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Development of an Adaptive PID Controller for Superheating Control Employing Artificial Bee Colony

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ABSTRACT

Electronic Expansion Valves (EEV) have been used in refrigeration systems to replace conventional expansion devices. Their quick response to changes in the operating conditions improves the steady-state superheating, what contributes to increase the system efficiency. EEV are usually used with automatic controllers and among the controllers employed in these devices, the Proportional, Integral and Derivative (PID) controller is the most common. In general, this controller allows for adjustments in the proportional, integral, and differential gains. If these gains are not properly adjusted, the system can display a slow, oscillatory, or unstable closed-loop response, poor disturbance rejection ability and low robustness. In the last decades, several tuning methods for PID controllers were proposed. Among them, the methods based on bio-inspired optimization techniques, in special the Artificial Bee Colony (ABC), are relatively new in PID controller tuning. This work presents an adaptive PID controller to regulate the opening of an EEV. The controller gains were determined using ABC algorithm for each operating point. A dynamic model obtained from experimental tests was used in the controller design. The controller effectiveness was evaluated through computer simulations. Preliminary results indicated that the proposed controller provides good disturbance rejection and set point tracking, and was able to control the superheating efficiently.

1. INTRODUCTION

Due to the limited resources and the increasing energy demand, the industries are investing in energy saving alternatives in order to improve the efficiency of their products. Within this context, there are approaches focusing more efficient heat exchangers and compressors (Park *et* al, 2015) and more efficient algorithms to control the superheating at the outlet of the evaporator (Maia et al., 2014). The superheating control can contribute to increase the system efficiency (Borja, 2006). Its accurate control can increase the amount of two phase refrigerant fluid inside the evaporator. Since the liquid refrigerant presents much higher heat transfer coefficient than the vaporized refrigerant, by filling the evaporator with a two phase refrigerant will improve the cooling capacity. At the same time, to ensure safe compressor operation, the superheating control algorithm should be good enough to ensure that only vaporized refrigerant fluid enters in the compressor.

The superheating is generally regulated by controlling the mass flow rate of refrigerant fluid that enters in the evaporator. Among the expansion devices developed for this purpose, the electronic expansion valve (EEV) is the most effective if the system operates in a wide range of operating conditions. Their quick response to changes in the operating conditions improves the steady-state superheating, which contributes to increase the system efficiency (Aprea & Mastrullo, 2002). Refrigeration Systems with EEVs presents smaller decrease in the refrigeration capacity and a bigger coefficient of performance (COP) through the ideal control of superheating (Choi & Kim, 2004; Lazzarin & Noro, 2008). EEVs are usually used with automatic controllers in order to keep the superheating close to its optimal value. Among the controllers employed in these devices, the Proportional, Integral and Derivative (PID) controller is the most common (Maia *et* al, 2010). In general, this controller allows adjustments in the proportional, integral, and differential gains. If these gains are not properly adjusted, the system can display a slow, oscillatory, or unstable closed-loop response, poor disturbance rejection ability and low robustness (Maia *et* al, 2014).
Classic approaches such as Ziegler-Nichols and Cohen-Coon methods have been used for years in tuning PID controllers, especially when there is not much information about the system subject to control. Besides these

methods allow stable and robust control (Batista *et* al, 2015), the gains are never guaranteed for being optimal. When the plants are nonlinear, of high order or have time delay, the conventional tuning methods sometimes fail to achieve satisfactory performance. Thus, other approaches have been used such as Fuzzy techniques, neural networks and other bio-based methods. The natural behavior and collective activities of bees, ants, termites, wasps and other social insects has been inspiring researchers on swarm intelligence and led to studies of bio inspired optimization methods (Bonabeau *et* al, 1999; Dorigo & Stutzle, 2004). Due to its high organizational capacity, bees are among the most studied social insects and several approaches to different behavioral characteristics of bee were proposed. The Artificial Bee Colony (ABC) algorithm is based on the foraging behavior and can be used in several problems solution (Serapião, 2009).

