2. W.Wójcik, A.Smolarz , A.Kotyra, C.Wojciechowski, P.Komada: Fibre optic flame monitoring system, Proceedings of SPIE *The Internatio*
and their Applications" 2000, p. 129-131.

3. Trade information of Durag GmbH.

4. Trade information of BFI Automation.

5. Trade information of Fireye Inc.

6. W.Wójcik, A.Kotyra, A.Smolarz: Sprzęganie objętościowych źródeł światła ze światłowodami Materiały V Konferencji „Światłowody i ich Zastosowanie", Białowieża 1998, tom 2, str. 309-319. (in Polish).

7. W.Wójcik, W.Surtel, A.Smolarz, A.Kotyra, P.Komada: Optical fiber system for combustion quality analysis in power boilers, Proceedings of SPIE, Optoelectronic Information Technologies, vol. 4425, 2001, pp.517-522.

8. B.Jähne, Digital Image Processing, Springer-Verlag, Berlin Heidelberg New York 2002.

9. W.Wójcik, T.Golec, A.Kotyra, M.Duk: Combustion assessment of coal and biomass mixtures using image processing, Proceedings of SPIE, Optical Security Systems, vol. 5954, 2005, pp.117-122.

10. W.Tao, H. Burkhardt: Vision-Guided Flame Control using Fuzzy Logic and Neural Networks Particle & Particle Systems Characterization*, 12(2/95), 1995 pp. 87-94.*

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STEADY STATE OPTIMIZATION ALGORITHM FOR INDUSTRIAL PROCESS CONTROL

Наведено новий алгоритм "прив'язки до сітки", який встановлює верхній шар ієрархічної керуючої системи. Цей алгоритм використовується для вибору реперних точок робочої оптимізації. Подано деякі особливості системи і розглянуто основні досягнення оптимізації стабільного стану.

The paper presents a new algorithm Snap To Grid (STG) that constitutes the top layer of hierarchical control system. This algorithm was used for beet-slicers points of work optimization.

Some features of the system were presented and general steady-state optimization approach was discussed.

1. Introduction

The process industry is experiencing important changes due to quality requirements of the high quality, cheap final product as well as decreasing prices of hardware and implementation of optimization techniques feasible from a financial perspective.

Optimization benefits the operation of industrial processes in terms of reduced operating costs and maximized product quality in response to differing feed, market and environmental conditions. The economic optimization of the operating conditions of a process involves the design of an economic objective, which should quantify the factors known to have an economic impact in the way the plant operates. These factors include, for instance, process yield, energy efficiency, costs of energy and raw materials, product prices, etc. The economic objective, together with the process steady state relations, constraints associated with physical limits, safety, environmental regulations, etc. define the optimal operating conditions of the process. For a continuous flow process, these optimal operating conditions usually refer to a steady state operating point, called the steady state optimum. Steady state optimization techniques have also been called optimizing control. For batch processes, the optimal operating conditions refer to dynamic trajectories. In steady state optimization, it is often the case that the optimum operating conditions lay at the intersection of a number of process constraints. Regulating the steady state operation of a multivariable process at such constrained conditions is difficult using conventional controllers.

In this article, similar solution, supporting above idea is presented. The paper discuss STG controller, which main objective is beet slicer set productivity management, regarding to continuous work (standstills leveling).

The STG controller is situated in the top layer of hierarchical control system as well as stands the superior device for two nonlinear model predictive controllers, situated in the direct layer.

2. Process background

The beet slicer set stands the first chain of sequential sugar production process, which has influence on the whole process as well as economical income of the enterprise. Compensation of variable demand from diffuser and keeping cassets at the appropriate level is the objective task for slicing process.

Beet slicer works under stochastic disturbances such as inhomogeneity of material (beets), contaminations and temperature, so that it's proper work depends on knives waste level as well as drums velocity (which are controlled outputs).

Currently both slicers work under about fifty percent of their abilities, though they are equipped with modern control drives allowing them for point of work rapid changes. It means, that half o their potential is wasted.

On one hand the appropriate quality level of cassets depends on drums velocity. But on the other hand stochastic disturbances such as inhomogeneity of material (beets), contaminations and temperature lead to knives blunt as well make productivity lower in the effect or even standstills. This is a serious problem, and it exists even though there are some preventers like pneumatic knives cleaning system or dirtiness snatch set are installed.

3. Control system structure

Complex systems require process decomposition, where the plant is decomposed on fast (executive) processes as well as slow (optimized) [1],[2]. Control system decomposition is presented in the Fig. 1.

