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Optimisation method to obtain marginal abatement cost-curve through EnergyPLAN software

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ABSTRACT

The scope of energy system modelling is to support policy-makers in the definition of an energy strategy. Energy system models typically provide one single optimal solution. On the contrary, presenting the results of energy system modelling in the form of a set of optimal or sub-optimal alternatives improves the transparency towards the policy makers. A method to achieve this is marginal abatement cost curve. It estimates the relationship between potential reduction of CO_2 emissions and relative costs. Model based methods to obtain marginal abatement cost curve lack of simultaneous high resolution in time and in sector coupling. Moreover, model based methods obtain smooth curves which can be transformed in step-wise only through a decomposition analysis. This latter shape is particularly important for providing the explicit technological detail in the graphical representation. The paper aims at developing a method to address these two issues in marginal abatement cost curves. The method, called EPLANoptMAC, is based on the EnergyPLAN software, developed by Aalborg university, and a hill climbing algorithm for expansion capacity optimisation. It is presented by applying it to the Italian energy system in 2030. The results show how in the initial phase of the decarbonisation process it is cheaper to generate over-generation and curtailments from variable renewable energy sources than save these curtailments through balancing and storage solutions. This is driven by the low cost of generation of VRES and the high cost of balancing and storage solutions.

1. Introduction

Energy system modelling is the discipline which supports and guides policy-makers in the definition of an energy strategy. Energy system models provide the best set of technologies to be implemented in a certain energy system. Solving a cost minimization problem typically returns a single optimal best set of technologies as solution. However, as stated by Neumann and Brown [1] “feasible but sub-optimal solutions may be preferable for reasons that are not captured by model formulations because they are difficult to quantify [2]”. Large infrastructure projects and their visual impact, land-use conflicts, problematic concentration of renewables in single regions are all political implications which are difficult to be quantified in energy system models [1]. However, as reported by Neumann and Brown [1] these implications could justify a policy-makers choice towards a solution which is slightly more cost expensive than the unique optimal one.

Presenting the results of energy system modelling as a set of alternatives instead of one single optimal solution improves the transparency towards the policy makers for two main reasons [1]. a) It allows policy makers to choose between different alternatives depending on their political inclination and requirements [1]. b) It allows the identification of the common and missing elements of the different optimal and sub-optimal solutions (must-haves and must-avoids) [1]. This is useful to better support policy makers through a participatory process in the identification of the decarbonisation measures.

Different approaches and techniques have been elaborated to assess this challenge: i) identification of multiple near-optimal solutions, ii) multi-objective optimisation approach, iii) marginal abatement cost (MAC) curves.

i) DeCarolis [3] discussed the utility of Modelling to Generate Alternatives (MGA) as a technique to achieve multiple near-

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optimal solutions in the energy system context. In [2], DeCarolis et al. used MGA together with Temoa bottom-up energy system model to study multiple near-optimal solutions of the U.S. power sector. Neumann and Brown [1] utilized MGA to study the near-optimal feasible space for the European power system under CO2 reduction targets between 80% and 100%. As energy system model they used PyPSA-Eur [4,5]. The results highlighted the existence of several similarly costly, but technologically diverse solutions. A contained cost deviation of 0.5% produces a large range of feasible solutions. The results showed among the must-have the following technologies: offshore or onshore wind, hydrogen storage and transmission reinforcement. Lombardi et al [6], building upon the work of DeCarolis [3], developed a method to generate spatially explicit, practically optimal results (SPORES). The method utilizes the bottom-up energy system model Calliope framework [7].

ii) Completely different approach is achieved by implementing a Multi-Objective expansion capacity optimisation. This approach allows the achievement of the Pareto front of non-dominated solutions. The objective functions that are usually selected are economic, environmental variables such as total annual costs, CO_2 emissions or renewable energy share. In fact, economic development and CO_2 emissions reduction are often in conflict with each other. Policy makers thanks to this tool have the possibility to graphically analyse and compare different optimal solutions and select the favourite scenario depending on their predilection towards the economic or environmental objective. Several publications have applied this approach [8–10].

iii) Marginal abatement cost curve is a very popular tool to estimate the relationship between potential reduction of CO_2 emissions and relative costs. Similarly to multi-objective optimisation approach, MAC curve allows the achievement of different alternatives solutions depending on where the policy makers decide to locate on the curve. This will be driven again by their inclination towards the environmental and economic objectives.

This paper focuses on this latter approach. Huang et al. [11] presented a review of MAC curves identifying two main approaches: Expert-based and model-based. Expert-based MAC curves are created through the individual assessment of abatement measures. These models calculate the incremental cost of alternative abatement measures with respect to the starting situation of the energy system, which is then divided by the emission reduction. The MAC curve is thus derived by ranking individual measures costs of CO_2 emissions abatement. The advantage of this approach is the resulting step-wise MAC curve. This type of graphical representation allows the very clear and explicit visualisation of the curve by means of single discreet steps. Each of them is achieved by a different decarbonisation measure showing immediately which measure is responsible for the emission reduction. The disadvantages of this approach are related to the difficulties in capturing system-wide sectorial interactions leading to problems of double-counts of CO_2 emissions abatement [12]. Moreover, another disadvantage of expert-based MAC curves is connected to possible inconsistencies in the baseline assumptions [13].

Model-based MAC curves achieve the result by mean of an energy system model which can use a bottom-up, top-down or hybrid approach. This model is used to perform several model runs with two different methods: i) with progressively higher CO_2 emissions tax levels, ii) with stricter constraints on carbon emissions reduction. The problems of the expert-based approach are overcome: the risks of double counts of emissions reduction and not considering sectorial interactions are removed. The advantages and disadvantages of this approach are related to the adopted type of model. Bottom-up models, implementing partial equilibrium approach, reach a high technological detail in the energy sector but do not consider macro-economic impacts [14]. Top-down models based on Computable General Equilibrium (CGE) capture the effects of a certain energy transition on the whole economy system but lack of technological detail in the energy sector [14]. For more pros and cons of these methods there are the studies of Zhang and Folmer [15], Stoft [16] and Kesicki [13].

A disadvantage of model-based approach is that the final result is not a step-wise MAC curve but a smooth one. This version generally omits the technological detail in the graphical representation. The steps which constitute the MAC curve are continuous and each level of CO_2 emissions reduction is achieved by a mix of technologies. To overcome this limitation, Kesicki [17] introduced a new method called decomposition analysis. He implemented a model-based MAC curve approach through the use of UK MARKAL and decomposition analysis to inspect mitigation costs and CO_2 emissions reduction potentials in the UK transport sector [18].

Model-based MAC curves adopting bottom-up energy system models are the focus of this paper. As already mentioned, the limits of this approach are related to the limits of bottom-up models. As highlighted by Prina et al. [19] the main challenge of bottom-up energy system models is the simultaneous achievement of high resolution in four identified pillars: resolution in time, in space, in techno-economic detail and sector coupling. Lowering the resolution in one or more than one of these fields is usually necessary to contain the computational effort. However, this introduces approximation and inaccuracies as demonstrated by Poncelet et al. [20].

Table 1 shows the main features of reviewed studies implementing a model-based MAC curve through the use of a bottom-up energy system model.

It is possible to notice how none of them simultaneously implement sector coupling and a high temporal resolution. Moreover, few of them produce a step-wise MAC curve and only through a decomposition method.

