Energy 149 (2018) 213–221

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

Multi-objective optimization algorithm coupled to EnergyPLAN software: The EPLANopt model

Matteo Giacomo Prina [a, b, *], Marco Cozzini [a], Giulia Garegnani [a], Giampaolo Manzolini [b], David Moser [a], Ulrich Filippi Oberegger [a], Roberta Pernetti [a], Roberto Vaccaro [a], Wolfram Sparber [a]

[a] *Institute for Renewable Energy, EURAC Research, Viale Druso 1, I-39100 Bolzano, Italy*
[b] *Dipartimento di Energia, Politecnico di Milano, Via Lambruschini, 4, 20156 Milano MI, Italy*

ARTICLE INFO

Article history:
Received 31 October 2017
Received in revised form
24 January 2018
Accepted 10 February 2018
Available online 12 February 2018

Keywords:
Energy scenarios
EnergyPLAN
EPLANopt
Renewable energy
Energy planning

ABSTRACT

The planning of energy systems with high penetration of renewables is becoming more and more important due to environmental and security issues. On the other hand, high shares of renewables require proper grid integration strategies. In order to overcome these obstacles, the diversification of renewable energy technologies, programmable or not, coupled with different types of storage, daily and seasonal, is recommended. The optimization of the different energy sources is a multi-objective optimization problem because it concerns economical, technical and environmental aspects. The aim of this study is to present the model EPLANopt, developed by Eurac Research, which couples the deterministic simulation model EnergyPLAN developed by Aalborg University with a Multi-Objective Evolutionary Algorithm built on the Python library DEAP. The test case is the energy system of South Tyrol, for which results obtained through this methodology are presented. Particular attention is devoted to the analysis of energy efficiency in buildings. A curve representing the marginal costs of the different energy efficiency strategies versus the annual energy saving is applied to the model through an external Python script. This curve describes the energy efficiency costs for different types of buildings depending on construction period and location.

1. Introduction

One of the greatest challenges of the international community to mitigate climate change is to lower anthropogenic greenhouse gas (GHG) emissions [1], [2]. The heat, electricity, transport and industry sectors account for 60% of the total amount [3]. To address this challenge and improve the security of the energy system, an increasing number of countries have set strict energy targets and expanded their share of renewables. The European Union adopted the “2020 climate and energy package” in 2007 [4] and the “2030 climate and energy framework” in 2014 [5]. Energy planning is therefore taking a central role in assessing the future energy system and helping policy makers to set targets and subsidizing mechanisms.

Policy makers need tools capable to simulate energy systems over the years to develop efficient energy policies. Energy system models represent a simplified picture of the real system and its related operation costs. In literature, two main approaches can be distinguished: top-down models, with focus on economic theory, and bottom-up models, with focus on technology analysis. A. Herbst et al. [6] present a review of the two approaches applied to energy system modeling. Each has advantages and limitations and differs in the detailing aspects of the energy system. Connolly et al. [7] reviewed existing models for simulating and analyzing the integration of renewable energy into the energy system. The EnergyPLAN software developed by Aalborg University [8] is based on a bottom-up approach and is one of the most comprehensive tools to describe future energy systems in a very short computational time [9–11].

EnergyPLAN is a deterministic input/output model that integrates the three primary sectors of the energy system: electricity, heat and transport. EnergyPLAN simulates an energy system but cannot find the best mix of technologies through an optimization

* Corresponding author. Institute for Renewable Energy, EURAC Research, Viale Druso 1, I-39100 Bolzano, Italy.
E-mail address: matteogiacomo.prina@eurac.edu (M.G. Prina).

https://doi.org/10.1016/j.energy.2018.02.050
0360-5442/

process.

The optimization of different technologies and sources within an energy system is a multi-objective problem because it concerns economical, technical and environmental aspects. The optimization of these competing objectives produces a Pareto front of “best”, i.e. Pareto-optimal, solutions or future configurations of the energy system. The aim of this study is to present (i) an optimization model integrated with EnergyPLAN, named EPLANopt [12], (ii) the adopted methodology to include energy efficiency measures into the analysis and (iii) its application to South Tyrol, a region in northern Italy. EPLANopt has been developed by Eurac Research and couples EnergyPLAN with a multi-objective evolutionary algorithm (MOEA) implemented in the Python library DEAP [13].

Bjelic et al. [14] launched EnergyPLAN within the single-objective optimization program GenOpt to identify the minimal increase in the costs of the national energy system for Serbia under the EU 2030 framework. Mahbub et al. [15] coupled EnergyPLAN to a MOEA written in Java to evaluate the Pareto front of best configurations of the energy system. Similarly to these two approaches, this paper couples EnergyPLAN with a MOEA, with the important extension that the wrapper – an open-source tool written in Python – besides calling EnergyPLAN and providing an optimization algorithm, makes it possible to set dependencies among optimization variables and constraints. In particular, this is used to include building renovation as an additional optimization variable (not directly available in EnergyPLAN), properly connecting it with energy efficiency and heap pump installations (see below).

The paper is structured as follows. Section 2 describes and explains EnergyPLAN, EPLANopt, and how energy efficiency is modelled within the latter. Section 3 presents the main results of the model and its application to South Tyrol. Finally, Section 4 provides conclusive remarks.

2. Methodology

This section introduces at first the EnergyPLAN software with a short presentation of its main characteristics. In the second subsection, it then describes more in detail the EPLANopt model and its main features. Section 2.3 shows how to add input variables to the EPLANopt model that could not enter directly in EnergyPLAN, such as energy efficiency of buildings.

2.1. The EnergyPLAN software

EnergyPLAN developed by Aalborg University follows a bottom-up approach. It is considered one of the most complete tools to describe future energy systems [7,9,10] in very short computational time. EnergyPLAN integrates the three primary sectors of any national energy system, electricity, heat and transport, according to predefined priorities. This allows for a simulation of the interactions between different energy system sectors and shows advantages compared to other software focusing on single sectors [16–29]. The program simulates a regional or national energy system on an hourly basis. Thus, it is suitable for modeling non-programmable renewable energy sources. Furthermore, an hourly time-step shows advantages over simulating a year through characteristic days [30].

