

OPTIMIZATION OF PI CONTROLLER BASED ON HYBRID SIMPLEX-GENETIC APPROACH APPLIED TO A THERMAL SYSTEM

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Abstract. *This paper presents the design of a control system applied to a building heating process. A lumped approach is used to model the room air temperature and a multi-layer model for the building envelope. Temperature control is realized by a PI (proportional-integral) control. Since the mathematical model is high order and nonlinear, classical strategies for PI tuning can be hardly applied. In this case study, it is proposed the use of genetic algorithm with local search using Nelder and Mead simplex method to optimize the parameters of PI controller. Genetic algorithms are search and optimization techniques of artificial intelligence that derive their inspiration from biological natural selection and genetics. Simulation results from application to PI controller optimized by genetic algorithm for a building heating process are presented which demonstrate the potentialities of this design approach.*

Keywords: *PI control, temperature control, optimization, genetic algorithms, simplex method.*

1. Introduction

In spite of the advancements made in microprocessor technology and its impact on the development of new control methodologies for building heating systems aiming at improving their energy efficiency, the process of operating a heating, ventilating, and air conditioning equipment in commercial and industrial buildings is still an inefficient and high-energy consumption process [1].

The conception of control algorithm design for control of building heating processes is a research topic which has received considerable attention over the last two decades [2]-[4]. Classical control techniques such as the on-off controllers, proportional-integral (PI), and proportional-integral-derivative (PID) controllers are still very popular because of their low cost.

Despite the huge development in control theory, the majority of industrial processes are controlled by the well-established PI and PID controllers. The popularity of PI control can be attributed to its simplicity (in terms of design and from the point of view of parameter tuning), its applicability, its robust performance in a wide variety of operating scenarios, and to its good performance in a wide range of operating conditions.

However, PI controllers present as a disadvantage the need of a new tuning whenever the processes are subjected to some kind of disturbance or when processes present complexities. So, over the last few years, significant development has been established in the process control area to adjust the PI controller parameters automatically, in order to ensure adequate servo and regulatory behaviour for a closed-loop plant [5]-[9].

Recently, the combination of advantages of computer technology, modern control techniques, and artificial intelligence theory has been motivated toward intelligent control. Intelligent controls were originally proposed by Fu [10] to increase the flexibility and to extend the range of automatic control. They are defined in terms of specific algorithms but employ techniques which can sense and reason about their environment and execute commands in a flexible and robust manner.

The design of intelligent control methodologies is justified when exist the necessity of (i) requirements of prior knowledge about the structure of process is unavailable or only partially known, (ii) improve the performance of the process over wide range of operating conditions, (iii) increased flexibility, and (iv) reduced design costs.

A possible solution to deal with complex processes of high order and nonlinear, such as building thermal systems, is the implementation of PI control systems based on knowledge and learning. In this paper, the temperature control is performed by a PI control design based on a genetic algorithm with local search based on simplex method.

Genetic algorithms (GAs) are search and optimization techniques originated from artificial intelligence, that manipulate a potential solution space utilizing random operations based on mechanism of the natural selection of Charles Darwin and genetic of Gregor Mendel. GAs have been successfully applied to engineering search and optimization problems such as system identification [11] and control design [12]-[14]. In spite of the effort of various researchers there is not a formal test of GAs convergence and, additionally, the algorithms do not guarantee an optimal solution [15].

The paper is organized as follows. The basic concepts of GAs are presented in section 2. In section 3, the procedure description of PI tuning based on hybrid genetic algorithm is focused. The case study description of building thermal process is presented in section 4. Simulation results and conclusion are discussed in section 5 and 6, respectively.

2. Evolutionary algorithms

Evolutionary algorithms (EAs) are computer-based problem-solving systems based on principles of evolution theory. The interest in EAs is increasing very fast, their robust and powerful adaptive search mechanisms. EAs have been used in many problems, dealing with multidimensional and multimodal search.

There are a variety of evolutionary models that have been proposed and studied, such as genetic algorithms, evolution strategies, evolutionary programming, genetic programming, which are referred as EAs. They share a common conceptual base of simulating the evolution of individual structures via selection and reproduction procedure. The basic idea is to maintain a population of candidate solutions which evolve under selective pressure that favors better solutions.

