Genetic algorithm in optimisation of measurement system

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Abstract: - Measurement uncertainties of indirect measured values and their influences can be calculated with a computing model of a measurement based on a general Gaussian procedure for calculating the measurement results and their covariance matrix which serves as a measure of the uncertainties. Model is given in terms of a system of equations. Critical parts of measurement system can be found with optimisation procedure in which the goal is minimal final uncertainty in predefined limits. In paper is introduced genetic algorithm for optimisation and is compared with analytical algorithm.

Key-Words: - genetic algorithms, reasoning under measurement uncertainty, simulation

1 Introduction

In scientific, industrial and legal metrology, the investigator and engineer are confronted with measurement tasks, which go far beyond the measurement of only a single physical quantity with a suitable measuring instrument. Beside carefully carried out measurement, the data obtained must be analysed in order to assess the uncertainty of the measurement performed. The aim of experiment is to get small individual and mutual uncertainties. Modification necessary to achieve aim can be expensive and time dependent. Better solution is to find computing model of measurement system or experiment, that can be modified on computer. Optimisation process must stay in predefined real limits. Parts of a measurement will be changed in that process to find predefined uncertainty. If a measurement system can be described with a mathematical model, one can find optimal solution on computer. Computed optimisation process can not solve all problems. With practically designed best solutions can then be found final optimum. The idea of optimisation is to find the parts of a measurement system, that effect final uncertainty the most. Since uncertainty can be described as a scalar value, it can be used in genetic algorithm. The procedure to involve genetic algorithm is introduced and algorithm is used in optimisation of a capacitor sensor. The optimisation showed parts of a sensor, that effect final uncertainty the most.

2 Measurement Uncertainties

Computing model of a measurement is based on a general Gaussian procedure for calculating the measurement results and their covariance matrix, which serves as a measure of the uncertainties. Model is given in terms of a system of m equations like

$$y_k = F_k\left(x_1, .., x_n\right); \left(k = 1, .., m\right). \qquad (1)$$

Here, the n physical quantities are called input quantities and represent all the quantities for which data from measurement and other information are directly used in the evaluation. The m physical quantities are related to the input quantities by the functions F_k and are called output quantities. These are the measurands of interest which are to be determined with covariance matrix

$$\mathbf{S}_y = \mathbf{F}_y^{-1}\mathbf{F}_x\mathbf{S}_x\mathbf{F}_x^{\mathrm{T}}\mathbf{F}_y^{\mathrm{T}^{-1}} \quad , \qquad (2)$$

where F_x and F_y are partial derivatives of F_k: $\partial F_k/\partial x_n$ and $\partial F_k/\partial y_m$.

3 Basics of optimisation

It seems plausible that an experiment for certain measurands resulting in small individual and mutual uncertainties should be regarded as a good experiment. The quality measure of an experiment can therefore be found on the covariance matrix, which expresses the uncertainties of the measurements. Optimisation used in genetic algorithm seek for a best final uncertainty. That value is presented with a last diagonal element of a covariance matrix.

In optimisation procedure parts of a measurement system that will act as a chromosomes in a genetic algorithm must be defined. In a measurement system the parts of interest are uncertainties and values of all input quantities in a mathematical model. One can also use basic properties of measurement system (change of a measurement instrument). After each modification new covariance matrix must be calculated.

4 Optimisation Procedure

Optimisation is made with basic procedures of genetic algorithm: mutation, crossover and evaluation. To define an initial population for a measurement system a Gaussian procedure is used. As chromosomes are defined uncertainties and values of all input quantities. With calculated covariance matrix evaluation can be performed.

Defined number of parents is developed from initial population with mutation. In mutation chromosomes are randomly changed in defined limits. In measurement systems chromosomes must not have negative value and must not be doubled.

Limits for chromosome i are defined as

$$a = g_i - k \cdot g_i, b = g_i + k \cdot g_i; k < 1 \ . \qquad (3)$$

In these limits is randomly defined new value for uniformed distribution:

$$g_i = (b - a) \cdot rnd(1) + a \ , \qquad (4)$$

and for normal distribution:

$$g_i = g_i + k \cdot g_i \cdot \sqrt{-2 \cdot \ln(rnd(1))} \cdot \cos(2p \cdot rnd(1)); k < 1 \qquad (5)$$

A rnd(1) is random number generator with values from 0 to 1.

With parent's population an optimisation loop is started. Loop is calculated in predefined number of iterations. Genetic algorithm must only show parts of highest influence on final uncertainty. At start of algorithm chromosomes are too mixed. If there is too many iterations, optimum can not be designed in reality.

In optimisation loop parents are recombined. Randomly defined pair of parents changed randomly defined chromosomes. Recombined parents are mutated into children. Evaluation of best individuals is than made with sorting of last part in diagonal of covariance matrix - output uncertainties of measurement system. At the end of the loop best individuals become parents.

