Optimising the self-consumption and self-sufficiency: a novel approach for adequately sizing a photovoltaic plant with application to a metropolitan station

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ABSTRACT

The recent trends in designing sustainable power systems emphasize the importance of self-consumption (SC) both at individual and community level. This new paradigm changes the way in which we design photovoltaic facilities for residential houses and for various municipality services as well.

In this context, the paper aims to formulate several optimisation problems using criteria such as self-consumption, self-sufficiency (SS) and net present value (NPV) as objectives to provide an optimal photovoltaic (PV) plant size for a singular power system - a subway station. By using this multi-objective approach, the work emphasizes how each criteria impacts the profitability and value of the overall investment, involving possible shareholders in the design process by choosing a desired solution from the Pareto-efficient set of configurations. Moreover, a global optimal solution is provided by formulating an optimisation problem through a single-objective Mixed Integer Linear Programming (MILP) approach involving an equivalent metric, the net-energy exchanged with the grid (NEEG).

The proposed methodology is validated in a case study on the power system of a subway station in Bucharest (Romania), thus identifying a configuration that focuses on self-consumption maximisation and a solution that reduces the yearly energy bill of the respective power system by 25%.

1. Introduction

In the quest for achieving a cleaner and sustainable environment, the renewable energy obtained from PV panels represents a very attractive solution, especially from an economic point of view. In this regard, both researchers and private corporations conclude that a renewable energy investment is an important step in minimising the energy consumed from conventional sources and consequently minimising the CO_2 emissions generated by them.

Considering the novel data-driven instruments, researchers focused in recent years to develop new optimal methods for designing sustainable systems (Wang et al., 2019; Fina et al., 2019). The key aspect in such a problem is to properly choose the criteria for an optimisation model. Often, researchers consider an unified cost-based criteria (Fina et al., 2019), but it would be interesting to see if other metrics would shape a design optimisation model in a better way through a multi-objective approach.

From another point of view, *self-consumption* will play an important role both at individual level, but also at community level. The introduction of other novel metrics, such as self-sufficiency has been crucial for evaluation of different systems in various research works (Roberts et al., 2019). Considering this aspect, it would be rather interesting to use SC and SS in the design process of a renewable power system as criteria in an optimisation problem. Since future power systems are profoundly related to capitalising the produced energy, more research is needed to investigate SC based systems at individual and then at community level.

Most of the recent works address residential design challenges (McKenna et al., 2017), however the European Green Deal (EUComission, Accessed 2021) clearly underlines that more effort is required in sustainable investments, especially in the public transportation sector. In this case, we considered a step forward is needed, so the proposed optimisation model is developed for a large urban consumer - a subway station. The method will focus on emphasising the importance of each criteria for investors, with respect to possible limitations and risks through the multi-objective perspective. Therefore, our work focuses on a singular utility scale consumer, although we consider as relevant starting points other works that integrate PV with commercial structures (Allouhi, 2020).

In this framework the paper represents a first step, with the objective to investigate SC, SS and NPV as criteria in a multi-objective optimisation problem to size a PV plant. The research focuses on formulating several single-objective and multi-objective optimisation scenarios to determine the impact of each respective metric in the design process of a PV plant. The Pareto solutions are discussed in different scenarios, emphasising possible optimal design configurations for investors. Furthermore, the proposed approach indicated a path towards another objective (NEEG) so the equivalence between maximising SC and SS and minimising the NEEG is presented. Moreover, a new single-objective optimisation problem is formulated in the MILP form in order minimise the NEEG. The proposed methodology is implemented on a case study concerning a subway station in Romania.

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Table 1
Terminology

Abbreviation	Description
PV	Photovoltaic
G	Supply from the distribution grid
GTR	Transformer-Rectifier Unit
TS	AC Power Transformer
SC	Self-Consumption index
SS	Self-Sufficiency index
Δt	sampling time
PBP	Payback Period [years]
NPV	Net Present Value [€]
r	actualization rate [%]
j	Panel category (HE,AB,ST,LC)
$CapEX$	Capital Expenditure [€]
$OpEX_t$	Operational Expenditure at year t [€]
G_t	(Electricity bill) Saving at year t [€]
B_{month}	monthly energy bill value [€]
E_{grid}	energy consumed from the grid over a month [kWh]
$E_{injected}$	energy injected into the grid over a month [kWh]
c_{grid}	grid energy cost [EUR/kWh]
DAM	Day Ahead Market from the previous year
c_{DAM}	energy price from DAM [EUR/kWh]
$n_{lim\_inf,j}$	Inferior limit to the number of panels for the panel category j
n	Number of PV panels
$n_{lim_{sup},j}$	Superior limit to the number of panels for the panel category j
P_M	Module power rating [W]
$P_{M_{lim\_inf,j}}$	Inferior limit to the module power for the panel category j [W]
$P_{M_{lim\_sup,j}}$	Superior limit to the module power for the panel category j [W]
$P_{PV_{Prod}}$	Estimated produced PV power
f	Scaling factor [%]
G	Incident solar radiation $[W/m^2]$
G_{STC}	Incident solar radiation at standard temperature conditions $[1kW/m^2]$
$c_{wp,j}$	PV indexed price for the panel category j $[€/Wp]$
B_{ref}	Bill value without PV investment [€]
B_{new}	Bill value with PV investment [€]
T	Simulation time for optimising the SC,SS and NEEG [hours]
Y	Simulation time for optimising the NPV [years]
NEEG	Net energy exchanged with the Grid [kWh]
MILP	Mixed Integer Linear Programming
CBC	COIN-OR Branch and Cut Solver
MODE	Multi Objective Differential Evolution

2. Specialized literature review

The stepping stone of this research is represented by other relevant studies concerning PV solutions for the residential sector (Roberts et al., 2019; Roldán Fernández et al., 2021; Rae and Bradley, 2012). It emphasizes the importance of PV investments in the present context, the economic challenges that arise in the residential sector considering the financial impact of laws and taxes in different countries, as well as the most relevant metrics used. In this regard, many studies infer to the notion of *techno-economic model*, an explicit formulation of the problem that conjure both economic and energy related metrics particular to power systems (Xiang et al., 2020; Jiménez-Castillo et al., 2020; McKenna et al., 2017).

For the residential sector, the specialised literature identifies some of the most relevant metrics for this type of analysis, indicators such as *self-consumption* (Litjens et al., 2017; Camilo et al., 2016), *self-sufficiency* (Roberts et al., 2019; Jiménez-Castillo et al., 2020), aiming to indicate how much of the provided PV energy is used for internal consumption and if that quantity satisfies the load demand. On the economic side, the studies analyze indicators such as the *payback period* (PBP) (Şenol et al., 2016), the *NPV* (Roth et al., 2020; Fina et al., 2020) and also provide insights about how price regulation and taxes in different countries affect the profitability of PV investments for the average household, and also include investigations into even more complex applications such as hybrid energy systems (Nižetić et al., 2015). Furthermore, the model obtained in this manner is often used as an instrument in assessing a global objective, a matter which is often formulated as an optimisation problem. For example, in the residential context it is often desired to minimise the costs of purchasing energy from the grid (Martins and Musilek, 2016), or to maximise the NPV for a certain period of time for apartment buildings Fina et al. (2019) or even formulate an optimisation problem for designing a PV plant considering also environmental-related objectives (such as minimising carbon emissions (Wang et al., 2019)). These studies reflect very interesting approaches for assessing a PV plant investment for the residential sector, and even offer valuable methods that provide good results in this specific context. However, the same case must be made also for utility scale applications, where several challenges arise from the problem formulation point of view, the constraints, the economic evaluation of such a project and also the long term impact (which is critical from an investor's point of view) and also to consider SC, SS and NPV as criteria.

There are also interesting multi-objective optimisation models for renewable systems design, aiming to minimise the costs and emissions and then determine the Pareto optimal solutions for the respective model (Sun, 2021), or other optimisation frameworks that focus on cost and the environmental impact related to the usage of renewable energy (Barakat et al., 2020; Allouhi, 2020). These works present a novel perspective in designing sustainable systems by including both economical and environmental related criteria. Consequently, this paper aims to take a step further and investigate several other multi-objective approaches to provide a global point of view over the impact of SC, SS and NPV.

Comparing to other related works that use cost-related objectives (Martins and Musilek, 2016; McKenna et al., 2017; Roth et al., 2020), multi-objective optimisation (Wang et al.,

2019) or other works that use self-consumption and self-sufficiency as evaluation metrics in PV system design problems (Jiménez-Castillo et al., 2020; Şenol et al., 2016), the paper uses instead self-consumption, self-sufficiency and NPV as criteria in a multi-objective optimisation problem through an applied approach - to determine the optimal size of a PV plant. The discussion presented includes important SC and SS related insights, limitations, in an applied context. Furthermore, the proposed methodology paves the way for optimising a new criteria - the NEEG. Therefore, we explain why maximising SC and SS is equivalent to minimising the NEEG.

Furthermore, the paper includes a case study that focuses on the power system of a subway station. In the past years, the complexity of such a system has been analysed in terms of the most important energy consumers through an insightful case study over a subway station in Barcelona, Spain (Casals et al., 2014). In this direction, specialised literature emphasized that this type of system uses a large portion of energy produced by conventional resources, and in the present context it would be an improvement to reduce grid power consumption from both the municipality company point of view and the city strategy of reducing carbon emissions. From this point, studies identified several opportunities by using regenerative breaking (Liu et al., 2019), energy-efficient driving techniques, as well as investing in infrastructure related solutions (González-Gil et al., 2014) that are still being evaluated from different modeling approaches (Simoiu et al., 2020). Even though solutions such as energy-efficient driving or optimal train timetable represent good alternatives due to the simplicity and the available computational instruments, the infrastructure related solutions are questionable mainly due to the economic viability.

In this context, the paper integrates SC, SS and NPV in several single-objective and multi-objective optimisation problems and analyses the impact of each criteria in the design stage of a PV plant for an utility scale urban consumer. Furthermore, it is investigated whether a novel optimisation problem formulation based on SC, SS and NPV would have a single-objective problem equivalent that may provide a global optimal solution that satisfies all aforementioned criteria.

