

## Research Article

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# Getting efficient choices in buildings by using Genetic Algorithms: Assessment & validation

<https://doi.org/10.1515/eng-2019-0026>

Received Nov 26, 2018; accepted Apr 03, 2019

**Abstract:** The energy consumption in buildings, can be reduced through a rational choice of the household appliances to be acquired. This choice can be based, on a specific criteria, settled according to the consumer needs.

However, such choice, still needs to be optimized, since in general, an efficient equipment has a high investment, although a low energy consumption.

Genetic Algorithms (GAs) are used therefore, as an optimization technique, to get efficient and several solutions, based on those pre-selected from the market, and according to a set of criteria.

However, there is a need to assess its robustness as well as its consistence in terms of convergence results. The quality of its solutions is also assessed, by comparing GAs results with those, obtained from Simplex method.

The problem formulation, and its influence on GAs results, is also considered on this work, where it's chosen the best one, among four proposed.

In this paper it is presented a methodology that allows to promote energy efficiency in buildings, by achieving savings in terms of initial investment, energy consumption and CO<sub>2</sub> emissions for the consumer.

It is shown that GAs, can provide several and optimal solutions, through formulation and parameters suitable.

**Keywords:** Energy Efficiency, Multi-criteria, Optimization, Genetic Algorithms, Simplex, Household Appliances

## 1 Introduction

Energy plays an essential key rule in a society, with energetic necessities, highly correlated with issues, like the

grow of population, economic development, and technology innovation [1].

Although the recent advances in technology progress, there was an increase on energy demand in the last years, which can compromise the several agreements made, in order to reduce the Greenhouse Gas Emissions to the atmosphere, where the electrical energy production is responsible for a significant part of these emissions [2].

In this sense, the reduction of energy consumption, is a priority in order to achieve sustainability [3], with buildings accounting for about 30-45 percent of the energy consumed in most countries [4].

Regarding the residential sector, the share of electrical energy consumption, is about 13,9% of the world's consumed final energy in 2012 [5]. In other countries, like Portugal, this value, could reach 18% [5], representing thus a relevant area and therefore an opportunity, to improve energy efficiency.

There were made some energy efficiency improvements in the last years, regarding electrical household appliances. One of such measures, was the European Directive 2010/30/EU, and more recently, the Regulation, (EU) 2017/1369 of 4 July 2017, of the European Parliament and of the Council, where it was established the mandatory labeling, by classifying these appliances regarding their consumption, promoting therefore the energy services cost reduction, and their equivalent CO<sub>2</sub> emissions [6, 7].

The labelling system, allows to inform the consumer about relevant issues, specifically regarding each appliance (e.g. energy consumption, noise, capacity in liters (fridge), clothe capacity (washing machine), among others), promoting therefore an adequate use of each appliance, suitable to the consumer needs [8].

However, and despite the energy efficiency improvements, regarding electrical household appliances (and buildings in general), the main issue nowadays, is to know which energy retrofit technology/measure, can be applied for a project, in terms of effective and reliable issues, especially in the long term (e.g. [8]).

In this sense, and given the several options, available on the market, it's hard to analyze what's the best solution

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to choose, regarding the issues referred before, in order to satisfy the individual needs of each consumer [9, 10].

The problem gets worse, when each appliance has its own and distinct characteristics, which varies by brand and model to buy, making the cost-benefit ratio very different, and sometimes difficult to analyze given the different equipment life cycle, energy consumption, among other issues [8].

Considering the different number of options/dimension, available from the market, the number of possible combinations will increase substantially, as we include more dimensions to be considered (e.g. lighting, clothes dryer machines, electric ovens, etc.), as well as with the addition of options/dimension, available on the market, given the possible existence, of several tradeoffs between them.

Therefore, and by taking into account a decision maker (consumer) who wishes to acquire different types of household appliances, one will have to deal with a problem of combinatorial nature, which can be tackled by using optimization techniques.

The use of traditional optimization techniques (particularly those based on gradient methods) presents some inconveniences or disadvantages. One of them is related with the strong possibility of these algorithms, can get stuck into a local minima/maxima, having therefore, some limitations on exploitation of the entire feasible region.

The use of Genetic Algorithms (GAs), allows to obtain different and feasible solutions, to attend the consumer needs.

However, as like other metaheuristic, GAs presents the inconvenience of having too many control parameters, making it quite sensitive to their initial values, therefore the need to tuning them, as well as test its robustness, to improve the quality of its results.

Therefore, this paper presents a method to provide efficient solutions from the market, directly to the consumer (decision-agent), that allows to reduce Energy and CO<sub>2</sub> consumption, through its correspondent savings achieved during its usage phase. The solutions will consider the consumer needs, according to a set of criteria previously established and regarding each dimension/appliance considered, as well as the limited budget to perform the initial investment.

The method will be applied on this work by using a case study where the quality of its solutions is tested, by comparing such results with those obtained from another optimization method (Simplex). The robustness of the method referred above, will also be assessed, as well as its convergence, demonstrating therefore its validation on providing several and efficient solutions to the consumer.

The influence of the objective function considered, will also be assessed. At the end it will be chosen the best objective function, from a set, that was pre-defined, based on model behavior.

## 2 Literature review

In the last years, there was a set of initiatives made by several entities, including governments, associations and manufactures, to sensitize the population to the problem of energy efficiency in the residential sector [2]. This was made by establishing some measures and practices. However, most of this common practices, employs methods like simulation (e.g. [11, 12]), based on analysis of type *what if*, which (in general), consists on a set of techniques that allows to investigate only a limited number of an alternative options.

Other studies, found on literature, follows an approach, which is mainly economical, where, and for the same initial investment, it allows to achieve the highest energy savings through a set of actions taken (e.g. [13]). Considering this principle, there are some approaches, regarding energy management, like the ones based on control techniques, or even those, based in schedule methodologies for instance.

Although, most of these approaches, do not account other relevant factors (e.g. environmental, financial costs, legal, and social, among others) to find the best compromise suitable to the final occupant needs and requirements [14–17].

Other approaches, are based on multicriteria decision making (MCDM) techniques, where it's chosen the best alternative in each set of viable options. However, such criteria, are usually conflicting on nature, giving therefore a solution that it is impossible to be optimal against all criteria, and at same time, a feasible solution that satisfies the requirements of the building's final user/occupant.

Nowadays, some works have suggested MCDM models to support professionals to solve problems, associated with the retrofitting of buildings, by taking into consideration factors, such as the degradation of building elements, energy efficiency, and internal environment comfort (e.g. [18]). Other similar approaches can be found on literature, based on ranking of alternative solutions (e.g. [19]).

Some works are even concerned into provide the decision-maker with a rating of retrofit plans of the considered building, according to an extended list of criteria like energy efficiency, environmental impact, economical

rationality, comfort and duration under life cycle among others (e.g. [19]).

In the same context, there are also other MCDM models found on literature, that combines optimization with multicriteria techniques in order to obtain feasible solutions, by exploring a large number of alternative measures/solutions, which were pre-selected, according to a set of criteria, suitable to the consumer needs (e.g. [13, 20]). Some of these approaches, explore several issues (e.g. benefit-cost analysis, initial investment, CO<sub>2</sub> savings, energy savings, among others) of retrofitting measures (e.g. [14, 21]). There also approaches that combines such measures with technologies (e.g. [13, 22]). However, such approaches don't consider the different criteria regarding each household appliance, available on the market, regarding each dwelling and its occupants.

This issue becomes even more relevant, when it comes to electrical household appliances, since it's considered a critical issue for the consumer, the evaluation of a set of alternative appliances, based on a set of criteria (e.g. energy consumption, environmental impact, investment cost, comfort, among others) to perform efficient decisions [16].

