Evolutionary Split Range Controller for a Refrigeration System

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Abstract: Every year more than 80 million units of domestic refrigerators are produced worldwide. Hundreds of millions are used continuously so the impact on electricity is significant. Typical initiatives in energy efficiency for refrigeration systems are aimed at: a) redesigns b) new materials and c) good use practices. A different approach in energy efficiency for Vapour Compression Refrigeration Systems (VCRS) is the implementation of control strategies that directly reduce energy consumption while guaranteeing operating conditions. The difficulty lies in the multiple energy domains of the system (electric/mechanical/hydraulic/thermal), high coupling, multiplicity of variables, strong non-linearity and non-stationary regime. This paper focuses on increasing the energy efficiency of a VCRS with the implementation of an optimal split range and multi-objective evolutionary control. The evolutionary control is expanded to variable speed compressors and electronic expansion valves. The effectiveness of the evolutionary method was demonstrated through the Benchmarking of the IFAC. Now, in the multi-domain model of the VCRS, the MAGO algorithm is applied to optimally tune a split range controller to achieve a more precise behaviour and multi-objective to save energy. The cases studied go from traditional control to multivariable and multivariable-multi-objective control, the results in energy saving are outstanding.

1 INTRODUCTION

Heating, ventilation and air conditioning (HVAC) has become a technological option that provides many ways to contribute to humanity, the conservation of meals through the control of indoor air quality, etc. Approximately 30% of the total energy in the world is consumed in HVAC processes, as well as in refrigerators and water heaters (Jahangeer, Tay and Raisul Islam, 2011). It is expected that the world's energy consumption rates will increase by 33% from 2010 to 2030 (Khan, Ryan and Abebe, 2017). In industry, refrigeration systems consume large amounts of electricity, where refrigeration can be responsible for up to 85% of total energy consumption (depending on the industry sector). To address this problem, the aim is to improve the efficiency of the systems (HVAC).

The IIR (Industrial Info Resources) estimates the number of refrigeration systems in operation worldwide (Coulomb, Dupon and Pichard, 2015), as summarized in Figure 1. The total number of HVAC in operation worldwide is approximately 3 billion, including 1.5 billion domestic refrigerators. Annually, more than 80 million units of domestic refrigerators are produced worldwide (Corte *et al.*, 2014). Today hundreds of millions are used, therefore the global impact of the electric power consumption of these systems is significant. In some countries, the use of refrigeration systems has become an increasing need allowing the development of technologies and equipment with high efficiencies to fulfil this type of tasks, in addition to the concern to reduce the environmental impact.

Applications	Sectors	Equipment	Number of units in operation
Refrigeration and food (see § 2.1.)	Domestic refrigeration	Refrigerators and freezers	1.5 billion [1] [2]
	Commercial refrigeration	Commercial refrigeration equipment (including condensing units, stand-alone equipment and centralized systems)	90 million [1] [2]
	Refrigerated transport	Refrigerated vehicles (vans, trucks, semi-trailers or trailers)	4 million [3]
		Refrigerated containers (« reefers »)	1.2 million [2]
Air conditioning (see § 2.2.)	Air conditioners	Air-cooled systems	600 million [2] [4]
		Water chillers	2.8 million [2]
	Mobile air-conditioning systems	Air-conditioned vehicles (passenger cars, commercial vehicles and buses)	700 million [5]
Refrigeration and health (see § 2.3.)	Medicine	Magnetic Resonance Imaging (MRI) machines	25,000 [6]
Refrigeration in industry (see § 2.4.)	Liquefied Natural Gas (LNG)	LNG receiving terminals	110 [7]
		Liquefaction trains	92 [7]
		LNG tanker fleet (vessels)	421 [7]
Heat pumps (see § 2.5.)		Heat pumps (residential, commercial and industrial equipment, including reversible air-to-air air conditioners)	160 million [8] [9]
Leisure and sports (see § 2.6.)		Ice rinks	13,500 [10]

Figure 1: Refrigeration systems in operation worldwide (Coulomb, Dupon and Pichard, 2015).

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This paper presents a proposal to improve the energy performance of a vapour compression refrigeration system (VCRS) by means of implementing an evolutionary control structure. To do this, two case studies are presented. The first case seeks to improve the energy performance of the system by controlling the superheat temperature therefore improving the thermal cycle of the system. For the second case, the aim is to directly reduce the energy consumption on the external power source by implementing different evolutionary control strategies. In both cases the temperature behaviour inside the cold chamber is the direct control goal to satisfy. In the second case, saving energy from the external power source is added as a new objective.

This paper is organized as follows. In section 2 the basics on VCRS is presented. In section 3 the evolutionary control method is described together with the optimizing process. In Section 4, the effectiveness of the evolutionary control method is verified with two case studies. Conclusions are presented in section 5

2 VAPOUR COMPRESSION REFRIGERATION SYSTEMS

The VCRS are the most used among all refrigeration systems. These systems belong to the general class of vapour cycles, where the working fluid (refrigerant) presents phase changes at least during one compression process. In a VCRS, cooling is obtained by extracting thermal energy from an insulated space to reduce its temperature. The input to the system is in the form of mechanical energy required to run the compressor. Hence, these systems are also called as mechanical refrigeration systems. VCRS are available to suit almost all applications with refrigeration capacities ranging from few watts to few megawatts. A wide variety of refrigerants can be used to suit different applications, capacities etc. The actual vapour compression cycle is based on Evans-Perkins cycle, which is also called as reverse Rankine cycle. In principle, all vapour compression refrigeration systems are used to remove heat from one location and transfer it to another by means of mechanical power (compression).