The hourly time-step is particularly relevant when modelling energy systems with high penetration of variable renewable energy sources (VRES). Poncelet et al. [20] showed the importance of the time resolution in energy system modelling. They demonstrated how the resolution in time should be prioritized compared to the resolution in techno-economic detail and how the use of a low number of time-slices (usually 12 time-slices) produces an error that cannot be considered negligible.

Sector coupling is also a relevant feature for energy system models. Several studies have shown the advantages of sector coupling compared to single sectors modelling approach. In this regards, it is important to mention the contribute of Aalborg University in the definition of the smart energy system concept through which they showed the advantages of studying the interactions and synergies between different energy sectors to maximize efficiency and reduce costs [34,35]. Lund in Ref. [35] and Connolly et al. [36] have introduced the concept of the smart energy system and the opportunities and synergies among energy sectors. In Ref. [37] Mathiesen et al. have inspected the smart energy system concept with particular attention to the integration of the transport sector.

To summarise, two main issues have been highlighted: a) model-based MAC curve carries around the limits of the bottom-up models used for the analysis. The literature review has showed how bottom-up models used for developing model-based MAC curves lack of simultaneous resolution in time and in sector coupling. b) The model-based MAC curve achieved with these bottom-up

Table 1
Main features of reviewed studies implementing a model-based MAC curve through the use of a bottom-up energy system model.

Model name	Energy sectors covered	Time resolution	MAC curve shape	Reference
MARKAL UK	Transport	6 time-slices	**Step-wise** (decomposition analysis)	[21]
MARKAL UK	Transport	6 time-slices	Smooth	[22]
TIMES_PT	**All sectors**	16 time-slices	Smooth	[23]
LUSYM	Power	**Hours**	Smooth	[24]
AIM/Enduse	**All sectors**	1 time-slices	Smooth	[25]
TIMES_GECCO	Transport	42 time-slices	Smooth	[26]
MARKAL_GEORGIA	Power and heating (residential and commercial sectors)	8 time-slices	**Step-wise** (decomposition analysis)	[27]
AIM/Enduse	Power and heating (residential sector)	1 time-slice	**Step-wise** (decomposition analysis)	[28]
AIM/Enduse	Industry	1 time-slice	**Step-wise** (decomposition analysis)	[29]
OSeMOSYS	Power	48 time-slices	Smooth	[30]
METER	Power	73 time-slices	Smooth	[31]
TIMES	**All sectors**	12 time-slices	**Step-wise** (decomposition analysis)	[32]
EPLANoptMAC	**All sectors**	**Hours**	**Step-wise**	[33]

models produces a smooth curve which is transformed in step-wise only through a decomposition method. This latter is particularly important for providing the explicit technological detail in the graphical representation.

This paper aims at developing a method to address these two issues. In particular the scope of the paper is the development of an optimisation method for model-based MAC curves creation adopting a bottom-up energy system model with sector coupling and high temporal resolution. Moreover, the aim is to achieve a resulting MAC curve with a step-wise shape.

The method which is presented in this paper is named EPLANoptMAC. It is based on the EnergyPLAN software [38] which has a particularly large community [39]. The source code is openly available to favour the spread and use of this method among this community [33]. This paper mainly focuses on the presentation of this novel method while it does not go in detail in the final results. The model is applied to the Italian case study at the year 2030 to show the potentialities of the developed method. This allows the study of the competing decision variables and the reasons why certain best energy mixes are reached.

The paper is structured as follows. The methodology section describes and explains EPLANoptMAC model starting from the original EnergyPlan and EPLANopt versions. The Italian case study presents the main sources and assumptions to populate the EnergyPLAN model for the Baseline year 2015 and the main assumptions on the decision variables. The results section discusses the main results of the model and its application to the Italian energy system selected for demonstration purposes. Finally, last section provides conclusive remarks.

2. Material and methods

EPLANoptMAC adopts a simple hill climbing algorithm coupled to EnergyPLAN software [38]. The hill climbing algorithm is used to perform expansion capacity optimisation and achieve the model-based MAC curve. EnergyPLAN is used to accomplish the operational calculations over the year and thus the matching between demand and supply in each hour of the simulation year. EPLANoptMAC inherits the features of EnergyPLAN: all sectors are considered (electricity, heating, cooling, industry and transport) and a high temporal resolution through an hourly timestep is adopted [35].

2.1. EnergyPLAN software

EnergyPLAN software has been developed and maintained by Aalborg university [40] since 1999. It has a user-friendly graphical user interface. It is free to download, documentation and tutorials are provided in the EnergyPLAN website [34], but it is not open source. It is programmed in Delphi Pascal. The main characteristics of the software are the following:

- It is a deterministic input/output model. Uncertainty and stochastic variables are not directly considered. Thus the same input will always return the same output. The inputs that have to be included by the users are energy demands, technological components of the energy system, their capacities and efficiencies, costs specifications and regulation strategies.
- It is designed to properly model future scenarios with high penetration of renewables. It focuses on one-year period (the simulation year) with an hourly time-step. It implements sector-coupling by integrating the main energy sectors of the energy system such as electricity, heating, cooling, industry and transport.
- EnergyPLAN follows a heuristic approach. Through analytical programming, it implements different priorities for the sources that have to cover the energy demand. This allows the containment of the computational effort which is in the order of seconds for each run.

EnergyPLAN model has been applied at different geographical scales: at European level [41], at national level [42–52], at regional level [53,54], to towns and municipalities [55,56] and to small island [57–60].

EnergyPLAN is used in the EPLANoptMAC method adopting the single-node option thus assuming a ideal and perfect transmission grid without bottlenecks or losses. For this reason it is important to define two concepts: overgeneration and curtailment. These will be particularly relevant in the analysis of the results. The overgeneration, $Overgeneration_t$ [GW], is the electric power production, p_t [GW], which exceeds the demand, d_t [GW], in a determined hour t (see Equation (1)). The overall annual overgeneration, $Overgeneration$ [GWh], is given by the sum of the hourly $Overgeneration_t$ [GW] contributions (Equation (2)).

$$Overgeneration_t = \begin{cases} p_t - d_t & d_t \le p_t \\ 0 & d_t > p_t \end{cases} \tag{1}$$

$$Overgeneration = \sum_{t=0}^{T} Overgeneration_t \tag{2}$$

Curtailment, $Curtailment_t$ [GW], is the electric power which is not used by the system in a determined hour, it exceeds the demand and it is not used by balancing and storage solutions (Equation (3)). bss_t is the electric demand requested by balancing and storage solutions for charging or generation of different energy vectors. The overall annual curtailment, *Curtailment* [GWh], is given by the sum of the hourly $Curtailment_t$ [GW] contributions (Equation (4)).

$$Curtailment_t = \begin{cases} Overgeneration_t - bss_t & bss_t \leq Overgeneration_t \\ 0 & bss_t > Overgeneration_t \end{cases} \tag{3}$$

$$Curtailment = \sum_{t=0}^{T} Curtailment_t \tag{4}$$

The abovementioned overgeneration and curtailment are theoretical indicators useful for this paper and its evaluations on the energy self-sufficiency of the considered case study. In reality, the excess electricity generation can be used as electricity export towards other countries.

