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IMPLEMENTATION OF STOCHASTIC SEARCHING FOR COMPLEX PROCESS IDENTIFICATION

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ABSTRACT

This paper presents implementation of stochastic searching method for complex technological process identification. As the first step of control systems design is identification of a process mathematical model. The author uses certain stochastic algorithms created & explained in some of his earlier published papers. The basis of the said algorithms is a non-linear stochastic searching. From general mathematical process description this paper considers a process steady state property as an object of identification. Some of presented examples are useful to observe possible problems most of control system designers face through attempts to solve control problems or to modify process technology. As fas as the implemented algorithms are concerned certain advantages & efficiency have been obtained vs regular gradient methods. Since the said algorithms are with some modification useful for training of artificial neural networks, the future development could be toward an intelligent control systems design & implementation. Numerical procedures have been processed by using MATLAB.

KEY WORDS

stochastic searching algorithms, mathematical model identification, complex technological process, process control systems, intelligent control.

1. INTRODUCTION

Theoretical basis of Stochastic Search Algorithms (SSA) were introduced by mid of previous century [1, 2, 3]. An application of the said methods in process identification & optimisation was not significant during the late decades of previous century. The said refers to implementation od Stochastic Direct Search (SDS). Last few decades back the trend was changed [4,5,6] since numerical processing of SDS showed advantages over methods based on gradient [7, 8,9].

The main property of SDS is its heuristic nature suitable for various modifications related to the problem under consideration [10]. Besides, SDS algorithms are operational with both determined or stochastic process models. Further on SDS are also suitable for set-up and planning of complex multifactor mathematical models experiments and in evolutive optimization as well (EVOP) [3, 11].

From the reference point of view it is worthwhile to mention the author experiences regarding practical implementation of SSA & SDS in various real process optimization. The obtained results were presented on international conferances [12,13]. Besides, some ten years back SDS algorithms were successfully implemented in various project related to analysis, syntesis & training of artificial neural networks (ANN) [*14*,15,16,17]. The gained experience throughout theoretical & practical implementation of SDS gave confidence to introduce a so called MN-SDS algorithm [19] (Modified Non-linear SDS). By other words it is certain modification of basic non-linear SDS [2]. The main motivation is to create a simple but effective procedure than back propagation [20], and at the same time to be useful for training of ANN. Further on MN-SDS is widely applicable whenever problems of identificastion & optimization of complex control systems are under consideration [6]. In this paper MN-SDS is applied in identification of complex technological processes having in minds their non-linear properties [13].

During last 50 years numerous research works showed impresive application of fundamental mathematical tools in industry [22, 23, 24]. Those days experienced intensive development of computational technics useful for massive numerical experiments necessary for advanced control systems. During that period of time modern control theory had intensive development [25, 26, 27] etc. Main concerns have been optimization of process operation specifically those having multi-product-mix either final or semi-final products. By other words objectives have been quality, optimal capacity operation and profitability as well. A process indentification is one of unavoidable stage of optimal process control.

It is wothwhile to point out the basic process nature, what mathematical model is to describe an object i.e. by linear or non-linear modelling. Linearised non-linear models are in essential aspects non-linear. Such cases are considered as specific ones and each is treated as individual case. This paper consider similar case focusing attention to identification and control of a piro-metallurgical processing of non-ferrous metals.

Numerical data processing was carried on by using of SDS ans MN-SDS algorithms. Suitable tools offering MATLAB [28] were fully applicable the case under consideration.

2. METHODS & MATERIALS

2.1 Basic introductory notes

Identification of process math model should be handled the way to match appropriate computational method including real-time processing. According to the previously said the following process description is used[27]:

$$\frac{dx}{dt} = f(x,u,s,a,t); t_0 \geq 0, x(t_0) = x_0 \quad (2\text{-}1)$$

$$y = g(x,\eta,b,t) \quad (2\text{-}2)$$

$$h_1(x,\eta,c) = 0 \quad (2\text{-}3)$$

$$h_2(x,\eta,d) \geq 0 \quad (2\text{-}4)$$

where are:

$f(\cdot)$ i $g(\cdot)$ non-linear vectorial functions, $h_1(.)$ i $h_2(.)$ constrains over variables, parameters & functions, x-state variables, u-control vector, s-measurable disturbances; a,b,c,d process parameters describing structure (constants, matrices, vectors), η-noise mostly added in (2-2).