A VCRS has four main components: a compressor, a condenser, an expansion device and an evaporator. In a cycling process, a circulating refrigerant enters the compressor as saturated vapour and it is compressed to a higher pressure, resulting in a higher temperature as a superheated vapour. This hot compressed vapour is condensed to liquid by cooling air flowing across a coil carrying away heat from the system. This high-pressure, high temperature liquid leaving the condenser when passing through an expansion valve is cooled and reduced in pressure. In the evaporator, this low pressure, low temperature liquid is converted to vapour, absorbing heat from the refrigerated space and keeping it cool, to then return to the compressor and repeat the process. (see Figure 2).

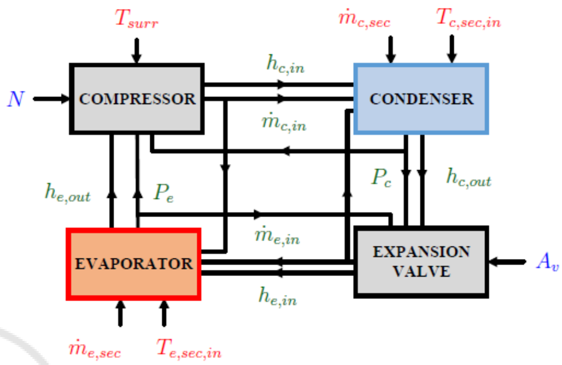

Figure 2: A vapour compression refrigeration cycle scheme (Bejarano, 2017).

3 EVOLUTIONARY CONTROL STRATEGIES FOR A VCRS

VCRS refrigeration systems are closed cycles whose components are connected through several pipes and valves. This implies a difficulty in controlling these processes due to some of the characteristics of the system, such as multiple energy domains (electric / mechanical / hydraulic / thermal), high coupling and multiplicity of variables; operating under conditions of strong non-linearity and in a non-stationary regime. The inherent complexity of these systems combined with the implementation of new control strategies is not a trivial task. To overcome these complexities, an optimization problem arises, since the main objective is to find a combination of controller parameters whose objective function through maximization or minimization guarantees the search for solutions that allow to improve the indexes of efficient performance of the process. Given its nature as a global optimizer of problems in different areas of science, engineering and other branches of knowledge (Fleming and Purshouse, 2002) one way to address the problem of energy efficiency in VCRS is through evolutionary algorithms (EA). The EA will calculate the optimum points of operation of the process based not only on the achievement of the desired production objectives, but also on the reduction of energy consumption; both objectives are to be met in this work.

The traditional control system for VCRS is an on/off strategy applied on the expansion valve. The highest efficiency of the evaporator is achieved if the refrigerant at the outlet of the evaporator is saturated vapour. Through the development of new technologies such as variable speed compressors or electronic expansion valves, it is possible to operate the cycle with a certain degree of superheating of the refrigerant at the outlet of the evaporator. This approach requires a multivariable control, which is very demanding technique in the system modelling and in the tuning of the controllers. This paper describes the strategy to tune a PID controller applied to two actuating elements on the system (compressor speed and expansion valve) to satisfy the expected cooling demand and maximizing the energy efficiency of the VCRS. The applied strategy is based on the split range control (Smith, 2010). This control technique is used when a single controller is applied to manage two final control elements. The PID controller strives to keep a temperature behaviour in the cooling chamber manipulating simultaneously the compressor speed and the expansion valve aperture. In strong coupled systems, as VCRS, the split range control could oscillate. The common practice is configuring the sequencing of the final control elements, in complementary, exclusive or progressive modes, defining their range of operation, and establishing a dead band between the two ranges. But, here, the split range controller is complete free. Besides this, the split range controller is tuned for a multiobjective system, saving energy in the power source and simultaneously fulfilling the desired behaviour.

3.1 Multidynamics Algorithm for Global Optimization (MAGO)

The MAGO (Hernández-Riveros and Ospina, 2010) is an auto-organized EA that has only two parameters: number of generations and population size. MAGO uses statistical operators instead of genetic operators and through the covariance matrix of the population in each generation considers the relationships among variables from the problem. MAGO is a real-value EA that has shown its capacity solving engineering problems (Hernández-Riveros Jesús-Antonio and Cindy, 2018), (Balarezo-Gallardo and Hernández-Riveros, 2017), (Bejarano *et al.*, 2018). MAGO has three different autonomous dynamics for evolving the population, this way getting a larger exploration-exploitation balance and less likelihood to convergence to a local optimum are guaranteed.