This work presents an adaptive PID controller to regulate the superheating at the evaporator outlet. The controller gains were determined using ABC algorithm for each operating point. These data were utilized in the development of the adaptation rules. The controller effectiveness was evaluated through computer simulations.

2. SYSTEM MATHEMATICAL MODEL

The mathematical model used in the simulation represents a vapor compression refrigeration system with R134a as the refrigeration fluid and pure water as a secondary fluid in the evaporator and the condenser. The model was obtained from tests at evaporating temperatures of −5◦C, 0◦C, 5◦C, and 10◦C by Maia *et* al. (2014). The refrigeration system was set to operate at a superheating of approximately 7 K at the evaporator output, the condenser temperature was approximately 50°C and the compressor speed was 650 rpm. The superheating was estimated though the difference between the input and output temperatures of the evaporator. The superheating response was modeled using a first order function plus time delay (Equation 1). K represents the static gain, τ the time constant, θ the time delay and s is the Laplace operator (Maia *et* al, 2014).

$$G(s) = \frac{Ke^{\theta s}}{\tau s + 1} \qquad (1)$$

K and T were estimated by Maia *et* al (2014) for different evaporation temperatures between -5°C and 10°C and mathematical relations were presented to describe their evolution. The equation above is the transfer function that was used in Matlab® to perform the simulations. In the Equation 2 T_1 is the evaporating temperature (Maia *et* al, 2014). Maia *et* al estimated the gains using the relation $\Delta(\Delta T_s)/\Delta \dot{m}_f$ and the time constant is the time instant in which the superheating reached 63% of its final change.

$$G(s) = \frac{(0{,}0027T_1^2 + 0{,}321T_1 - 1{,}7163)e^{2s}}{(-0{,}0399T_1^2 - 0{,}3338T_1 + 20{,}254)s + 1} \qquad (2)$$

3. THE ARTIFICIAL BEE COLONY ALGORITHM

The ABC (Artificial Bee Colony) algorithm is based on the foraging behavior of bees. In this algorithm there are three types of bees: employed, onlooker and scout. An employed bee search for food sources, memorize the quality of it and shares it with other bees by a waggle dance. The onlooker bee is an unemployed bee that tries to find a new food source using the information of employed bee. The scout bee ignores the other's information and searches randomly around the hive (Abachizadeh *et* al, 2010). In this algorithm, the position of a food source represents a possible controller gain. Each food source has a quality that is defined based on the system response, when using this potential controller gain. The source can be improved by testing the quality around it. If it can not be improved after a certain number of trials and it is not the best source then this source of food is abandoned. The steps below describe the ABC algorithm (Bhagade & Puranik, 2012).

1. Determine the size of the bee colony (COL); the initial number of employed bees (BN); the number of food sources (SN), which is equal to BN; the number Initial onlooker bees (BC), which is equal to the difference between COL and BN; the number of scout bees (BE)j; and the number of attempts to release a source of food (lim);
2. Send randomly the employed bees to the initial food sources;

3. Send the onlooker bees to the best food sources found by employed bees and determine the quality of each food source by $\mathrm{fit}(x_i)$ (Equation (3)). This quality is based on the system response, the Error based indices (ITAE, IAE, ITSE and ISE) were evaluated in order to be used in $\mathrm{fit}(x_i)$ calculation and provide a better response;

$$\mathrm{fit}(x_i) = \frac{1}{\mathrm{Error}} \tag{3}$$

4. Calculate the probability P (Equation (4)) of sources to be chosen by onlooker bees;

$$P_i = \frac{\mathrm{fit}(x_i)}{\sum_{n=1}^{SN} \mathrm{fit}(x_n)} \tag{4}$$

5. Stop the exploration of the worst sources;
6. Send the scout bees to search randomly around the hive;
7. Memorize the best food source found;
8. If the number of attempts (nt) to discover new food sources fail (nt > lim), or if the food sources do not improve, the scout bees should leave their stagnant sources and search randomly for new food sources (xi);
9. If the stop conditions are not reached, go to step 3.