A process parameters identification assumes some variables measurements observing criteria (cost) function

Q= Q(x,u,s,y) (2-5)

The function Q in (2-5) does not include constrains $h_{1i}(\cdot)$ i $h_2(\cdot)$, but if not possible that the following is used [29]:

$$Q_h = Q + \sum_i \lambda_i h_{1,i}(\cdot) + \sum_j \lambda_j h_{2,j}(\cdot)$$

$$i = 1,2,...q;\ j = 1,2,3...l \quad (2\text{-}6)$$

where are: λ_i and λ_j Langrage- multipliers; $\lambda_i>0$ and λ_j={0 for $h_{2,j}\geq0$; Λ_j for $h_{2,j}<0$, $\Lambda_j>0$}

When λ_i and λ_j tends to have increased value toward ∞ than Q_h and Q have the same value for the same variables x, u, s i.e. for assumed optimal parameters of model.

2.2 An approuch of identification substantial non-linear processes

In Chapter 2.1 is given the internal mathematical description of process. The Fig.1a) and Fig. 2 present a process block diagrams and identification procedure. When the production process is in stacionary steady-state for which dx/dt = 0, the diagram in the Fig. 1a) is transpose to the diagram in the Fig. 1b). Mathematical model in (2-1), (2-2), (2-3) and (2-4) is reduced to:

$$y = G(v, a, b, s, t) + \eta \tag{2-7}$$

$$h'_1 = h'_1(v, c, s) = 0 \tag{2-8}$$

$$h'_2 = h'_2(v, d, s) \geq 0 \tag{2-9}$$

Where are: G(.), h'_1 i h'_2 vectorial functions, v-vectorial variable incorporating all measurable process variables used for process observation and control. It is assumed that non-linear function G (.) is not possible to be linearised but it is possible to be as sum of separable non-linear functions $\varphi_i(v_i)$ i.e. :

$$y = \sum_{i=1}^{i=4} \varphi_i(v_i) + R(v_1, v_2, v_3, v_4) \tag{2-10}$$

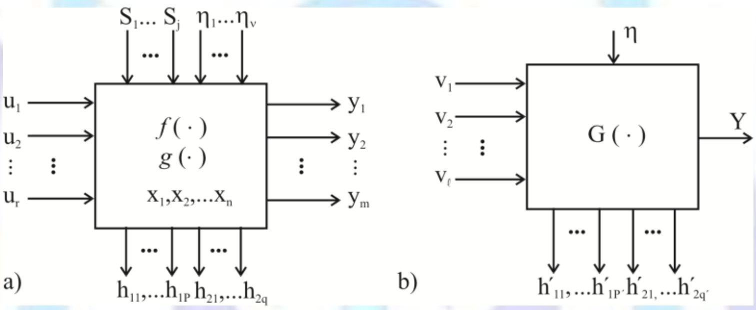

Fig 1: a) Multivariable system, b) Non-linear stacionar static model

Non-linear functions φ(.) could be in the form of: a *exp(bv)*, *P(a,v)/Q(b,v)* or *1/Q(b,v)* where *P(.) i Q(.)* are relatively simple polinomial function of *v* and parameters *a* and *b*; *R* is residual of approximation.

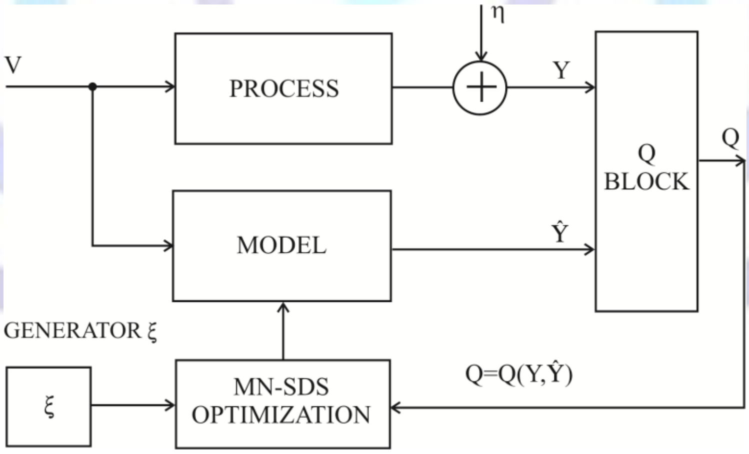

Fig 2: Block scheme of process identification

For a set of data obtained from process steady state a regression model is mostly applicable what brings the identification to method of data fitting [21]. Having in minds that linearisation is not poossible that fitting-optimal approximation could be performed by use of some gradient iterative methods or similar. Mostly fast gradient deepest descent is used [24,31]. In this paper SDS i.e. MN-SDS is applied [19]:

$$\Delta x_{i+1} = \begin{cases} \alpha\zeta_i, \Delta Q_i < 0, \Delta Q_i = Q_i - Q_{i-1} \\ -\alpha\zeta_R^{(i,J)} + \alpha\zeta_i, \Delta Q_i \geq 0; \\ \Delta Q_i^{(j)} = Q_i^{(j-1)} - Q_i^{(j-2)} \geq 0 \end{cases} \tag{2 - 11}$$

where are: ζ = *ort* ξ, ξ –vector of random variable the same dimension as vector of parameters in parameters space of optimization, a $\zeta_{R(i,J)}$ – presents number on failed tests and it is cumulative information enabling possibilities for self-training of MN-SDS algorithms; ΔQ_i *i* $\Delta Q_i^{(j)}$ increment of cost function *Q(v,y)* both at success or failed tests, α – iterative procedure step usually takes values: 0.1; 0.01; 0.001; 0.0001 or even less.

