2

Model Predictive Controller Employing Genetic Algorithm Optimization of Thermal Processes with Non-Convex Constraints

Goran Stojanovski and Mile Stankovski

Ss Cyril and Methodius University, Skopje, Faculty of Electrical Engineering and Information Technologies, Institute of Automation and System Engineering Republic of Macedonia

1. Introduction

In every aspect of professional life, improving the work conditions, reducing the costs and increasing the productivity are the goals that managers try to achieve. Nevertheless, one must have in mind that compromises has to be made along the way. The process where we chose what is most important usually is called optimization.

No mater the field of optimization, the problem must be transfered to a problem of mathematical optimization. The mathematical optimization refers to the selection of a best element from some defined domain. Depending on the type of the problem it can be solved by one of the many techniques for mathematical programming. Here we give a list of commonly used mathematical programming techniques:

- Linear programming;
- Second order cone programming;
- Quadratic programming;
- Convex programming;
- Nonlinear programming;
- Stochastic programming;
- Robust programming, etc.

As many as there are, the standard techniques are usually designed to solve some specific type of problem. On the other hand, in industry we deal with specific problems in different plants, and for some of them, we cannot find a solution to the optimization problem easily. That is why the engineers around the world work hard to improve these techniques and to make them more general.

Optimization in industry is very important since it directly affects the cost of the production, hence the cost of the product itself. One of the most used algorithms for optimal control in the industry is the Model Predictive Control or MPC.

In this paper we will present a model predictive controller that uses genetic algorithms for the optimization of the cost function. At the begining in the next section we will explain the general idea behind MPC in details. In section 3 we will present the considered plant, and we will give some details about the modeling and identification of the industrial furnace. Also we will present the constraints that should be considered in order to match the physical conditions on the plant. Later, in section 4 the basic idea for GA-based MPC will be presented, along with an overview of the development of this algorithm in the recent years. In section 5 we will present the proposed technique for implementing GA-based optimization that allows straightforward implementation of non convex constraints and we will illustrate the effectiveness of this method through one simulation example of industrial furnace control. At the end we will give final remarks and propose the possibilities for future research in this area.

2. Model Predictive Control - basic concept and structure

Process industries need an easy to setup predictive controller that costs low and maintains an adaptive behavior which accounts for time-varying dynamics as well as potential plant miss-modeling. Accounting these requirements, the MPC has evolved into one of the most popular techniques for control of complex processes.

The essence of model predictive control lies in optimization of the future process behavior with respect to the future values of the executive (or manipulated) process variables Camacho & Bordons (2004). The general idea behind MPC is very simple. If we have a reliable model of the system, represented as in equation (1) or similar, we can use it for predicting the future system outputs. At each consecutive time of sampling k the controls inputs are calculated according to equation (2).

$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k);\; x(0) = x_0 \\ y(k+1) &= Cx(k) + Du(k) + \theta \end{aligned} \tag{1}$$

$$u(k) = [u(k|k), u(k+1|k),\ ...,\ u(k+N_c-2|k),\ u(k+N_c-1|k)] \tag{2}$$

In equation (2), A, B, C, D are the system matrices, and θ is the vector of output disturbances; N_c represents the control horizon and the notation $u(k+p|k)$ means the prediction of the control input value for the future time $k+p$ calculated at time k. These control inputs are calculated in such a way as to minimize the difference between the predicted controlled outputs $y(k+p|k)$ and foreseen set points $r(k+p|k)$ for these outputs, over the prediction horizon N_p, $(p = 1, 2, \dots, N_p)$. Then only the first element from the calculated control inputs is applied to the process, i.e. $u(k) = u(k|k)$. At the next sample time $(k+1)$, we have a new measurement of the process outputs and the whole procedure is repeated. In every step of this algorithm, the length of the control and prediction horizons is kept same, but is shifted for one value forward (the principle of receding horizon).

One of the early conceptualizations of MPC is presented on figure 1. The control input trajectory over the control horizon is determined in the predictive algorithms on the basis of the model, by minimizing a cost function. A basic structure of MPC is presented in figure 2. In order to obtain proper results, we must to incorporate constraints to the system that we want to control.