EnergyPLAN is deterministic, i.e., a simulation with the same inputs always produces the same results. Consequently, it does not take into account randomness or probability distributions. It assesses the behaviour of a pre-selected energy system configuration, differently from an optimization model where the objective is to find the best technology mix for configuring the energy system. EnergyPLAN does not calculate the optimal hourly energy dispatch based on a set of constraints and an objective function. Instead, a set of priorities drives the energy balances, thus resulting in very short computational time. The main purpose of the model is to support the design of national energy planning strategies through a techno-economic analysis of different energy system configurations. The model has been applied at different scales: at European level [31], at national level [32–37], and to towns and municipalities [28,38]. In the present case, the EnergyPLAN model is applied to a region in northern Italy following a single node approach. Thus, transmission constraints are not considered in the model.

2.2. The EPLANopt model

With the final goal of finding “best alternatives”, i.e. Pareto-optimal solutions, for the future energy system of a region or nation, Eurac Research developed an open-source code called EPLANopt under the LGPL license. The solver in EPLANopt is a MOEA based on the Python library DEAP [13]. It is designed to work with EnergyPLAN (diagram shown in Fig. 1) by being linked to it, as shown in Fig. 2. The code gives the possibility to set an arbitrary number of objectives within the multi-objective optimization, to change operators and parameters of the genetic algorithm and to initialize part of the population with known solutions. The parameters and data are set in a Json file. It is possible to run EnergyPLAN in parallel, which saves computational time. Finally, a documentation and simple example are provided [12].

The MOEA is a meta-heuristic optimization algorithm inspired by the principle of natural selection [39]. A heuristic optimization algorithm is particularly suited for hard problems where finding an optimal solution is computationally impractical [15]. The MOEA family [40,41] is a subclass of evolutionary algorithms (EAs) designed for solving multi-objective optimization (MOO) problems.

The optimization follows several steps: i) An initial population of random solutions, called individuals, is generated. ii) The objective functions of each individual are evaluated by the simulation model. In our case, all hourly input profiles and costs are fixed input parameters of EnergyPLAN, as they do not change during the optimization. In this model, learning effects in terms of investment cost reduction are not endogenously modelled, the effects of this economic transition are accounted for considering expected technology costs at the time of investment. iii) Each individual is ranked according to “fitness”, i.e. its objective function values. iv) After ranking all individuals, the MOEA generates a new population of individuals (the next “generation”) by applying the typical operators of genetic algorithms: parent selection, crossover and mutation. v) After a pre-defined number of generations, a Pareto front is generated by the MOEA (see Fig. 2).

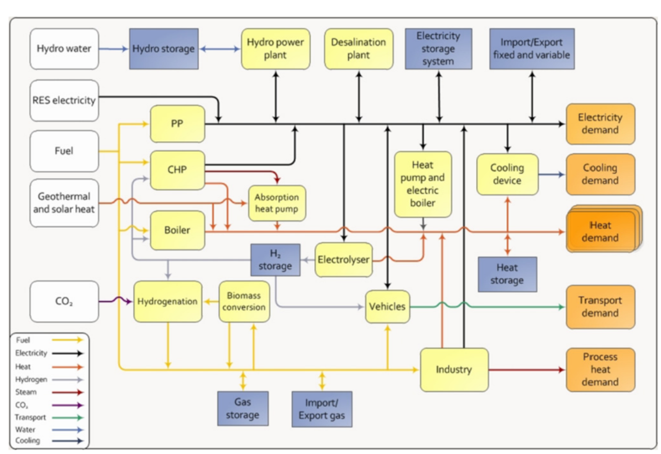

Fig. 1. Diagram of the EnergyPLAN's structure [9].

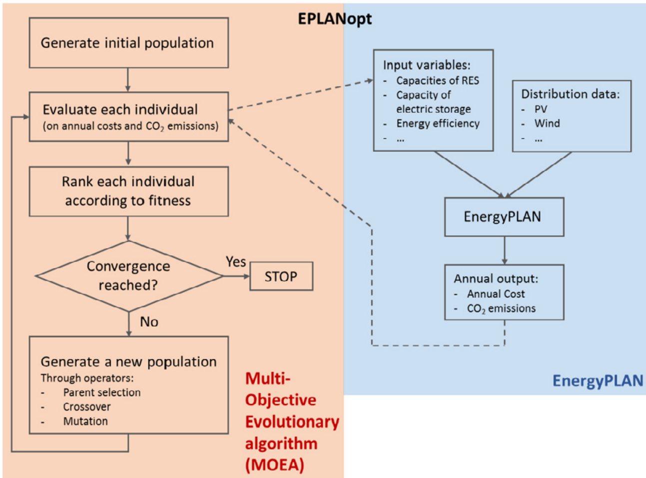

Fig. 2. Diagram of the EPLANopt model, dashed arrows detail the steps required to evaluate an individual.

Parent selection consists in the method to evaluate the non-dominated solutions of a population. In the model is based on NGSA-II algorithm [42]. Crossover and mutation are used in EAs to converge quickly to global optima while not getting stuck in local optima. Crossover is a strategy to create the offspring starting from a parent population. The EPLANopt model utilizes the uniform crossover operator. Uniform crossover swaps the attributes of two individuals according to a probability parameter. In EPLANopt, the probability of crossover is set to 90% while the probability to exchange each single attribute is set to 50%. The mutation operator preserves diversity within the population. EPLANopt uses a uniform mutation operator that replaces an attribute of an individual with a probability of 5% by an integer chosen between a lower and upper bound. The general structure of the multi-objective minimization problem is defined as follows.

Optimization function

$$\min_{\boldsymbol{x}}[f_m(\boldsymbol{x})] \quad m = 1, 2, \ldots, M$$

Subject to

$$x_i^{(L)} \leq x_i \leq x_i^{(U)} \quad i = 1, 2, \ldots, N$$

f_m denotes the m -th objective function to be minimized. $\boldsymbol{x}$ is the vector of the decision variables x_i within a lower $x_i^{(L)}$ and an upper bound $x_i^{(U)}$.

This methodology, therefore, implies running EnergyPLAN multiple times with different inputs. As a consequence, the computational time increases. A single run of EnergyPLAN typically lasts only a few seconds due to the internal handling of priorities, which is definitely a huge advantage of EnergyPLAN. The time required for the creation of the Pareto front depends on the complexity of the problem and the size of the input space.

Discussing in the detail the application of EPLANOpt model to the South Tyrol case, the first step consists of creating a reference scenario for the province in EnergyPLAN for the year 2014. The optimization optimizes the energy system for a future year starting from the reference case. Setting this future year is important in order to use suitable values for the costs of technologies, fuels, etc. For the case study of South Tyrol presented in this paper the selected year is 2050.