The pre-selection of efficient electrical household appliances from the market, according to a set of criteria previously defined, and integrated with optimization techniques, can also contribute to reduce the time in achieving such solutions, mainly due to the pre-reduction of the space decision. This becomes particularly relevant, since the consumer faces many alternative solutions available on market with different attributes, and therefore, facing several tradeoffs between them.

However, the use of traditional optimization techniques, usually begins with a single potential solution of the problem, which is iteratively manipulated until finding a final solution, normally unique [23], thus reducing the available feasible options to the DM (consumer), which is undesirable.

Additionally, some algorithms (like the ones based on gradient methods), have the inconvenient to find (frequently) a local minima or maxima, having therefore, some limitations on exploitation of the entire feasible region [24].

To cope with the difficulties presented above, they have been applied methods, based on metaheuristics, to provide a set of feasible solutions, such as greedy strategies (e.g. [25]), Particle Swarm Optimization (PSO) (e.g. [26, 27]), Simulated Annealing (SA) (e.g. [22]) and Genetic Algorithm (GA) (e.g. [28, 29]), among others.

These methods are characterized by stochastic nature, global search ability, and a large amount of implicit parallelism [30, 31]).

The use of evolutionary algorithms (GAs), like Genetic Algorithms (GAs), allows to obtain different and feasible solutions [31–33] *i.e.*, different sets of efficient appliances to attend the consumer needs.

However, this metaheuristic methods, presents some disadvantages, mainly related to its control parameters and the sensitivity to its values, which demands a proper tuning of them [34].

Besides the needs of tuning, robustness and quality assessment, referred before, there is the existence of some influence of the objective function, as it shown on some studies (e.g. [35, 36]) which uses several objective functions to test the model and its behavior.

## 3 Materials

### 3.1 Problem statement and proposed model

The problem presented here, will consider a decision-agent (consumer), who wants to buy a set of electrical household appliances (energy services) available on the market, regarding each type of appliance/energy service, as follows:

- Air conditioning
- Washing Machine
- Dishwasher
- Oven
- Clothes dryer machine
- Lighting
- Refrigerator

The consumer has a limited budget to acquire the household appliances need it, and after a market research, it achieved a set of available solutions (Figure 1).

Given the trade-off, and the diversity of features regarding each solution, the consumer will be confronted with a problem of combinatorial nature, where the number of combinations is dependent on the number of available options regarding each dimension.

Then, and for each type of appliance, it will be corresponded to a dimension of the problem, as it shown on Figure 1.

The number of possible combinations, can be reduced, according to a set of criteria previously established, to suit to the consumer needs. This number of combinations, can be even reduced, by assuming that the consumer cannot

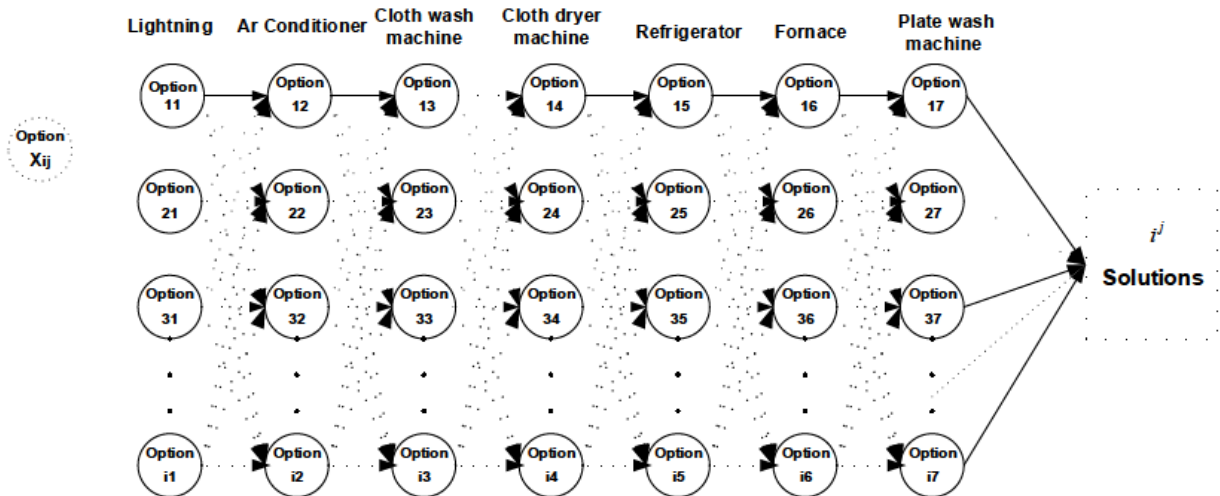


Figure 1: Consumer's decision space: Options and dimensions considered

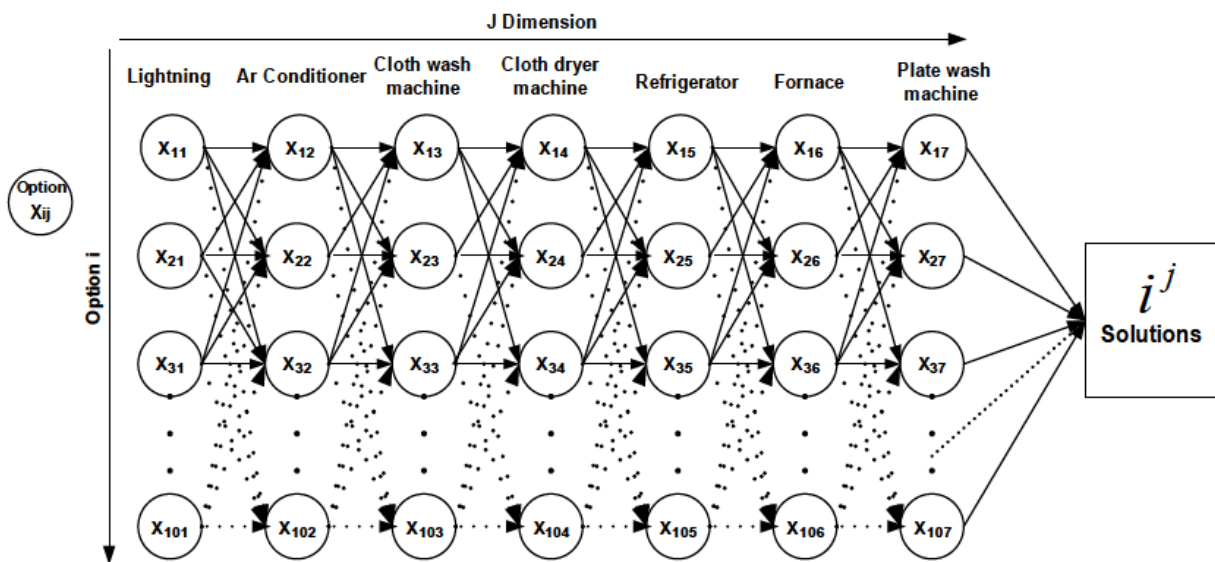


Figure 2: Consumer's decision space: Problem formulation

perform any choice or individual solution ( $x_{ij}$ ), given his limited budget.

Therefore, the number of combinations shown on Figure 1, can be reduced and formulated, after the appliances, being pre-selected from the market, according to a set of criteria, leading to the space decision, presented on Figure 2. The criteria is established and suitable, according to the case study considered; *i.e.* the correspondent values, are defined according to number of occupants and building dimensions (regarding air conditioner).

Each individual solution ( $x_{ij}$ ), corresponds to an option  $i$ , belonging to a problem dimension  $j$ , correspondent for each type of appliance, that will be purchased by the consumer.

