EPLANOptGUI for EnergyPLAN Documentation

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Preface

The EPLANOptGUI add-on tool for EnergyPLAN is developed as part of the collaboration of Carlos Santos Silva from Tecnico Lisboa with Aalborg University in 2025.

EPLANopt (EnergyPLAN Optimization) is an optimization python library for the EnergyPLAN software, develop by Matteo Prina from Eurac Research that couples a multi-objective evolutionary algorithm to perform the expansion capacity optimization with a multi-objective approach to EnergyPLAN models. The multiobjective optimization approach allows the modelers to present the final results to the policy makers in the most transparent way, enabling a participatory process for the selection of best future alternatives for the energy system. The model is publicly accessible through the GNU Lesser General Public License. The original version was published on a public GitLab EPLANopt repository (2016) and a more recent version is available at the GitHub EPLANopt repository (2023). The use of EPLANopt requires basic knowledge of python programming.

The EPLANOptGUI is an autonomous executable application that can be included in EnergyPLAN add-ons that allows EnergyPLAN users to use solve the capacity expansion optimization problem of energy systems through a graphical user interface. The tool is programmed in Python and is based on the EPLANopt library (2023).

Carlos Santos Silva, Prof. IST/UL has done the main development of the tool, but with assistant and feedback from Matteo Prina from Eurac Research, and Henrik Lund, Prof. AAU.

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The EplanOpt Concept

The EplanOpt library is an optimization tool for the EnergyPLAN software that uses a multi-objective evolutionary algorithm to perform the expansion capacity optimization with a multi-objective approach to EnergyPLAN models. The multi-objective optimization approach allows the modelers to present the final results to the policy makers in the most transparent way, enabling a participatory process for the selection of best future alternatives for the energy system.

Solving an optimization problem in EnergyPLAN

EnergyPLAN is primarily a simulation tool. Users adjust input parameters such as installed renewable capacity, storage size, or transmission capacity limits, and then observe the resulting system performance in terms of total costs or CO2 emissions. This approach is valuable for exploring scenarios, but it requires manual testing of many different configurations.

Optimization, by contrast, adds an automated layer that systematically searches the decision space to identify the best values of these inputs for achieving a specific objective — for example, minimizing system costs, reducing CO2 emissions, or maximizing renewable penetration in electricity. In this way, optimization transforms EnergyPLAN from a scenario-testing platform into a decision-support tool, helping planners move directly toward solutions that balance technical feasibility with policy goals.

Solving multi-objective optimization problems in EnergyPLAN

In EnergyPLAN, multi-objective optimization can be used to explore the trade-offs between different system goals. Instead of focusing on a single criterion, such as minimizing cost, the model allows us to evaluate several objectives simultaneously — for example, maximizing the share of renewable energy in primary supply or electricity generation, minimizing CO2 emissions, or reducing overall system costs.

Each solution depends on a set of decision variables, such as installed renewable capacity, storage size and power, transmission capacity, the maximum share of electric vehicles charging during peak demand, etc.

Because these objectives often conflict (e.g., higher renewable penetration may increase costs or decreasing costs may increase CO2 emissions), the optimization does not yield a single "best" solution but rather a set of solutions called the Pareto-optimal solutions. These represent different compromises among objectives, from which policymakers or planners can select according to their priorities.

Mathematical formulation of the Multi-Objective Optimization in EnergyPLAN

Decision Variables

The decision variables can be described as a vector

$$x \in \mathbb{R}^n, x = (\, C_{\text{RES}}, C_{\text{stor}}^E, P_{\text{stor}}^{\text{ch}}, P_{\text{stor}}^{\text{dis}}, T_{\text{cap}}, N_{\text{EV}}, \dots \,)$$

and the subset of feasible solutions $\mathcal{X}$

$$x \in \mathcal{X} \subseteq \mathbb{R}^n$$

is the subset of solutions that are within the define bounds and respect the energy balances.

Objective Functions

The objective functions of the problem can be described as

$$\max_{x \in \mathcal{X}}(f_1(x), f_2(x), \dots, f_n(x)) \bigwedge \min_{x \in \mathcal{X}}(g_1(x), g_2(x), \dots, g_m(x))$$

where: $f_1(x) = \text{RES\_share}^{\text{prim}}(x)$, $f_2(x) = \text{RES\_share}^{\text{elec}}(x)$, $g_1(x) = CO_2(x)$ and $g_n(x) = Total\,\text{Cost}(x)$. Please notice if in reality minimizing $CO_2(x)$ and $Total\,\text{Cost}(x)$ corresponds to maximizing their vertical reflection functions $f_3(x) = -CO_2(x)$ and $f_4(x) = Total\,\text{Cost}(x)$, so we the objectives functions can be defined as

$$\max_{x \in \mathcal{X}}(f_1(x), f_2(x), f_3(x), f_4(x), \dots, f_n(x))$$

where: $f_1(x) = \text{RES\_share}^{\text{prim}}(x)$, $f_2(x) = \text{RES\_share}^{\text{elec}}(x)$, $f_3(x) = -CO_2(x)$ and $f_4(x) = -Total\,\text{Cost}(x)$.