In this particular case study, the objective functions are the total annual costs, CO_2 emissions per person, and the share of renewable energy. For the sake of simplicity and to better represent the results, instead of maximizing the percentage of renewables within the system it has been decided to minimize the percentage of energy still covered by fossil sources. It is important to mention that minimizing both CO_2 emissions and the percentage of energy demand covered by fossil sources push the system to be fossil fuel independent rather than "carbon-neutral", i.e. trying to reach zero emissions through a balance between import and export.

The structure of the multi-objective minimization problem for the South Tyrolean energy system can be summarized as follow:

Optimization function

$$\min_{\boldsymbol{x}} \begin{bmatrix} TotalAnnualCosts[M€], \\ CO_2emissionsPerPerson\left[\dfrac{t}{person}\right], \\ 100 - \%RES[\%] \end{bmatrix}$$

Subject to

$$CurrentValue \leq x_i \leq PotentialValue \quad i = 1, 2, \ldots, N$$

The optimization decision variables are the following: (i) the photovoltaic installed power, (ii) the biogas power plants capacity, (iii) the batteries capacity, (iv) electrolysers and (v) fuel cells power, (vi) hydrogen storage capacity, (vii) large heat pumps and (viii) thermal storage connected to the district heating network, (ix) solar thermal capacity to satisfy the demand of domestic hot water (DHW), (x) building energy efficiency and (xi) heat pumps for the individual building sector. The South Tyrol case is characterized by 11 decision variables. The optimization of its energy system required around 12 h to obtain a stable Pareto front; this time could be reduced by running processes in parallel. This additional computational time requested by EnergyPLAN with respect to a single simulation in EnergyPLAN (few seconds) is paid back when considering the results of the multi-objective optimization.

Fig. 3 shows the non-dominated solutions after each generation for the case study of South Tyrol and how they converge to the true Pareto front.

2.3. Energy efficiency

This section is dedicated to the explanation of the optimization variables. Fig. 2 shows three examples of these decision or optimization variables: PV capacity, heat pumps capacity and thermal storage capacity. After selecting an optimization variable, the range in

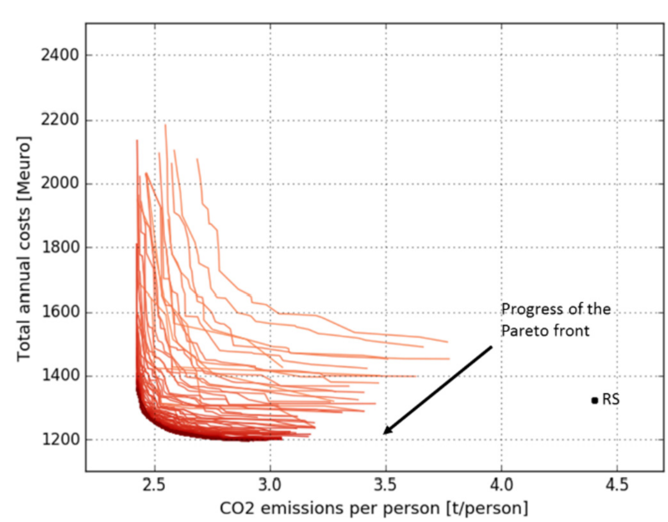

Fig. 3. Progress of the Pareto front during the optimization.

which the variable can change within the optimization algorithm must be identified. Usually, the lower bound is the current capacity in South Tyrol while the upper bound is the maximum capacity possible, i.e. the maximum potential of a technology. Other decision variables such as energy efficiency in buildings are not present among the input parameters of EnergyPLAN and need an external additional code that changes and includes them in the simulation.

The energy efficiency variable is defined as the percentage of the residential and tertiary heating demand reduction. The code reads the heat consumption of each sector and decreases it according to the value of the energy efficiency variable at each simulation. The external code takes also care of the costs connected to the energy efficiency measures. These costs have to be added to the final overall costs resulting from the EnergyPLAN simulation. As a first approximation, a constant marginal cost for energy savings could be assumed, thus obtaining a linear cost increase with energy efficiency. However, a more accurate method to estimate these costs, which consists in analyzing the building stock along with a variety of possible energy efficiency measures has been adopted. By sorting the marginal costs in ascending order, the energy efficiency measures are arranged according to cost-effectiveness. By plotting the marginal costs against the annual energy saving, a curve describing a cost-optimal sequence of the building renovation measures is obtained. As a consequence, lower values of the energy efficiency variable correspond to lower marginal costs.

This process is now further explained by applying it to the case study of South Tyrol. The steps taken to estimate the energy efficiency-costs curve were the following:

i. Analysis of the provincial residential building stock and classification according to construction period, housing type (single family, multi-family, detached, block) and heating degree days (HDD);
ii. Evaluation of the specific heat consumption for each municipality, construction period and housing type;
iii. Assessment of the renovation costs and related energy savings. Passive House Planning Package (PHPP) [43] simulations have been carried out for the following four types of housing, considered as representative of the residential building stock: single family house (SFH), multi-family house (MFH), detached home and apartment block. The useful floor areas for these housing types were 250, 904, 1363 and 2308 m^2, respectively. All types were simulated in pre-renovation and post-renovation conditions to quantify the energy savings in percent. As a general assumption for the evaluation, the energy saving percentages calculated for the typical buildings are assumed as independent from the municipality and the construction period of the buildings.;
iv. Calculation of the annual thermal energy savings in absolute numbers for each construction period, housing type and municipality. From the energy savings and renovation costs, the investment cost per annual kWh saved (related to the CO_2 avoidance cost) for each renovation can be computed and used to arrange renovations from the most to the least cost-effective one. Because we scaled the space heating consumption by the HDD, the same kind of building placed in a colder climate undergoes the same kind of renovation earlier.

Fig. 4 shows the energy efficiency-costs curve. The annual energy savings are expressed as percentage of the total heat demand of the residential and tertiary sector. Clearly, an increase of the annual energy savings entails a rise in the energy efficiency marginal costs. At the left end of the curve there are those interventions that generate high energy savings compared to the investment costs for renovation. The most cost-effective interventions on the building envelope are typically roof insulations for SFH built before 1946, followed by façade and basement insulations. At the right end of the curve, in order to reach annual energy savings between 70 and 80% for the residential building stock, retrofit measures have high costs compared to the resulting energy savings. An example of such a measure with low cost-effectiveness is a window replacement in a building erected after 2005.

