (used during peak demand, high marginal costs) and lignite/hard coal production (baseload supply, thermal restrictions in ramping up-down the output). In fact, EnergyPLAN has not been utilized to illustrate a EU27 energy transition, as the focus remains primarily at the country level [48]. This limitation hinders the applicability of WILIAM as a robust tool in discussions concerning centralized vs decentralized renewable energy systems [49].

The heat transition in the EU27 building sector has been simplified as a single node. However, a recent review suggests that decarbonization pathways are not merely about replacing technologies. Extensive knowledge is beneficial to address key issues such as decentralized systems, individual heat pumps, and their integrability in terms of space and technological design [50]. EnergyPLAN is able to represent 3 district heating groups and final energy demands from individual consumers for the region under analysis. The single-node approach was established by the sake of simplicity, but this limitation should be addressed in future developments.

Smart charge-discharge technology enables power exchange between the grid and batteries, offering flexibility from the transport sector. A recent review article highlights differences in terms of energy density (Wh/kg) and power density (W/kg) across different configurations of electric vehicle and charging station [51]. Balancing cost savings and battery degradation is especially relevant when assessing the viability of this flexibility option as ancillary service in this work. An aspect that requires further attention in future extensions of this work.

Two limitations are identified from the regression analysis. Due to the complexity of the method, we have focused on the reduction of capacity factor for the two main VRES (wind and solar photovoltaic). However, all capacity factors of facilities would be affected by variability, both flexibility options and the rest of power and heat plants. On the other hand, bringing relevant points already identified in the previous work [38] are still valid, such as clustering inputs or an excess of simplification for representing intermediate relationships of the energy chains (presence of intermediate effects).

WILIAM v1.2 also faces some limitations that affect the obtained results. In particular, relevant inter-module links between energy and economy are missing, so the economic impact of changing the structure of the power system is not captured. The bottom-up modelling of buildings and industry is a pending task. Consequently, technologies such as individual boilers and heat pumps could not be included as flexibility options.

Finally, scenarios only represent the electricity sector to be achieved, and the same priority in the allocation of flexibility options for scenario E is a hypothesis for the future market that may be further researched.

Due to these limitations, the main scope of this work is methodological, and it is one element more implemented in the in-development WILIAM model. EU27 region was used as case study.

When conceptualizing causal loops in the IAM, they effectively highlight the significant issue of curtailment and its impacts on regulating the expansion of variable renewables. Curtailment affects the capacity factor of variable renewables, leading to an oversizing of total installed capacity in the system. By introducing measures such as the stress signal or limiting maximum curtailment, the growth of VRES can be controlled. Failure to account for curtailment effects in a green growth scenario may result in promoting renewables by default, masking a potential future decrease in their capacity factor. This oversight could lead to an underestimation of 2000 GW of installed capacity in EU27 (difference between scenarios B and C). Neglecting the 5 % curtailment as a security measure could overestimate the variable renewable penetration by about 16 % in the capacity mix, with assumed curtailment levels reaching up to 30 % (as seen in scenario D with flexibility options). Although new data is emerging [5], the lack of data of curtailement for the historical period hinders the validation of these numerical results.

The results indicate that while regression models may have a negative impact on flexibility and curtailment, the current model version enables users to implement an exogenous policy. This policy ensures that electricity generation does not exceed the maximum recommended waste electricity threshold of 5 % for a profitable and sustainable development.

This study incorporates fast feedback loops between the capacity expansion and curtailment. A. Shivakumar et al. [52] have examined the current drivers influencing the expansion of VRES in EU27. Factors such as profitability, governmental policies, disruptions in other regions (global financial crisis, nuclear catastrophe, etc.), and social resistance were identified but not integrated into the IAM WILIAM. Exploring system dynamics approaches by researchers Bolin Yu et al. [53] could enhance the existing loops by introducing new variables and relationships.

