Chapter 6 Optimizing the control of a Peltier cell using genetic algorithms

Capítulo 6 Optimización del control de una célula Peltier mediante algoritmos genéticos

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Abstract

The Seebeck and Thompson effects explain thermal phenomena present in some materials when a certain electric current circulates in them. An application of these is found in some portable refrigeration units that use a semiconductor device called a thermoelectric cell or Peltier cell, which, according to specialized literature, is controlled by means of intelligent or classical control techniques, where a typical exponent of the latter is the PID controller, whose parameters are calculated using the Nichols criterion. An alternative for obtaining the proportional, integral and derivative constants is through the application of evolutionary algorithms which calculate these parameters to reduce the cooling time to a Desired temperature for this case in which the use of genetic algorithms is documented is 20 degrees.

Genetic algorithm, Thermoelectric cell, Peltier

Resumen

Los efectos Seebeck y Thompson explican los fenómenos térmicos presentes en algunos materiales cuando una determinada corriente eléctrica circula en ellos. Una aplicación de estos se encuentra en algunas unidades de refrigeración portátiles que utilizan un dispositivo semiconductor llamado celda termoeléctrica o celda Peltier, el cual, según la literatura especializada, es controlado por medio de técnicas de control inteligente o clásicas, donde un exponente típico de estas últimas es el controlador PID, cuyos parámetros se calculan utilizando el criterio de Nichols. Una alternativa para la obtención de las constantes proporcionales, integrales y derivadas es mediante la aplicación de algoritmos evolutivos los cuales calculan estos parámetros para reducir el tiempo de enfriamiento a una temperatura deseada para este caso en el que se documenta el uso de algoritmos genéticos es de 20 grados.

Algoritmo genético, célula termoeléctrica, Peltier

1. Introduction

Optimization is defined as the maximization or minimization of a process or function, it can be performed mathematically or numerically. Algorithms are used whose specific characteristics allow a certain type of problem to be solved; The function can range from a simple expression that includes and relates decision variables, to an equation that quantifies the behavior of a mathematical, probabilistic, or deterministic model. During the optimization process, the constraints or limitations associated with the function are taken into account, which are mathematical expressions that incorporate the particularities of the problem being solved.

One way to perform optimizations is through evolutionary algorithms, which were introduced by John Holland in the 1960s, suggesting the principles of this technique. Evolutionary algorithms include genetic, particle swarm, cultural, memetic, to name a few. The structure of an evolutionary algorithm is composed of a function that allows measuring the breadth of possible solutions for the resolution of the problem, to structure an evolutionary algorithm the following elements are required:

1. Generate a random population of N individuals.
2. Evaluate individuals in the population according to fitness function or target function.
3. Repeat for generations iterations:

– Apply the selection operator to choose N individuals from the population
– Apply the genetic operators to those N individuals to generate the offspring
– Evaluate new individuals according to fitness function or target function
– Replace the worst individuals in population with newly created individuals

Genetic algorithms are computationally modeled by simulating natural selection and interbreeding of species and thus prevail over time, evolving into better solutions. In the research carried out by (Reynolds, R. G., 1994) are based on the theories of some sociologists and archaeologists who have tried to model cultural evolution, these researchers indicate that evolution can be seen as a process of inheritance at two levels which are the micro evolutionary level which is the one that is inherited from the parents to their descendants and the macro evolutionary level which is the knowledge acquired by the individual through the generations (Reynolds, R. G., 1999).

Thermoelectric cooling is theoretically supported by some effects studied in physics such as those mentioned next to the thermoelectric cell or Peltier cell which is a semiconductor device based on the effects of Peltier, Thompson, Seebeck (Deng, M., Inoue, A., & Tahara, Y., 2008).

Peltier, which explains the generation or absorption of heat that occurs when an electric current circulates through two conductors of different material, then one of its faces generates heat and the other cools.

This technique is applied to a Peltier cell which will reduce its cooling time, depending on the values calculated by the genetic algorithms. $[\mathrm{k_p} \quad \mathrm{k_i} \quad \mathrm{k_d}]^{\mathrm{T}}$

Optimization is defined as the maximization or minimization of a process or that it can be performed mathematically or numerically. In the second option, algorithms whose specific characteristics allow solving a certain type of problem are used, since the function can vary from a simple expression that includes and relates the decision variables, to an equation that quantifies the behavior of a mathematical, probabilistic or deterministic model of a certain real system.

During the optimization process, the constraints or limitations associated with the function are taken into account, which are mathematical expressions that incorporate the particularities of the problem being solved or the system being simulated.

The concept of optimization can be reflected in equation (1)

$$\min(\max) f(x), x = [x_1, x_2, \dots x_n]^T \in \mathbb{R}^n \tag{1}$$

Constraints in a problem are usually expressed as

$$g_j(x) \leq 0, \qquad j = 1,2,\dots,m \qquad\qquad h_j(x) = 0, \qquad j = 1,2,\dots,r$$

Where y are scalar functions of the vector x. The components of are called variables, it is the objective function, and they are functions that describe the conditions of iniquity and equality respectively. The optimal vector that solves the expression (equation 1) is denoted by with the corresponding optimization value . Possible ways to solve the general problem described in (equation 1) are as follows. $f(x), g_j(x) h_j(x) x = [x_1, x_2, \dots x_n]^T f(x) g_j(x) h_j(x) x x^* f(x^*)$

Analytically emulating it and physically measuring the variables of interest, solving it through computational techniques, such as evolutionary algorithms, evolutionary algorithms had their origin in 1960 introduced by John Holland who in 1975 intuited the possibility of incorporating the semantics of natural evolution into optimization processes, thus suggesting the principles of this technique. which are well described in several texts that define them as a branch of artificial intelligence, based on stochastic processes (Jan A. Snyman, 2005).

Table 1 Parallelism between biological terms and evolutionary algorithms.

Population	A set of individuals or chromosomes. It is equivalent to a random sample of the solution space or a set of alternative solutions.
Chromosome	A chromosome is a carrier of the genetic information that each of your genes transmits. A possible solution.
Gene	Each of the traits or characteristics that make up the chromosome. They are also called parameters or aspects. Each gene equals a variable of the problem.
Genotype	In biology it is called the total genetic "package" in its internal form. In GA terminology it will be the genetic information of the entire chromosome in encoded form.
Phenotype	In genetics, the genetic package is called the way it interacts with the external environment. In artificial GAs it would be the aspects of the chromosome decoded.
Locus	It is the position of a gene, the chromosome
Allele	It is the value associated with a gene

Source: Authors' Own Creation

Evolutionary algorithms (AE) are a series of heuristics that have well-defined steps with application in optimization, they have 3 main characteristics which are mentioned below:

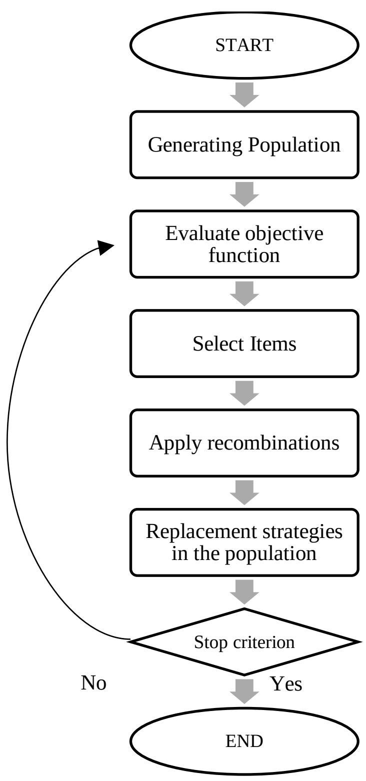
Population-based. An evolutionary algorithm maintains a set of solutions, called a population.

Fitness-oriented. Every solution in a population is called an individual, has a representation called a code, and the performance evaluation is called fitness.

Motor variation. Individuals in a population who undergo a series of operations in order to introduce variations in their code.

Broadly speaking, an algorithm that is described as simple evolutionary has the following structure (Figure 1)

Figure 1 Simple Evolutionary Algorithm



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The initial population is randomly generated from individuals with a normal probability distribution, which are then encoded in some specified form. The population of individuals is evaluated in the representative function of the problem to be optimized, and then some are chosen according to criteria, which depend on the heuristics.

The result of the selection processes is subjected to a series of operations that recombine the individuals who then replace, under heuristic criteria, the original population.