The random vector variables ξ are created by random generator [18,30]. So, for SDS searching it is necessary to create random vector of size *n* what correspond to number of parameters under identification.

$$\xi = [\, \xi_1,\ \xi_2,\ \xi_3,\ \ldots\ \xi_i,\ldots,\ \xi_n]^T\ ; \qquad (2\text{-}12)$$

The process data collection are usualy in the form of table. The proposed procedure does not require estimation of correlation and regression coefficients and other tests for data validity. For the sake of having relevant process data an averaging and mean square was applied. The aforesaid enables estimation of non-fitting data and by null hipothesis distribution of those data too [32]. Besides, obtained results can be used, if necessary for parallel procedures whenever data validity gained with SDS are under question. Main property of SDS algorithms refers to less sensibility on some linear corelation of model variables and parameters [33]. The validity of the model is estimated by considering the residue absolute value as an integral indication. The presented example shows an advantage of SDS algorithm having in minds that final result gives minimal both Q and residue.

3. RESULTS

An application of SDS algorithms whenever an identification of production process at state space stationary static concept is concern has shown rather competitive performanses. On the other hand it is necessary to observe possible instability of iterative procedure when SDS is implemented on dynamic process model. The previously said is because SDS algorithm in its basic version (used in this paper) can not follow changes in the process where differentiation is required. SDS algorithms have better performance (compared to gradient) whenever the noise is quite present since they operate in all options of ΔQ status ($\Delta Q > 0$ or $\Delta Q < 0$ or $\Delta Q = 0$). Ba appropriate scaling of iterative step *α*, SDS advance toward an optimum even when gradient method enters into saturation [10]. Presented examples enable insight into real results & properties of MN-SDS algorithms application. The results of real process identification during one month running (average increase of de-sulphurisation) showed some 2.5%. The previously pointed out that there are possiblities for FSR (fluo-solid reactor) control system improvements. Evaluation of numerical procedures of SDS and so MN-SDS algorithms is presented in the Fig 3.

