Bi-directional soft-linking between a whole energy system model and a power systems model

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***Abstract*—To decrabonise the entire energy system, introduction of large shares of variable renewable electricity generation will be needed. Long term energy system planing models are useful to improve the understanding of the decarbonisation pathways but struggle to take into the account the short term variations associated with the increased penetration of variable renewables. This can generate misleading signals regarding the levels of flexibility required in the system. This paper addresses this gap by a innovative bi-directional soft-linking methodology between a long term whole-energy system planing model (EnergyScope) and a multi-sectoral unit commitment and power dispatch model (Dispa-SET). The proposed methodology assesses the integration of short term variability, sizes the flexibility needs and analyses its strengths, limitations and applicability. Results of this study show that convergence criteria of the bi-directional soft-linking are met within two iterations meaning that the newly proposed system is stable and reliable.**

***Index Terms*—Bi-directional soft-linking, EnergyScope, Dispa-SET, Integrated energy systems, Low carbon energy systems**

I. Introduction

One important challenge of the transition to a low-carbon energy system is integration of variable renewable energy sources (VRES). Capturing the techno-economical challenges related to a large-scale penetration of VRES, therefore, requires accurate modelling of: i) the variability of renewable generation ii) the system load variability due to cross-sectoral interactions, and iii) limited flexibility of thermal units. This requires models with a high level of technical, temporal and spatial granularity. According to [1], long-term Energy System Optimisation Models (ESOM) are frequently applied to analyse scenarios that check the evolution of the energy system, usually over multiple years or decades. However, due to computational restrictions, the level of technical, temporal and spatial detail in these models is relatively low (i.e. typical days approach in combination with limited operational and geographical constraints). In contrast, operational power system models, also known as Unit Commitment and Economic Dispatch (UCED) models focus on highly detailed short-term operations of the energy system and do not consider the long-term evolution. To breach the gap between both paradigms, two main solutions have been identified: Soft-linking and Integrated modeling [2]. The soft-linking methodology is further divided into the uni-directional and bi-directional approaches.

The integrated modeling approach, also referred to as hard linking, directly improves one or more areas of interest inside the ESOM. According to [3], ESOM models usually overlook the impact of VRES intermittency on system operations due to the computational burden associated with large model size and long planning horizon. In order to address this issue, authors utilize constraints borrowed from UCED models and integrate them directly into a long-term system planning model. This approach does guaranty the spatial and to a certain extent technical optimality. However, computational tractability still imposes to keep the number of considered time slices low, which fails to address the temporal dimension of the problem.

Uni-directional soft-linking is a technique where the outputs of ESOM are used as inputs of and UCED model which post-checks the adequacy and flexibility of the proposed system. A uni-directional soft-linking approach, first proposed by [4], that investigates the power system in high technical and temporal detail for a target year by soft-linking the PRIMES and PLEXOS models was analysed by [5]. A similar uni-directional soft-linking framework between the JRC-EU-TIMES and Dispa-SET models was carried out in a multi-sectoral context in [6]. This approach provides new insights into system adequacy which are not possible using a single model approach. The increased accuracy provided by such framework relates to VRES generation, curtailment, congestion, wholesale electricity pricing and capacity factors, all variables directly impacting the costs and stability of the system as a whole.

In a bi-directional soft-linking approach (i.e. with feedback loops), significant differences in dispatch results from both models are expected. This was illustrated by [7] where system adequacy of the system proposed by the TIMES, an ESOM model, was assessed with ANTARES, an power system only UCED model. Feedback loops were based on capacity credit estimation and convergence was guaranteed within 7 iterations. The strengths and limitations of the proposed methodologies is presented in "Tab. I".

TABLE I
TABULAR COMPARISON OF MODELLING METHODOLOGIES

Methodology	Strengths	Limitations
Uni-directional soft-linking	Operational costs, fuel consumption, emissions High temporal and technical detail	UCED model in addition to ESOM, does not increase the optimality of the solution
Bi-directional soft-linking	Increased optimality of the solution, lower computational cost than integrated model	UCED model in addition to ESOM, optimality and convergence can't be guaranteed
Integrated modeling	Optimality can be guaranteed	Hight computational intensity

The novelty of this paper can be summarized as follows:

- Development of a multi-sectoral and bi-directional soft-linking platform between ESOM and UCED models and its application to two open-source models (EnergyScope[1] [8] and Dispa-SET[2])
- Fast convergence of the two models (within 2 iterations) in both convergence criteria, the energy not served (ENS) and optimality criterion.