2.2. EPLANoptMAC

In order to overcome EnergyPLAN limitation in providing an expansion capacity optimisation option, several methods coupling the software with different algorithms have been implemented. Cabrera et al. [61] developed a MATLAB toolbox to iteratively run EnergyPLAN for automatic evaluation of different future alternatives. Bjelić et al. [62]. applied a Single-Objective (SO) expansion capacity optimisation through the use of GenOpt. Mahbub et al. [63] coupled EnergyPLAN with a Multi-Objective (MO) expansion capacity optimisation algorithm written in Java. Prina et al. [54] developed the Python based EPLANopt model through the coupling of EnergyPLAN and a MO expansion capacity optimisation algorithm.

Starting from this latter approach, EPLANopt model has been further developed to produce model-based MAC curves. This new model version is called EPLANoptMAC. It is based on a hill climbing Single-Objective expansion capacity optimisation algorithm. In order to delineate the objective function it is important to define the Cost of CO_2 Abatement (CCA). Equation (5) shows its formulation. CCA is given by the quotient between the difference in costs and the difference in CO_2 emissions between the reference case and the one obtained implementing decision variable *m*.

$$CCA\ [€\,/\,t\ CO_2] = \frac{Costs_m - Costs_{reference}}{CO_{2,reference} - CO_{2,m}} \tag{5}$$

The objective function is the minimization of the CCA as shown in Equation (6). dv is the vector of the decision variables dv_m within a lower $dv_m^{(L)}$ and an upper bound $dv_m^{(U)}$ for each of them.

$$\begin{aligned} &\text{Optimization function } \min_{dv}\,[CCA] \\ &\text{Subject to } dv_m^{(L)} \leq dv_m \leq dv_m^{(U)} \end{aligned} \tag{6}$$

The steps through which the algorithm evolves to identify the MAC curve are shown in the diagram of Fig. 1 and are the following:

1) Input definition. The inputs of the model are the following: i) all EnergyPLAN inputs needed to define the reference system in EnergyPLAN, ii) the list or vector of decision variables on which the expansion capacity optimisation will be implemented together with the list of incremental values, one for each of decision variable (vector *I*). These incremental values are the additional values (in terms of installed power, capacity, additional share, etc.) of each decision variable. These guide the expansion capacity optimisation. iii) maximum number of steps (*Nsteps*). The number of steps, *Nsteps*, defines the number of iterations resulting in the number of discreet elements in the MAC curve.
2) At each step the possibility to expand the power, capacity or share of each decision variable is assessed. This is performed by reading the value of each decision variable, for example the capacity of Photovoltaics (PV), in the reference system and modifying it with by adding the incremental unit value for that decision variable (I_m). Then the modified version of the reference system is launched in EnergyPLAN. The total annual costs and CO_2 emissions are taken from the EnergyPLAN output file in order to calculate the CCA. This is done for each of the decision variables.
3) The result of phase 2 is a list of CCA values, one for each decision variable. The minimum value is chosen by the algorithm. All the outputs of the solution implementing the decision variable which produce the lowest CCA are saved and adopted to analyse the final results.
4) The energy system modified by the decision variable which generates the lowest value of CCA is selected as new reference system. The algorithm checks if the maximum potential of the different decision variables, $dv_m^{(U)}$, is reached or not. If it is reached it removes the decision variable from the dv vector. The step index moves forward of one unit and the phases 1,2, 3 are repeated considering the modified reference system.

The algorithm stops when the maximum number of steps, *Nsteps*, is met or when it not possible anymore to reduce the CO_2 emissions with the considered set of decision variables because the maximum potential of each of them, $dv_m^{(U)}$, is reached.

EPLANoptMAC is built as static bottom-up energy system model, thus it is applied at a future target year. EPLANoptMAC inherits the typical advantages and limitations of hill climbing algorithms. The advantage of this optimisation algorithm is the short computational time. The drawbacks regard the possibility to remain stuck in local minima.

3. Italian case study

In the previous chapter, the generic formulation of the model and optimisation process have been defined. In this chapter, the application case study is presented. The input variables and parameters of the model are listed together with the decision variables chosen for the selected case study, their lower ($\boldsymbol{dv_m^{(L)}}$), upper bounds ($\boldsymbol{dv_m^{(U)}}$) and incremental values (I_m).

This chapter is subdivided into two sub-sections. In the first, the assumptions regarding the Baseline scenario are presented. The Baseline represents the current state of the energy system. The year for which the Baseline is created is 2015 while the expansion capacity optimisation model EPLANoptMAC is run for the future target year 2030. In the second sub-section, the list of decision variables taken into account within the optimisation problem are presented and discussed.

3.1. Baseline 2015

The Baseline 2015 is created starting from the Heat Roadmap Europe 4 (HRE4) project [64]. It provides the 2015 EnergyPLAN input file for 14 EU member countries (Italy included) [65]. This 2015 HRE4 baseline is modified using more precise data taken from Italian authorities: GSE [64], RSE [66] and Terna [67] (see Table 2). For more details on the Baseline 2015 is possible to refer to the following publication [68]. Scope of this work is to present the novel methodology of EPLANoptMAC. In order to do this, the

