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ABSTRACT

This report describes a testbed for formulating and exploring complex policy design problems motivated by the case-studies settings provided by the consortium, specifically the allocation of grants to citizens in the Emilia-Romagna region of Italy to incentivize the installation of photovoltaic systems.

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1 Introduction

This report describes a testbed for formulating and exploring complex policy design problems motivated by the case-studies settings provided by the consortium. Specifically, we consider auction design for promoting renewable energy production, and in particular solar photovoltaics (PV) panel installations in Emilia-Romagna region.

In 2010, there were 40 GW of existing solar PV capacity world-wide, compared to 190 GW for wind power and 1,010 GW for hydro power. Italy was in forth place in existing capacity and in second place in annual additions of solar PV, Germany being in the first place[1].

There have been several incentive policies for renewable energy proposed around the world. For instance, Brazil is considered the world's sixth largest investor in renewable energy. A wind energy auction was held at the end of 2009. The government bought 1,805 MW of wind energy at a price of BRL148.39 per MW. The success of this auction has encouraged the government to hold additional auctions on an annual basis.

In 2012, there were more than 2,000 solar PV installations in Massachusetts producing 22 MW of electricity. The solar power rebate program started in 2007 with a $68 million budget with a goal of reaching 27 MW of installed solar by 2010. In just 2 years, the $68 million budget was completely exhausted, as many residents filed for free money from the state to go solar. Now, a specific target of 400 MW of solar electricity has to be generated by 2020.

The Massachusetts Solar Power Rebate Program defines a complex mechanism of solar rebate based on[2]:

- your income,
- your home value,
- whether or not the solar panels are manufactured in Massachusetts.

The rebate consists of:

- $750/kW regardless of your income or home value,
- an additional $850/kW if your household income is less than or equal to 120% of median income or if your home value is moderate,
- an additional $100/kW if your solar panels are produced in Massachusetts,
- a 30% Federal Solar Tax Credit, regardless of income or home size, with a maximum rebate of $20,000.

For a 5kW (maximum funded power), assuming the cost was $5.30/Watt installed (about 15% below going market rate as of March 2011), the total investment cost is about $\$26,500$ and it needs about $60m^2$ of roof. Rebate is $\$3,750$, i.e. around 14%, plus 30% tax credit and additional rebates (with maximum of $1,000). Additional reductions come from yearly electric savings (about $900 for ideal home and solar conditions) and feed-in tariff for produced electricity, implemented by a *solar renewable energy credit* (SREC) incentive funding mechanism. It results in an actual investment of $\$12,000$ for the first year. Electric savings and SREC will pay for the entire system in less than 6 years before it begins to make profits. So, initial grants are very important in order to promote solar PV installations.

[1] Taxes and incentives for renewable energy, `http://kpmg.com`, 2012.

[2] `http://solarpowerrocks.com/massachusetts/`

In [7], an efficient grant auction for PV subsidies was studied. It requires knowledge about the agent value of a device, depending on her roof pitch, orientation, and latitude, and the expected cash-flow stream, seen as private information revealed in sealed-bids[3]. In the following, we do not assume to have this knowledge but only for every agent to have a funding request for a given nominal power production. In Section 2, we show how to define a multi-unit reverse auction for allocating grants to agents. Instead of minimizing the maximum installation cost for any agent as in [7], we look at multiple objectives, maximizing the total power production under a fixed budget for the grants, while at the same time, maximizing the number of funded agents. This problem can be defined as a multi-objective knapsack problem where complete solving methods already exist. In Section 3, we study incentive compatible mechanisms, improving truthfulness, by allowing partial funding at a uniform price for the less efficient accepted requests. In Section 4, we describes the architecture of a Java-based prototype implementing the previous auction mechanisms. In Section 5, we report experimental results on real data collected by Emilia-Romagna region in 2004.

Note that non-monotonic behaviours in the allocation process may occur when multiple bids are made by the same agent. We restrict our study to single bids. Moreover, we do not consider mechanisms that are dynamic or reactive to future circumstances. Instead we provide an interactive tool making "what-if" analysis easier for a decision maker.

2 Multi-unit reverse auction as a multi-objective knapsack problem

We first define multi-unit reverse auctions. Then, we show the link to multi-objective knapsack problems. Next, we review some existing methods to solve multi-objective combinatorial optimization problems and more specifically knapsack problems. Finally, we propose a sequential solving process for solving the solar PV auction problem. For preliminaries on auction theory and mechanism design, we refer to [3, 7].

2.1 Multi-unit reverse auction

A procurement auction involves a single buyer and multiple sellers. It is also referred to as a reverse auction since classical auction theory assumes a single seller and multiple buyers. In this paper, we consider a reverse auction in which one buyer wants to purchase a number of indivisible and identical (homogeneous) units from one or more sellers under a total budget constraint.

We assume a single round sealed-bid discriminatory auction, where each seller bids for a fixed quantity of units. The accepted bidders are paid their bids. We will discuss incentive compatibility auctions, implying truthfulness, in Section 3.

Different objectives can be defined. One goal is to maximize the buyer's number of purchased units. This goal is similar to revenue maximization in classical auction theory. Another goal is to maximize the number of accepted bids. This goal should incentivize sellers with small capacity to participate and increase the overall participation in the auction.

[3] I.e., no bidder knows the bid of any other participant until the auction closes.

Note that sealed-bid auctions are less sensitive to collusion than ascending or descending price auctions and results in a higher expected number of purchased units for the buyer if bidders are risk-averse [7].

More formally, there are n sellers, which have private values for each unit. Each seller $j \in \{1, \ldots, n\}$ submits a single bid w_j for a given number of units p_j, and the buyer accordingly makes allocations for every seller $x = (x_1, \ldots, x_n)$ with $x_j \in \{0, 1\}$ and payment $(w_1 x_1, \ldots, w_n x_n)$ such that $\sum_{j=1}^{n} w_j x_j \leq c$, where c is a fixed budget.

In our case, the buyer is the public government, the sellers are citizens or companies and a unit is the nominal production in Watt. We have n bids, each providing power p_j and being funded w_j.

2.2 Multi-objective knapsack problem

A 0-1 knapsack problem is defined by a selection from among n possible items maximizing profit while consuming a restricted amount of resources [10]:

$$\begin{aligned} \max \quad & \sum_{j=1}^{n} p_j x_j \\ \text{s.t.} \quad & \sum_{j=1}^{n} w_j x_j \leq c \end{aligned}$$

with $x_j = 1$ (resp. 0) if item j is selected (resp. rejected), p_j measuring the profit given by item j, w_j being its weight, and c the capacity of the knapsack. All these constants are non-negative integers.

Several links between auctions and knapsack problems are reported in [9, 14, 3]. The multi-unit reverse auction problem corresponds to bids being items, requested prices being weights, and requested quantities being profits. The number of purchased units corresponds to the simple profit maximization criterion.

The 0-1 multi-objective knapsack problem consists of items having k profits: p_j^i is profit $i \in \{1, \ldots, k\}$ of item $j \in \{1, \ldots, n\}$ (non-negative integers). Each profit vector $(p_1^i, \ldots, p_n^i)$ represents a different criterion or objective, denoted $f^i(x) = \sum_{j=1}^{n} p_j^i x_j$, to be maximized such that it satisfies the weight constraint $\sum_{j=1}^{n} w_j x_j \leq c$.

The number of funded bidders in the reverse auction corresponds to a second criterion with $p_j^2 = 1 \; \forall j \in \{1, \ldots, n\}$.

2.3 Multi-objective combinatorial optimization

In a multi-objective combinatorial optimization problem with k objectives, a feasible solution $x = (x_1, \ldots, x_n)$ weakly dominates another feasible solution x' if $f^i(x) \geq f^i(x') \; \forall i \in \{1, \ldots, k\}$. For any instance of this problem, we aim at determining the set of non-dominated feasible solutions. This set, denoted s^{pareto}, is called the Pareto frontier.

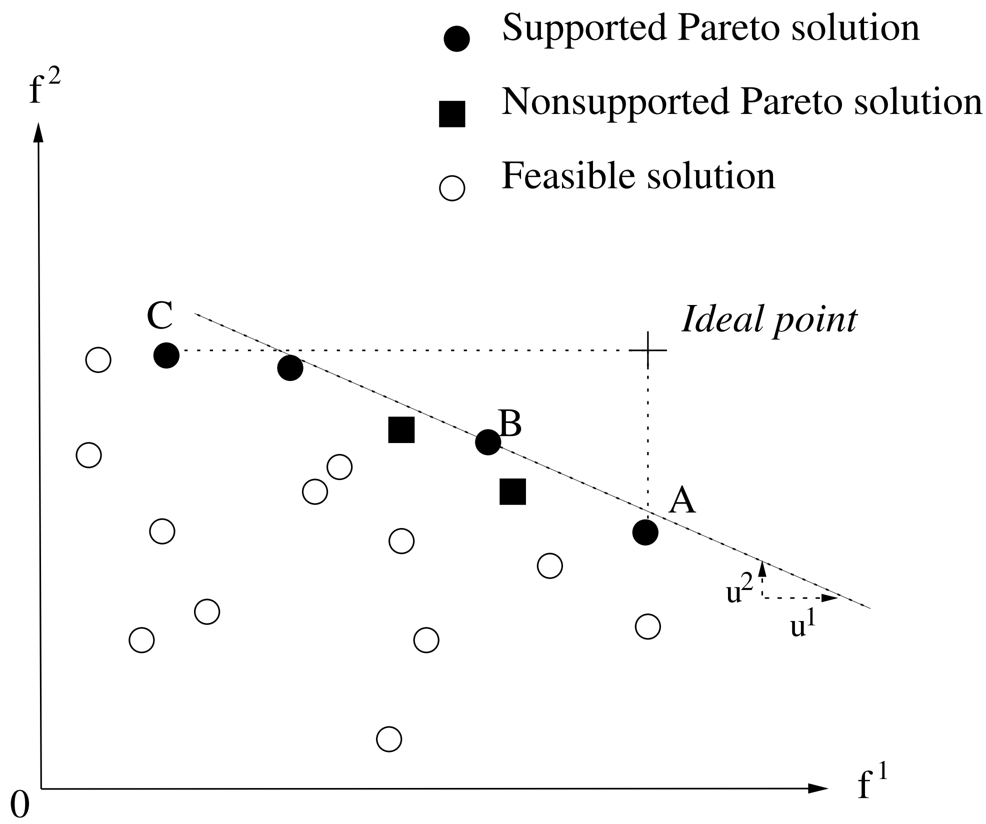


Figure 1: Pareto frontier in bi-objective combinatorial maximization.