Initially, as a cost function, it was considered four performance indexes (Equations (5-8)); ISE (Integral of Squared Error), ITSE (Integral of Squared Error Multiplied by the Time), IAE (Integral of the Absolute Error) and ITAE (Integral of the Absolute Error Multiplied by the Time). ITAE and ITSE are weighted by time so that the initial error has a smaller weight. In PID tuning this is interesting because of the overshoot.

$$\mathrm{IAE} = \int_0^\infty |e(t)|dt \tag{5}$$

$$\mathrm{ISE} = \int_0^\infty e^2(t)dt \tag{6}$$

$$\mathrm{ITAE} = \int_0^\infty t|e(t)|dt \tag{7}$$

$$\mathrm{ITSE} = \int_0^\infty te^2(t)dt \tag{8}$$

The initial values used by the algorithm were estimated empirically, thus the hive has 20 bees, the search area has a range of -5 to 5, the simulation has a number of attempts of 2500 iterations and the boiling temperature was varied from -5°C to 10°C. The system was simulated considering the use of each error based indices in $\mathrm{fit}(x_i)$ calculation and the system final response and the control action were compared in Figure 1. The superheating control when the ITSE, ISE and IAE were used in the PID Tuning presented a larger oscillation in the beginning when compared to the ITAE, which also presented a small overshoot, less than 0.5 °C. Thus, considering the quality of the final control, ITAE was chosen.

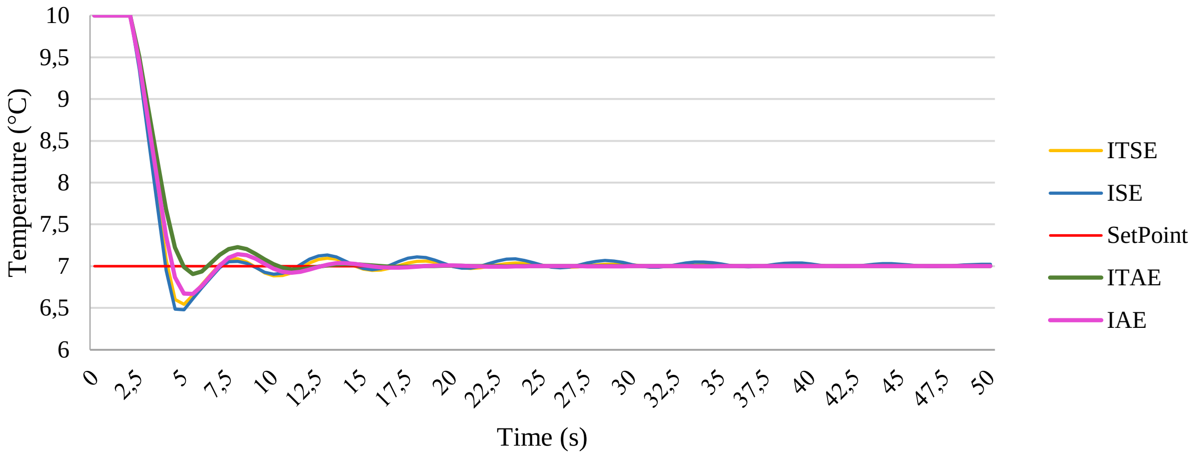

Figure 1: Comparison between control actions using ITAE, IAE, ITSE and ISE to calculate Fit(x_i)

