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TEMPERATURE CONTROLLER OPTIMIZATION BY COMPUTATIONAL INTELLIGENCE

by

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In this paper a temperature control system for an automated educational classroom is optimized with several advanced computationally intelligent methods. Controller development and optimization has been based on developed and extensively tested mathematical and simulation model of the observed object. For the observed object cascade P-PI temperature controller has been designed and conventionally tuned. To improve performance and energy efficiency of the system, several metaheuristic optimizations of the controller have been attempted, namely genetic algorithm optimization, simulated annealing optimization, particle swarm optimization and ant colony optimization. Efficiency of the best results obtained with proposed computationally intelligent optimization methods has been compared with conventional controller tuning. Results presented in this paper demonstrate that heuristic optimization of advanced temperature controller can provide improved energy efficiency along with other performance improvements and improvements regarding equipment wear. Not only that presented methodology provides for determination and tuning of the core controller, but it also allows that advanced control concepts such as anti-windup controller gain are optimized simultaneously, which is of significant importance since interrelation of all control system parameters has important influence on the stability and performance of the system as a whole. Based on the results obtained, general conclusions are presented indicating that metaheuristic computationally intelligent optimization of heating, ventilation, and air conditioning control systems is a feasible concept with strong potential in providing improved performance, comfort and energy efficiency.

Key words: thermal system, temperature control, controller optimization, computational intelligence

Introduction

It is very common nowadays that public buildings (business centres, schools, university buildings, *etc.*) are equipped with several or even large number of different systems such as surveillance systems, energy management systems, air conditioning, security systems, fire protection systems, and even systems for protection against earthquakes or wind gusts. Those systems are nowadays realized as integral part of individual buildings and are commonly integrated at the level of harmonization of all functional aspects of executing global strategy of the so called *intelligent buildings* [1].

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In order to have a rational energy consumption, one typical classroom in higher education institution building has been equipped in such manner to ensure high comfort for users by controlling of heating, ventilation, and air conditioning (HVAC). This representative classroom of 40 m^2 , used primarily for university lectures, has been constructed with three inner walls and one outer wall. The radiators preheat the classroom, while an air-handling unit (AHU) compensates heat loses. Objective of the control system is to control the temperature in the classroom by means of air from the AHU. Components taken into consideration for creating a mathematical model of the observed temperature control system are electrical pre heater, boiler heater, heat recovery unit, valve and room itself. All impacts for temperature changes have also been taken into consideration.

In contemporary HVAC systems various control techniques are used, from classical to contemporary [2-4]. However, in commercial applications cascade proportional-integral-derivative (PID) [5] controllers are largely dominant, where instead of a single conventional PID controller two cascade PID controllers are interconnected and used together in order to obtain superior dynamic performance.

Regarding application of computational intelligence in HVAC systems control, an adaptive learning algorithm based on genetic algorithms (GA) for automatic tuning of PID controllers applied to enhance the HVAC systems has been studied in [6]. The use of genetic algorithms to tune fuzzy logic controllers dedicated to HVAC systems is presented in [7, 8]. Optimization of control strategies using genetic algorithms in air conditioning system is treated in [9]. An overview of different control techniques in HVAC systems can be found in [4], while a variety of intelligent control methodologies applied to HVAC systems were reviewed in [10].

In this paper, computational intelligence is used for optimization of the temperature control system. For that purpose, a mathematical and simulation model have been developed, and several meta-heuristic methodologies have been considered, namely genetic optimization, simulated annealing, particle swarm optimization, and ant colony optimization.

Obtained results have been compared with advanced manual tuning of the controller, which has been done on the basis of vast experience and theoretical recommendations. Subproblem of heating in winter regime is considered regarding control for which cascade P-PI controller has been designed. Optimal parameters of system have been searched in terms of energy efficiency, dynamic characteristics and equipment wear.

Mathematical model of the system

The design of successful controllers for HVAC systems primarily depends on the availability of proper dynamic models of the systems and mathematical equations that describe its behaviour [11-13]. The complexity of a HVAC system with distributed parameters, interactions, and multivariable quantities makes it difficult to obtain an exact mathematical model in order to improve control quality [14-16]. Therefore, mathematical modelling of the HVAC system and simulation of the presented model are considered first.

The major components considered in the system can be divided in two groups: a zone model (classroom) and components of the HVAC system [17]. The functional schematics of the AHU with considered components is presented in fig. 1. Detailed mathematical descriptions of every component are given further in this paper.