Pareto efficiency, or Pareto optimality, is a central concept in game theory with broad applications in economics, engineering and the social sciences. The term is named after Vilfredo Pareto (1848-1923), an Italian economist who used the concept in his studies of economic efficiency and income distribution. If an economic system is not Pareto efficient, then it is the case that some individual can be made better off without anyone being made worse off. It is commonly accepted that such inefficient outcomes, which are dominated by better ones, are to be avoided, and therefore Pareto efficiency is an important criterion for evaluating economic systems.

Figure 1 gives a classical view of bi-objective combinatorial maximization. Each point represents a feasible solution of a given problem. The Pareto frontier is represented by the north-east boundary of the feasible set. The Pareto solutions are divided into two classes. The *supported Pareto solutions* can be obtained by a linear function of the objectives, for instance maximizing $u^1 \times f^1 + u^2 \times f^2$ with $u^1, u^2 > 0$ and $u^1 + u^2 = 1$ produces point B in the figure. They belong to the convex part of the Pareto frontier. The *non supported Pareto solutions* are on the concave part.

One of the commonly used multiple objective optimization methods involves the maximization of the weighted sum of the objectives, thus being restricted to find the supported Pareto solutions only. This method suffers from various drawbacks discussed in [4, 12, 11]. First, the method fails to capture the Pareto points where the Pareto frontier is non-convex. Second, an even distribution of scalar weights u^i often does not yield an even distribution of points. Third, the spacing of the points is largely dependent on the relative scaling of the objectives.

See [6] for an overview of the exact and heuristic methods to generate the Pareto frontier for different combinatorial problems. In Figure 1, there are two *extreme solutions* A and C which have maximum value for one objective and are Pareto optimal, i.e., they also maximize the second objective (they can be obtained by using the following weights $u_A^1 \gg 1, u_A^2 \gg 0, u_C^1 \gg 0, u_C^2 \gg 1$). The objective values can be normalized by applying the *range equalization factors* [13] which are equal to $\frac{1}{R^i}$, $i \in \{1, 2\}$ where $R^i = |f^i(A) - f^i(C)|$ is the range of objective f^i given by the two extreme solutions with coordinates $(f^1(A), f^2(A))$ for point A (resp. $(f^1(C), f^2(C))$ for C).

A special point – usually infeasible – is called the *ideal point* whose coordinates equal the best value for each objective (point $(f^1(A), f^2(C))$ in the figure). In order to select a *balanced or compromise* solution on the Pareto frontier automatically, a possible approach is to maximize a function which defines a global objective which is a measure of how close the decision maker can get to the ideal point. A possible measure of "closeness" to the ideal point is a family of L_m*−metrics* defined as follows:

$$L_m(x) = \left[\sum_{i=1}^{k} {u_i}^m \left| \frac{f^i(x) - f^i(I)}{R^i} \right|^m \right]^{\frac{1}{m}} \tag{1}$$

where $m \in [1, +\infty]$, $k = 2$ in bi-objective maximization, I is the ideal point, and u_i are the weights giving the relative importance of the objectives. In general, these weights are not related to the ones used in finding the supported Pareto solutions. Fixing u_i makes the objectives *commensurable* (in a common unit). Using the L_2-metric corresponds to minimizing the Euclidean distance to the ideal point. However, this overall objective is no longer linear which makes the problem often more difficult to solve.

Another approach, called $\epsilon-$*constraint method*, is based on the maximization of one (the most preferred or primary) objective, and considering the other objectives as constraints bound by some allowable levels ϵ^i. This trade-off method does not impose that the objectives are commensurable.

A good introduction to these mathematical programming techniques can be found in Coello's thesis [2].

In the case of the single-objective knapsack problem, it is well-known that, in order to obtain a good solution, items should usually be considered in decreasing order of profit to weight ratios p_j/w_j (assuming that ties are solved arbitrarily) [10]. For the multi-objective version, there is no such a natural order. A heuristic proposed in [1] consists in ranking every item for each objective and uses an order according to increasing values of the sum of the ranks of items in the k orders.

Despite the fact that in general, the number of Pareto solutions may be exponential in the problem size (see Theorem 2 in [5]), it is smaller than the number of bidders in our bi-criteria reverse auction problem. More generally, the size of this set is bounded by the minimum of the solution space size and the product of every objective range except one, assuming only one solution is kept for every criterion vector (i.e., keep x and remove x' if $f^i(x) = f^i(x')$ $\forall i \in \{1, \ldots, k\}$). We have $|s^{pareto}| \leq \min(2^n, \frac{\prod_{i=1}^{k} \max_x f^i(x)}{\max_{i=1}^{k} \max_x f^i(x)})$.

2.4 Solving the solar PV auction problem

Based on the previous section, we propose a sequential approach for solving the solar PV bi-criteria multi-unit reverse auction problem.

Given a list of n bids with request w_j (Euro) and power p_j (Watt), $j \in \{1, \ldots, n\}$, and a grant budget c (Euro), we define a linear mono-objective knapsack problem:
KP 1.

$$\begin{aligned} x^* &= \underset{x}{\text{argmax}} \sum_{j=1}^{n} (u_1 p_j + u_2) x_j \\ s.t. & \sum_{j=1}^{n} w_j x_j \leq c \\ & x_j \in \{0, 1\} \end{aligned}$$

with $u_1, u_2 \geq 0$.

The sequential solving process is:

1. Randomize the list of bids in order to break ties randomly in the final allocation phase.
2. Identify the two extreme solutions by first setting $(u_1 = 1, u_2 = 0)$ in the linear integer program KP1 whose optimum x^* gives the maximum total power $\overline{p} = \sum_{j=1}^{n} p_j x_j^*$ and a non-optimized number of funded bids $\underset{\sim}{x} = \sum_{j=1}^{n} x_j^*$. By setting $(u_1 = 0, u_2 = 1)$ in KP1, its new optimum x^* gives the maximum number of funded bids $\overline{x} = \sum_{j=1}^{n} x_j^*$ and a non-optimized total power $\underset{\sim}{p} = \sum_{j=1}^{n} p_j x_j^*$. Then, solving KP1 with both settings $(u_1 = \frac{1}{\overline{p} - \underset{\sim}{p}}, u_2 = \frac{10^{-3}}{\overline{x} - \underset{\sim}{x}})$ and $(u_1 = \frac{10^{-3}}{\overline{p} - \underset{\sim}{p}}, u_2 = \frac{1}{\overline{x} - \underset{\sim}{x}})$ gives the coordinates of the two extreme solutions: $(\overline{p}, \underline{x})$ and $(\underline{p}, \overline{x})$[4].
3. Following the *$\epsilon-$constraint method* previously described, choose a minimum required power production $\hat{p} \in [\underline{p}, \overline{p}]$, solve KP1 with $(u_1 = 0, u_2 = 1)$[5] and extra constraint $\sum_{j=1}^{n} p_j x_j \geq \hat{p}$, and allocate a grant w_j to every bidder j with $x_j^* = 1$.

3 Partial funding and incentive compatibility mechanisms

First, we define a simple knapsack problem to estimate the market price of Watt production:
KP 2.

$$\begin{aligned} x^* &= \underset{x}{\text{argmin}} \sum_{j=1}^{n} w_j x_j \\ s.t. & \sum_{j=1}^{n} p_j x_j \geq \hat{p} \\ & x_j \in \{0, 1\} \end{aligned}$$

[4]This two-step process allows to mitigate floating point precision issues in mixed integer programming solvers such as IBM ILOG CPLEX.

[5]Note that this setting does not allow to distinguish between two moderately efficient bidders i and j with the same power because changing an optimal allocation from $(x_i = 1, x_j = 0)$ to $(x_i = 0, x_j = 1)$ may still satisfy the budget and power constraints. It makes randomizing the bids even more crucial here. Another approach would be to sort bids based on their date such that bids that arrived early are given some preference.

with required total power $\hat{p}$ and for every bid j, request w_j and power p_j. The market price is defined by $\hat{w} = \max_{j=1}^{n} \frac{w_j}{p_j} x_j^*$.