An evolutionary algorithm ends when the stop condition is met, i.e. after a certain number of iterations or when individuals converge at a certain point

Genetic Algorithm

GAs are search methods based on the laws of natural selection and species genetics described by Charles Darwin and Gregory Mendel, combining the survival and reproduction of individuals best adapted to the conditions with recombination operators called mutation and crossover (Yang, X. S., 2010).

One of the main applications of GA's is problem solving and optimization problems where they have proven to be efficient and reliable, although before applying them to a problem, some characteristics listed below must be taken into account:

The search space must be delimited within a range.

It must be possible to define a fitness function (or objective function) which will be able to indicate whether the answer is good or bad

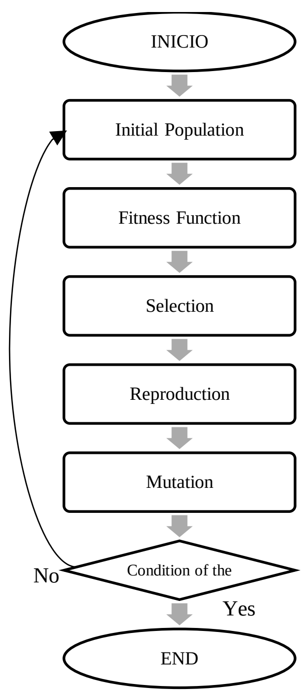
Coding should be done in a way that is easy to implement on the computer.

Structuring a simple genetic algorithm requires the following elements:

- Define a Skill Role or Target Role
- Generate a random population of N individuals
- Coding the population
- Evaluate the target function with the population, thus initiating the first generation
- Selection of solutions to be reproduced
- Population Crossing
- Mutation of elements resulting from crossbreeding
- Replacement of elements of the 1st generation population with the best elements of mutation and crossbreeding
- Stop if the stop criterion is met or re-evaluate the target function.

These replacement strategies for the population of a genetic algorithm are shown in Figure 2.

Figure 2 Replacement strategies in the population



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Target Function

The fitness function is the objective function of the optimization problem, the AG only maximizes, although for minimization only the reciprocal of the maximizing function is used.

The most common of the encodings is by binary strings, although real numbers and letters are also used. Binary strings are very popular due to the fact that they were originally proposed by John Holland and their simple implementation.

Codification

In a genetic algorithm, the space where the possible solutions to the problem to be solved are to be found must first be determined. It is necessary to encode the domain of the problem in some way to generate structures that can be handled by the genetic algorithm.

Since it was defined what type of coding will be handled in the problem and it is known as going from an element to its code and vice versa, it is necessary to set a starting point, genetic algorithms manipulate populations in successive generations, the algorithm will have an initial population and from this it will generate new populations where the parents will disappear leaving the place to their descendants and thus looking for one of the best options or until some termination condition of the algorithm is met.

Evaluation

It is necessary to establish criteria to decide which of the possible solutions of a population are better than the others, to determine which individuals are good solution proposals it is necessary to qualify them in some way and each individual will have a rating depending on the degree of adaptation or fitness. This real or negative rating will be greater the better the individual's solution.

Selection

Selection algorithms are responsible for choosing which individuals will be able to reproduce and which will not.

Since the individuals of a generation were qualified, the algorithm is given the task of selecting the most qualified individuals for a greater possibility of reproduction, thus increasing the possibility of having a better solution in a given generation, only those who meet a rating higher than a parameter established by the objective function are selected.

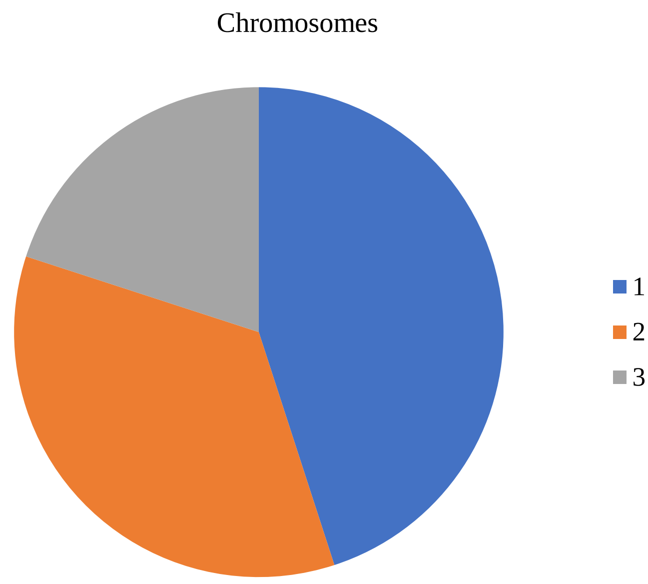
It is not convenient to have a strict selection strategy so that the population improves quickly and the algorithm converges, this is not good because it could happen that the population accumulates quickly around some individual who is good compared to the rest of the population considered but may not be the best possible, this is called premature convergence, The algorithm must not only select from the best it has found, it must explore the entire population at this is the function of crossover and mutation operators.

A common option is to select the first individual resulting from the crossing by some selection method as mentioned below:

Roulette Selection

It consists of creating a roulette wheel in which each chromosome has a fraction assignment depending on its aptitude, each of the individuals in the population is set a share equal to their roulette setting, the best individuals will be assigned a larger part of the roulette wheel compared to the less fit, Generally, the largest portions are at the beginning of the roulette wheel and to select an individual only a random number of an interval (0..1) is generated, as shown in Figure 3.

Figure 3 Gene Roulette



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Tournament Selection

It consists of making direct comparisons between individuals, there are two ways of making selection by deterministic and probabilistic tournament

Deterministic selection consists of selecting a number of individuals and then selecting the fittest among those selected to be part of the next generation

Probabilistic selection differs because the selection is not always the best, but a random number is generated within the interval (0..1) and, as the case may be, the highest or the opposite is selected.

Steady-state selection

The offspring of individuals selected in each generation revert to the pre-existing genetic population, replacing some of the less fit members of the previous generation. Preserving individuals between generations.

Selection by scale

When the average fitness of the population increases, selective pressure increases and the fitness function becomes more discriminatory, this method can be useful when all individuals have a high fitness and only minimal difference.

Hierarchical Selection

Multiple rounds of selection go through each generation. The first assessments are faster and less discriminatory while those that reach the higher generations are assessed more rigorously, the disadvantage of this selection method is that it reduces the total calculation time by making use of a faster and less selective assessment to eliminate the majority of unpromising or unpromising individuals subjected to a more rigorous and computationally expensive aptitude assessment highest only those who pass the initial test.

Elitist selection

Sometimes it can happen that after the crossing and mutation, the chromosome with the best adaptation is lost. This method of selection copies the best chromosome to some of the best chromosomes within the new population. The rest of the selection is done in the same way mentioned above. Elitism can improve the functioning of genetic algorithms by preventing the loss of the best solution.

A variation of elitism is that the best chromosome is only copied to the next generation if a better chromosome has not been generated after a mutation. (Garcia F. 2012)

Reproduction/crossover

The utility of the cross is a search operator that combines the genotypes of two solutions in order to obtain a new solution, the usefulness of this is based on the fact that the new solutions can become better than the parents if the best characteristics of both parents are combined.

Once individuals are selected, they recombine to produce offspring that will be inserted into the next generation. The goal of crossbreeding is to get offspring to improve their parents' aptitude.