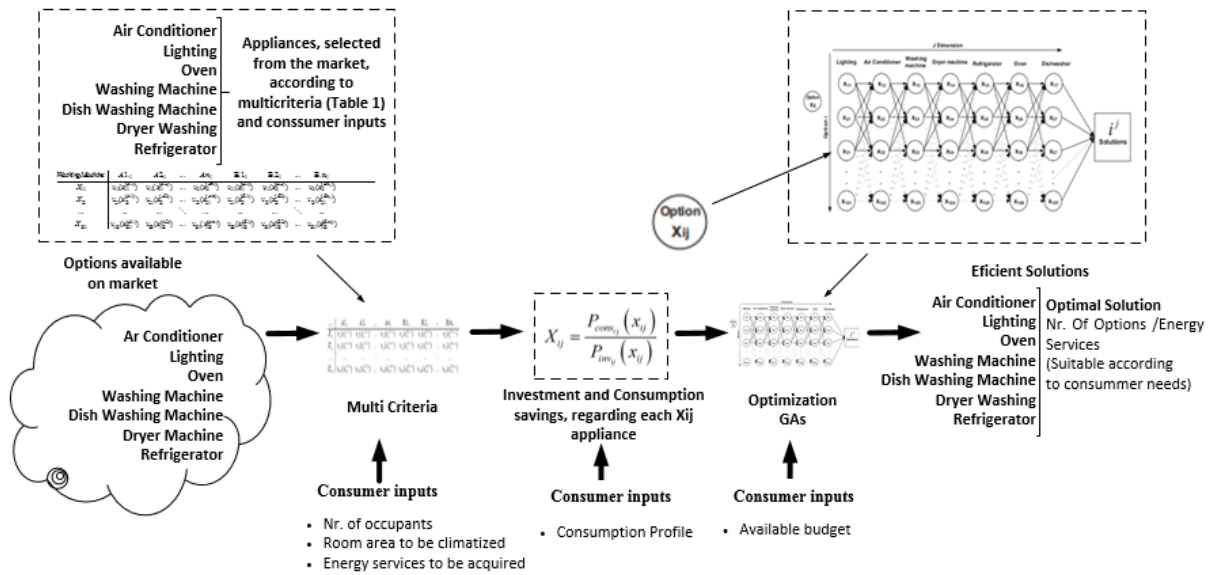
One way to promote energy efficiency through household's appliances is to maximize their utility, by selecting the adequate household appliances to suite the consumer needs. This can be done, by considering some aspects, such as number of household occupants, the user needs, etc.

The case study, used here, has considered a consumer as part of a household with three other occupants (*e.g.* family).

The influence of consumer usage profile, was also considered, by concerning the number of hours that each appliance will perform daily, extrapolating then for a monthly and yearly basis (Table 1).

**Table 1:** Assumptions taken, regarding the consumer usage profile

Emission factor [gCO2/kWh]	675	Discount Factor [%]	7	
Life cycle (usage phase) considered [years]:	10	Annual Factor	7,02	
Electrical Energy tariff [€/kWh]	0,162			
Energy Service	Usage Profile (h)			
	Daily	Weekly	Monthly	Annual
Air Conditioner	2	14	60	720
Washing Machine	1	7	30	360
Dryer Machine	1	7	30	360
Refrigerator	11	77	330	3960
Electric Oven	1	7	30	360
Dish Washing Machine	1	7	30	360
Lighting	3	21	90	1080

**Figure 3:** Proposed model

The impact of such parameters, relies on consumption, regarding each appliance. Therefore, and considering each individual efficient solution,  $i$ , belonging to energy service  $j$ , it was calculated the correspondent savings, regarding its consumption as well as its initial investment. This savings, results through the comparison of the values of efficient solutions (consumption and investment) to the standard (*i.e.* less efficient) ones, regarding each dimension  $j$ , and discounted according to the life cycle period (usage phase), by using a discount factor, both considered on Table 1.

Solutions were pre-selected, according to a set of criteria to reduce the decision space, accounting only the suitable solutions to the consumer needs, increasing at the same time GAs efficiency (by achieving optimal solutions

with less time). Such criteria, are presented next. Given what was referred before, the proposed approach, can be represented, according to the diagram presented on Figure 4.

### 3.2 Adopted criteria considering the case study

#### Air conditioning

The Air Conditioner electric consumption share, represents about 2% of the total electric energy, regarding the residential buildings in Portugal [7].

In this work, we have considered the following types of air conditioner:



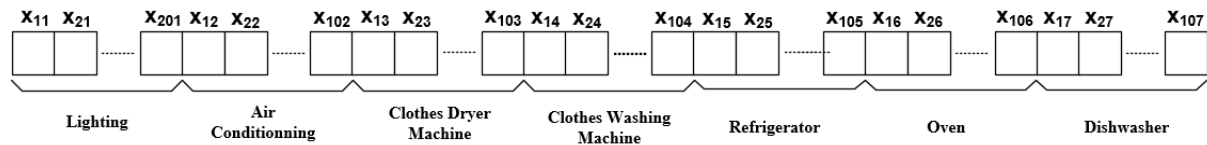


Figure 4: Encoding problem using genetic algorithms

- Wall (mono split)
- Wall (multi split)
- Monoblock
- Portable

In this work it was considered just the living room as the zone to be heated/ cooled by the air conditioner. In order to define the needs for heating / cooling, and therefore the air conditioner capacity, it was considered the following issues, adopted on thermal loads calculations [37–39]:

- Internal gains (Nr. of occupants, electric appliances, etc.)
- Air change (forced or natural)
- Solar radiation (windows, etc.)
- Heat losses through the envelope (conduction through the external walls)

As a result of these calculations, the minimum capacity obtained was 10189 Btu/h, and the devices were pre-selected respecting the minimum value obtained, both for heating, as well for cooling needs.

### Washing Machine

The washing machine is nowadays one of the most used appliances in households, representing thus about 5% of the total building electric energy consumption [6].

The highest cloth capacities of some machines, normally expressed in kilograms (kg) [6], requires sometimes higher costs of consumed water.

The cloth capacity allows to adjust the capacity of the washing machine according to the consumer needs, to avoid situations like having washing cycles with the machine far from a full load, which leads to a situation of waste of water and electric energy losses.

Therefore, it is important to consider the number of household's occupants, to determine the washing machine Load Capacity. This is shown in Table 2.

Thus, and for the present case study, the choices were made by taking into consideration, seven kilograms of load capacity.

Table 2: Washing machine load capacity [6]

No. Occupants	Load Capacity [kg]
1-2	6
3-4	7-8
5 or more	>8

### Dishwasher

The dish-washer machine represents about 3% of the overall consumption of a residential sector [6]. The choice of the type of appliance can be done by adjusting the appliance capacity to satisfy the occupant's needs. In this case, the capacity to be considered, was defined by choosing the value through Table 3.

Table 3: Dish washing machine load capacity [6]

No. Occupants	Load Capacity [cutlery]
1	<10
2-3	10-12
4 or more	>12

Thus, and for the case study only dish washing machines with a 12 cutlery of load capacity were considered.

### Ovens

Electric ovens, represents about 1% of the overall consumption of a residential fraction [7].

However, if we take into consideration the consumption and use of many households (e.g. a city, region, country, etc.) the aggregate consumption, can assume significant values.

The criteria for choosing ovens were the useful volume, or the volume available to cook the food, adjustable to the number of occupants, although this can vary from model to model, as it shown on Table 4.

The choices were made by taking into consideration, the average size.

**Table 4:** Ovens volume capacity [6]

Size	Volume (l)
Small	12-35
Average	35-65
Large	65

### Clothes dryer machines

The consumption of these machines represents about 2% of total consumption of electricity in a household [7].

For these machines the previous selection was made by considering two types of clothes dryer machines:

- Clothes dryer machines by exhaust
- Clothes dryer machines by condensation

Another criteria, that has been considered, was the load capacity, by choosing a value from Table 1, according to the number of occupants.