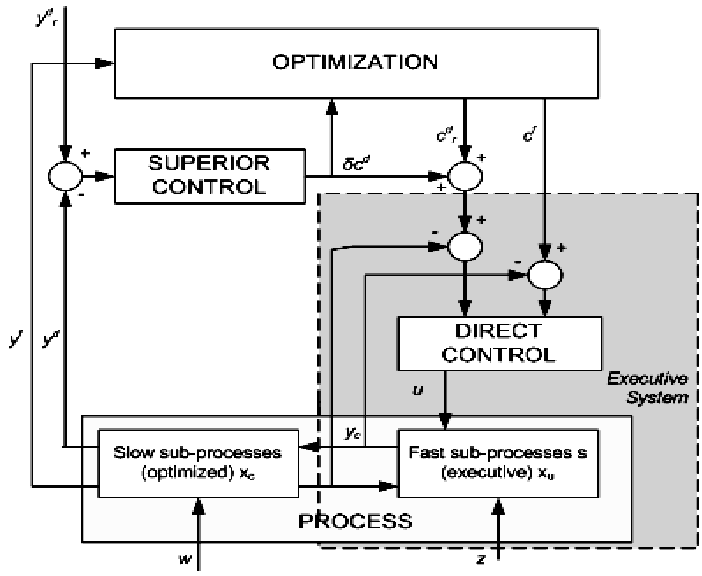

Fig. 2. Hierarchical control system decomposition with several layers

In this case, to the first, executive group can be classified: velocity stabilization and productivity stabilization on the diffuser input. It is obvious that productivity depends on velocity so the concept of several slicer control scheme is connected with leading the process as close as possible to the optimal operating points trace.

Predictive control refers to a class of algorithm, that compute a sequence of predicted manipulated variable moves in order to achieve specified control objective, so it is the task for direct control layer, where predictive controllers are able to provide disturbances. Predicted output variables of the process are computed over a given time interval, when using a dynamic process model. Process input and output constraints are often included in the problem formulation so that the activation of constraints may be anticipated. The first element of the computed manipulated variable sequence is applied to the process and the problem is solved again at the next interval using updated process measurements[5].

Apart from this ‘intelligent’ productivity managing is necessary for the process continuity. So that the current points of work of several devices ought to be optimized (see Fig. 2).

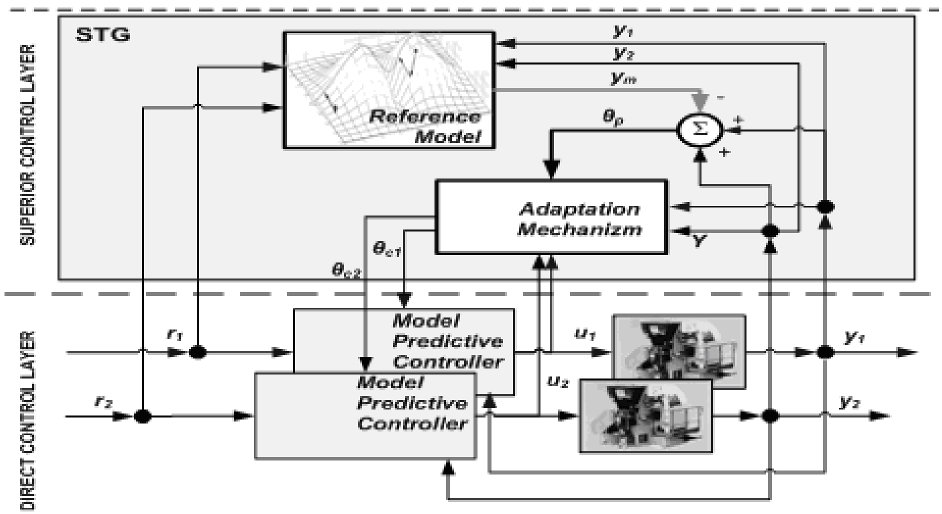

Fig. 2. Proposal hierarchical control system scheme

4. Point of work optimization

In the previous paragraph several layer control system structure was described as well as the optimization layer was distinguished. Determining the optimal from economical point, reference signal values for controllers situated lower in the hierarchy (direct control layer) stands the objective of the layer. These values ought to warrant the influence on outputs, essential for computing object working optimized criterion and it's constraints [1],[2]. However, the basis for accurate work of each part of the hierarchical structure is the proper model for control task in the appropriate layer realization.

The optimal trajectories of optimization layer variables can be in general:

- Dynamically changed - they come from the solution of optimal control task,
- Steady - they come from the solution of task static optimization. Moreover, the optimum values should be adopted to the slow disturbances and then it is named as a optimizing steady-state set-point control.