The idea comes from *uniform-price auction* where all accepted bidders pay a per unit price equal to the lowest winning bid regardless of their actual bid, conversely to discriminatory auctions where bidders pay their bid. The uniform-price single-bid auction provides an incentive for bidders to bid truthfully [3, 8]. An example of such an auction was conducted for greenhouse gas allowances in Ireland in 2006[6]. However, we do not implement a uniform price auction, but a quasi-uniform one. The aim is to allow more participants to be funded by allocating partial funds to the less efficient accepted bids. The uniform market price is used to quantify the exact funding for those bids and is equal to $\min(w_j, p_j\hat{w})$. The most efficient accepted bids remain completely funded.

Now, the accepted bidders have the choice to refuse their grant[7] if it is too far from their request. We assume that below a given threshold rw_j with $r \in [0, 1]$, bidders prefer to quit the auction. By decreasing r, we allow to accept more bids but increase the risk that the actual power is lower than the predicted one. Instead of maximizing the number of accepted bids, we maximize the overall satisfaction of the accepted bidders. The satisfaction of a bidder j is supposed to be $-\infty$ if $p_j\hat{w} < rw_j$, and strictly greater than zero otherwise, being equal to 1 if $p_j\hat{w} = w_j$. It is proportional to $\frac{p_j\hat{w}}{w_j}$. In the following, we maximize the overall sum[8]. The resulting new objective $\sum_{j=1}^{n} \frac{p_j\hat{w}}{w_j} x_j$ is also proportional to the product of two criteria which are the average efficiency $\frac{\sum_{j=1}^{n} \frac{p_j}{w_j} x_j}{\sum_{j=1}^{n} x_j}$ of the accepted bids and the number of accepted bids $\sum_{j=1}^{n} x_j$. Maximizing this objective should result in allocations which are both efficient and satisfying a large number of participants.

Next, we define another mono-objective knapsack problem for our partial funding policy:
KP 3.

$$
\begin{aligned}
x^* \quad = \quad & \underset{x}{\text{argmax}} \sum_{j=1}^{n} \frac{p_j\hat{w}}{w_j} x_j \\
s.t. \quad & \sum_{j=1}^{n} \min(w_j, p_j\hat{w}) x_j \leq c \\
& \sum_{j=1}^{n} p_j x_j \geq \hat{p} \\
& x_j = 0 \quad \textit{if}\; p_j\hat{w} < rw_j \\
& x_j \in \{0, 1\}
\end{aligned}
$$

with total budget c, required power $\hat{p}$, and unit market price $\hat{w}$.

The sequential solving process is now the following:

[6] `http://www.eprg.group.cam.ac.uk/wp-content/uploads/2008/11/eprg_euets_workshop_120107_macken.pdf`

[7] Assuming the grant is delivered after the PV panels are installed.

[8] KP3 maximizes the so-called *l1-norm* of the satisfaction levels. We could use the *l2-norm* instead, i.e. $\text{argmax}_x \sum_{j=1}^{n} \frac{p_j\hat{w}(2w_j - p_j\hat{w})}{w_j^2} x_j$.

1. Randomize the list of bids in order to break ties randomly in the final allocation phase.
2. Choose a minimum required power production $\hat{p} \in [\underline{p}, \overline{p}]$, solve KP2 to determine the market price in Euro for each Watt produced: $\hat{w} = \max_{j=1}^{n} \frac{w_j}{p_j} x_j^*$ corresponding to the worst accepted bid completely funded to achieve the power target at minimum cost.
3. Select a threshold funded ratio $r \in [0, 1]$ where bidder j receiving less than rw_j will prefer to quit the auction. Then, solve KP3 and allocate a grant $\min(w_j, p_j\hat{w})$ to every bidder j with $x_j^* = 1$. Note that a bid j that provides the same power but for a smaller request than bid i is always preferred to i.

4 A Java-based Prototype

This section describes the prototype and how to use it. The prototype provides a way for the user to load in data that describes the bids and compute the allocation of funds to bids according to a number of scenarios. It does not assume any knowledge of the underlying mechanisms and should be usable by people with basic computer skills. The data can be imported and exported into Microsoft Excel format so that the user can perform arbitrary analyses in a familiar environment. In addition, the application itself also provides a few basic visualizations.

In its initial form, the prototype uses the IBM CPLEX version 12.5 commercial software to solve the problem of allocating funds to bids and requires this software to be installed. CPLEX is used only for testing purposes and will be replaced by an open source solver such as SCIP[9]. Java is required as well, but there are no other requirements. The prototype is distributed as a compressed archive. After uncompressing, copy the CPLEX jar file into the `lib/` directory – we cannot distribute this file because of licensing restrictions. The software can then be run as follows.

```
java -Djava.library.path=<path to CPLEX shared libraries> -jar pver-0.1.jar
```

The initial screen of the application is shown in Figure 2. No data is shown to start with. Lists of the loaded objects can be displayed by selecting the appropriate option in the `Window` menu, as shown in Figure 3.

Selecting the `Bid` entry opens a tab that displays a list of the bids (Figure 4). As no data has been loaded, the list is empty.

Data can be imported from Microsoft Excel by selecting the `Import...` option from the `File` menu (Figure 5). The prototype includes example data from the auction that the Emilia-Romagna region ran in 2004 in the file `Proposals_2004.xlsx`. At present, the software assumes that data is given in exactly the same format as the example data; otherwise importing it will not work.

After importing the example data, the display of the bids automatically updates (Figure 6).

The user interface of the prototype provides much more functionality that enables exploring and adapting the data. A full description is beyond the scope of this document and we focus on the functionality immediately relevant to the ePolicy project.

[9] http://scip.zib.de/

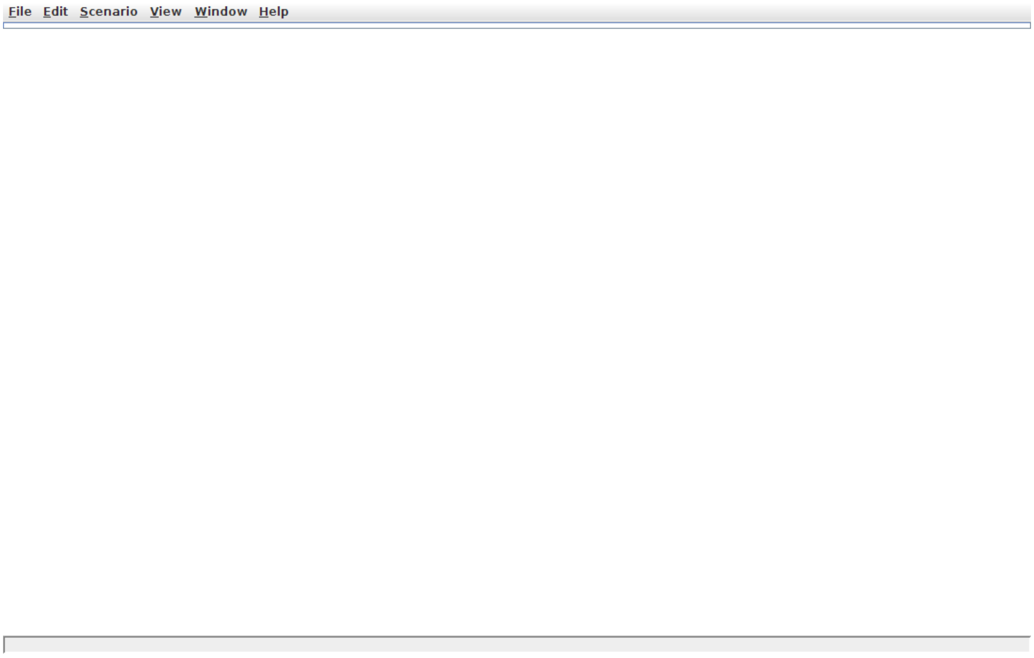


Figure 2: Initial screen.

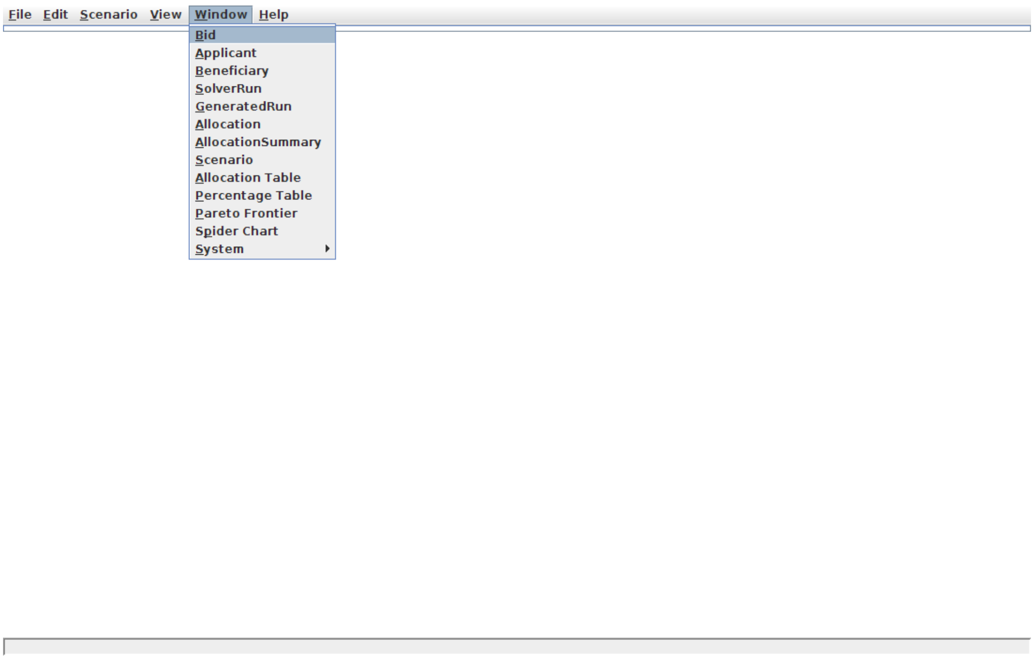


Figure 3: Selecting data to display.