Therefore, the previous choices were made by taking into consideration, seven kilograms of load capacity.

### Lighting

Representing about 12% of total electric energy consumption in the residential sector [7], lighting is one of the most relevant appliances to reduce energy consumption, therefore the several technologies, available on market. The technologies and the used criteria for the present case are shown on Table 5.

Thus, and for the number of occupants, considered in this case, the options were made by taking into consideration, the quantity of investments needed by technology to be equal to other, for the same considered period (10 years).

### Refrigerator

The refrigerators are appliances with the highest penetration rate in the residential sector in Portugal, contributing with about 22% of domestic energy consumption [7].

There are on the market several types of refrigerators according to its capacity (Table 6).

Based on Table 6, and considering the number of occupants in this case, the options were made by considering, the Combined type.

## 3.3 Problem formulation

### Decision variables

Based on the diagram of Figure 2, we can define the decision variables of the problem:

$$\exists x : x_{ij} = \{0, 1\} \quad w/i, j \in N \wedge i = \{1, \dots, n_j\} \wedge \quad (1) \\ \wedge j = \{1, \dots, 7\} \wedge n_j = \{20, 11, 10, 10, 10, 10, 10\}$$

Where  $x_{ij}$  represents the option  $i$  regarding the dimension  $j$  of the problem.

### Formulation hypothesis

Let  $V_R$  be the value associated with the objective function expressed as follows:

$$V_R(x) \in \wedge \exists x : x_{ij} = \{0, 1\} \quad (2) \\ w/i = \{1, \dots, n_j\} \wedge j = \{1, \dots, 7\}$$

$V_R(x)$  is a cost function that may be written in the form of:

$$V_R = \sum_{i=1}^{20} a_{i1}(x_{i1}) + \sum_{i=1}^{11} a_{i2}(x_{i2}) + \sum_{j=3}^7 \sum_{i=1}^{10} a_{ij}(x_{ij}) \quad (3)$$

with

$$a_{ij}(x_{ij}) \in w/i = \{1, \dots, n_j\} \wedge j = \{1, \dots, 7\} \quad (4)$$

The parameter  $a_{ij}(x_{ij})$ , is a function regarding option  $i$  and dimension  $j$ . It's defined in accordance with the formulation, considered in this work.

The parameters  $P_{cons.ij}(x_{ij})$  and  $P_{inv.ij}(x_{ij})$  are the savings regarding consumption and investment, respectively, which are relative to each solution  $x_{ij}$ .

Both parameters were obtained, by preforming LCCA calculations in order to compare each solution values, with those from the respective standard (i.e. less efficient) ones.

One of the objectives of this work, was to assess the influence of formulation (by modifying the fitness function) in getting good solutions to the problem presented before. The constraints, used on each formulation, are the same, and they were presented before.

Therefore, it was considered four different types of formulation, which are presented on the following sections.

### 1<sup>st</sup> Formulation

In this case, and for the  $a_{ij}(x_{ij})$ , it was considered the sum of existing savings, regarding consumption as well as the

**Table 5:** Light technologies and criteria [6]

Features/ criteria	Incandescent Lamps		Fluorescent Lamps	
	Classic	Halogen	Tubular	CFL
Power (W)	15-2000	20-2000	15-58	9-23
Light Efficiency (lumen/W)	8-15	15-25	58-93	55-65
Life Cycle (h)	1000	2000	12000 - 18000	6000 - 15000

**Table 6:** Types of refrigerators [6]

Type	No. Stars	N. Occupants	Average Capacity [l]
Simple	**	1-2	180/200
Combined	**	2-6	225/320
“American” type	**	>6	550

investment, i.e.:

$$a_{ij} = P_{inv,ij}(x_{ij}) + P_{cons,ij}(x_{ij}) \quad (5)$$

Thus, based on expressions (3) and (5), we obtain:

$$V_R = \sum_{i=1}^{20} (P_{inv,i1}(x_{i1}) + P_{cons,i1}(x_{i1})) + \sum_{i=1}^{11} (P_{inv,i2}(x_{i2}) + P_{cons,i2}(x_{i2})) + \sum_{j=3}^7 \sum_{i=1}^{10} (P_{inv,ij}(x_{ij}) + P_{cons,ij}(x_{ij})) \quad (6)$$

Therefore, it is obtained an objective function, whose terms reflect the sum of savings, regarding the investment and consumption, with the choice of a given solution  $x_{ij}$ .

## 2<sup>nd</sup> Formulation

This formulation aims to establish a relationship between the values of savings, regarding the consumption made during the appliance's life cycle, as well as the savings, regarding the investment, considered for each appliance, by using the same parameters as in the 1<sup>st</sup> Formulation, i.e.:

$$a_{ij}(x_{ij}) = \frac{P_{cons,ij}(x_{ij})}{P_{inv,ij}(x_{ij})} \quad (7)$$

Therefore, through the expressions (3) and (7), we obtain:

$$V_R = \sum_{i=1}^{20} \left( \frac{P_{cons,i1}(x_{i1})}{P_{inv,i1}(x_{i1})} \right) x_{i1} + \sum_{i=1}^{11} \left( \frac{P_{cons,i2}(x_{i2})}{P_{inv,i2}(x_{i2})} \right) x_{i2} + \sum_{j=3}^7 \sum_{i=1}^{10} \left( \frac{P_{cons,ij}(x_{ij})}{P_{inv,ij}(x_{ij})} \right) x_{ij} \quad (8)$$

However, and when trying to reach the best solution by using this formulation, some of the dimensions, have revealed more influence over the others, which has resulted in a problem to obtain the global solution. As it has been pointed by [40–44], this situation can happen, since, and when finding the best solution, the search occur only in the dimensions with greater influence on the objective function, resulting thus into bad exploitation of the space decision.

## 3<sup>rd</sup> Formulation

In order to try to avoid the previous situation referred before, it was tested a 3<sup>rd</sup> formulation, by considering a factor  $\gamma(x_{ij})$  applied to  $a_{ij}$ , expressed on (7), i.e.:

$$a_{ij}(x_{ij}) = \frac{P_{cons,ij}(x_{ij})}{P_{inv,ij}(x_{ij})} \gamma_{ij}(x_{ij}) \quad (9)$$

Then, and through the expressions (3) and (9), we obtain the follow expression for objective function ( $V_R$ ):

$$V_R = \sum_{i=1}^{20} \left( \frac{P_{cons,i1}(x_{i1})}{P_{inv,i1}(x_{i1})} \right) \gamma_{ij}(x_{ij}) x_{i1} + \sum_{i=1}^{11} \left( \frac{P_{cons,i2}(x_{i2})}{P_{inv,i2}(x_{i2})} \right) \gamma_{ij}(x_{ij}) x_{i2} + \sum_{j=3}^7 \sum_{i=1}^{10} \left( \frac{P_{cons,ij}(x_{ij})}{P_{inv,ij}(x_{ij})} \right) \gamma_{ij}(x_{ij}) x_{ij} \quad (10)$$

Being  $\gamma_{ij}(x_{ij})$ , the factor applied to each dimension, given by:

$$\gamma_{ij}(x_{ij}) = 1 - \frac{Inv_{ef,ij}(x_{ij})}{Inv_{total}} = \frac{Inv_{total} - Inv_{ef,ij}(x_{ij})}{Inv_{total}} \quad (11)$$



This factor evaluates the influence of a given option  $i$  belonging to a given dimension  $j$  in terms of the total investment made, related to the global solution obtained.

