Coupled evolutionary tuning of PID Controllers for the Benchmark on Vapor Compression Refrigeration

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Abstract: In the present work, an evolutionary tuning is used to determine in a coupled manner the controllers of a refrigeration system (VCRS) proposed in the challenge of the 2018 IFAC Conference on Advances in PID Control. The evolutionary strategy finds the parameters of the controllers that best satisfy the problem, fulfilling all the requirements and restrictions imposed by the challenge. The evolutionary strategy is independent of the structure and domain of the model, both the plant and the controllers.

Keywords: Adaptive and learning systems, control design, evolutionary algorithms, multivariable control.

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, the control of air quality in the interior, etc. Without refrigeration, modern life is impossible; approximately 30% of the total energy in the world is consumed in HVAC processes, as well as in refrigerators and water heaters (Jahangeer, Tay, & Raisul Islam, 2011).

Although in some cases, the air conditioning and refrigeration systems are considered separately, all these systems work in the same way: they use the reverse Rankine cycle to remove the heat from a cold store and transfer it to a hot deposit, generally the environment. In such tasks, a large amount of energy is required, which negatively affects the economic equilibrium (Buzelin, Amico, Vargas, & Parise, 2005). Despite this, the use of refrigeration systems has become a growing need in some countries, which has allowed the development of technologies and equipment with high efficiencies to meet this type of tasks, added to the concern to reduce the environmental impact. Therefore, achieving a high-energy efficiency and simultaneously satisfying the cooling demand represents a huge challenge, but at the same time, an unbeatable opportunity to solve one of the most serious problems facing humanity as it is the energy consumption. Most of the global warming effect from cooling systems comes from the generation of energy that is used to power them. Only a small proportion comes from the release of certain refrigerants.

A challenge based on a vapour compression refrigeration system (VCRS) was proposed in the 2018 IFAC Conference on Advances in Proportional-Integral-Derivative Control. Refrigeration systems are used to remove heat from one location and transfer it to another. A VCRS has four components: a compressor, a condenser, a thermal expansion 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; going again to the compressor repeating the process.

Addressing the problem of energy efficiency is widely recognized that the heat transfer is much greater when the refrigerant flow is two phases (saturation zone). Therefore, the highest efficiency of the evaporator is achieved if the refrigerant at the outlet of the evaporator is saturated vapour. Currently, 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 (Tsh) of the refrigerant at the outlet of the evaporator, a value that must be kept low to approach to the ideal behavior.

This paper describes the strategy to tune two controllers applied to two actuating elements on the system (compressor and expansion valve) to satisfy the expected cooling demand and maximizing the energy efficiency of a vapour compression refrigeration system achieving certain degree of superheating of the refrigerant (Tsh). For this target the model proposed by (Bejarano, Alfaya, Rodríguez, & Ortega, 2018) is used.

The paper is organized as follows. In section 2 the cooling system and its control are presented, later in section 3 the problem of the selected MIMO control is studied. Section 4 describes how the test and comparative evaluation of multivariable controllers was carried out. Afterwards, an analysis of results is presented, this is discussed in section 5, and the conclusions are presented in section 6.

2. MODELING THE REFRIGERATION CYCLE

The model for the Benchmark proposed by (Bejarano et al., 2018) has been developed in Simulink. (Fig. 1) shows a canonical refrigeration cycle of one compression stage and one load, where the main components are represented (the expansion valve, the compressor, the evaporator and the condenser).

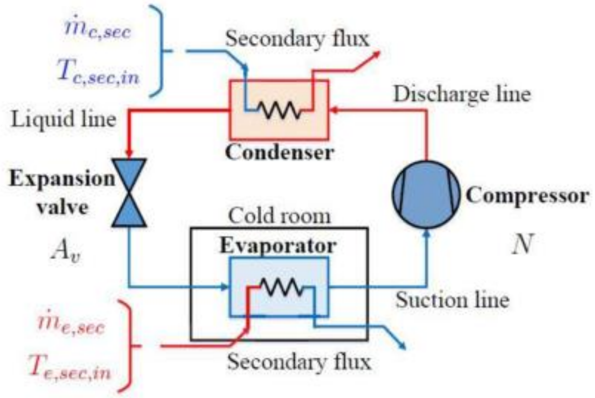

Fig. 1 Schematics of the refrigeration cycle by vapour compression (Bejarano et al., 2018)