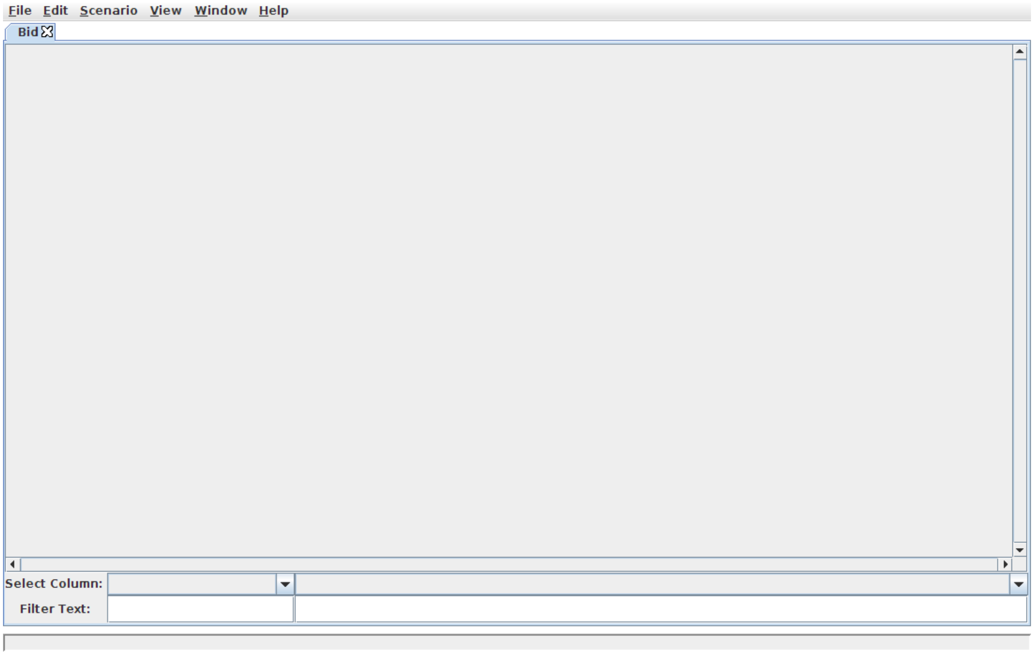


Figure 4: List of bids with no data.

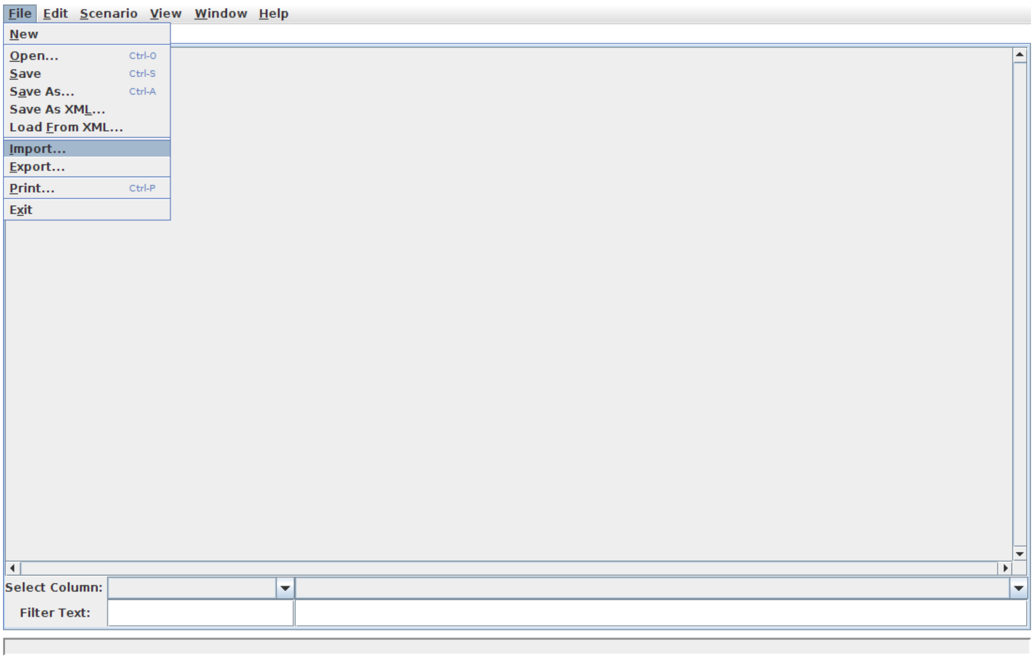
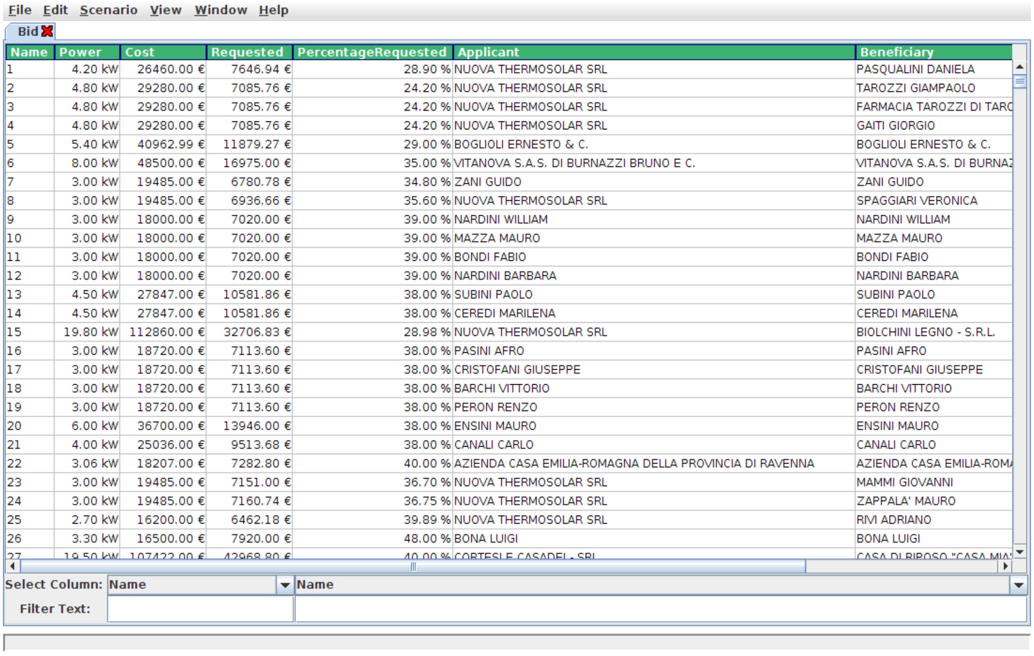


Figure 5: Importing data.