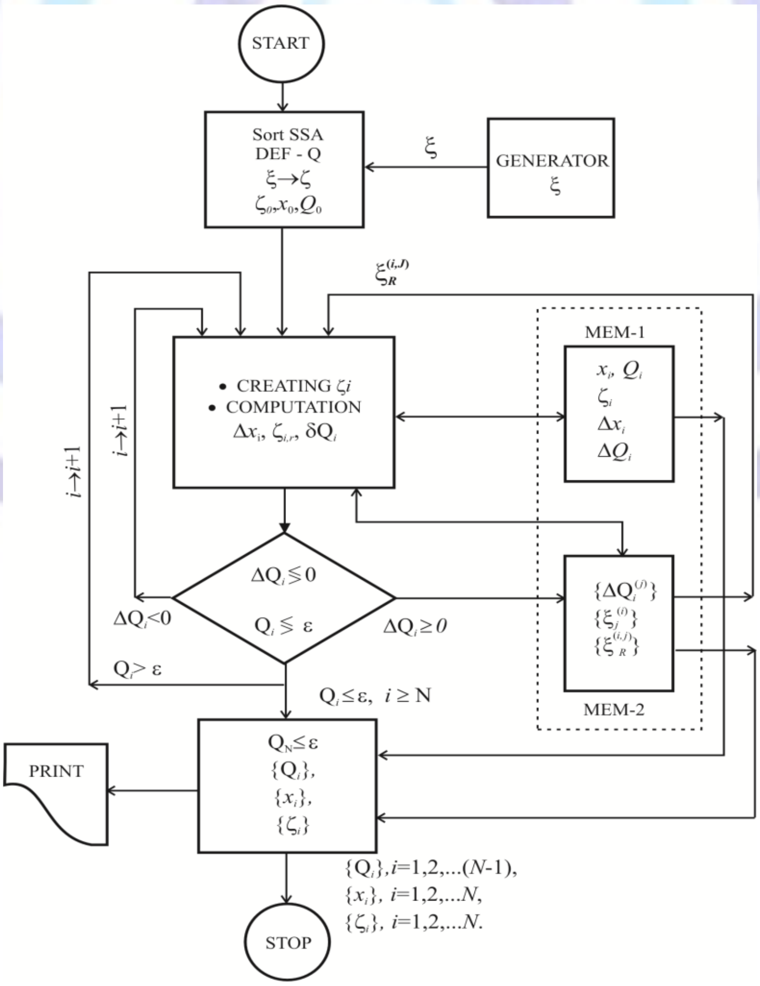

Fig 3: Flowchart of procedure computer processing of SDS MN-SDS

3.1 Example of a process identification in non-ferrous metallurgy

The copper concentrate roasting process (de-sulphurisation in FSR) having capacity of some 60 t/h each requires appropriate control system having in minds its instability in general. The smelter plant of RTB Bor (Mining & Metallurgical Complex Bor) has two FSR units. The system complexity is created by input raw-materials i.e. Cu concentrate since components vary in wide range (chalcopyrite- $CuFeS2$, pyrite- $FeS+FeS2$ and elementary Sulphur- S). Averaging content of concetrate per component S in the concetrate storage arrangement in front of the FSR is impotant operation for the process's stability.

The simplified scheme of FSR is shown in Fig 4. The FSR is cylindrical shape steel walls some 10 mm thick thermo-isolated, the FSR bed is made of steel sheet thickness of 10-25 mm. The rated temperature is average 625^0C inside of FSR space, fluo-bed is boiling layer having temperature of some 85-90^0C. The initiation of the process is done by heating up with burners and when working temperature is achieved than the process maintains by burning of sulphur. The hot air (prox 90^0C) is brought by blowers. So, working parameters of the FSR are: temperature 625^0C, gases pressure of 2350 Pa, air flow q ranging 14.913m3/h<q<36.972m3/h provide turbulent environment enabling set-up particles sweep ranging 30cm/sec<Vod<50 cm/sec [39].