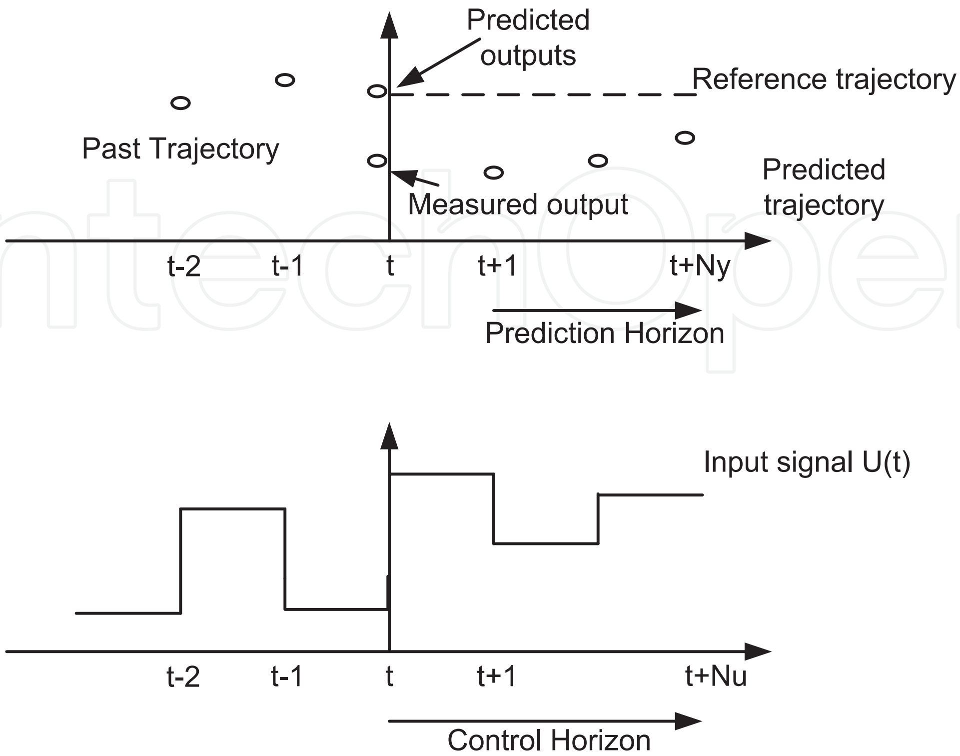


Fig. 1. Conceptualization of model predictive control algorithms

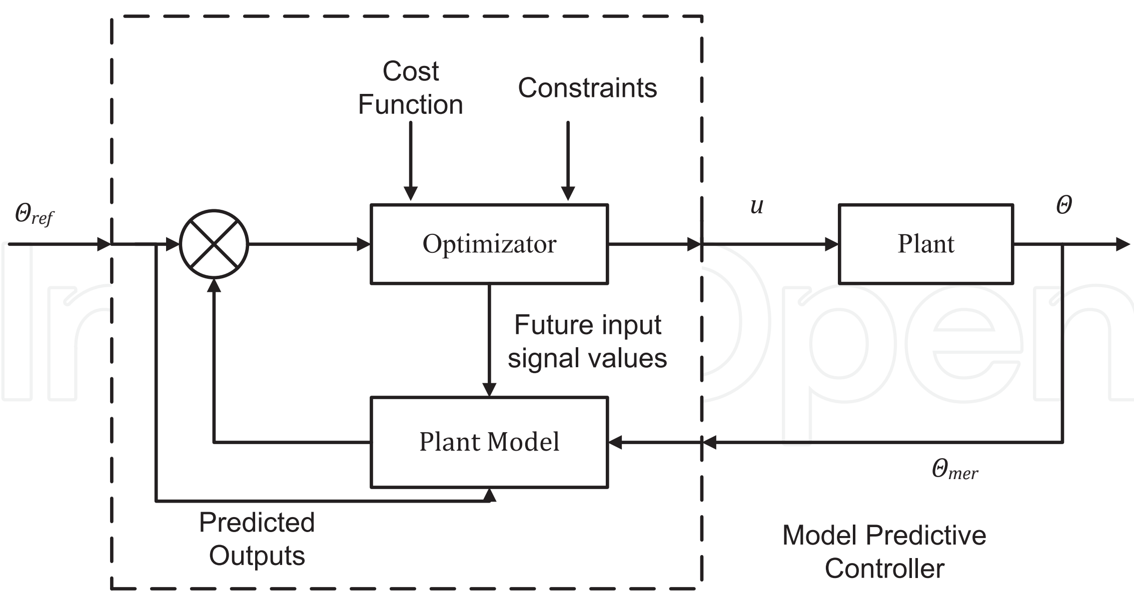


Fig. 2. The basic structure of a MPC

This cost function in general consists of two parts. The first one represents the differences between the set points and the predicted outputs and is known as the cost of predicted control errors. The second part represents the penalties for the changes of the control value. The most common used cost function is the quadratic, and it can be formulated as in equation (3).

$$J(k) = \sum_{p=N_1}^{N_p} \|w(k+p|k) - y(k+p|k)\|^2 + \lambda \sum_{p=0}^{N_c} \|\Delta u(k+p|k)\|^2 \quad (3)$$

The idea is to use one function not only to minimize the output errors, but in a way to keep the changes of the control value at the minimum. The notation in equation 3 is obvious, and the control horizon must satisfy the constraints $0 < N_c \leq N_p$. In order to get decreased dimensionality of the optimization problem which will lead to a smaller computational load, we usually assume that $N_c < N_p$. The value of λ differs depending on the process that we want to control and determines how big control change we will allow to be performed at one step of the algorithm. The predicted control values are obtained with minimizing the cost function.

What is crucial for the MPC is the plant-model mismatch. In case of precise simulation model, the algorithm guarantees optimal behavior of the plant, but in case of significant plant-model mismatch that can occur due to linearization in the point that is different from the working point of the plant, or mistake in the modeling of the plant, a robust approach must be considered when designing the control.

In this direction, improved modeling and identification methods are required for use in MPC design. The use of linear, non-linear, hybrid and time-delay models in model-based predictive control is motivated by the drive to improve the quality of the prediction of inputs and outputs Allgöwer et al. (1999); Dimirovski et al. (2004; 2001); Jing & Dimirovski (2006); Zhao (2001).

Model-based predictive control algorithms have been successfully applied to industrial processes, since the operational and economical criteria may be incorporated using an objective function to calculate the control action. The main advantages of MPC (Keyser (1991); Prada & Valentin (1996)) can be summarized as pointed out below.

- Multi-variable cases can be fairly easily dealt with;
- Feed-forward control is naturally introduced to compensate measured disturbances;
- Dynamical processes featuring large time-delays or with non-minimum phase or even instability phenomena can be successfully controlled;
- Constraints can be readily included.

Based on the characteristics, the thermal systems suites best for control process in MPC algorithms (Dimirovski et al. (2004; 2001)). In thermal systems such as high-power, multi-zone furnaces the complexity of energy conversion and transfer processes it seems to be ideally suited to the quest for an improved control and supervision strategies. Additionally, if we consider that the biggest part form the expences of the industry is the price of the energy resources, it is logical for the scientists to push towards designing and implementing intelligent control algorithms such as MPC. These algorithms trend to reduce the cost and improve the quality of the final product of the companies.

Although commonly used, MPC algorithms still have difficulties dealing with non convex constraints. In order to overcome these difficulties, scientists throughout the world work on developing new nonlinear and soft-computing based MPC algorithms.

3. The 20 MW industrial furnace in FZC 11 Oktomvri

As a test plant we use a MIMO system representation with three inputs and three outputs. This system represents a model of a high consumption 20 MW gas-fried industrial furnace, and it has been previously identified in Stankovski (1997). Structural, non-parametric and parameter identification has been carried out using step and PRBS response techniques in the operational environment of the plant as well as the derivation of equivalent state realization. With regard to heating regulation, furnace process is represented by its 3x3 system model. The families of 3x3 models have 9 controlled and 9 disturbing transfer paths in the steady and transient states Stankovski (1997). The structural model of the furnace is depicted in figure 3.