$$V_R = \sum_{i=1}^{20} \left( \frac{P_{cons,i1}(x_{i1})}{P_{inv,i1}(x_{i1})} \right) \cdot \left( \frac{Inv_{total} - Inv_{ef,i1}(x_{i1})}{Inv_{total}} \right) x_{i1} + \sum_{i=1}^{11} \left( \frac{P_{cons,i2}(x_{i2})}{P_{inv,i2}(x_{i2})} \right) \cdot \left( \frac{Inv_{total} - Inv_{ef,i2}(x_{i2})}{Inv_{total}} \right) x_{i2} + \sum_{j=3}^7 \sum_{i=1}^{10} \left( \frac{P_{cons,ij}(x_{ij})}{P_{inv,ij}(x_{ij})} \right) \cdot \left( \frac{Inv_{total} - Inv_{ef,ij}(x_{ij})}{Inv_{total}} \right) x_{ij} \quad (12)$$

#### 4<sup>th</sup> Formulation

The 4<sup>th</sup> Formulation, wants to assess GAs behavior - and therefore the solutions obtained - by the consumption during each standard option life cycle ( $C_{std,j}$ ) with its initial investment ( $I_{std,j}$ ). It was also used the same parameters as before, i.e.,  $P_{cons,ij}(x_{ij})$  and  $P_{inv,ij}(x_{ij})$ .

Thus, and based on referred before, the  $a_{ij}(x_{ij})$ , can be defined as:

$$a_{ij}(x_{ij}) = \frac{\frac{P_{cons,ij}(x_{ij})}{C_{std,j}}}{\frac{P_{inv,ij}(x_{ij})}{I_{std,j}}} = \frac{P_{cons,ij}(x_{ij})}{P_{inv,ij}(x_{ij})} \frac{I_{std,j}}{C_{std,j}} \quad (13)$$

Based on expressions (3) and (14), we obtain:

$$V_R = \sum_{i=1}^{20} \left( \frac{P_{cons,i1}(x_{i1})}{P_{inv,i1}(x_{i1})} \frac{I_{std_1}}{C_{std_1}} \right) x_{i1} + \sum_{i=1}^{11} \left( \frac{P_{cons,i2}(x_{i2})}{P_{inv,i2}(x_{i2})} \frac{I_{std_2}}{C_{std_2}} \right) x_{i2} + \sum_{j=3}^7 \sum_{i=1}^{10} \left( \frac{P_{cons,ij}(x_{ij})}{P_{inv,ij}(x_{ij})} \frac{I_{std_j}}{C_{std_j}} \right) x_{ij} \quad (14)$$

or:

$$V_R = \sum_{i=1}^{20} \left( \frac{P_{cons,i1}(x_{i1})}{P_{inv,i1}(x_{i1})} \right) \alpha_{i1}(x_{i1}) x_{i1} + \sum_{i=1}^{11} \left( \frac{P_{cons,i2}(x_{i2})}{P_{inv,i2}(x_{i2})} \right) \alpha_{i2}(x_{i2}) x_{i2} + \sum_{j=3}^7 \sum_{i=1}^{10} \left( \frac{P_{cons,ij}(x_{ij})}{P_{inv,ij}(x_{ij})} \right) \alpha_{ij}(x_{ij}) x_{ij} \quad (15)$$

Being  $\alpha_{ij}$ , the factor applied to each dimension, obtained here by making:

$$\alpha_{ij}(x_{ij}) = \frac{Inv_{ef,ij}(x_{ij})}{I_{std,j}} \quad (16)$$

Like the 3<sup>rd</sup> Formulation, it is also applied a factor so that the GAs, can perform a search as uniform as possible considering all the problem dimensions.

## 3.4 Application

### Introduction to case study

In order to present an example of a solution, obtained from the method, it was considered a case of a family formed by 4 elements (building occupants), with an element (consumer) pretending to acquire a set of appliances (referred before), although having a limited budget to do.

### GAMS & GAS implementation

For the application we have considered the case study presented before and used a VBA MS Excel Spreadsheet software for the implementation of GAs, and GAMS software for the Simplex implementation, in order to validate the obtained results within the GAs use.

According to the formulation presented before, each problem solution/individual, will be coded in GA's, according to the framework presented on Figure 4, by using binary coding, where each "active bit", represents one optimal choice, regarding each individual solution.

For GA's implementation, it was considered the following parameters:

- Initial population: 100 individuals
- Selection method: Roulette
- Crossover method: single point
- Crossover rate: 0.45
- Mutation: Normal Random
- Mutation rate: 0.01
- Convergence: 0.001
- Maximum number of generations: not defined

## 4 Results & Discussion

### 4.1 1<sup>st</sup> Part – GAs behavior with formulation

The following simulations, regarding each formulation, was performed by taking a set of assumptions:

Average No. Runs/budget scenario: 30

The remain ones are presented on Section 3.3.

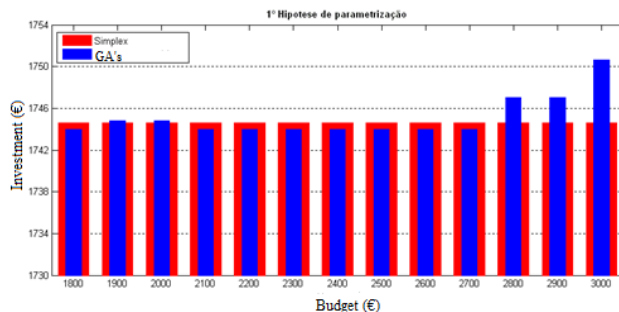
The following results, presented on this section, regards the average solution of the objective function ( $V_r$ ) and it concerns each value of the available budget.

Regarding the investment made by the consumer, it was considered a budget scenario that varies from 1800 up to 3000 euros.

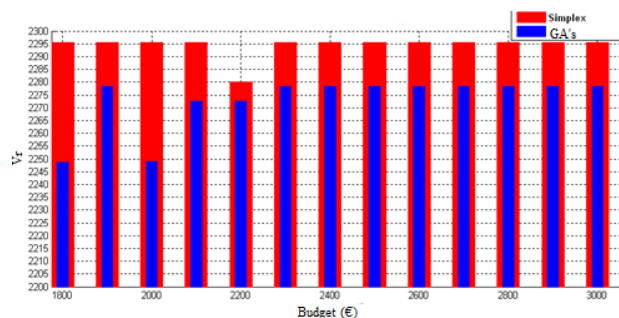
#### 1<sup>st</sup> Formulation

The results, obtained with the 1<sup>st</sup> Formulation, are shown on Figures 5-6, respectively to the investment and the value of the objective function.

Based on Figures 5 and 6, it is noticed that GAs can provide more and different solutions (when compared with Simplex results) by exploring more effectively the feasible



**Figure 5:** Average values (30 runs) of total investment to be supported, at each value of the budget considered (1<sup>st</sup> Formulation)



**Figure 6:** Average values (30 runs) of the objective function ( $V_r$ ) for each scenario / budget (1<sup>st</sup> Formulation)

region, compared to Simplex, and for the different values of budget considered.