The number of bees in colony is an important parameter to be determined, because a small number of bees may not led to an optimum value and a bigger number of bees increase the total time of simulation. To determine a suitable number of bees, simulations were performed considering a colony of 16, 20, 26, 30, 36, 40, 46 and 50 bees. The ideal number of bees was chosen considering the quality of the system response, the simulation duration and the ITAE value. The simulation duration is also related to the computational effort, more bees means more simulations to find the optimal gains. Figure 2 shows the final ITAE value found for each temperature. It is possible to observe in Figure 2 that the final ITAE is in a range between 22 and 25 where the smaller error represents a better control action with less oscillation. Considering the number of bees, the simulation performed with 30 bees presented the ITAE between 23 and 22 which is good considering the control action

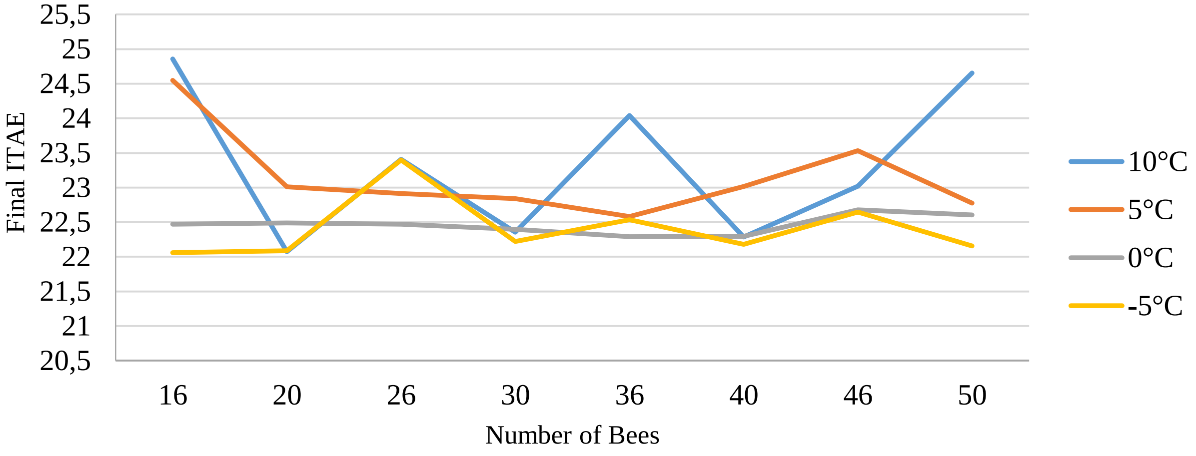

Figure 2: Comparison between the number of bees and the final ITAE

The best closed loop system response was obtained when the ITAE was 23 or lower. To define the maximum number of iterations, initially the algorithm was limited to 5000 iterations, for the temperatures of -5, 0, 5 and 10°C. It was observed no relevant change in the gains values after 2000 iterations. For this reason, the maximum number of iterations was set to be 2000. Figure 3 presents the number of iterations when the best gain was reached for each temperature and number of bees. It is possible to observe in Figure 3 that none of the simulations reached the maximum number of iterations. The simulations using 20, 30 and 46 bees also reached a good results before 1500 iterations whith is good when considering the computer effort. The algorithm stops searching for better controller gains when the maximum number of iterations (2000) is reached or when the ITAE is smaller than stablished (23). Considering the analysis of Figure 2 and 3, the number of bees chosen was 30, first because of the small ITAE and also because of the number of iterations when the best gain was found.