In the next section are presented the fundamentals and details of genetic algorithms and the Lamarckian evolution method combining GA and simplex method.

2.1. Genetic algorithm

Conventional numerical optimization methods can fall foul of such local maximum due to hill-climbing. Several problems of identification and control systems design arise from difficulties in applying calculus-based analytical methods to parameter optimization under constraint conditions, when the design criteria or performance index may not be differentiable. Further, the objective functions needed in these numerical methods must be “well-behaved”.

In other way, the evolutionary algorithms — genetic algorithm, evolution strategies, evolutionary programming, and genetic programming — are lines of investigation in simulated evolution, but they are broadly similar: each maintains a population of trial solutions, imposes random changes to each solution, applies a selection criterion to assess the adequacy of proposed solutions, and determines which to retain for further exploration. The methods differ in the specific representation, mutation operations, and selection procedures.

GAs are powerful non-deterministic iterative search heuristics. GAs which were originated from the work of J.H. Holland [16], thirty years ago, constitute the most studied branch of evolutionary computation. GA allows that a population composed of many individuals to evolve under specified selection rules to a state that maximizes the fitness through of operations of selection, crossover, and mutation.

Some of the advantages of a GA include that it: (i) optimizes with continuous or discrete parameters, (ii) doesn't require derivative information, (iii) simultaneously searches from a wide sampling of the cost surface, (iv) deals with a large number of parameters, (v) provides a list of optimum parameters, not just a single solution, and (v) optimizes parameters with extremely complex cost surfaces (it an jump out of a local minimum).

The starting point of GA is a population of individuals, each representing a possible solution to a problem. Each individual is allocated a fitness measure according to the quality of the solution it produces. The fittest individuals survive to the next generation while the individuals that produce unsatisfactory solutions are eliminated. This represents survival of the fittest.

The main steps of a GA are as follows: (i) initialize a population of individuals; (ii) evaluate the fitness function values of individuals of population; (iii) selection of fittest individuals; (iv) create new individuals by mating current and applying mutation and crossover operations; (v) if the stopping criterion is satisfied, stop and output the best individual; otherwise, go to step (ii).

Before running a GA, the following decisions should be made: (i) the choice of a representation of individuals; (ii) the choice of a way to create the initial population of solutions; (iii) the choice of evaluation function; (iv) the definition of crossover and mutation operators and their probabilities; (v) the definition the selection operator; (vi) the setting of the system parameters, including population size and topology, etc.

Eiben et al. [17] present two approaches for configuration of a GA: (i) parameter tuning (before the run the GA), and (ii) parameter control (during the run of GA) that can be classified into one of three categories: deterministic parameter control, adaptive parameter control, and self-adaptive parameter control.

There is several research approaches about parameter control of GAs [18], [19]. However, there is not a deterministic rule for a “perfect” configuration of a GA. In the case of small population size, it is very easy to be prematurely converged cause occurrence of individuals is dominated or recessive in search the solution space. In case of big population size, the computational complexity for GA application is very computationally intensive.

The parameter tuning through of trial and error procedure is the usual practice in GA. The parameters configuration of GA through of a heuristic procedure causes sub-optimal choice because the GA parameters interact frequently of complex way. Eiben et al. [13] summarize the drawbacks to parameter tuning based on experimentation by following aspects: (i) parameter are not independent, but trying all different combinations is practically impossible; (ii) the procedure of parameter tuning is time consuming; (iii) for a given problem the selected parameter values are not necessarily optimal.

2.2. Hybrid GA with simplex method

The hybrid method proposed in this paper is composed by a combination of GA and the simplex method. This approach combines local and evolutionary searches that characterize a form of Lamarckian evolution. Hybrid algorithms can combine global search using EAs and local search using individual learning algorithms using individual learning algorithms. Hybrid evolutionary algorithms can exploit learning either actively via Lamarckian inheritance or passively via the Baldwin effect [20], [21]. In the 19th century, Darwin’s theory was challenged by Jean Baptiste Lamarck, who proposed that environmental changes throughout an organism’s life cause structural changes that are transmitted to offspring. This theory lets organisms pass along the knowledge and experience that they acquire in their lifetime [22], [23]. This is analogous to Lamarckian inheritance in evolutionary theory, whereby characters acquired during a parent’s lifetime are passed on their offspring [21].