The most important contributions emphasised by the paper are:

- a methodology is proposed to provide the necessary framework to formulate the sizing problem based on SS, SC and NPV for any type of power system through a dual approach: a multi-objective approach to emphasize the impact of each criteria and limitations (based on Pareto efficiency) and a single-objective approach to determine the global optimal solution.

- a mathematical model of the power system of the subway station is developed, emphasising the characteristics, limitations and complexity of such an application.

- several optimisation problems are investigated, whether using SS, SC and NPV in all possible combinations as different objectives or in a single objective optimisation problem in the equivalent form of NEEG, a proposed metric.

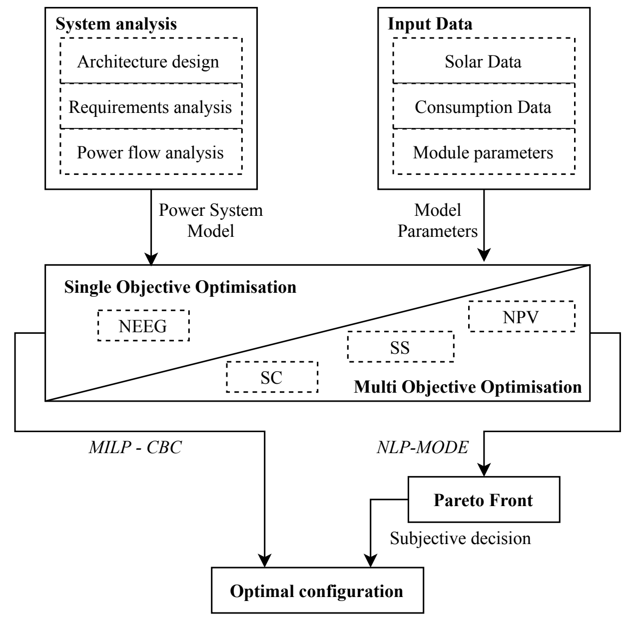

Figure 1: Proposed sizing methodology based on self-consumption and self-sufficiency

3. Proposed methodology

Fig. 1 illustrates the proposed methodology, which can be easily used as an instrument in designing a PV plant for any type of power system, and it can also be adapted to include multiple optimisation criteria as well. For the presented case study, the idea is to develop an instrument that can be used by several joint shareholders (for example the municipality, transport companies) in the investment process for a "green" subway station with PV panels (and possibly storage, electric vehicles).

The first step in implementing the proposed methodology can be divided in two stages: a *system analysis* stage and a *data-gathering* stage. Since the methodology can be used even for complex utility scale power systems, the first stage focuses on identifying the characteristics of the respective power system, with respect to the technical limitations, available resources, consumer types and available power measuring units. Then, an architecture is obtained, along with a model of the power flow inside the system. At the same time, for each subsequent power subsystem, relevant data is acquired. For example consumption data, voltage and power levels, conversion efficiencies are mostly needed at this point to allow future simulation scenarios to be executed. These two stages must be done simultaneously, since a good overall understanding of the system and an adequate model must be accompanied by data.

Then, the next step is to formulate several optimisation problems. The main focus of this architecture is to find the optimal PV plant size based on objectives such as maximum

SC, maximum SS and maximum NPV. Since the problem focuses on several objectives, a multi-objective approach is considered at first. The usefulness of the instrument resides in the problem formulation, since objectives can be formulated nowadays in terms of quantifiable metrics and indicators so that the investor may clearly assess how the objectives are fulfilled and in what manner the investment can be categorized as 'profitable'. Moreover, by using the multi-objective approach, the Pareto set of equally optimal solutions can be obtained, thus rendering the possibility for the shareholders to choose a preferable solution according to subjective preference.

Through the multi-objective optimisation approach, investors may see the impact of each criteria in the overall design problem, thus providing a framework where some criteria may be removed or some other relevant criteria may be added to the problem. It provides a certain degree of flexibility in the design process.

On another hand, most problem formulations and algorithms developed focus on the single objective optimisation paradigm, however in the present context it is challenging and rather interesting to define a single objective if the shareholders require profit, maximum SC and even a low PBP at the same time. More specifically, it is yet to be determined if SC or SS alone (or even a stand-alone cost objective) may determine the optimal solution for the shareholders by simultaneously generating profit, providing value to the community and also limiting the grid dependency.

As a consequence, the methodology proposes a dual approach:

- **a multi-objective optimisation approach** - where all relevant criteria (SC, SS and NPV) are used as objectives and Pareto Front is determined to emphasize the trade-offs between optimal solutions and provide an overall view over the impact of each criteria. Here, the focus is on the respective shareholders, where they may choose a configuration based on preference towards a certain criteria, or external information ca be used in the decision process. Also, other relevant criteria may be added through this approach.

  To solve the non-linear programming (NLP) multi-objective optimisation problems, a Multi-Objective Differential Evolution (MODE) (Alyafi et al., 2018; Pal et al., 2019) algorithm is used. The algorithm finds the Pareto optimal set through an iterative, evolutionary way, generating new candidate solutions based on existing ones in a specific mutation process. Since evolutionary algorithms work in an iterative manner, we have used a Python implemented version of MODE out of other possible algorithms due to its simplicity and speed, as reported in (Pal et al., 2019).

- **a single-objective optimisation approach** - in which mathematical modeling enables us to formulate a single objective that can be significant to the shareholders, but subject to several constraints and hypotheses. To find the global optima, the problem is formulated in a Mixed Integer Linear Programming (MILP) approach and solver using the COIN-OR Branch and Cut solver (CBC).

Thus, the methodology not only identifies the global optimal solution, but also provides an overall view over the impact and limitations of each criteria through the multi-objective approach.

3.1. Technical and economical instruments

Several metrics (technical (Roberts et al., 2019) and economical) are used in formulating the optimisation problem.

3.1.1. Technical Indicators

- **Self-Consumption** - indicates how much of the PV energy produced is consumed internally by the power system. The value of the SC is between 0 and 1 and, while 0 indicates that no energy produced by the PV is consumed internally, 1 emphasizes that all energy produced is consumed internally. The SC index in discrete form can be defined using Eq 1.

$$SC = \frac{\sum_{k=1}^{k=T} min\left(P_{Prod,k}, P_{Load,k}\right)\Delta t}{\sum_{k=1}^{k=T} P_{Prod,k}\Delta t} \tag{1}$$

  where $P_{Prod,k}$ represents the average power produced from PV panels over the k^{th} interval Δt (which represents the sampling time), $P_{Load,k}$ represents the average load over the same interval and T represents the total time period.

- **Self-Sufficiency** - indicates how much of the total load is covered by the energy produced and consumed internally. Using the same variable names, the SS index in discrete form can be defined by Eq. 2.

$$SS = \frac{\sum_{k=1}^{k=T} min\left(P_{Prod,k}, P_{Load,k}\right)\Delta t}{\sum_{k=1}^{k=T} P_{Load,k}\Delta t} \tag{2}$$

While energy autonomy is desired in many cases, the SS index alone used in an optimisation problem would provide the necessary information to achieve this objective. However, such a formulation may lead to a large number of PV modules and consequently to large amounts of excess power over the load profile. Even if this excess power can be injected into the grid or can be redirected internally through load management techniques or storage system integration, the problem formulation would be incomplete.

On the other hand, if the SC index alone is used in an optimisation problem, the evaluation may not provide the largest configuration possible or the most profitable one from an economic point of view. For example, it is clear that all the energy produced by a PV panel is internally used in the power system of the subway station, thus rendering the SC index equal to 1.

So, in an optimisation problem formulation, both SC and SS indexes should be used simultaneously, either as separate objective functions in a multi-objective optimisation problem, or using a different equivalent objective in a single-objective optimisation problem.

3.1.2. Economic Indicators

These indicators offer information especially regarding the estimated time that is required to recover the investment (PBP) and if the investment is long-term profitable (NPV). The NPV (Eq. 3) is an indicator that a present investment has a positive evaluation in the future, considering the balance of cash inflows and outflows over the following Y years and an actualization rate r (Roth et al., 2020).

$$NPV = -CapEX + \sum_{t=1}^{t=Y} \left(G_t - OpEX_t\right) \frac{1}{(1+r)^t} \quad (3)$$

To estimate the $CapEX$ we used (Eq. 4), where C_{wp} is the indexed PV acquisition cost for the European countries (PVMagazine, Accessed 2020), P_M is the rated module power and n is the number of modules.

$$CapEX = C_{wp} \cdot P_M \cdot n \quad (4)$$

Furthermore $OpEX$ costs at year t are estimated using Eq. 5.

$$OpEX_t = 0.03 \cdot CapEX \quad (5)$$

On the other hand, the PBP represents the period of time in which the initial investment is recovered. Thus, the PBP represents the number of years Y such as NPV is 0.

The gain G_t is correlated with the many contextual features such as the law in the respective country regarding the activity of *prosumers*, regulations, whether energy can be injected into the grid (and also how much can be injected), and so on. For the case study presented in this paper, the present context suggests that utility scale PV plants over 100kW are not included yet in the *prosumer* related laws. Moreover, currently the technical capabilities of the power transformers in the subway station investigated here do not allow a reversible current flow from the station to the grid, so currently all the gain obtain from the PV utility comes strictly from the electricity bill reduction. Thus, the gain is modeled by Eq. 6.

$$G_t = B_{ref} - B_{new} \quad (6)$$

where B_{ref} represents the total value paid in year t for the energy bill without any PV investment, (thus this is considered a reference value), while B_{new} represents the estimated value of the bill for a power system with integrated PV power production. The energy is billed monthly, however in the case study we have considered the total value of the bill for one year, excluding taxes. Moreover, for the case study that will be presented in the following sections, the energy tariff applied in the simulation is part of an agreement between the subway company and the energy distribution company through a public procedure. It represents a fixed value for an entire year, at a lower rate then the residential tariff. Since we cannot estimate future changes in this tariff, we will consider the actual real value at which the the grid energy was bought in year 2020.