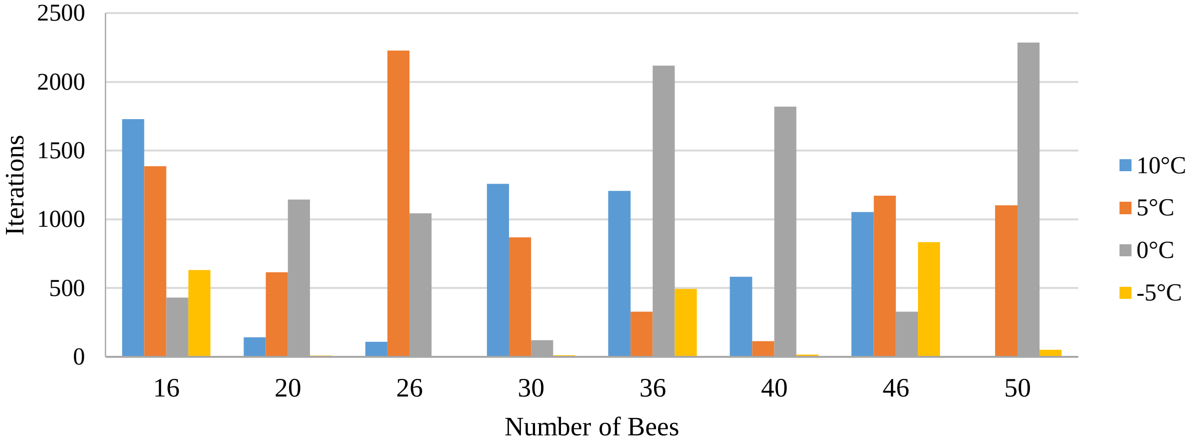

Figure 3: Comparison between the Number of Bees and Max Number of Iterations

The initial searching area for food sources was from -5 to 5. In order to improve the algorithm performance, after reaching the stop criteria, the searching area was reduced to the minimum and maximum gains values, decreased and increased of 10%, respectively. In Table 1 is presented the optimal PID gains for each evaporating temperature, form 10°C to -5°C. The temperatures of the table are the evaporating temperatures T_1 of the transfer function (Equation (2)), this way, the controller gains are adjusted for different temperatures, leading to an adaptive PID Controller. The Kp, Ki and Kd values were obtained varying T_1 in the transfer function and running the ABC algorithm to find the optimal PID gains for each temperature.

To evaluate the proposed methodology, the controller tuned employing the ABC algorithm was compared with a controller tuned using the SIMC method (Skogestad, 2003). The SIMC method is an optimization of the IMC PID tuning presented by Rivera et al. (1986). In Table 1 is presented the gains and the ITAE index obtained for each controller design method. In all simulations, the response achieved using SIMC method presented a ITAE that was, at least, three times higher than the response obtained with the ABC algorithm.

Table 1: PID Controller Parameters and ITAE

Temp. (°C)	**Kp (ABC)**	**Kp (SIMC)**	**Ki (ABC)**	**Ki (SIMC)**	**Kd (ABC)**	**Kd (SIMC)**	**ITAE (ABC)**	**ITAE (SIMC)**
10	-2.9846	-2.4265	-0.1631	-0.1742	-2.3528	-2.2523	24.2354	70.5441
9	-2.9838	-2.4362	-0.1521	-0.1622	-2.3081	-2.2740	23.8899	74.9220
8	-2.9838	-2.4428	-0.1418	-0.1527	-2.3723	-2.2904	23.4945	79.1269
7	-3.0384	-2.4468	-0.1359	-0.1529	-2.5321	-2.3026	23.3276	88.4599
6	-3.0032	-2.4487	-0.1288	-0.1530	-2.4079	-2.3113	23.2513	96.0490
5	-3.2737	-2.4488	-0.1296	-0.1531	-3.4961	-2.3171	23.4929	102.3215
4	-3.2844	-2.4474	-0.1315	-0.1530	-2.9914	-2.3204	23.1913	107.4927
3	-3.2844	-2.4445	-0.1273	-0.1528	-2.9914	-2.3216	22.9646	111.7369
2	-3.0176	-2.4403	-0.114	-0.1525	-2.3888	-2.3208	22.8944	115.2229
1	-3.1712	-2.4348	-0.114	-0.1522	-3.0457	-2.3182	22.3961	118.0414
0	-3.2489	-2.4282	-0.114	-0.1518	-3.3954	-2.3139	22.5899	120.2746
-1	-3.2658	-2.4203	-0.114	-0.1513	-3.3954	-2.3080	23.1771	121.9725
-2	-3.2334	-2.4112	-0.114	-0.1507	-3.0105	-2.3004	22.8193	123.1771
-3	-3.2334	-2.4008	-0.114	-0.1501	-2.9933	-2.2912	22.5422	123.9213
-4	-3.2334	-2.3892	-0.114	-0.1493	-2.9993	-2.2803	22.5506	124.2209
-5	-3.2334	-2.3761	-0.114	-0.1485	-2.9993	-2.2677	23.4568	124.0821

