# Evolutionary Algorithms in Discredibility Detection

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#### INTRODUCTION

Evolutionary algorithms are well known optimization techniques suitable for solving various kinds of problems (Ruano, 2005). The new application of evolutionary algorithms represents their use in the detection of biased control loop functions caused by controlled variable sensor discredibility (Klimanek, Sulc, 2005). Sensor discredibility occurs when a sensor transmitting values of the controlled variable provides inexact information, however the information is not absolutely faulty yet. Use of discredible sensors in control circuits may cause the real values of controlled variables to exceed the range of tolerated differences, whereas zero control error is being displayed. However, this is not the only negative consequence. Sometimes, sensor discredibility is accompanied with undesirable and hardly recognizable side effects. Most typical is an increase of harmful emission production in the case of combustion control (Sulc, Klimanek, 2005).

We have found that evolutionary algorithms are useful tools for solving the particular problem of finding a software-based way (co-called software redundancy) of sensor discredibility detection. Software redundancy is a more economic way than the usual hardware redundancy, which is otherwise necessary in control loop protection against this small, invisible control error occurrence.

Namely, the standard genetic algorithm and the simulated annealing algorithm have been successfully applied and tested to minimize the given cost function; by means of these algorithms newly developed method is able to detect controlled variable sensor discredibility. When applied to combustion processes, production of harmful emissions can be kept within accepted limits.

Used application of evolutionary algorithms inclusive terminology transfer reflecting this application area can serve as an explanatory case study helping readers in better understanding the way how the evolutionary algorithms operate.

# BACKGROUND

The above-mentioned controlled variable sensor discredibility detection represents a specific part of the fault detection field in control engineering. According to some authors (Venkatasubramanian, Rengaswamy, 200 3, Korbic, 2004), fault detection methods are classified into three general categories: quantitative model-based methods, qualitative model-based methods, and process history based methods. In contrast to the mentioned approaches, where priori knowledge about the process is needed, for the controlled variable sensor discredibility detection it is useful to employ methods of evolutionary algorithms. The main advantage of such a solution is that necessary information about the changes in controlled variable sensor properties can be obtained with the help of evolutionary algorithms based on the standard process data – this is, in any case, acquired and recorded for the sake of process control.

In order to apply evolutionary algorithms to controlled variable sensor discredibility detection, a cost function was designed as a *residual function e* defined by the absolute value of difference between the sensor model output  $(y_m)$  and the real sensor output  $(y_{real})$ ,

 $e = |y_{real} - y_m| \tag{1}$ 

The design of residual function *e* has been explained in detail (e.g. in Sulc, Klimanek, 2005).

In most sensor models it is assumed that the sensor output is proportional only to one input (Koushanfar, 2003), so that the sensor model equation is

$$y_m = k_m x_{est} + q_m, \tag{2}$$

where parameter  $k_m$  represents the gain of the sensor model, parameter  $q_m$  expresses the shift factor, and  $x_{est}$ is the estimated sensor model input, which represents the physical (real) value of the control variable. The physical value of the control variable is not available for us because we expect that the sensor is not reliable and we want to detect this stage. However, we can estimate this value from the other process data that are acquired usually for the purposes of the information system. This estimation is usually based on steady-state data, so that it is important to detect the steady state of the process.

Basically, the underlying idea of applying the evolutionary algorithm is then based on finding a vector of the sensor model parameter for which the value of residual function *e* is minimal.

# Advantages of the Evolutionary Algorithm Applied to Discredibility Detection

In principle, any optimization method could be used for the mentioned optimization task. The problem is that the sensor model input is an unknown, dynamically-changing variable. Therefore, the choice and the parameter selection must include certain element of a random selection from many alternatives, which is fulfilled in the case of evolutionary algorithms. The higher computational time requirements do not matter in the case of sensor discredibility detection, because the loss of credibility is the result of a gradual development.

# **Problem Statement**

A particular task of evolutionary algorithms in the solved problem is e.g. a finding extreme of a given cost function. We have utilized the evolutionary algorithms to minimize the given cost function (in fault detection terminology a residual function). Based on this minimization, it is possible to detect that the control variable sensor is providing biased data.

# THE STANDARD GENETIC ALGORITHM AND THE SIMULATED ANNEALING ALGORITHM IN DESCREDIBILITY DETECTION

Both methods have been tested and proved to be legitimate for use. Unlike general genetic presentations of the methods, we will present the methods in a transformed way, based on the use of terms from the field of fault detection. From the engineering view point this should facilitate understanding of both procedures (Klimanek, Sulc, 2005). In our text, the terms introduced in the theory of evolutionary algorithms are indicated by the abbreviation "ET".

# The Standard Genetic Algorithm

In controlled variable sensor discredibility detection that uses genetic algorithm methods, the following steps are required (procedure by Fleming & Purshouse, 1995) (Figure 1):

1. Initialization – during initialization, the evolutionary time is set to zero and an initial set of vectors containing the sensor model parameters (called population in ET) is randomly generated within an expected range of reasonable values for each of the parameters. For each of the parameter vectors of the sensor model (in ET, individuals of the population), the value of the residual function

Figure 1 A flow chart of the standard genetic algorithm applied for discredibility detection



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