According to [3], continuous productive processes in practice can be characterized almost by the second case, with regard to the wide class of processes with steady optimum states, as well as the fact leading the object near suboptimal steady states (even for processes with optimal dynamically variables. It is conditioned with:

- Credible static model is easier to obtain than dynamic, moreover it is simpler to find the solution of static optimization task than dynamic,
- Easier the and more safe is leading the process by operators, especially when detecting and counteracting the emergency situations.

Starting from dynamics equations and comparing derivatives of state variables to zero is the elegant and very demonstrative way of finding the mathematical model of the plant. However, in professional approaches detailed static models are used. They are built on basis of the physical models, computed for the settled states. These models are described with complex, nonlinear equations or even nonlinear iterative schemes, when searching balanced relations. These actions lead to high exactitudes in modeling, difficult or even hardly possible to achieve, when constructing the useful models of dynamic objects. Nevertheless, some or almost all outputs often occur in the very complicated way and they are hard to accomplish the equation:

$$y = g_c(x_c, c). \quad (1)$$

The set of equations general feature is the following:

$$0 = f_c(x_c, c, w, a), \tag{2}$$

$$0 = g_{yc}(y, x_c, c), \tag{3}$$

where x_c represents process states, depending from settled controls c, measured disturbances w and model parameters a.

To solve the high dimensionality set of equations (2) and (3) the numeric methods that manage with iterative algebraical loops are applied. Such models were worked out by the specialized software, mainly for simulating. However, because of their complexity they do not always guaranteed the correct result. That is why such models are not suitable for optimal points of work in real-time computation. They can only stand a basis for on-line optimization for simpler models like (4).

$$y = F(c, w, a), \tag{4}$$

where F represents the static model, achieved by elimination of state variables in the set of equations:

$$\begin{cases} 0 = f_C(x_C, c, w, a) \\ y = g_C(x_C, c) \end{cases}, \tag{5}$$

Simplified models satisfying equation (4) are often constructed as approximation of large amount input-output data, generated by the full simulating models. Some possibly small number of key parameters is left for current tuning of simplified model. The notable tendency of using the static physical models for on-line optimization can be observed in literature as well as control environment applications.

Steady-state point of work optimizing control does not mean that once best settled controls c can be provided by longer time period, independently from essential unmeasured inputs or even object properties itself.

Set-point optimization control means regulators reference signals successive tuning to optimal values, whose changes because of unmeasured inputs or object internal properties (slower change according to controlled plant dynamics).

Assuming, that the economical criteria of object working, being subject to static optimization, has the form:

$$J = Q(c, y), \qquad c \in \Re^{n_c} \wedge y \Re^{n_y}, \tag{6}$$

This function (see eq. 6) represents economical aim, usually an interest.

Regulators inputs c (object points of work) stands decision variables of optimization layer and they are always constrained and the set of these constraints C is defined:

$$c \in C = \{c \in \Re^{n_c} : g(c) \le 0\}, \tag{7}$$

where $g : \Re^{n_c} \to \Re^{n_c}$ is constraints function vector.

Outputs constraints Y in steady states also appear and are defined:

$$y \in Y = \{y \in \Re^{n_y} : h(y) \le 0\}, \tag{8}$$

where $h : \Re^{n_y} \to \Re^{r_y}$ is constraints function vector, usually simple.

Generally, current points of work optimization task is realized in presence of approximated disturbances and with inaccurate model. That's why for realization of this task it is necessary to distinguish available, steady-state control plant model on one hand, and unknown true representation F^* on the other hand.

$$y = F^*(c, w). \tag{9}$$

The main objective of the steady-state points of work in uncertainty conditions is designated as optimizing steady-state set-point control task (OSC).

Lemma 1. For current values of unmeasured inputs w find optimal controls c , that minimize the cost function *Q(c,y)*, complying controls constraints $g(c) \le 0$ as well as outputs constraints $h(y) \le 0$, where y stands outputs steady-state measurement, that represent previously used values c. $y = F^*(c, w)$.

The mathematical formulation of lemma 1 is following:

$$\begin{aligned} & \min Q(c,y) \\ & \text{with constr. } y = F^*(c,w) \\ & g(c) \le 0 \\ & h(y) \le 0 \end{aligned} \tag{10}$$

Given form optimizing steady-state set-point control task is practically unavailable to realize, because of lack of $y = F^*(c,w)$, but when the control model $F(c,w,\alpha)$ is accurate enough, it can be replaced by $y = F(c,w,\alpha)$. It is possible only when the unmeasured controls are defined. They can be estimated with particular precision. So that optimizing steady-state set-point control task become model optimization deterministic control task (MODC):

$$\begin{aligned} & \min Q(c,y) \\ & \text{with constr. } y = F(c,w,\alpha) \\ & g(c) \le 0 \\ & h(y) \le 0 \end{aligned} \tag{11}$$

This is a typical static optimization problem, nonlinear for nonlinear model, constraints or cost function.