A constraint regarding heat pumps for the individual building sector was added in the external code to increase the reliability of the results. The application of heat pump in the building stock is allowed in the model only in deeply renovated buildings. This assumption was made in order to avoid inefficient heat pump's installation in an old non-refurbished building.

3. Results

This section shows the results obtained by applying EPLANopt and the external code related to the energy efficiency variable and constraint on heat pumps (see Section 2.3) to the South Tyrolean energy system.

3.1. South Tyrol baseline 2014

South Tyrol is a province located in the Italian Alps, characterized by an extension of 7400 km^2 and a population of around 524

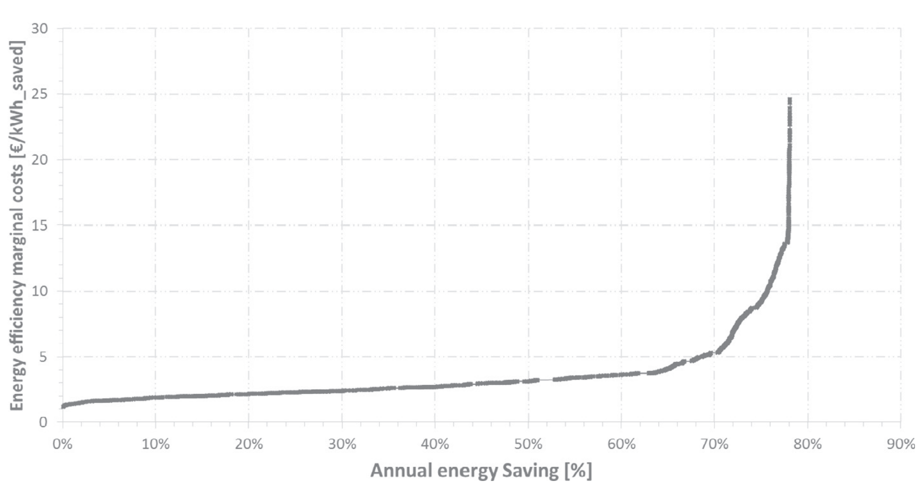

Fig. 4. Energy efficiency-costs curve.

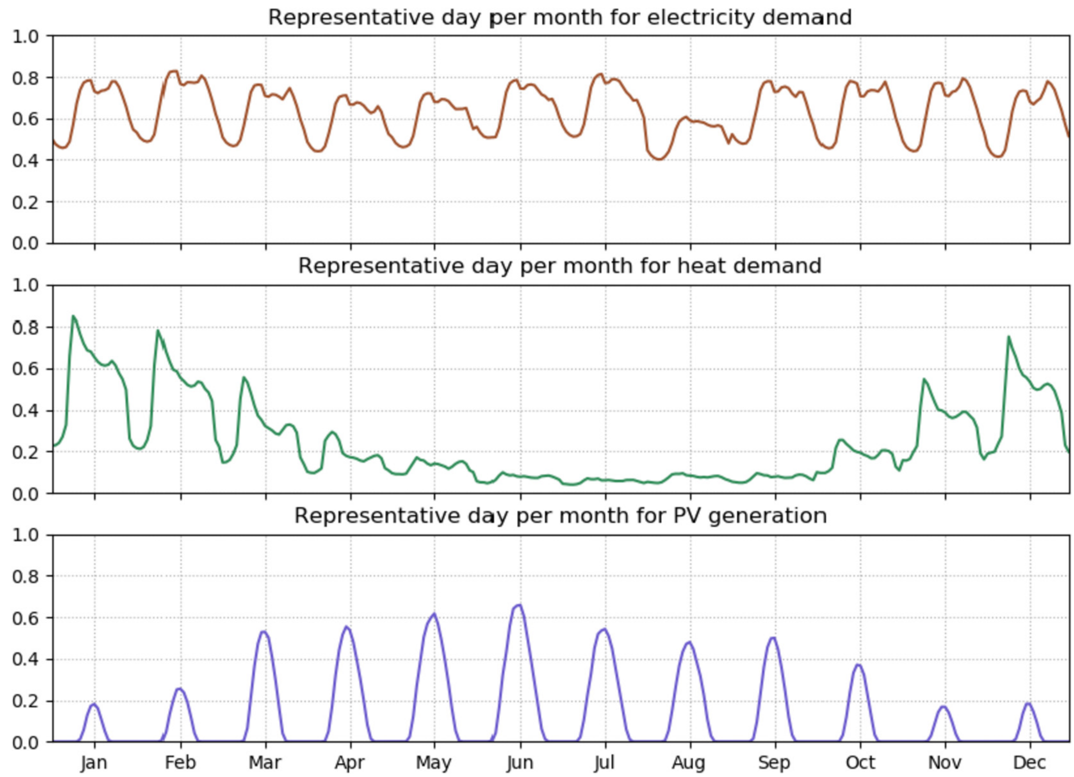

Fig. 5. Representative day per month for electricity demand, heat demand and PV generation for South Tyrol in 2014.

thousand inhabitants [44]. It has a low population density but is extensively visited by tourists. The energy system is characterized by high shares of renewable energy production. Hydropower and biomass (forest wood) are used extensively for electricity and heat production. Therefore, an increased use of these energy sources has been considered to be very limited in the future scenarios. Imported energy is mainly natural gas for industry, services and residential heating, and fossil liquid fuels for the transportation sector.

EnergyPLAN requires three different types of input data to simulate one configuration of the energy system: i) one year of hourly values normalized to a scale from 0 to 1 (called a "distribution" in EnergyPLAN) for energy sources with fixed profiles, such as electricity demand, heat demand and non-programmable renewable energies, ii) costs for fuels and technologies, iii) capacities of energy sources and efficiencies for each source. Fig. 5 shows the representative day per month of different distributions: electricity demand, heat demand and PV generation. This is just an artifice to depict the daily and seasonal variability of the distribution profiles that are used in the EnergyPLAN simulations. Each hourly value of a representative day is obtained by averaging the daily values for that hour over the month.