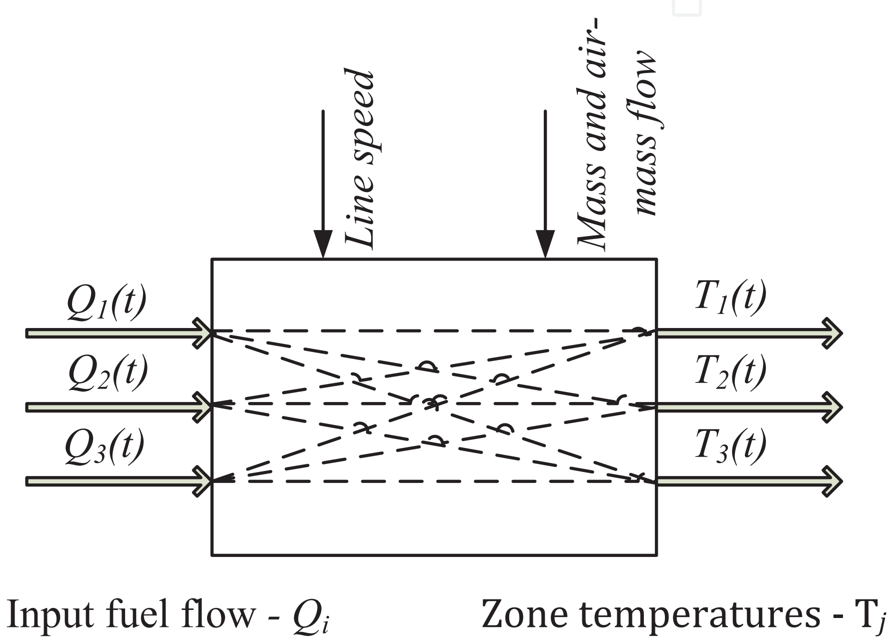


Fig. 3. Input/Output Diagram of the conceptual MIMO system model for gas-fired furnace in FZC "11 Oktomvri"

Experiments involved the recorded outputs (special thermocouples): temperature changes in the three zones in response to input signal change solely in one of the zones. Firstly, only the burners at the first zone were excited and data for the temperatures in all three zones is collected; the temperature T_j and the corresponding fuel flow Q_i for each input-output process channel (transfer path) were recorded.

After collecting the data, the parameter modeling of the furnace was conducted and the system's state space model presented in equation 4 was derived.

$$\begin{aligned} \dot{x} &= Ax + Bu \\ y &= Cx + Du \end{aligned} \tag{4}$$

Where the values od matrix A are defined in equation (5), the values od matrix B are defined in equation (6), and the values od matrices C and D are defined in equation (7).

$$A = diag(P_i), i = 1, 2, ...9; P_{ij} = \begin{bmatrix} -1/T_1 & -1/T_1 \\ 0 & -1/T_2 \end{bmatrix} \quad (5)$$

$$B = [S, S, S], S = \begin{bmatrix} 0 & 1.93 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1.29 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.2 \end{bmatrix} \quad (6)$$

$$C = \begin{bmatrix} V & \overline{0} & \overline{0} \\ \overline{0} & V & \overline{0} \\ \overline{0} & \overline{0} & V \end{bmatrix}$$

$$V = [1, 0, 1, 0, 1, 0]\,,\ \overline{0} = [0, 0, 0, 0, 0, 0] \quad (7)$$

$$D = 0$$

The time constants are $T_1 = 6.22\ min$ and $T_2 = 0.7\ min$.

The plant we are dealing with is powered by two fuel lines each with capacity of 160 units per sampling period. Each of the three control valves can supply (if the control algorithm needs to) up to 100 fuel units per sampling period. For the three valves that is maximum 300 fuel units per sampling period used, which is covered by the 320 units power of the fuel lines. Nevertheless, it is usual to use only one of the fuel lines and to keep the second line as a backup in case of malfunctioning of the first. In that kind of situation we need to consider the additional constraints on the systems that has been produced by the defect. Although it can implement standard constraints as in equation (8), the standard MPC algorithm, with some improvments, can implement the constraints in the form of equation (9).

$$0 <= u_i \leq 100, i = 1, 2, 3 \quad (8)$$

$$u_1 + u_2 + u_3 \leq 160 \quad (9)$$

What is usual for such plant is that when the process is starting, additional power supply line is started that allows the plant to produce more than 160 fuel units. Nevertheless, this power supply line cannot be used for a long time and must be turned off during steady state regime of the plant. It supplies additional 20 fuel units, that can be used in the sampling period, and 10 more that can be used in the next sampling period. By adding this constraint to our system we derive equation (10).

$$\begin{gathered} u_1(k) + u_2(k) + u_3(k) \leq 180 \\ u_1(k+1) + u_2(k+1) + u_3(k+1) \leq 170 \\ u_1(k+i) + u_2(k+i) + u_3(k+i) \leq 160,\ i = 2, 3, ...,\ N_c. \end{gathered} \quad (10)$$

This mathematical formulation defines a non convex constraint over the optimization problem. Through the literature there can be found only few algorithms that can successfully solve an optimization problem with non convex constraints. One of these algorithms uses an genetic algorithm optimization search in order to optimize the cost function. Using this type of algorithm the designer can easily solve optimization problems over nonlinear plant models and plants with non convex constraints. For further reading of optimization problems subject to non convex constraints, the reader may refer to Raber (1999)

4. Presentation of algorithm employing GA in MPC

4.1 MPC optimization using genetic algorithms

Genetic algorithms (GA) inspired by Darwinian theory, represent powerful non-deterministic iterative search heuristic Al-Duwaish & Naeem (2001). Genetic algorithms operate on a population consisted of encoded strings, where each string represents a solution. This algorithm uses the crossover operator in order to obtain the new solutions. Like in humans, the new generation of the solution inherits properties from its parent solutions, both good and bad properties. Each solution from the set has its own fitness value. This value represents a merit that defines the likeliness for surviving in the next generation. It is essential for these algorithms to produce new properties in the next generation. For that purpose the mutation operator is used. This procedure is iteratively repeated until it derives a solution that satisfies some norm or the run time exceeds to some threshold.

To apply this idea to an optimization problem, a first generation is composed of a set of points in the optimization domain. After that a chromosome is defined for each of these points. When the algorithm start to work iteratively in order to obtain new (and better) population, a genetic operator is applied to the chromosomes. Usually, when optimization is the problem, the algorithm chooses the chromosomes with the best evaluation function. These chromosomes have more probabilities to be selected from the chromosomes of the current population. The selected elements are part of the mating, crossover and mutation processes. For detailed reading on genetic algorithms the reader may refer to Goldberg (1989). Also we would like to recommend some other texts for further reading such as Mitchell (2008), Konak et al. (2006), Poli et al. (2008) and Weise (2009) that are considering optimization using genetic algoritms form different aspects.

One of the first papers about the genetic algorithms for optimization of MPC were presented by Onnen et al. (1997) and Blasco et al. (1998). In Onnen et al. (1997) the authors present an algorithm that is a combination of GA and MPC and explore its behaviour in controlling non-linear processes with model uncertainties. In Blasco et al. (1998) the authors also investigate the use of GAs for optimization in nonlinear model-based predictive control but focus on dealing with real-time constraints. Besides the good results showed in the start, there are only few more papers about applications with GA-MPC and algorithm improvements. Most of these papers exploit GA based MPC for nonlinear process control like the ones presented in Al-Duwaish & Naeem (2001) and Potocnik & Grabec (2000). Nevertheless the potential, the algorithm for GA based MPC is rarely used.