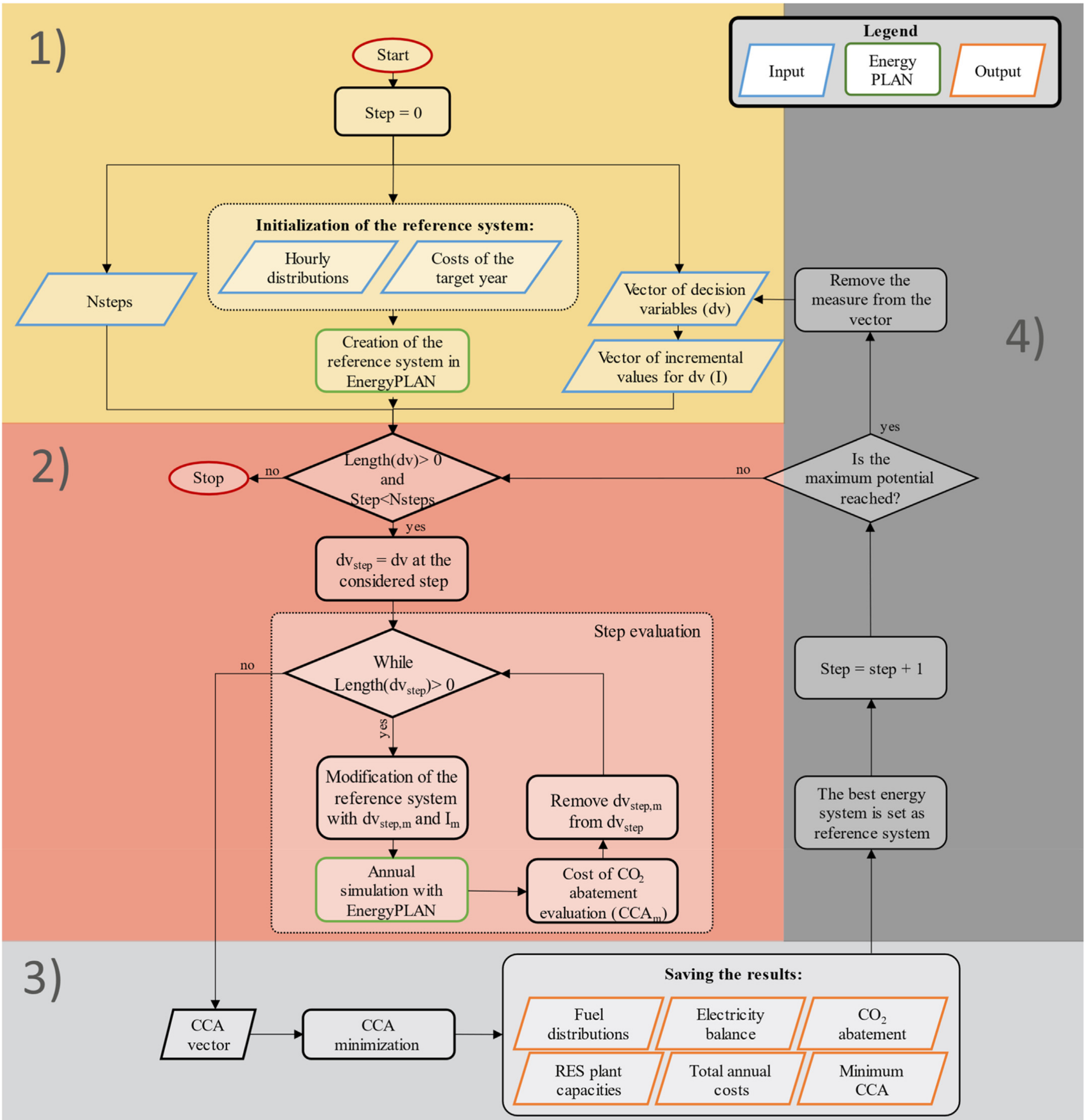

Fig. 1. Diagram of the EPLANoptMAC algorithm.

Table 2
Baseline 2015 main additional sources in the power sector to HRE project data [64].

Data	Source
Installed capacity for VRES	GSE [69], Terna [70]
Hourly distribution for VRES	GSE [69], Terna [70]
Installed capacity for other technologies	Terna [70], HRE [65]

application of the model is necessary. However, the focus of the paper is not on the final results of the case study.

Different assumptions have been formulated to create the EnergyPLAN input file for the expansion capacity optimisation in 2030. One of these is the phase out from coal. Moreover, all the costs of the different technologies are updated following different sources. All the different assumptions, emissions factors, costs of technologies and fuels for the year 2030 in the Italian energy system are listed in Ref. [68].

3.2. Decision variables

The decision variables are the decarbonisation measures on which the expansion capacity optimisation is performed. It is important to identify them in order to define the domain of the optimisation problem. Therefore, it is important to define the decarbonisation measures that are relevant for the considered case study starting from the different sectors to exploit the synergies between them. It is also important to define their bounds. $\boldsymbol{dv_m^{(L)}}$ corresponds to the current state of the decision variable while $\boldsymbol{dv_m^{(U)}}$ is the upper bound and corresponds to its maximum potential. In addition, the incremental value I_m for each decision variable $\boldsymbol{dv_m}$ is defined.

The considered decision variables are listed in Table 3 and are chosen from different energy sectors.

- Power sector. In the power sector there are generation sources such as rooftop residential and utility scale photovoltaic systems, onshore and offshore wind power. The implementation of these decision variables in the model is straightforward. Their installed capacity is increased at each step of their incremental value I_m and the resulting energy system is evaluated in terms of CCA. The costs associated to the expansion of the installed power of these sources are the investment, operation and maintenance costs in 2030.

In the power sector there are also measures classified under balancing and storage category: lithium-ion batteries and power to gas. Their implementation in the model requires some additional expedients. For lithium-ion batteries the installed capacity is increased at each step by its incremental value I_m under the assumption that batteries are not limited in charging and discharging power. The costs of batteries are given by the investment, operation and maintenance costs projections in 2030 [68]. Power to gas exploits excess electricity by VRES to produce hydrogen and inject it in the natural gas grid. The decision variable is the amount of produced hydrogen in TWh. The produced hydrogen maximum potential is assumed to be 15% of the overall natural gas consumption. At the increase of the generation of hydrogen the electrolyser installed power is forced to increase. For each TWh of produced hydrogen an installed power of 2000 MW of electrolyser is imposed. The overall costs of power to gas are connected to the investment, operation and maintenance costs of the electrolyser in 2030.

- Heating sector. Energy efficiency of buildings is implemented as formulated in Ref. [10]. Similarly, the assumption that in all refurbished buildings there is the switch from boilers to heat pumps to cover the remaining space heating is implemented. The incremental value I_m for this source is 1% of energy efficiency refurbishment. The costs connected to this decision variable results from the following: the decrease of fuels, decrease of installed capacity of individual boilers and the increase of heat pumps. In addition, the costs related to energy refurbishment are considered by the model. These costs can be found in Ref. [10].
- Transport sector. The decision variable considered in this sector is electric vehicles. The assumptions regarding this decision variable are reported in Ref. [68]. The model considers only the infrastructural costs of electric mobility and does not take into account the costs of the vehicles.

4. Results and discussion

Fig. 2 shows the MAC curve (top part) and the Cost of CO_2 Abatement (bottom part) of the different decision variables at each step. The MAC curve allows the visualisation of the potential CO_2 abatement of each decision variable for each step through the width of each bar. The height of each bar shows the cost of CO_2 abatement for a specific decision variable at a specific step. At the successive step the energy system characteristics are changed. The impact of the same decision variable in terms of potential CO_2 abatement and CCA can change in two different steps.

The subplot on the bottom in Fig. 2 allows to compare the values of different decision variables at each step. The lowest value for each step in this subplot is depicted in the first subplot through the bar plot mode. The subplot on the bottom in Fig. 2 it is particularly important to highlight the dynamic, synergies and correlations between the decision variables in the decarbonisation process and to understand the reasons why certain best energy mixes are reached.

Looking at the results depicted in Fig. 2 it is possible to point out the following key aspects.

i) In the first part of the curve (below 10 Mt of CO_2 abatement), electric mobility is the only decision variable selected. This is due to the lowest CCA driven by the considered assumptions (only cost of electric mobility infrastructure is considered). It is also possible to see that the implementation of electric mobility and the consequent increase of electric vehicles share does not affect the CCA of the other decision variables. Electric mobility affects the electricity sector by increasing the electric demand. In energy systems with high penetration of renewables in the electricity sector this would have had an impact on CCA of the others generation sources as well. However, the renewable energy share in the Italian power sector is contained and equal to 35% in 2015. The overgeneration is negligible and the potential installation of additional installed power of VRES is far from the production of overgeneration. The increase of overgeneration from VRES

Table 3
List of decision variables per sector and type, their current state $\boldsymbol{dv_m^{(L)}}$, their incremental value I_m, their maximum potential $\boldsymbol{dv_m^{(U)}}$.