5 Example Of Optimisation

Optimisation was made on measurement system for gas flow in chimneystacks. System uses input values presented in table 1.

value	description
H=0.028	vapour concentration
N2=78	nitrogen concentration
O2=15.8	oxygen concentration
CO2=2	carbon dioxide concentration
d1=1100	chimney diameter
d=8	tube diameter
Pb=993	outside pressure
Tc1=22	outside temperature
dP=24.6	differential pressure
Ps=989	static pressure in chimney
Tc=180.4	temperature in chimney
t=28.49	measuring time

table 1 : input values

Sensor can be described with system of equations:

absolute pressure in chimney:

$$Pc = Ps + \frac{dP \cdot 0,75006}{tHgc}, \qquad (6)$$

partial vapour pressure:

$$Pv = \frac{H \cdot Pc}{H + \frac{H2O}{Vc}}, \qquad (7)$$

vapour concentration at work conditions:

$$Ru = \frac{H2O \cdot T0c \cdot Pv}{Vc \cdot (T0c + Tc) \cdot Hgc}, \qquad (8)$$

normal dry air concentration:

$$Rsn = \frac{28 \cdot N2 + 32 \cdot O2 + 44 \cdot CO2}{Vc \cdot 100}, \qquad (9)$$

dry air concentration at work conditions:

$$Rs = Rsn \frac{T0c \cdot (Pc - Pv)}{(T0c + Tc) \cdot Pc}, \tag{11}$$

air mass at work conditions:

$$R = RU + Rs, \tag{12}$$

gas velocity:

$$v = \sqrt{\frac{Kc \cdot 2 \cdot gc \cdot dP}{R}}, \tag{13}$$

chimney area:

$$Ac = p \cdot \left(\frac{d1}{2}\right)^2, \tag{14}$$

real gas flow:

$$Qe = v \cdot Ac \cdot 0.0036, \tag{15}$$

normal flow at Tc:

$$Qn = \frac{Qe \cdot (T0c + Tc) \cdot Pc}{(T0c + Tc) \cdot Hgc}, \tag{16}$$

normal dry flow:

$$Qs = Qn \frac{Pc - Pv}{Pc}, \tag{17}$$

izokinetic flow in tube:

$$Qf = v \cdot Au \cdot 0.06 \cdot T0c \frac{Pc - Pv}{(T0c + Tc) \cdot Hgc}, \tag{18}$$

measured gas:

$$Qt = Qf \cdot t. \tag{19}$$

In initial population are defined all input values and their measurement uncertainties as chromosomes in genetic algorithm. Optimisation criterion is measurement uncertainty of a measured gas.

Population of 100 parents and children were evaluated in genetic algorithm. Optimisation loop was calculated in 100 iterations. Best results were calculated with uniformly distributed mutations. Limits of mutation were narrowed with each iteration:

$$k = \frac{0.01}{i} \tag{20}$$

with i as number of iterations.

After optimisation chromosomes were changed as shown on figure 1.

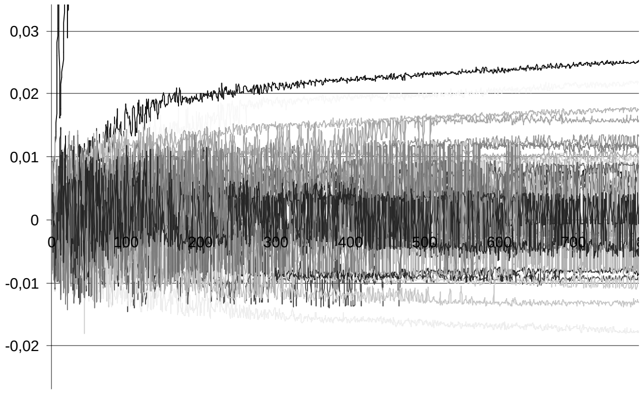

figure 1 : changed chromosomes

All changes are normalised to initial values. On figure 1 some lines are clearly shown in upper and lower part. Upper lines indicate that chromosomes must be smaller in optimum case and lower indicate that chromosomes must be bigger. In upper part are input values d, t, Ps, dP and measurement uncertainties of N2, d and dP. In lower part are input values Tc, O2 and N2.

Since genetic algorithm is a random process, algorithm was repeated ten times with same initial values to confirm results. Changes of final chromosome values are shown on figure 2.

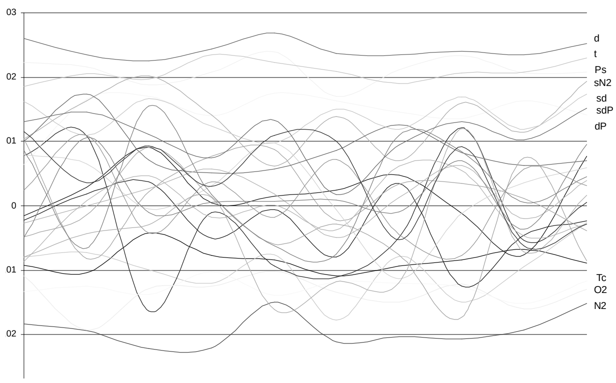

figure 2 : changes of final chromosome values

Chromosomes with no influence to optimum uncertainty of a Qt are randomly changed in central part. All chromosomes of interest are in start positions with small deviations. Deviations indicate optimum solutions different from solutions obtained with analytical calculations of a measurement system.

6 Conclusion

Genetic algorithm is effective in optimisation of complex measurement systems. Since the similar results can be calculated with analytical procedure one must define advantages and disadvantages of each procedure. In Gaussian procedure all input quantities must not be correlated. Correlation is not observed in analytical procedure. With random genetic algorithm correlation and new optimum solutions can be found.

Advantage of an analytical procedure is that is quick and has a clear solution. Genetic algorithm on the other hand needs a lot of computer memory and calculation takes a lot of time. So the best idea of using genetic algorithm is in combination with analytical procedure, when correlations are not clearly defined.

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