The basic flow diagram of genetic algorithm optimization that is used in this work is presented in figure 4.

The GA-MPC controller allows a very flexible cost function, and there are no limitations in the model or the index type used to minimize it. These characteristics enable application to non-linear processes and could therefore solve many industrial processes control problems. It is necessary to mention that this control type has the inconvenience of a noticeable computational burden, and this could affect its application to processes that need to consider real-time control. Nevertheless, this controller is very useful for dealing with slow dynamics processes and for implementing complex cost functions. These aspects of GA-MPC are studied below.

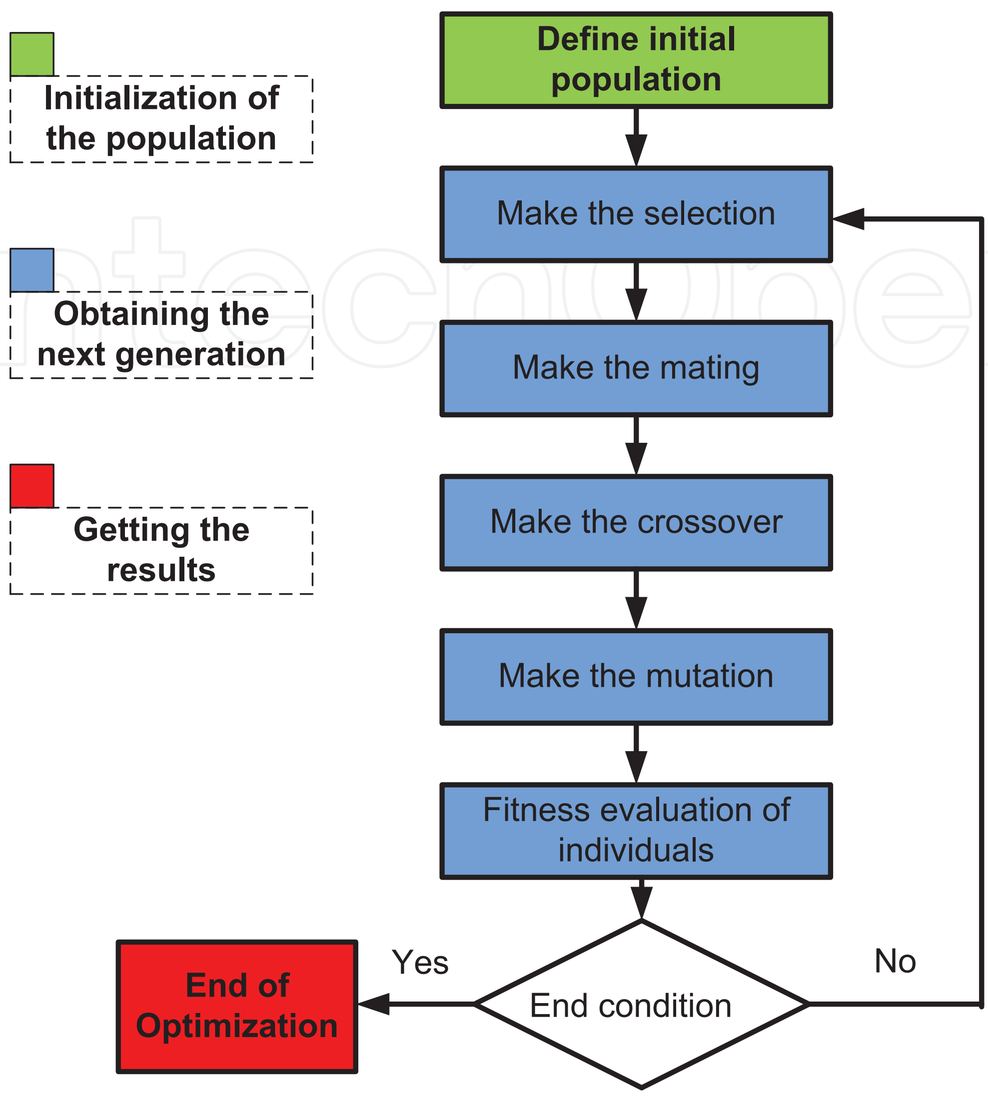


Fig. 4. Basic flow diagram of genetic algorithm

4.2 Non convex constraints

Model predictive control algorithms are usually implemented on models with linear or fixed constraints of the process and control variables. Although sufficient for most of the controllers and processes, in some particular cases, complex constraints can not be neglected. In this work we present an easy to go method for incorporating non convex constraints in model predictive controllers using genetic algorithm optimization of the cost function.

5. GA-MPC algorithm for easy implementation of non convex constraints

In this subsection we will present an effective algorithm for GA-MPC for dealing with non convex and/or nonlinear constraints. The basic structure of an GA-MPC algorithm is presented in figure 5.

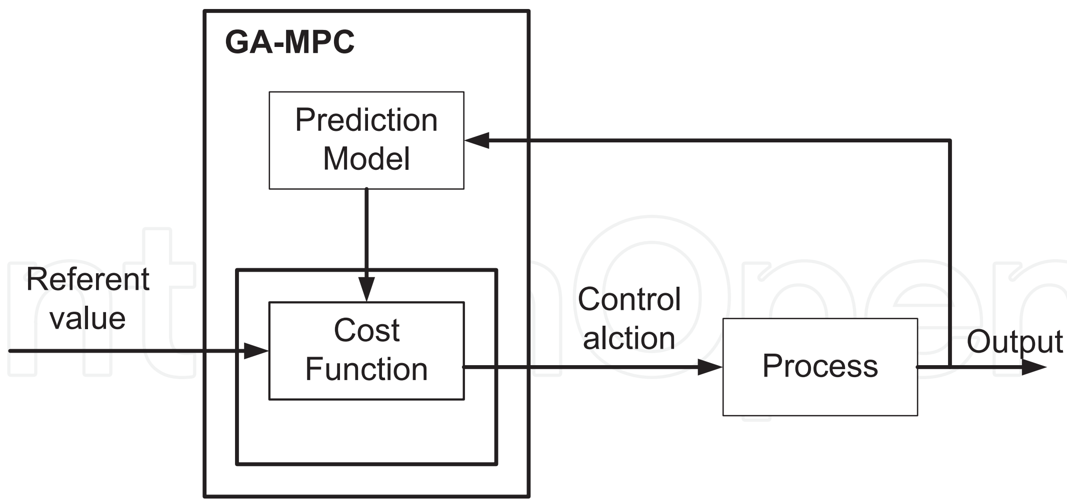


Fig. 5. Predictive control loop with GA

As said before, the optimizer used in the GA-MPC is a genetic algorithm. Genetic algorithms are optimization techniques based on the laws of species evolution. With each generation, a species evolves spreading to adapt better to their environment Blasco et al. (1998). In order to make the optimization, we need to define a cost function that will serve as a criteria for evaluation of the chromosomes.