Pareto Optimality

Pareto optimality describes the set of system configurations where **no objective can be improved without worsening at least one other**. For example, increasing renewable capacity may reduce CO2 emissions but could raise overall system costs. A solution is considered Pareto-optimal if there is no alternative configuration that achieves lower emissions, higher renewable penetration, or lower costs simultaneously. Instead of yielding a single "best" answer, the optimization produces a Pareto front — a collection of trade-off solutions that represent different balances between objectives such as cost, emissions, and renewable share. Decision-makers can then select the most appropriate solution from this front according to their policy priorities or institutional goals.

In multi-objective optimization, each system configuration corresponds to a point in the objective space (for example, cost vs. CO2 emissions vs. renewable share). A solution is said to be **dominated** if there exists another configuration that performs at least as well in all objectives and strictly better in at least one. For instance, if Scenario A has lower cost and equal emissions compared to Scenario B, then Scenario B is dominated by Scenario A and would not be considered optimal. Conversely, a solution is **non-dominated** if no other configuration can improve one objective without worsening another. The collection of all non-dominated solutions forms the **Pareto front**, which represents the set of trade-offs available to decision-makers. In practice, this means that EnergyPLAN optimization does not deliver a single "best" scenario, but rather a frontier of balanced alternatives — each non-dominated solution offering a different compromise between minimizing costs, reducing emissions, and maximizing renewable penetration.
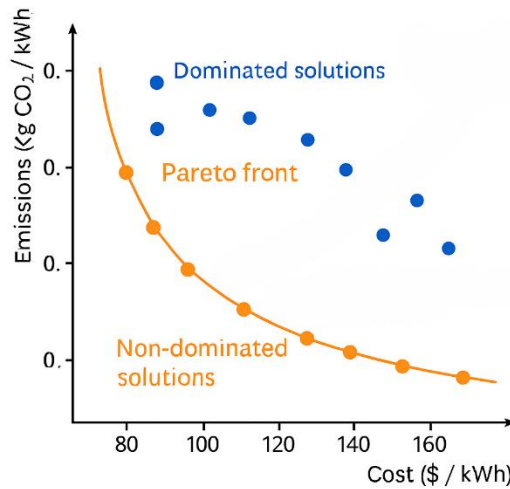

Figure 1 - Pareto front example

In this way we say that x_a dominates x_b if

$$f_i(x_a) \leq f_i(x_b) \forall i, \exists j: f_j(x_a) < f_j(x_b)$$

In this way, the Pareto set of solutions (Pareto-front) is the set of solutions

$$\mathcal{P} = \{ x \in \mathcal{X} \mid \nexists\, y \in \mathcal{X} : \text{dominates } x \}$$

i.e there is no solution x that dominates the set of solution y.

Solving a Mutli-objective problem

There are several approaches to solve a multi-objective optimization problem. Here, we will focus on the two methods:

Evolutionary Algorithms

Evolutionary algorithms (EAs) are population-based metaheuristics that approximate the Pareto front by evolving a set of candidate solutions over multiple generations. They do not require gradient information or convexity assumptions, making them ideal for complex, nonlinear systems like those modeled in EnergyPLAN. EAs use mechanisms inspired by natural selection — such as mutation, crossover, and selection — to explore the decision space and maintain diversity among solutions.

In EA, each candidate solution can be represented as a chromosome where the genes correspond to different decision variables, such as RES 1, RES 2, Storage Power, and Transmission Capacity, as for example

$$x = [RES_1, RES_2, Storage_{capacity}, Transmission_{Capacity}] = [1000\ MW, 3000\ MW, 1\ MWh, 500\ MW]$$

were x represents a system with 1000 MW of installed capacity of RES_1, 3000 MW of installed capacity of RES_2, 1 MWh of energy storage capacity $storage_{capacity}$ and 500 MW of cross-border transmission capacity $Transmission_{capacity}$,

This encoding allows the algorithm to evolve different energy system configurations by applying genetic operators to these decision variables. The result will be a set of non-dominated configurations that reveal the full spectrum of trade-offs between objectives like cost, emissions, and renewable penetration.

The evolutionary optimization implemented in EPLANopt uses the Python library **DEAP (Distributed Evolutionary Algorithms in Python)**, which provides flexible tools for solving multi-objective algorithms like NSGA-II. NSGA-II (Non-dominated Sorting Genetic Algorithm II) is a widely used evolutionary algorithm for solving multi-objective optimization problems. At each step, solutions are ranked based on Pareto dominance and sorted into non-dominated fronts. To maintain diversity, NSGA-II uses a crowding distance metric that favors solutions spread across the objective space. This combination of elitism and diversity preservation allows NSGA-II to approximate a well-distributed Pareto front, making it especially effective for complex, nonlinear problems.

In this way, two of the most important parameters to implement an evolutionary approach is to determine the number of solutions that will be evaluated in each iteration of the algorithm – which in EA is called the size of the population - and the number of total iterations of the algorithm – which in EA is called the number of generations.

Weighted Sum Method

The weighted sum method transforms a multi-objective problem into a single-objective one by assigning a weight to each objective and minimizing the weighted combination.

Mathematically, it solves the problem

$$\min \sum_{i=1}^{n} w_i \widehat{f_i(x)}$$

where w_i are non-negative weights summing to one. This approach is simple and computationally efficient, making it suitable for problems where trade-offs are well understood.