First, mathematical model of all AHU components is given and then model of the classroom. HVAC system components that have been taken into consideration for system modelling are: electrical preheater, water heater, recovery unit, mix valve and classroom itself [18].

conditioning system



Mathematical description of the electrical preheater can be written:

$$m_{\rm l}c_{p}T_{\rm l} + \dot{m}c_{p}T_{\rm l} = \dot{m}c_{p}T_{\rm 0} + Q_{gr} \tag{1}$$

where m_1 is the mass of air in the preheater (GR1, fig. 1), c_p – the specific heat capacity of the air, $T_1(t)$ – the temperature of the air after the preheater, $T_0(t)$ – the temperature of the outside air, \dot{m} – the mass flow of the air through the AHU, and Q_{gr} – the power of the electrical preheater.

Mathematical model of the heat recovery unit is based on assumption that the air flow through the AHU is constant. Hence, only the law of energy conservation is needed to find the mathematical model of the temperature changes through the heat recovery unit. From this law the following equations can be derived [11]:

$$m_{\rm r}c_p T_2 = \dot{m}c_p (T_1 - T_2) + H_{\rm r}A_{\rm r} (T_{\rm wa} - T_1)$$
 (2)

$$m_{\rm r}c_p \dot{T}_{\rm wa} = \dot{m}c_p (T_i - T_{\rm wa}) + H_{\rm r}A_{\rm r} (T_{\rm wa} - T_1)$$
(3)

where m_r is the mass of the air in the heat recovery unit, $T_2(t)$ – the temperature of the recuperated air, $T_i(t)$ is temperature of the room air (returned air), $T_{wa}(t)$ – the temperature of the waste air, and H_rA_r is the resulting heat transmission number of heat recovery unit.

By combining (2) and (3) it is obtained:

$$\left(\frac{m_{\rm r}}{\dot{m}}\right)^2 \ddot{T}_2 + \left(2\frac{m_{\rm r}}{\dot{m}} + \frac{H_{\rm r}A_{\rm r}m_{\rm r}}{\dot{m}^2c_p}\right) \dot{T}_2 + \left(1 + \frac{H_{\rm r}A_{\rm r}}{\dot{m}c_p}\right) = \frac{m_{\rm r}}{\dot{m}} \left(1 + \frac{H_{\rm r}A_{\rm r}}{\dot{m}c_p}\right) \dot{T}_1 + T_1 + \frac{H_{\rm r}A_{\rm r}}{\dot{m}c_p} T_i \tag{4}$$

where \ddot{T} is the second time derivative of the temperature $T_2(t)$.

Mathematical model of the heating coil (GR2, fig. 1) describes the temperature change both in the water and the air passing through this component. The mathematical model is based on the assumption that both the airflow and the water flow through heating coil are constant. The following equation is dynamic heat balance for the air in the heating coil:

$$m_g c_g \dot{T}_{w0} = \dot{m}_w c_{pw} (T_{wi} - T_{w0}) + H_g A_g (T_{w0} - T_2)$$
(5)

and the corresponding heat balance equation for the water is:

$$m_{vg}c_pT_4 = \dot{m}c_p(T_2 - T_4) + H_gA_g(T_{wo} - T_2)$$
(6)

where m_g is the total mass of the heating coil (including water), m_{vg} – the mass of air in the heating coil, \dot{m}_{w} – the mass flow of the water through coil, c_{pw} – the specific heat capacity of water, c_g – the resulting specific heat capacity of the heating coil, $T_{wo}(t)$ – the water temperature from the coil exit, $T_{wi}(t)$ – the water temperature from the coil entrance, $T_3(t)$ – the temperature of air after heating coil, and H_gA_g – the resulting heat transmission number of the heating coil.

By rearranging (1) it is obtained:

$$m_g c_g \dot{T}_{wo} + (H_g A_g + \dot{m}_w c_{pw}) T_{wo} = \dot{m}_w c_{pw} T_{wi} + H_g A_g T_2$$
(7)

and further by combining (6) and (7):

$$\ddot{T}_{4} + \left(\frac{\dot{m}}{m_{vg}} + \frac{H_{g}A_{g} + \dot{m}_{w}c_{pw}}{m_{g}c_{g}}\right)\dot{T}_{4} + \frac{\dot{m}}{m_{vg}}\frac{H_{g}A_{g} + \dot{m}_{w}c_{pw}}{m_{g}c_{g}}T_{4} =$$

$$= \frac{\dot{m}c_{p} - H_{g}A_{g}}{m_{vg}c_{p}}\dot{T}_{2} + \left[\frac{(\dot{m}c_{p} - m_{wg}c_{pw})H_{g}A_{g}}{m_{vg}m_{g}c_{p}c_{g}} + \frac{m_{w}\dot{m}c_{pw}}{m_{vg}m_{g}c_{g}}\right]T_{2} + \frac{H_{g}A_{g}\dot{m}_{w}c_{pw}}{m_{vg}m_{g}c_{p}c_{g}}T_{wi}$$
(8)