In the case of the evaporator, neither the secondary mass flux nor the inlet temperature of such secondary flux are intended to be controlled. Therefore, the demand for refrigeration can be expressed as a reference in the outlet temperature of the secondary flux of the evaporator, where the mass flux and the inlet temperature act as measurable perturbations. With respect to the condenser, the inlet temperature and the secondary mass flux are also considered disturbances. Next, the main features of the model are described:

1) It has a relatively low complexity, while faithfully capturing the dynamics of the essential plant and its non-linearity in a wide range of operation.
2) The model is oriented to control because the manipulated variables, the controlled variables and the significant disturbances are explicitly shown.
3) The model is realistic since restrictions are considered in the manipulated variables.

Because the dynamic of the heat exchangers is usually at least one order of magnitude faster than of the evaporator and the condenser, the most important elements with respect to dynamic modeling are the heat exchangers, while the expansion valve, the compressor and the thermal behavior of the secondary flows are statically modeled. Another important element in the refrigeration cycle is the refrigerant, which is subject to changes of state, modifying its temperature and pressure as it circulates through the system.

To measure the cooling efficiency, the Coefficient of Performance (COP) is used, which is defined as the ratio between the cooling power generated in the evaporator $\dot{Q}e$ and the mechanical power provided by the compressor $\dot{W}comp$, as indicated in Equation (1).

$$COP = \frac{\dot{Q}_e}{\dot{W}_{comp}} = \frac{\dot{m}(he,out - he,in)}{\dot{m}(hc,in - he,out)} \tag{1}$$

In this work, the COP is one of the variables to be controlled and it will depend only on the intensive variables, specifically the characteristic enthalpies of the cycle, which are represented in a p-h diagram.

3. CONTROLLER DESIGN

To achieve more effective control strategies in the cooling process, the underlying problem is the inherent energy consumption. The new adjustable speed compressors and electronic expansion valves allow the development of more intelligent control strategies, not only to save energy, but also to reduce fluctuations in the controlled variables and, therefore, achieve a more precise control.

3.1 Approaching to the Control Problem.

Cooling systems are, as they are generally known, closed cycles whose components are connected through various pipes and valves, which causes a difficulty when controlling these processes due to system conditions such as high thermal inertia, dead times, high coupling between variables, and strong non-linearity. Dynamic modeling of a VCRS is definitely not trivial.
The conventional control scheme is very simple: in addition to the reference imposed by the cooling demand, it must be as efficient as possible. The variables to control are the outlet temperature of the evaporator secondary flux and the degree of superheating (Table 1).

Table 1 Definition of objectives for the control system

Objective (Controlled Variable)	Variable name	Units
Guarantee a desired cooling value	Tsec_evap_out	ºC
Guarantee a desired value for superheating degree.	Tsh	ºC

The actuators are the speed of the compressor, **N**, which regulates the degree of heating, **Tsh**, and the opening of the expansion valve, **Av**, acting on the cooling demand, **Tsec_evap_out** (Table 2).

Table 2 Actuating Elements

Manipulated Variables	Variable name	Units	Rank
Compressor speed	N	Hz	[30-50]
Expansion valve opening	Av	%	[10-100]

The control system is designed to obtain those two variables, tracking their references as efficiently as possible, in the presence of disturbances, which are included in (Table 3). The coefficient of performance COP is used as an indicator of steady-state quality.

Table 3 Disturbances

Disturbances	Variable name	Units	Rank
Condenser			
Inlet temperature of the secondary flux	$Tc{,}sec{,}in$	ºC	[27-33]
Mass flow of the secondary flux	$\dot{m}c{,}sec$	$g\ s^{-1}$	[125-175]
Inlet pressure of the secondary flux	$Pc{,}sec{,}in$	bar	-
Evaporator			
Inlet temperature of the secondary flux	$Te{,}sec{,}in$	ºC	[22-18]
Mass flow of the secondary flux	$\dot{m}e{,}sec$	$g\ s^{-1}$	[0.055-0.0075]
Inlet pressure of the secondary flux	$Pe{,}sec{,}in$	bar	-
Other			
Compressor surroundings temperature	$Tsurr$	ºC	[20-30]

The multivariable control included by default in the PID Benchmark 2018 consist of a discrete decentralized control scheme with a sampling time of 1 second, where the expansion valve controls the outlet temperature of the secondary flux of the evaporator, while the speed of the compressor controls the degree of superheating. (Table 4) shows the transfer functions of the respective controllers.