The main advantage of GA based MPC algorithms are that they have no restrictions regarding the model of the system that needs to be optimized. That is why this type of algorithms is suitable for use in nonlinear control processes and respectively they can be very useful for solving many industrial processes control problems. One of the downsides of this algorithm is the big computational burden that it introduces. In order to compute the optimal solution of a problem, this algorithm may take up to few seconds, depending of the population and the other settings of the GA, which makes it unsuitable for use in processes that have fast dynamics. On the other hand, the complex thermal processes that exist almost in every industrial plant, usually have very large time constants, and a sampling period that is measured in seconds or even in minutes. That is why we decided to test this algorithm on a complex thermal plant, specifically, for controlling the process of a high consumption industrial furnace.

The proposed genetic-based control algorithm is shown in figure 5. This controller uses the model obtained with identification of the industrial furnace in FZC 11 Oktomvri factory in Kumanovo to search for the optimal control signals. In the same time this algorithm must comply with the constraints of the system, and optimize the cost function as given in the previous section. At every step time k the algorithm executes the following operations in the listed order.

1. Evaluate the outputs of the system, using the identified model.
2. Use genetic algorithm optimization search to find the optimal control moves for the cost function that satisfy the constraints. This can be accomplished as follows:
   (a) generate a set of random possible control moves.

(b) find the corresponding process outputs for all possible control moves using the identified models.

(c) evaluate the fitness of each solution using the cost function and the process constraints.

(d) apply the genetic operators (selection, mating, crossover and mutation) to produce new generation of possible solutions.

(e) repeat this procedure until predefined number of generations is reached and thus the optimal control moves are determined.

3. Apply the optimal control moves generated in step 2 to the process.
4. Repeat steps 1 to 3 for time step $k+1$

This algorithm was originally proposed in Al-Duwaish & Naeem (2001), we have used it with some adoptation as it can be seen from the text.

The practical implementation of the GA based MPC is performed in MATLAB software package, using the Genetic Algorithm Toolbox. This package also lets you specify:

- Population size
- Number of elite children
- Crossover fraction
- Migration among subpopulations (using ring topology)
- Bounds, linear, and nonlinear constraints for an optimization problem

The constraint can be implemented using a constraint property of the toolbox in the following format:

$$\begin{gathered} c = [u_{pc}(1) + u_{pc}(2) + u_{pc}(3) - 180; \\ u_{pc}(4) + u_{pc}(5) + u_{pc}(6) - 170; \\ u_{pc}(7) + u_{pc}(8) + u_{pc}(9) - 160; \\ u_{pc}(10) + u_{pc}(11) + u_{pc}(12) - 160; \\ u_{pc}(13) + u_{pc}(14) + u_{pc}(15) - 160;]; \end{gathered}$$

Here $u_{pc}(1), u_{pc}(2), u_{pc}(3)$ are the control actions for the three valves in the following sampling period and these values need to be calculated in a way to optimize the control of the furnace. Respectively $u_{pc}(4), u_{pc}(5), u_{pc}(6)$; $u_{pc}(7), u_{pc}(8), u_{pc}(9)$; $u_{pc}(10), u_{pc}(11), u_{pc}(12)$ and $u_{pc}(13), u_{pc}(14), u_{pc}(15)$ are the control actions for the three valves in the second, third forth and fifth sampling period. The presented constraint is in the case of control horizon of 5 sampling period.

6. Simulation results

The control goal is to keep the temperature in the three zones of the furnace at the referent temperature, with minimum possible fuel consumption. The simulation experiment will be conducted in conditions of malfunctioning of one of the power lines, so the maximum fuel units that can be supplied to the process is 160 (without the additional power supply line that can provide 20 fuel units for limited period of time). According to our previous research we have chosen the most appropriate values for the prediction and control horizon Stojanovski et al. (2009). In this paper we will compare the result obtained form the GA-MPC algorithm witn and without imlementation of the non convex constraints to the model. In this experiment we are changing the referent temperature in the furnace to three different values, and the controller is trying to minimize the error during the simulation. The temperature in the three zones of the industrial furnace is presented on figure 6, figure 7 and figure 8 respectively.