To avoid bias based on the different scales of the objective functions, the objectives functions $f_i(x)$ are normalized into $\widehat{f_i(x)}$ using the Min-Max normalization

$$\widehat{f_i(x)} = \frac{f_i(x) - \min f_i(x)}{\max f_i(x) - \min f_i(x)}$$

The EPLANoptGUI tool

In this section, we explain how to use the EPLANoptGUI tool, based on the example **DK2020_2018edition_costs update.txt.**

Installation

The executable file EPLANoptGUI.exe can be downloaded at the GitHub CarlosSantosSilvaTecnico/EnergyPLAN_tools repository and copied directly to the "energyPlan Tools" folder of energyPLAN (Figure 2).

Figure 2 - EnergyPLAN folder structure

When the executable file is available in "energyPlan Tools" folder (see Figure 3), it will be visible in the Add-on Tools menu in EnergyPLAN (see Figure 4)
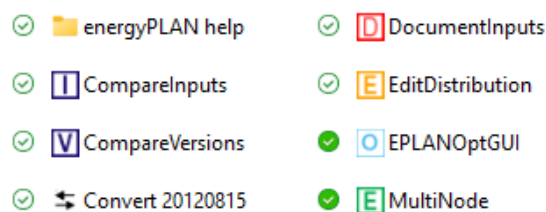
Figure 3 - EnergyPLAN tools folder contents

In EnergyPLAN main window, go to the tab "Add-On Tools" and the tool will be available together with other add-ons.
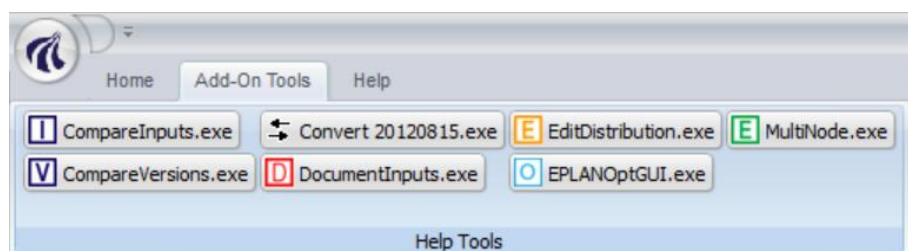

Figure 4 - Accessing EPLANoptGUI from the Add-on Tools menu in EnergyPLAN.

When clicking the EPLANoptGUI.exe application (see Figure 4), the tool will open the following application window (see Figure 5).
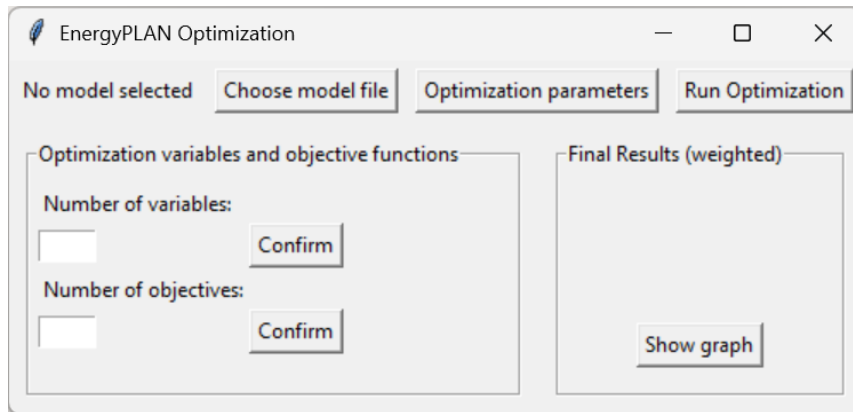
Figure 5 - EPLANoptGUI main window.

Loading the model to optimize

To demonstrate how the tool works, we will solve the **"DK2020_2018edition_costs update.txt"**. The first step is to choose the model file of the system that is going to be optimized, by clicking in the button "Choose model file" (see Figure 6)
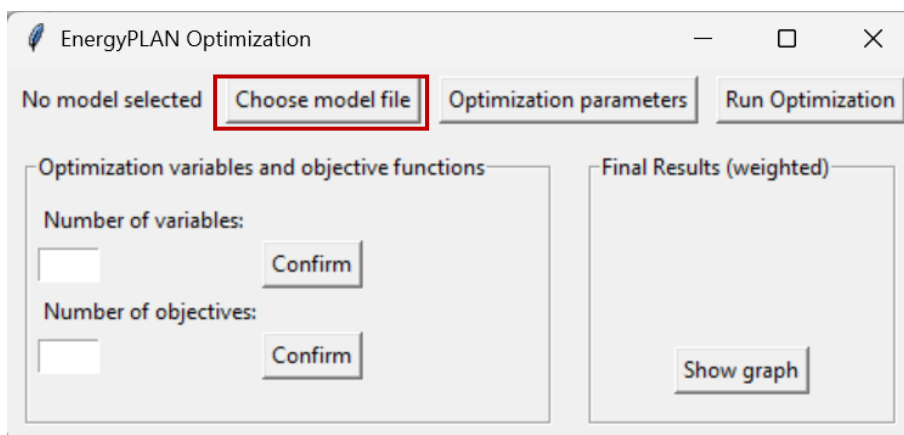

Figure 6 - Clinking the "Choose model file" button.