Conventional GA produce the offspring of the next generation through the evaluation function to determine its fitness. This procedure can benefit from the advantages of Lamarckian theory. By letting some of the organism’s “experiences” be passed along to future organisms. Following a Lamarckian approach, first would try inject some “smarts” into the offspring organism before returning it be evaluated. A traditional hill-climbing routine could use the offspring organism as a starting point and perform quick, localized optimization. The hill-climbing procedure is realized by Nelder-Mead’s simplex approach.

Nelder-Mead’s simplex method (NMSM) [24] is local search method that uses the evaluation of the current data set to determine the promising direction search. This method is a direct search procedure based on heuristic ideas and its strengths are that it requires no derivatives to be computed. The basic procedure of the simplex method is to start with an initial basic feasible solution, i.e., at the vertex of the convex polyhedron. A simplex is the structure formed by $(n+1)$ points, not in same plane, but in a n -dimensional space. The essence of the algorithm is as follows: the function is evaluated at each point (vertex) of the simplex and the vertex having the highest function value is replaced by a new point with a lower function value. This is done in such a way that the simplex adapts itself to the local landscape, and contracts on the final minimum. There are four main operations which are made on the simplex: reflection, expansion, reduction and contraction. Details of the NMSM can be find in [24].

The hybrid method of GA with NMSM is useful when addressing heavily optimization problems both in terms of computational efficiency and solution accuracy in mathematical form of the objective function to be optimized for gain tuning of PI controllers.

3. PI control based on simplex-genetic tuning

The PI algorithm is simple, reliable and robust for the control of first and second order processes and even higher order processes with well-damped modes. A PI controller is typically described by the following equation:

$$u(t) = K_p \left(e(t) + \frac{1}{T_i} \int_0^t e(\tau) d\tau \right) \quad (1)$$

where $e(t) = y_{sp}(t) - y(t)$ is the system error (i.e. the difference between the setpoint value $y_{sp}(t)$ and the process output $y(t)$), $u(t)$ is the control variable, K_p is the proportional gain, and T_i is the integral time constant. Alternatively, equation (2) can be written as:

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau \quad (2)$$

where $K_i = K_p / T_i$ is the integral gain constant. The tuning problem consists of determining the values of controller's parameters. In general, it is not easy to satisfy different design specifications at the same time.

Usually a traditional PI controller tuning method requires the practitioners to possess a great deal of control system knowledge and tuning experience. The tuning procedure is generally heuristically done, and this task can be very time consuming and tedious. Therefore there is a need for some alternative approach which would achieve a certain level of automation of the tuning procedure, and would not require the practitioners to have much domain knowledge. In this paper the used alternative approach for PI tuning is the GA.

4. Case study: thermal building system

This section presents a dynamic model for thermal building performance analysis [25] with PI control, which includes an electric heater. The room is considered hermetically closed with a uniform distribution of internal energy. We considered thermal losses just by heat transfer through the building envelope. Applying the energy conservation equation for each element, the following mathematical formulation is obtained. For the room enclosed by m surfaces, we find,

$$\rho_A c_A V_A \frac{dT_A(t)}{dt} = \sum_{i=1}^m h_{int} A_i [T_{n,i}(t) - T_A(t)] + h_c A_c [T_c(t) - T_A(t)] + (\dot{m}_{inf} + \dot{m}_{vent}) c_{pu} [T_{ext}(t) - T_A(t)] + D(t), \quad (3)$$

where $T_{n,i}(t)$, A_i are respectively the n -th layer temperature of wall i , and the i surface area. The perturbation $D(t)$ includes the heat exchanged with the external air through low mass surfaces of the building envelope such as doors and windows and internal gains of energy due to equipment, lights and people. This term can be written as:

$$D(t) = \sum_{j=1}^m \frac{T_{eq}(t) - T_A(t)}{R_j} + q_p + q_e + q_l + \dot{m} L \left(\frac{T_{ext}(t) + T_A(t)}{2} \right) (w_{ext}(t) - w_A(t)) \quad (4)$$

where q_p , q_e and q_l are the internal gains under the presence of people, equipment and lighting system. The thermal resistance R of j -th surface is calculated as:

$$R_j = \frac{1}{h_{ext} A_j} + \frac{L_j}{\lambda_j A_j} + \frac{1}{h_{int} A_j} \quad (5)$$

where A_j is the low-mass surface- j area. For each layer k within the wall i , we can obtain the following energy balance equation:

$$\rho_{k,i} c_{k,i} V_{k,i} \frac{dT_{k,i}(t)}{dt} = K_{k+1,i} A_i [T_{k+1,i}(t) - T_{k,i}(t)] - K_{k,i} A_i [T_{k,i}(t) - T_{k-1,i}(t)] \quad (6)$$

where the thermal conductance K , can be estimated by a harmonic mean as:

$$K_{k,i} = \frac{1}{(L_{k-1,i} / 2) / \lambda_{k-1,i} + (L_{k,i} / 2) / \lambda_{k,i}} \quad (7)$$

where $L_{k,i}$ denotes the thickness of layer k and $\lambda_{k,i}$, its thermal conductivity. The boundary condition for the external layer can be written as,

$$K_{1,i} (T_{2,i} - T_{1,i}) = h_{ext} (T_{1,i} - T_{eq}) + q_r(t) - \varepsilon_{ceil} R_{LW} \quad (8)$$

where the term $(\varepsilon)_{ceil}$ represents the ceiling emissivity and R_{LW} the long-wave emissivity. T_{eq} represents the equivalent temperature (Air-Sun) given by the following expression:

$$T_{eq} = T_{ext} + \frac{\alpha I}{h_{ext}} \quad (9)$$

where α , is the wall external surface absorptivity, I , the total solar radiation (direct plus diffuse). For the internal layer ($k=n$) of the i -th wall, we can write the following boundary condition equation:

$$K_{n,i} A_i (T_{n-1,i} - T_{n,i}) = h_{int} A_i (T_{n,i}(t) - T_A(t)) + \sigma \varepsilon_c A_c F_{s,c-i} [T_{n,i}^4(t) - T_c^4(t)] + \sigma \varepsilon_i A_i \sum_{j=1}^m F_{s,j-i} [T_{n,i}^4(t) - T_{n,j}^4(t)] \quad (10)$$

where σ , ε and F_s represent the Stefan-Boltzmann constant, emissivity and shape factor. However, for the floor ($i=5$), we consider for $k=1$, a constant soil temperature at a depth of 5m and we apply the boundary condition of imposed temperature. The electric heater is globally modeled as:

$$\rho_c c_c V_c \frac{dT_c(t)}{dt} = Q(t) - h_c A_c [T_c(t) - T_A(t)] - \sigma \varepsilon A_c \sum_{i=1}^m F_{s,c-i} [T_c^4(t) - T_{n,i}^4(t)] \quad (11)$$

where $Q(t)$ is the energy rate generated within the heater by Joule effect, ρ_c , the heater density, c_c , the specific heat, V_c , the oil volume within the heater, h_c , heat transfer convection coefficient between room air and heater and A_c the heat exchange area. The heating system sensor temperature $T_s(t)$ can be modeled as:

$$\rho_s c_s V_s \frac{dT_s(t)}{dt} = h_s A_s [T_A(t) - T_s(t)] \quad (12)$$

where ρ_s , c_s , V_s , h_s and A_s are respectively the sensor density, specific heat, volume, convection heat transfer between the sensor copper sphere and the air and the sensor heat exchange area.

In terms of water-vapor balance, it was considered ventilation, infiltration and internal generation from equipment and people breath so that the lumped formulation can be written as:

$$\rho_A V_A \frac{dw_A}{dt} = (\dot{m}_{inf} + \dot{m}_{vent}) (w_{ext} - w_A) + \dot{m}_b + \dot{m}_{ger} \quad (13)$$

The water-vapor mass flow from the people breath is calculated as it was shown in ASHRAE [26] which takes into account the room air temperature, humidity ratio and physical activity as well.