Temperature of the supply air is controlled by the three port valve with continuous drive (Y3, fig. 1). The heat balance for the water in the three-way valve can be written:

$$T_{wi} = (1 - x)T_{wo} + xT_c$$
(9)

where x is the relative valve position and T_c – the central heating flow temperature.

The classroom is an integral part of the higher education institution, and it is designed for teaching purposes of the area of 40 m². One side of the classroom is exposed to an open space and other three sides are bounded with offices. The envelope of the building has been made of a porous brick with thickness of 200 mm. Windows are double glazed, thus the overall ratio of glass to the exterior walls is 50%, where the total area of exterior walls is 20 m².

Controlled variable is the room air temperature. It assumed that the air pressure is constant and the room air temperature field is homogenous. Disturbances affecting the temperature are taken also into account, such as people, lights, walls and windows loses, *etc.* With these assumptions energy balance equation is:

$$\dot{T_i} + \frac{H_u A_u + H_s A_s + \dot{m}c_p}{m_z c_p} T_i = \frac{\dot{Q_d} + H_u A_u T_u + H_s A_s T_o + \dot{m}c_p T_4}{m_z c_p}$$
(10)

where T_i is the current air temperature, H_uA_u and H_sA_s are the heat transfer through inner and outer walls, respectively, m_z is the mass of air in the room, \dot{Q}_d – the disturbances originating from lights, people, *etc.* and T_u – the temperature in areas surrounding room.

Temperature controller concept and modelling

Cascade control strategy

Cascade control is used when there are several measurement signals and one control value. Cascade control is especially useful when there is a large time delay between the control signal and the output or for plants with large time constants. It is thus considered a good choice for control of temperature and humidity at the air systems. Cascade control is particularly suitable in cases where it is desirable to control quickly the building, *e. g.* in a large hall that fills or empties with users in the short terms. Big thermal fluctuations are not desirable, thus due to the large volume of rooms in such cases, there is a small number of air exchanges. Control of these facilities is very difficult for the main reason that control system only works on fresh air.

In cascade control, there are two interconnected PID controllers, where the first one controls the input of the second PID controller. Outer PID controller controls the primary physical parameters such as water level, or speed. The other controller acts as a regulator of the inner loop, which reads the output from the controller on the outer feedback loop, that can receive changes that occur much faster, such as flow velocity and acceleration.

It can be proven mathematically that the system responds faster and better when cascade PID controllers are used [1]. In addition, by means of the cascade controller a limitation thermostat of the supply air temperature can be omitted. Therefore, in the considered HVAC system cascade PID controller has been applied. Figure 2 shows the structural difference between ordinary and cascade PID controller.



Figure 2. (a) classical PI controller, (b) cascade P-PI controller

The most common additional (inner) controller is PI controller which controls supply air temperature. The main (outer) controller, which controls temperature in the room space, is most often selected to be a simple P controller. Such control system is called P-PI cascade control system. Cascade control operates in such manner that in case of the occurrence of deviations of controlled values, they are not controlled directly but rather the desired value of the additional controller is changed instead. The main reason for applying cascade controller is faster internal feedback loop, which detects disturbances much faster than external feedback. The result of such strategy is that it causes very quick action of the executive device.

The equation of the outer (master) P controller is:

$$T_{uz} = T_{un} + K_p \varepsilon = T_{un} + K_p (T_z - T_i)$$
⁽¹¹⁾

where T_{uz} is the desired inlet air temperature *i. e.* desired value for inner (slave) controller, T_i – the room air temperature, and T_z – the desired value of room temperature.