Table 4 Discrete transfer functions used within the predetermined controllers

Controller	Transfer Function
$T_{e,sec,out}–A_v$	$\dfrac{-1.0136-0.0626z^{-1}+0.9988z^{-2}}{1-1.9853z^{-1}+0.9853z^{-2}}$
$T_{SH}–N$	$\dfrac{0.42-0.02z^{-1}}{1-z^{-1}}$

3.2 Control Strategy Proposal

Due to the challenge proposed in the Benchmark PID 2018, the model of the VCRS applied is taken directly from (Bejarano et al., 2018). It is a Simulink model that uses the switched moving boundary (SMB) approach to model the refrigerant behaviour when circulating through the heat exchangers. Two controllers are tuned upon a decentralized approach. However, in this work, the strategy for the control system applied is different from the one in the Benchmark. Here, the two controllers are simultaneously tuned. When the plant is operating, at a same instant, is calculated the error of each variable of interest, according to its respective reference. Those errors are put together to form a cost function. This cost function, i.e. one of the ITAE family, feeds an evolutionary algorithm (EA), which takes that cost function to adjust the parameters of each controller. In an iterative process of concurrently minimizing the error of the cooling demand and maximizing the COP, the EA searches for the best combination of parameters of the two controllers satisfying the problem.

Being the VCRS a multivariable processes, the interaction between variables is inherent. The paradigm of coupling control facilitates the operation of the control system, but the interaction between variables requires mathematical models and computational methods considerably more sophisticated than basic PID loops. The path taken to avoid these difficulties aiming such a complex problem as the multivariable control is allowing an evolutionary algorithm to solve directly the interrelationships among the variables of the control problem. The Multidynamics Algorithm for Global Optimization is very appropriate for this task. This is an EA based on statistical operators and uses the covariance matrix to deal with the interrelationships among variables in a natural way. The selected EA is explained next.

3.3 Multidynamics Algorithm for Global Optimization – MAGO.

MAGO is an auto-organized evolutionary algorithm that has only two parameters: number of generations and population size. It bases on statistics from the same evolving population and handles evolution global strategies. 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 et al, 2018) (Balarezo et al., 2017). Unlike others EA, 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 dynamic. These three subgroups are the Emergent Dynamics, the Crowd Dynamics and the Accidental Dynamics. To determine the amount of individuals for each dynamics, 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. MAGO through these three dynamics produces new individuals in each generation. Each dynamics produces a subset for the new population.

Once the number of individuals within each dynamics 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 compose the Emergent Dynamics. The amount N1 matches to those individuals within one standard deviation of the actual population. The N1 individuals obtaining the best values in their objective function mutate applying the Nelder-Mead method of numerical derivation, equation (2).

$$x_T^{(j)} = x_i^{(j)} + F^{(j)} \times (x_B^{(j)} - x_m^{(j)}) \qquad (2)$$

Where $x_B^{(j)}$ is the best individual of generation j and $x_m^{(j)}$ is a randomly selected individual, usually the same test individual. $F^{(j)}$ is a matrix that includes information about the covariance of the problem variables, equation (3).

$$F^{(j)} = \frac{S^{(j)}}{\|S^{(j)}\|} \qquad (3)$$

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

Emergent Dynamics is improved elite seeking solutions in a neighbourhood getting closer to the very best of all the individuals. This subgroup has the function of 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. This subgroup seeks possible solutions in a neighbourhood close to the population mean on the hyper-rectangle [$LB^{(j)}$, $UB^{(j)}$]. Equations (4) and (5) are vectors with the diagonal of the population dispersion matrix of the generation j, described by equation (6).

$$LB^{(j)} = x_M^{(j)} - \sqrt{diag(S^{(j)})} \qquad (4)$$

$$UB^{(j)} = x_M^{(j)} + \sqrt{diag(S^{(j)})} \qquad (5)$$

$$S^{(j)}\ diag(S^{(j)}) = \begin{bmatrix} S_{11}^{(j)} & S_{22}^{(j)} & \dots & S_m^{(j)} \end{bmatrix}^T \qquad (6)$$

The Individuals of 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 over the search space.
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 2, 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.