3. RESULTS

3.1 Simulation Results

In order to evaluate the adaptive controller effectiveness and the superheating response, the system mathematical model was simulated in different operating points. The controller gains were adjusted as shown in Table 1. For each evaporating temperature, different gains were used. Figure 4 represents the system in normal conditions without any disturbances. The simulation initiates with a difference of temperatures of 10°C and the objective is to have a superheating of 7°C, as the setpoint stablished. The simulation was performed for the evaporation temperatures of -5°C, 0°C and 10°C with a superheating setpoint of 7°C. It is possible to observe that the ABC control action tracked the setpoint for all the temperatures simulated with a small overshoot and small oscillations in the beginning that disappeared after 15 seconds of simulation. It is also presented a comparison between the ABC and the SIMC. Besides SIMC response tracked the setpoint with almost none overshoot or oscillations, it took more than 40 seconds to get to the setpoint value. This longer time to respond justifies the bigger ITAE found for all SIMC gains.

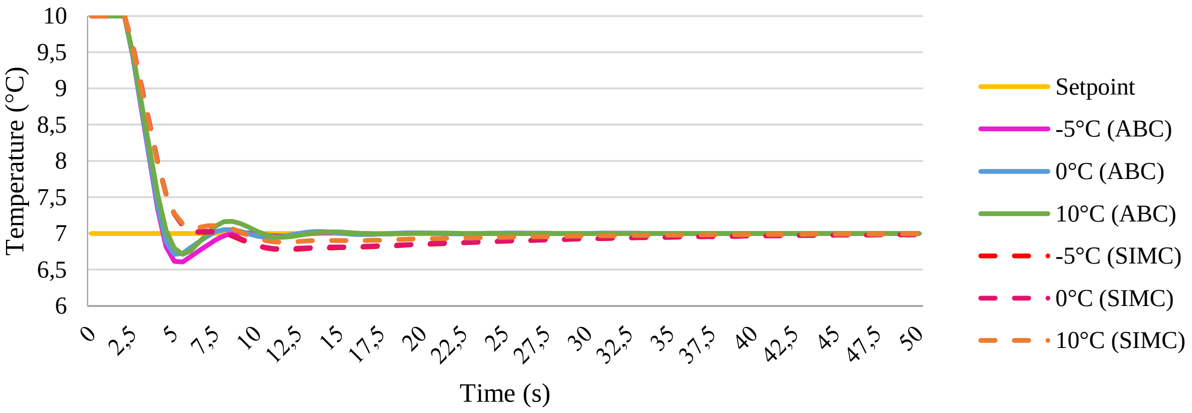

Figure 4: Simulation Results of control action with a setpoint of 7°C

Figure 5 represents the superheating response to a set point change from 7°C to 9°C after 20 seconds of simulation. This simulation represents the capacity of the system to work at new operating condition. The results show that the control algorithm could effectively maintain the superheating close to the reference value. The superheating response tracked the setpoint with a small overshoot and, after the setpoint change, the superheating response tracked the new reference value without presenting an oscillatory behave.