In each generation, MAGO partitions the population in three subgroups, each one with its own evolutionary dynamics. To determine the number of individuals for each dynamic, the actual population is observed as in a normal distribution. The average of the current generation, really a virtual individual, is calculated on purpose. The number of elements within one standard deviation of the actual population conforms the cardinality of the Emergent Dynamics. The cardinality of the Crowd Dynamics corresponds to the difference between the first and second deviation. The number of remaining elements is the cardinality of the Accidental Dynamics. These cardinalities change in each generation. Once the number of individuals within each dynamic is determined, MAGO proceeds to create individuals who will make up the new population and so continuing with the evaluation of new solutions. From the fitness function evaluation of each individual, the actual population is reorganized from the best to the worst individual. The first N1 individuals within one standard deviation of the actual population compose the Emergent Dynamics. This N1 individuals obtaining the best values in their objective function mutate applying the Nelder-Mead method of numerical derivation, Equation 1.

$$x_T^{(j)} = x_i^{(j)} + F^{(j)} \times (x_B^{(j)} - x_m^{(j)}) \tag{1}$$

Where $\boldsymbol{x_B^{(j)}}$ is the best individual of generation j and $\boldsymbol{x_m^{(j)}}$ is a randomly selected individual, usually the same test individual. $\boldsymbol{F^{(j)}}$ is a matrix that includes information about the covariance of the problem variables, Equation 2.

$$F^{(j)} = \frac{S^{(j)}}{\|S^{(j)}\|} \tag{2}$$

With $\boldsymbol{S^{(j)}}$ is the sample covariance matrix of the individual population in generation j.

Emergent Dynamics is improved elite making faster convergence of the algorithm but keeping an equilibrium between exploitation-exploration among the best individuals.

The Crowd Dynamics keeps the memory of the evolution process and is a sampling from a uniform distribution determined by the upper and lower limits of the second dispersion and the mean of the current population, on the hyper-rectangle [$LB^{(j)}$, $UB^{(j)}$]. Equations3 and 4 are vectors with the diagonal of the population dispersion matrix of the generation j, described by Equation 5.

$$LB^{(j)} = x_M^{(j)} - \sqrt{diag(S^{(j)})} \quad (3)$$

$$UB^{(j)} = x_M^{(j)} + \sqrt{diag(S^{(j)})} \quad (4)$$

$$S^{(j)} diag(S^{(j)}) = \left[S_{11}^{(j)}\ S_{22}^{(j)} \dots S_{m}^{(j)}\right]^T \quad (5)$$

The Accidental Dynamics are samples from a uniform distribution throughout the searching space, similarly as in the initial population. It is smaller in magnitude but has two basic functions: maintaining the diversity of the population, and ensuring numerical stability of the algorithm. Following is the MAGO pseudo code:

1: j:= 0; Random initial population with a uniform distribution.
2: Repeat
3: Evaluate each individual with the fitness function.
4: Calculate the population covariance matrix and the first, second and third dispersion of the population.
5: Calculate cardinalities N1, N2 and N3 of the 3 dynamics.
6: Select the N1 best individuals, move toward the best of all according to equation 1, make compete with their parents, and choose the best of them to the next generation j + 1.
7: Sample N2 individuals from a uniform distribution in the hyper rectangle [LB(j), UB(j)], and pass to the next generation j + 1.
8: Sample N3 individuals with a uniform distribution over the entire search space. Pass to the next generation j + 1.
9: j = j + 1
10: Until to satisfy a stopping criterion.

4 SPLIT RANGE CONTROL STUDY CASES

Next, two cases of application of the MAGO algorithm in different control structures for a VCRS to improve its efficiency and control the temperature inside the cold chamber are presented. The first study case corresponds to the IFAC benchmark which only represents the thermodynamic behaviour of the VCRC. This case is presented to demonstrate the effectiveness of the evolutionary control strategy using the MAGO. The second case study corresponds to a complete VCRS, whose entire model includes multiple energy domains (electric, mechanical, hydraulic and thermal). Three multivariable and multi-objective control strategies are proposed. Besides to the temperature control inside the cooling chamber, an additional objective is added, that is, the energy saving on the power source of the VCRS.

4.1 Case 1: Benchmark IFAC (Only Thermal Model)

The model for the Benchmark (Bejarano *et al.*, 2018) is a refrigeration cycle of one compression stage and one load. This model cannot be modified. The main features of the model are:

1) Relatively low complexity, while faithfully capturing the dynamics of the essential plant and its non-linearities in a wide range of operation.

2) Oriented to control because the manipulated variables, the controlled variables and the significant disturbances are shown.

3) The model is realistic since restrictions are considered in the manipulated variables.

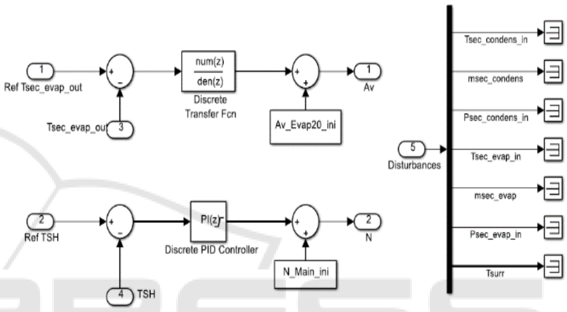

Figure 3: Discrete decentralized controllers included by default in the refrigeration control benchmarking (Bejarano *et al.*, 2018).

Table 1: Benchmark control strategy.