3.4 Coupled Evolutionary Tuning

Because MAGO is a real-valued evolutionary algorithm, the representation of an individual is a vector containing the parameters of the two controllers. The structure of the evolutionary individual is, first, the coefficients of the numerator (n_1, n_2, n_3) and denominator (d_2, d_3) for the controller of the opening of the expansion valve, and then the coefficients of the PI controller of the compressor speed. The values are real numbers in a continuous domain (Table 5).

Table 5 Structure of the evolutionary individual

n1	***n2***	***n3***	***d1***	***d2***	***P***	***I***
$\in$ R	$\in$ R	$\in$ R	$\in$ R	$\in$ R	$\in$ R	$\in$ R

Two errors are calculated at the same instant. The error *e1* of the degree of superheating, and the error *e2* of the cooling demand, see equations (6) and (7). The total error is the sum of these variable errors, equation (8), and it is calculated for each point of time throughout the measurement horizon.

$$e_1(t) = Tsh - refTsh \qquad (6)$$

$$e_2(t) = Tsec\_evap\_out - ref\ Tsec\_evap\_out \qquad (7)$$

$$e_T(t) = e_1(t) + e_2(t) \qquad (8)$$

The control problem consists in determining both controllers' settings minimizing a chosen cost function. The objective is minimizing the integral of the total error, $e_T(t)$, multiplied by the time (ITAE). This involves finding the values for the whole parameters of each one of the two controllers, such that the system gets the desired r(t) values of the cooling demand and the degree of superheating, as fast as possible and with few oscillations. The fitness function for MAGO is in equation (9).

$$J\,(n1, n2, n3, d1, d2, P, I) = \min \{ J_{ITAE} = \int t|\, e_T(t)|dt \} \qquad (9)$$

In (Fig. 2), the evolutionary procedure to estimate the parameters for several controllers considering the coupling of the problem variables can be observed. All the controllers act simultaneously over the plant responding to deviation from the references. At the same instant, different partial errors are calculated and they are gathered to assemble the total error of the system. When a cost function involves concurrently the errors of all variables in study, intrinsically is considering the coupling of the problem variables. MAGO takes into account this interdependence when estimates the parameters of the several controllers in the system while minimizing the ITAE. A new family of controllers act over the plant expecting a decrease in the deviation from a desired behaviour. The procedure repeats until a stop criterion. Regardless the modelling of the plant and the structure or domain of the controllers, this procedure applies equally.

4. TUNING OF THE PID CONTROLLERS AND OPTIMIZATION OF THE VCRS.

As can be seen in (Fig. 2), the VCRS is composed of two controllers; the first is a discrete PID controller that corresponds to the speed of the compressor and the second a discrete transfer function that acts on the opening of the expansion valve. (Table 6) shows the input data for the MAGO algorithm. In addition, the bounds of the parameters of each controller. The first five values are for the parameters from the controller structure in transfer function, for the evaporation valve. The last two values correspond to the bounds for the tuning the PI, for the compressor speed. For all the tests, two different evaluation criteria were established: (1) a quantitative comparison by means of the ITAE and ISTSE performance criteria, and (2) a qualitative comparison through graphs that determine the quality of the response of the system.

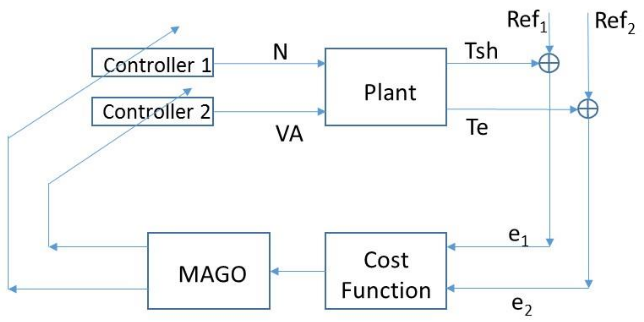

Fig. 2 Coupled evolutionary tuning procedure

The possibility of finding a good solution is subjected to the availability of time for testing. However, it was possible to find good results from the minimization of the ITAE mainly. Exemptions were also considered with minimization of the ISTSE cost function. In an Intel (R) Xeon (R) CPU @ 2.30GHz with 7.20GB and 64 bit, the average execution time was 11 hours, this because the structure of the Benchmark. Each evaluation of an individual by the MAGO requires an own execution of the plant in Simulink.