In industry, most infrastructure developments take into consideration only the PBP metric, however for a PV investment that constantly generates a form of income either by grid injection or electrical bill reduction, it would be more significant to use the NPV as a reference indicator.

Even if NPV represents an important metric and also the main reference of the economic evaluation, the PBP must be considered as well. This aspect is related to the fact that however the large the NPV is for a specific project, it may not be considered by investors if it has a long PBP.

3.2. Approaches for solving the optimisation problems

A wide range of optimisation algorithms are available nowadays as very useful instruments, however the challenge appears in adequately formulating the optimisation problem. In this paper, the genetic algorithm *Differential Evolution* is used in the multi-objective optimisation problem context since the problem is nonlinear. The disadvantage, however, is that a large number of iterations is required to provide a solution that is close to the global optimum.

Furthermore, the multi-objective approach is formulated based on the concept of Pareto-efficiency and dominance among solutions. More specifically, a solution composed of multiple objective functions values $f_i(x^*)$ dominates another solution $f_i(x)$ if there is at least a value $f_i(x)$ that is strictly greater in the objective space. Thus, dominance can be defined by Eq. 7 (Price et al., 2005).

$$f_i(x^*) \leq f_i(x) \qquad \forall i \in \{1, ...N\} \quad (7a)$$

and

$$f_i(x^*) < f_i(x) \quad \text{for some} \quad i \in \{1, ...N\} \quad (7b)$$

Consequently, a solution for a multi-objective optimisation problem is Pareto-Efficient if there is no other solution that dominates it (thus, being called non-dominated solution). The Pareto-Front is the set of all the non-dominated solutions of the problem and represent a decision platform upon which the investor may choose one solution or another based on higher-order information or external criteria.

The multi-objective optimisation approach is used mostly because in a PV sizing problem there may be multiple criteria of interest for the investors and also because it represents an important starting point for solving a complex non-linear optimisation problem. So, in this case, we use multi-objective optimisation to emphasize the impact of each criteria and also to emphasize possible limitations.

However, for the single-objective optimisation problem formulation, a discussion evolves over which objective is more important to the problem context and how can all criteria be mathematically modeled as a single formulation. In some non-linear programming situations, each objective has a certain weight assigned and a new objective function is defined by summing all initial objective multiplied by its respective weight. However, in complex problems where it is challenging to quantify the impact of one criteria over another, it can be difficult to assign these weights.

So, the approach used in this paper is to consider at first a multi-objective approach and to investigate the impact of each criteria in overall optimisation process, and then try to formulate an equivalent single objective optimisation that offers a global optimal solution according to the conclusions obtained through the multi-objective approach.

4. Modeling of a subway station in Bucharest (Romania)

A case study is further conducted on the power system of a subway station in Bucharest (Romania). The idea is to investigate new system design methods based on SC and SS on urban large consumers, in order to provide viable solutions for future sustainable investments. Moreover, the subway station is considered as an individual power system, representing a first step exploring the opportunities provided by SC and SS related systems.

Currently in Romania, users defined as *prosumers* (energy consumers that produces power from own renewable sources) can use PV power to reduce the monthly energy bill. Generally, The monthly energy bill value is computed (Eq. 8) based on the consumed energy from the grid E_{grid}, bought at a contract established price from the grid c_{grid} and the injected energy into the grid $E_{injected}$ valued at a corresponding varying price c_{DAM} from the Day Ahead Market (DAM) of the previous year ANRE (Accessed 2021). If B_{month} becomes negative, the two possible scenarios are described in Table 2. However, for this case, c_{grid} has been obtained from the public acquisition contract between the subway company and the energy distribution company for year 2020.

$$B_{month} = E_{grid} \cdot c_{grid} - E_{injected} \cdot c_{DAM} \quad [€] \qquad (8)$$

Table 2
Negative bill scenarios

Scenario	Effect
- B_{month} < 20 EUR	The value is reported for the bill of the next month
- B_{month} > 20 EUR	The bill value is payed entirely to the client

However, the users are limited and must not use the renewable sources strictly for financial purposes, the intent is to encourage citizens and businesses to increase individual SC.

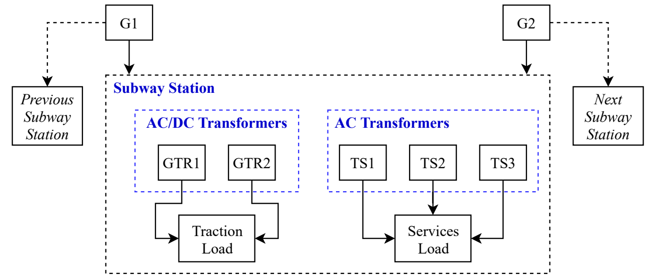

Figure 2: Subway Station Power Flow Diagram

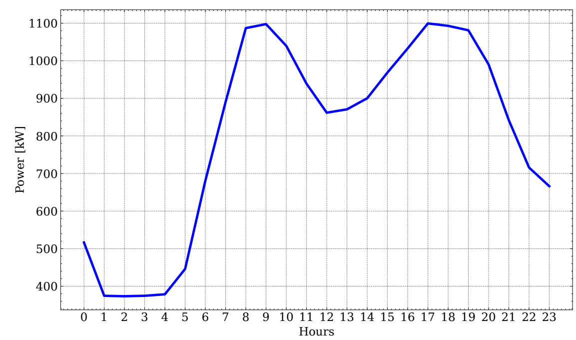

Figure 3: Daily active power profile of the subway station (during workdays) computed from the measured data

The typical subway station power system architecture can be visualised in Fig. 2. As it can be noticed, the power system may be divided in two parts: **the traction part** (responsible for powering the rolling stock) and the **services part** (responsible for powering the lighting systems, the ventilation systems etc.).

The data used in this paper has been obtained from an energy measurement study conducted by the subway company on the specific subway station for the duration of a week in October, in which consumption has been measured for all power transformers presented in Fig. 2. The optimal sizing procedure might use the available data acquired during the working days, however the consumption might be higher in other months and also solar radiation is quite different in time. So, by using data from October, it might result a potential PV configuration that is not suitable, also considering the modeling uncertainties to which this method is subject to. To properly size the PV plant, the consumption over a year must be estimated based on other independent factors such as passenger traffic or the train program.

So, according to the measurements, the average hourly active power profile of the subway station during weekdays is presented in Fig. 3. It can be noticed there are two consumption peaks correlated to intense passenger traffic peaks, thus indicating that there might be a high degree of correlation between the energy consumption and passenger traffic.

Consequently, the power profile is estimated based on the hourly passenger traffic measurements which are conducted using the station access gates.

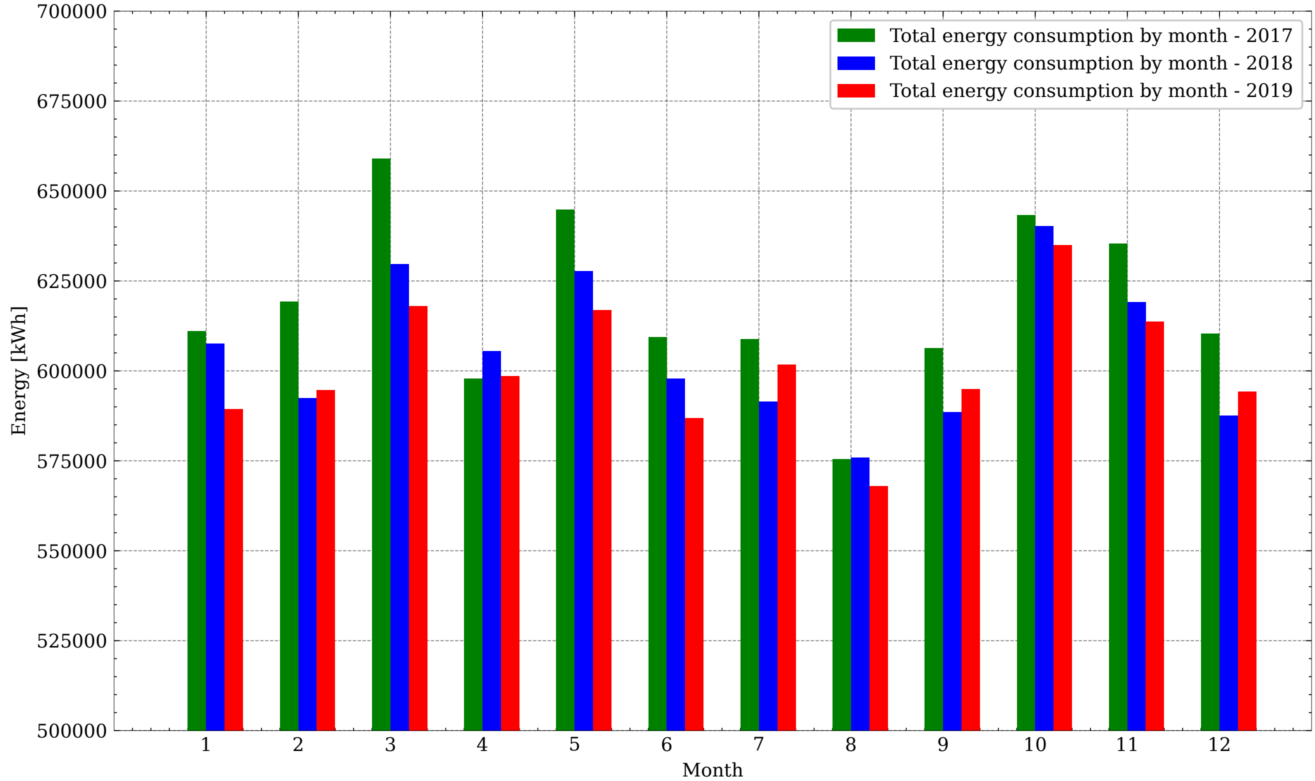

Figure 4: Total predicted energy consumption by month

The following standard linear regression model has been used (Eq. 9), where x represents the hourly measured number of passengers accessing the respective station during October and $\hat{y}$ represents the predicted hourly power profile.

$$\hat{y} = 0.05x + 534.48 \tag{9}$$

Fig. 5 shows a comparison between the hourly predicted power profile using the passenger traffic and the measured power profile during the respective period. The overall fit of the model has been evaluated according to the R^2 score.