5.1. Future work may follow different paths

(1) With the improved experimental design based on uniform distributions further work could use more sophisticated energy planning models such as H2RES [54], PyPSA [55], or PLEXOS [56].
(2) The future availability of empirical data about curtailment could allow to improve model validation.
(3) This topic is surrounded by uncertainties, hence an uncertainty analysis considering the CI of the coefficients of regressions, the inter-annual and due to climate change impacts variability of the hourly profiles, as well as different combinations of the priorities for the allocation of the PROFLEX could be very promising.
(4) Soft-/Hard-linking between the hourly model and WILIAM, as identified in Ref. [6]. Other frameworks can better seize the opportunity to focus directly on specific aspects of the energy system transition by linking models [57].
(5) In order to design a sustainable energy scenario many aspects left out in this paper should be integrated, which are beyond the scope of the current research: mineral requirements, socioeconomic and net energy metabolic effects of using such a low threshold for solar PV potential (EROImin = 8:1) or the transition to RES in other sectors than electricity, as well as a more ambitious scenario for transport (e.g., see Fig. 16, where GHG emissions are far to reach net zero by 2050 for the scenario E). That exercise is a very ambitious currently ongoing work requiring the joint contribution of WILIAM developers.

6. Conclusions

The ongoing climate emergency is driving the promotion of decarbonization initiatives centred around variable renewable projects, electrification of the economy, and balancing technologies for demand and supply. This paper follows up a set of methods to address potential disruptions in the efficiency of power systems within IAMs by parametrizing the impact of energy variability on the growth of wind and solar power technologies.

The entire process involves complex steps but relies on open programming codes accessible to the research community. Starting from input and output selection, proceeding with parallel processing of files using EnergyPLAN, conducting logistic regression analysis, and culminating in integration into the IAM, this proposal is now fully developed.

If the impact of curtailment is disregarded, our model indicates that a green growth scenario would haphazardly boost renewables, resulting in an underestimation of the installed capacity and energy harnessed for the transition. Limiting the maximum system curtailment allows to accelerate the decarbonization in the first decades; however, after 2040 the emissions would increase again.

Further investigation is needed to determine whether using uniform distributions to generate input values for EnergyPLAN improves the stochastic representation of the system. This addresses the question of how many simulations would be necessary. Moreover, the integration of new regression models could enhance the evaluation of the system's performance. For example, incorporating a grid stability indicator and capacity factors of other energy facilities would be beneficial. A critical task that remains is comparing this approach with others in the research field. Specifically, selecting a case study to harmonize inputs and test the approach employed in this study against other approaches like the Residual Load Duration Curve (RLDC), time slices, and hard-linking between EnergyPLAN and WILIAM.

CRediT authorship contribution statement

Gonzalo Parrado-Hernando: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis, Conceptualization. **Luka Herc:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Conceptualization. **Felipe Feijoo:** Visualization, Software, Methodology, Conceptualization. **Iñigo Capellán-Pérez:** Writing – review & editing, Supervision, Software, Methodology, Conceptualization.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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APPENDIX A. Inputs and values selected for the simulations with EnergyPLAN

Table A.1. Inputs selected from EnergyPLAN to create the clusters. Values and the reason for selecting the inputs is included, based on a system with a legacy electricity demand (LegElecDem_TWh) of 100 TWh. Yellow-coloured cells corresponds to representative inputs of clusters. "X" is an ad-hoc factor to estimate the values.