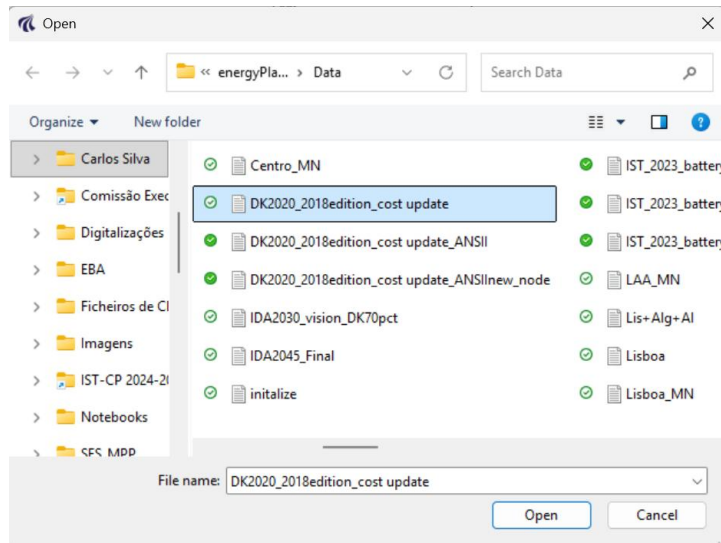A dialog box (see Figure 7) is used to choose the file.

Figure 7 - Dialog box to choose the model file.

Defining the optimization variables and objective functions

After loading the model file, it is necessary to define the optimization variables and objective functions.

Optimization variables

In the number of variables choose for example "2" and then click the button "Confirm" (see Figure 8)
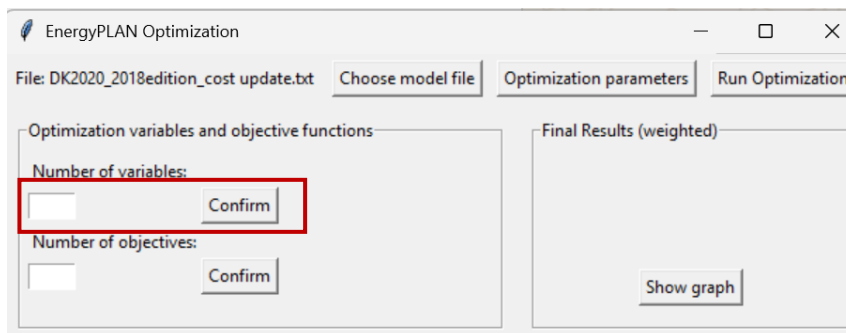

Figure 8 - Choosing the number of optimization variables.

As it is represented in Figure 9, two decision variables appear in the window, although they are the same (in this case "input_RES1_capacity").
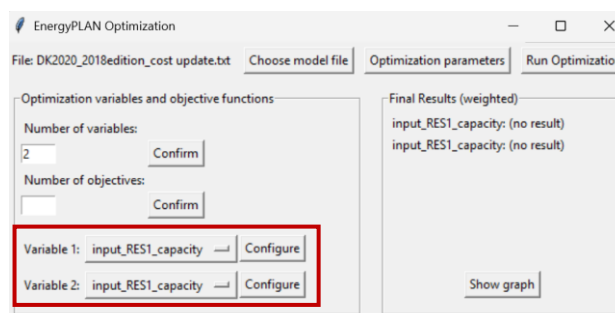

Figure 9 - Variables definition

To choose a different variable (for example changing Variable 2 to "input_RES2_capacity"), click in the button of the variable and a popup menu with all possible optimization variables is open (see Figure 10). Choose "input_RES2_capacity".
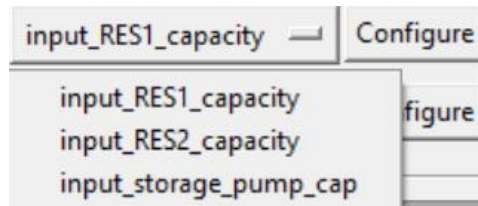

Figure 10 - Changing the decision variable

Then, it is necessary to configure the decision variable parameters. Click in the "Configure" button after the decision variable and a new window pops-up (see Figure 11).
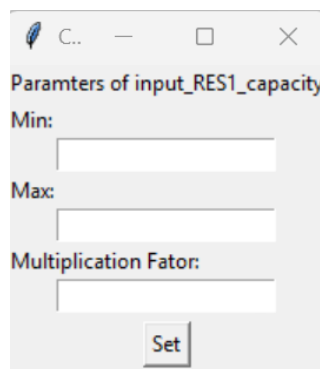

Figure 11 - Setting the decision variables parameters

For each decision variable it is necessary to define three parameters:

- **Min** – is the minimum value that this decision variable can take in the system (it can be zero)
- **Max** – is the maximum value that this decision variable can take in the system (it can be zero)
- **Multiplication factor** – this is a multiplication factor applied to the range of the decision variable.

Consider that you want to explore the capacity of "input_RES1_capacity" between 0 and 10000 MW. You have different options:

- *Min=0 / Max=10000/ Multiplication factor=1*: In this case the decision variables can take any unitary value between 0 and 10000, such as 537, 9172 or 12.
- *Min=0 / Max=10/ Multiplication factor=1000*: in this case the decision variables can take unitary values between 0 and 10 multiplied by 1000. In this case only 0, 1000, 2000, …,9000, 10000 values will be assumed
- *Min=0 / Max=100/ Multiplication factor=100*: in this case the decision variables can take unitary values between 0 and 100 multiplied by 100. In this case only 0, 100, 200, …,9000,…,9900 and 10000 values are assumed

At the end, click Set.