The results illustrating total energy consumption by month for several years can be visualised in Fig. 4.

It can be noticed that the profile does not change very much in time, following the same trends around several months. For example, consumption peaks are recorded in March, October and May, corresponding to several national events and festivities, and even a remarkable drop in August correlated with holidays.

Regarding PV power estimation, specialised literature (Ionescu et al., 2016) indicates that solar profile models can be impacted by many external factors. In this context, a suitable formulation based on solar radiation is used especially adapted for an optimisation problem. So, solar data at the particular location is extracted from the online service *OpenWeatherMap*. Then, PV power is estimated using Eq. 10 (HOMER, Accessed December 2020).

$$P_{PV_{Prod}} = P_M \cdot n \cdot f \cdot \frac{G}{G_{T_{STC}}} \quad [\text{kW}] \tag{10}$$

where P_M is the rated power of a module, n represents the number of modules, f is a scaling factor for real world conditions such as power losses in electrical wiring and shading. G represents the measured average incident radiation over the panel and $G_{T_{STC}}$ is the incident radiation at Standard Temperature Conditions (1000 W/m^2).

So, the produced PV power is estimated for the best slope and direction for the specified coordinates (which is 60°, directed to the South) to yield maximum power over a day.

4.1. Multi-Objective Problem Formulation

Based on the power system and the solar power models developed in the previous section, we can formulate several optimisation problems using SC, SS and NPV indexes to find the optimal size of a PV plant that can supply the station.

First, considering the fact that there are several criteria involved in such an optimisation problem, a multi-objective approach is further investigated. Single-objective approaches involving only one criteria (for example maximise SC or SS) have also been considered as starting points, however such formulations are incomplete. More specifically, the optimal size of a PV plant that would maximise SC would be one PV module, while the theoretical optimal size of a PV plant that

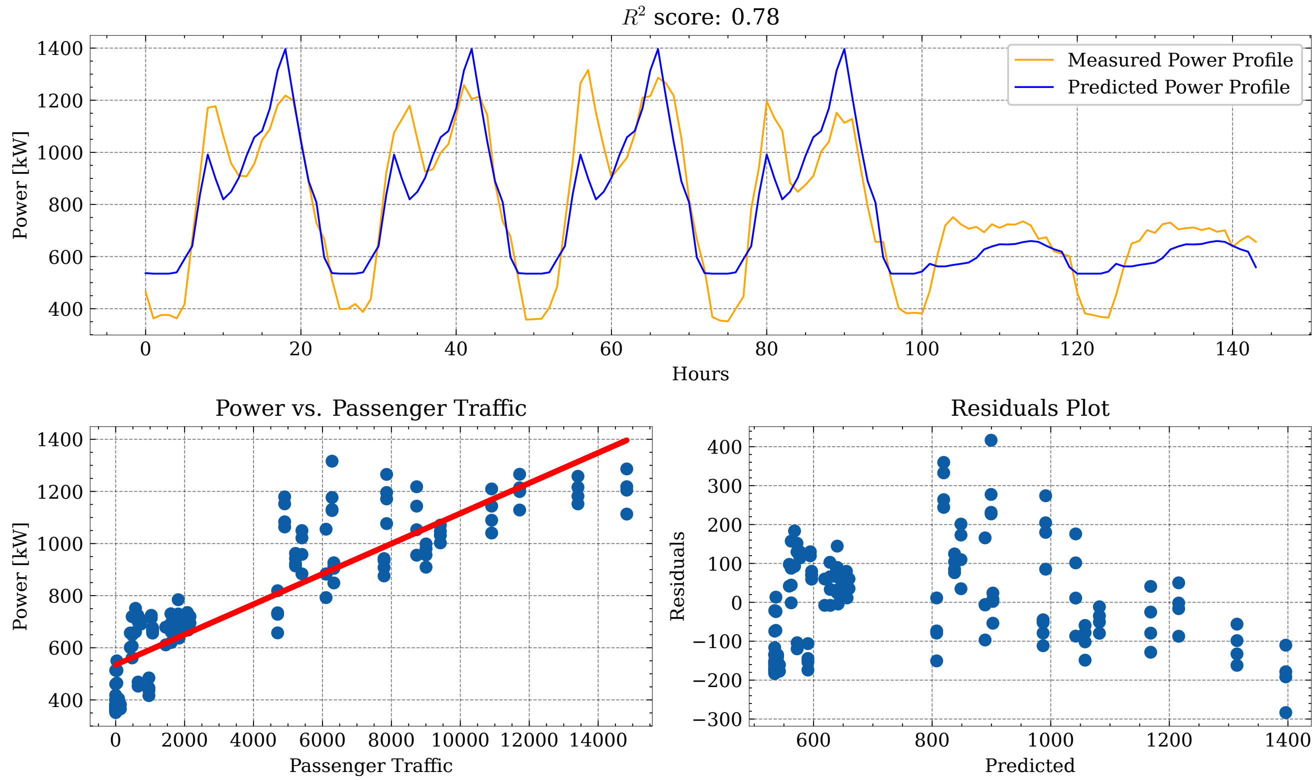

Figure 5: Comparison between measured and predicted data

would maximise SS would be a an infinite number of panels.

$$\begin{aligned} \max \quad & \text{SC} && \text{(11a)} \\ \max \quad & \text{NPV} && \text{(11b)} \\ \text{where} \quad & n_{lim\_inf,j} < n < n_{lim\_sup,j} && \text{(11c)} \\ & P_{M_{lim\_inf,j}} < P_M < P_{M_{lim\_sup,j}} && \text{(11d)} \end{aligned}$$

So, the first scenario we considered focused on formulating the optimisation problem with two main objectives: SC (Eq. 1) and NPV (Eq. 3) maximisation. The problem formulation can be analysed in Eq. 11. The decision variables are the number of panels n and the module power rating P_M. Limits are considered for the two variables since it is not physically possible to implement a very large PV plant and also it is important to offer the investor the possibility to choose between multiple categories of panels that are different both in price and rated power. So, $P_{M_{lim\_inf,j}}$ and $P_{M_{lim\_sup,j}}$ represent limit values for each category based on the power ratings (Table 4) (PVMagazine, Accessed 2020). The scenario is implemented for each category of panels j, over a year converted as a total number of hours T. The hourly average PV power has been modeled using Eq. 10. Since Low cost panels have a lifespan of 10 years, we also considered a replacement cost (90% of the initial $CapEX$) for the low cost modules that is applied to the NPV every 10 years.

Using MODE, the Pareto Set is determined and it can be analysed in the 2D objective space in Fig. 6. The problem is solved for four different panel types (Table 4). Configuration parameters are presented in Table 3.

Table 3
Configuration parameters

Parameter	Value
Δt	1h
c_{grid}	7.796€/MWh
r	7%

By analysing the results in Fig. 6, it can be noticed that the Pareto fronts are represented as concave shapes instead of the usual convex shapes. This form of representation is derived from the fact that SC and NPV are maximised.

Furthermore, each Pareto Front can be interpreted by focusing on several segments: the left-side segment, the right-side segment and the middle side segment. By analysing the shape of the obtained Pareto Front in Fig. 6, the left-side segment favors a high NPV, while the right-side segment favors a high SC index. It can be noticed in the right-side segment of the Pareto Front that a SC index equal to 1 renders a relatively low NPV, while the left-side segment implies that the highest achievable NPV can be obtained only by a consistent compromise in self-consumption. However, the middle-side segment offers a good trade-off between self-consumption and NPV.