5. Simulation results

The need to provide heating control inside buildings to improve comfort levels and hence productivity is very desirable. However, the cost of design or redesign to achieve the desired comfort levels has to be economically evaluated.

In this case study, the analysis of building thermal performance is done by the dynamic model and PI control implementations in MATLAB/Simulink environment (see figure 1). The simulation parameters for the thermal building system building are presented in tables 1 and 2.

The parameter set of the population are coded as a finite-length string where each individual is composed by parameters K_p and K_i . In this case is adopted the following search space by GA: $K_p \in [0;10]$ and $K_i \in [0.0001;1.0]$.

The parameters of the GA are selected as 10, 0.8 and 0.1 for the population size, crossover probability and mutation probability, respectively. The number of generation is set to 15. The adopted criterion for Lamarckian evolution is the realization of local search after of fitness evaluation of GA in each generation of $w\%$ best fitness values of population members. The local search based on simplex method is realized with the 1% best individuals (the individual with best fitness) of population.

As GA obtains a set of solutions at each generation, it needs to supply it with an evaluation function so that GA can calculate a fitness value for each solution according to this function. The following fitness function (maximization problem) is adopted in this paper:

$$f(K_p, K_i) = \frac{1}{1 + \sum_{t=1}^N t [y_{sp}(t) - y(t)]^2} \quad (14)$$

where k is a scale factor (adopted $k=500$), $y(t)$ is the output of thermal building system (room air temperature) and $y_{sp}(t)$ is the desired reference (setpoint) for system output.

The best result for the PI tuning based on GA with local search was with $K_p = 0.2004$ and $K_i = 0.0001$. In this case, the maximum room air temperature was 22.69°C with variance of 0.0327°C. Simulation result of best tuning of PI is

presented in figure 2. In this figure, the evolution of internal temperature is compared with the external one, when the electric heating system described by equation 11 is placed with the room. Heater control is made by PI control strategy. In this case, the temperature setpoint is 22°C and the mass flow is 0.02 kg/s. The time sampling is of 100 seconds.