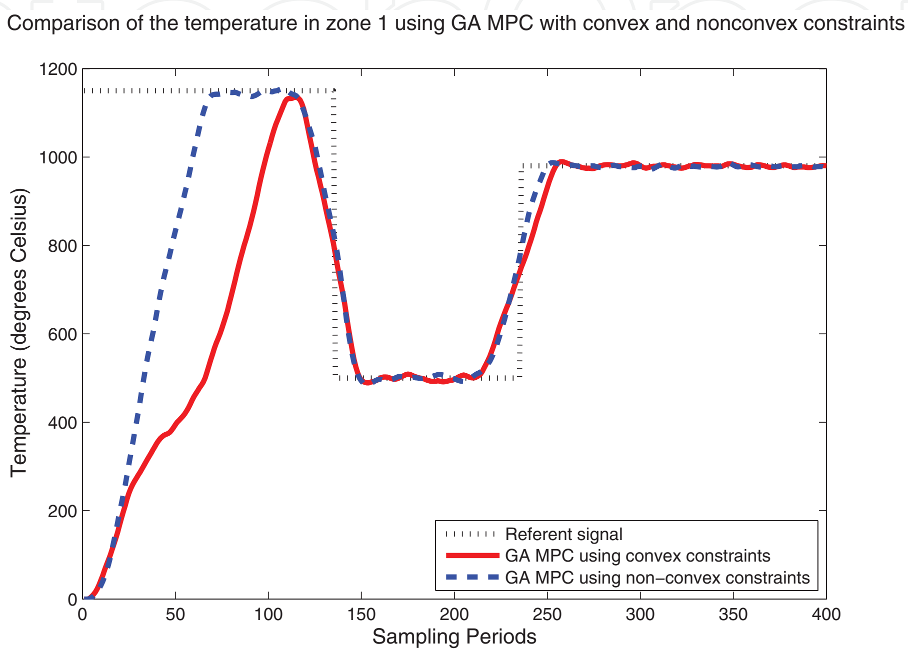


Fig. 6. Temperature in the first zone of the furnace

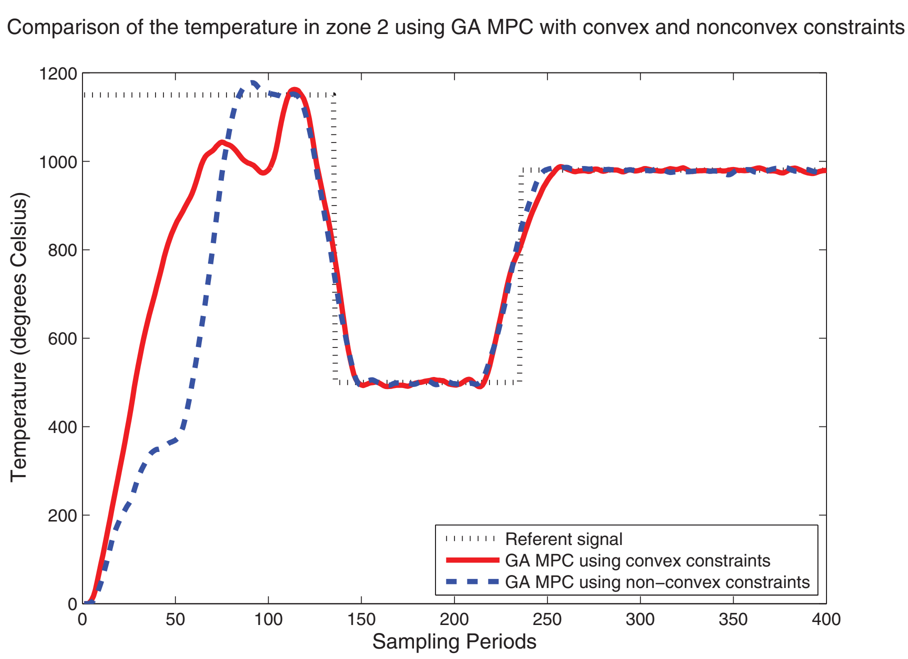


Fig. 7. Temperature in the second zone of the furnace

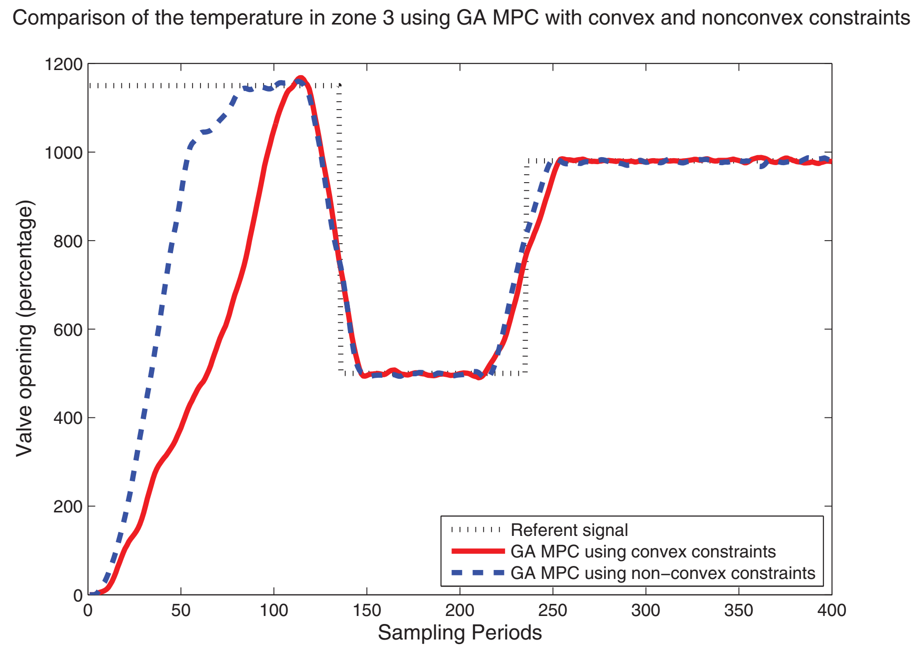


Fig. 8. Temperature in the third zone of the furnace

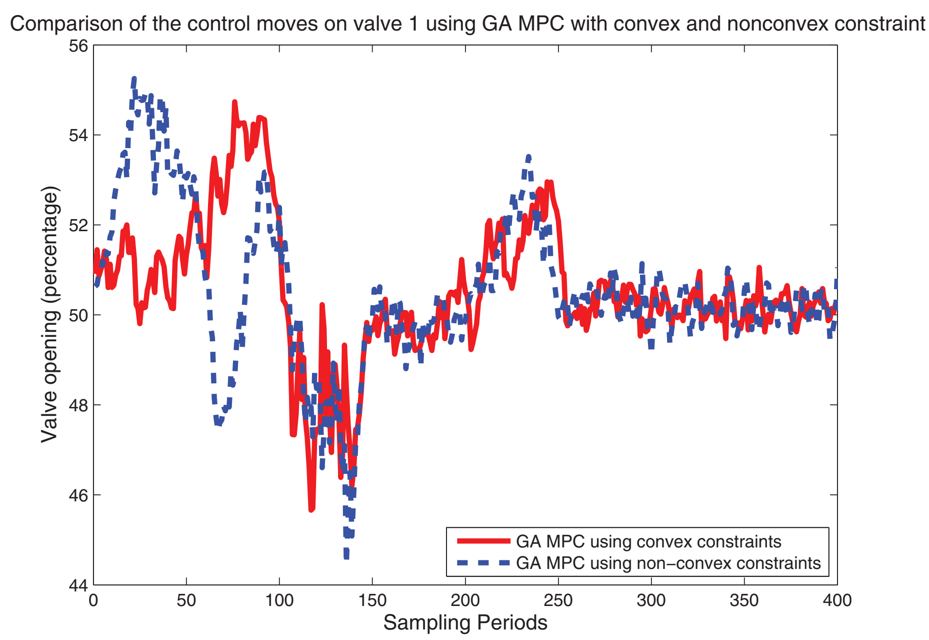


Fig. 9. Comparison of the calculated control moves for control valve 1 (convex vs. non-convex GA-MPC)

The sum of the control signals, that is subject to the nonstandard constraint is presented on figure 12. We can notice that the control signal, calculated using the genetic optimization based MPC algorithm, never violate the constraints. On the other hand, when using the GA algorithm that consideres the non convex constraints we have small constraint violations during the optimization. From the pictures depicted it is obvious that the second control method, that consideres non convex constraints, is slightly better. The values for the first zone of the furnace, both for GA based MPC that are and are not considering non convex constraints are depicted on figure 9. For the second and third control valve the results are depicted on figures 10 and 11 respectively.