If you need to change the parameters you can, but the previous values are not visible.

To choose the optimization variables, the procedure is the same. Please notice that EPLANopt is a multi-objective tool but you can choose only 1 objective (and it performs a single objective optimization).

In the number of objectives, choose for example "2" and then click the button "Confirm" (see Figure 12). As it is represented Figure 12), two objectives appear in the window, although they are the same (in this case "TOTAL ANNUAL COSTS").
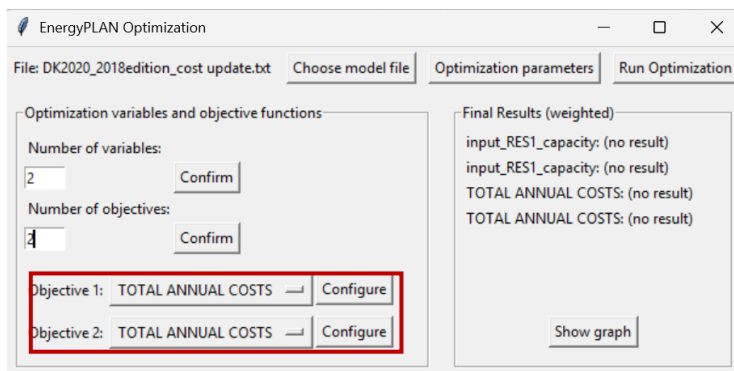

Figure 12 - Choosing the number of optimization objectives

To choose a different variable (for example changing Objective 2 to "CO2-emission (total)", click in the button of the objective and a popup menu with all possible optimization variables is open (see). Choose "CO"-emission (total)".
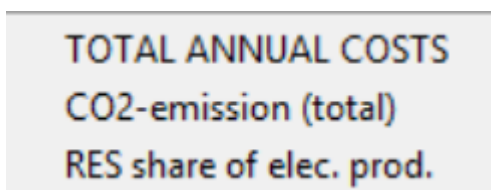

Figure 13 - Choosing the objective function

Then, it is necessary to configure the decision variable parameters. Click in the "Configure" button after the objective and a new window pops-up (see Figure 14).
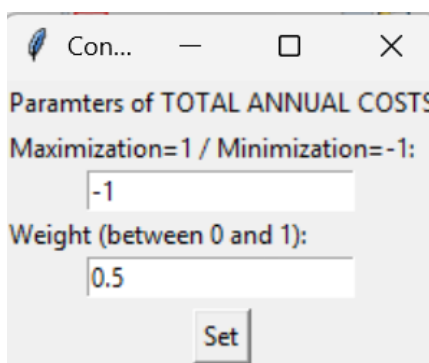

Figure 14 - Setting the parameters of the objective functions

For each objective function it is necessary to define two parameters:

- **Maximization =1 / Minimization=-1** – it indicates if the objective should be maximized (for example RES share of electricity production) or if the objective should be minimized (for example Total Annual Costs). The choice is given by setting to 1 for maximization or -1 for minimization.
- **Weight** – in case there is more than one objective, the tool will construct 2-D Pareto fronts that show the non-dominated solutions (optimal solutions) for all combinations of 2 objectives. However, the tool can also present one single solution that aggregates all optimal solutions, taking into consideration a weigh that reflects the importance of each objective (see section Weighted Sum Method in page 10). In principle the weights should be given as a percentage where the sum of all weights equals 1, but the tool accepts that the objectives are weight considering other values, as it normalizes the sum of all weights into 1.
    - For example, if Total Costs and CO2 emissions are equally important, we can assume that the weight is 0.5 for each.
    - If Total Costs is two times more important than CO2, then we can assume a weight of 0.66 for Total Costs and 0.33 for CO2 or simply a weight of 2 for Total Costs and a weigh of 1 for CO2.

At the end, click Set.

If you need to change the parameters you can, but the previous values are not visible.

Optimization Parameters

The last set of parameters that need to be defined is regarding the evolutionary approach that is used to solve the multi-objective problem. It is necessary to define two parameters, as represented in Figure 15
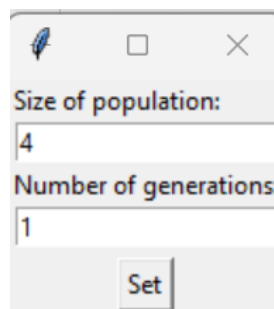

Figure 15 - Setting the optimization algorithm parameters.

- **Size of population**: as in any evolutionary approach, it defines the number of solutions that is going to be solved in each generation (see section Evolutionary Algorithms in page 9). This number needs to be a multiple of 4 higher than 0, but the tool makes sure that regardless of the size of the population it is transformed to the closest multiple of 4.
- **Number of generations:** as in any evolutionary approach, it defines the number of generations that will be used to solve the optimization problem.

Please notice that the number of runs of the EnergyPLAN model will result from the product between the size of the population and the number of iterations.

At the end, click Set.