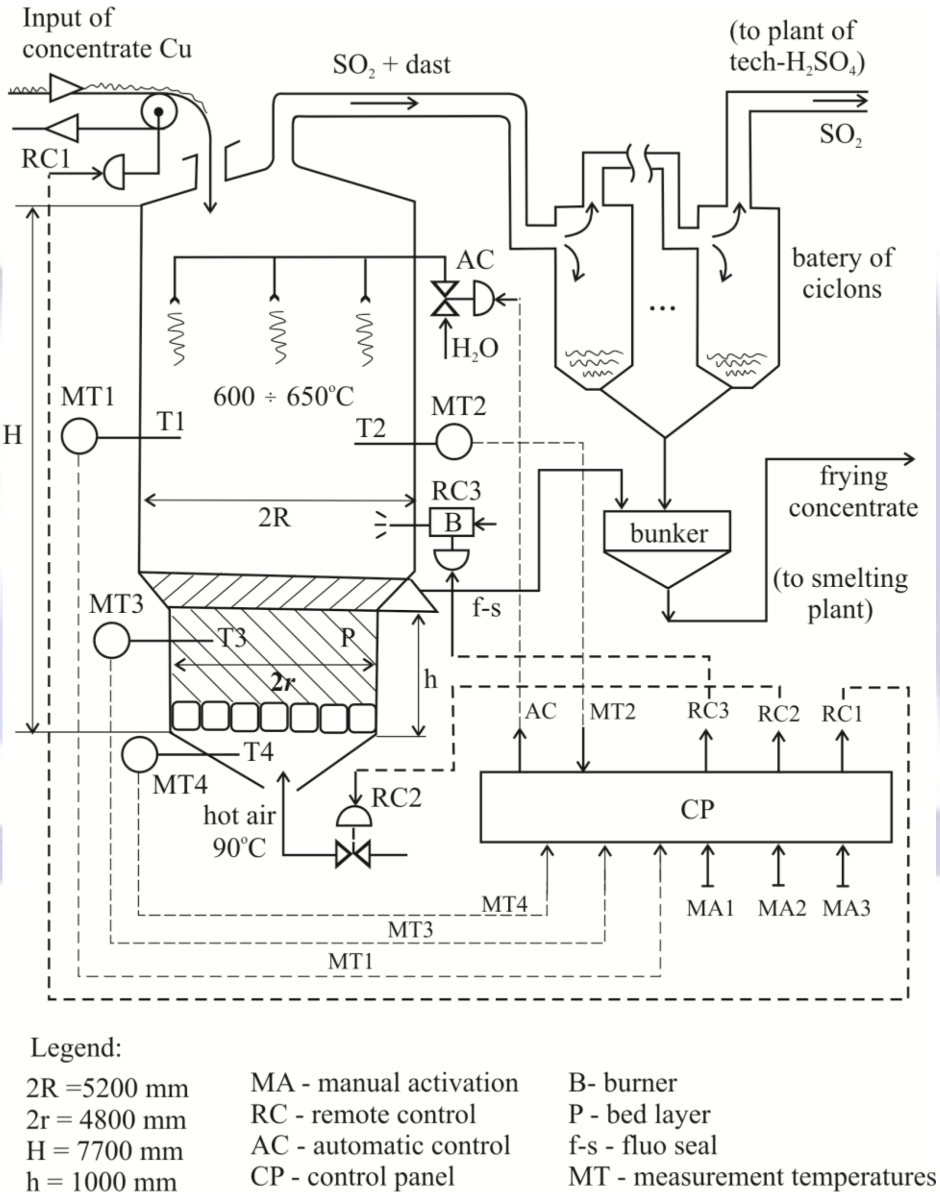

Fig 4: Fluo-solid reaktor plant

Input raw materials (Cu concentrate) contains : 90% of chalcopyrite&pyrite & sulphur; 10% quartz as flux.

Concentrate contains so 10% moisture.

Particles size is within the range of 0,004mm<*d*<0,85mm, where *d* is particle diameter. Working regime is defined by Reynolds number Re (usually in the range 0<*Re*<30) [39]. Since the process itself is not stable makes rather difficult to apply tests of active experiment. It is more convenient to create a model based on samples at normal funcioning of proces, during 24 hours campaign per any hour.

The process observation can be done by reading of instruments & recorders (Fig 4). The process control is remotely based on data reading. The operators change the level of control variables by $\pm \Delta u_r$ as step functions.

Control variables and other parameters change are done in longer period of time (Tu) compared to process kinetics (*Tk)*; $Tu \gg Tk$. The aforesaid is a key to approve an implementation of state stacionary static modeling of the FSR. So, exact process dynamics are by-passed having in minds balances of input raw-materials, thermodynamics & process kinetics[.37,38]. Correlation between variables under observation is relevant for regression modeling for majority of procedures. For the presented procedure the residuals after parametric optimization are relevant for each sub-model and master model as well.

Table 1

№ \ v_i	v_1(%)	v_2(%)	$v_{3(\%)}$	$v_{4\ (t/h)}$	Yx100 (m^3/h)
1.	31.20	19.01	22.20	46.00	27.00
2.	31.80	20.42	18.20	42.00	22.00
3.	32.40	24.91	19.20	42.10	21.50
4.	31.10	20.30	18.30	41.90	22.00
5.	32.20	20.58	19.60	44.00	26.00
6.	30.10	19.05	21.60	46.10	28.10
7.	32.60	20.30	19. 30	46.00	25.00
8.	33.20	19.71	20.80	42.00	27.00
9.	31.20	19.85	21.20	38.00	25.50
10.	33.40	21.29	19.00	34.00	24.00
11.	31.80	26.31	18.80	45.00	23.00
12.	30.80	23.21	18.20	41.90	22.00
13.	32.40	21.28	18.90	42.00	21.00
14.	32.90	28.74	22.00	42.00	21.50
15.	28.80	17.42	18.10	36.00	24.00
16.	35.40	19.98	21.80	30.00	23.10
17.	37.00	16.74	20.40	30.10	24.10
18.	36.60	15.90	23.40	44.10	25.10
19.	32.50	18.20	21.80	28.00	24.10
20.	31.80	23.00	21.70	41.00	20.00
21.	32.90	18.86	20.70	30.00	24.00
22.	31.60	16.82	21.40	36.10	26.00
23.	31.80	18.38	20.20	30.00	24.00
24.	31.60	18.13	21.80	44.00	28.00

Data sampling of variables are done each hour according to site practice and shown in the table Table 1(collection data from the year 2010). Based on the aforesaid the following steps determine the process state stationary-static regression model of the FSR. For the observed data in the Table 1 average values and square average variation are shown ih the table Table 2.

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Table 2

v_i	v_1	v_2	v_3	v_4	Y
$\bar{v}_i$	32.1600	19.6800	20.8652	42.0000	24.5800
σ_{vi}	1.7019	2.0846	1.5912	6.0017	2.1389

The choice of variables is dictated aiming to get relation air flow vs variation of S- sulphur (v_1 , %) in input raw-materials, Cu- content in concentrate (v_2 , %), S- content in roasted concentrate (v_3 , %), process actual capacity (v_4 , t/h) and hot air (v_5=Y, m^3/h) (see Table 1).