Name	Power	Cost	Requested	PercentageRequested	Applicant	Beneficiary
1	4.20 kW	26460.00 €	7646.94 €	28.90 %	NUOVA THERMOSOLAR SRL	PASQUALINI DANIELA
2	4.80 kW	29280.00 €	7085.76 €	24.20 %	NUOVA THERMOSOLAR SRL	TAROZZI GIAMPAOLO
3	4.80 kW	29280.00 €	7085.76 €	24.20 %	NUOVA THERMOSOLAR SRL	FARMACIA TAROZZI DI TARC
4	4.80 kW	29280.00 €	7085.76 €	24.20 %	NUOVA THERMOSOLAR SRL	GAITI GIORGIO
5	5.40 kW	40962.99 €	11879.27 €	29.00 %	BOGLIOLI ERNESTO & C.	BOGLIOLI ERNESTO & C.
6	8.00 kW	48500.00 €	16975.00 €	35.00 %	VITANOVA S.A.S. DI BURNAZZI BRUNO E C.	VITANOVA S.A.S. DI BURNAZ
7	3.00 kW	19485.00 €	6780.78 €	34.80 %	ZANI GUIDO	ZANI GUIDO
8	3.00 kW	19485.00 €	6936.66 €	35.60 %	NUOVA THERMOSOLAR SRL	SPAGGIARI VERONICA
9	3.00 kW	18000.00 €	7020.00 €	39.00 %	NARDINI WILLIAM	NARDINI WILLIAM
10	3.00 kW	18000.00 €	7020.00 €	39.00 %	MAZZA MAURO	MAZZA MAURO
11	3.00 kW	18000.00 €	7020.00 €	39.00 %	BONDI FABIO	BONDI FABIO
12	3.00 kW	18000.00 €	7020.00 €	39.00 %	NARDINI BARBARA	NARDINI BARBARA
13	4.50 kW	27847.00 €	10581.86 €	38.00 %	SUBINI PAOLO	SUBINI PAOLO
14	4.50 kW	27847.00 €	10581.86 €	38.00 %	CEREDI MARILENA	CEREDI MARILENA
15	19.80 kW	112860.00 €	32706.83 €	28.98 %	NUOVA THERMOSOLAR SRL	BIOLCHINI LEGNO - S.R.L.
16	3.00 kW	18720.00 €	7113.60 €	38.00 %	PASINI AFRO	PASINI AFRO
17	3.00 kW	18720.00 €	7113.60 €	38.00 %	CRISTOFANI GIUSEPPE	CRISTOFANI GIUSEPPE
18	3.00 kW	18720.00 €	7113.60 €	38.00 %	BARCHI VITTORIO	BARCHI VITTORIO
19	3.00 kW	18720.00 €	7113.60 €	38.00 %	PERON RENZO	PERON RENZO
20	6.00 kW	36700.00 €	13946.00 €	38.00 %	ENSINI MAURO	ENSINI MAURO
21	4.00 kW	25036.00 €	9513.68 €	38.00 %	CANALI CARLO	CANALI CARLO
22	3.06 kW	18207.00 €	7282.80 €	40.00 %	AZIENDA CASA EMILIA-ROMAGNA DELLA PROVINCIA DI RAVENNA	AZIENDA CASA EMILIA-ROMA
23	3.00 kW	19485.00 €	7151.00 €	36.70 %	NUOVA THERMOSOLAR SRL	MAMMI GIOVANNI
24	3.00 kW	19485.00 €	7160.74 €	36.75 %	NUOVA THERMOSOLAR SRL	ZAPPALA' MAURO
25	2.70 kW	16200.00 €	6462.18 €	39.89 %	NUOVA THERMOSOLAR SRL	RIVI ADRIANO
26	3.30 kW	16500.00 €	7920.00 €	48.00 %	BONA LUIGI	BONA LUIGI
27	19.50 kW	107422.00 €	42968.80 €	40.00 %	CORTESI E CASADEI - SRL	CASA DI RIPOSO "CASA MIA"

Figure 6: List of bids with example data.

The prototype encapsulates the parameters of an incentive design in `SolverRun` objects. These objects contain the optimization objective, the total budget, the target power output and a few other parameters. Figure 7 shows a list of the `SolverRun` objects that are defined by default. The screen was obtained by selecting the `SolverRun` entry in the `Window` menu.

The choice of which set of parameters is to be used when modelling a scenario and running it can be made in the list of scenarios (Figure 8). In addition to choosing the `SolverRun` object, the prototype also allows a few other parameters to be set, such as a timeout to be imposed when running the solver.

To generate the model, run the solver and calculate the allocation of funds to bids given the current scenario, it suffices to select the `Run...` option from the `Scenario` menu (Figure 9).

Selecting this option produces the window depicted in Figure 10 which allows to set a few additional parameters for the run. These parameters allow to disable individual constraints – that the total allocation of funds has to be at most the total available budget, that the power output has to be at least the target, and that a certain minimum number of funded bids has to be achieved. These parameters allow the user to explore "what-if" scenarios that facilitate judging the effect of these particular constraints.

After selecting the `Run` button, the prototype will transform the bids and other scenario parameters into a CPLEX model and run the CPLEX solver. The solution variables determine the allocation of funds to bids. They are automatically converted to objects that can be displayed in the application. Figure 11 shows the computed allocations for a particular scenario. This screen was obtained by selecting the `Allocation` entry from the `Window` menu.

The prototype associates a solution and each allocation within in with the `SolverRun` object that contains the parameters that determined the run that obtained the solution. It thus

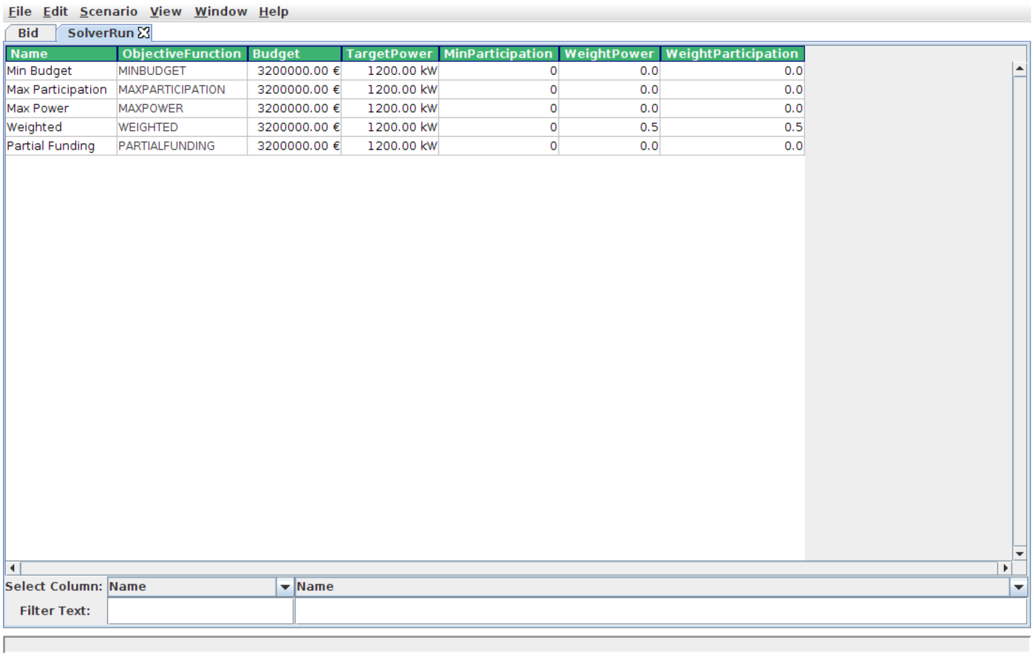


Figure 7: List of SolverRun objects.

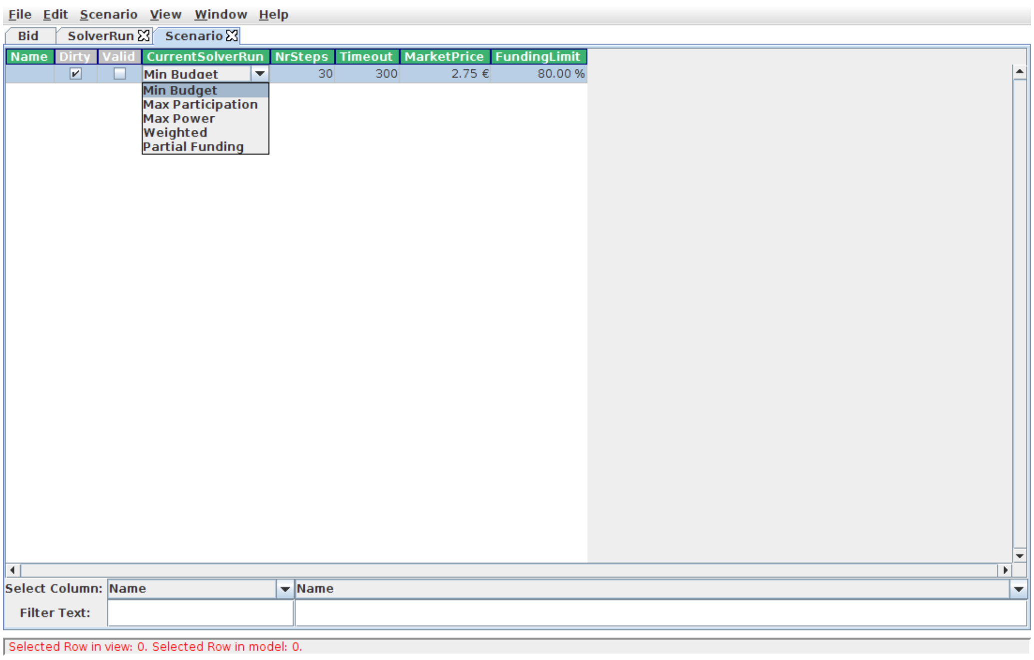


Figure 8: The current scenario.

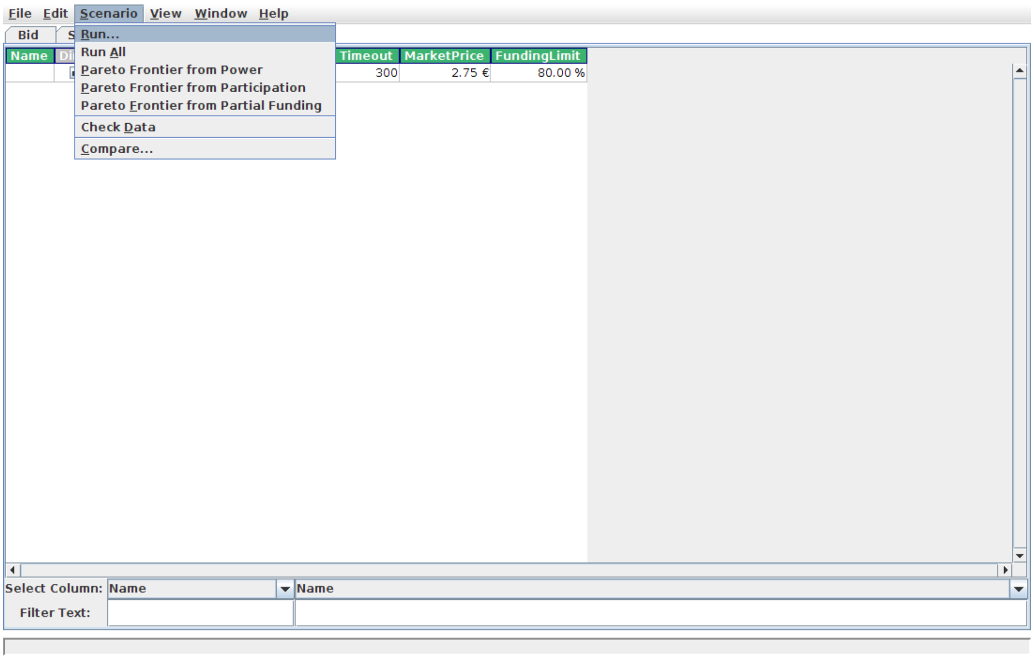


Figure 9: Running a scenario.