The cost functions used did not have any weight associated with the valve controller or the compressor controller, so in tuning both controllers are equally important. (Table 7) shows that even with few generations and individuals it was possible to find a cost function better than the one proposed in the Benchmark.

Table 6 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 7 Parameters of each controller applying MAGO

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

For both approaches, 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 Figures 3 to 6. They include the dynamics in the behavior of the actuators, and in the variables that determine the thermal behavior of the system. Although the response is quantitatively improved, qualitatively there is a margin for improvement, and the solution presented in the Benchmark behaves with greater smoothness in the system. This is because the cost function used punishes the error in time and requires a rapid follow-up of the reference. For the comparison, the best result found so far with the MAGO was used, which has an ITAE = 26.35.

The Benchmark PID-2018 also facilitates the quantitative comparison of two controllers based on the same simulation. Using that structure, the C1 controller corresponds to the Benchmark proposal and C2 to the results obtained with MAGO. According to the benchmark quantitative analysis, eight individual performance indices and a combined index are evaluated in this comparison (Bejarano, Alfaya, Rodríguez, & Ortega, 2018). That is, for the results (see Table 8) the structure predefined by the authors was used. This comparative procedure is very useful and allows seeing how a control strategy behaves in relation to another in terms of the changes and phenomena that should be known about the system. The original Benchmark indicator J is calculated assigning a weight value to each error indicator; however, such values are unknown.

Table 8 Relative indices and combined index according to the Benchmark for the comparison of controllers

C_1: Benchmark; **C_2**: MAGO	
Index	Value
$RIAE_1(C_2,C_1)$ Te,sec,out	0.7520
$RIAE_2(C_2,C_1)$ T_{SH}	0.6558
$RITAE_1(C_2,C_1,tc_1,ts_1)$ Te,sec,out	5.4358
$RITAE_2(C_2,C_1,tc_2,ts_2)$ T_{SH}	0.4454
$RITAE_2(C_2,C_1,tc_3,ts_3)$ T_{SH}	0.4970
$RITAE_2(C_2,C_1,tc_4,ts_4)$ T_{SH}	0.4548
$RIAVU_1(C_2,C_1)$ Av	1.0658
$RIAVU_2(C_2,C_1)$ Compressor	1.1159
$J(C_2,C_1)$	1.7472

In this paper, ease of use indices to measure the ITAE error equation (9) throughout the whole simulation period for each control variable are proposed equations (10) and (11), see (Table 9), where **C_1**: Benchmark PID and **C_2**: MAGO. In order to know the error rate between the MAGO strategy and the PID Benchmark strategy, in equation (12) the total cost functions for each approach are related, see (Table 10).

$$J_1(C_2,C_1)\ Te,sec,out = \frac{J_{ITAE_1}(C_2)}{J_{ITAE_1}(C_1)} \tag{10}$$

$$J_2(C_2,C_1)\ Tsh = \frac{J_{ITAE_2}(C_2)}{J_{ITAE_2}(C_1)} \tag{11}$$

$$J_T(C_2,C_1) = \frac{J_{ITAE_T}(C_2)}{J_{ITAE_T}(C_1)} \tag{12}$$

Table 9 Cost functions throughout the whole simulation period for the two approaches

Control Strategy	J_{ITAE1} $T_{e,sec,out}$	J_{ITAE2} T_{SH}	J_{ITAET} J_T
C2	2,894.7	267.4089	26.3511
C1	4,274	353.0790	38.55

Table 10 Relative indices and the combined index throughout the whole simulation period

Index	Value
$J_1(C_2,C_1)$ Te,sec,out	0.6772
$J_2(C_2,C_1)$ T_{SH}	0.7573
$J_T(C_2,C_1)$ System Cost Function	0.6835

5. CONCLUSIONS

The results of the simulation show that the control strategy with the MAGO achieves remarkable results considering the high coupling and the complexity of the system.