The difference between GAs and Simplex (average) solutions, was assessed, by considering the worst and the best budget scenarios:

#### Worst budget scenario

$$\begin{aligned} \varepsilon_{V_r(1800\text{€} | \text{Budget Scenario})} &= \\ \frac{\|V_R(\text{Simplex}) - V_R(\text{GAs})\|}{V_R(\text{Simplex})} &= \frac{\|2295 - 2248\|}{2295} \approx \\ 0,0205 &\approx 2,0\% \end{aligned} \quad (17)$$

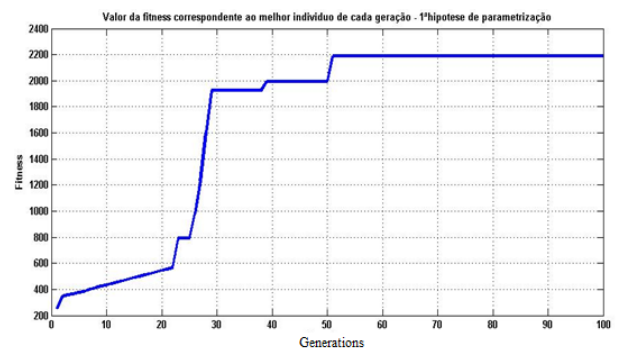
#### Best budget scenario

$$\begin{aligned} \varepsilon_{V_r(2500\text{€} | \text{Budget Scenario})} &= \\ \frac{V_R(\text{Simplex}) - V_R(\text{GAs})}{V_R(\text{Simplex})} &= \frac{2295 - 2285}{2295} \approx 0,0044 \approx \\ 0,44\% \end{aligned} \quad (18)$$

Although Simplex, has provided better  $V_r$  values (Figure 6), the difference between GAs and Simplex (on average), can reach 2.0% in the worst scenario and 0.44% in the best scenario.

On average, GAs have presenting an average number of generations/run of 56 and an average CPU time of 8,7 s.

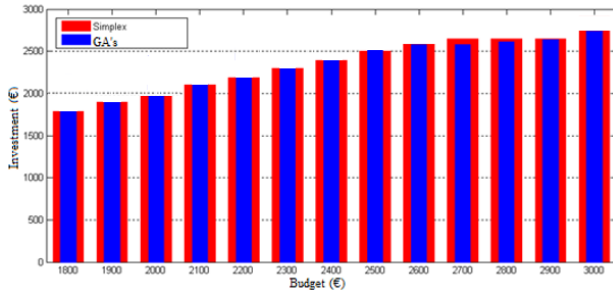
In order to illustrate the performance of GA's with the formulation considered, on Figure 7 it is illustrated the evolution of fitness value for a budget of 1900 euros, corresponding to the best individual on each generation.



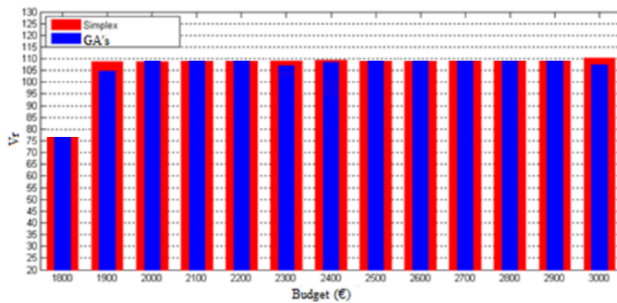
**Figure 7:** Evolution of fitness, corresponding to the best individual of each generation, for a budget constraint of 1900 euros (1<sup>st</sup> Formulation)

## 2<sup>nd</sup> Formulation

The results, obtained with the 2<sup>nd</sup> Formulation, are shown on Figures 8 and 9, respectively to the investment and the value of the objective function.



**Figure 8:** Average values (30 runs) of total investment to be supported, at each value of the budget considered (2<sup>nd</sup> Formulation)



**Figure 9:** Average values (30 runs) of the objective function ( $V_r$ ) for each scenario / budget (2<sup>nd</sup> Formulation)

By observing Figures 8 and 9, and comparing the 2<sup>nd</sup> Formulation with the 1<sup>st</sup> one, there is more exploitation of the feasible region by GAs or even by *Simplex*, which reveals some influence by the formulation chosen, as it already referred in some published works [39–41].

The difference between GAs and *Simplex* (average) solutions, was also assessed, by considering the worst and the best budget scenarios:

## Worst budget scenario

$$\begin{aligned} \varepsilon_{V_r(1900\text{€} | \text{Budget Scenario})} &= \\ \frac{\|V_R(\text{Simplex}) - V_R(\text{GAs})\|}{V_R(\text{Simplex})} &= \frac{\|109,0 - 105,5\|}{109,0} \approx \\ 0,0321 &\approx 3,21\% \end{aligned} \quad (19)$$

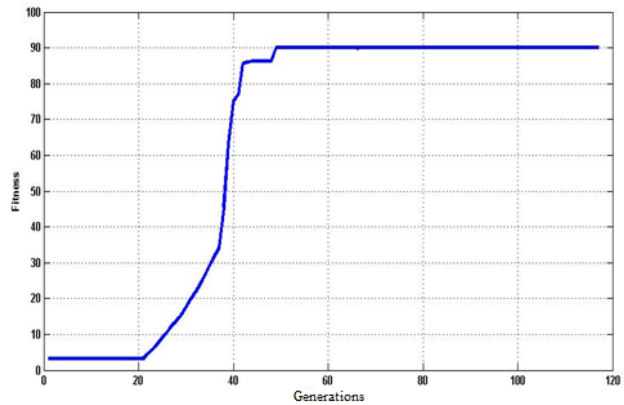
## Best budget scenario

$$\begin{aligned} \varepsilon_{V_r(1800\text{€} | \text{Budget Scenario})} &= \\ \frac{\|V_R(\text{Simplex}) - V_R(\text{GAs})\|}{V_R(\text{Simplex})} &= \frac{76,0 - 75,6}{76,0} \approx 0,0053 \approx \\ 0,53\% \end{aligned} \quad (20)$$

Although *Simplex*, has provided better  $V_r$  values (Figure 9), the difference between GAs and *Simplex* (on average), can reach 0,53% in the worst scenario and 3,21% in the best scenario.

On average, the 2<sup>nd</sup> Formulation have allowed GAs to converge with less time than the 1<sup>st</sup> one, by presenting an average number of generations/run of 48 and an average CPU time of 6,6 s.

In order to illustrate the performance of GA's with the formulation considered, on Figure 10 it is illustrated the evolution of fitness value for a budget of 1900 euros, corresponding to the best individual on each generation.



**Figure 10:** Evolution of fitness, corresponding to the best individual of each generation, for a budget constraint of 1900 euros (2<sup>nd</sup> Formulation)

Compared to the 1<sup>st</sup> Formulation, and by observing Fig.9, it is noticed that GAs is on average faster (i.e., with less generations) when achieving a steady fitness value.

## 3<sup>rd</sup> Formulation

The results, obtained with the 1<sup>st</sup> Formulation, are shown on Figures 11 and 12, respectively to the investment and the value of the objective function.

The difference between GAs and *Simplex* (average) solutions, was assessed, by considering the worst and the best budget scenarios:

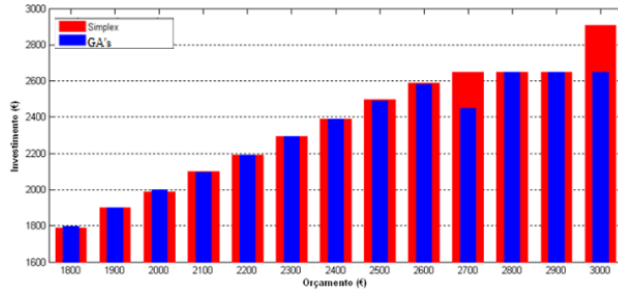


Figure 11: Average values (30 runs) of total investment to be supported, at each value of the budget considered (3<sup>rd</sup> Formulation)

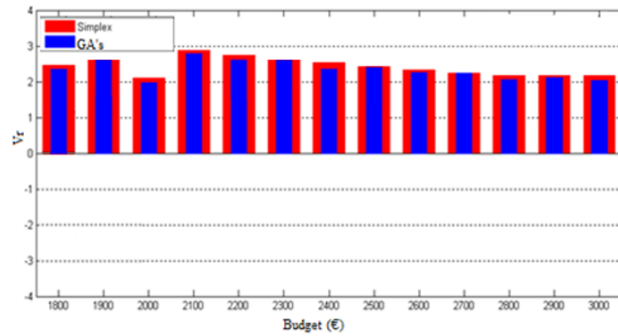


Figure 12: Average values (30 runs) of the objective function (Vr) for each scenario / budget (3<sup>rd</sup> Formulation)