The electricity profile has been estimated from data provided by Terna, the Italian transmission system operator [45]. The heat demand profile has been provided by the local district heating distribution company Alperia [46]. The PV generation profile has been calculated from data provided by 13 weather stations in South

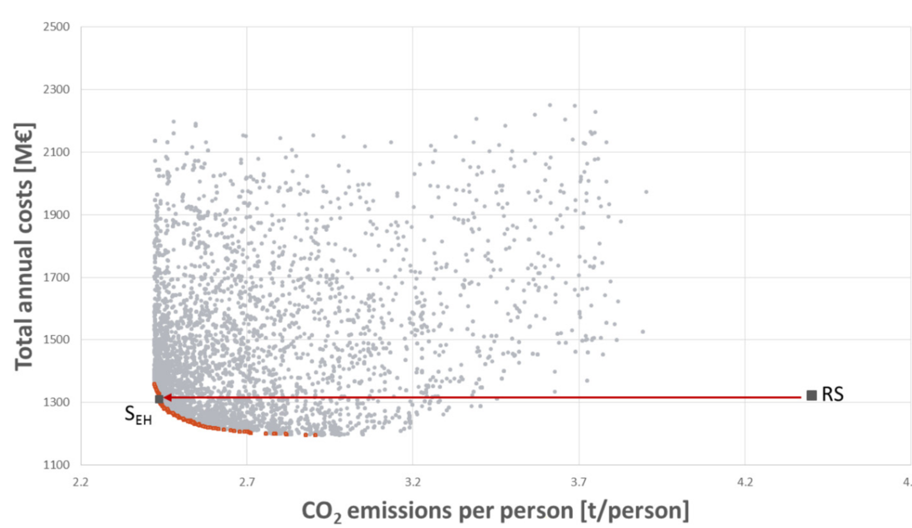

Fig. 6. Future energy system configurations for South Tyrol (gray dots) and Pareto front of best configurations (red dots). The square labelled RS refers to the reference scenario, which is the South Tyrolean energy system in 2014. The S_{EH} scenario is an optimized scenario with the same costs as the reference scenario.

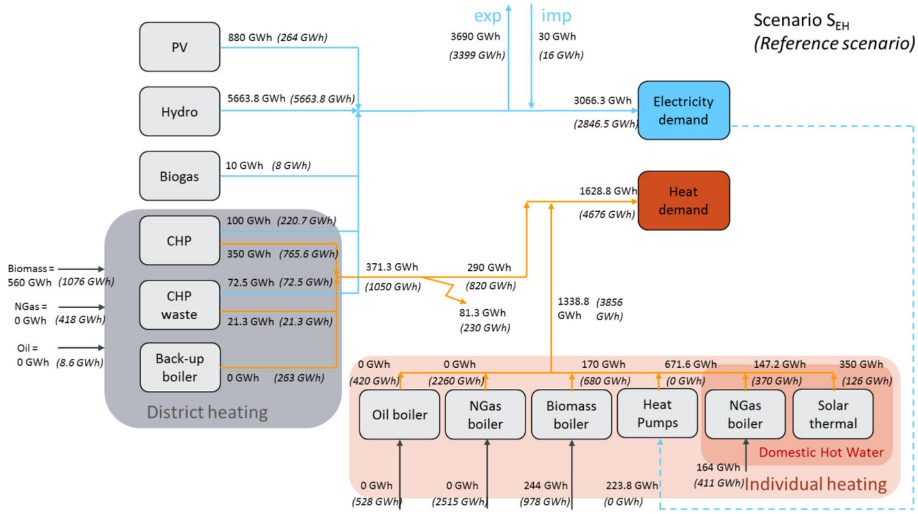

Fig. 7. Energy flows in the electricity and heat sector for the reference (*in italic*) and the S_{EH} scenario.

Tyrol. The reference scenario has been created from data collected by Eurac Research in previous studies [47,48] as well as from data provided by the province of Bolzano [49], the local energy provider [46], the local statistics office [44] and Terna [50]. The reference year taken into consideration is 2014.

The EnergyPLAN reference scenario for South Tyrol has been validated comparing the final indicator of CO_2 emissions to the data reported by the public authority in the white paper on the South Tyrolean Climate Strategy [51] and to the data provided by the Ministry of Economic Development [52].

3.2. Future energy scenarios

After creating the baseline for the South Tyrolean energy system and filling in the data in the EnergyPLAN spreadsheet, EPLANopt was launched. Fig. 6 shows the results of all simulations and the Pareto front, i.e. the non-dominated solutions. In Fig. 7, only two of the three objectives are represented for an easier understanding of the results.

Compared with the reference scenario (RS), numerous points on the Pareto front lead to a significant improvement in CO_2 emissions without a relevant increase in costs. The scenario S_{EH} has been analyzed in detail because it allows for a massive decrease of the CO_2 emissions per person at the same costs of the reference scenario. Transport sector is included as it is i.e. considering the related CO_2 emissions and costs but is not part of the optimization. In other words, strategies to increase the penetration of renewables and to reduce CO_2 emissions are not considered for this sector.

Fig. 7 compares the reference scenario with the S_{EH} scenario in terms of energy flows between export, import, sources and sinks in the electricity and heat sector. The heat sector experiences the largest differences due to deep renovation combined with the installation of heat pumps. The latter leads to a slight increase in the overall electricity demand.

Fig. 8 shows the hourly electricity production profiles in winter and summer. In winter, it is possible to notice a slight increase of the electricity demand due to heat pumps. However, the graphs show that the electricity generation from renewable energy sources is still enough to cover the electricity demand during most of the year (transport sector excluded). Fig. 9 shows the annual electricity balance and an increase in electricity demand equal to 7.7%.

Fig. 10 shows the hourly heat production within the district heating network in two selected weeks. The S_{EH} scenario, compared to the reference scenario, is characterized by a remarkable 75% increase in the energy efficiency of buildings that drastically reduces the load. It is important to highlight that the S_{EH} scenario, which is on the Pareto front, abates the share of non-organic municipal solid waste in favor to the organic renewable share. Fig. 10 also shows the use of thermal energy storage connected to the district heating network, which allows cogeneration plants to operate more flexibly, increasing production whenever electrical production is limited and shutting down when there is excess electricity production from renewables.