Cluster name	Input of EnergyPLAN	Values in the previous work [6]	Values in the present study (limits of the uniform distributions)		Unit	Selection criteria
			Lower limit	Upper limit		
SOLAR	input_RES1_capacity	5708; 17123; 28539	10000	100000	MW	Representation of solar power plants. $= X \cdot LegElecDem\_TWh \cdot \frac{10^6}{8760}$
WIND	input_RES2_capacity	5708; 17123; 28539	10000	100000	MW	Representation of wind power plants. $= X \cdot LegElecDem\_TWh \cdot \frac{10^6}{8760}$
ZERO_GHG_SEMIFLEX	input_nuclear_cap	2854; 8562; 17123	1	17123.29	MW	Representation of semiflexible power plants (nuclear, geothermal and dam hydropower). $= X \cdot LegElecDem\_TWh \cdot \frac{10^6}{8760}$
ZERO_GHG_SEMIFLEX	input_Nuclear_partload	0.5	0.5	0.5	Dmnl	Ratio of inflexible generation (minimum share of rotating capacity).
ZERO_GHG_SEMIFLEX	input_nuclear_eff	0.3157	0.3157	0.3157	Dmnl	Efficiency of semiflexible power plants (nuclear, geothermal and dam hydropower)
STATIONARY_STORAGE	input_cap_pump_el	2854; 8562; 17123	1	171232.9	MW	Representation of utility-scale stationary storage (grid batteries and PHES). $= X \cdot LegElecDem\_TWh \cdot \frac{10^6}{8760}$
STATIONARY_STORAGE	input_eff_pump_el	0.9	0.9	0.9	Dmnl	Efficiency to save electricity in utility-scale electric storage.
STATIONARY_STORAGE	input_cap_turbine_el	2854; 8562; 17123	1	171232.9	MW	It is assumed the same capacity for pumping and turbine modes. $= input\_cap\_pump\_el$
STATIONARY_STORAGE	input_eff_turbine_el	0.9	0.9	0.9	Dmnl	Efficiency to deliver electricity in utility-scale electric storage.
STATIONARY_STORAGE	input_storage_pump_cap	11.4; 34.25; 68.49	0.004	684.9315	GWh	Energy storage capacity $= input\_cap\_pump\_el * \frac{4}{1000}$
HEAT_DEMAND	input_dh_ann_gr3	200; 300; 400	1	800	TWh	Demand of heat (as a whole) $= X \cdot LegElecDem\_TWh$
CHP	input_cap_pp_el	3710; 11130; 22260	0.769231	17123.29	MW	CHP capacity (condensing mode). Only electricity supply. $= input\_cap\_chp\_el \cdot 1.3$
CHP	input_cap_chp3_el	2854; 8562; 17123	1	22260.27	MW	CHP capacity (back-pressure mode) to supply electricity. $= X \cdot LegElecDem\_TWh \cdot \frac{10^6}{8760}$
CHP	input_eff_pp_el	0.4312	0.4312	0.4312	Dmnl	Efficiency of thermal power plants (dispatchable).
CHP	input_eff_chp3_el	0.4312	0.4312	0.4312	Dmnl	Efficiency to supply electricity in CHP units.
CHP	input_eff_chp3_th	0.1164	0.1164	0.1164	Dmnl	Efficiency to supply heat in CHP units.
CHP	input_storage_gr3_cap	15; 45; 89	0.004	684.9315	GWh	Thermal storage capacity in CHP facilities. $= input\_cap\_chp3\_thermal * \frac{4}{1000}$
CHP	input_cap_chp3_thermal	3710; 11130; 22260	0.004	89.0411	MWth	CHP capacity (back-pressure mode) to supply heat. $= input\_cap\_chp3\_el$