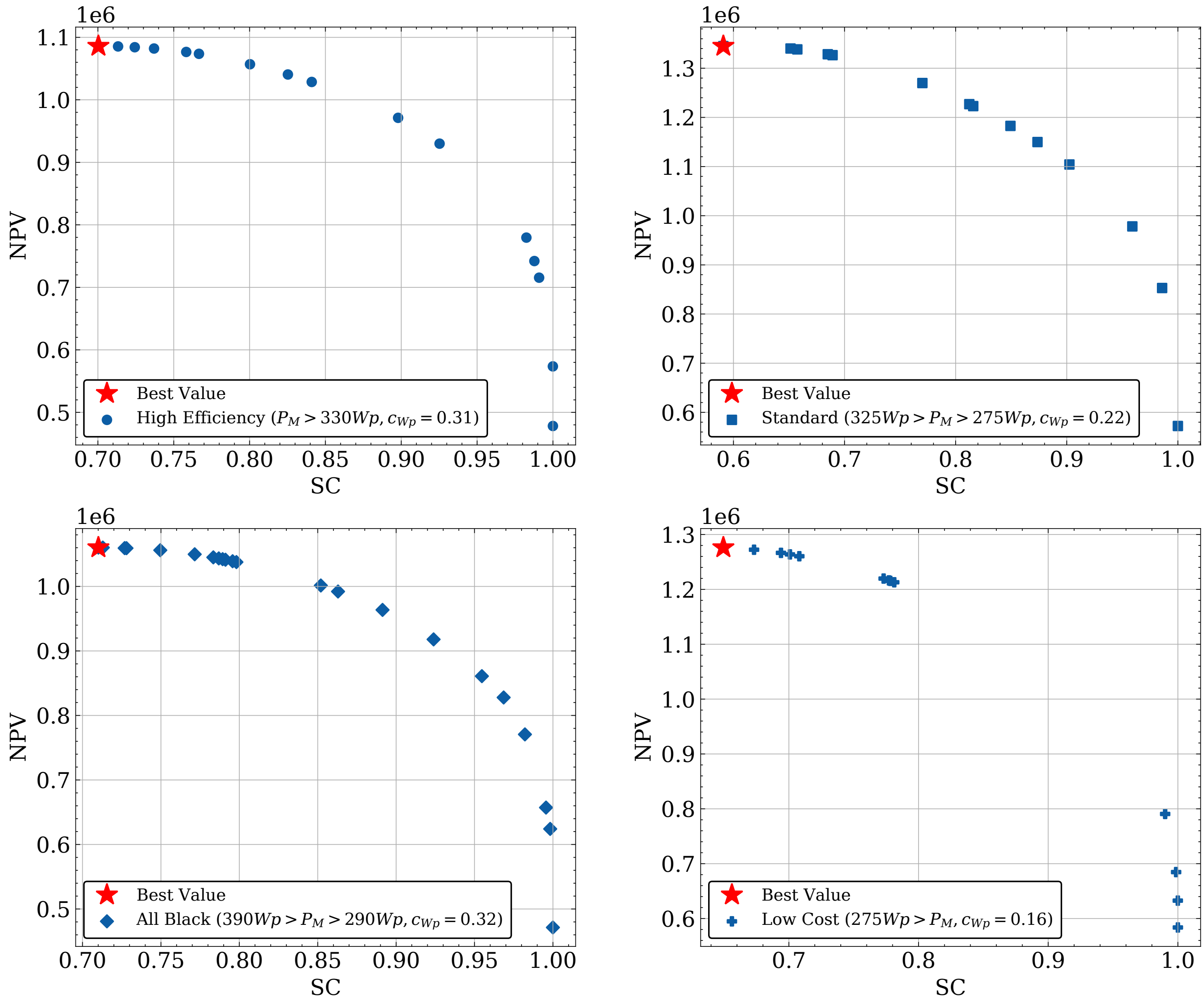

Figure 6: Pareto Set for the SC-NPV multi-objective optimisation problem

Table 4
PV modules techno-economic specifications

Category	$P_{M_{lim\_inf,j}}$	$P_{M_{lim\_sup,j}}$	$C_{wp,j}$	Description
High Efficiency	330 W	500 W	0.31 €/Wp	crystalline modules
All Black	290 W	390 W	0.32 €/Wp	modules with black sheets and frames
Standard	275 W	325 W	0.22 €/Wp	mainstream modules with 60 multicrystalline cells
Low Cost	0 W	275 W	0.16 €/Wp	modules representing factory seconds, limited warranty products with a lower lifetime (around 10 years) and low power output

From another point of view, we can consider the ideal solution where NPV tends to infinity and SC is equal to 1 to be on the upper right corner of the plot. Thus, the solution that has the minimum distance to the upper-right corner (or the maximum distance from the origin of the plot) may possibly represent a good configuration. In this context, it is not clear whether this recommended solution is the best one in a general sizing problem, so more investigation was done on another case: SS and NPV maximisation.

The problem is formulated according to Eq. 12, with the same constraints (Eq. 11c, 11d) as the first problem.

$$\max \quad \text{SS} \tag{12a}$$
$$\max \quad \text{NPV} \tag{12b}$$

In this case, results can be analysed in Fig. 7.

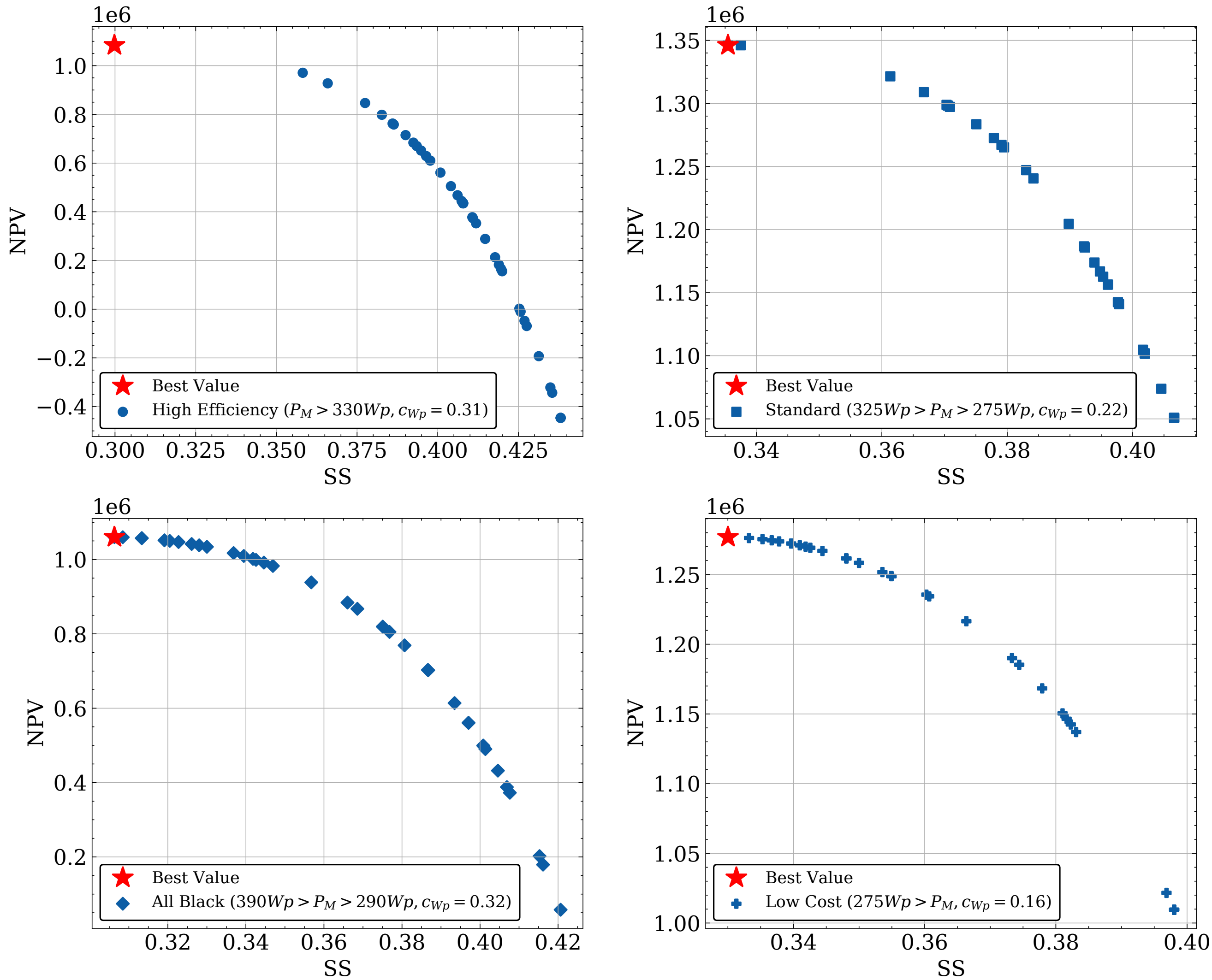

Figure 7: Pareto Set for the SS-NPV multi-objective optimisation problem

Doing the same analysis over the obtained Pareto front in Fig. 7, it can be noted on the left-side segment of each plot that the best solution is represented by the configuration with the highest NPV, while the right-side segment of each plot emphasizes even negative vales for panels that have a high indexed price (for example high efficiency or all black). This aspect provides an insight regarding a limitation in sizing a PV plant: if a high self-sufficiency index is desired, then the investment may not be profitable long-term.

Similar to the first case where SC and NPV are maximised, the recommended solution that is closest to the ideal point is the solution with the highest NPV.

A final two-objective optimisation problem is investigated by maximising SC and SS (Eq. 13), with the same constraints (Eq. 11c, 11d) as the previous problems.

$$\max \quad SC \tag{13a}$$

$$\max \quad SS \tag{13b}$$

From a first point of view, the maximum SC value is placed on the upper left location of the front and can be achieved by all types of panels, however the SS index varies depending on the panel power output. In this regard, a SC very close to 1 yields a small SS index, close to 0.1. Consequently, all the produced energy is used internally in the subway station, thus covering 5-10% of the total demand.

On the other hand, a high SS can be achieved for a compromise in SC. This solution might provide more value by covering a large part of the load, an aspect that can also be correlated with energy bill reduction. More specifically, if a SS index of 0.25 is achieved for one year, then the new energy bill for that year will be 25% smaller.

It can also be observed that, if we consider High Efficiency and Low cost modules, the recommended solution tends to be placed closer to left-side of the plot, subsequently rendering a lower SS index, while the other cases show a more balanced trade-off between SC and SS. It becomes more imperious to investigate all criteria together to have a better understanding over the economical impact of this trade-off,