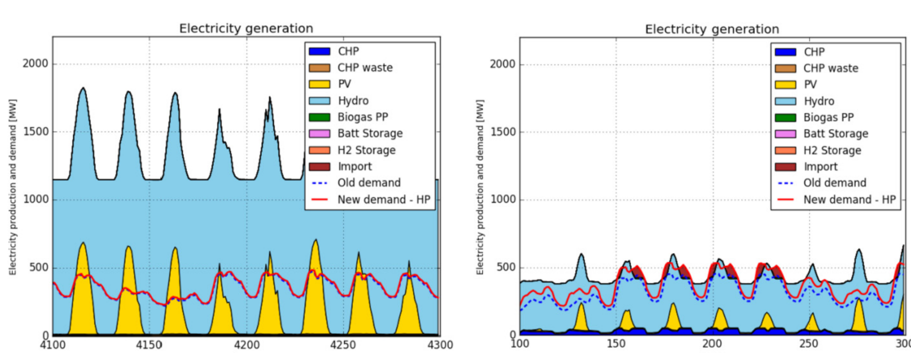

Fig. 8. S_{EH} scenario. Hourly electricity production of a week in June (from hour 4100 to 4300, left panel) and of a week in January (from hour 100 to 300, right panel).

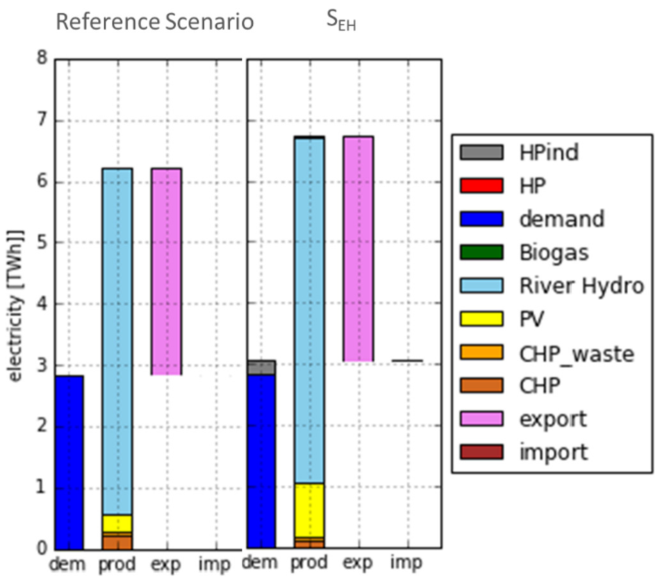

Fig. 9. Annual electricity balance, comparison between the reference scenario and the S_{EH} scenario.

Fig. 11 shows the overall energy demand and distribution among the three sectors of the energy system in the two scenarios. While the transport sector energy demand is constant in absolute numbers in both scenarios, the overall energy demand of the heat sector drastically decreases. As already mentioned, this is consequence of energy efficiency strategies in buildings and installation of heat pumps. As described in Section 2.3, traditional heating systems are replaced with heat pumps only in renovated buildings. Leading to an electricity demand slight increase.

Fig. 12 compares the total annual costs of the reference scenario and the S_{EH} scenario. From left to right, the three columns for each scenario represent the total costs, the costs per source (including building renovation) without considering revenues from exported electricity, and the income from export. Hence, the total (net) costs shown on the left are given by the difference between the costs by source and the revenues from exported electricity. The scenario S_{EH} has been selected to have the same total costs of the reference scenario (see Fig. 12). In particular, costs connected to the fuels such as natural gas and oil are replaced in the S_{EH} scenario by building stock renovation costs.

In addition to the environmental benefits, the scenario S_{EH} has an important impact on regional economy. The investment in the regional energy systems and construction sector through building renovation is drastically enhanced while the cost for fossil fuel decreases. Thus, a higher local added value is achieved while keeping similar costs of the whole energy system.

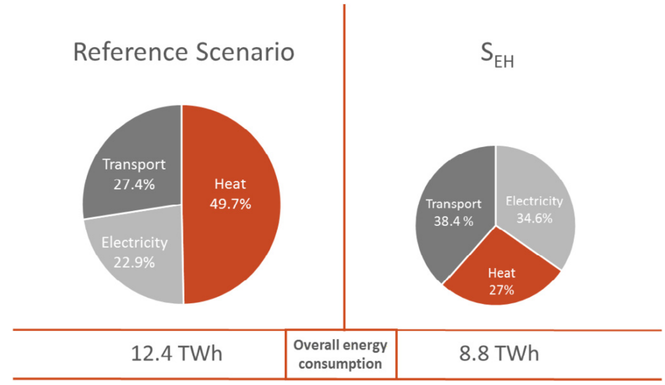

Fig. 11. Comparison of the overall energy consumption between the reference scenario and the S_{EH} scenario.

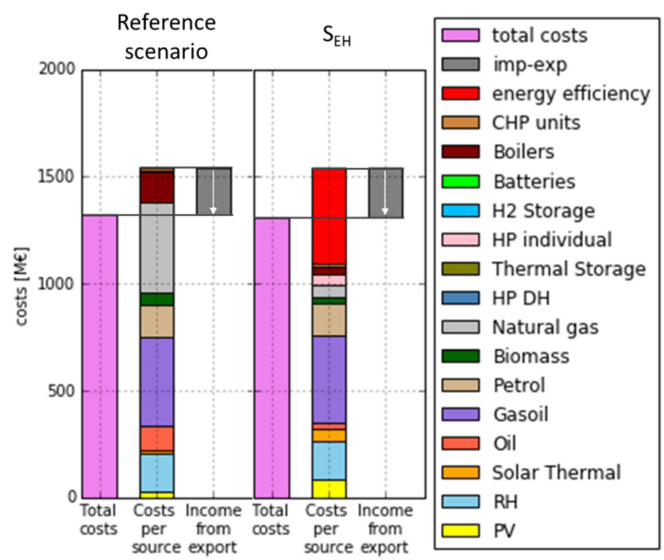

Fig. 12. Comparison between the total annual costs of the reference scenario and the S_{EH} scenario.

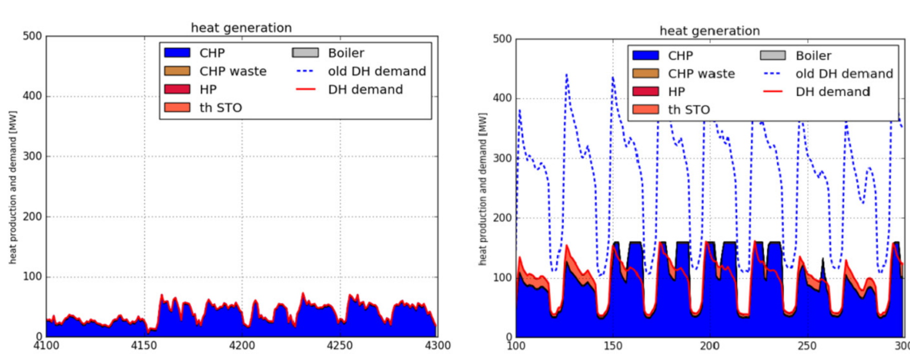

Fig. 10. S_{EH} scenario. Hourly district heat production for a week in June (from hour 4100 to 4300, left panel) and a week in January (from hour 100 to 300, right panel).