HEAT PUMPS	input_cap_hp3_el	2854; 8562; 17123	1	171232.9	MW	Capacity of heat pumps (electricity). $= X \cdot LegElecDem\_TWh \cdot \frac{10^6}{8760}$
HEAT PUMPS	input_eff_hp3_cop	3.5	3.5	3.5	Dmnl	Efficiency (COP).
HEAT PUMPS	input_storage_gr3_cap	11.4; 34.25; 68.49	0.004	684.9315	GWh	Energy storage capacity. $= input\_cap\_hp3\_el * \frac{4}{1000}$
ELEC_BOILERS	input_cap_boiler3_th	2854; 8562; 17123	1	171232.9	MWth	Capacity of electric boilers (thermal). $= input\_eh3$
ELEC_BOILERS	input_eh3	2854; 8562; 17123	1	171232.9	MW	Capacity of electric boilers (electricity). $= X \cdot LegElecDem\_TWh \cdot \frac{10^6}{8760}$
ELEC_BOILERS	input_eff_boiler3_th	0.8649	0.8649	0.8649	Dmnl	Efficiency of electric boilers.
ELEC_BOILERS	input_storage_gr3_cap	11.4; 34.25; 68.49	0.004	684.9315	GWh	Energy storage capacity. $= input\_eh3 \cdot \frac{4}{1000}$
EV_DEMAND	input_transport_TWh_V2G	25; 50; 100	1	100	TWh	Demand of electricity for transport. $= X \cdot LegElecDem\_TWh$
EV_DEMAND	input_V2G_MaxShare	0.2	0.2	0.2	Dmnl	Maximum share of vehicles which are driving during peak demand hour.
EV_DEMAND	input_V2G_Cap_Charge	64750; 129500; 259000	2590	259000	MW	Capacity of the grid to battery connection.
						$= input\_transport\_TWh\_V2G \cdot \frac{10^{12}}{(average\ EV\ efficiency)} \cdot \frac{1}{average\ EV\ distance\ driven\ annu} \cdot \frac{average\ EV\ charge\ cap}{1000}$
EV_DEMAND	input_V2G_ConnectionShare	0.7	0.7	0.7	Dmnl	Share of parked V2G vehicles connected to the grid.
EV_DEMAND	input_V2G_Eff_Charge	0.9	0.9	0.9	Dmnl	Efficiency of the grid to battery connection.
EV_DEMAND	input_V2G_Battery	1050; 2100; 4200	42	4200	GWh	Capacity of the battery storage. $= input\_transport\_TWh\_V2G \cdot \frac{10^{12}}{(average\ EV\ efficiency)} \cdot \frac{1}{average\ EV\ distance\ driven\ annu} \cdot \frac{\text{average EV stor cap}}{10^6}$
V2G	input_V2G_Cap_Inv	64750; 129500; 259000	1	259000	MW	Capacity of the battery to grid connection. $= input\_V2G\_Cap\_Charge$
V2G	input_V2G_Eff_Inv	0.9	0.9	0.9	Dmnl	Efficiency of the battery to grid connection.
HYDROGEN_DEMAND	input_fuel_CSHP[6]	18; 37; 73	1	73.1999	TWh	Demand of hydrogen. $= input\_cap\_ELTtrans\_el \cdot \frac{1000}{155950}$
HYDROGEN_SUPPLY	input_cap_ELTtrans_el	2854; 5708; 11416	1	11415.53	MW	Capacity of electrolysers. $= X \cdot LegElecDem\_TWh \cdot \frac{10^6}{8760}$

. (*continued*).

HYDROGEN_SUPPLY	input_eff_ELTtrans_fuel	0.9			-	Efficiency of electrolysers.
HYDROGEN_SUPPLY	input_H2storage_trans_cap	350; 700; 1400	0.12264	1399.998	GWh	Capacity to store hydrogen. $= input\_fuel\_CSHP[6] \cdot \frac{10^3}{8760} \cdot 168$
HYDROGEN_SUPPLY	Input_CO2HydroSequestrationEle cEff	0.289	0.289	0.289	TWh/TW h	Electric efficiency in the CO_2 sequestration process of hydrogenation.
HYDROGEN_SUPPLY	Input_CO2HydroSequestrationCO 2Eff	0.252	0.252	0.252	Mton/TW h	Efficiency in the CO_2 sequestration process of hydrogenation.
HYDROGEN_SUPPLY	Input_CO2HydroMaxCapacity	9999999	9999999	9999999	ton CO2/hour	Proxy for infinite value to unconstraint the CO_2 source inflow in hydrogenation facilities.
FLEX_DEMAND	input_flexible_day_TWh	25; 50; 100	1	100	TWh	Legacy demand considered as flexible. $= X \cdot LegElecDem\_TWh$
FLEX_DEMAND	input_flexible_day_max	4166; 8331; 16662	1	16662	MWe	Maximum power capacity that can be moved from one hour to other in one day. $= 16662 \cdot \frac{\text{input\_flexible\_day\_TWh}}{100}$
OTHER PARAMETERS OF ELECTRIC TRANSPORT						
average EV distance driven annual		150000	150000	150000	km	Average distance of electric vehicles in a year.
average EV efficiency		142.85714 29	142.85714 29	142.85714 29	Wh/km	Average mechanical efficiency of electric vehicles.
average EV charge cap		3.7	3.7	3.7	kW	Average charging capacity of an electric vehicle.
average EV stor cap		40	40	40	kWh	Average electricity storage capacity of an electric vehicle.
EV number		35000000	35000000	35000000		Number of electric vehicles considered in the system.
Autonomy		350	350	350	km	Distance of autonomy of an electric vehicle.
Mileage		100000	100000	100000	km	Average maximum mileage of an electric vehicle.
Lifetime		10	10	10	years	Average lifetime of an electric vehicle.