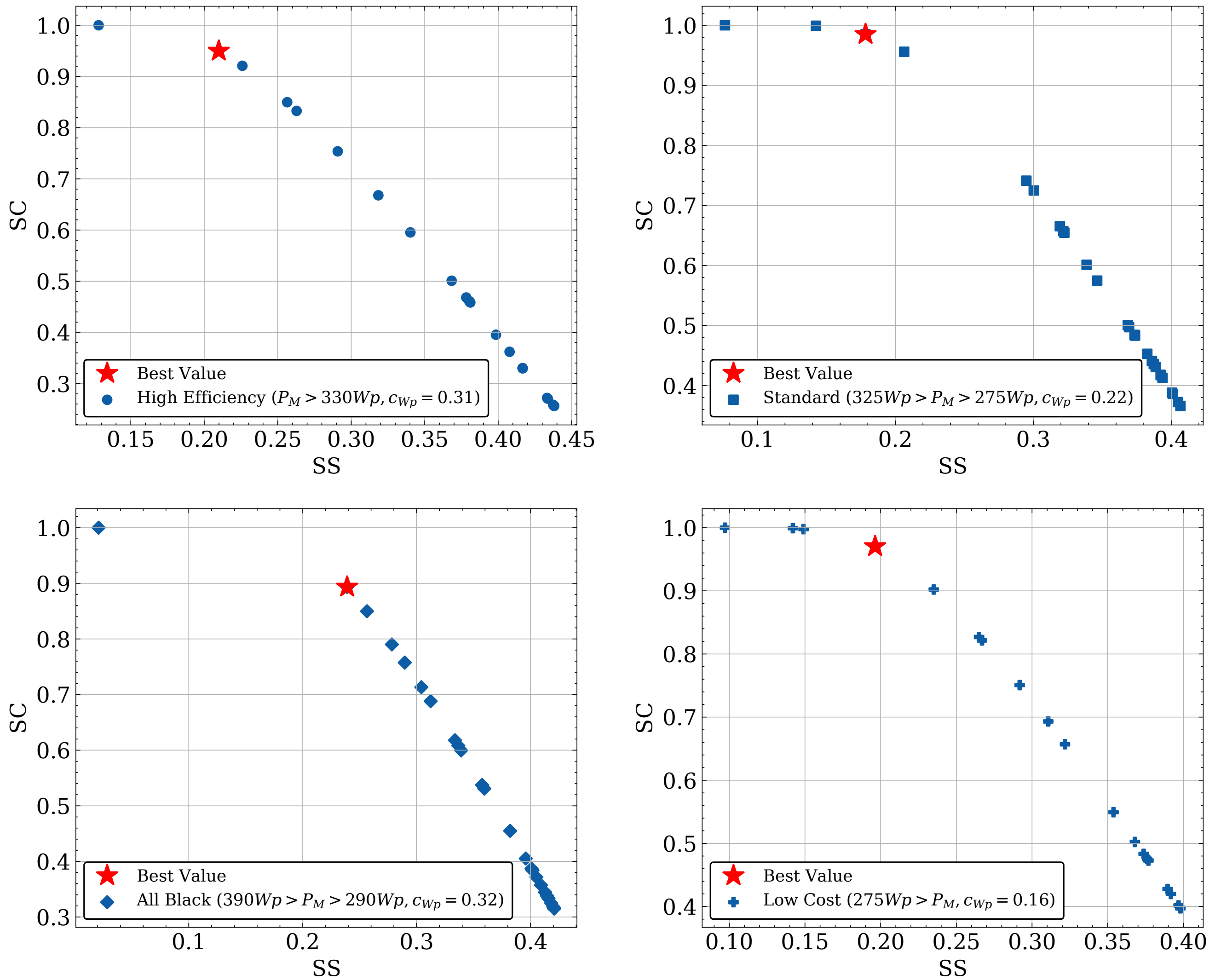

Figure 8: Pareto Set for the SS-SC multi-objective optimisation problem

however the recommended solution in these cases might represent an important insight to determine the global optimal solution.

While the Pareto Front represents the set X of the non-dominated solutions $x_{i_{SS,SC}}$ and the investor has no particular preference regarding the selected criteria, we can consider again the distance between each Pareto solution and the ideal point. Since the ideal solution would be a configuration that would give maximum SS and SC i.e. $x_{i_{1,1}}$, the best solution in this case would be the one that has the minimum distance to the ideal point in the maximisation problem objective space, or maximum distance in the minimisation problem objective space. In Fig. 8, this point is marked with red. In this context, the solution is very close to the point in which SC is equal to 0.9, which indicates that some energy may not be consumed internally in some months of the year, but in other months the PV profile increases the SS index substantially.

Overall, the shareholders can make a subjective choice between the different Pareto-optimal solutions, whether there is a preference towards SC or towards SS.

Starting from the first problem formulation in Eq. 13, another objective is added in the form of NPV maximisation. This objective is added to investigate the profitability and pay-back period for the investment, thus adding another dimension in the problem objective space. The new multi-objective optimisation problem is defined in Eq. 14, with the same constraints (Eq. 11c, 11d).

To analyse the results, a 3D representation of the objective space is introduced (Fig. 10). In this representation, a Pareto set is represented for each PV module category. Also, by grouping the criteria, the Pareto front can be visualised in 2D representations of the objective space according to Fig. 9.

$$\max \quad SC \tag{14a}$$

$$\max \quad SS \tag{14b}$$

$$\max \quad NPV \tag{14c}$$

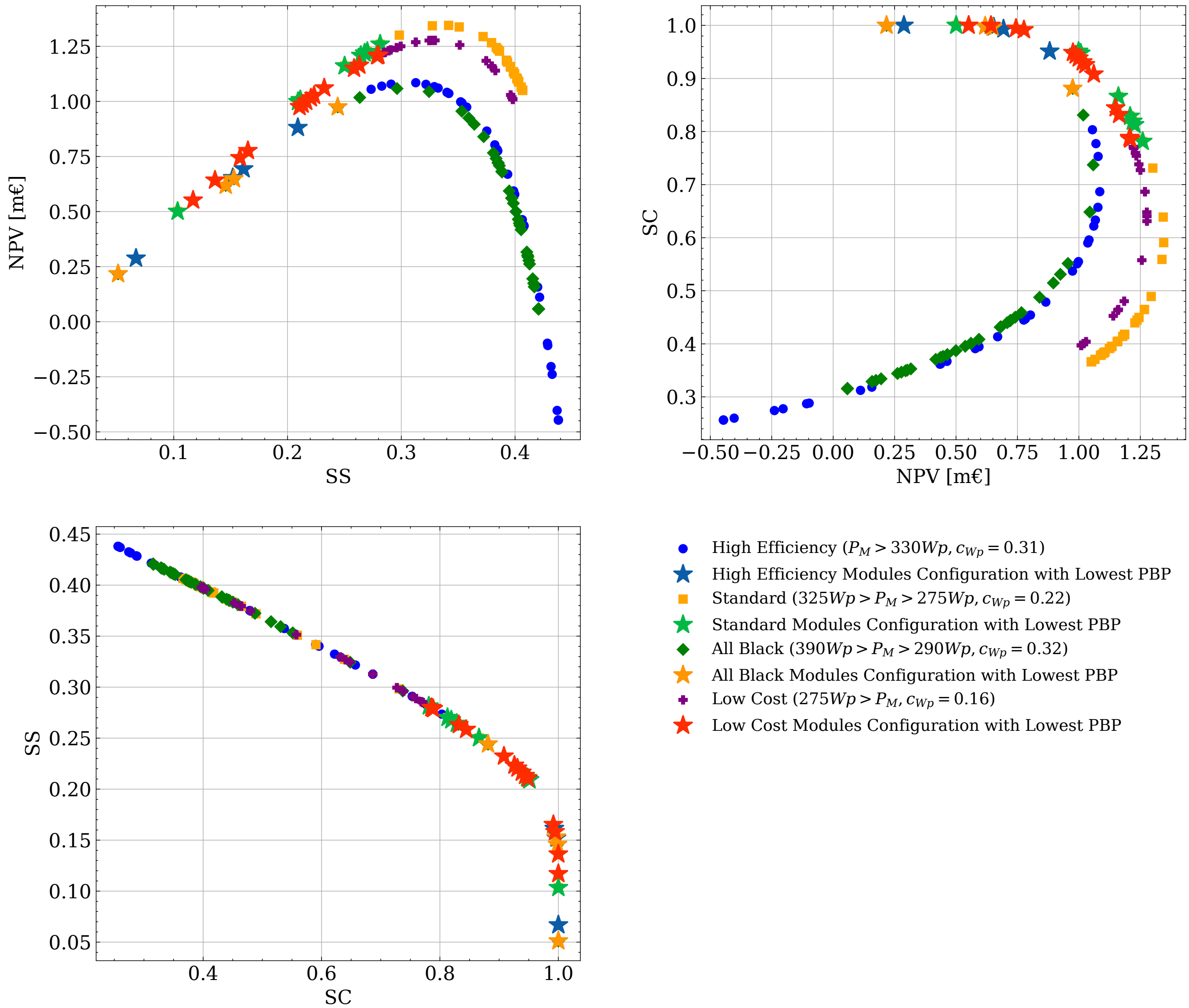

Figure 9: Pareto Front represented in 2D objective spaces

The problem is solved considering a single year expressed in hours T for the SS and SC and a number of years Y for the NPV. Also, using the same approach as the previous optimisation problem, the problem is solved using MODE for each category of panels j.

While in the previous problem formulation the best value was determined using the distance between the ideal point and the Pareto values, in this analysis it is more suitable to use an economic indicator such as the PBP as a higher level criteria since investors are interested by both the NPV and the PBP of a system.

Using the same interpretation of Pareto fronts as before, we can consider three categories in this case (Table 5).

By analysing the Pareto front in the NPV and SS objective space (Fig. 9), it can be noticed that the standard modules provide the highest NPV. This is because of the low index cost C_{wp} that infers a low initial investment and so the project is more profitable and also because of the relatively high SS index obtained. Even if all-black panels provide a similar SS index, the initial $CAPEX$ affects the long-term profitability, thus providing a NPV that is approximately 35 % lower then the standard modules scenario.

Table 5
Interpretation for Pareto solutions according to the position in the solution set

Category	Position in Pareto Set	Interpretation
1	beginning of the set	solutions with $SC > 0.9$ and have the lowest PBP
2	middle of the set	solutions with high NPV, with low SC and a higher SS
3	ending of the set	solutions with high SS and high initial $CAPEX$; risky investments

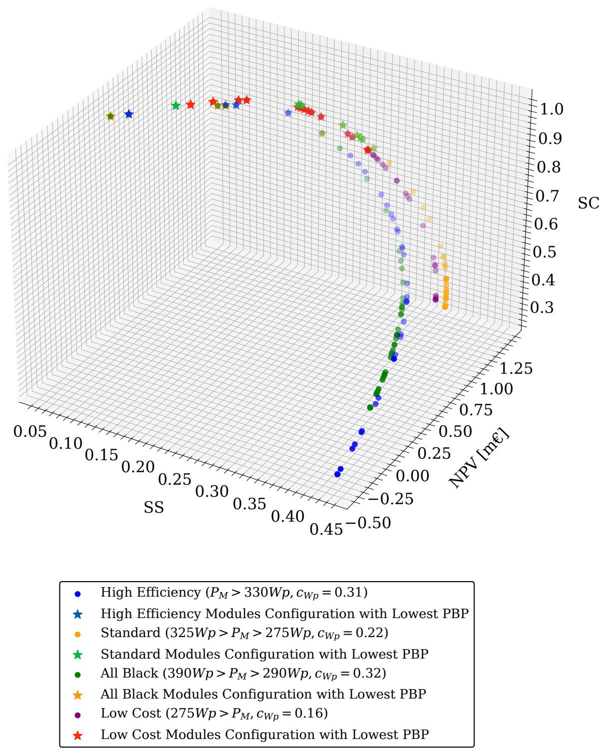

Figure 10: Pareto Front represented in the 3D objective space

Moreover, by analysing the Fig. 10 it can be noticed that this methodology also emphasizes limitations related to the initial $CAPEX$. More specifically, it can be observed that a size increase of a plant based on highly efficient modules that provides a SS index of almost 0.4 has a PBP of almost 25 years and if the higher SS index is achieved, then the investment is not profitable anymore. The all black modules also become less and less profitable after the SS index increases after the value of 0.35.