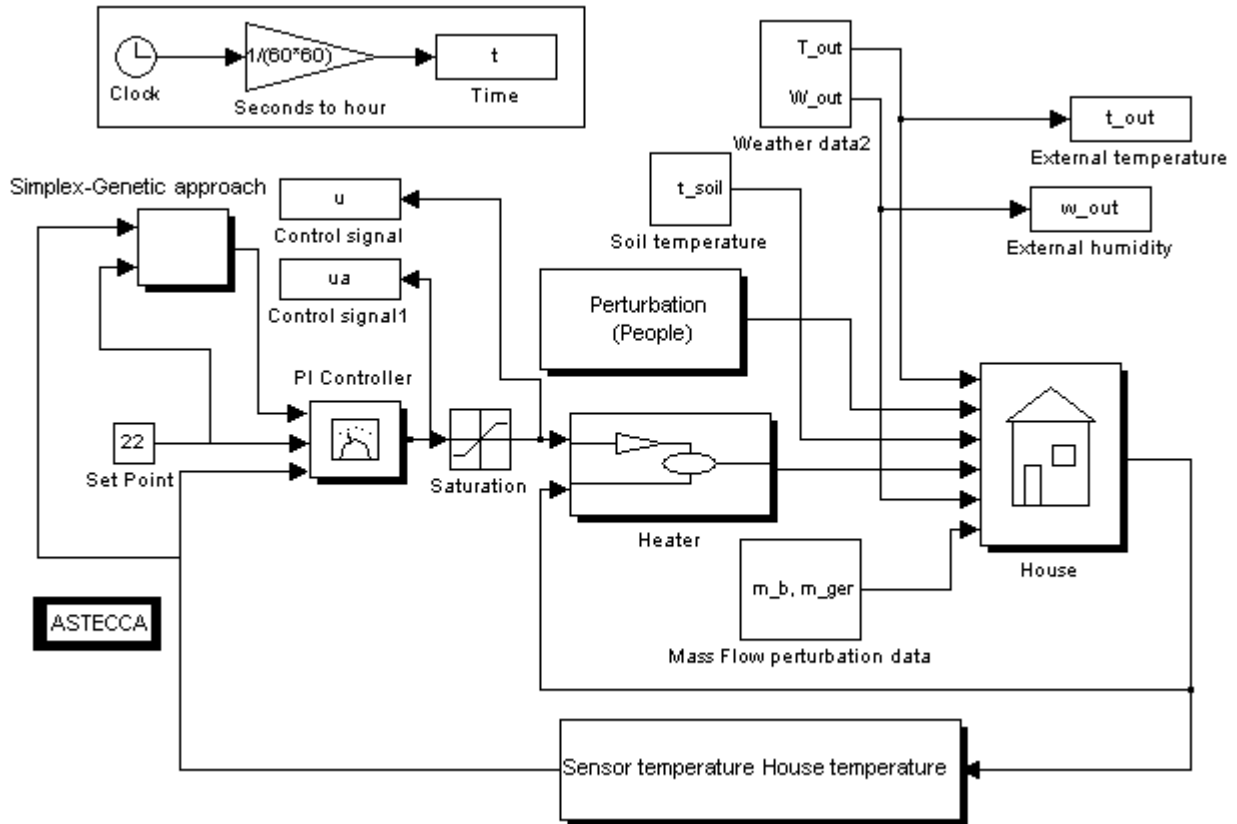


Figure 1. Building system scheme using Matlab/Simulink.

Table 1: Dimensions and thermal properties (part I).

	ρ (kg/m ³)	c (J/kg-K)	λ (W/m-K)	h (W/m ² -K)
Heater (c)	884.1	1909	---	5.0
Room (A)	1.16	1007	---	5.0
Sensor (s)	8933	385	---	5.0
Walls and ceiling	2050	950	1.92	5.0
	1900	920	0.985	
	2050	950	1.92	
Floor	2050	1840	0.52	5.0
	998	900	1.4	
	550	2385	0.2	

Table 2: Dimensions and thermal properties (part II).

	A (m ²)	L (cm)	V (m ³)
Heater (c)	5	---	0.002
Room (A)	25 *	---	62.5
Sensor (s)	1.26×10^{-5}	0.1	4.2×10^{-9}
Walls and ceiling	12.5	2	0.25
	12.5	10	1.25
	12.5	2	0.25
Floor	25	20	5.00
	25	250	62.50
	25	10	2.50

* Floor and ceiling surface area.

The building heating simulations are realized for 12.5 days of June in Curitiba city, Brazil. This mass flow is in accordance with Brazilian standards for a residential room with 2 people inside. This result shows that the GA with local search by simplex method is as well fit for doing the parameters tuning of PI controller.