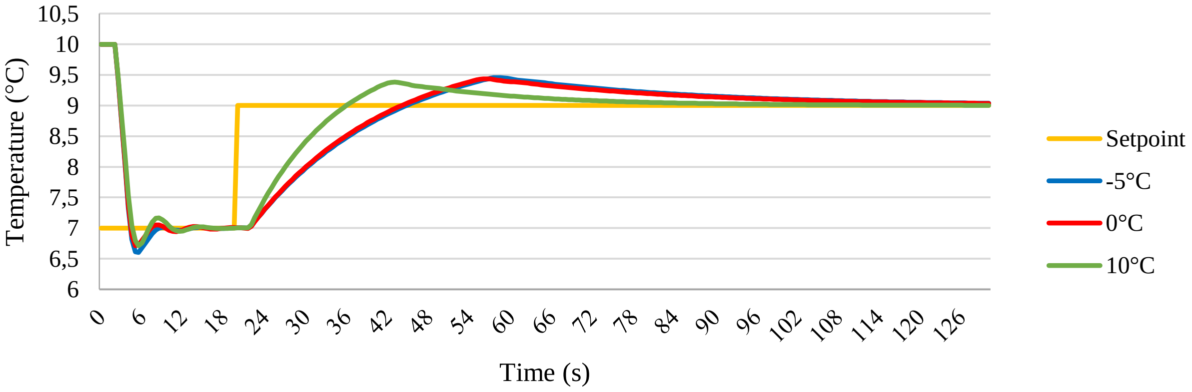

Figure 5: Simulation Results of control action with a setpoint of 9°C

Figure 6 presents the results of the superheating response with a setpoint of 7°C and evaporation temperatures of -5°C, 0°C and 10°C. A disturbance was added after 25 seconds of simulation and the superheating response presented a small overshoot and continued tracking the setpoint.

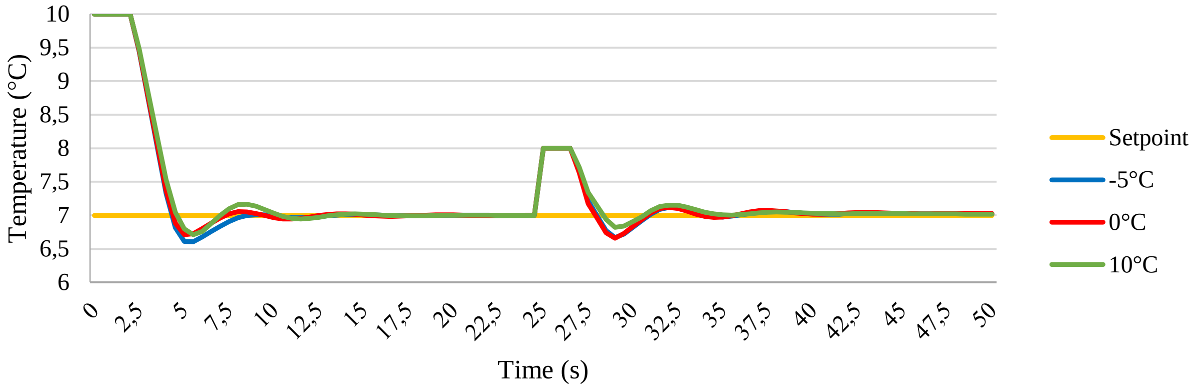

Figure 6: Simulation Results with disturbance rejection

4. CONCLUSIONS

This work presents the tuning of an adaptive PID controller to regulate the opening of an EEV. The controller gains were determined using ABC algorithm for each operating point. These gains were adjusted depending of the evaporating temperature. The controller effectiveness was evaluated through computer simulations and by means of experimental tests.

The computer simulations showed that the superheating response was good over the tests. Compared with the SIMC, the ABC response presented a small overshoot but a faster response, tracking the setpoint quickly with a small ITAE, the SIMC response tracked the setpoint with almost none overshoot or oscillations although it took more than 40 seconds to get to the setpoint value and had a bigger ITAE.

When the setpoint changed from 7 °C to 9 °C the superheating response tracked the reference value with small overshoot. This simulation represents the capacity of the system to work at new operating condition. Other simulations testes the disturbance rejection and the results were also satisfactory once a disturbance was added after 25 seconds of simulation and the superheating response presented a small overshoot and continued tracking the setpoint.

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