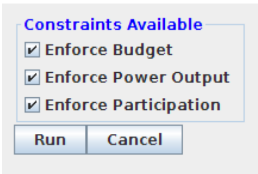
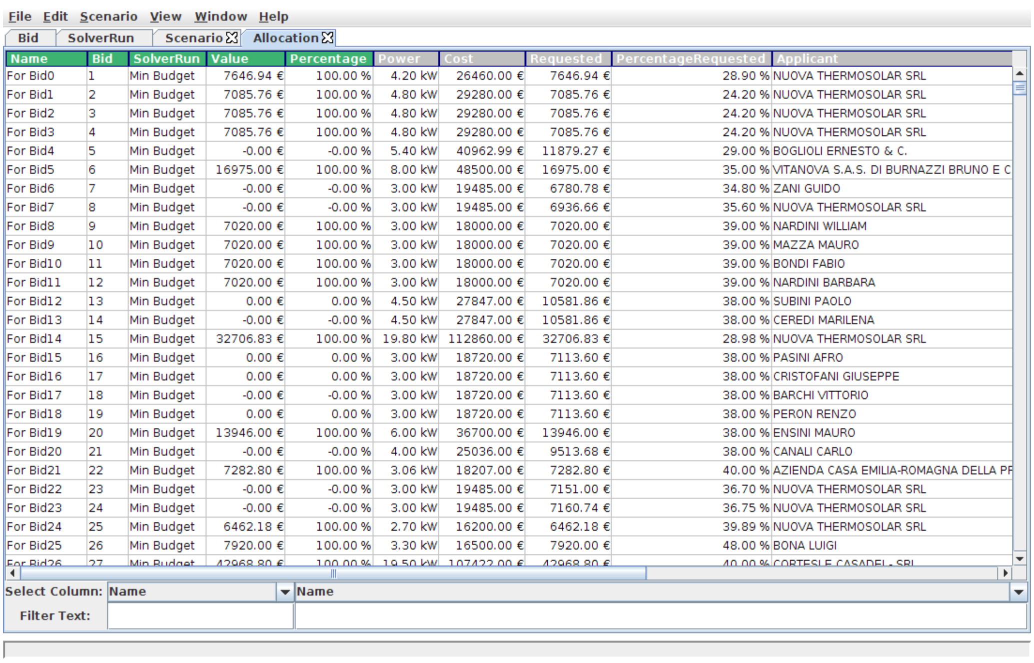


Figure 10: Setting parameters for a run.



Name	Bid	SolverRun	Value	Percentage	Power	Cost	Requested	PercentageRequested	Applicant
For Bid0	1	Min Budget	7646.94 €	100.00 %	4.20 kW	26460.00 €	7646.94 €	28.90 %	NUOVA THERMOSOLAR SRL
For Bid1	2	Min Budget	7085.76 €	100.00 %	4.80 kW	29280.00 €	7085.76 €	24.20 %	NUOVA THERMOSOLAR SRL
For Bid2	3	Min Budget	7085.76 €	100.00 %	4.80 kW	29280.00 €	7085.76 €	24.20 %	NUOVA THERMOSOLAR SRL
For Bid3	4	Min Budget	7085.76 €	100.00 %	4.80 kW	29280.00 €	7085.76 €	24.20 %	NUOVA THERMOSOLAR SRL
For Bid4	5	Min Budget	-0.00 €	-0.00 %	5.40 kW	40962.99 €	11879.27 €	29.00 %	BOGLIOLI ERNESTO & C.
For Bid5	6	Min Budget	16975.00 €	100.00 %	8.00 kW	48500.00 €	16975.00 €	35.00 %	VITANOVA S.A.S. DI BURNAZZI BRUNO E C
For Bid6	7	Min Budget	-0.00 €	-0.00 %	3.00 kW	19485.00 €	6780.78 €	34.80 %	ZANI GUIDO
For Bid7	8	Min Budget	-0.00 €	-0.00 %	3.00 kW	19485.00 €	6936.66 €	35.60 %	NUOVA THERMOSOLAR SRL
For Bid8	9	Min Budget	7020.00 €	100.00 %	3.00 kW	18000.00 €	7020.00 €	39.00 %	NARDINI WILLIAM
For Bid9	10	Min Budget	7020.00 €	100.00 %	3.00 kW	18000.00 €	7020.00 €	39.00 %	MAZZA MAURO
For Bid10	11	Min Budget	7020.00 €	100.00 %	3.00 kW	18000.00 €	7020.00 €	39.00 %	BONDI FABIO
For Bid11	12	Min Budget	7020.00 €	100.00 %	3.00 kW	18000.00 €	7020.00 €	39.00 %	NARDINI BARBARA
For Bid12	13	Min Budget	0.00 €	0.00 %	4.50 kW	27847.00 €	10581.86 €	38.00 %	SUBINI PAOLO
For Bid13	14	Min Budget	-0.00 €	-0.00 %	4.50 kW	27847.00 €	10581.86 €	38.00 %	CEREDI MARILENA
For Bid14	15	Min Budget	32706.83 €	100.00 %	19.80 kW	112860.00 €	32706.83 €	28.98 %	NUOVA THERMOSOLAR SRL
For Bid15	16	Min Budget	0.00 €	0.00 %	3.00 kW	18720.00 €	7113.60 €	38.00 %	PASINI AFRO
For Bid16	17	Min Budget	0.00 €	0.00 %	3.00 kW	18720.00 €	7113.60 €	38.00 %	CRISTOFANI GIUSEPPE
For Bid17	18	Min Budget	-0.00 €	-0.00 %	3.00 kW	18720.00 €	7113.60 €	38.00 %	BARCHI VITTORIO
For Bid18	19	Min Budget	0.00 €	0.00 %	3.00 kW	18720.00 €	7113.60 €	38.00 %	PERON RENZO
For Bid19	20	Min Budget	13946.00 €	100.00 %	6.00 kW	36700.00 €	13946.00 €	38.00 %	ENSINI MAURO
For Bid20	21	Min Budget	-0.00 €	-0.00 %	4.00 kW	25036.00 €	9513.68 €	38.00 %	CANALI CARLO
For Bid21	22	Min Budget	7282.80 €	100.00 %	3.06 kW	18207.00 €	7282.80 €	40.00 %	AZIENDA CASA EMILIA-ROMAGNA DELLA PF
For Bid22	23	Min Budget	-0.00 €	-0.00 %	3.00 kW	19485.00 €	7151.00 €	36.70 %	NUOVA THERMOSOLAR SRL
For Bid23	24	Min Budget	-0.00 €	-0.00 %	3.00 kW	19485.00 €	7160.74 €	36.75 %	NUOVA THERMOSOLAR SRL
For Bid24	25	Min Budget	6462.18 €	100.00 %	2.70 kW	16200.00 €	6462.18 €	39.89 %	NUOVA THERMOSOLAR SRL
For Bid25	26	Min Budget	7920.00 €	100.00 %	3.30 kW	16500.00 €	7920.00 €	48.00 %	BONA LUIGI

Figure 11: List of allocations.

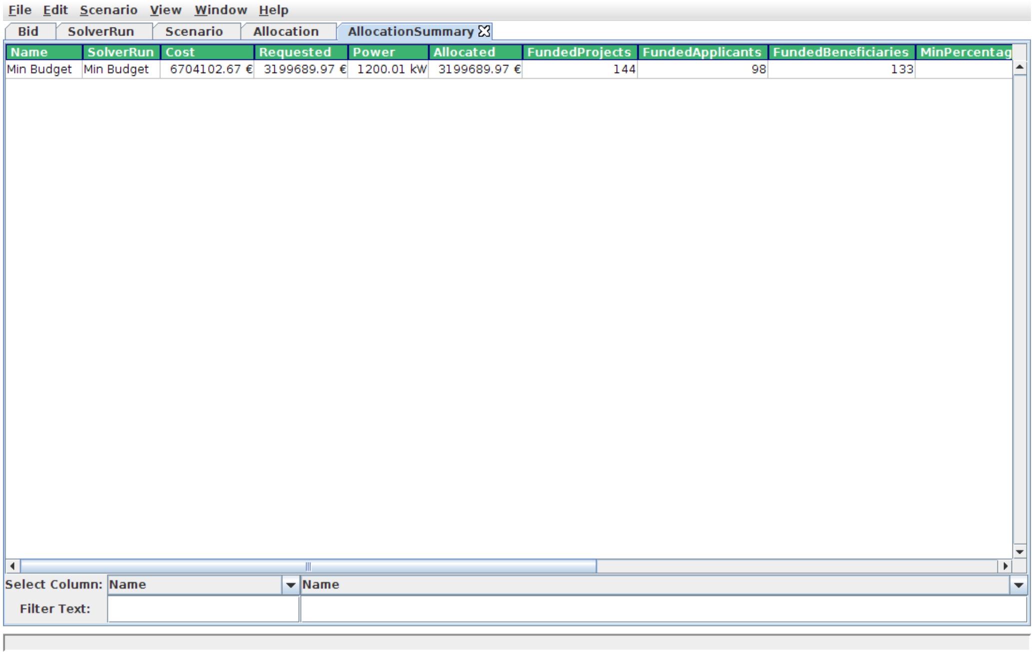


Figure 12: Summary of allocations.

makes it easy to track which scenarios have been explored and compare them. Summaries of the allocations achieved for particular scenarios are provided in the `AllocationSummary` window (Figure 12).