The MAGO improves the ITAE criteria in comparison with the Benchmark strategy. Qualitatively the improvement is not evident due to the presence of oscillations, having a faster follow-up of the reference. The oscillation can be reduced by rewriting the cost function in such a way that the overshoot or other criteria are punished. Increasing the population size and/or the generations number for the execution of the MAGO, or by expanding the search space are another ways to obtain a better response.

On the other hand, optimization through the MAGO is very useful for highly coupled complex systems. This method can be implemented without any inconvenience in future developments for control of cooling systems of multiple loads and stages. Here, the same structure presented in the Benchmark of a discrete transfer function and a PI controller was used, however, the MAGO is independent of the structure and the domain of the controller to be tuned. Future work is twofold, applying standard PID controllers in the time domain, and using Pareto front for the tuning.

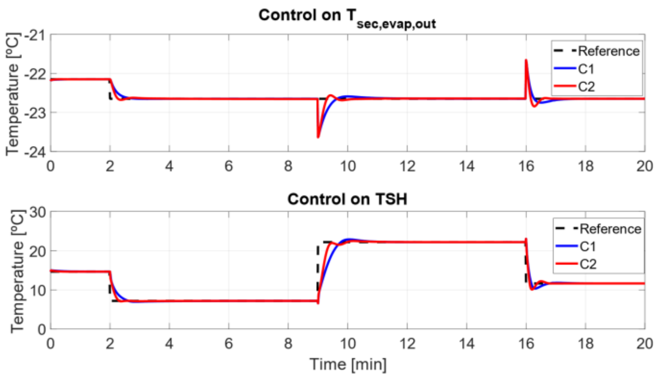

Fig. 3 Controlled variables

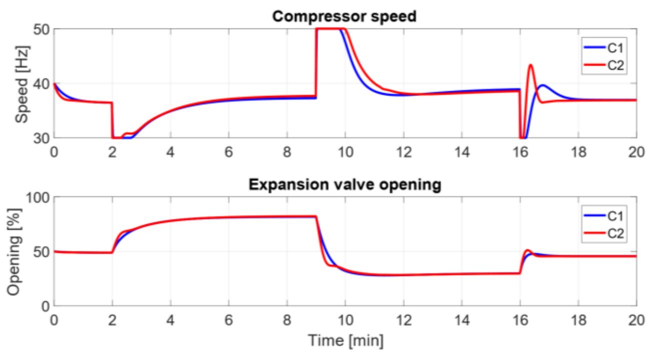

Fig. 4 Manipulated Variables

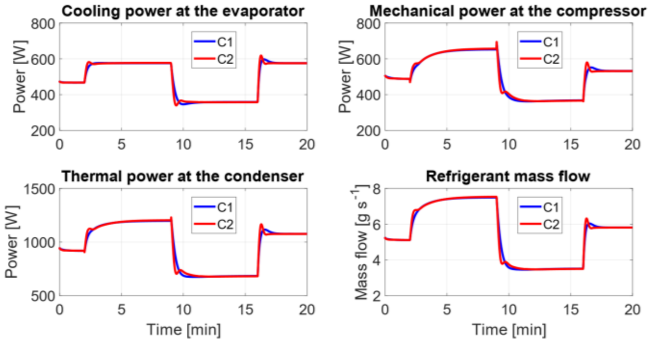

Fig. 5 Thermal and mechanical power at each component and refrigerant mass flow

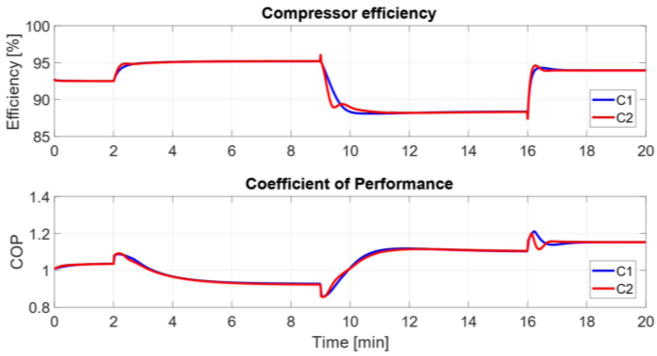

Fig. 6 Compressor efficiency and Coefficient of Performance.

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