Control Objectives
1. Reach a desire value of outlet temperature of the evaporator secondary flux by manipulating the opening of the expansion device. **2.** Reach a desire value of superheat temperature by manipulating the compressors speed.
Control Variables
Output variables ***y1*****:** outlet temperature of the evaporator secondary flux ($T_{sec,evap,out}$) ***y2*****:** superheat temperature (T_{sh}) *Controlled variables* ***u1:*** Expansion device opening (A_V) ***u2:*** Compressors speed (N)
Elements
System**:** VCRC ***Actuator 1*****:** Expansion Valve. ***Actuator 2*****:** Compressor.
Mono Objective Optimization Problem *Minimization of the controlled variables error*

The multivariable control structure included by default in the PID Benchmark 2018 consist of a discrete decentralized control scheme (Figure 3) in which the variables to control are the outlet temperature of the evaporator secondary flux and the degree of superheating (Table 1). The control system is designed to obtain these two variables, tracking their references as efficiently as possible, in the presence of disturbances. The coefficient of performance COP is used as an indicator of steady-state quality.

Tuning Procedure of the Discrete Controllers and Optimization of the IFAC Benchmark's VCRS.

As can be seen in Figure 4 the VCRS is composed of two controllers; the first one is a discrete transfer function that acts on the aperture of the expansion valve. The second is a discrete PI controller that corresponds to the compressor's speed.

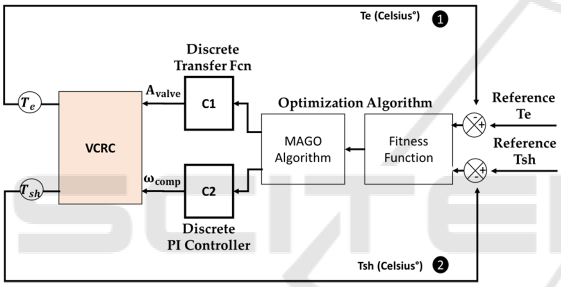

Figure 4: Coupled evolutionary tuning procedure for the Benchmark IFAC 2018.

Table 2 shows the input data for the MAGO algorithm. This mono-objective optimization approach seeks to minimize the error between the reference and output signals of the control variables.

Table 2: Input data for MAGO.

Data	Values
Individuals	20
Generations	10
Upper bound	[-1 0 1 -1.9 1 2.7 2.7]
Lower bound	[-1.3 -0.6 0.7 -2 0.9 0.4 0.5]

Table 3 presents the obtained parameters for each controller for the benchmarking applying MAGO.

Table 3: Parameters of each controller applying MAGO.

	Expansion Valve (Controller1)	Compressor (Controller 2)
Benchmark C1	$\frac{-1{,}0136 - 0{,}0626\ 0{,}9988}{1 - 1{,}9853\ 0{,}9853}$	P: 0,4200 I: 0.9524
MAGO C2	$\frac{1{,}1039 - 0{,}2901\ 0{,}8961}{1 - 1{,}9185\ 0{,}9184}$	P: 1,2829 I: 1,6916

The results obtained for the temperature of the secondary flux in the evaporator, Te sec out, and the temperature of superheating, Tsh, are presented in Figure 5 and Figure 6. The C1 controller corresponds to the Benchmark and C2 to the results with MAGO. The MAGO was implemented with a decentralized MIMO control structure consisting of two discrete controllers (a transfer function and a PI). The MAGO, independent of the structure and domain of the controller, finds the parameters in the function of achieving both control objectives. As can be seen in Figure 5 the optimal tuning method of controllers applying the MAGO evolutionary strategy manages to reach the reference values, achieving a behaviour like the Benchmark's default strategy but improving in the handling of temperature variation. The facility to implement evolutionary tuning through the MAGO algorithm in a complex system is highlighted, whose model was not available to adapt it to the control strategy that was to be applied.

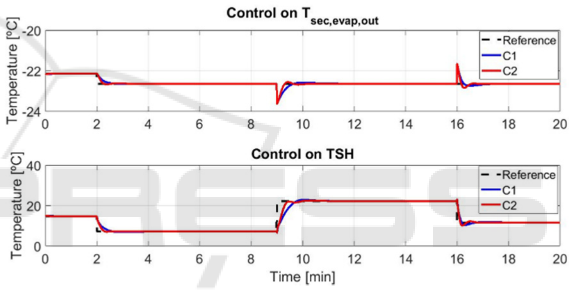

Figure 5: Controlled variables.

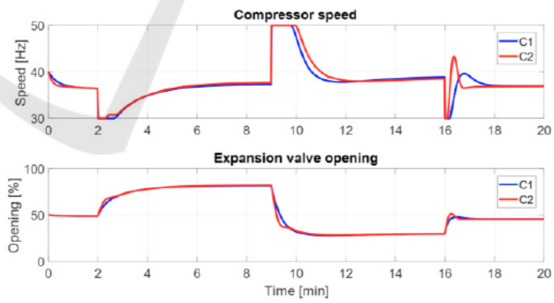

Figure 6: Manipulated variables.