Finally, the data can be exported back into Microsoft Excel format using the `Export...` entry in the `File` menu (Figure 13). The computed allocations will be written to the chosen file, which will contain a single worksheet with columns for the applicant, the beneficiary, the power output of the bid, the total cost of the proposed project, the amount requested from the regional government, and the amount that was allocated by the incentive design.

While the intention is to perform most of the analysis and visualization in tools that the user of prototype is more familiar with (such as Microsoft Excel), the prototype itself does provide basic functionality to analyse both the bids and the computed allocations. As an example, Figure 14 shows the values of a few key output variables for four different scenarios in a spider chart.

5 Experimental evaluation

5.1 Case Study: Emilia-Romagna Region

We performed preliminary experiments on the data from the auction that the Emilia-Romagna region ran in 2004. Recall that in this auction, participants had to put in bids that were ranked according to the following criteria. The ranking score r_j for a particular bid j was computed according to equation 2.

$$r_j = 100 \cdot k \cdot \frac{c \cdot p_j}{y \cdot z} = k \cdot \frac{c \cdot p_j}{w_j} \tag{2}$$

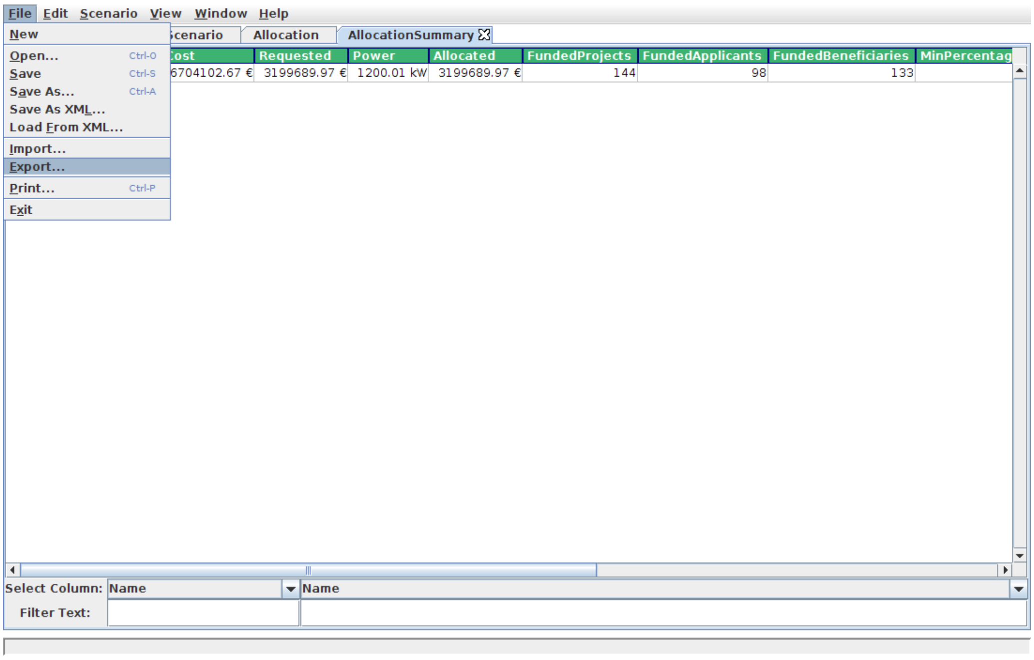


Figure 13: Exporting incentive design results.

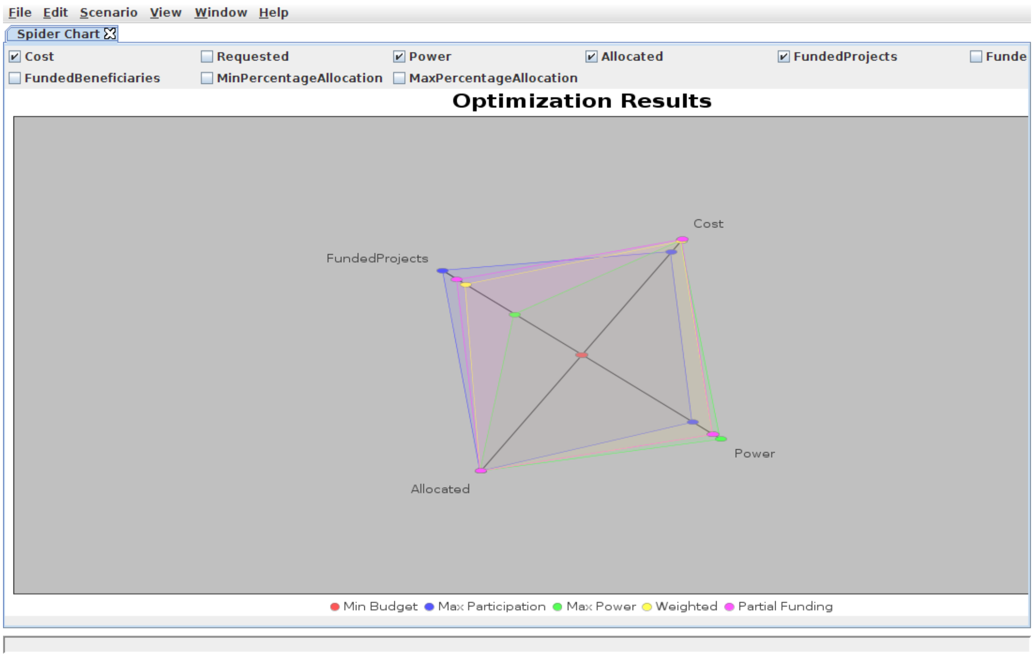


Figure 14: Spider chart comparing key outputs of different scenarios.

In this equation, k denotes a multiplicative factor of 1.3 if the proposal includes integration into existing architecture, c is the unitary maximum cost in Euro per Kilowatt, p_j is the expected nominal output of the proposed power plant, y_i are the expected expenses, z_i is the percentage of these expenses requested as incentive, and w_j is the corresponding requested fund.

The funds were allocated to proposals in a greedy manner, starting with the bid with the highest score. After that, the bid with the second highest score was funded and so on until the budget was exhausted. Each bid was either funded entirely or not at all; no partial allocation of funds took place.

In the data, there is a total of 1032 bids with a total requested amount of 18,445,915 Euro and a total power output of 5,079.37 kW. Of these, 268 bids were funded with a total of 3,194,643 Euro, achieving a total power output of 1,228.73 kW. In the following, we do not take into account the multiplicative factor k.

5.2 Comparison to new incentive design mechanisms

The basis for our comparisons are the parameters set for the Emilia-Romagna auction. We assume a budget of 3.2 Million Euro and a target power output of 1200 kW. These values are rounded from the actual ones.

The evaluated scenarios are as follows.

minimize expenditure (KP2) Proposals are funded such that the target power output is achieved with the minimum amount of funds spent.

maximize power (KP1 with $(u_1 = 1, u_2 = 0)$) Proposals are funded such that the total allocated amount is within the budget and the maximum power output is achieved.

maximize participation (KP1 with $(u_1 = 0, u_2 = 1)$ and additional power constraint) Proposals are funded such that the total allocated amount is within the budget and the maximum amount of individual proposals is funded while achieving the target power output.

partial funding (KP3) Proposals are funded such that the total allocated amount is within the budget and the target power output is achieved. Each proposal may be allocated less than the amount that was requested and we aim to maximise the satisfaction of the bidders and the efficiency of the funded proposals.

There are a number of additional, more preliminary and exploratory scenarios implemented in the prototype. These will be refined and considered in future versions of this document.

Table 1 presents a comparison of the key outputs that the different incentive design mechanisms implemented in the prototype achieve on the data of the 2004 Emilia-Romagna region auction. For comparison, we also give the results for this auction.

The results clearly show that the way in which the 2004 auction was conducted was not optimal for any of the objectives that we consider here. We can achieve a higher power output, spend less money or fund significantly more bids. While optimizing the amount of money spent or the total power gives only relatively small changes, optimizing the number of funded proposals almost doubles it and the partial funding scenario improves the number further.