Sector	Type	Name	Unit	Current state, $\boldsymbol{dv_m^{(L)}}$	Incremental value, $\boldsymbol{I_m}$	Maximum potential, $\boldsymbol{dv_m^{(U)}}$
Power sector	Generation source	Residential photovoltaic	MW	15863	1000	120000
		Utility scale photovoltaic	MW	4245	1000	70000
		Wind power	MW	10265	1000	49000
		Offshore wind power	MW	0	1000	10000
	Balancing & storage	Batteries	GWh	0	10	600
		Power to gas	TWh	0	1	15
Transport sector	Dump charge	Vehicle electrification	%	0	1	20
Heating sector	Energy refurbishment	Energy efficiency	%	0	1	75

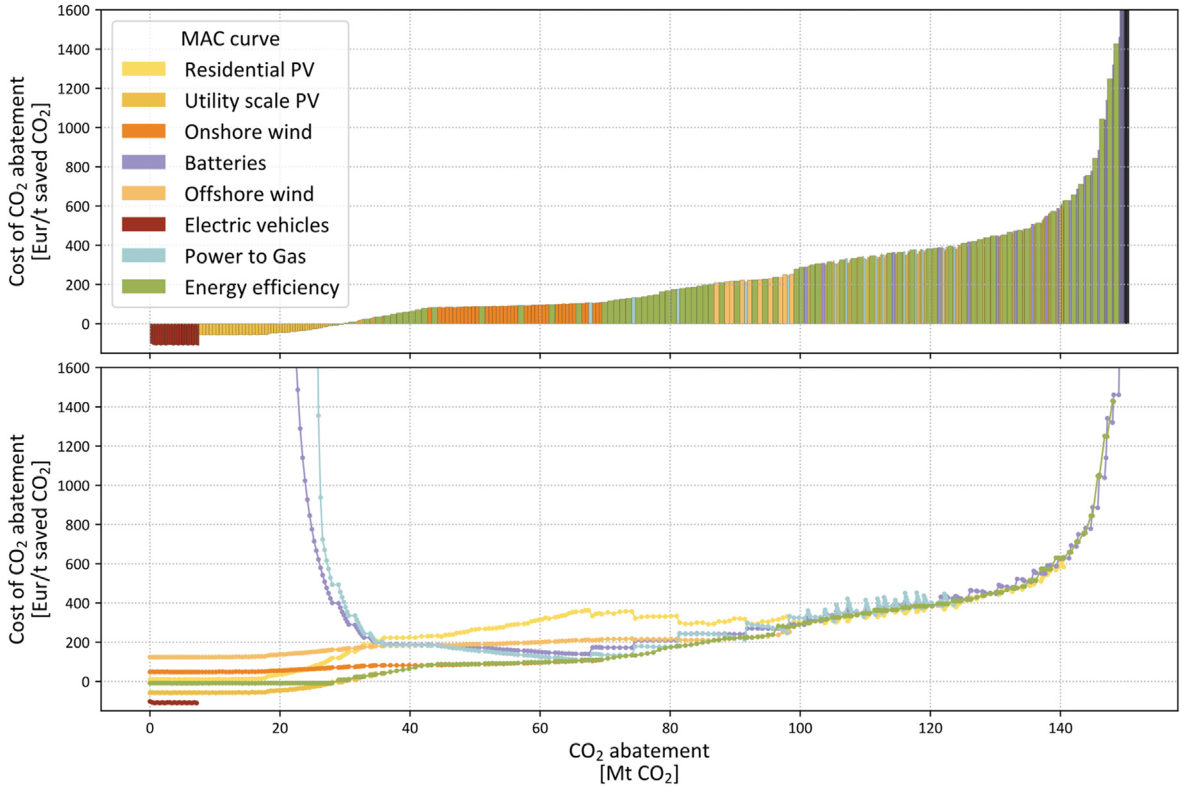

Fig. 2. MAC curve at 2030 for the Italian case study (subplot on the top) and comparison of the Cost of CO_2 Abatement of the different decision variables (subplot on the bottom).

in absence of balancing and storage technologies produces lower CO_2 emission reduction due to the lower reduction in the generation from fossil fuels power plants.

ii) In the second part of the curve (between 10 and 100 Mt of CO_2 abatement), high installation of VRES occurs starting with utility scale PV which has the lowest cost of electricity [€/MWh] in 2030. At the beginning it has a negative CCA, then increasing the overall installed power of this source leads to overgeneration reducing the benefits; CCA becomes positive for the last steps of utility scale PV installation. It is interesting to see the behaviour of CCA of the others generation sources decision variables in this segment. CCA of residential PV increases with the same trend of utility scale PV as they share the same hourly generation profile. The potential installation of residential PV after the installation of utility scale PV and without balancing and storage solutions would increase the overgeneration in the middle hours of the day without any additional relevant benefits in CO_2 emissions reduction. The CCA of onshore and offshore wind also increases but with a different trend. In fact, the difference in the hourly profile of generation would favour the integration of PV and wind generation profiles, as already demonstrated by Weitemeyer et al. [71]. They showed how a mix of PV and wind power generation allows a better integration of renewables compared to the case with only PV or only wind power. It is possible to observe also how installing utility scale PV the CCA of VRES reduces the CCA of balancing and storage solutions such as batteries and power to gas. After the installation of utility scale PV which reaches its maximum potential, there is a segment in which the less expensive passive measures of energy efficiency refurbishment of buildings are chosen. After that, onshore wind power is chosen until its maximum potential is reached, after that another part of energy efficiency measures and then offshore wind power.

iii) In the third and last part of the MAC curve (from 100 Mt of CO_2 abatement), different decision variables alternates: passive measures of energy efficiency refurbishment of buildings, residential PV, batteries and power to gas. The introduction of batteries and power to gas results in small discontinuities affecting the successive steps where the decision variable chosen is mainly residential PV (the last remaining generation source which has not reached its maximum potential yet). Its CCA is lower than the previous one due to the fact that the additional VRES generation can exploit the balancing and storage benefits introduced in the last step. These discontinuities are mainly driven by the introduced discretisation method. Tending to smaller incremental values for all the decision variables would decrease these discontinuities.

Fig. 3 describes the power sector highlighting the following aspects: the electricity consumption, generation, curtailments and overgeneration together with the MAC curve depicting the changes in the power sector among the expansion capacity path found by EPLANoptMAC. The electricity consumption shows how the electric boiler contribution disappears due to energy efficiency of buildings. As a consequence of energy efficiency of buildings conventional boilers are replaced with heat pumps. In fact, the electric demand contribution for heat pumps increases from left to right. Electric demand due to electric vehicles increases at the beginning and then remains constant. The graph also shows the electric demand plus overgeneration to better understand how this overgeneration is used or unused giving rise of curtailments. This is used from the beginning by pumped hydro storage (PHS) which is already present in the Italian energy system and does not have any additional