Some of values in the sample were neglected (marked items) since rather far from average values $\bar{v}_i$, i=1,2,3,4. For others data it is possible to create regression model (Fig. 5a).

$$\hat{Y} = a_0 + a_1 v_1 + a_2 v_2 + a_3 v_3 + a_4 v_4 = a_0 + \sum_i a_i v_i \qquad (3\text{-}1)$$

$$i = 1,2,3,4$$

The objective function Q is determined as per the following [21, 32]:

$[\hat{Y}] = [v][a]; \; Q = ([Y]-[v][a])^T([Y]-[v][a])^2$ (3-2)

out of $\frac{\partial Q}{\partial a_i} = 0$ attends $[a]=([v]^T[v])^{-1}([v]^T[Y]);$ (3-

$[a]=[21.0491, - 0.4930, -0.2182, 0.9591, 0.1052]^T;$ with confidence's interval 95 %. (3-4)

$\hat{Y} = 21.0491 - 0.4930v_1 - 0.2182v_2 + 0.9591v_3 + 0.1055v_4$; $Y = \hat{Y} + R_L(Y, \hat{Y})$, $\| R_L \| = 24.4700$. (3-5)

The linear regression model is not adequate due to rather high norm of residue R_L. So, it is undertaken measures to find which of non-linear models is more competitive[21].

In order to use measured input data for getting functional dependence some correlation coefficients Y_i and v_i are tested.

It is shown that dependence of the following type $\varphi_i(v_i)$ in relaion (2-10) could fit i.e.

$$a_i \exp(-b_i v_i), \;\; a_i + b_i \exp(-b_j v_j), \;\; \frac{a_i v_i}{1+b_i v_i}, \;\; \frac{a_i}{1+b_i v_i} \text{ and } a_i + \frac{b_i}{v_i} \;;\;\; i=j=1, 2, 3, 4 \qquad (3\text{-}$$

The shape of the set of measurement data on the accumulation process(see Fig.5,a)) does not show anything whish was be facilitated by the selection of separable model of (3-6) and thus integrated

Model Ŷ can be obtained of some combination of separable models in (3-6) but this model will not in all aspects simulated the original process as static mode operation[35]. Frequent outbursts for wich reason can be any of the variables determining the final choice selection of integral model :

$$Y = a_0 + \sum_{i=1}^{4} \frac{a_i v_i}{1+b_i v_i} + R(v_1, v_2, v_3, v_4) = \hat{Y} + R_N(Y, \hat{Y}), \quad \hat{Y} = a_0 + \sum_{i=1}^{4} \frac{a_i v_i}{1+b_i v_i}; \;\; \|R_N\| \le NQ, \qquad (3\text{-}7)$$

Although the model Ŷ is rather simple having non-linear property with roots explaining why the process is unstable. The process frequently “fails” because of the aforesaid. If one failure during 24 h took place than some 10% less in capacity (since servicing of FSR is complex).

The process parameters identification is achieved by minimizing of the objective function i.e min Q ;

$$Q = \frac{1}{N} \sum_i \sum_j \left(Y_{ij} - \hat{Y}_{ij}\right)^2 \; ; \; N=4, \; i=1-4, \; j=1-20; \qquad (3\text{-}8)$$

N-number of sebarable models, j- number of samples.

The MATLAB software package was used for random numbers generation. For initial values $\{a_i\}$ is determined randomly, or they can use for the start parameters values of linear regression model (3-4).

The parameters $\{b_i\}$ are taken as per local conditions imposing boundary of process campagn (Table 3, Fig 5). It was experienced that for certain capacity range process fails if going beyond values of v_1, v_2 , v_3 and v_4 .

Each of variable v_i during operation has the limit values $v_{i,min}$, $v_{i,max}$ and each separable model has root at $b_i' = -1/v_i$ and then apply relations :

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$v_{i,min} < v_i < v_{i,max}$ and $1/v_{i,min} > 1/v_i > 1/v_{i,min}$ or $-1/v_{i,min} < -1/v_i < -1/v_{i,max}$ (3-9)

i=1,2,3,4

Based on the above may be to forme the Table 3 by areas of the inadmissible values for the parameters b_i :

Table 3

$v_{i,min}$	v_i	$v_{i,max}$	$b'_{i,min}$	b'_i	$b'_{i,max}$
29	$< v_1 <$	36 ,	-0,0344	$< b'_1 <$	-0,0277
16	$< v_2 <$	24 ,	-0,0625	$< b'_2 <$	-0,0416
19	$< v_3 <$	23 ,	-0,0526	$< b'_3 <$	-0,0434
28	$< v_4 <$	46 ,	-0,0357	$< b'_4 <$	-0,0217

In Fig.5, b) the area outside the segment AB is an area of stable numerical procedure, but region on the segment CD is the immediate environment of root b_i' and represent the area of instability model and the same technological process. The parameters b'_j should be avoided in the process of SDS search. For the starting vektor of paramiters is taken the combination of coefficients of the linear model in expression (3-5) for $a_{0i,}$ and the value b_{0i} accordance with Table 3.