With previous elaborations, energy balance equation is:

$$m_{z}c_{v}T_{i} + (\dot{m}c_{v} + K_{sz}A_{sz} + K_{uz}A_{uz} + K_{p}A_{p})T_{i} = \dot{m}c_{v}T_{u} + K_{sz}A_{sz}T_{0} + K_{uz}A_{uz}T_{uz} + K_{p}A_{p}T_{p} + Z$$
(12)

where m_z is the mass of the air in the classroom, $T_i(t)$ – the current temperature of the room air, $K_{uz}A_{uz}$ – the resulting heat transmission number of the inner walls, $K_{sz}A_{sz}$ – the resulting heat transmission number of the outside wall, K_pA_p – the the resulting heat transmission number of the floor, $T_u(t)$ – the supply air temperature, $T_{us}(t)$ – the temperature of the surrounding rooms, $T_p(t)$ – the temperature of the floor, and Z(t) – the disturbance which is caused by people inside the classroom, lights, *etc*.

Inner (slave) PI controller is described with:

$$Y = K_p \varepsilon + K_i \int \varepsilon dt, \quad \varepsilon = T_{uz} - T_3$$
⁽¹³⁾

where *Y* is the control voltage for three port valve.

Anti-windup control

Problem of switching control modes from one to another mode arises in situations when the practical requirements of the management of the process have to be taken into account as well as physical limitations.

For example, when actuator has been saturated *i. e.* the regulator valve is completely opened (or closed), controller should stop sending control signals to the valve because it cannot deliver to the process more than the maximum value which is achieved. If this is not done, the calculated value of the controller output will continue to grow. The controller/regulator sends a signal to the process that constantly increases (or decreases), while the process receives the signal that is constant, because the valve is in saturation. That occurrence is called reset windup and has to be stopped. There are a several different methods which are used to remove windup, and are called anti-windup strategies [19].

Anti-windup control strategy has been implemented in observed system, for the mentioned reason. That further complicates controller tuning since anti-windup gain needs to be set along with other cascade controller gains. Nevertheless, computationally intelligent optimization allows that anti-windup gain is adjusted along with other controller parameters, which is important step towards complete automated tuning of the controller in such manner that wider set of demands is fulfilled.

Simulation of system behaviour and initial controller tuning

The components of thermal systems described in the previous section were used to build simulation model [20], which is shown in fig. 3.



Figure 3. Simulation model

Developed mathematical and simulation models have been used to verify parameters of the real system, for initial suboptimal setting of the controller and finally for the optimization of all controller parameters. It could also be used to further develop and test others potentially more sophisticated control algorithms and for further development of the model as to include more working regimes.

Parameters that have been adopted in the simulation model are summarized in tab. 1. Parameters of the pre-heater, heat recovery unit and heater have been defined by the manufacturer, while the other have been calculated by constructive characteristics of the room.

Characteristics of the pre-heater	$m_1 = 0.37$ $c_v = 1012$ $T_0 = 273+5$ $\dot{m} = 1.33/4$	Mass of air in the preheater [kg] Specific heat capacity of air [JkgK ⁻¹] Input temperature of air chamber (output temp.) [K] Mass flow of air through air chamber (max. 1.33 kg/s)		
Heat recovery unit parameters	$K_r A_r = 337$ $m_r = 1$	Coefficient of through passage×surface of heat recovery unit [WK ⁻¹] Air mass in heat recovery unit (assumption)		
Heater parameters	$K_{g}A_{g} = 2.5 \times 80$ $m_{vg} = 0.5$ $m_{w} = 2$ $m_{c} = 5$ $m_{g} = m_{w} + m_{c}$ $c_{w} = 4181.3$ $c_{c} = 385$ $c_{g} = (m_{w} \times c_{w} + m_{c} \times c_{c})/mg$ $m_{w} = 0.311$	Coefficient of through passage×surface of heater [WK ⁻¹] Mass of air into the heater Water mass into the heater Mass of the heater (metal) Mass of heater including mass of water Specific heat capacity of water Specific heat capacity of heater (just metal) Specific heat capacity of heater including water Mass flow of water through the heater [kgs ⁻¹]		
Room parameters	$K_{sz}A_{sz} = 86$ $K_{uz}A_{uz} = 75$ $K_pA_p = 78$ $m_z = 226$ $T_{uz} = 291$ $T_p = 283$	Coefficient of through passage×surface of outer barrier/wall [WK ⁻¹] Coefficient of through passage×surface of inner barrier/wall [WK ⁻¹] Coefficient of through passage×surface of floor [WK ⁻¹] Mass of air in the room [kg] Temperature in surrounding rooms [K] Floor temperature [K]		
Controller parameters	$a = \dot{m}c_v + K_{uz}A_{uz} + K_{sz}A_{sz} + K_pA_p$ $b = \dot{m}c_v$ $q = K_{uz}A_{uz}T_{uz} + K_{sz}A_{sz}T_0 + K_pA_pT_p$ $T_{switch} = 2500$	Coefficients for calculation depending of added air from desired temperature of room, which have also been used for initial setup of P operation of "master" regulator Moment when PID controller is switched on		