II. Methodology

This section describes the bi-directional soft-linking methodology that aims to better capture the techno-economic challenges related to the integration of high shares of VRES. It highlights the strengths and limitations of individual models and builds upon them.

In the proposed approach, the energy system designed by the ESOM is used as input for UCED model, which then recomputes system operation using a higher level of technical, temporal and spatial detail. The output data from the UCED model is used to readjust certain parameters of interest or/and to add additional constraints to the ESOM. Both models are executed in an iterative procedure until a certain level of convergence between them is obtained. According to [5], this methodology poses additional difficulties, i.e., modellers expertise, but the final outcome moves closer to the global optimum, i.e., the solution that could have been found if the ESOM was solved with higher spatial, technical and temporal resolution. The added value of a bi-directional soft-linking is the increased accuracy of the results. Literature suggests [9] that the discrepancy between the ESOM and UCED models is higher with the increased penetration of VRES. Hence, the more emissions are reduced, the more essential this coupling approach becomes.

The developed bi-directional soft-linking methodology relies on a rather long list of variables continuously exchanged between the models. The upcoming sections only describe the most important set of rules and variables. The step-by-step (SBS) bi-directional soft-linking methodology used in this analysis is presented as follows:

1) Definition of a shared database, i.e., common inputs used by both ESOM and UCED models, such as time series in form of VRES availability, power/heating and other demands, and overlapping costs.
2) Selection of ESOM parameters (time-horizon, pathway, image) and scenario definition (green house gas (GHG) limit, renewable targets, resources availability etc.).
3) Execution of ESOM.
4) Extraction of the capacity mix, fuel and carbon prices to populate the UCED model. Inclusion of technical parameters such as start-up and shut-down times and costs, ramping rates, minimum on and off times, partial load etc.
5) Executing the UCED model in an iterative loop with the stop condition trigger.
6) Compare results between both models and identify differences in terms of adequacy and flexibility of the system.
7) Compute the modelling accuracy and modelling errors and check if the stop condition is satisfied. If not, continue to the next step, otherwise, stop the iterative process and save the results.
8) Use the insights gained from the results comparison to introduce additional constraints (i.e. additional reserve requirements, capacity margin, VRES curtailment etc.) into the ESOM. Repeat the procedure starting from point 3) and continue until the stop condition is met.

A simplified summary of the proposed bi-directional soft-linking methodology is presented in "Fig. 1".

The stop conditions of the iterative is defined by the following rule: the convergence error between both models is lower than the numerical accuracy of the UCED model. This accuracy is arbitrarily defined as the one provided by the Optimality Gap of the MILP method:

$$Accuracy_z = OptimalityGap \cdot ObjectiveFunction_z \quad (1)$$

[2]EnergyScope https://energyscope.readthedocs.io/en/latest/
[2]Dispa-SET http://www.dispaset.eu/en/latest/

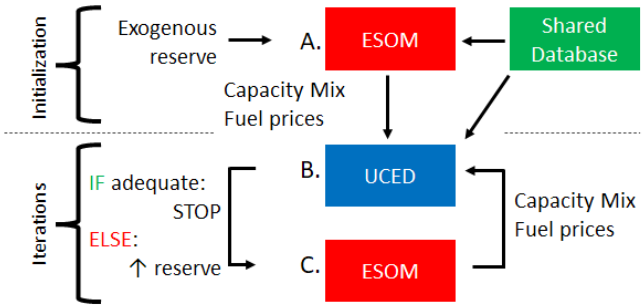

Fig. 1. Bi-directional soft-linking between ESOM and UCED models. During the initialization, only model A is executed. During the iterative procedure models B and C are executed consecutively until the stop condition is met (i.e. system adequacy lies within the initially-defined targets)

where $OptimalityGap$ represents the difference between the incumbent solution in mixed integer programming and a value that bounds the best possible solution of the objective function (%), and $ObjectiveFunction_z$ stands for the total operational system costs of the rolling optimization horizon z of the UCED model (EUR).