For the sake of parallel comparison it was used Levenberg-Marquardt method[34] with the same starting vector of parameters and the same steps of iteration, as for MN-SDS method:

$[a_0,a_{0i},b_{0i}] = [21.0491, -0.4930, -0.2182, 0.9591, 0.1052, -0.0150, -0.0120, -0.0829, -0.0572]^T$; α = 0,0001. (3-10)

By applying of MN-SDS after minimization cost function Q, the model coefficients Ŷ get the following values:

$[a,b] = [36.5539; -0.0967; -0.0427; 0.0437; 0.0159, -0.0251; -0.2630; -0.0630 ; -0.0411]^T$ (3-11)

By applying Levenberg-Marquardt method after minimization Q the model coeficients get the following values:

$[a,b]=[26.7515;-0.0968;-0.1410;0.0447;0.0426;-0.0250;-0.2620;0.0408;0.0630]^T$ (3-12)

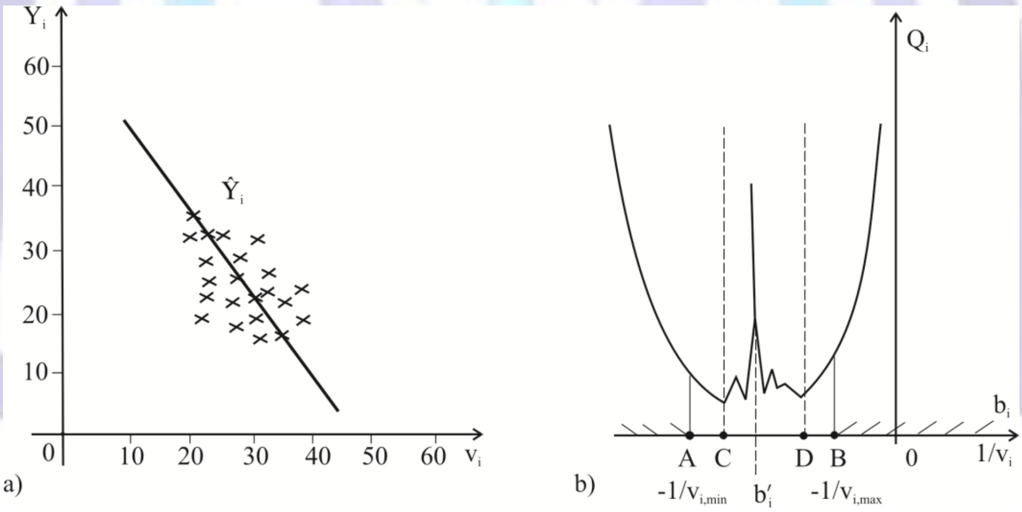

Fig 5: a) Linear regression model, b) Constraints for parameters b_i

After replacing [a,b] with specific values of (3-11) in expression [3-7] finally gives a model prepared using the MN-SDS algorithm:

$$\hat{Y} = 36.5539 - \frac{0.0967v_1}{1-0.0251v_1} + \frac{0.0427v_2}{1-0.0262v_2} + \frac{0.0437v_3}{1-0.0630v_3} + \frac{0.0159v_4}{1-0.0411v_4} \quad (3\text{-}13)$$

. By implementing of MN-SDS method at step iteration α=0.0001 and after 700 iterations $minQ_{SS} = 0.9685$.

By implementing of Levenberg-Marquardt method after 900 iterations $minQ_{LM}$ could not go below $minQ_{LM}$=1.7531 and with rezidual norm $||R_{LM}||$ = 19.2815. Based on lines (3-5) and (3-7) follow:

$$||R_{SS}|| < ||R_{LM}|| < ||R_L||, \quad (3\text{-}14)$$

where are: R_{SS} - residual of stochastic serching, R_{LM}- residual of applying Levenberg-Marquardt method's and RL - residual of linear regression model.

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The above results show the greater efficiency of MN-SDS. .The average relative error devation from the original MN-SDS model is 5%. Model derived Levenberg- Marquardt method slightly worse results These results are the concequence of the existence of relatively high noise level and efficiency of methods in such conditions [10, 23]. For further research should provide new collect of data and use of new composite mathematical models.

For regression models offered by mathematicaly statistics some complex procedures are required mostly when interrelations of variables and parameters are present. Some tests are used in order to complete rigorousness but usually fail[32]. The reasons for that is poor or inadequate sample. Whenever stochastic search methods are applied such problems are not emphasized enabling modest range of samples to be satisfectory. It is'nt necessary to observe that sample itself should be statistical representative for SDS numerical procedures [33].