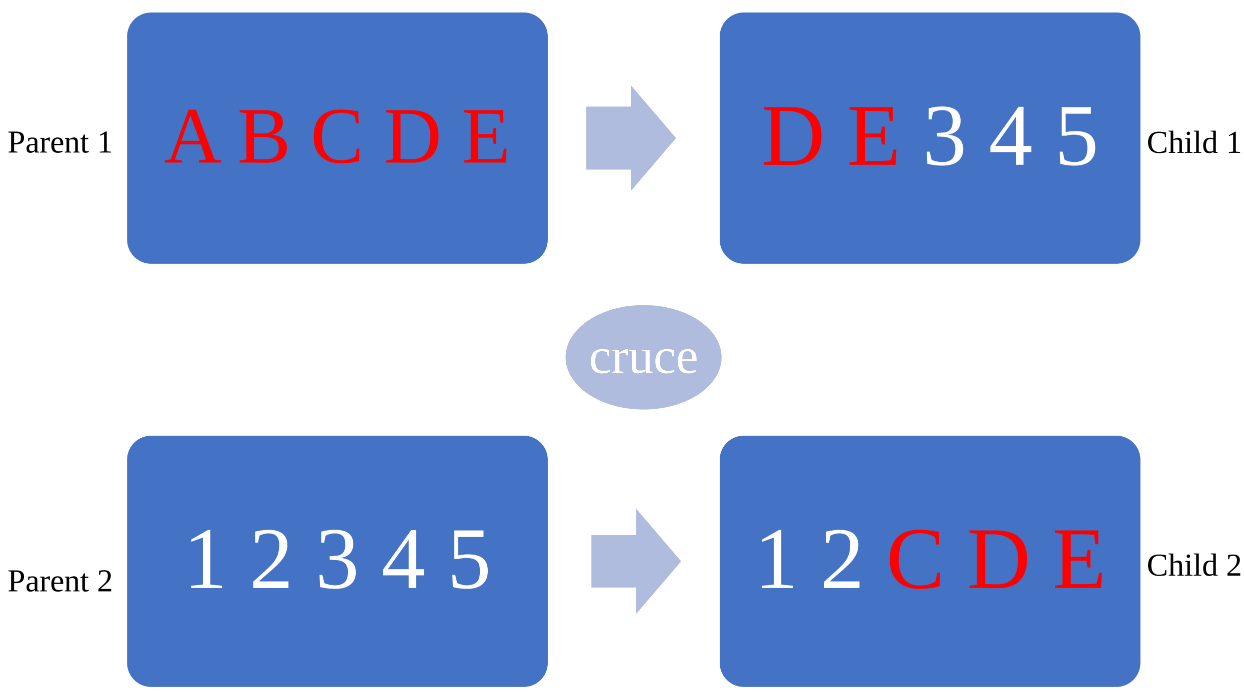
There are several crossover algorithms, however, the most commonly used ones are mentioned below:

1-point junction
2-point junction
Uniform Crossing

1-point junction

Since the individuals were selected to cross, they cut the chromosomes at a randomly selected point so that the segments, the head and tail, are generated, the heads and tails are exchanged between the selected individuals to generate the new dependency or children, in this way the two inherit genetic information from the parents. In the literature we can find reference to this type of cross with the name of SPX (Single Point Crossover)

Figure 4 1-point junction



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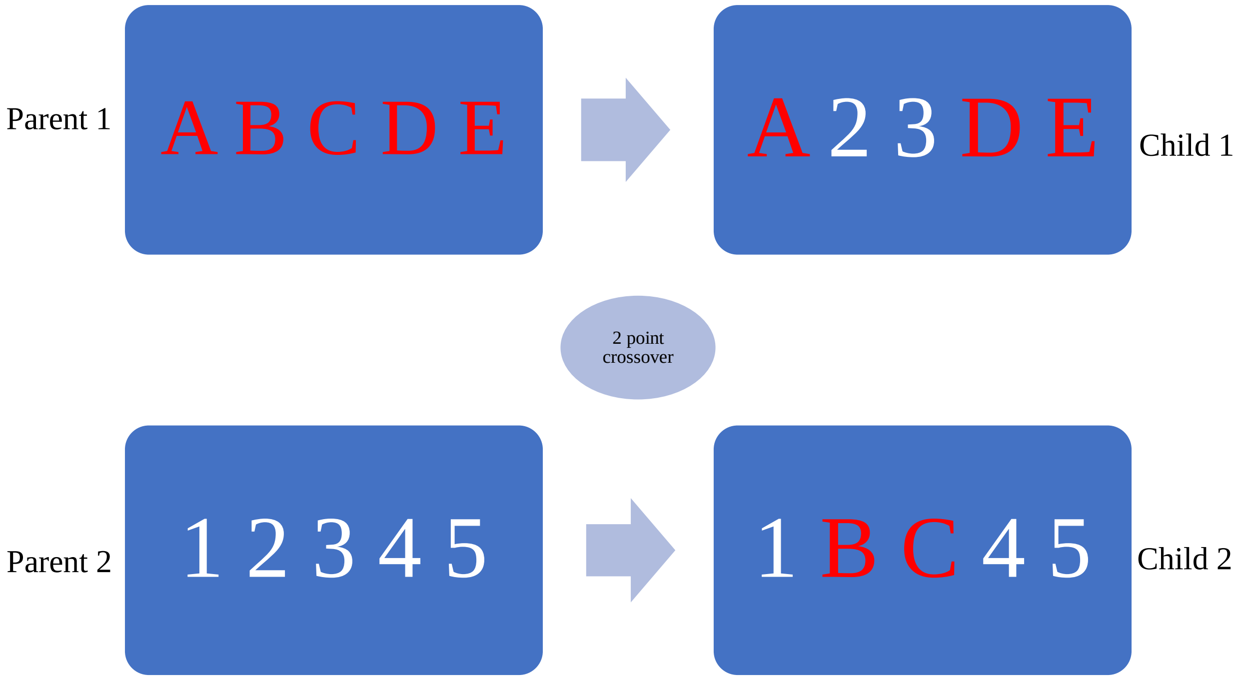
2-point junction

It is a generalization of the 1-point crossover only that instead of making a single cut in the chromosomes two cuts are made, it must be taken into account that none of these cut-off points coincide with the end of the chromosomes so that it is guaranteed that three segments originate, to generate the offspring or children the central segment of one of the parents and the lateral segments of the other parent are selected.

Figure 5 2-Point Crossing



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Uniform Crossing

This technique is completely different from the previous ones, each of the genes of the offspring is obtained from either of the parents randomly, although it has several ways of implementation, the technique involves the generation of a mask with binary values. If in one of the positions of the mask there is a 1, the gene that is in this position in one of the offspring is copied from the first parent, while if there is a zero the gene is copied from the second parent, for the generation of the second offspring the parents are exchanged or the interpretation of the ones and zeros of the crossing mask

Figure 6 Uniform Crossing

Source: Authors' Own Creation

Mutation

The mutation is thought of as a basic operator that provides a small element of randomness in the environment of individuals in the population.

Mutation consists of the modification of certain genes randomly taking into account the probability of the established mutation. The mutation depends on coding and reproduction, if the mutation is abused, it can fall into the use of the GA as a random search, a very low percentage can cause premature convergence or that some areas of space are left unexplored.

The mutation is used in a low percentage, between 1% and 5% in binary or finite coding, and up to 10% or 15% in real coding, because there is a risk that it operates on the only copy of the individual, which is the best solution, and can ruin it.

The probability of mutation is very low, usually less than 1%, because individuals usually have a lower adjustment after the mutation. However, mutations are performed to ensure that no point in the search space has a zero chance of being examined.

For the proper functioning of a GA, it is necessary to have a method that indicates whether or not the individuals in the population represent the best solutions to the problem

2.9.1 Gene inversion: Genes are randomly selected and their value is reversed. It is used in representations of bits, changing 0 by 1 or vice versa.

$$11001001 \Rightarrow 10001001$$

2.9.2 Change of order: Two genes are randomly selected and their positions are swapped. It is used in representations based on permutations.

$$(1\ 2\ 3\ 4\ 5\ 6\ 8\ 9\ 7) \Rightarrow (1\ 8\ 3\ 4\ 5\ 6\ 2\ 9\ 7)$$

2.9.3 Gene modification: Small modifications are made to genes. For example, in a coding based on real numbers, sums of very small positive or negative numbers are made (De Jong, K. A., 1975 & GALIPIENSO, A., ISABEL, M., Cazorla Quevedo, M. A., Colomina Pardo, O., Escolano Ruiz, F., & LOZANO ORTEGA, M. A., 2003 & Syswerda, G., 1991).

$$(1.29\ 5.68\ 2.86\ 4.11\ 5.55) \Rightarrow (1.29\ 5.68\ 2.73\ 4.22\ 5.55)$$

Control System

It is the set of several components that act in conjunction with the common objective for the proposed objective and that can regulate its behavior or that of other systems to minimize error in order to achieve the predetermined operation.

Elements of a control system:

Variable to be controlled. Generally known as the output signal, it forms the signal that we want certain values to acquire.

Screen or system. The plant forms the set of elements that perform a certain function, it is the one that is in charge of controlling or regulating.

Sensor. It is the element that allows the value of the variable to be controlled in a given time to be taken.

– Reference signal. It will be the control objective, the signal setpoint or value that you want the output signal to acquire.

– Actuator: this is the element that will act on the signal of the system, converting it into another signal that can be applied or another process.

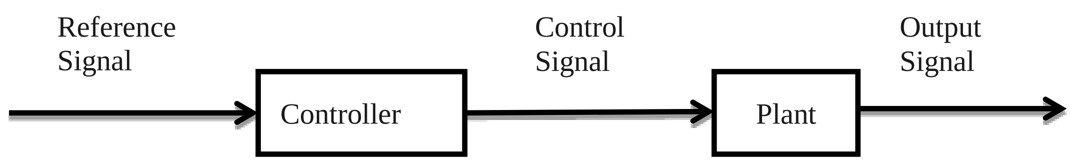
– Controller. O regulator is the element that drives the actuator depending on the control objective to process the difference between the input and output signals to generate a correct signal for the plant.