Result analysis

In the interface

2-objectives

At the end of all the required simulations, the results will be presented in the main window as represented in Figure 16.
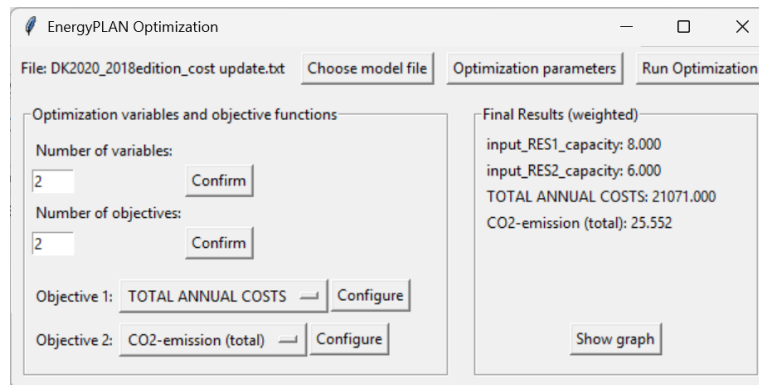

Figure 16 - Final results with the representation of the Pareto front (2D) and the best weighted solution

The Final results area is divided into two areas:

- the final result from the weighted solution, represented in Figure 17;
- the Pareto front representation if you click the button "Show graph", represented in **Error! Reference source not found.**.

In Figure 17, we can see the decision variables values for the best solution (weighted solution considering equal weights) and the objective function values for those solutions. If you change the original system file with these values for the decision variables, the system will obtain these values for Total annual Costs and CO_2-emisisons (total).

Figure 17 - Weighted solution

When you click the "Show graph" button, you will be able to see the Pareto front, as represented in **Error! Reference source not found.**.
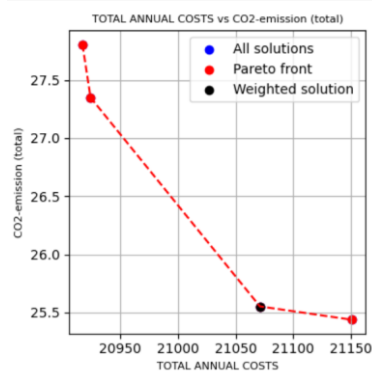
Figure 18 – 2D Pareto front

In **Error! Reference source not found.**, since there was only two objectives, there is only 1 Pareto front. (In Figure 19, it shows the result considering three objectives, from which results 3 2D - pareto fronts that represent all possible combinations of 2 objectives)

In this picture we can see:

- in red the non-dominated solutions connected by a dashed line, which represent the pareto from (the set of optimal solutions) ;
- in blue the dominated solutions (solutions that have been tested but are not optimal).
- In black the weighted solution, which corresponds to the solution in the pareto Front that reflects better the balance between the 2 objectives given the considered weights.

3-objectives

In this example, we have increased the number of objectives to 3 and considered that all of them are equally important (have the same weights, equal to 0.33). In this case we see three 2D Pareto-fronts that result from

all possible combinations of 2 objectives. We can observe that the weighted solution is the one that achieved the highest share of renewables, the lowest CO2 emissions, but the higher Total Costs.
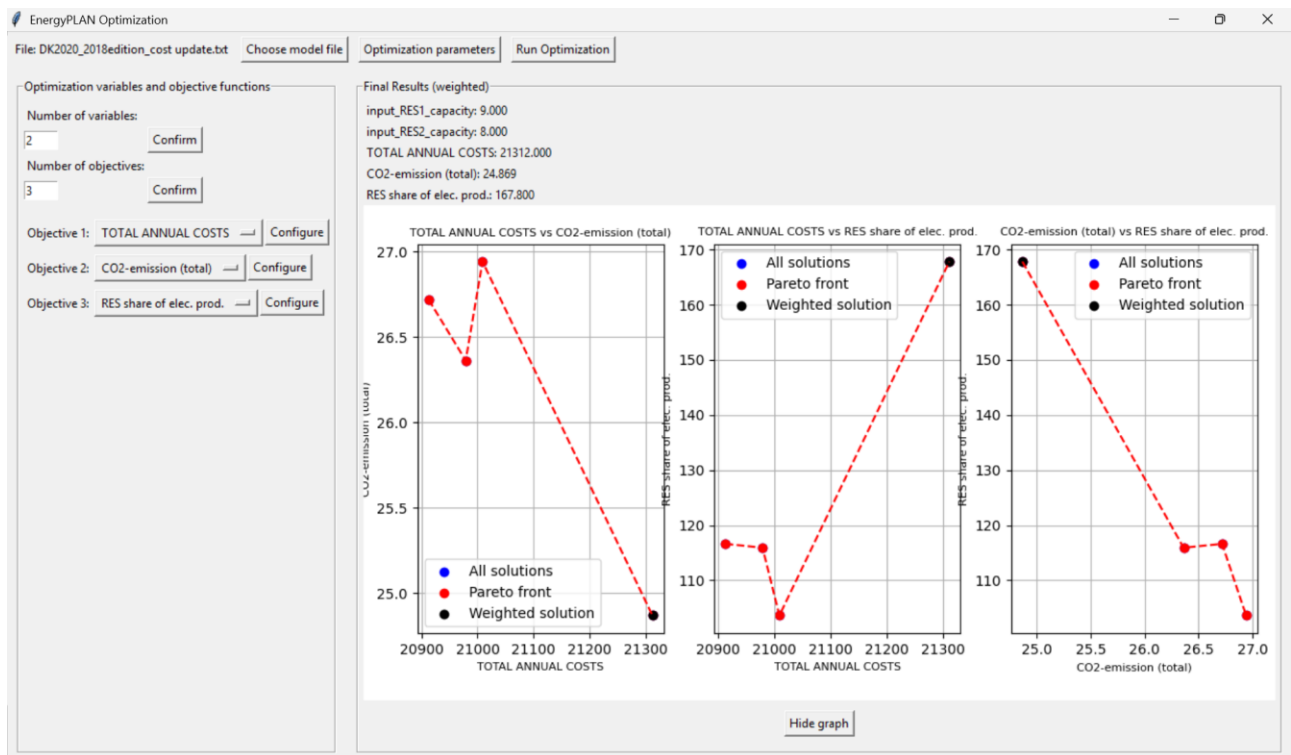