4.2 Case 2: Complete VCRS (Multi-domain Energy based Model)

The multi-domain energy-based model for a complete VCRS is presented in Figure 9. The bond-graph (BG) method is a graphical modelling approach in which energy ports are connected by bonds that specify the transfer of energy between system components. Power, the rate of energy transport between components, is the universal currency of physical systems (Gawthrop and Bevan, 2007). The main advantage of the BG technique lies in its ability to determine the energy consumption of a system, in general, as well as its components, which is of vital relevance for this second case study. Another advantage is that the mono-domain models generated from the BG have a modular coupling facility (unified base) which can result in a coupled multi-domain model.

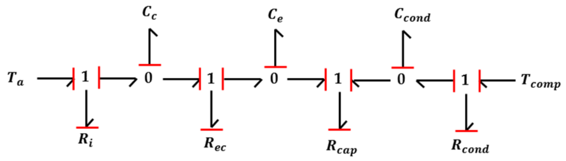

Figure 7: BG base model of a VCRC (thermal behaviour).

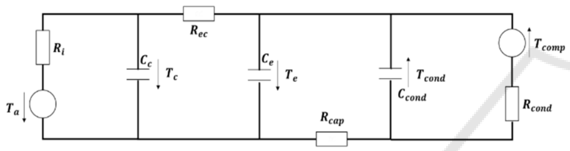

Figure 8: Base model of a VCRS. Adapted from (Schné, Jaskó and Simon, 2015).

The final model arises from the modular union of the BG base model Figure 7 that corresponds only to the thermal dynamics of the VCRC whose approach was developed by (Schné, Jaskó and Simon, 2015) Figure 8. The construction of the step-by-step model is detailed in (Amador Soto, 2019).

From the base model described above representing the dynamics of a VCRS, there is a need to detail with greater precision the action of the compressor (simplified in the base model by its output temperature Tcomp). The reason for this is that the impact of the compression action on the cooling system is usually known, but it is not its direct energy consumption seen from the power source. That is why once having the BG representation of the thermal cycle it is necessary to have also the representation for the compressor and finally joint both models, which does not imply a problem in the use of the BG technique due to its modular nature (see Figure 9). The system of coupled differential equations (6-11) emerges from of the BG model. The state variables are $\boldsymbol{i_a}$: Armature current, $\boldsymbol{\omega_m}$: Motor rotational speed, $\boldsymbol{Q_h}$**:** Hydraulic flow, $\boldsymbol{Tc_{cond}}$: Temperature in the condenser, $\boldsymbol{Tc_e}$: Temperature in the evaporator, $\boldsymbol{Tc_c}$: Temperature inside the cold chamber.

4.2.1 On-off Control Baseline

To control the temperature inside the refrigerator there is thermostat, whose sensor is connected to the evaporator, Figure 10. The round knob inside a refrigerator compartment can do the thermostat setting. When the set temperature is reached inside the refrigerator, the thermostat stops the electric supply to the compressor and the compressor stops. When the temperature falls below certain level it restarts the supply to the compressor.

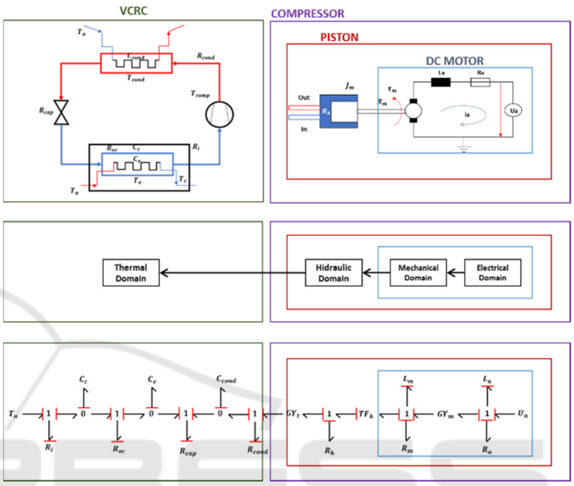

Figure 9: BG representation for the complete energy-based model of the VCRS.

$$\frac{d\boldsymbol{i_a}}{dt} = -\left[\frac{r_m * \boldsymbol{\omega_m} - V_s + R_a * \boldsymbol{i_a}}{L_a}\right] \tag{6}$$

$$\frac{d\boldsymbol{\omega_m}}{dt} = -\left[\frac{r_h * \boldsymbol{Q_h} - r_m * \boldsymbol{i_a} + R_m * \boldsymbol{\omega_m}}{J_m}\right] \tag{7}$$

$$\frac{d\boldsymbol{Q_h}}{dt} = \frac{r_h * \boldsymbol{\omega_m} - R_h * \boldsymbol{Q_h} + \frac{r_t(\boldsymbol{T_{c_{cond}}} - r_t * \boldsymbol{Q_h})}{R_{cond}}}{J_h} \tag{8}$$

$$\frac{d\boldsymbol{T_{c_{cond}}}}{dt} = -\left[\frac{\frac{\boldsymbol{T_{c_{cond}}} - r_t * \boldsymbol{Q_h}}{R_{cond}} + \frac{\boldsymbol{T_{c_{cond}}} + \boldsymbol{T_{c_e}}}{R_{cap}}}{C_{cond}}\right] \tag{9}$$

$$\frac{d\boldsymbol{T_{c_e}}}{dt} = \frac{\frac{\boldsymbol{T_{c_c}} - \boldsymbol{T_{c_e}}}{R_{ec}} - \frac{\boldsymbol{T_{c_{cond}}} + \boldsymbol{T_{c_e}}}{R_{cap}}}{C_e} \tag{10}$$

$$\frac{d\boldsymbol{T_{c_c}}}{dt} = -\left[\frac{\frac{\boldsymbol{T_{c_c}} - \boldsymbol{T_{c_e}}}{R_{ec}} + \frac{\boldsymbol{T_{c_c}} - \boldsymbol{T_a}}{R_i}}{C_c}\right] \tag{11}$$