Open Loop Control System

An open-loop control system is one in which the output signal has no influence on the action of the control, in this way the controller does not take into account the output signal or compare it with the reference signal to decide the performance of the system, these work reasonably well as long as it has been studied perfectly and there are no alterations on the system.

Open-loop control (Figure 7) is mainly used when the relationship between input and output is known, as well as if there are no internal and external disturbances.

Figure 7 Open Loop Controller



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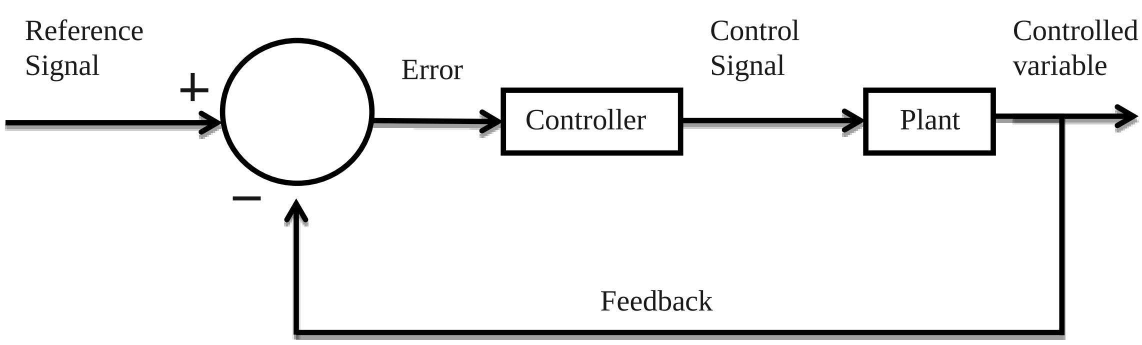
Closed-loop control systems

In the closed-loop control system, there is feedback from the output signal, in this type of system there is a comparison of the variable to be controlled with the reference variable, so that depending on this difference between the two, the controller modifies the control actuator on the plant actuator Figure 8 (Asdrúbal, V. 2004, Holton, G. J. 1996).

Figure 8 Closed-loop control



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Control PID

The PID (Proportional Integral Derivative) controller is a feedback controller that has the purpose of making the error that is in steady state between the output signal and the plant reference signal zero asymptotically in time, this is achieved using the integral action.

PID Controllers

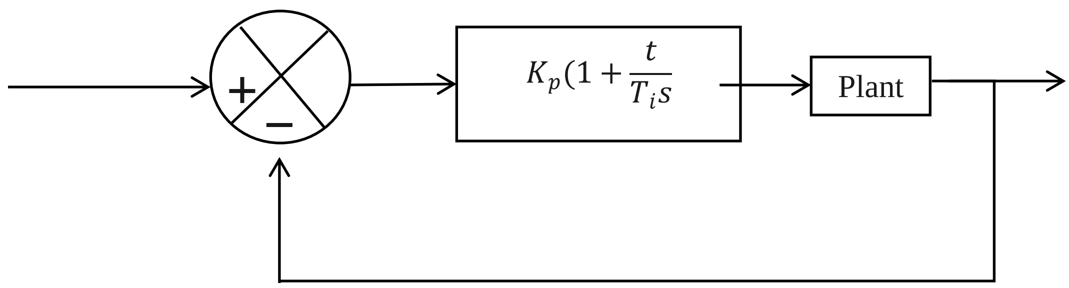
PID controllers make it possible to improve the responsiveness of a system, even if this response is not always optimal. The proposed tuning rules present a way to obtain the parameters of the PID controller, as long as you have a mathematical model of the system. A PID driver allows a system's response to have a null error.

Setting rules for PID controllers are convenient when the system model is known. By obtaining the parameters of a PID controller and observing the response of the controller and the system, it is possible to work on a system that allows the obtaining of these parameters autonomously and thus allow the PID controller to be self-adjusting (Ogata, K., 1997).

PID Driver Tuning Rules

If the mathematical model of the plant is obtained, it is possible to apply several design techniques to determine the control parameters so that the specifications of the transient and the steady state of the closed-loop system are met, on the contrary, if the plant is too complicated to not be able to obtain its mathematical model, an analytical method for the design of a PID controller is also not possible. In this case, experimental models are used for the tuning of PID controllers.

Figure 9 PID control of a plant



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In the process of selecting r the controller parameters that meet the behavior specifications are known as controller tuning. Ziegler and Nichols suggested rules for tuning PID controllers

Which means to give values to , and this is based on step responses K_P $T_i T_d$

Electrical phenomena associated with a thermoelectric cell

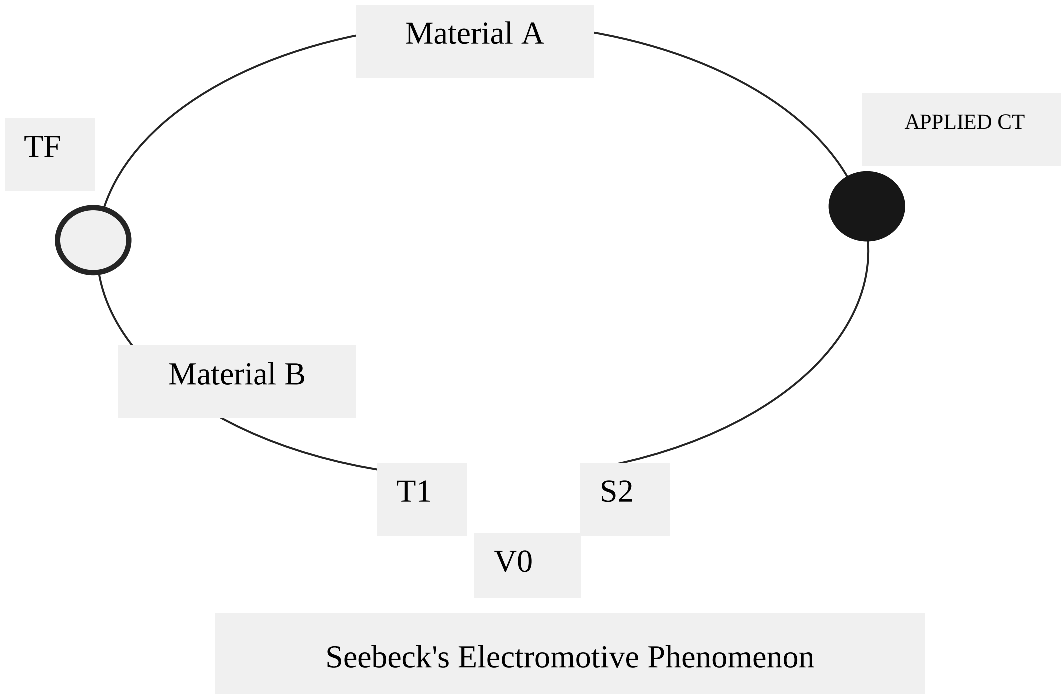
Thermoelectric effect

Thomas Seebeck, a German scientist, demonstrated in 1821 that if two different semiconductor materials were joined together, he deflated the needle of a compass by placing the welds between the two materials at different temperatures. In 1822 his experiments were published in the Proceedings of the Prussian Academy of Sciences under the title "Magnetic Polarization of Metals and Ores by Difference of Temperature", later Hans Chistian Oersted perceived that the difference of temperatures in the circuit induced a difference of electric potential and discovered that the circulation of a current through a conductor had similar effects on the needle of a compass (Hasdrubal, V., 2004 & Holton, G. J., & Brush, S. G., 1996).

Seebeck Effect

Thomas Johann Seebeck discovered that an electromotive phenomenon occurred in a circuit composed of two semiconductor materials when the junctions met at different temperatures, and that the materials responded differently to the difference in temperature creating a magnetic field, so he called the phenomenon the thermomagnetic effect, therefore, the electromotive phenomenon of the circuit was named Seebeck's fem figure 10.