It is obvious that both control algorithms have satisfactory behaviour and are reaching the referent temperatures. Anyway, one must point out that the GA-MPC algorithm that has not

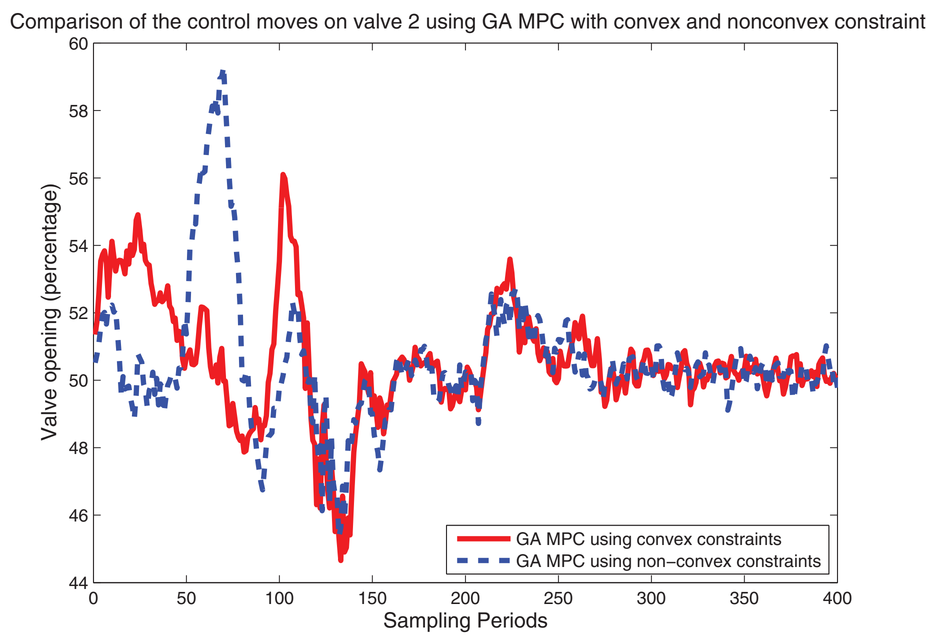


Fig. 10. Comparison of the calculated control moves for control valve 2 (convex vs. non-convex GA-MPC)

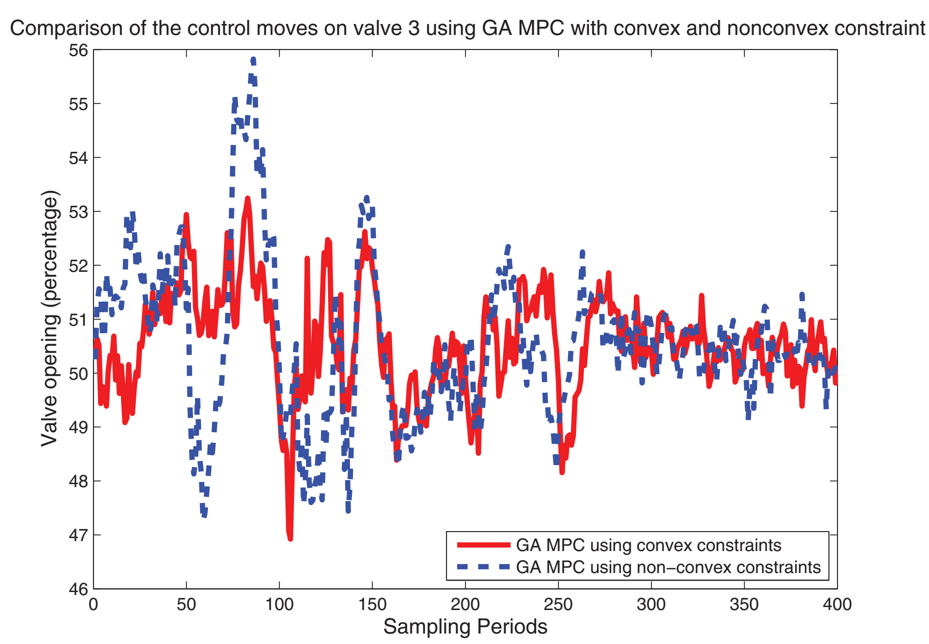


Fig. 11. Comparison of the calculated control moves for control valve 3 (convex vs. non-convex GA-MPC)

implemented non convex constraints on the cost function has worse performance than the one that has implemented non convex constraints. The difference in the calculation of the control signal is obvious if we look at figure 12, where the algorithm with convex constraints can not include the additional power supply line into the calculation of the optimal control moves.

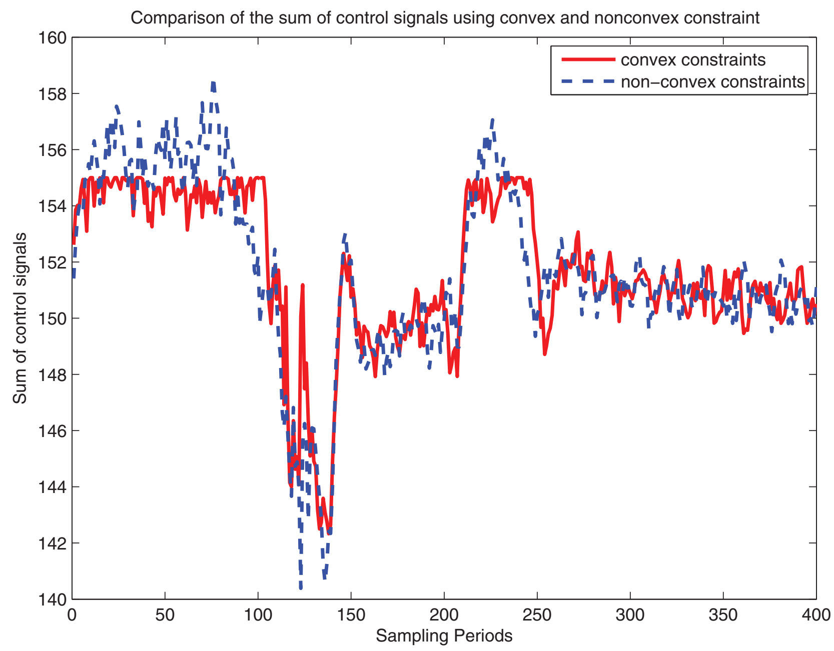


Fig. 12. Comparison of the calculated control actions regarding the energy consumption constraint (convex vs. non-convex)

7. Conclusion

The simulations of the proposed MPC with genetic algorithm optimization can track the referent temperature reasonably good under the defined constraints. We have presented an easy solution for implementing nonstandard constraints in MPC algorithms that improves the results of the standard MPC algorithms while slightly increasing the processing power.