The convergence error between both models can be captured through several variables relating to system adequacy. First, the amount of $ShedLoad_i$ (i.e. the reduction of demand when the offer is insufficient), accompanied by $LostLoad_i$ (i.e. a purely mathematical high cost variable used to avoid optimization infeasibilities in the UCED model when load shedding is bounded) and $SlackLoad_i$ (analogous variable to lost load, but for non-electricity sectors such as gas and heating). ENS is equal to the sum of these three variables. Since these variables are null in the ESOM model, the modelling error in rolling horizon z of the UCED model is defined as follows:

$$\begin{aligned} Error_z = &\sum_i ShedLoad_i \cdot CostLoadShedding \\ &+ \sum_i LostLoad_i \cdot CostLostLoad \\ &+ \sum_i Slack_i \cdot CostSlack \end{aligned} \tag{2}$$

where $CostLoadShedding$ is the price of load shedding ($\approx 10^3$ EUR/MWh), $CostLostLoad$ is an arbitrarily high price of lost load ($\approx 10^5$ EUR/MWh) and $CostSlack$ is an arbitrarily high price for unserved energy in other sectors than electricity ($\approx 10^6$ EUR/MWh). The price of slack is set to be the highest to force the lack of energy in the electricity sector only. This modelling approach ensures that the volumes in non-electricity sectors are the same in both ESOM and UCED models. This lumps various system adequacy indicators into one single variable used as the objective function of the iterative process. The stop condition is defined as follows:

$$StopCondition = \begin{cases} j+1, & Error_z \geq Accuracy_z \\ stop, & \text{otherwise} \end{cases} \tag{3}$$

where j indicates the active loop inside the iterative procedure.

Another important part of the coupling methodology is the integration of new adequacy constraints inside the ESOM. A new fictive demand, i.e. reserve or system balance demand, is added on top of the existing electricity demand. The operational constraints inside ESOM, i.e. constraints related to the power balance and state of charge of storage units, are duplicated and solved at each time step without additional operational costs. This forces the model to install new assets whose capacity is high enough for covering the fictive demand. This demand is imposed to the model exogenously during the initialization phase. Once the iterative procedure is executed, the feedback from the UCED model improves the design and adequacy of the whole energy system. This adapted version of EnergyScope and the data used can be found on Github[3].

III. Case Study

The proposed bi-directional soft-linking methodology is applied on a low-carbon Belgian energy system for the target year 2035 as proposed by [10]. For the purpose of this study, the extended and updated version of EnergyScope which includes the non-energy demands was used [11]. Majority of input data was revised to account for the latest developments inside the Belgian energy system. Increased techno-economical and operational detail of individual generation technologies (i.e. partial load, ramping rates, minimum on/off time, start-up/shut-down time, CHP-type and associated costs) which complement the outputs from EnergyScope are included into Dispa-SET and are elaborated in more detail in [6]. Reserve sizing is based on the probabilistic methodology used by various European TSO's and is further elaborated in [12].

Convergence of the soft-linking between EnergyScope and Dispa-SET models will be tested under three cases: a reference scenario and two carbon constrained scenarios. In the reference scenario, the evolution of the Belgian energy system is unconstrained (i.e. commodities such as oil and gas can be imported and no carbon emission policies are considered). In the first low-carbon scenario the carbon emission reduction of 70% compared to 2015 is analysed (i.e. $37.5Mt_{CO_{2,eq}}/y$). In the second low-carbon scenario a reduction of 90% compared to 2015 (i.e. $12.5Mt_{CO_{2,eq}}/y$) is analysed. All three scenarios underline the iterative evolution of the system design.

IV. Results and Discussion

The results from the second low-carbon scenario are analysed and discussed in this section. The entire analysis revolves around comparing the outputs from the stand alone version of EnergyScope model (No Reserve), with the version where an exogenous reserve demand is included (Initialization) and the different soft-linking iterations (Iteration x). The accuracy of the proposed bi-directional soft-linking methodology, including the stop-condition is presented in "Fig. 2". The accuracy of the modelling framework as well as the overall system reliability increases with each iteration until final convergence between both models is reached. The proposed modelling

[3]https://github.com/energyscope/EnergyScope_coupling_Dispa_set/tree/ES-DS_PAC2022