Figure 10 Seebeck Effect



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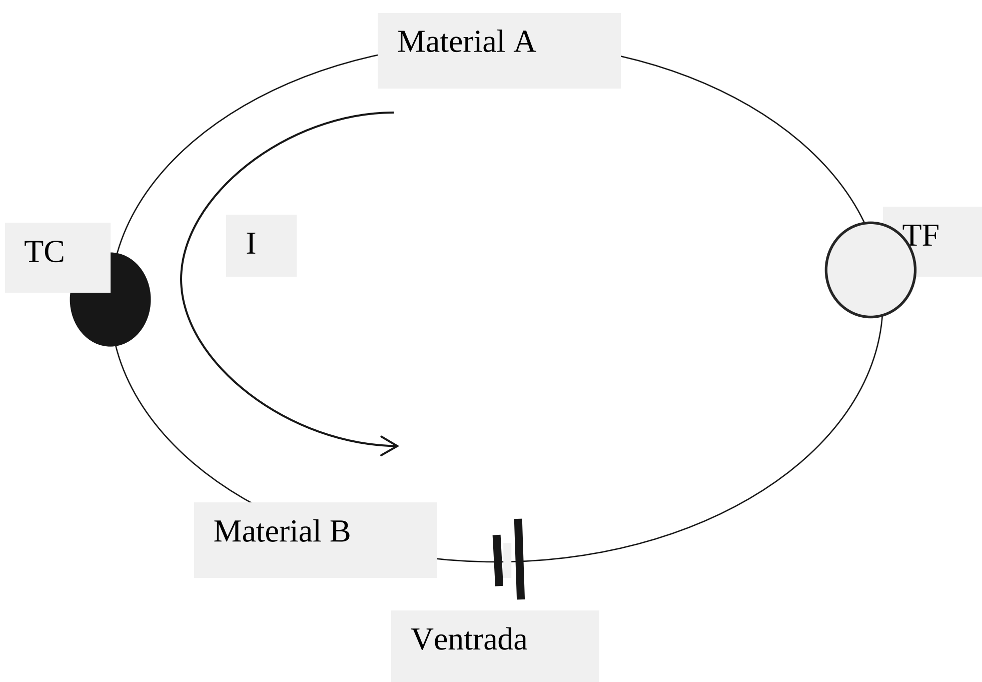
Peltier Effect

This phenomenon was discovered by Jean Charles Peltier, a French physicist, and is considered the inverse of the Seebeck effect; says that if an electric current passes through the junction of two semiconductor materials, a release or absorption of heat is generated at the junction, depending on the direction of the current flow Figure 9, i.e., one of the joints is heated while the other is cooled, The amount of heat absorbed or emitted at the junction is proportional to the electric current by the Peltier coefficient (Sanchez, J. A., 2013 & Areny, R. P., 2004).π

Figure 11 Peltier Effect (Sánchez, J. A., 2013)



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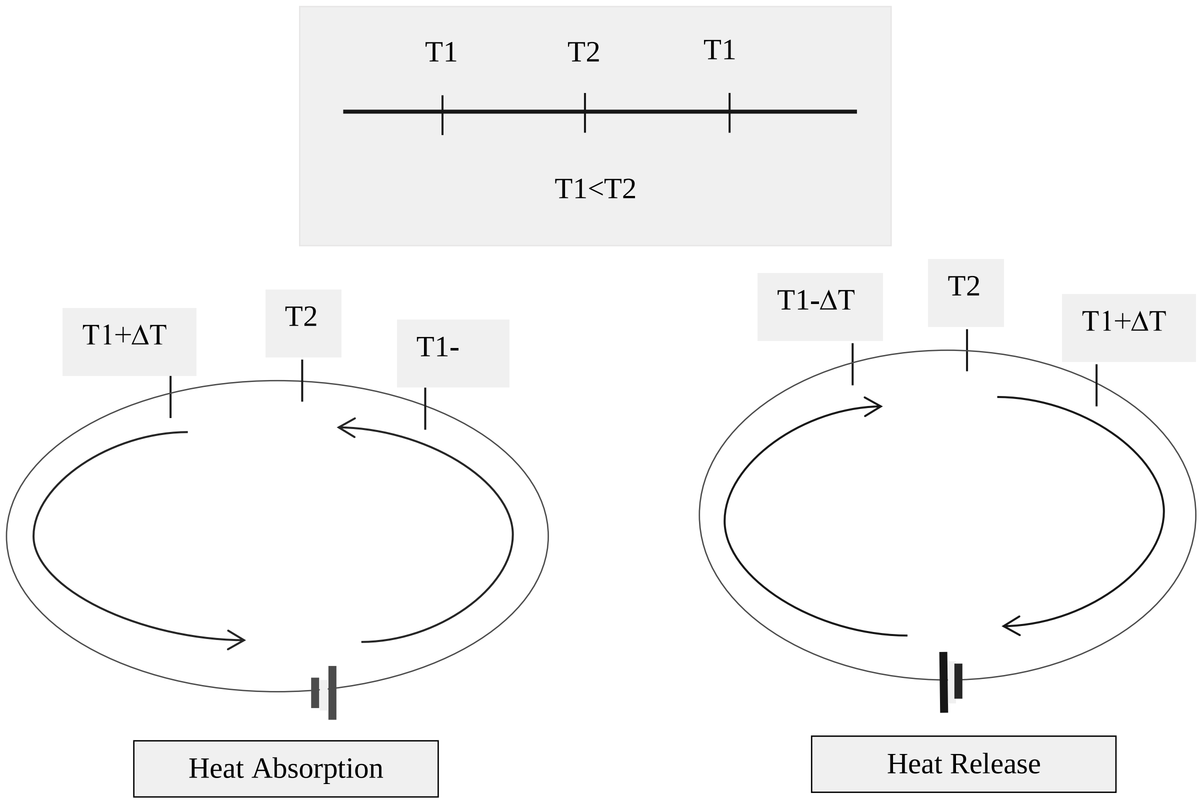
Thomson Effect

The Thomson effect is a thermoelectric effect and was discovered by William Thomson, and consists of the absorption or release of heat through a homogeneous metal, with a non-homogeneous temperature, through which a current circulates, that is, there is an absorption of heat whenever the current flows in the opposite direction of the heat and is released if the heat and the current flow in the same direction (Sánchez, J. A., 2013 & Areny, R. P., 2004).

Figure 12 Thomson Effect (Sanchez, J. A., 2013)



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Mathematics of a thermoelectric cell

A thermoelectric cell (TEC) is a semiconductor device with the ability to generate heat or cold depending on the magnitude and polarity of an electric power current, TECs have application in the field of micro-refrigeration and mobile refrigeration given their small size and easy location not depending on the position in which they are located. long operating life and fluorocarbon-free operation (Stoecker, W. F., & Chaddock, J. B., 1963).

The functioning of a ECT is represented by a mathematical expression described in equation 2 (Bywaters, R. P., 1969).

$$\tilde{T}_L(s) = G_1(s)\tilde{I}(s) + G_Q(s)\tilde{Q}_L(s) + G_a(s)\tilde{T}_a(s) \tag{2}$$

Where

$G_1(s)$, are represented by equations 3, 4, 5 respectively$G_Q(s), \tilde{Q}_L(s), G_a(s)$

$$G_I(s) = \frac{N(s)}{sD(s)} \tag{3}$$

$$G_Q(s) = \frac{E_H\, sinh(qL) + Akq\, cosh(qL)}{D(s)} \tag{4}$$

$$G_a(s) = \frac{AA_F\, hkq}{D(s)} \tag{5}$$

While , are characterized by equations 6, 7, 8, 9, 10 respectively.$N(s), D(s)\ p(s), q(s)\ \ E_H$

$$N(s) = \{Akq[\alpha_L \bar{T}_L \cosh(ql) - \alpha_H \bar{T}_H] + \alpha_L \bar{T}_L E_H \sinh(qL)\}s + \frac{Akq\beta}{C\gamma}[E_H(1 - \cosh(pL) - Akpsinh(pL)] \tag{6}$$

$$D(s) = AkqE_L \cosh(qL) + E_H E_L \sinh(qL) + AkqE_H \cosh(pL) + A^2k^2pqsinh(pL) \tag{7}$$

$$p(s) = \frac{\left(\frac{\tau\bar{I}}{A} + \sqrt{\frac{\tau^2\bar{I}^2}{A^2} + 4kC\gamma s}\right)}{2k} \tag{8}$$

$$q(s) = \frac{\left(\frac{\tau\bar{I}}{A} - \sqrt{\frac{\tau^2\bar{I}^2}{A^2} + 4kC\gamma s}\right)}{2k} \tag{9}$$

$$E_H(s) = (M_F C_F + M_H C_H)s + hA_F - (\tau + \alpha_H)\bar{I} \tag{10}$$

Finally, it is determined by equation 11 and assumes the value of equation 12 in $E_L \alpha_H$