We have shown that the use of GA-MPC can significantly improve industrial control of complex processes through implementing complex cost functions, but the engineers must have in mind that this algorithm still cannot be implemented on a fast dynamics processes. Besides GA-MPC's great potential for industry application, this technique is rarely used in industry.

8. References

Al-Duwaish, H. & Naeem, W. (2001). Nonlinear model predictive control of hammerstein and wiener models using genetic algorithms, *Control Applications, 2001. (CCA '01). Proceedings of the 2001 IEEE International Conference on*, pp. 465 –469.

Allgöwer, F., Badgwell, T., Qin, S., Rawlings, J. & Wright, S. (1999). Nonlinear predictive control and moving horizon estimation - and introductory overview, *in* P. Frank (ed.), *Advances in Control, Highlights of ECC-99*, Springer, pp. 391–449.

Blasco, X., Martinez, M., Senent, J. & Sanchis, J. (1998). Generalized predictive control using genetic algorithms (gagpc). an application to control of a non-linear process with model uncertainty, *Engineering Applications of Artificial Intelligence* 11: 355–367.

Camacho, E. & Bordons, C. (2004). *Model Predictive Control*, Springer-Verlag, London.

Dimirovski, G., Dinibutun, A. T., Vukobratovic, M. & Zhao, J. (2004). Optimizing supervision and control for industrial furnaces: Predictive control based design (invited plenary lecture), *in* V. Sgurev, G. Dimirovski & M. Hadjiski (eds), *Automatic Systems for Building the Infrastructure in Developing Countries - Global and Regional Aspects DECOM-04*, Union for Automation & Informatics of Bulgaria and the IFAC, pp. 17–28.

Dimirovski, G., Dourado, A., Ikonen, E., Kortela, U., Pico, J., Ribeiro, B., Stankovski, M. J. & Tulunay, E. (2001). Learning control of thermal systems, Springer-Verlag, London, pp. 317–337.

Goldberg, D. (1989). *Genetic Algorithms in Search Optimization and Machine Learning*, Addison Wesley Publishing Co.Inc.

Jing, Y. & Dimirovski, G. (2006). Decentralized stabilization control for composite systems with time-varying delays and uncertainties, *Information and Communication Technologies*, Vol. 1, pp. 1404–1409.

Keyser, R. D. (1991). Basic principles of model based predictive control, *European Control Conference, Proceedings of*, pp. 1753–1758.

Konak, A., Coit, D. W. & Smith, A. E. (2006). Multi-objective optimization using genetic algorithms: A tutorial, *Reliability Engineering and System Safety* (91): 992 – 1007.

Mitchell, M. (2008). *An Introduction to Genetic Algorithms (Complex Adaptive Systems)*, A Bradford Book; Third Printing edition.

Onnen, C., Babuska, R., Kaymak, U., Sousa, J. M., Verbruggen, H. B. & Isermann, R. (1997). Genetic algorithms for optimization in predictive control, *Control Engineering Practice* 5(10): 1363 – 1372.

Poli, R., Langdon, W. B. & McPhee, N. F. (2008). *A Field Guide to Genetic Programming*, Lulu Enterprises, UK Ltd.

Potocnik, P. & Grabec, I. (2000). Model predictive control using neural networks and genetic algorithms, *in* M. Dville & R. Owens (eds), *Proceedings of the 16th IMACS World Congress 2000 on Scientific Computation, Applied Mathematics and Simulation*, pp. 1–6.

Prada, C. D. & Valentin, A. (1996). Set point optimization in multivariable constrained predictive control, *13th World Congress of the International Federation of Automatic Control, Proceedings of the*, Oxford, UK: Pergamon Press, pp. 351–356.

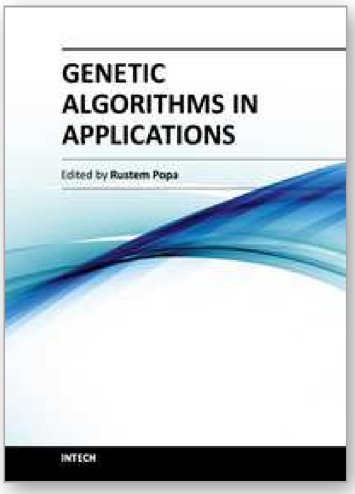
Raber, U. (1999). *Nonconvex All-Quadratic Global Optimization Problems: Solution Methods, Application and Related Topics*, PhD thesis, zur Erlangung des akademischen Grades eines Dr. rer. nat.

Stankovski, M. (1997). *Non-conventional control of industrial energy processes in large heating furnaces*, PhD thesis, Ss Cyril and Methodius University - Skopje.

Stojanovski, G., Stankovski, M. & Kolemisevska-Gugulovska, T. (2009). Performance analysis on mpc of industrial furnace depending on the control and prediction horizon, *Proceedings of the 9th ETAI Conference*, pp. A2–2.

Weise, T. (2009). *Global Optimization Algorithms - Theory and Application -*.

Zhao, J. (2001). Hybrid control for global stabilization of a class of systems, *in* T. Leung & H. Qin (eds), *Advanced topics in nonlinear control systems*, Vol. 40, World Scientific, (Singapore, River Edge, NJ), chapter 4, pp. 129–160.



Genetic Algorithms in Applications

Edited by Dr. Rustem Popa

ISBN 978-953-51-0400-1
Hard cover, 328 pages
Publisher InTech
Published online 21, March, 2012
Published in print edition March, 2012

Genetic Algorithms (GAs) are one of several techniques in the family of Evolutionary Algorithms - algorithms that search for solutions to optimization problems by "evolving" better and better solutions. Genetic Algorithms have been applied in science, engineering, business and social sciences. This book consists of 16 chapters organized into five sections. The first section deals with some applications in automatic control, the second section contains several applications in scheduling of resources, and the third section introduces some applications in electrical and electronics engineering. The next section illustrates some examples of character recognition and multi-criteria classification, and the last one deals with trading systems. These evolutionary techniques may be useful to engineers and scientists in various fields of specialization, who need some optimization techniques in their work and who may be using Genetic Algorithms in their applications for the first time. These applications may be useful to many other people who are getting familiar with the subject of Genetic Algorithms.

InTech Europe
University Campus STeP Ri
Slavka Krautzeka 83/A
51000 Rijeka, Croatia
Phone: +385 (51) 770 447
Fax: +385 (51) 686 166
www.intechopen.com

InTech China
Unit 405, Office Block, Hotel Equatorial Shanghai
No.65, Yan An Road (West), Shanghai, 200040, China
中国上海市延安西路65号上海国际贵都大饭店办公楼405单元
Phone: +86-21-62489820
Fax: +86-21-62489821