Figure 19 - Final results with the representation of the 3 Pareto front (2D) and the best weighted solution

1-objective

It is also possible to optimize one single objective. In this case, it is still necessary to indicate if the tool will minimize or maximize the objective and the weighted should be 1. As there are no Pareto-solutions, the graph that is displayed is the representation of all solutions, with the indication of the best found solution, as shows in Figure 20.
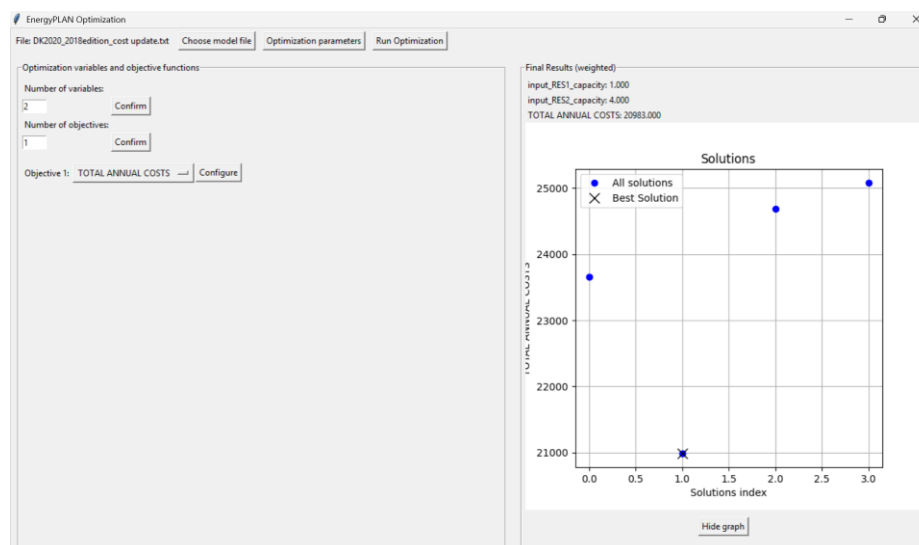
In the history.csv file

When the tool is used for the first time, a new folder called "Outputs" inside the "energyPlan Data\Data folder". This folder is used to record an "output.txt" file with the output of each EnergyPLAN run and a "history.csv" file that summarizes all the solutions and results that have been tested, as show in Figure 21 - Files in Outputs folder

Figure 21 - Files in Outputs folder

The "history.csv" file is a csv file that presents the input variable names and the objective functions names in the columns of the first row and then the values considered for the inputs in each simulation and the corresponding objective function values, as represented in Figure 22 - "history.csv" file

Figure 22 - "history.csv" file

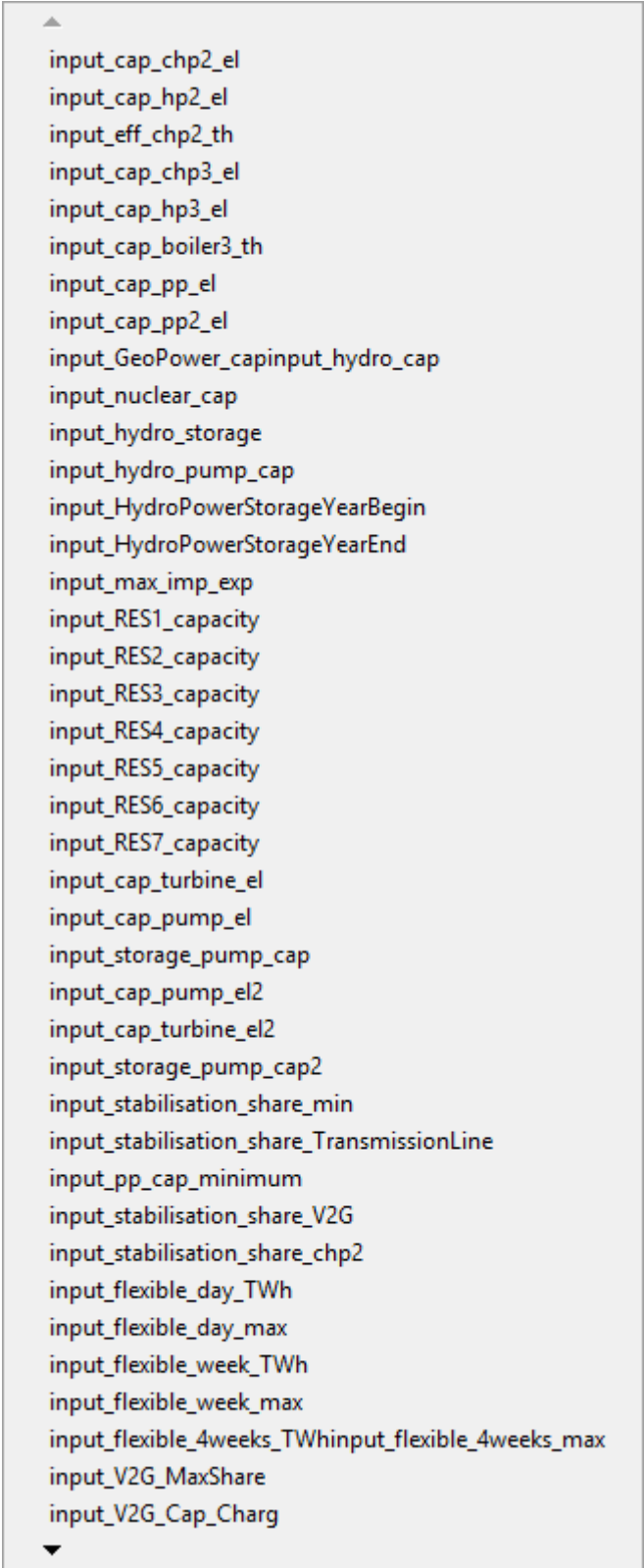This file can be used to perform more detailed analysis of the optimization results.