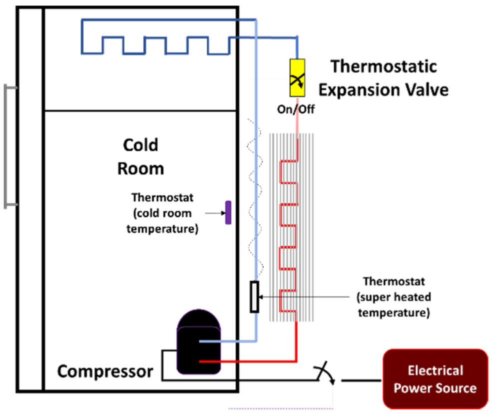

Figure 10: Conventional ON-OFF VCRS basic scheme.

While conventional on-off control commonly has a fluctuating behaviour (Figure 11), other control options have arisen due to the growth of the electronics field. Variable speed compressors and electronic expansion valves have gradually replaced older single speed compressors and thermostatic expansion valves, respectively. Such new components allow the development of smarter control strategies, not only to save energy but also to reduce fluctuations in the controlled variables and therefore achieve a more accurate control (Bejarano et al., 2018). In this sense, in this document continuous controllers are implemented for temperature control and simultaneously reduce energy consumption.

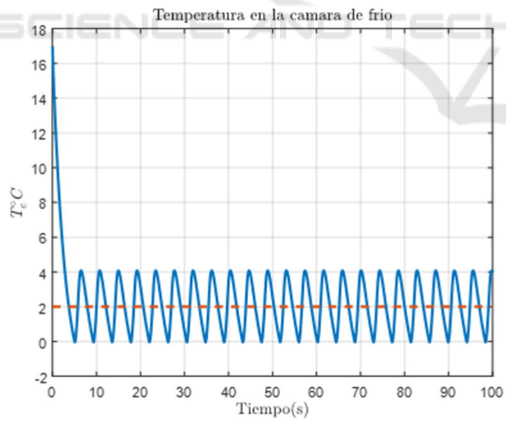

Figure 11: Typical thermal behaviour for a conventional VCRS by ON-OFF control.

4.2.2 Continuous Control Strategies

A multivariable SISO and MISO control structures are presented, both consisting on a continuous centralized control scheme in which the variable to control is the outlet temperature of the cold chamber while at the same time reducing the energy consumption from the power source.

Tuning Procedure of the Energy-based Complete VCRS Model.

Three different control strategies are applied.

- **First Control Strategy:**

Centralized control SISO (manipulated Variable: aperture of the expansion valve). See Table 5, Table 6, Figure 12, Figure 13, and Figure 14.

- **Second Control Strategy:**

Centralized control SISO (manipulated Variable: compressor speed). See Table 7, Table 8, Figure 15, Figure 16, and Figure 17.

- **Third Control Strategy:**

Centralized control MISO (manipulated Variables: compressor speed + aperture of the expansion valve). See Table 9, Table 10, Figure 18, Figure 19, Figure 20.

In all cases the MAGO runs with the same set of parameters of the algorithm, Table 4. The operation of the actuator opening the expansion valve goes from 0% to 100%, and the compressor speed goes from 0 to 1200 RPM. For the evolutionary tuning of the split range controller, there is not sequencing, restrictions on the range nor dead band among the two actuators.

Table 4: Input data for MAGO.

Data	Values
Individuals	50
Generations	25
Upper bound	[10 10 10]
Lower bound	[-10 -10 -10]

Table 5: First, control strategy (by expansion valve aperture).

<table>
<tr><td colspan="2">Control objective
A set of stable temperature inside the cold chamber (2, 1, 0 -1 ℃)</td></tr>
<tr><td colspan="2">Energy objective
Reduce the energy consumption of the power source of the system.</td></tr>
<tr><td>Control variables (SISO)
Output variable (y): Temperature inside the cold chamber (T_C)
Controlled variable (u): Expansion device opening (A_V)</td><td>Elements
System: CompleteVCRC
Actuator: Expansion Valve.</td></tr>
<tr><td colspan="2">Multi objective optimization problem
1. Minimization of the controlled variable error
2. Minimization power source energy</td></tr>
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Table 6: Obtained controller parameters applying MAGO.

Expansion Valve (PID Controller)	**Kp**: 0.0959 **Ti**: 1.8297 **Td**: 4.3237

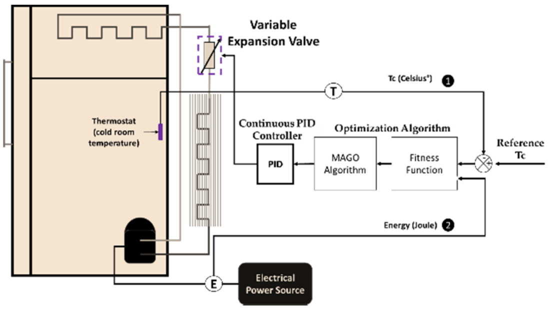

Figure 12: VCRC intervention applying the first control strategy for temperature control and power source's energy reduction.