Overall, all module types prove to be profitable options if the SS index is less then 0.3 and if the SC is higher then 0.8. Moreover, by analysing the SC and NPV objective space, the configurations that have the lowest PBP are the ones that provide a SC index close to 0.9.

In the end, the best solution from each respective module category was chosen based on the PBP metric and the number of PV panels. These solutions can be visualised in Table 6 and have been marked accordingly in the Figs. 10, 9 . If several solutions provided the same PBP, then the solution with the highest SS index was chosen, thus making the investment more attractive in terms of bill reduction. Even if this choice renders a smaller SS index, it has been determined in the previous problem formulation that it is very difficult to obtain a high enough SS index without a large number of PV panels. It can also be noticed that some configurations using low-cost modules provide good performances, however the required large number of PV modules could pose problems related to available mounting space and maintenance that could infer additional costs. Overall, it can be concluded that the best solution in terms of economic profitability is represented by a configuration with standard modules that provides SC close to 0.9 and a PBP of 3 years. Moreover, an important limitation is emphasized in the usage of high efficiency modules, an aspect that may not provide the same PBP and long term profit but will however represent a configuration with the smallest number of panels. It is may result in a very good alternative in the future if PV acquisition costs continue to decrease.

4.2. Single-Objective Problem Formulation

In multi-objective optimisation, as presented before, Pareto efficiency emphasizes the trade-off between different optimal solutions and also possible limitations. However, in each situation, we identified an ideal case where the objective functions reaches the maximum values (for example in the multi-objective optimisation of SC and SS, the ideal solution was SC=1 and SS=1).

The concept of evaluating the distance between the Pareto solutions and the ideal solution may pave the path towards formulating a single objective optimisation problem and also to identify one global optimal solution. A similar principle is used in (Alyafi et al., 2018) for a different context and different criteria.

More specifically, considering the relation between SS and SC, the problem of maximising self-consumption and self-sufficiency can be rewritten as a problem to minimise the distance between the load and the produced energy.

So, we want to show that maximising 1 and 2 is equivalent to minimising:

$$\text{NEEG} = \sum_{k=1}^{k=T} |P_{PV,k} - P_{Load,k}|\Delta t \quad [\text{kWh}] \tag{15}$$

We start by assuming all power variables represent the average hourly power (i.e. $\Delta t = 1\text{h}$) and also by considering the two coordinate objective space of SS and SC maximisation problem. Since we know $SC, SS \in [0, 1]$, the objective space can be visualised in Fig. 11.

If we look at the objective space in Fig. 11, we can consider an ideal point $x_{1,1}$ case where we have $SC = 1$ and $SS = 1$.

Furthermore, we consider the Manhattan distance between two points P and Q in a 2D coordinate system such as the one in Fig. 11:

$$d(P, Q) = \sum_i |x_i - y_i| \tag{16}$$

where $P = (x_1, x_2, ..., x_n)$ and $Q = (y_1, y_2, ..., y_n)$

Thus, in an optimisation problem where we aim to maximise SC and SS, the objective of the problem would be to find the optimal solution that has the minimum distance to the ideal point $x_{1,1}$:

$$\min \quad Dist(x_{SC,SS}, x_{1,1}) \tag{17}$$

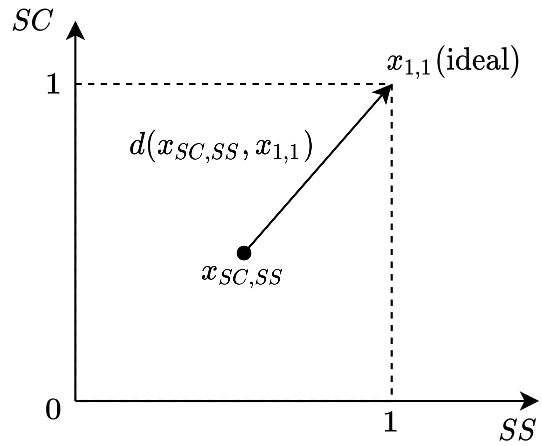

Figure 11: Max SC and Max SS objective space

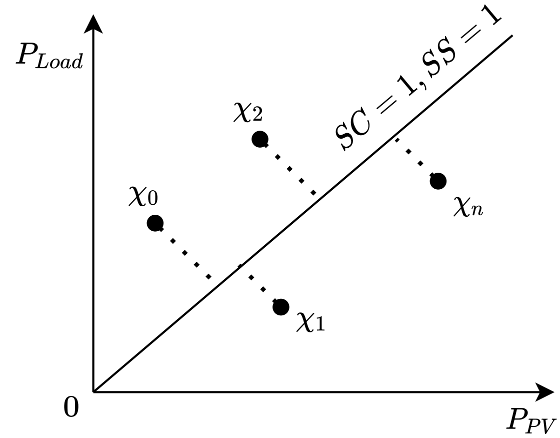

Figure 12: Min NEEG optimisation problem

where $x_{SC,SS}$ is a solution in the objective space.

Let us consider an arbitrary point $P = (a, b)$ in the objective space. The distance between this point and the ideal point, according to Eq. 16 is:

$$Dist(P_{a,b}, x_{1,1}) = |a - 1| + |b - 1| \tag{18}$$

where a and b represent the SC and SS indexes of the solution P.

By replacing a and b with definitions for SC and SS (Eq. 1, 2), we obtain:

$$\begin{aligned} &\left| \frac{\sum_{k=1}^{k=T} min(P_{PV,k}, P_{Load,k})}{\sum_{k=1}^{N} P_{Load,k}} - 1 \right| + \\ &\left| \frac{\sum_{k=1}^{k=T} min(P_{PV,k}, P_{Load,k})}{\sum_{k=1}^{N} P_{PV,k}} - 1 \right| \end{aligned} \tag{19}$$

which, if used as an objective in a weighted optimisation problem, could represent the minimisation of two distances: the distance between SC and 1 and the distance between SS and 1.

We also consider the following transformation:

$$min(P_{PV,k}, P_{Load,k}) = \frac{P_{PV,k} + P_{Load,k} - |P_{PV,k} - P_{Load,k}|}{2} \tag{20}$$

By rewriting Eq. 19 using Eq. 20 and after several simplifications, we obtain:

$$\begin{aligned} &\frac{1}{2} \left| \frac{\sum_{k=1}^{k=T} P_{Load,k}}{\sum_{k=1}^{k=T} P_{PV,k}} - \frac{\sum_{k=1}^{k=T} |P_{PV,k} - P_{Load,k}|}{\sum_{k=1}^{k=T} P_{PV,k}} - 1 \right| + \\ &\frac{1}{2} \left| \frac{\sum_{k=1}^{k=T} P_{PV,k}}{\sum_{k=1}^{k=T} P_{Load,k}} - \frac{\sum_{k=1}^{k=T} |P_{PV,k} - P_{Load,k}|}{\sum_{k=1}^{k=T} P_{Load,k}} - 1 \right| \end{aligned} \tag{21}$$

We can observe in Eq. 21 that the minimum value of the distance can be obtained only when all the production is equal to consumption, i.e Eq. 15 is 0.

If we analyse a general plot between P_{PV} vs. P_{Load} (Fig. 12), we can conclude that the vector of ideal solutions where $P_{PV,k} = P_{Load,k}$ is equivalent to $SC = 1$ and $SS = 1$. Thus, instead of minimising a distance to an ideal point, by minimising Eq. 15, we aim to minimise the distance between any candidate solution $X = (\chi_1, \chi_2, ...\chi_n)$ and the vector of ideal solutions where $P_{PV,k} = P_{Load,k}$.

The multi-objective problem formulations presented in the previous sections emphasize the impact of each objective through the Pareto set. However, considering the equivalency between Eq. 1,2 and Eq. 15, we can formulate a more suitable single-objective optimisation problem to minimise the NEEG.

Before formulating the problem, the following assumption is considered: the module power rating P_M in the PV power model is considered a known value and will be replaced by $P_{M_{lim\_sup,j}}$ from Table 4. This assumption reduces the complexity of the LP optimisation problem and also provides the best solution in terms of used mounting space. More specifically, if only the best PV modules in terms of rating power will be used, then the smallest mounting surface will be occupied.

Moreover, it has been observed in the multi-objective optimisation problem that the NPV and SS index are correlated based on the assumption that the yearly gain G_t is obtained only by bill reduction, so NPV is not included anymore in the single-objective optimisation problem formulation.