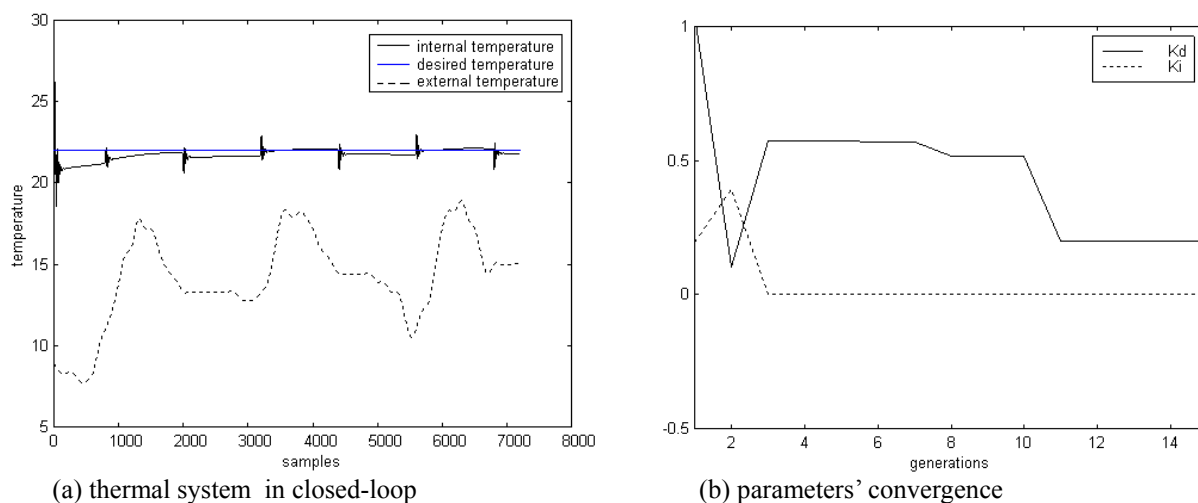


Figure 2. Temperature evolution with heating system controlled by PI algorithm with tuning based on GA with local search based on simplex method.

6. Conclusion and future works

The controllers' design for applications of thermal building systems has always been subject of interest researchers and engineers. The need to provide climate control inside buildings to improve comfort levels and hence productivity is very desirable.

Many controllers design methods have been proposed in literature to tune PIs [5]-[7]. In spite of the fact that the most frequently controllers used in industry are PI and PID, studies presented by many authors have shown that a great amount of control problems are caused by inappropriate tuning of the PI parameters. In this work, it has been demonstrated that the PI control methodology based on tuning by genetic algorithm with local search can be used to an application of building heating process.

GAs are direct search techniques and require no prior knowledge of the process mathematical model for PI tuning. The genetic algorithm has proven to be robust and powerful for tuning of PI controller. GAs are characterized for their robustness in applications where the global search is adequate for the solution of the problem. The proposed approach in this paper combines local (simplex method) and evolutionary searches that characterize a form of Lamarckian evolution. This hybrid evolutionary algorithm exploits the optimization of PID gains tuning efficiently and the presented results in this paper for PI control shown the efficiency of this control conception design for heating systems.

The main disadvantage of hybrid GA with simplex method is that for each generation of the algorithm, the whole population of solutions needs to be evaluated for the calculation of the fitness. Other limitation is that the effectiveness of a GA with simplex method depends on many of its components, e.g., representation, operators, probabilities, etc., and the interactions among them. The variety of parameters included in these components, the many possible choices, and the complexity of the interactions between various components and parameters make the selection of a "perfect" genetic algorithm for a given problem very difficult, if not impossible.

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7. References

- [1] Shoureshi, R., "Intelligent Control Systems: Are they for Real," J. Dynamic Syst., Measurement, Contr., vol. 115, June 1993.
- [2] Arguello-Serrano, B. and Velez-Reyes, M., "Nonlinear Control of a Heating, Ventilating, and Air Conditioning System with Thermal Load Estimation," IEEE Trans. on Control Systems Technology, Vol. 7, No. 1, pp. 56 -63, 1999.
- [3] Kim, T., Kato, S. and Murakami, S., "Indoor Cooling/Heating Load Analysis Based on Coupled Simulation of Convection, Radiation and HVAC Control," Building and Environment, Vol. 36, pp. 901-908, 2001.