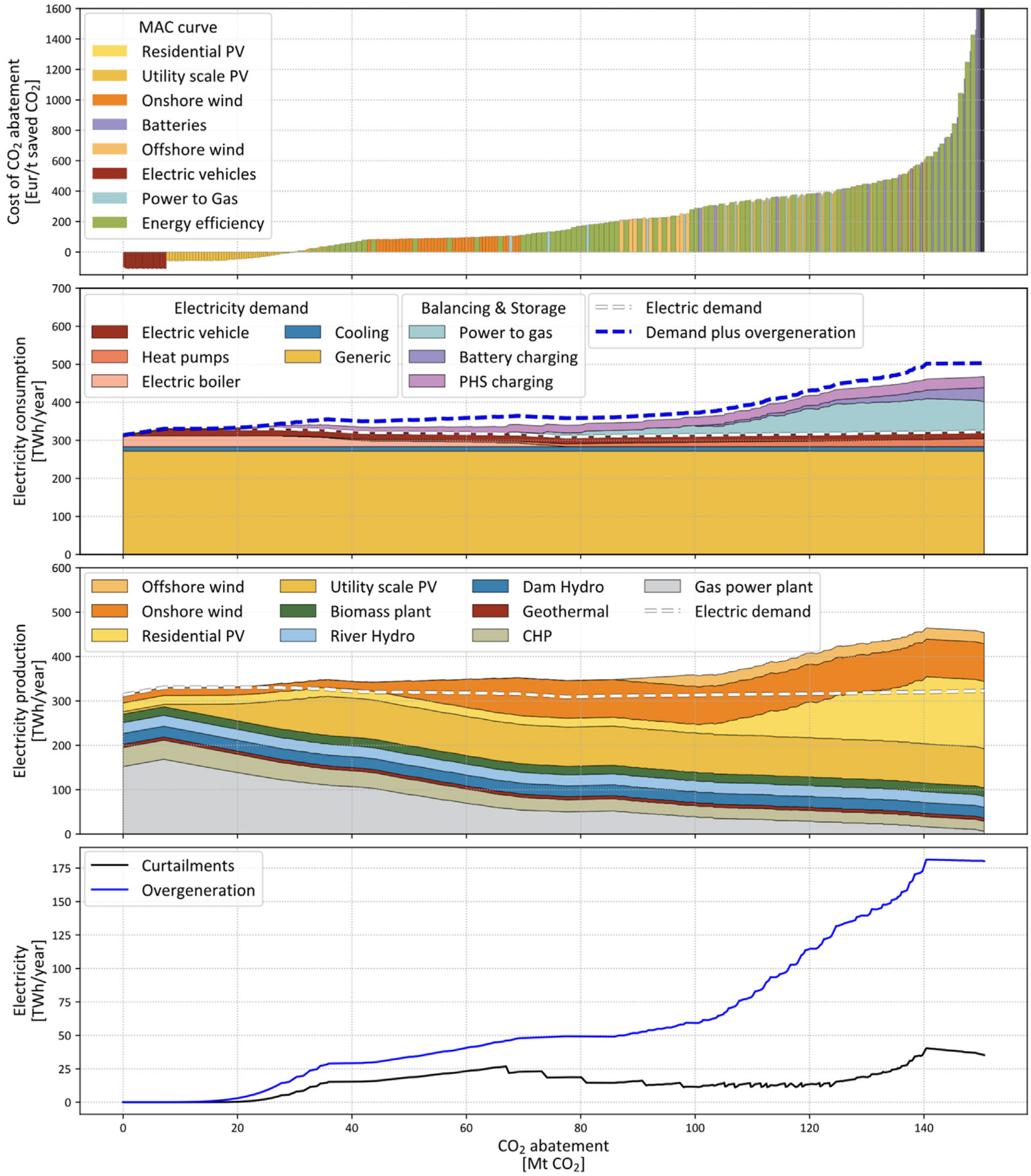

Fig. 3. MAC curve at 2030 for the Italian case study (first subplot on the top), different contributions to the electricity consumption (second subplot from the top), electricity generation from different sources (third subplot from the top) and comparison between curtailments and overgeneration (subplot on the bottom).

potential in terms of installed power and capacity. The contribution of electric consumption from batteries and power to gas instead particularly increases in the last part of the curve.

The electricity generation depicted in Fig. 3 allows the following considerations:

- The initial part of the curve presents an increase of electricity demand due to electric mobility. This cause an increase of electricity produced by natural gas power plants. This increase of fossil fuels is balanced by a decrease of fossil fuels consumption in the transport sector due to the highly efficient electric engines.
- After this first part, the installation of VRES is visible and produces a decrease of natural gas power plants generation and an increase of overgeneration.

The last subplot (on the bottom) shows the overgeneration and the curtailments. The overgeneration increases until the maximum potential of the different VRES decision variables is reached. The curtailments rise in the first part (until almost 65 Mt of CO_2 abatement), then decrease due to the introduction of balancing and storage measures (until almost 120 Mt of CO_2 abatement) and finally rise again in the last part of the curve. A counter-intuitive but important message can be highlighted: in the first phase of the

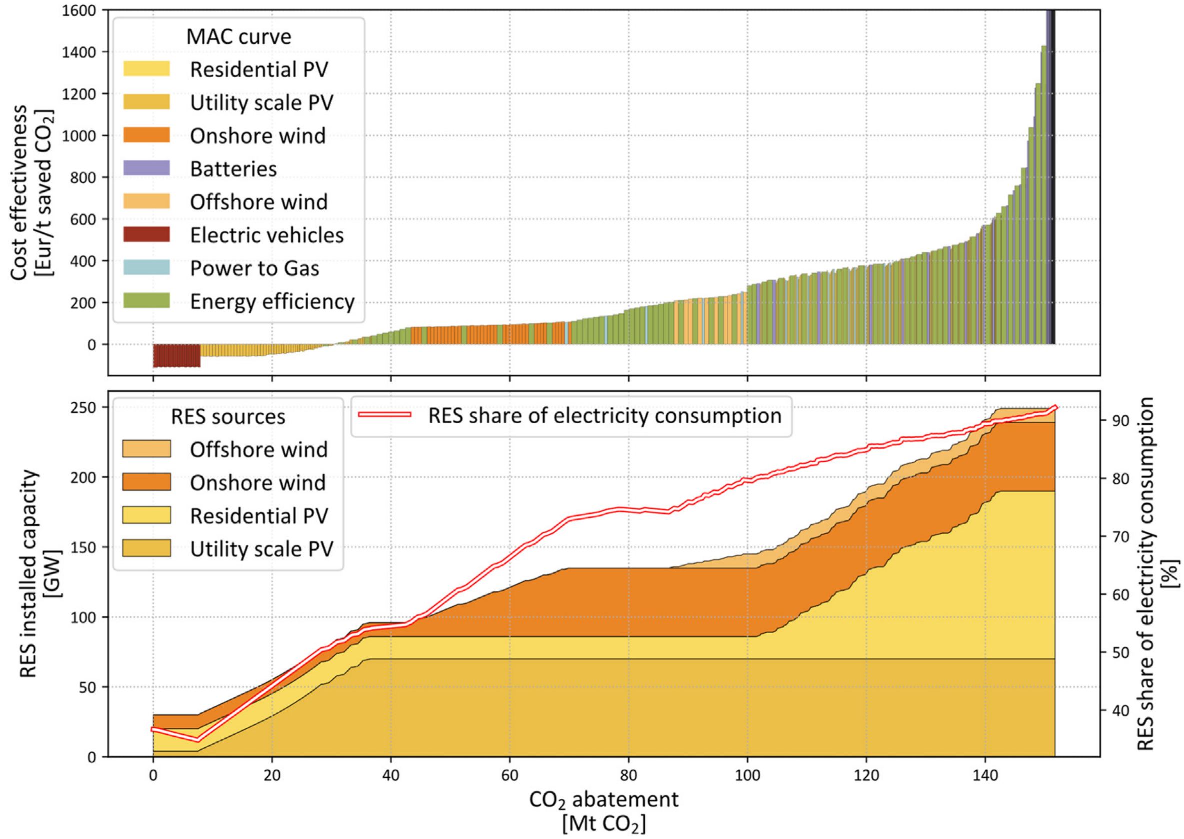

Fig. 4. MAC curve at 2030 for the Italian case study (subplot on the top) and installed power of VRES with renewable energy sources share of the electricity consumption (subplot on the bottom).