. (*continued*).

APPENDIX B. Hourly profiles for the EU27 in the reference simulation

Fig. B.1. Hourly profile of legacy electricity demand over the year (MWh) for EU27 for the reference simulation.

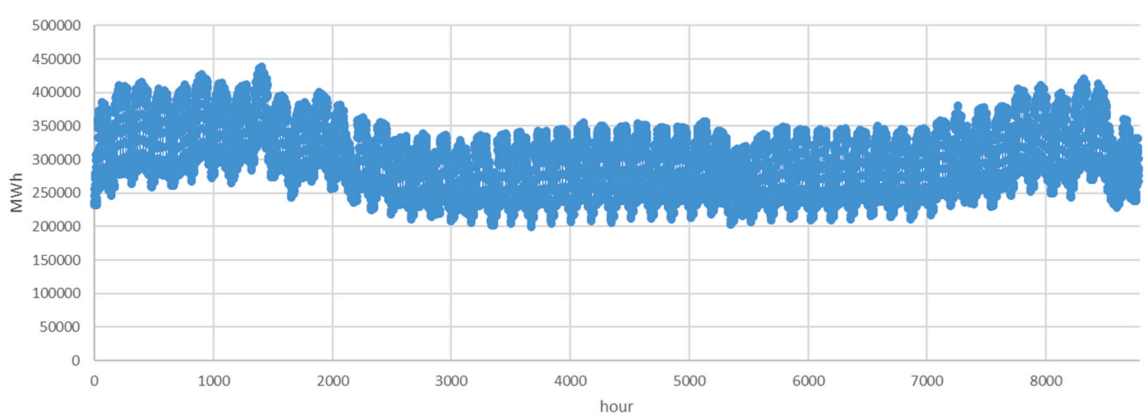


Fig. B.2. Hourly profile of heat demand in the district heating group for EU27 for the reference simulation.

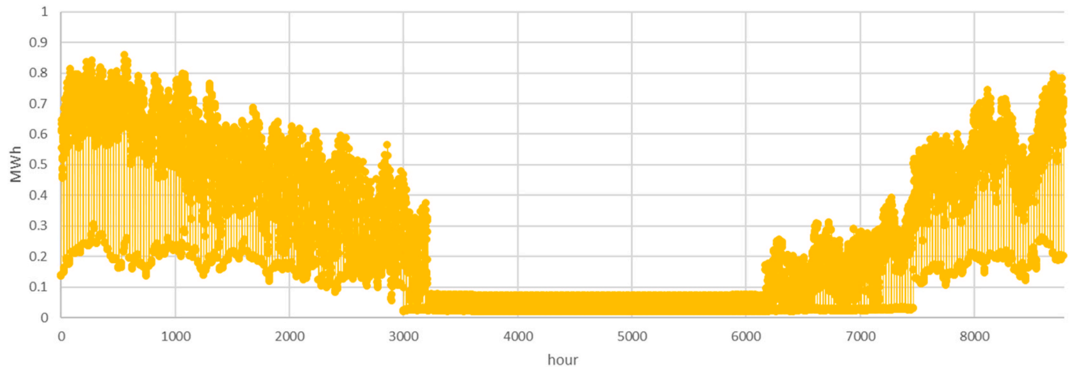


Fig. B.3. Hourly profile of solar-PV production over the year for EU27 for the reference simulation.