4. Conclusions

A methodology coupling multi-objective optimization and the energy system simulation software EnergyPLAN has been developed and demonstrated through the creation of the EPLANopt model. The main features and capabilities of this model – the open-source approach, the possibility to set an arbitrary number of objectives, running parallel simulations to save computational time – have been presented.

The final scope of this methodology is to find the best configurations of the energy system according to multiple objectives. The objective functions used in the South Tyrol application are: total annual costs, CO_2 emissions and percentage of renewables in the system.

Through an external code it has been possible to consider the effects of building renovation on energy demand and cost within the EnergyPLAN simulation tool, and to link building renovation with the installation of individual heat pumps. The methodology used to estimate the energy efficiency-costs curve is presented in Section 2.3 along with its application to South Tyrol.

When modeling future energy systems, multi-objective optimization (MOO) shows advantages if compared to single-objective optimization (SOO). While MOO can detect a whole set of (Pareto-) optimal solutions or trade-offs, even multiple SOO runs may not be equally efficient to find the entire Pareto front.

When a simulation tool like EnergyPLAN is used to determine future scenarios without using any optimization tool, the real solver is the human expert. As demonstrated by Mahbub et al. [15], an energy scenario found by an expert can be very close to the Pareto front found by a MOO. However, the MOO gives the user a set of general solutions, independent of assumptions based on rather "arbitrary" preferences (like the choice of giving priority to environmental or economic issues). With the MOO approach, once a set of solutions is available, these preferences can be introduced (e.g. by a policy maker) to select the desired solutions without the need to run additional numerical calculations and with the advantage of having a global view of all Pareto-optimal solutions. In this sense, the introduced methodology can support energy policy makers in the energy strategy formulation. The methodology allows the user to present the best techno-economic solutions for the future energy system to energy policy makers, leaving them the choice to implement one scenario or another depending on their political preferences towards a balance between environmental and economic objectives.

EPLANopt has been applied to the energy system in South Tyrol in order to analyze the best options for the region. The current system is characterized by a large export of electricity generated by hydroelectric plants. Thus, a main option for the future energy system is a shift of part of the heat and transport demand to the electricity sector. The other main option is a reduction of the heat demand by renovating the building stock. Exerting these and minor other options results in scenario S_{EH}, which is characterized by a deep renovation of the building stock and an increase of the overall electricity demand equal to 7.7% due to the installation of heat pumps in the renovated buildings. Increasing the energy efficiency in buildings and the installed PV capacity allows reducing the CO_2 emissions by 44% while keeping the total annual costs of the reference scenario. Moreover, this future scenario has great benefits for the regional economy because it increases the investments on the territory through building renovation and reduces the cash flow due to fossil fuel expenses directed to foreign countries.

Acknowledgements

The authors wish to acknowledge the use of EURAC internal funding for the project "Regional Energy Modeling". The authors would like to thank the different offices from and within the province of Bolzano for the fruitful discussions and the given access to energy data. The authors thank the Department of Innovation, Research and University of the Autonomous Province of Bozen/Bolzano for covering the Open Access publication costs.

References

[1] IPCC report. 1990. www.ipcc.ch/ipccreports/far/wg_I/ipcc_far_wg_I_full_report.pdf.
[2] Breidenich C, Magraw D, Rowley A, Rubin JW. The Kyoto protocol to the United Nations framework convention on climate change. Am J Int Law Apr. 1998;92(2):315.
[3] Pichs-Madruga R, et al. Climate change 2014 mitigation of climate change summary for policymakers technical summary part of the working group iii contribution to the fifth assessment report of the intergovernmental panel on climate change. 2015.
[4] 2020 climate & energy package | Climate Action. 2007 [Online]. Available, https://ec.europa.eu/clima/policies/strategies/2020_en.
[5] 2030 energy strategy - European commission. 2014 [Online]. Available, https://ec.europa.eu/energy/en/topics/energy-strategy-and-energy-union/2030-energy-strategy. [Accessed 19 July 2017].
[6] Herbst A, Toro F, Reitze F, Jochem E. Introduction to energy systems modelling. Statistics 2012;148(2):111–35 (Ber).
[7] Connolly D, Lund H, Mathiesen BV, Leahy M. A review of computer tools for analysing the integration of renewable energy into various energy systems. Appl Energy Apr. 2010;87(4):1059–82.
[8] Aalborg University - Knowledge for the World." [Online]. Available: http://www.en.aau.dk/. [Accessed: 25-Oct-2017].
[9] Aalborg University, "EnergyPLAN | Advanced energy systems analysis computer model." [Online]. Available: http://www.energyplan.eu.
[10] Lund H. Chapter 4 – tool: the EnergyPLAN energy system analysis model. In: Renewable energy systems; 2014. p. 53–78.
[11] Mathiesen BV, et al. Smart Energy Systems for coherent 100% renewable energy and transport solutions. Appl Energy May 2015;145:139–54.
[12] Garegnani G, Prina MG, Vaccaro R, Cozzini M, Filippi Oberegger U, Moser D. EPLANopt: EnergyPLAN optimization library. 2016 [Online]. Available, https://gitlab.inf.unibz.it/URS/EPLANopt.
[13] Fortin F-A, De Rainville F-M, Gardner M-AG, Parizeau M, Gagné C. DEAP: evolutionary algorithms made easy. MIT Press; 2001. vol. 13, no. 1.
[14] Batas Bjelić I, Rajaković N. Simulation-based optimization of sustainable national energy systems. Energy Nov. 2015;91:1087–98.
[15] Mahbub MS, Cozzini M, Østergaard PA, Alberti F. Combining multi-objective evolutionary algorithms and descriptive analytical modelling in energy scenario design. Appl Energy Feb. 2016;164:140–51.
[16] Nastasi B, Lo Basso G. Power-to-Gas integration in the transition towards future urban energy systems. Int J Hydrogen Energy Sep. 2017;42(no. 38):23933–51.
[17] Nastasi B, Lo Basso G. Hydrogen to link heat and electricity in the transition towards future Smart Energy Systems. Energy Sep. 2016;110:5–22.
[18] Lund H, Möller B, Mathiesen BV, Dyrelund A. The role of district heating in future renewable energy systems. Energy Mar. 2010;35(3):1381–90.
[19] Connolly D, et al. Heat Roadmap Europe: combining district heating with heat savings to decarbonise the EU energy system. Energy Pol Feb. 2014;65:475–89.
[20] Novosel T, et al. Integration of renewables and reverse osmosis desalination – case study for the Jordanian energy system with a high share of wind and photovoltaics. Energy Dec. 2015;92:270–8.
[21] Connolly D, Mathiesen BV, Ridjan I. A comparison between renewable transport fuels that can supplement or replace biofuels in a 100% renewable energy system. Energy Aug. 2014;73:110–25.
[22] Xiong W, Wang Y, Mathiesen BV, Zhang X. Case study of the constraints and potential contributions regarding wind curtailment in Northeast China. Energy Sep. 2016;110:55–64.
[23] Lund H, et al. Energy storage and smart energy systems. Int J Sustain Energy Plan Manag Jan. 2016;11:3–14.
[24] Mikulandric R, et al. Performance analysis of a hybrid district heating system: a case study of a small town in Croatia. J Sustain Dev Energy Water Environ Syst Sep. 2015;3(3):282–302.
[25] Čulig-Tokić D, Krajačić G, Doračić B, Mathiesen BV, Krklec R, Larsen JM. Comparative analysis of the district heating systems of two towns in Croatia and Denmark. Energy Dec. 2015;92:435–43.
[26] Lund R, Mathiesen BV. Large combined heat and power plants in sustainable energy systems. Appl Energy Mar. 2015;142:389–95.
[27] Lund H, Andersen A, Østergaard PA, Mathiesen BV, Connolly D. "From electricity smart grids to smart energy systems – a market operation based approach and understanding. Energy Jun. 2012;42(1):96–102.
[28] Prina MG, et al. Smart energy systems applied at urban level: the case of the municipality of Bressanone-Brixen. Int J Sustain Energy Plan Manag 2016;10.
[29] Lund H, Duic N, Østergaard PA, Mathiesen BV. Smart energy systems and 4th generation district heating. Energy Sep. 2016;110:1–4.
[30] Welsch M. Enhancing the treatment of systems integration in long-term energy models. Industrial Engineering and Management. In: KTH royal institute of technology; 2013.