$$E_H(s) = (M_L C_L + M_C C_C)s + (\tau + \alpha_H)\bar{I} \tag{11}$$

$$\alpha_{pn}(T) = \alpha_H + \frac{\tau}{\tilde{T}_H}\tilde{T}_H \tag{12}$$

Table 2 shows the nomenclature of the literals of the equations presented above

Table 2 Literals of the equations that describe the behavior of an ECT

Literal	Meaning
$\tilde{T}_L(s)$	Cooling Face Temperature
$I(s)$	Supply current
$\tilde{T}_a(s)$	room temperature
L	Length of thermoelectric elements
A	Total cross-sectional area of thermoelectric material
k	Thermoelectric conductivity of the P-N pair ()W m^{-1} K^{-1}
h	Convection Heat, Thermal Trigger Transfer Coefficient ° W m^{-2} K^{-1}
γ	Heat Density of Thermoelectric Material(kg m^3)
A_F	Total Heat Transfer Surface
M_F	Thermal Trigger Mass
C_F	Thermal Capacity of Thermal Trigger (kJ kg^{-1} K^{-1})
M_H	Hot Plate Mass Thermoelectric Module End
C_H	Heat Capacity of Thermoelectric Module Heating Plate (kJ kg^{-1} K^{-1})
τ	Thompson's coefficient (V K^{-1})
α_{pn}	Seebeck coefficient of thermoelectric material (V K^{-1})
$\bar{I}$	Average Supply Current
M_L	Mass Thermal Trigger Cooling Charge
C_L	Heat Exchanger Charge Cooling Heat Capacity
M_C	Cooling Mass Plate of Thermoelectric Module
C_C	Thermoelectric Module Cooling Plate Heat Capacity (kJ kg^{-1} K^{-1})
s	Complex Variable

Source: Authors' Own Creation

Development

The original population proposed as a possible solution is randomly generated and consists of a total of 40 individuals with a uniform distribution, encoding the chromosomes with real numbers, in such a way that the format of the chromosome has the following shape $cromosoma = [k_p, k_i, k_d]^T$

The percentage of individuals to cross is 60%

This indicates that only 24 of the 40 individuals will be stochastically crossed by the roulette method where the entire population has the same probability of being within the possible solution to the problem, in none of the simulations will the same result come out since the algorithm always looks for one of the best solutions to the problem and the results vary according to the crossed individuals.

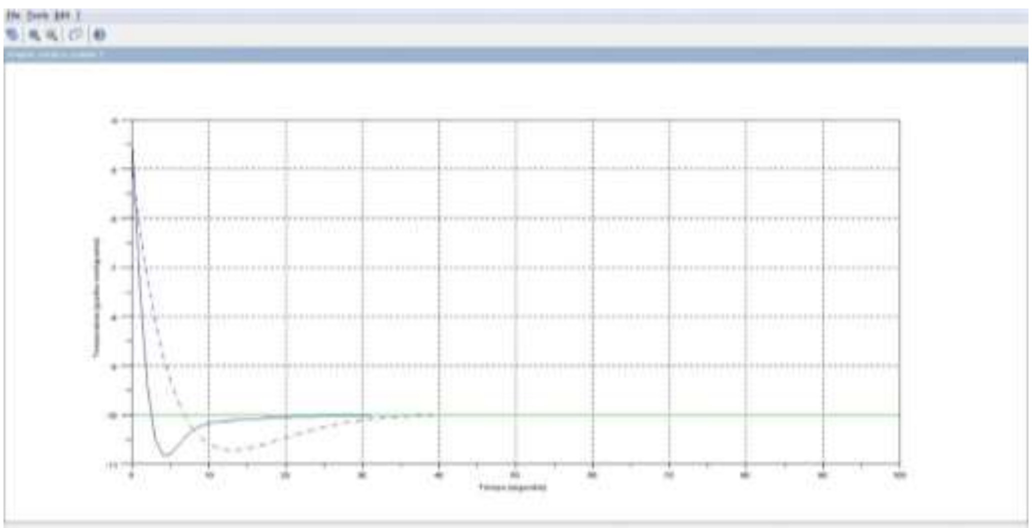
By varying the variable α from 0 to .3, the results change in terms of the time in which the Tec stabilizes, the over-impulse and the values of $[k_p \quad k_i \quad k_d]^T$

Table 3 Test α = 0

α	0
Cross-population	24
Uncrossed population	16
Generation in which it stabilizes	29
Time of Establishment of the Tec	38.9
RMS Value	0.4993431
About Impulse	-10.83
Values $[k_p \quad k_i \quad k_d]^T$	$-3.3780554 \quad -2.4647874 \quad -1.9349458$

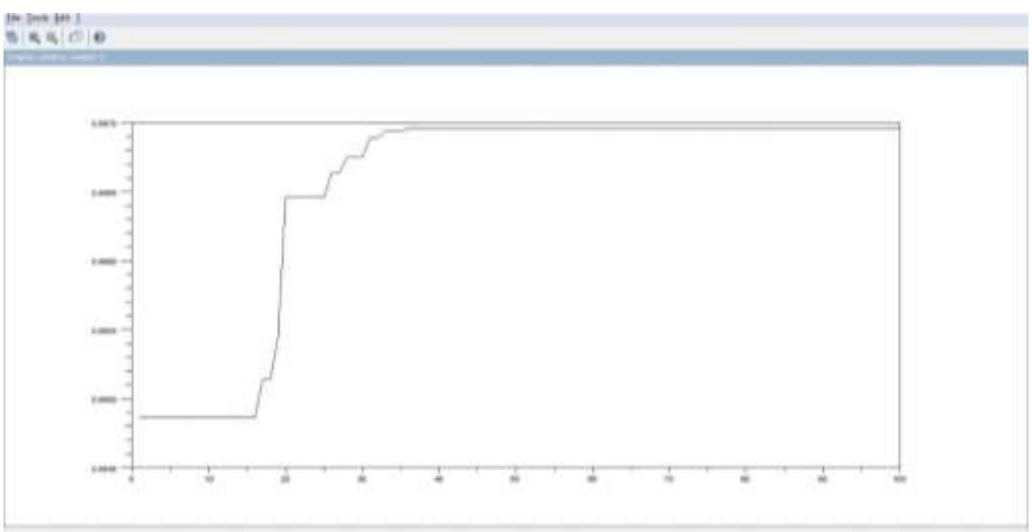
Source: Authors' Own Creation

Figure 13 ECT Establishment Time



Source: Authors' Own Creation

Figure 14 Objective function with a value α= 0'



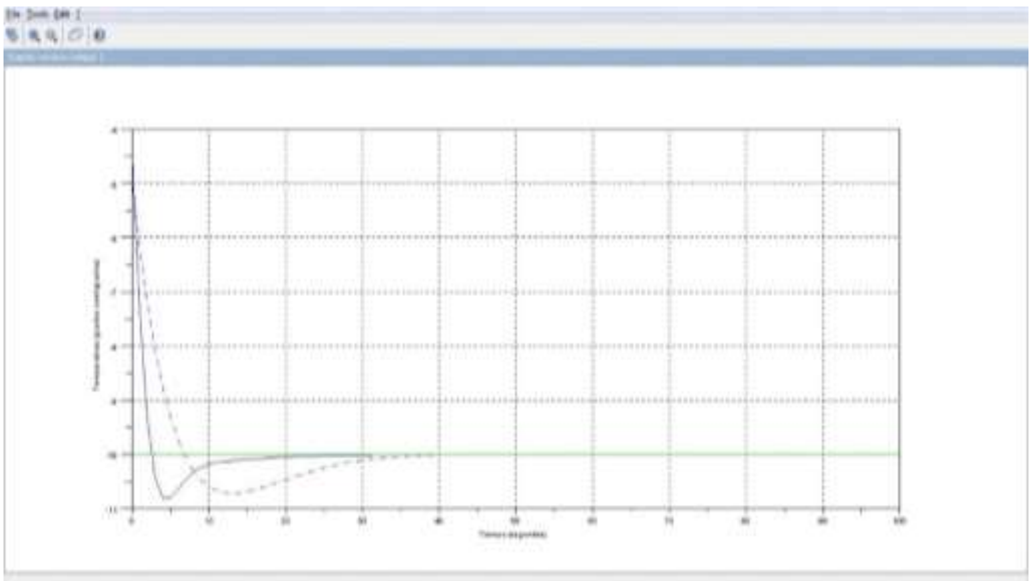
Source: Authors' Own Creation

Table 4 Test α = .1

α	.1
Cross-population	24
Uncrossed population	16
Generation in which it stabilizes	27
Time of Establishment of the Tec	39
RMS Value	0.6648669
About Impulse	-10.8
Values $[k_p \quad k_i \quad k_d]^T$	$-3.3746832 \quad -2.4124418 \quad -1.9899383$