### Worst budget scenario

$$\begin{aligned} \varepsilon_{Vr(2400\text{€}|Budget\ Scenario)} &= \\ \frac{\|V_R(\text{Simplex}) - V_R(\text{GAs})\|}{V_R(\text{Simplex})} &= \frac{\|2,44 - 2,40\|}{2,44} \approx \\ 0,0164 &\approx 1,64\% \end{aligned} \quad (21)$$

### Best budget scenario

$$\begin{aligned} \varepsilon_{Vr(2700\text{€}|Budget\ Scenario)} &= \\ \frac{\|V_R(\text{Simplex}) - V_R(\text{GAs})\|}{V_R(\text{Simplex})} &= \frac{\|2,30 - 2,29\|}{2,30} \approx \\ 0,0043 &\approx 0,43\% \end{aligned} \quad (22)$$

Although Simplex, has provided better Vr values (Figure 12), the difference between GAs and Simplex, can reach on average, 7,69% in the worst scenario and 0,43% in the best scenario.

On average, the 2<sup>nd</sup> Formulation have allowed GAs to converge with less time than the 1<sup>st</sup> Formulation, although slower than 2<sup>nd</sup> one, by presenting an average number of generations/run of 43 and an average CPU time of 6,9 s.

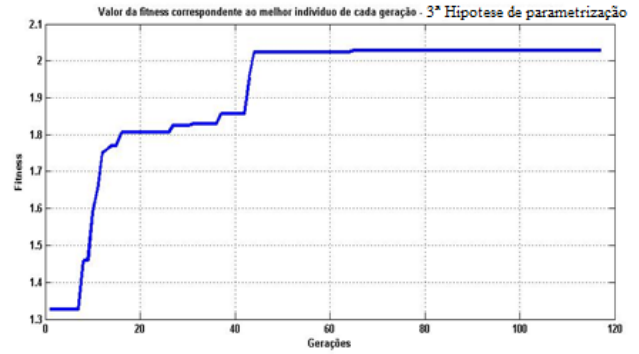


Figure 13: Evolution of fitness, corresponding to the best individual of each generation, for a budget constraint of 1900 euros (3<sup>rd</sup> Formulation)

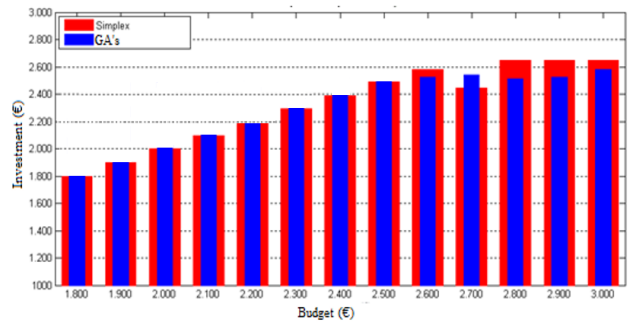


Figure 14: Average values (30 runs) of total investment to be supported, at each value of the budget considered (4<sup>th</sup> Formulation)

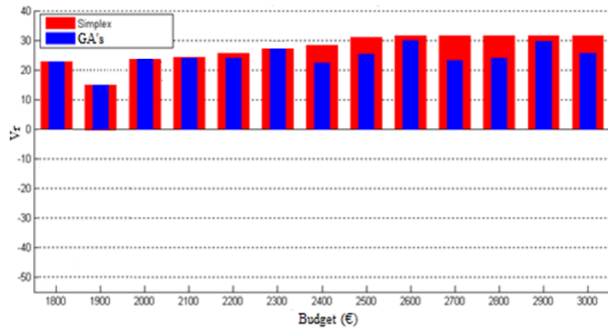
In order to illustrate the performance of GA's with the formulation considered, on Figure 13 it is illustrated the evolution of fitness value for a budget of 1900 euros, corresponding to the best individual of each generation.

With the present formulation, GAs has revealed a little faster than the previous formulations presented before, by reaching the steady fitness value earlier with an average of 43 generations.

### 4<sup>th</sup> Formulation

The results, obtained with the 4<sup>th</sup> Formulation, are shown on Figures 14 and 15, respectively to the investment and the value of the objective function.

The difference between GAs and Simplex (average) solutions, was assessed, by considering the worst and the best budget scenarios:



**Figure 15:** Average values (30 runs) of the objective function ( $V_r$ ) for each scenario / budget (4<sup>th</sup> Formulation)

### Worst budget scenario

$$\varepsilon_{V_r(2700\text{€} | \text{Budget Scenario})} = \frac{\|V_R(\text{Simplex}) - V_R(\text{GAs})\|}{V_R(\text{Simplex})} = \frac{\|31,0 - 22,0\|}{31,0} \approx 0,2903 \approx 29,03\% \quad (23)$$

### Best budget scenario

$$\varepsilon_{V_r(2300\text{€} | \text{Budget Scenario})} = \frac{\|V_R(\text{Simplex}) - V_R(\text{GAs})\|}{V_R(\text{Simplex})} = \frac{\|26,0 - 26,0\|}{26,0} \approx 0,00 \approx 0,00\% \quad (24)$$

Although Simplex, has provided better  $V_r$  values (Figure 14), the difference between GAs and Simplex, can reach (on average) 29,03% in the worst scenario and 0,0% in the best scenario, where GAs results are (on average) better in this budget scenario.

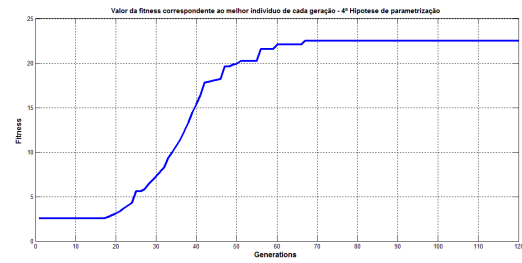
In order to illustrate the performance of GAs with the formulation considered, on Figure 16 it is illustrated the evolution of fitness value for a budget of 1900 euros, corresponding thus to the best individual on each generation.

It is noticed an average of 67 generations/run to reach the steady value of the objective function, which is more than the previous formulations.

On average, the 4<sup>th</sup> Formulation have allowed GAs to converge with an average CPU time of 7,1 s.

### Formulation chosen

Considering the presentation and discussion of the four formulations presented before, it was obtained a set of results which are summarized on Table 7, as follows:



**Figure 16:** Evolution of fitness, corresponding to the best individual of each generation, for a budget of 1900 euros (4<sup>th</sup> Formulation)

**Table 7:** Summary results obtained from the four Formulations considered

Form.	Worst $V_r(\%)$	Best $V_r(\%)$	Time(s)	Gen./run
1	2,00	0,44	8,7	56
2	3,21	0,53	6,6	48
3	1,97	0,43	6,9	43
4	29	0,00	7,1	67

Therefore, and based on the results presented on Table 7, it was decided to choose the 2<sup>nd</sup> Formulation, in order to proceed with the robustness test, as well as its validation, with an example of its application through the case study presented before. A statistical analysis, was also performed to both Formulations presented here. In the next subsection, it shall be presented the statistical analysis, preformed for the 3<sup>rd</sup> Formulation.

## 4.2 2<sup>nd</sup> Part – Statistical & Robustness analysis

### Statistical Analysis

Due to the stochastic nature of the method, it was performed a statistical analysis to assess its consistency, as it suggested in some of related works with metaheuristics (e.g. [45, 46]).

The statistical analysis, was performed with 30 runs/budget constraint scenario on solving the same problem by GAs, whose results were obtained and presented on Table 8.