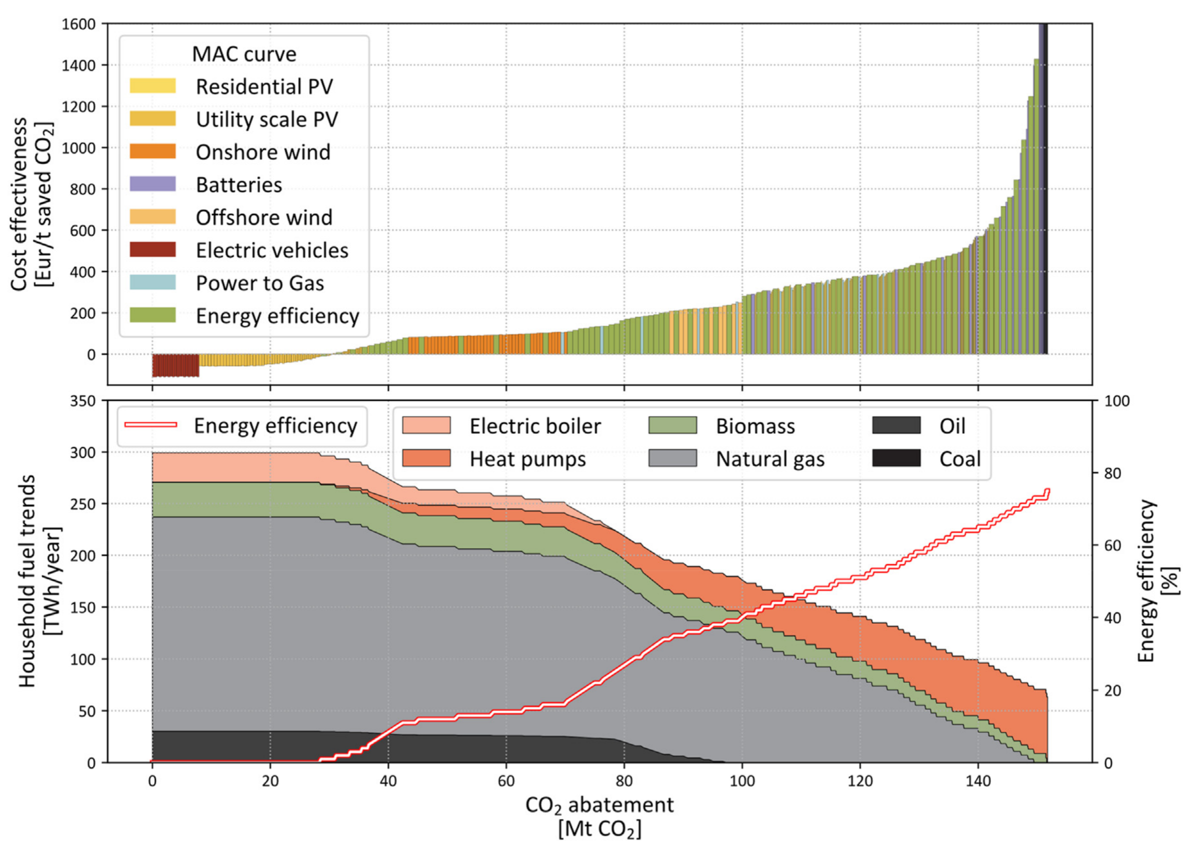

Fig. 5. MAC curve at 2030 for the Italian case study (subplot on the top), household fuel and energy efficiency trends (subplot on the bottom).

decarbonisation of the energy system it will be cheaper to generate overgeneration and curtailments from VRES than save these curtailments through balancing and storage solutions. This is driven by the low cost of generation of VRES and the high cost of balancing and storage solutions. This is also in line with several studies: Perez et al. [72], Pierro et al. [73], Budischak et al. [74] and Perez et al. [75].

Fig. 4 shows the installed power of the VRES decision variables and the achieved Renewable Energy Sources (RES) share in the electricity sector. The graph shows that the initial adoption of electric mobility results in a decrease of the RES share in the electricity sector. After this initial part the RES share of the electricity sector increases. The increase is higher in correspondence of the sections in which the installed capacity of VRES rises. RES share of electricity sector also increases in sections in which balancing and storage solutions are adopted due to the better exploitation of the existing overgeneration. RES share also increases when energy efficiency measure is selected by the algorithm, the segment around 40 Mt of CO_2 abatement clearly shows this. This is due to the higher electricity demand of heat pumps in the central hours of the day in which the overgeneration from PV is high.

Fig. 5 depicts the trends of the fuels consumption of the heating sector. It shows the decrease of fuel consumption as consequence of energy efficiency measures. In the refurbished buildings the algorithm substitutes the conventional boilers with heat pumps. This is reflected in the results of Fig. 5. With the increasing of energy efficiency it is possible to observe an additional reduction of fuel with the following order of priorities: electric boilers, oil boilers and natural gas boilers.

Fig. 6 shows the total annual costs evolution trough the solution on the MAC curve. Costs of fossil fuels decrease due to the lower consumption. Over 100 Mt of CO_2 emissions can be reduced with a slight increase of the annual costs of the system, equal to about 10%. The graph particularly highlights the effort in terms of costs that needs to be done in the space heating sector for passive energy efficiency measures and the electrification of the sector.

5. Conclusions

In order to overcome the limitations in literature about methods to create Marginal Abatement Cost curves the novel EPLANoptMAC model has been presented in this paper. The main limitations found in literature for this type of models are the following: i) model-based Marginal Abatement Cost curve methods carry around the limits of the bottom-up models used for the analysis. The literature review has showed how bottom-up models used for developing model-based MAC curves lack of simultaneous resolution in time and in sector