 Table 1. Parameters adopted in the simulation model

Based on previous elaboration, vast experience with similar systems and also based on extensive numerical simulation experiments with the developed mathematical model, initial parameters of P-PI controller have been selected. Best results have been obtained for the values of parameters $K_p = 7$ for proportional P gain of P master controller, and $K_p = 0.5 \text{ K}^{-1}$, and $K_i = 0.01 \text{ K}^{-1} \text{s}^{-1}$ for proportional and integral gains of PI (slave) of regulator. Figure 4. shows time changes of desired (reference) temperature in the classroom and response of system with cascade P-PI controller. Control signal of cascade regulator is shown in fig. 5.







Figure 4. System response with experimentally suboptimally tuned cascade control

Figure 5. Control signal of cascade controller

Computationally intelligent optimization of temperature controller

As it has been demonstrated in this case and well documented in everyday practice reports, tuning of PID controllers is often difficult and long lasting procedure, while widely accepted Ziegler-Nichols procedure does not guarantee optimal closed loop performance which makes its application being fairly limited. Therefore, the computationally intelligent meta-heuristic optimization techniques have been proposed as an alternative mean of tuning HVAC controllers, providing simple and robust approach, so it was used here as an alternative to the experimental controller parameter adjustment.

Offline controller optimization has been performed, as it is presented in fig. 6. To perform computationally intelligent controller optimization, fitness function has been defined which minimizes cumulative absolute controller error:

$$J = \sum_{i=1}^{N} \left| e_i \right| = \sum_{i=1}^{N} \left| r_i - y_i \right|$$
(14)

where r is the reference variable – desired room temperature, y – the controlled output – measured room temperature, e – the control error, and N – the number of patterns.

Several alternative meta-heuristic methodologies have been considered: genetic algorithms, simulated annealing, particle swarm optimization and ant colony optimization.

Genetic algorithms (GA) [21] are one of the evolutionary computational intelligence techniques, inspired by Darwin's theory of biological evolution. GA provide solutions using randomly generated bit strings (chromosomes) for different types of problems, searching the most suitable among chromosomes that make the population in the potential solutions space. Genetic optimization is an alternative to the traditional optimal search approaches which make difficult finding the global optimum for nonlinear and multi-modal optimization problems. Thus, GA have been successful in solving combinatorial problems as well as in many control applications such as parameter identification and control structure design.

Simulated annealing (SA) [22] is a probabilistic technique for approximating the global optimum of a given function. It is an optimization method similar to the physical process of heating up a solid until it melts, followed by cooling it down until it crystallizes into a perfect lattice. Specifically, it is a meta-heuristic method for approximate global optimization in a large search space. It is often used when the search space is discrete (*e. g.*, all tours that visit a given set of cities). As with other optimization methods used, with the SA the solutions were chosen randomly and evaluated by the same fitness function as in the case of the GA algorithm and adopted if the fitness of the new solution was less than the previous one.



Figure 6. Computationally intelligent optimization of cascade temperature P-PI controller

Particle swarm optimization (PSO) [23] shares many similarities with evolutionary computation techniques such as GA. The technique is derived from research on swarms such as bird flocks and fish schools. System is initialized with a population of random solutions and searches for optima by updating generations. However, unlike GA, PSO has no evolution operators such as crossover and mutation. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles. Each particle keeps track of its coordinates in the problem space which are associated with the best solution (fitness) that has been achieved so far. The fitness value is also stored. Best fitness value is taken as final solution.

Ant colony optimization (ACO) [24] is suited for finding solutions to different optimization problems. Colony of artificial ants co-operates to find good solutions, which are an emergent property of the ant's co-operative interaction. Based on their similarities with ant colonies in nature, ant algorithms are adaptive and robust and can be applied to different versions of the same problem as well as to different optimization problems. The main traits of artificial ants are taken from their natural model. These main traits are that artificial ants exist in colonies of co-operating individuals, they communicate indirectly by depositing pheromone, they use a sequence of local moves to find the shortest path from a starting position to a destination point, they apply a stochastic decision policy using local information only to find the best solution, *etc.* Since the optimal solution can only be found through the global cooperation of all the ants in a colony, it is an emergent result of such co-operation.