[31] Connolly D, Lund H, Mathiesen BV. Smart Energy Europe: the technical and economic impact of one potential 100% renewable energy scenario for the European Union. Renew Sustain Energy Rev Jul. 2016;60:1634–53.

[32] Ćosić B, Krajačić G, Duić N. A 100% renewable energy system in the year 2050: the case of Macedonia. Energy Dec. 2012;48(1):80–7.

[33] Connolly D, Lund H, Mathiesen BV, Leahy M. The first step towards a 100% renewable energy-system for Ireland. Appl Energy Feb. 2011;88(2):502–7.

[34] Fernandes L, Ferreira P. "Renewable energy scenarios in the Portuguese electricity system. Energy May 2014;69:51–7.

[35] Lund H, Mathiesen BV. Energy system analysis of 100% renewable energy systems—the case of Denmark in years 2030 and 2050. Energy May 2009;34(5):524–31.

[36] Connolly D, Lund H, Mathiesen BV, Pican E, Leahy M. The technical and economic implications of integrating fluctuating renewable energy using energy storage. Renew Energy Jul. 2012;43:47–60.

[37] Connolly D, Lund H, Mathiesen BV, Leahy M. Modelling the existing Irish energy-system to identify future energy costs and the maximum wind penetration feasible. Energy May 2010;35(5):2164–73.

[38] Novosel T, Pukšec T, Krajačić G, Duić N. Role of district heating in systems with a high share of renewables: case study for the city of Osijek. Energy Proc Sep. 2016;95:337–43.

[39] Simon D. Evolutionary optimization algorithms: biologically-Inspired and population-based approaches to computer intelligence. John Wiley & Sons Inc; 2013.

[40] Bernal-Agustín JL, Dufo-López R. Efficient design of hybrid renewable energy systems using evolutionary algorithms. Energy Convers Manag Mar. 2009;50(3):479–89.

[41] Konak A, Coit DW, Smith AE. Multi-objective optimization using genetic algorithms: a tutorial. Reliab Eng Syst Saf Sep. 2006;91(9):992–1007.

[42] Deb K, Pratap A, Agarwal S, Meyarivan T. A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Trans Evol Comput Apr. 2002;6(2):182–97.

[43] "Passive House Planning Package (PHPP)." [Online]. Available: http://passivehouse.com/04_phpp/04_phpp.htm. [Accessed: 23-Oct-2017].

[44] "Istituto provinciale di statistica | Provincia autonoma di Bolzano - Alto Adige." [Online]. Available: http://astat.provincia.bz.it/it/default.asp. [Accessed: 19-Oct-2017].

[45] "Terna - Transparency Report." [Online]. Available: http://www.terna.it/en-gb/sistemaelettrico/transparencyreport.aspx. [Accessed: 17-Jan-2018].

[46] "Alperia: we are energy." [Online]. Available: http://www.alperia.eu/en.html. [Accessed: 17-Jan-2018].

[47] "Sinfonia Smartcities - Bolzano." [Online]. Available: http://www.sinfonia-smartcities.eu/en/demo-city/bolzano. [Accessed: 17-Jan-2018].

[48] "Solar Tirol - webGIS." [Online]. Available: http://webgis.eurac.edu/solartirol.

[49] Battiston CC. Autonome PROVINZ BOZEN -SÜDTIROL PROVINCIA AUTONOMA DI BOLZANO -ALTO ADIGE Bilancio energetico. 2008.

[50] "Terna website." [Online]. Available: http://www.terna.it. [Accessed: 14-Dec-2017].

[51] A. Provinz Bozen-Südtirol, "PIANO CLIMA Energia-alto Adige-2050.".

[52] "Statistiche dell'Energia - Ministero dello Sviluppo Economico." [Online]. Available: http://dgsaie.mise.gov.it/dgerm. [Accessed: 17-Jan-2018].