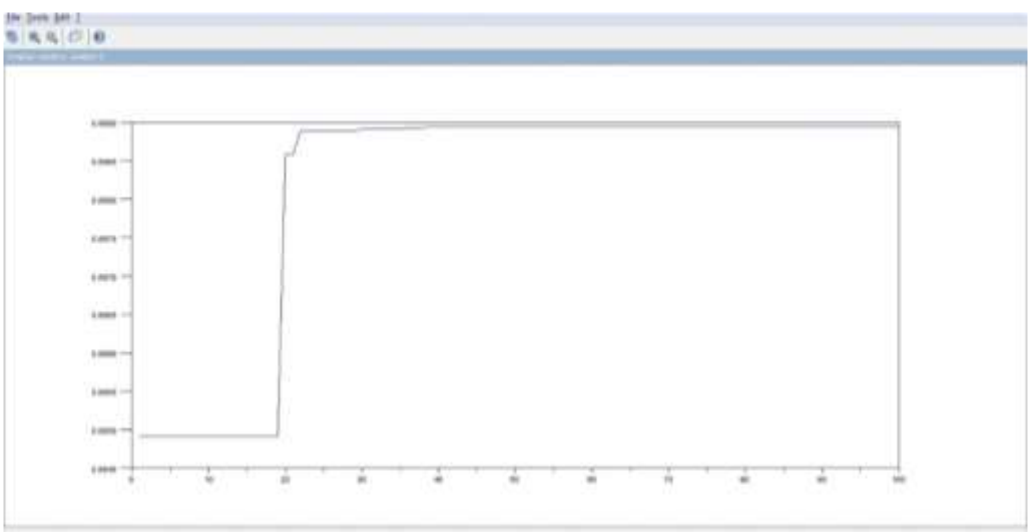
Source: Authors' own creation

Figure 15 ECT Establishment Time α = .1



Source: Authors' Own Creation

Figure 16 Objective function 'with a value α= .1'



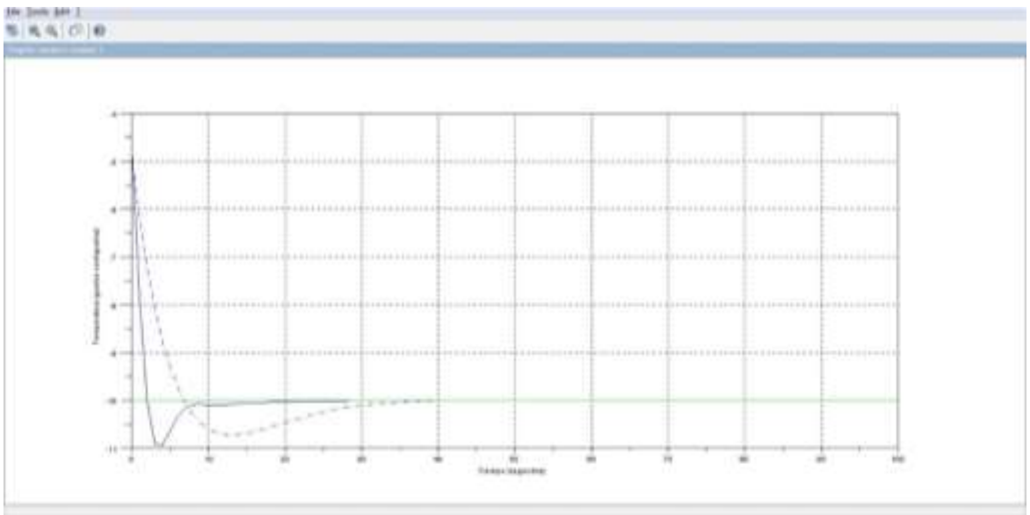
Source: Authors' Own Creation

Table 5 Test α = .2

α	.2
Cross-population	24
Uncrossed population	16
Generation in which it stabilizes	28
Time of Establishment of the Tec	38.5
RMS Value	0.6876463
About Impulse	-10.93
Values $[\mathbf{k_p} \quad \mathbf{k_i} \quad \mathbf{k_d}]^T$	$-3.7085573 \quad -3.5835899 \quad -2.1844144$

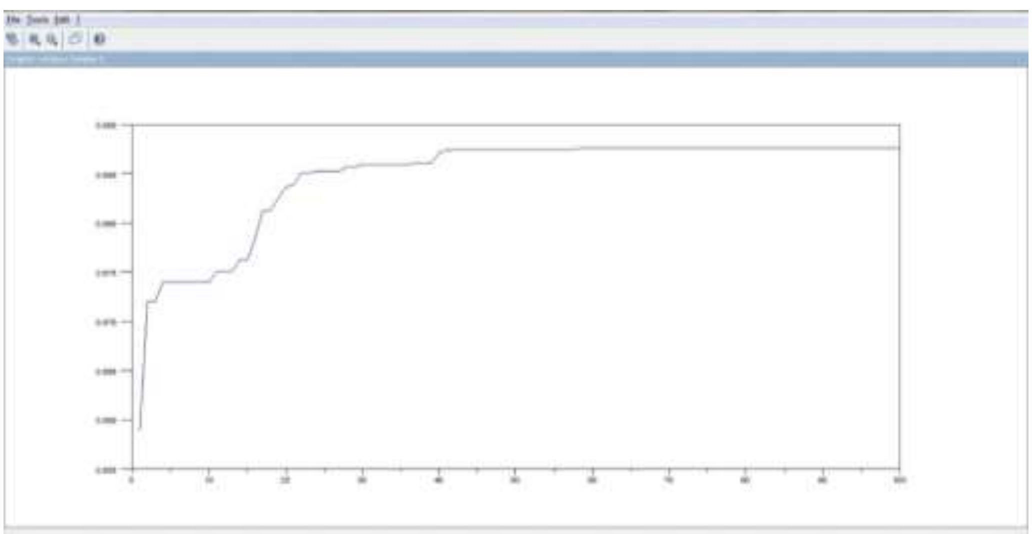
Source: Authors' Own Creation

Figure 17 ECT Establishment Time α = .2



Source: Authors' Own Creation

Figure 18 Objective function 'with a value α= .2



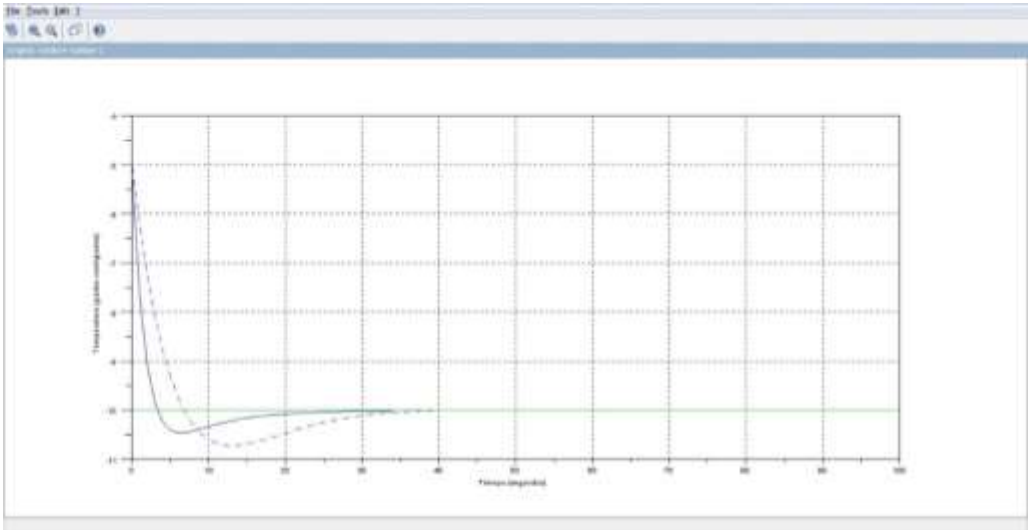
Source: Authors' Own Creation

Table 6 Test α = .3

α	.3
Cross-population	24
Uncrossed population	16
Generation in which it stabilizes	27
Time of Establishment of the Tec	44
RMS Value	0.6939176
About Impulse	-10.45
Values $[\mathbf{k_p} \quad \mathbf{k_i} \quad \mathbf{k_d}]^T$	$-4.5094422 \quad -1.8841904 \quad -2.5851778$