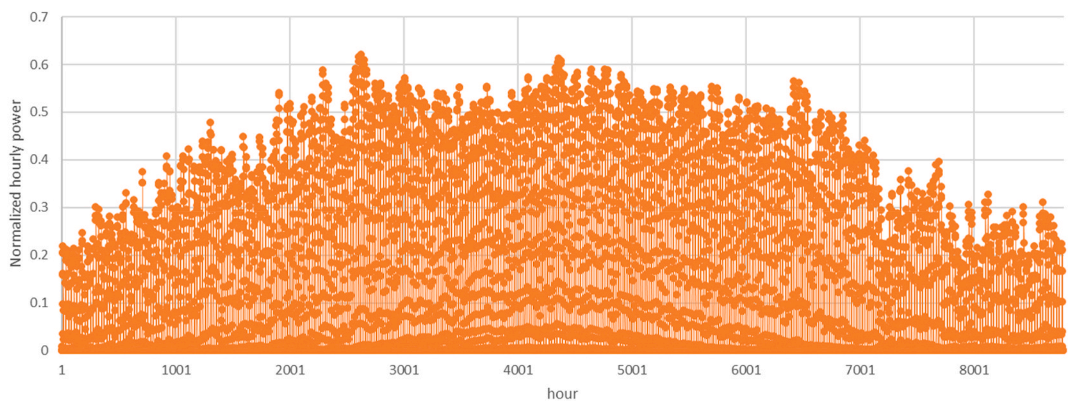
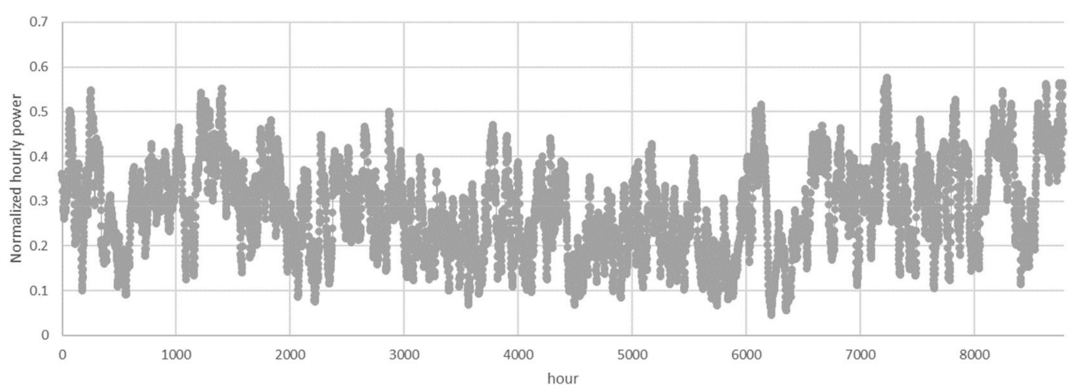


Fig. B.4. Hourly profile of wind production over the year for EU27 for the reference simulation.



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Gonzalo Parrado-Hernando [a,b,*], Luka Herc [c], Felipe Feijoo [d], Iñigo Capellán-Pérez [a,b]

[a] Group of Energy, Economy, and System Dynamics, University of Valladolid, Spain
[b] Department of System Engineering and Automation, School of Industrial Engineering, University of Valladolid, Valladolid, Spain
[c] Department of Energy, Power Engineering and Environment, Faculty of Mechanical Engineering and Naval Architecture, University of Zagreb, Zagreb, Croatia
[d] School of Industrial Engineering, Pontificia Universidad Católica de Valparaíso, Valparaíso, Chile

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Consequently, the authors and related affiliations should be the re-written as follows:

Gonzalo Parrado-Hernando[a,b], Luka Herc[c], Felipe Feijoo[d], Iñigo Capellán-Pérez[a,b]

[a] Group of Energy, Economy, and System Dynamics, University of Valladolid, Valladolid, Spain

[b] Department of System Engineering and Automation, School of Industrial Engineering, University of Valladolid, Valladolid, Spain

[c] Department of Energy, Power Engineering and Environment, Faculty of Mechanical Engineering and Naval Architecture, University of Zagreb, Zagreb, Croatia

[d] School of Industrial Engineering, Pontificia Universidad Católica de Valparaíso, Valparaíso, Chile.

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* Corresponding author. Group of Energy, Economy and System Dynamics, University of Valladolid, Spain.
E-mail address: gonzalo.parrado@uva.es (G. Parrado-Hernando).

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