	Total allocated funds (Euro)	Total power (kW)	Total funded bids
2004 auction	3,194,643	1228.73	268
minimize expenditure	**2,946,247**	1200.01	219
maximize power	3,199,906	**1291.81**	235
maximize participation	3,198,308	1200.09	**415**
partial funding	3,199,473	1219.73	431

Table 1: Comparison of key outputs of the different incentive designs. The output that is optimized in a particular scenario is shown in **bold**.

The choice of which of these objectives is the most important one is ultimately up to the policy maker. The prototype provides a way of easily and systematically exploring the alternatives and making informed decisions. In fact, it can even give an approximation of the Pareto frontier for two objectives, maximising the total power and maximising the total funded bids, as shown in Figure 15. The power target of $\hat{p} = 1200$kW seems to be a good compromise between the two objectives and is approximately the closest non-dominated point to the ideal point at $\approx (1290kW, 480)$.

Figures 16 to 18 show a graphical summary of the behaviour of the different incentive designs. The graphs show the density distribution of the number of funded proposals over the requested amount, the power output, and the efficiency. For comparison, the bids submitted to the 2004 auction and the funded bids are shown. It again makes clear that the incentive designs that optimize a specific objective are significantly different from the design of the 2004 auction. As an example, none of the incentive schemes investigated here would have funded the most expensive proposals that were funded in the 2004 auction.

In terms of the distribution of funded proposals, there is not much difference between minimizing the budget and maximizing the power output. In both cases, the number of proposals with low cost and a small power output is lower than for the other schemes, while the more expensive and high power proposals are funded. They both fund most proposals at an efficiency of approximately 0.0004 Kilowatt per Euro. This appears to be the “sweet spot” for all incentive designs and is particular pronounced in the partial funding scenario.

The scenario that maximizes the number of funded proposals prefers, as would be expected, small proposals that do not cost a lot, but do not produce a lot of power either. It noticeably funds proposals with a much lower efficiency than any of the other scenarios.

6 Conclusion

We have developed a tool that supports a policy-maker to, given an incentive budget and a target power output, determine the distribution of these incentives to interested parties. The constructed design aims to achieve at least the target power production while remaining within budget.

For the moment, due to available data, we used only grants in the incentive policy. There are a number of other incentive mechanisms (feed-in-tariffs, reduced interest, fiscal incentives,. . .)

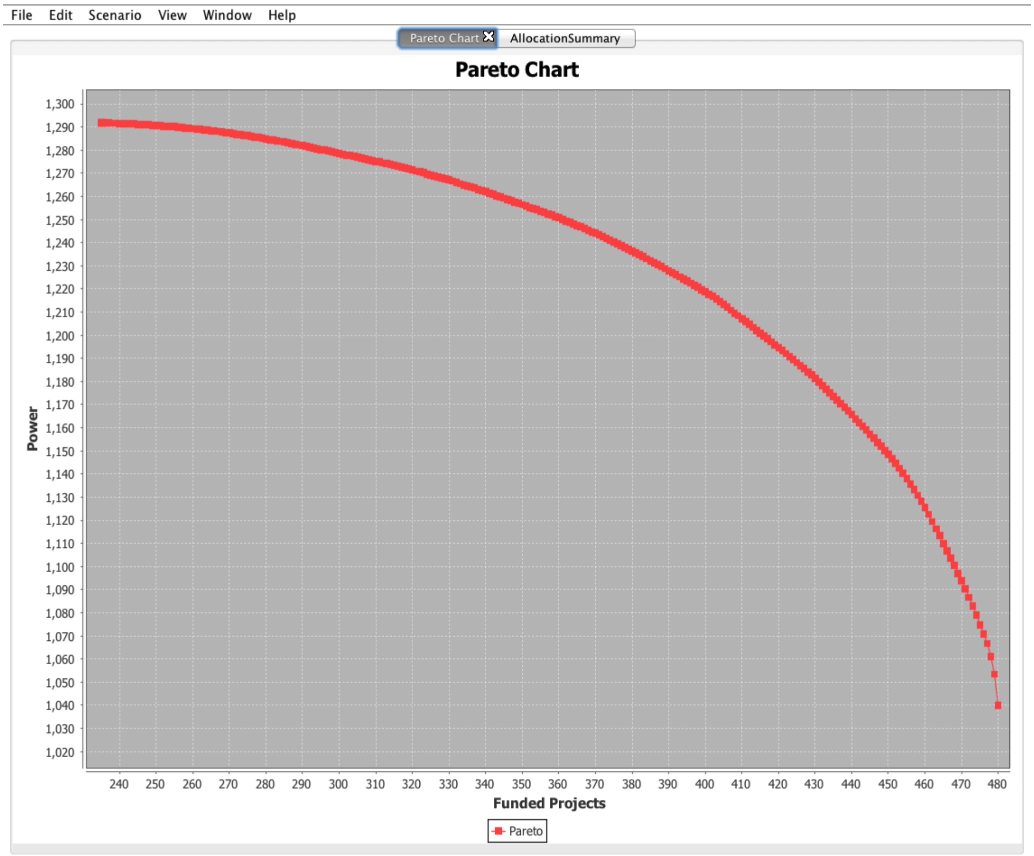


Figure 15: Pareto frontier on 2004 Emilia-Romagna data using discriminatory auction (complete request funding, KP1).

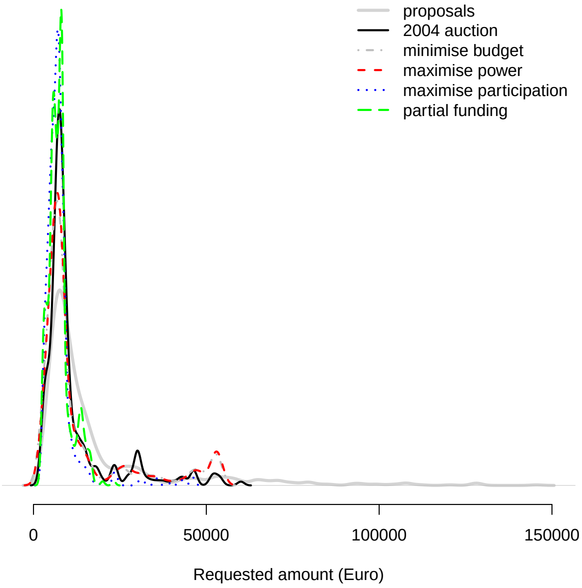


Figure 16: Number of proposals over requested amount.

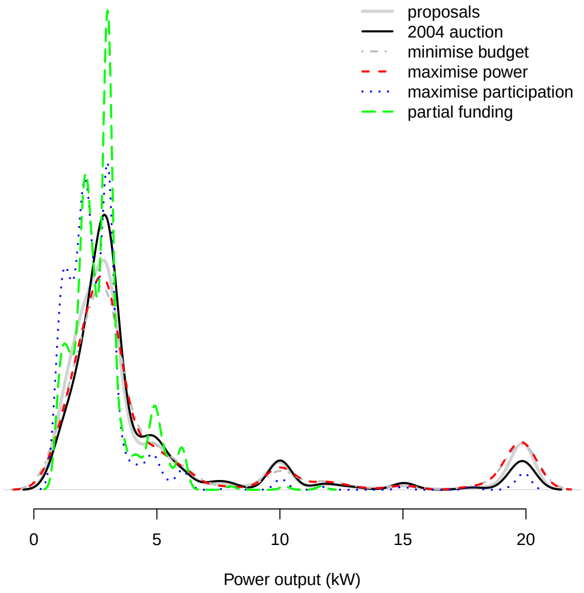


Figure 17: Number of proposals over power output.

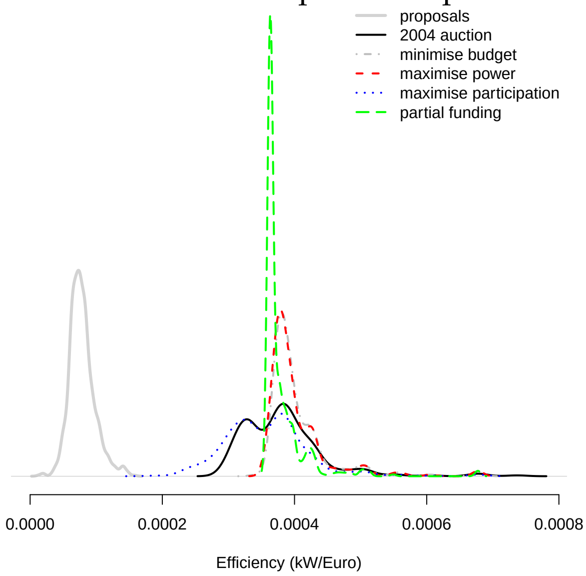


Figure 18: Number of proposals over efficiency.

that will be taken into account later in the project. In addition a number of interaction strategies with the global optimization and the simulator will be considered.

The criteria for incentivizing participants include not only the efficiency of the proposed installation in terms of power produced per Euro invested, but also the fairness of the allocation across all applicants. Additionally, we want to encourage an allocation process where participants reveal their private information truthfully and purposeful misrepresentation does not gain them an advantage.

As notions of fairness and efficiency may be subject to policy decisions, the incentive design will not provide a single solution, but rather allow the policy maker to explore and adapt different scenarios. The result of the incentive design is passed to the social simulator that will evaluate the effectiveness of the design. Several iterations of this process are possible to allow the policy maker to achieve a result that satisfies his or her requirements. Supporting this iterative design process will be the focus of our further development of the approach and system presented here.

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