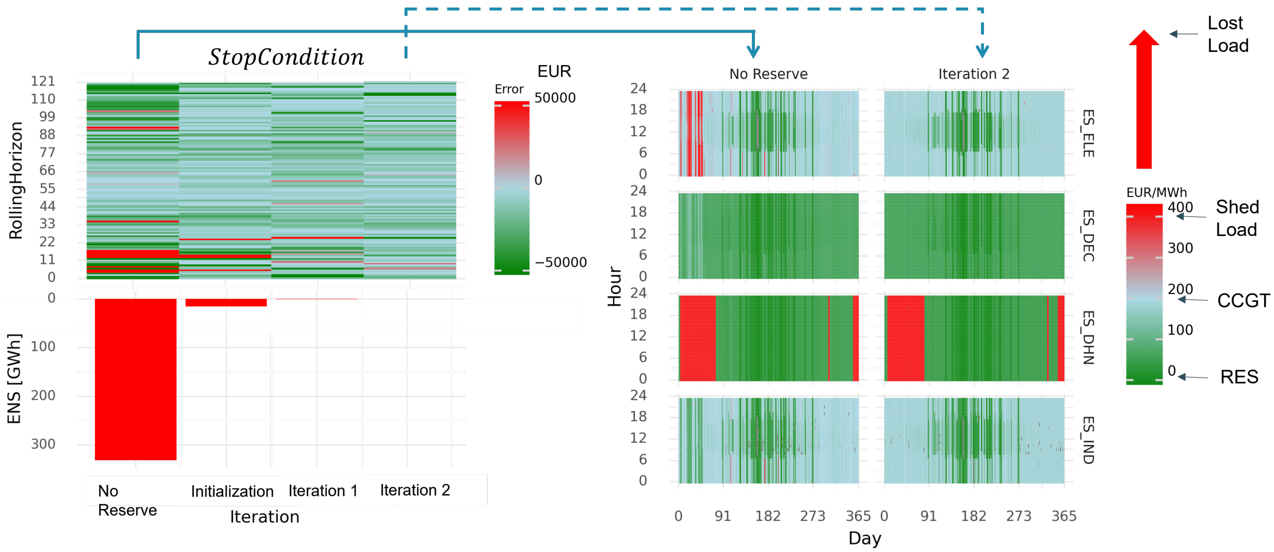

Fig. 2. Evolution of modelling accuracy of Dispa-SET model inside individual rolling horizon loop (top left) and ENS (bottom left) over each iteration and accompanying shadow prices in the No Reserve and Iteration 2 step of the soft-linking framework

framework ensures a quick convergence between the two models within two iterations. The total computation time, No reserve and Initialization steps included, on an Intel(R) 2.90GHz Xeon(R) E-2186M with RAM 32GB took around 45 min. 87% of the CPU time was spent on the dispatch model with a rolling horizon (The optimization problem is split into smaller ones that are run recursively throughout the year) of 3 days.

The proposed framework reaches convergence after 2 iterations. At the end, the whole-energy system has a total cost of 49.68 Bn.EUR/y which represents an increase of 0.46% compared to initial EnergyScope run (emission costs included). This increase is mainly due to increased size of Combined Cycle Gas Turbine (CCGT) and seasonal thermal storage in the district heating network zone (ES_DHN). The annualized investment and maintenance cost increases by 232 Mil.EUR/y and 25 Mil.EUR/y respectively.

Fig. 3 presents the evolution of installed capacities and capacity factors of different power generation technologies. As the emission cap is very low, renewable technologies are always installed to their maximum potential. They produce 58.8% of the electricity mix, knowing that the mobility and heat demands are electrified inducing at total electrical demand of 177.7 TWh.

The entire energy system can cope with the intermittency of renewable energy sources in three different ways: (i) back-up generation (e.g. a CCGT, a industrial gas cogeneration), (ii) storage (e.g. pumped hydro storage), and/or (iii) sector-coupling possibilities from other sectors such as electric vehicle batteries or thermal storage. Fig. 3 and Fig. 4 present the evolution of the size of those assets participating to flexibility on the electricity grid.

The size of the CCGT needed is underestimated during the initial ESOM run (No Reserve in Fig. 3). After soft-linking, The CCGT capacity increases from 11.4 GW to 14.7 GW. However, its yearly production stays roughly the same and totals 39.7 TWh which induces a reduction of the load factor. Hence, this additional capacity is installed only to ensure reliability of the system and cover extreme events. The industrial gas cogeneration, on the contrary, doesn't change in size. As it is linked with the industrial heat demand, it is less flexible and behaves more like a baseload load technology.