In considered case, performances of all computationally intelligent meta-heuristic methods have been dependent on selection of parameters, which have been carefully selected by performing several consecutive simulation experiments for each of them. For example, for

22 [cmperature [°C] 21 2 20 19 Response with computationally inteligent optimal tuning ($K_{prn} = 17, K_{ps} = 0.61, K_{is} = 0.03$) 18 Reference signal Response with initially tuned controller ($K_{prn} = 7, K_{ps} = 0.5, K_{is} = 0.01$) 17 16 15 14 500 1000 1500 2000 2500 3000 3500 4000 0 Time [s]

applied genetic algorithm with real coding population of 50 has been selected and elitism of 5, while range of gains *i. e.* search space has been determined on the basis of experience.

Figure 7. Comparison of performance of HVAC control system with experimentally suboptimally tuned parameters and after computationally intelligent optimisation, where K_{prn} is the proportional gain of master controller, K_{ps} – proportional gain of slave controller, and K_{is} – integral gain of slave controller

Also, scattered crossover function has been applied and all individuals except for elite has been subject to adaptive feasible mutation. Individuals have been randomly selected by roulette wheel selection. Genetic algorithm has demonstrated good convergence with selected parameters.

By comparing the results of all applied methods, each of them executed in several consecutive runs over the same search space, the overall best solution has been selected. All of the optimization methods were well suited for the problem and managed to improve initial tuning, but there were no significant differences among them regarding suitability for this particular problem. Values of proportional gains of outer (master) and inner (slave) controllers and value of integral gain of slave controller before computationally intelligent optimization (initial suboptimal experimentally tuned values) and values obtained as best outcome of several advanced optimization techniques have been presented in tab. 2. Also, corresponding values of fitness function have been shown representing cumulative absolute error.

-		1 1		
	<i>K</i> _P master	$\overline{K_P}$ slave [K ⁻¹]	K_I slave [K ⁻¹ s ⁻¹]	Cumulative absolute error (fitness)
Initial (experimentally, suboptimal)	7.0	0.5	0.01	3034
Computationally intelligent optimized	17.0	0.61	0.031	2778

Table 2. Controller parameters before and after computationally intelligent optimization

Comparison of performance of initially tuned control system, which has been obtained by experimental-simulation tuning by using expert experience on the performance of similar systems, and performance of optimized system by computationally intelligent methodologies, is presented in fig. 7. Peak performance presented in fig. 7 by parameters listed in tab. 2 has been obtained by GA methodology, while all other computationally intelligent methods obtained similar but slightly worse results. It is easily noticeable that although initially suboptimally tuned system obtains very good performance, computationally optimized controllers demonstrated clearly improved performance. It is worth mentioning that anti-windup gain has been optimized along with main gains of cascade controller, and set to optimized value of 0.1. The behaviour of all controllers, after the adjustment and optimisation, have been additionally validated in order to be compliant with appropriate norms [25].

Conclusions

Mathematical model of air conditioning system in winter regime of a classroom is presented, which was used as a basis to develop and validate reliable simulation model. On the basis of theoretical recommendations cascade temperature P-PI controller has been developed with anti windup component. Initial controller parameters have been selected using careful experimental tuning process and by exploiting vast experience in HVAC controller adjustments, as to obtain good dynamic characteristics, settling time and precision, and with aim to provide control signal that provides minimal energy consumption. Obtained result has been very good and its further improvement was a challenging task.

Basic conclusion that can be drawn from the results is that application of advanced computationally intelligent optimization provided controller gains that ensure superior performance which also leads to energy efficiency increase, while at the same time component wear is reduced since aperiodic response without overshoot is provided with remark that fault detection could also be researched [26].

It is worth mentioning that computationally intelligent optimization is capable of simultaneous attainment of other goals since optimization criterion could be almost arbitrary complex, and could include multicriteria optimization. Results obtained here indicate that computationally intelligent optimization is a very feasible concept for HVAC controller optimization, even when requirements are demanding and initial tuning is extremely good, while on the other hand in our case several advanced meta-heuristic optimization methods (SA, PSO, ACO) did not demonstrated significant difference in comparison to performance referent real coded genetic algorithms.

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