Thus, by transforming Eq. 15 in a linear form, the optimisation problem to minimise NEEG becomes:

$$\min \sum_{k=1}^{T} e_k \tag{22a}$$

$$\text{s.t. } e_k - P_{PV,j,k} + P_{Load,k} \geq 0 \quad k = 1..T \tag{22b}$$

$$e_k + P_{PV,j,k} - P_{Load,k} \geq 0 \quad k = 1..T \tag{22c}$$

$$n_{lim\_inf,j} < n < n_{lim\_sup,j} \tag{22d}$$

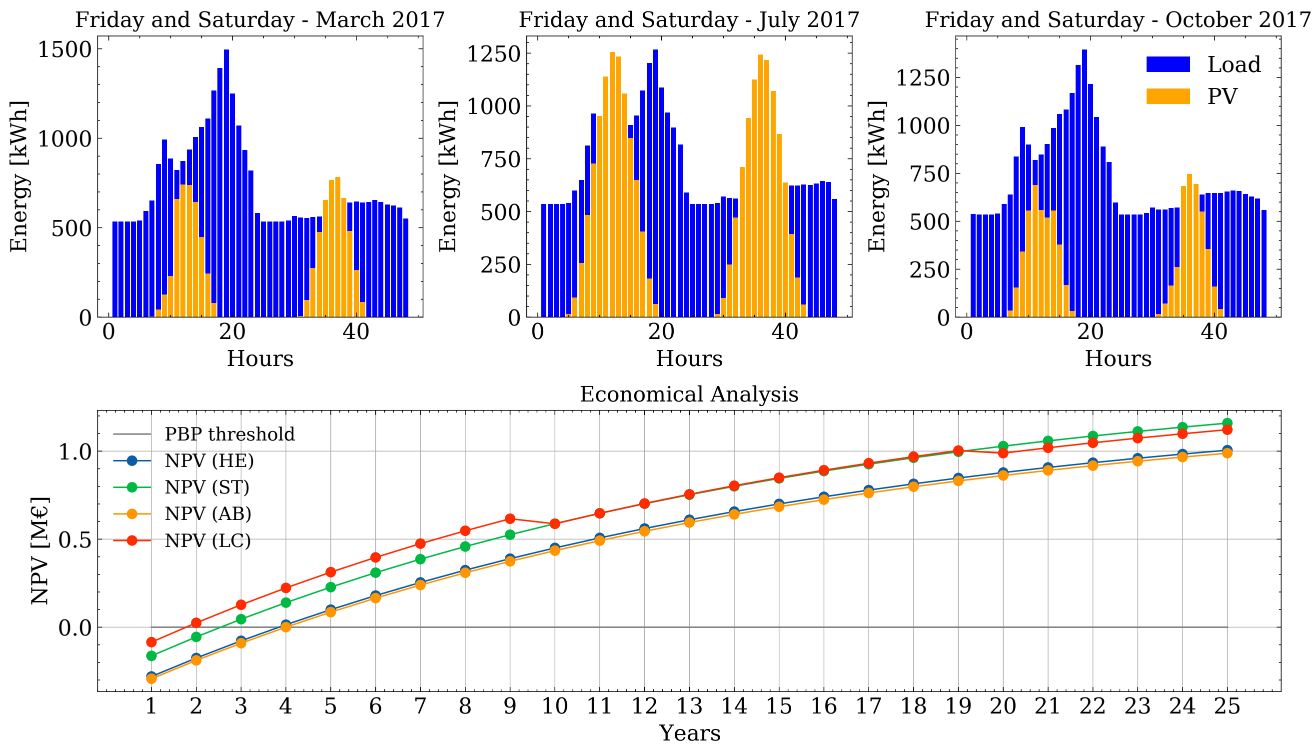

Figure 13: Min NEEG optimisation problem results

where e represents a newly introduced variable, T represents the time interval in hours (1 year in this case), and the other notations are similar to the previously investigated problems.

The results can be observed in Fig. 13 and also analysed in Table 6. The figure also includes a comparison between the production and consumption in three different cases: two worst case scenarios during March and October and a comparison in July. These cases emphasize the variation of PV production and energy consumption during the most important months of the year determined through estimation in Fig. 4. The figure also focuses on two days to emphasize the difference between an average working day and weekend.

Overall, the multi-objective approach involving SC and SS is useful for seeing the possible limitations in terms of NPV evolution in time and also for establishing the relation between PBP, NPV, SC and SS, however it might not be the best way to formulate a sizing problem if a single optimal solution is desired. If we focus, for example, on maximising SC and NPV, then we can conclude that the highest NPV can be easily achieved at consistent decrease in self-consumption. On another hand, if we focus on maximising SS and NPV, we might consider a small SS index for a high NPV, but up to a certain threshold to avoid a potential unprofitable investment. The combination of the three criteria in a multi-objective optimisation problem and also considering the PBP in choosing an unique solution can be considered a good approach for finding the optimal size, however the genetic algorithm approach might render a long time in finding the results due to its stochastic nature. As a consequence, the single-objective equivalent linear approach of minimising the NEEG represents a better alternative.

Regarding the obtained results in the case study, it can be observed that the global optimal solution in this case represents a trade-off between SC and SS, providing a SC index of 0.87 and SS index of 0.25. The trade off is essentially depicted in Fig. 13. In demanding months such as March and October, the production is adequate to maximise the SS index and to lower to extra energy, however in some months over the summer where PV production reaches its peak, there is a quite large quantity of energy that exceeds the energy demand (especially during the weekend) and must be used somewhere else.

These results could be expected considering the multi-objective optimisation problem discussed beforehand and the fact that profit is obtained through bill reduction. It can be noticed that, by choosing the module power rating as the maximum possible value for each category (thus considering the smallest mounting space), the algorithm provides the corresponding number of PV panels that achieves the maximum SC and SS index. For the economical evaluation, results are very similar to the multi-objective optimisation scenario and show that standard modules provide the highest NPV over 25 years, a PBP of almost 2.5 years.

So, it can be concluded that a single-objective optimisation problem formulated in this way is generally suitable for a PV plant sizing problem, being equivalent to maximising SC, SS and NPV in a multi-objective approach.

Table 6
Simulation results

		High Efficiency	*All Black*	*Standard*	*Low Cost*
max SC, max NPV (*MODE*)	n	4003	5198	**9228**	8557
	P_M	483	363	**275**	256
	SC	0.7	0.71	**0.59**	0.65
	$CapEX$ [€]	599,369	603,800	**558,294**	350,495
	PBP [years]	6	6	**5**	3
	NPV after 10 years [€]	416,391	399,115	**588,840**	615,298
	NPV after 25 years [€]	1,085,988	1,060,245	**1,345,040**	1,276,147
max SS, max NPV (*MODE*)	n	5491	5285	**8507**	12301
	P_M	330	360	**283**	187
	SS	0.3	0.31	**0.34**	0.33
	$CapEX$ [€]	561,729	608,832	**529,646**	368,046
	PBP [years]	5	6	**4**	3
	NPV after 10 years [€]	430,085	397,092	**600,880**	608,016
	NPV after 25 years [€]	1,083,897	1,060,205	**1,346,132**	1,276,846
max SS, max SC (*MODE*)	n	1984	3111	**2891**	12339
	P_M	489	390	**275**	72
	SS	0.21	0.24	**0.18**	0.2
	SC	0.95	0.89	**0.98**	0.97
	$CapEX$ [€]	300,755	375,773	**174,906**	142,145
	PBP [years]	4	4	**3**	2
	NPV after 10 years [€]	413,104	429,971	**448,726**	489,931
	NPV after 25 years [€]	883,685	961,123	**859,828**	916,411
max SS, SC, NPV (*MODE*)	n	2494	3119	**5398**	16000
	P_M	387	390	**293**	97
	SC	0.95	0.88	**0.78**	0.79
	SS	0.21	0.24	**0.28**	0.28
	NPV after 25 years [€]	880,962	974,728	**1,259,490**	1,206,393
	NPV after 10 years [€]	412,078	432,815	**620,848**	618,102
	$CapEX$ [€]	299,205	389,251	**347,955**	248,320
	PBP [years]	4	4	**3**	2
min NEEG (*MILP*)	n	2529	3242	**3891**	4598
	SC	0.87	0.87	**0.87**	0.87
	SS	0.25	0.25	**0.25**	0.25
	NPV after 10 years [€]	450,240	434,926	**588,036**	587,309
	NPV after 25 years [€]	1,005,448	988,350	**1,159,070**	1,121,797
	$CapEX$ [€]	391,995	404,601.6	**278,206.5**	202,312
	PBP [years]	4	4	**2.5**	2

5. Conclusions

The paper presents an investigation over several optimisation problems based on self-consumption, self-sufficiency and NPV to identify the optimal configuration of a PV plant for an utility-scale power system of a subway station.

In the first sections, a methodology is proposed and discussed considering other literature perspectives from the residential sector and also considering the available instruments for assessing the profitability and technical viability of such a project. A first contribution emphasized by this paper has been obtained proposing this methodology based on self-consumption and self-sufficiency used as criteria in optimisation problems. The research showed that these indexes cannot be used alone in optimisation problems and therefore must be used together as different objectives of the same problem, or in the form of a newly introduced metric, the NEEG.

The next sections place the focus of the investigation on the problem formulation and mathematical modeling of the power balance in a metro station, considering the typical architecture, available data and possible constraints. Through this step, a method to determine the load profile of a subway station is obtained, resulting in another contribution.

In the latter sections of the paper, several optimisation problems are formulated in a case study conducted for a subway station in Bucharest (Romania). For the multi-objective optimisation approach, the problems are solved with MODE, while in the single-objective optimisation approach, the problem is properly adapted for the MILP framework, thus paving the way for identifying the global optimal solution. These problem formulations based on SC and SS represent the third and most important contribution of the paper.

The results are analysed considering the distance to an ideal solution where SC and SS are maximised and equal to 1, and also considering the PBP as an additional criteria. Consequently, observations indicate that, from a technical perspective, a self-consumption index close to 0.9 represents an important objective in designing a PV plant configuration for a subway station, providing both the lowest PBP and also a positive NPV. This result is important in a context where value can be obtained only from bill reduction. On the other hand, such an investment also has significant limitations emphasised by the initial CAPEX used in the economical analysis. As such, while standard quality PV modules provide the biggest NPV in long-term estimations, high quality modules correlated with a high acquisition cost and a low SC index may result in an unprofitable investment. This limitation is observed in the multi-objective optimisation problem involving SC, SS and NPV, thus rendering the importance of such an approach in the proposed methodology.

Furthermore, in the context of obtaining income only by reducing the energy bill, it was observed that the NPV is correlated to the SS index. This identified aspect provided the necessary framework to formulate a LP optimisation problem for minimising the NEEG, a newly introduced metric based on SS and SC. The global solution obtained in this case showed a 25% reduction in yearly energy bill, while internally consuming almost 87% of the produced energy and also by recovering the initial investment in just 2.5 years.

A limitation of the proposed study is related to the investigation focused on one singular power system that has a relatively similar power profile over the year - the metropolitan station. The idea is to investigate, as a first step, designing and management strategies based on self-consumption and self-sufficiency for such systems at individual level, and later for residential systems with a more varying load profile. Also, another future direction assess collective SC, were we will focus on a district of houses that includes a subway station. Another possible research direction may focus on investigating the impact of the flexibility provided by energy storage systems, or involving citizens in the energy management strategy.

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