Other information

Decision variables

In EnergyPLAN, all fields where it is necessary to include numerical values could be used as decision variables. In general, all the inputs can be classified into one of the following categories

- Demand (PWh, TWh, GWh or GJ)
- Capacity (GW, MW, kW)
- Efficiencies (between 0 and 1)
- Storage (PWh, TWh, GWh or GJ)
- Costs (in DKK, EUR, etc.)

In the current version, we focus mostly on the capacity and storage values of the technologies. The order follows the different energy tabs (Demand, Supply, Balance)

input_cap_chp2_el
input_cap_hp2_el
input_eff_chp2_th
input_cap_chp3_el
input_cap_hp3_el
input_cap_boiler3_th
input_cap_pp_el
input_cap_pp2_el
input_GeoPower_capinput_hydro_cap
input_nuclear_cap
input_hydro_storage
input_hydro_pump_cap
input_HydroPowerStorageYearBegin
input_HydroPowerStorageYearEnd
input_max_imp_exp
input_RES1_capacity
input_RES2_capacity
input_RES3_capacity
input_RES4_capacity
input_RES5_capacity
input_RES6_capacity
input_RES7_capacity
input_cap_turbine_el
input_cap_pump_el
input_storage_pump_cap
input_cap_pump_el2
input_cap_turbine_el2
input_storage_pump_cap2
input_stabilisation_share_min
input_stabilisation_share_TransmissionLine
input_pp_cap_minimum
input_stabilisation_share_V2G
input_stabilisation_share_chp2
input_flexible_day_TWh
input_flexible_day_max
input_flexible_week_TWh
input_flexible_week_max
input_flexible_4weeks_TWhinput_flexible_4weeks_max
input_V2G_MaxShare
input_V2G_Cap_Charg

Figure 23 - Decision variables options

Objective functions

In energy plan, all fields that are calculated by EnergyPLAN could be used as decision variables. In the current version, we consider that the objective functions are the values that in the EnergyPLAN results are listed as the main indicators for analysis:

- For the ANNUAL CO2 EMISSIONS (Mt) we may choose:
  - CO2-emission (total)
  - CO2-emission (corrected)
- For the SHARE OF RES (incl. Biomass) we may choose:
  - RES share of PES
  - RES share of elec. prod.
  - RES electricity prod.
- For the ANNUAL FUEL CONSUMPTIONS (TWh/year) we may choose:
  - Fuel Consumption (total)
  - CAES Fuel Consumption
  - Fuel(incl.Biomass excl.RES)
  - Fuel Consumption (incl. H2)
  - Fuel Consumption (corrected)
  - Coal Consumption
  - Oil Consumption
  - Ngas Consumption
  - Biomass Consumption
  - Nuclear Fuel Consumption
  - Waste Input
  - V2G Pre Load Hours
- For the ANNUAL COSTS (M DKK) we may choose:
  - Fuel ex. Ngas exchange
  - Coal
  - FuelOil
  - Gasoil/Diesel
  - Petrol/JP
  - Gas handling
  - Biomass
  - Food income
  - Waste
  - Ngas Exchange costs
  - Marginal operation costs
  - Electricity exchange
  - Import
  - Export
  - Bottleneck
  - CO2 emission costs
  - Variable costs
  - Fixed operation costs
  - Annual Investment costs
  - TOTAL ANNUAL COSTS

CO2-emission (total)
CO2-emission (corrected)
RES share of PES
RES share of elec. prod.
RES electricity prod.
Fuel Consumption (total)
CAES Fuel Consumption
Fuel(incl.Biomass excl.RES)
Fuel Consumption (incl. H2)
Fuel Consumption (corrected)
Coal Consumption
Oil Consumption
Ngas Consumption
Biomass Consumption
Nuclear Fuel Consumption
Waste Input
V2G Pre Load Hours
Fuel ex. Ngas exchange
Coal
FuelOil
Gasoil/Diesel
Petrol/JP
Gas handling
Biomass
Food income
Waste
Ngas Exchange costs
Marginal operation costs
Import
Export
Bottleneck
CO2 emission costs
Variable costs
Fixed operation costs
Annual Investment costs
TOTAL ANNUAL COSTS

Figure 24 - Objective functions options