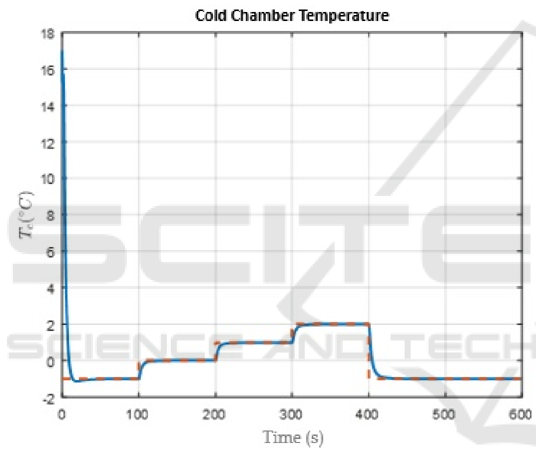

Figure 13: Controlled variable for the first control strategy.

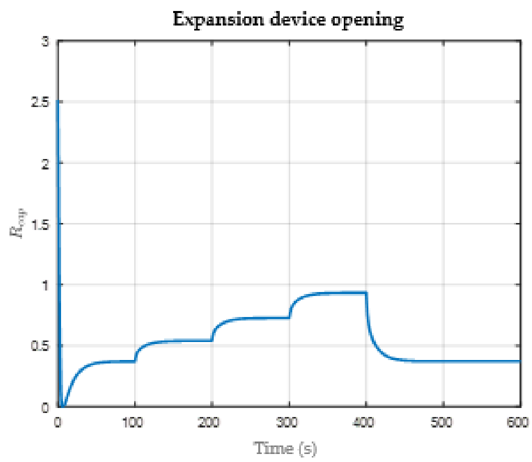

Figure 14: Manipulated variable for the first control strategy.

Table 7: Second control strategy (by compressor speed).

Control Objective A set of stable temperature inside the cold chamber (2, 1, 0 -1 ℃).	
Energy Objective Reduce the energy consumption on the power source of the system.	
Control Variables (SISO)	**Elements**
***Output variable (y)*:** Temperature inside the cold chamber (T_C) ***Controlled variable (u)*:** Compressors speed (ω_m)	***System*:** CompleteVCRC ***Actuador*:** Compressor.
Multi Objective Optimization Problem 1. Minimization of the controlled variable error 2. Minimization power source energy	

Table 8: Obtained controller parameters applying MAGO.

Compressor (PID Controller)	**Kp**: 0.0965 **Ti**: 2.993 **Td**: 1.5037

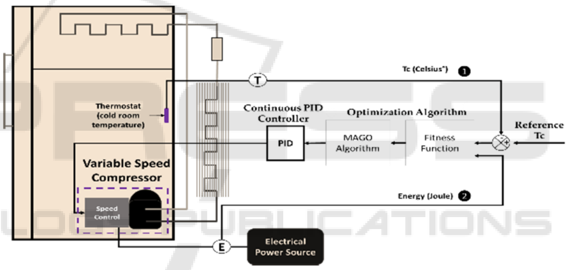

Figure 15: VCRC intervention with the second control strategy for temperature control and power source's energy reduction.

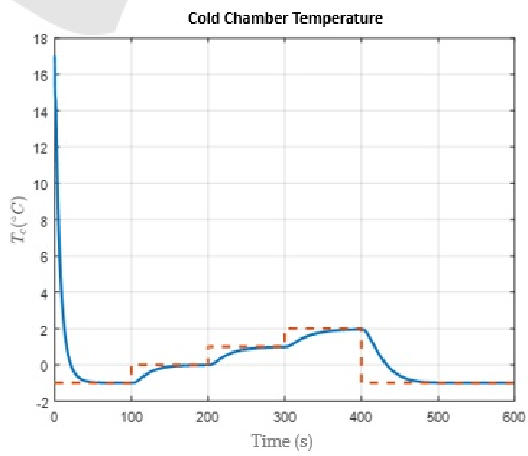

Figure 16: Controlled variable for the second control strategy.

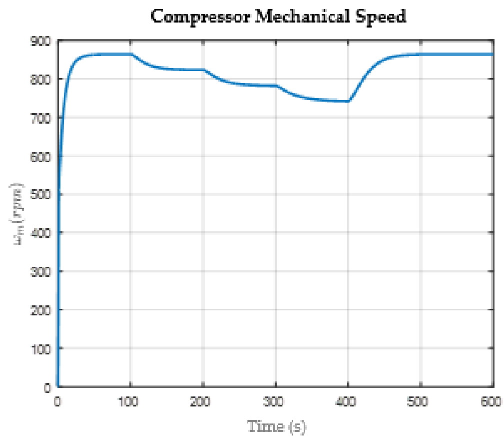

Figure 17: Manipulated variable for the second control strategy.

Finally, the energy consumption corresponding to each control strategy applied to the system is presented in Table 11.