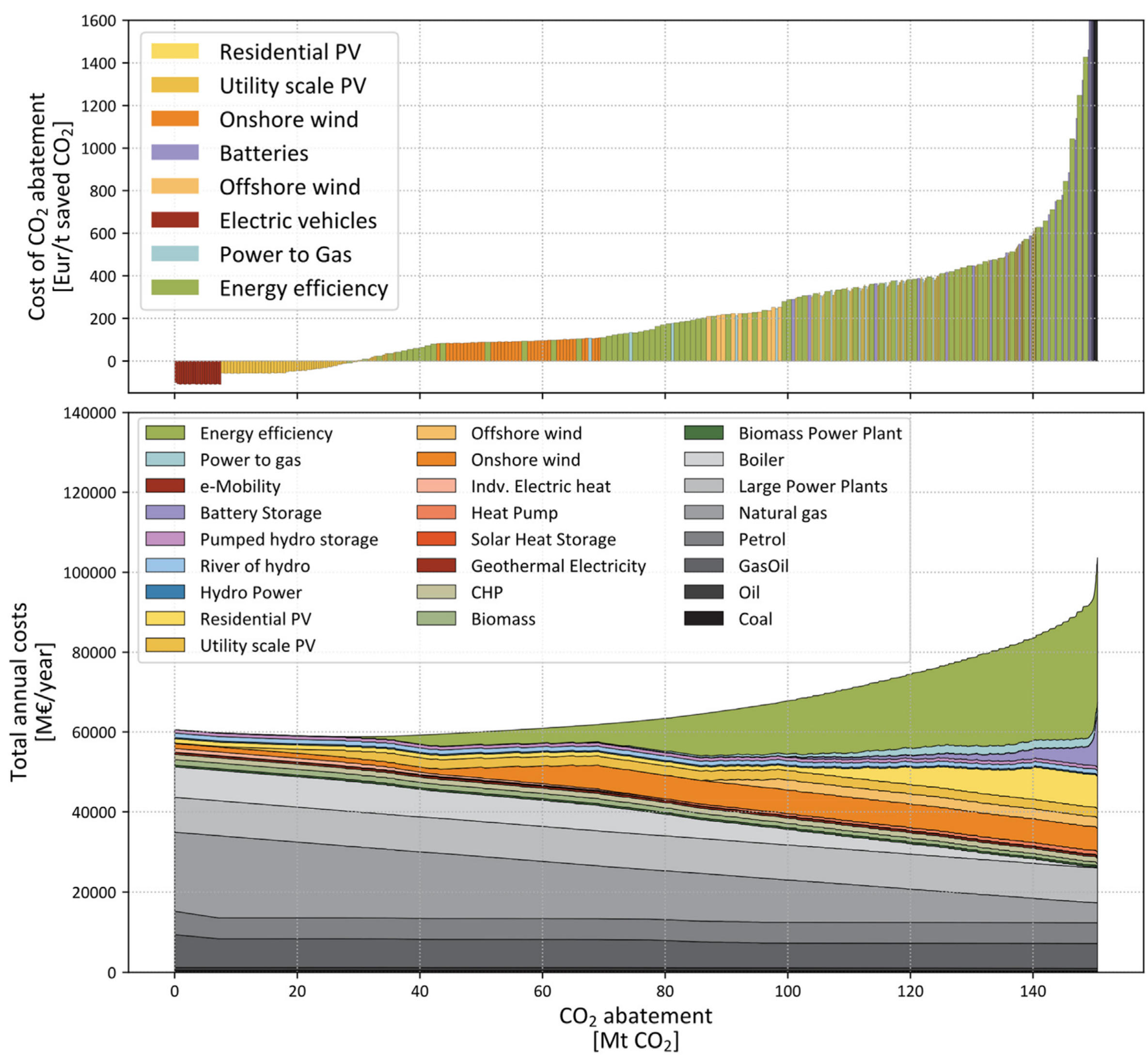

Fig. 6. MAC curve at 2030 for the Italian case study (subplot on the top), costs trends (subplot on the bottom).

coupling. ii) The model-based MAC curve achieved with bottom-up models found in literature produces a smooth curve which is transformed in step-wise only through a decomposition method. This latter is particularly important for providing the explicit technological detail in the graphical representation. EPLANoptMAC overcomes these limitations through the creation of a method for marginal abatement cost curves based on a static bottom-up energy system model which couples EnergyPLAN software and a hill climbing algorithm for the expansion capacity optimisation.

However, the algorithm presents some limitations. The hill climbing optimisation algorithm presents the possibility to remain stuck in local minima. Moreover, static or short-term models do not consider the whole transition but focus on a future target year. The consequence is the difficulty to include in the study time-dependent phenomena like plant decommissioning or costs evolutions.

The EPLANoptMAC model has been applied to the Italian energy system and its results have been presented with the aim of showing the potentialities of the novel method. The results have shown the potentialities of the model in studying the competing decision variables, their interactions and how a certain best energy mix is reached. It has highlighted the dynamics between the Cost of CO2 abetment of the different decision variables belonging to different energy sectors. This has been possible thanks to the smart energy concept included in the EPLANoptMAC method through the implementation of sector coupling. The results have shown how the increase of overgeneration by variable renewable energy sources produces a decrease of the Cost of CO2 abetment of balancing and storage solutions such as batteries and power to gas. The introduction of electrification decision variables in the heating and transport sectors can increase the renewable energy share in the power sector depending on the availability of overgeneration and the contemporaneity with the increase of electric demand.

The results have shown a counter-intuitive but important message. In the initial phase of the decarbonisation process it will be cheaper to generate overgeneration and curtailments from Variable Renewable Energy Sources than save these curtailments through balancing and storage solutions. This is driven by the low cost of generation of VRES and the high cost of balancing and storage solutions.

The results have shown how over 100 Mt of CO2 emissions can be cut with a very contained increase of total annual costs by installing variable renewable energy sources and electrifying the transport and heating sectors. This once again underlines the importance of the smart energy system concept and the implementation in the modelling of a high resolution in time and sector-coupling.

Declaration of competing interests

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

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Glossary

Nomenclature

$\boldsymbol{Overgeneration_t}$	Overgeneration for timestep $\boldsymbol{t}$
$\boldsymbol{p_t}$	Electric power production [GW]
$\boldsymbol{d_t}$	Electricity demand [GW]
$\boldsymbol{Overgeneration}$	Overall annual overgeneration [GWh]
$\boldsymbol{Curtailment_t}$	Electric power which is not used by the system in a determined hour, it exceeds the demand and it is not used by balancing and storage solutions [GW]
$\boldsymbol{bss_t}$	Electric demand requested by balancing and storage solutions for charging or generation of different energy vectors [GW]
$\boldsymbol{Curtailment}$	*Overall annual curtailments [GWh]*
$\boldsymbol{t}$	Index of the hourly time-step
$\boldsymbol{T}$	Vector of the timesteps, hours in a year
$\boldsymbol{m}$	Decision variable index
$\boldsymbol{dv}$	Vector of decision variables
$\boldsymbol{step}$	Index for the step
$\boldsymbol{dv_{step}}$	Vector of decision variables at step step
$\boldsymbol{dv_{step,m}}$	Decision variables m at step step
$\boldsymbol{Costs_m}$	Total annual costs of the case implementing decision variable m [M€]
$\boldsymbol{Costs_{reference}}$	Total annual costs of the reference case [M€]
$\boldsymbol{CO_{2,reference}}$	Total annual CO_2 emissions of the case implementing decision variable m [Mt]
$\boldsymbol{CO_{2,m}}$	Total annual CO_2 emissions of the reference case [Mt]
$\boldsymbol{CCA}$	Cost of CO_2 Abatement [€/t]
$\boldsymbol{dv_m^{(L)}}$	Lower bound of the decision variable m
$\boldsymbol{dv_m^{(U)}}$	Upper bound of the decision variable m
$\boldsymbol{I}$	Vector of the incremental values, one for each decision variable
$\boldsymbol{I_m}$	Incremental value of decision variable m
$\boldsymbol{Nsteps}$	Number of steps

Acronyms

MAC	Marginal abatement cost
MGA	Modelling to Generate Alternatives
SPORES	Spatially explicit, practically optimal results
CGE	Computable General Equilibrium
VRES	Variable renewable energy sources
SO	Single-Objective
MO	Multi-Objective
CCA	Cost of CO_2 Abatement
PV	Photovoltaics
HRE4	Heat Roadmap Europe 4
PHS	Pumped hydro storage
RES	Renewable Energy Sources

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