- [4] Wang, S. and Jin, X., "Model-Based Optimal Control of VAV Air-Conditioning System Using Genetic Algorithm," *Building and Environment*, Vol. 35, pp. 471-487, 2000.
- [5] VanDoren, V. J., "Advanced Control Software Goes Beyond PID," *Control Eng. Int.*, pp. 57-60, Jan. 1998.
- [6] Yeo, Y.-K. and Kwon, T.-I., "A Neural PID Controller for the pH Neutralization Process," *Ind. Chem. Res.*, vol. 38, pp. 978-987, 1999.
- [7] Coelho, L.S. and Coelho, A.A.R., "Computational Intelligence in Process Control: Fuzzy, Evolutionary, Neural, and Hybrid Approaches," *Int. Journal of Knowledge-Based Intelligent Engineering Systems*, Vol. 2, No. 2, pp. 80-94, 1998.
- [8] Chen, C.L. and Chang, F.Y., "Design and Analysis of Neural/Fuzzy Variable Structural PID Control Systems," *IEE Proc.-Control Theory Appl.*, Vol. 143, No. 2, pp. 200-208, 1996.
- [9] Chen, W.-H., Ballance, D.J., Gawthrop, P.J., Grimble, J.J. and Reilly, J.O., "Nonlinear PID Predictive Controller," *IEE Proc.-Control Theory Appl.*, Vol. 146, No. 6, pp. 603-611, 1999.
- [10] Fu, K. S., "Learning Control Systems and Intelligent Control Systems: An Intersection of Artificial and Automatic Control," *IEEE Trans. on Automatic Control*, Vol. 16, pp. 70-72, 1971.
- [11] Kristinsson, K. and Dumont, G.A., "System Identification and Control Using Genetic Algorithms," *IEEE Trans. on Systems, Man, and Cybernetics*, Vol. 22, No. 5, pp. 1033-1046, 1992.
- [12] Wang, P. and Kwok, D.P., "Optimal Design of PID Process Controllers Based on Genetic Algorithms," *Proc. of 12th IFAC World Congress, Sydney, Australia*, Vol. 5, pp. 261-265, 1993.
- [13] Man, K.F., Tang, K.S., Kwong, S., "Genetic Algorithms: Concepts and Applications," *IEEE Trans. on Industrial Electronics*, Vol. 43, No. 5, pp. 519-534, 1996.
- [14] Potocnik, P.; Grabec, I.; "Nonlinear Model Predictive Control of a Cutting Process", *Neurocomputing*, Vol. 43, No. 1-4, pp. 107-126, 2002.
- [15] Bäck, T.; Fogel, D. B.; and Z. Michalewicz, *Handbook of Evolutionary Computation*. Bristol, Philadelphia: Institute of Physics Publishing, New York, Oxford: Oxford University Press, 1997.
- [16] Holland, J. H., "Adaptation in Natural and Artificial Systems", University of Michigan Press (Reprinted in 1992 by MIT Press), 1975.
- [17] Eiben, A.E.; Hinterding, R. Michalewicz, Z., "Parameter Control in Evolutionary Algorithms," *IEEE Trans. on Evolutionary Computation*, Vol. 3, No. 2, pp. 124-141, 1999.
- [18] Srinivas, M. and L. M. Patnaik, "Adaptive Probabilities of Crossover and Mutation in Genetic Algorithms," *IEEE Trans. on Systems, Man, and Cybernetics*, vol. 24, no. 4, pp. 656-667, 1994.
- [19] Kim, B. M.; Y. B. Kim, and C. H. Oh, "A Study on the Convergence of Genetic Algorithms," *Computers on Ind. Eng.*, vol. 33, no. 3-4, pp. 581-588, 1997.
- [20] Pham, D. T. and G. Jin, "Genetic Algorithm Using Gradient-like Reproduction Operator," *IEE Electronics Letters*, vol. 31, no. 18, pp. 1558-1559, 1995.
- [21] Anderson R. W., Fogel, D. B. and M. Schütz, "Other Operators," In: Bäck, T., Fogel, D. B., Michalewicz, Z. (eds) *Handbook of Evolutionary Computation* IOP Publishing, Bristol, Philadelphia and Oxford University Press, Oxford, pp C3:4:1-C3:4:15, 1997.
- [22] Kennedy, S. A., "Five Ways to a Smarter Genetic Algorithm," *AI Expert*, December, pp. 35-38, 1993.
- [23] Whitley, D., Gordon, S. and Mathias, K.; "Lamarckian Evolution," the Baldwin effect and function optimization In: Davidor Y, Schwefel H P, Manner R (eds), *Parallel Problem Solving for Nature*, Springer-Verlag, Berlin, pp 6-15, 1994.
- [24] Nelder J. A. and R. Mead, "A Simplex Method for Function Minimisation," *Computer Journal*, vol. 7, pp. 308-313, 1965.
- [25] Mendes, N., Oliveira, G. H. C.; Araújo, H. X. "The Use of Matlab/Simulink to Evaluate Building Heating Processes," *Proceedings of ESDA 2002, 6th Biennial Conference on Eng. Systems Design and Analysis*, Istanbul, Turkey, 2002.
- [26] ASHRAE Handbook-Fundamentals, Atlanta: ASHRAE, 1993.

8. Responsibility notice

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