Table 9: Third control strategy (by expansion device aperture + compressor speed).

Control Objective A set of stable temperature inside the cold chamber (2, 1, 0 -1 ℃).	
Energy Objective Reduce the energy consumption of the power source of the system.	
Control Variables (MISO)	**Elements**
Output variable (y): Temperature inside the cold chamber (T_C) ***Controlled variable (u1):*** Expansion device opening (A_v) ***Controlled variable (u2):*** Compressors speed (ω_m)	***System*:** CompleteVCRC ***Actuador1*:** Expansion device ***Actuador2*:** Compressor.
Multi Objective Optimization Problem 1. Minimization of the controlled variable error 2. Minimization Power Source energy	

Table 10: Obtained controller parameters applying MAGO.

Expansion Valve (PID Controller 1) + Compressor (PID Controller 2)	**Kp**: 0.7096 **Ti**: 4.295 **Td**: -1.7924

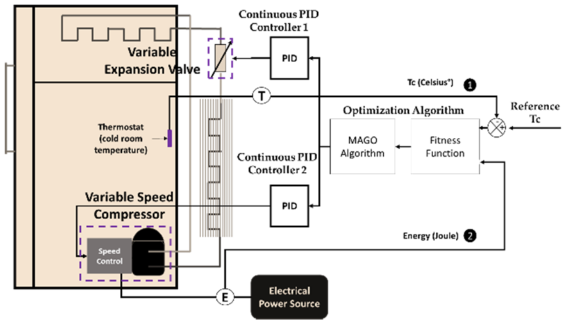

Figure 18: VCRC intervention with the third control strategy for temperature control and power source's energy reduction.

Table 11: Summary energy consumption of control strategies applying MAGO.

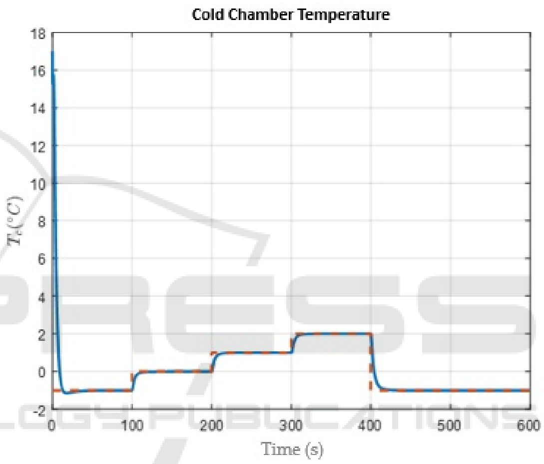

Figure 19: Controlled variable for the third control strategy.

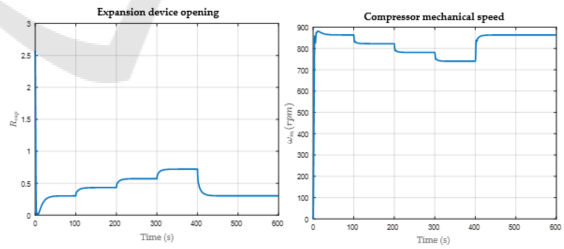

Figure 20: Manipulated variables for the third control strategy.

Comparing results between the three proposed control strategies, it was found that, by controlling the speed of the compressor, applying a voltage profile, it is possible to obtain better results in reducing energy consumption. On the other hand, manipulating the expansion device improves the behaviour of the controlled variable (temperature), reaching the reference values in less time. However, changing the opening value of the expansion device alters the demands on the compressor, increasing the motor current while applying a fixed voltage. This is reflected in an increase in energy consumption. For its part, the third strategy combines the benefits of both previous strategies, so it is possible to achieve good results in reducing energy consumption and good behaviour of the controlled variable, quickly reaching the reference values without increasing the demand of the compressor.

4 CONCLUSIONS

The proposed evolutionary control approach was applied for two different developments in VCRS (case study 1 - only the thermal part, and case study 2 - including the electrical, rotational, hydraulic and thermal parts) under conditions of multivariability, high coupling, non-linearity and restrictions, among others. The results obtained for both study cases show that intervention inside the refrigeration system by means of applying control structures can achieved energy savings for the thermal circuit and for the whole system. The MAGO algorithm achieves remarkable results for the different control strategies, independently of both the structure and the domain of the controller to be tuned.

For the first study case, we use a predefined model formulated for control purpose (by transfer function) that tries to reach the temperature behaviour improving indirectly the energy performance of the system. On the other hand, case study 2 illustrates the use of a single unified energy based model (by differential equations of the whole system) to reduce directly the source's energy consumption and at the same time achieving the desired temperature behaviour for the system using three different control strategies. Evolutionary tuning was applied to the two different systems without additional procedures. The split range controller was expanded to multivariable and after to multiobjective purposes. This evolutionary control method can be implemented without any inconvenience in developments for control of cooling systems of multiple loads and stages.

Savings and control opportunities were identified according to the strategy (MISO or MIMO). The more variables in the process are controlled, the greater energy savings are obtained.

Future work is to combine the advantages of the manipulation of the compressor speed and the opening of the expansion valve with two independent but coupled controllers. A greater range of solutions is foreseen to improve the savings in energy consumption while satisfying the expected cooling demand.

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