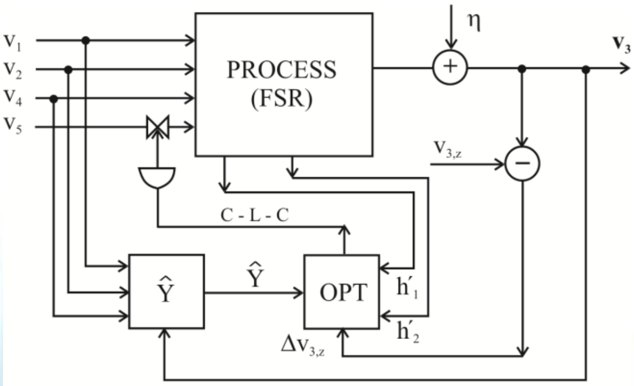

Fig 6: Identification and optimization process

The above results indicate that it is possible to create a model simulating FSR steady state stacionary static process operation. Based on various FSR process capacities and modeling, it is possible to design an advance control system than currently in operation. The advance control system assumes to have adequate measuring instruments and process computer for both process identification & optimization.

The Fig. 6 shows a basic scheme of an improve control arrangement for one close loop. The proposed model indicates that the FSR dynamic behavior would be uncertain [35,36,37,38]. It leads to conclusion that more complex control system requires vast range of experiments over dynamic regime. Thise experiments disrupt a normal functioning of the process and increases the cost of introdusing higher levels of automation.

4 . DISCUSSION

Creating regression mathematcal model of production processes is well established theme backwards. But it is still current, spesial when they are substantially non-linear models of complex technological processes .When characteristic of complexity inherent to any number of elements vector parameters, then the higher dimension of this vector it is advisable that the choice of method is SDS. In the present Example the vector dimension is *n=9.* SDS i.e. MN-SDS algorithm operate efficiently at far more complex cases. The SDS algorithms do not require large collections of data as opposed to the methods of mathematical statistic .Minimum number of dissimilar measurement data is how mach is unknown parameters. The results of Example show that it is achievable for a valid model FSR by MN-SDS algorithm. The same model can be the basis for project of magnification level of automatic control (Fig.6). The advaced level of control over the existing ned of more instrumental and regulating devices and selection process computer. Process computer in addition to the identification performed the optimization of the production technological process's. Fully automated process in the present case woud too much costly investment. Complexity and objectively present uncertaintly in the control of process often imposes alternative to changes the same thehnology.

5. CONCLUSION

This paper presents implementation of stochastic searching method for complex technological process identification. As the first step of control systems design is identification of a process mathematcal model. The author uses certain stochastic algorithms created & explained in some of his earlier published papers. The basis of the said algorithms is a non-linear direct stochastic searching. Method and algorithmic procedure, that have been used in this paper are effective when applied to the identification and optimization of highly complex systems. From general mathematical process description this paper considers a process steady state property as an object of identification. Research work is focused on own production technological processes in stacionary static mod of functioning. The presented example are useful to observe possible problems most of control system designers face through attempts to solve control problems or to modify process technology. As fas as the implemented algorithms are concerned certain advantages & efficiency have been obtained vs regular gradient methods. Since the said algorithms are with some modification useful for training of artificial neural networks, the future development could be toward an intelligent control systems design & implementation. Numerical procedures have been processed by using MATLAB package. Numerical procedure performed in this papers can be inplemented even on simple mulitcore PC.

Conflict of interests:

"The author declare that there is no conflict of interests regarding the publication of this paper".

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Kostantin P. Nikolic was born in 1947 in Kalovo in the Republic of Serbia. Primary and secondary education completed in Bor. Studies and post - studies completed at the Faculty of Electrical Engineering, University of Belgrade. His business career began in the TIR RTB Bor. His professional focus is the theory and practice of automatic control and computing. After working at the facility moved to the University of Belgrade at Department RM Faculty in Bor. He taught the lessons of automatic control of technological processes at universities in Belgrade and Novi Sad. A longer period (20 years), he worked in IT where he managed data centers in Copper Institute in Bor and later in Novi Sad. He was collaborator and leading designer a number of researches, which was in the field of complex processes as well as micro-computer support which was mandatory companion. In the last ten years Prof. Nikolic is visiting professor at the Faculty of Management in Novi Sad, where he taught lessons of Artificial Intelligence. He is author of two students books about Computers and Artificial Intelligence.

Prof. Nikolic left behind a number of professional papers and projects. On the research plan was a participant of a number of studies related to the identification and optimization of processes. He has participated in conferences and symposium of international importance and some of his research results are published in proceedings of the same. In this article is dedicated to identifying processes in plants TIR in RTB Bor where he began with a working career.