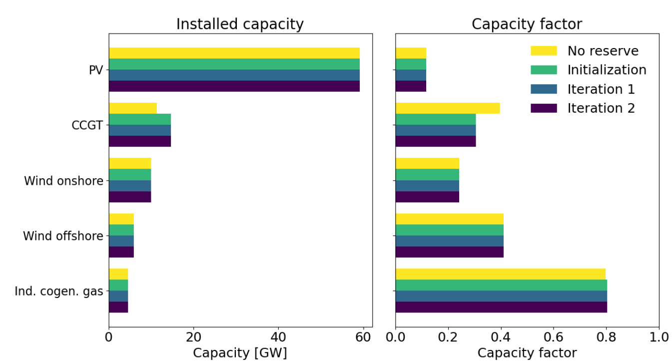

Fig. 3. Evolution of the installed capacity (left) and capacity factor (right) of electricity assets (Abbreviations: Photovoltaic Panels (PV), Combined Cycle Gas Turbine (CCGT), Industrial (ind.), Cogeneration (Cogen.))

Fig. 4 illustrates the evolution of the installed storage capacity throughout the iterations. The only seasonal storage installed is the thermal storage on the ES_DHN. As it is seasonal, its size is 1 or 2 order of magnitudes larger then other thermal storage units connected to industrial (ES_IND) and decentralized (ES_DEC) zones, which are used as daily buffers. After successful soft-linking the size of seasonal storage increases by 46.7% compared to the initial EnergyScope run. Seasonal storage related to power-to-gas (i.e. hydrogen sector) does not seem to be cost-effective and is neglected by the models. This is due to the specific case study of Belgium where the total demand of all energy sectors outscales the renewable potential. Hence, there is not enough power for electrolysers to be profitable. This bi-directional soft-linking methodology will be validated on another case study with higher renewable energy potential in future works.

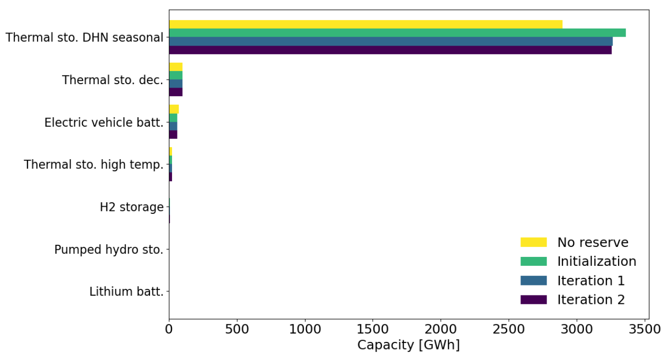

Fig. 4. Evolution of the installed capacity of storage assets (Abbreviations: Storage (sto.), District Heating Network (DHN), Batteries (batt.), Decentralised (dec.), Temperature (temp.))

The framework is set up in such a way that CostShedLoad is lower than the three ENS cost variables related to the electricity, heating and H_2 sectors. This strategy is designed to reduce the complexity of the problem and allows easier and more intuitive monitoring of potential bottle-necks inside the multi-sectoral energy system. For example, if the initial installed capacity is undersized in the heating sector, this lack of capacity will manifest itself in the electricity sector only, which will activate all the power-to-heat units available, even if this causes load shedding. Fig. 2 also presents the evolution of shadow prices (i.e. the dual values of energy balance equations, also known as marginal heat or electricity prices) in the initial (No Reserve) and final (Iteration 2) step of the soft-linking method. In the initial No Reserve iteration, shadow prices are high in the ES_ELE sector, indicating the potential lack of capacity. If the proposed system is undersized, the optimization error is smaller than the optimization accuracy and total ENS is greater than 0 the stop condition of the soft-linking platform is triggered. After the convergence in Iteration 2, system adequacy is sufficient and Shadow prices are within the expected range. In the ES_DHN zone, prices remain exceptionally high, especially during the winter season, however, as there is enough capacity to cover the heating demand even during the peak hours, system is adequately sized and stop condition criterion is met.

V. Conclusion

In this article a bi-directional soft-linking framework for the assessment of sector-coupling options in future energy system is proposed. It is applied to the Belgian 2035 energy system with a cross-sectoral representation and high time-resolution. The proposed data sources, methods and models are released under the open license to ensure reproducibility and transparency of the work and can be freely downloaded from Zenodo repository[4]. In order to quantify the outcomes of the bi-directional soft-linking framework, three scenarios were defined.

Simulation results indicate that the proposed modelling framework ensures fast convergence within 2 iterations. Furthermore, results also show that, after successful soft-linking, the system reliability of the proposed system increases and VRES curtailment decreases.

Future work will extend the spatial coverage of the methodology by testing it on a multi-nodal case study where regional energy systems are allowed to communicate and exchange commodities. The representation of sector coupling will also be further improved, allowing higher penetration of renewable energy which trigger exchanges with other sectors such as renewable fuels and hydrogen.

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