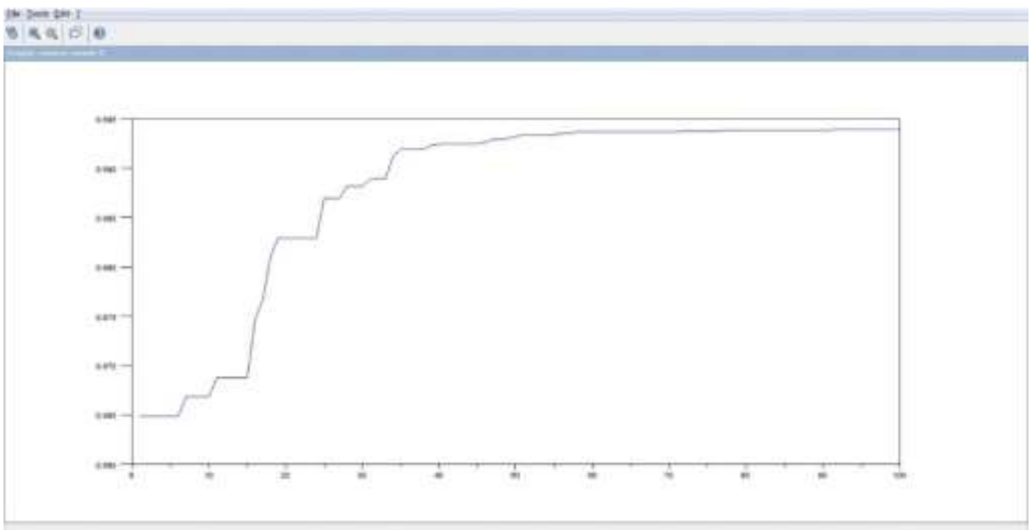
Source: Authors' Own Creation

Figure 19 ECT Establishment Time α = .3



Source: Authors' Own Creation

Figure 20 Objective function with a value α= .3



Source: Authors' Own Creation

Table 7 Probability of crossing

Percentage of individuals to cross	10%	20%	30%	40%
Population without crossing	36	32	28	24
Generation in which it stabilizes	22	15	26	23
Time of Establishment of the Tec.	27	31	27	33
RMS Value	15.218525	13.803818	13.172133	17.04658
About Impulse	-11.6	-10.5	-10.8	-10.7
Values K_P K_i K_d	 -2.0404459 -3.013042 -1.3450577	 -4.1833099 -2.0256428 -1.547587	 -4.4147529 -3.5777777 -0.5881394	 -3.0476789 -1.5794054 -1.1260359

Source: Authors' Own Creation

Table 8 Crossover Probability

Percentage of individuals to cross	50%	60%	70%	80%
Population without crossing	20	16	12	8
Generation in which it stabilizes	21	27	26	39
Time of Establishment of the Tec.	33	30	33	30
RMS Value	15.78307	14.625429	14.928188	15.557047
About Impulse	-10.7	-10.7	-10.6	-10.9
Values K_P K_i K_d	 -3.3973984 -1.9188595 -0.9764242	 -3.5448038 -2.1360178 -1.3928514	 -3.8585455 -1.8573233 -1.1983353	 -2.980842 -2.2484185 -1.0834272

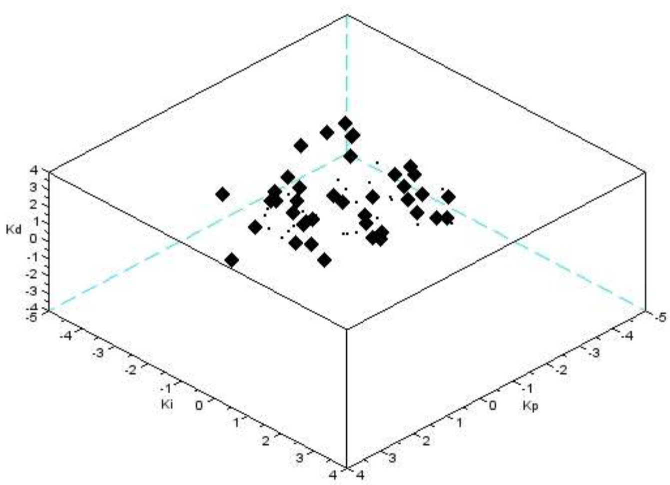
Source: Authors' Own Creation

Results

Algorithm convergence

Stochastic traversal through the population each dark rhombus represents the best individuals of during each generation, they explore the entire search space to find the best individual, each of the dots represents an individual or chromosome, the graph represents the search space.

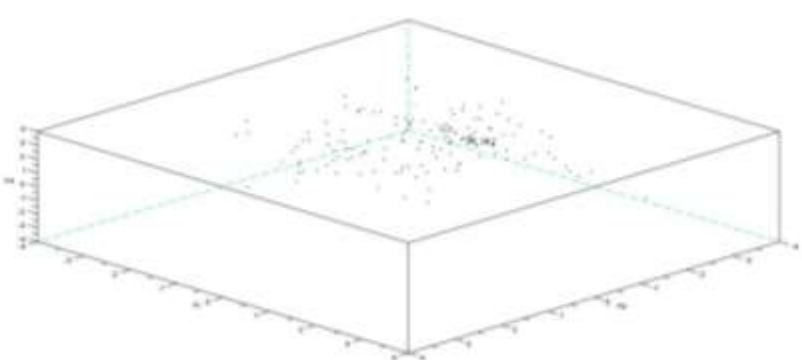
Figure 21 Beginning of the route through the town



Source: Authors' Own Creation

The randomly generated solutions with a uniform distribution, where the blue rhombus represents the optimal solution found when making the journey through the population.k_p, k_i, k_d

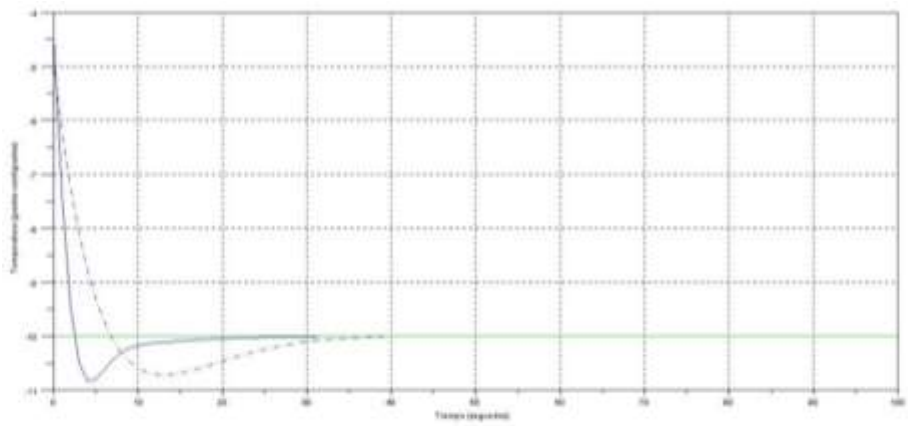
Figure 22 Solutions kp,ki,kd



Source: Authors' Own Creation

The following figure shows the solid blue line as the response obtained by means of the PID adjusted with genetic algorithms, the dotted blue line shows the Nichols fit, and the green line represents the reference.

Figure 23 Response obtained



Source: Authors' Own Creation

In the present work, the reduction of mean square error of a PID applied to a peltier cell decreased with the implementation of a simple genetic algorithm, the proposal presented decreases the mean square error by at least 20%.

In addition to the above, it was observed that the real crossover -α is suitable for this type of optimization as long as α does not exceed the value of 0.3, since it generates non-viable solutions, (values of) that caused an unstable operation in the cell.$BLXk_pk_ik_d$

Conclusions

The reduction of mean square error of a PID applied to a Peltier cell decreased with the implementation of a simple genetic algorithm, the proposal presented decreases the mean square error by at least 20%. As shown in Figure 21, where the solid blue line represents the response of the cell and the dotted blue line represents the Nichols criterion.

In addition to the above, it was observed that the real crossover -α is suitable for this type of optimization as long as α does not exceed the value of 0.3, since it generates non-viable solutions, (values of) that caused an unstable operation in the cell$BLXk_pk_ik_d$

Future Jobs

It is proposed to use a multiobjective genetic algorithm that considers various properties of a PID controller, it is also necessary to implement the use of constraints that control the convergence of the algorithm and the valid values.

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