Through the values presented on Table 8, we observe that the low values of the standard deviation of the objective function ( $V_r$ ) achieved by GAs, validates its robustness for solving the problem, presented in this case study.

The highly similar optimal results with worst negligible standard deviation (0.001), validates the robustness of



**Table 8:** Statistical analysis, considering 30 runs/budget constraint scenario of GAs (vs Simplex)

		Objective function (Vr)												
Constraint Budget Scenario (x1000) [€]		1.8	1.9	2.0	2.1	2.2	2.3	2.4	2.5	2.6	2.7	2.8	2.9	3.0
Simplex	-	-3.64	3.13	2.10	2.35	2.12	2.16	2.14	2.12	2.10	2.25	2.17	2.11	2.17
GAs	Min.	1.77	1,82	1.91	2.19	2.01	2.02	2.02	2.05	1.93	2.19	2.05	1.91	2.02
	Average	1.78	1,90	1.92	2.20	2.02	2.02	2.03	2.06	1.94	2.20	2.05	1.90	2.03
	Max.	1.78	1,93	1.93	2.22	2.02	2.03	2.05	2.06	1.95	2.20	2.07	1.97	2.06
	Std. dev. (x10 <sup>-1</sup> )	0.11	0,12	0.01	0.17	0.18	0.12	0.12	0.17	0.19	0.12	0.14	0.17	0.10

**Table 9:** Sensitivity analysis (mutation rate and population size), considering 30 runs/budget constraint scenario of GAs (compared with Simplex)

Mutation rate (%)		0	1	2	3	4	5	6	7	8	9	10			
GAS	Simplex	3,07	3,07	3,07	3,07	3,07	3,07	3,07	3,07	3,07	3,07	3,07			
	Minimum	1,74	2,21	2,44	2,92	3,05	3,06	3,06	3,05	3,04	3,01	2,83			
	Average	1,74	2,21	2,44	2,93	3,05	3,06	3,06	3,05	3,04	3,01	2,83			
	Maximum	1,75	2,21	2,44	2,93	3,06	3,06	3,07	3,05	3,04	3,02	2,83			
	Standard dev. (x10 <sup>-3</sup> )	0,88	0,69	1,18	0,88	0,98	0,78	0,87	0,95	0,98	1,47	0,87			
Population size (individuals)		50	100	150	200	250	300	350	400	450	500	550	600	650	700
GAS	Simplex	3,07	3,07	3,07	3,07	3,07	3,07	3,07	3,07	3,07	3,07	3,07	3,07	3,07	3,07
	Minimum	2,64	2,74	2,92	3,06	3,05	3,04	3,06	3,05	3,04	3,03	2,98	2,94	2,79	2,19
	Average	2,65	2,74	2,93	3,06	3,05	3,04	3,06	3,05	3,04	3,04	2,98	2,94	2,79	2,19
	Maximum	2,65	2,75	2,93	3,07	3,05	3,04	3,07	3,05	3,04	3,04	2,99	2,95	2,80	2,19
	Standard dev. (x10 <sup>-3</sup> )	0,88	0,69	1,18	0,98	0,98	0,78	1,27	0,95	1,18	1,47	0,87	0,78	1,12	1,14

GAs for solving the problem of the considered case study (for a budget constraint scenario of 2000 euros). Although, and according to Table 7, the biggest range of the objective function (Vr) obtained by GAs for 30 independent runs, is between 1.82 to 1.93 (budget constraint scenario of 1900 €), which also shows that GAs converge to almost the same optimal.

### Robustness Analysis

As it was referred before, GA's are affected by its control parameters (crossover and mutation rates, as well as population size) therefore the need to tune both, as it shown on several studies (e.g. [42]).

The crossover rate value, was fixed into 0.70 and the last two parameters, were obtained by preforming a sensitivity analysis, with 15 runs/budget constraint scenario.

The mutation rate was varied, from 0 up to 10%. The population size was varied, from 50 up to 700.

The correspondent results are presented on Table 9, where the maximum iteration values (number of generations) was remained unfixed.

By analyzing the average values of Vr, for a given budget constraint scenario, the sensitivity analysis was carried out to find the best control parameter. The results have shown, that for an interval of 4-7% of mutation rate, the average value of Vr, are on its maximum value, although the interval between 200 and 400 individuals, has revealed to be the most suitable one, given the adopted formulation.

### 3<sup>rd</sup> Part – A model solution

On Table 10, it's presented an example of a feasible solution obtained by the GAs, considering a budget of 2600 Euros, and using the 3<sup>rd</sup> Formulation.

**Table 10:** Example of an efficient solution obtained from this approach

Dimension	Stand. Solution Total Invest. (€)	Effic. Sol. Total Invest. (€)	Invest. Saving (€)	Consum. Saving (€)	CO <sub>2</sub> Savings (kg)	Life cycle	Brand	Model
Lighting	15,89	10,55	5,34	58,44	28,5	8000h	A	A1
Air Conditioning	368,0	299,0	69,0	1315,6	1315,57	10 yrs	B	B2
Refrigerator	250,0	529,0	-279,0	704,11	8,5	10 yrs	C	C2
Dishwasher Machine	310,0	349,0	-39,0	3,2	6,2	10 yrs	D	D4
Washing Machine	262,0	294,0	-32,0	6,85	94,8	10 yrs	E	E1
Oven	170,0	199,0	-29,0	1,3	2,6	10 yrs	F	F2
Clothes dryer	349,0	419,0	-70,00	11,32	1,8	10 yrs	C	C6
Total:	1724,9	2099,6	-374,7	2100,8	1458,0	-	-	-

It is also presented the CO<sub>2</sub> savings, regarding the choice of this solution, compared with the less efficient (standard) one (approx. values).

CO<sub>2</sub> savings were calculated by using a carbon footprint indicator (emission factor), obtained from [44].

According to Table 10, if the consumer, opts for the efficient solution, he can save up to € 215.6 (€ 1,447.1€ - 1231.5), further contributing to a reduction of about 1452,9 kg of CO<sub>2</sub> for a time horizon of 10 years, according to life cycle considered in this work.

## 5 Conclusions

In this work, it was presented an approach, to support the decision-agent (consumer) with an efficient or a set of efficient solutions, that attends its specific needs, promoting therefore, savings on energy consumption, initial investment and CO<sub>2</sub> emissions.

The decision agent (consumer), has the possibility to use the method to select an optimal set of appliances from the market, and according to its needs.

The criteria used, is regarding each type of energy service (electrical appliance) to be considered by the consumer on its decision. The optimization was then performed by using Genetic Algorithms (GAs) to provide several alternative efficient solutions.

Besides the advantage of GAs, in getting several optimal solutions to the consumer, there is a need to assess the quality of such solutions, as well as its behavior in terms of convergence and robustness, due its control parameters.

The influence of the adopted formulation was also studied, by proposing four different approaches. The average results, were very different, as well as GAs behavior,

which shows the importance of the formulation to achieve better results, with the 3<sup>rd</sup> to be chosen.

In general, GAs have provided quality solutions, given the small difference, between GAs solutions and the ones achieved with Simplex method, even for each budget constraint scenario.

The statistical analyzes of its convergence behavior, has shown that GAs have demonstrated some consistency on the final achieved results, given the negligible standard deviation reached, as well as on convergence characteristics, demonstrating therefore high convergence on early iterations.

The high robustness of GAs was also demonstrated, even for mutation rate, or

even for the population size, by previously tuning its parameters (mutation rate and population size).

At the end, the approach has provided an example of an efficient solution, given the case study presented here.

Although the best results, was achieved with Simplex, GAs allows diversity and quality within obtained solutions

The model can also be extended into other problem dimensions or energy services.

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