According to beet slicer set, regular model tuning is necessary because of slow changeable uncontrolled inputs, even if received estimations are less accurate. Two stages way of tuning are used [1],[4]:

- Steady-state model parameter estimation stage,

- Model optimization deterministic control task solving stage, with tuned model and achieved point of work usage (see Fig.3a).

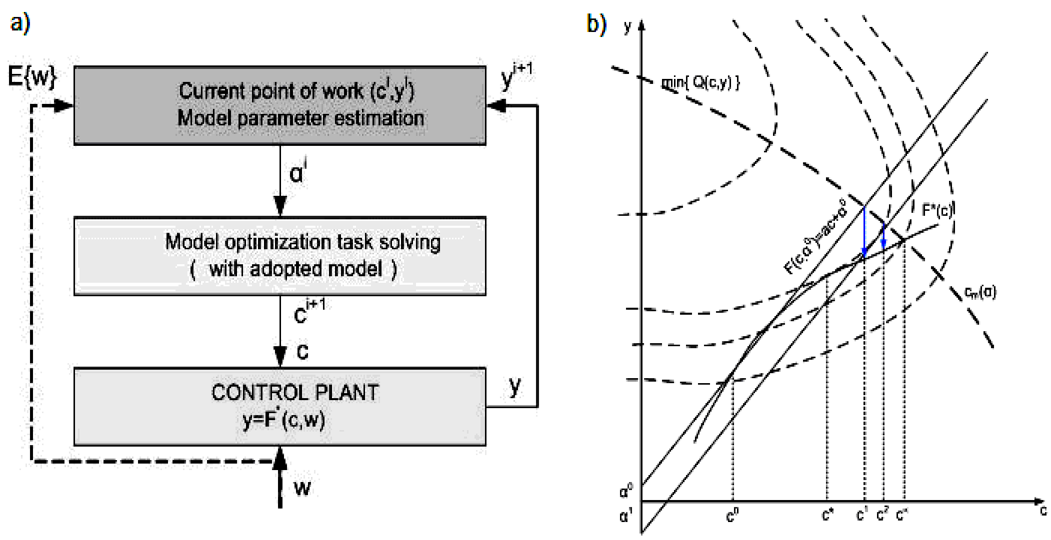

Fig. 3. MODC block diagram

Model optimization deterministic control may be illustrated in Fig. 3b, for exemplar one-dimensional process where $y \in \Re$, $c \in \Re$, with no y constraints. The graph illustrates: nonlinear static characteristics $y = F^*(c)$; linear model $F(c,\alpha) = ac + \alpha$ for some values of α ,where model output is adopted according to (simplified) condition $ac + \alpha = F^*(c)$; isoheights of minimized function $Q(c,y)$ and minimized solutions curve $c_m(\alpha)$. There also maintained iterations of the optimization method beginning from c^0 to convergence point c^∞ for model $\alpha(c)$ parameters adaptation . It is notable, that condition $c^\infty = c^*$ is fulfilled only when $a = (F^*)'(c^*)$. Presented example shows iterative process and the fact, that optimization algorithm do not achieve improvement of real cost function $Q(c, F^*(c,w))$ values.

Discussed solution was the basis for STG controller development.

5. Snap-To-Grid controller

Top layer of beet slicer set control system uses Snap-To-Grid (STG) adaptive approach, based on reference model, represented by the surface with two global maxima (see Fig.4) given by the general equation 12:

$$F_s(x,y,z) = W \cdot \left| x \cdot e^{\left(-A(x-B)^2 - C(y-D)^2\right)} \right| - z\,. \tag{12}$$

Coefficients A, B, C, D, W, allow to adapt the model to the current state of the devices. Each extreme represent the optimum point of work of every slicer, e.g. the highest value of productivity, possible to obtain.

For coefficients $B = D$ values these are the same. In remaining cases ($B > D$, $B < D$) it is different and characterize waste level of the slicers. The function F_s was achieved from gained, historical data approximation in NMSE sense [4]. The arguments of F_s represent drums velocity, knives waste level and productivity. An important topic of adaptive control is performance. Such description intends the calculations simplifying as well as controller 'acceleration' in case of possible on-line implementation. On one hand more precise model, will result in longer computation cycle, but on the other hand it never gain unknown true representation (see paragraph 4).

The principal aim of the STG controller is assurance of process continuity, providing appropriate productivity, thanks the fluent work of the slicer set.

The idea algorithm of STG controller is formulated in Lemma 2. statement and presented in the Fig.4.

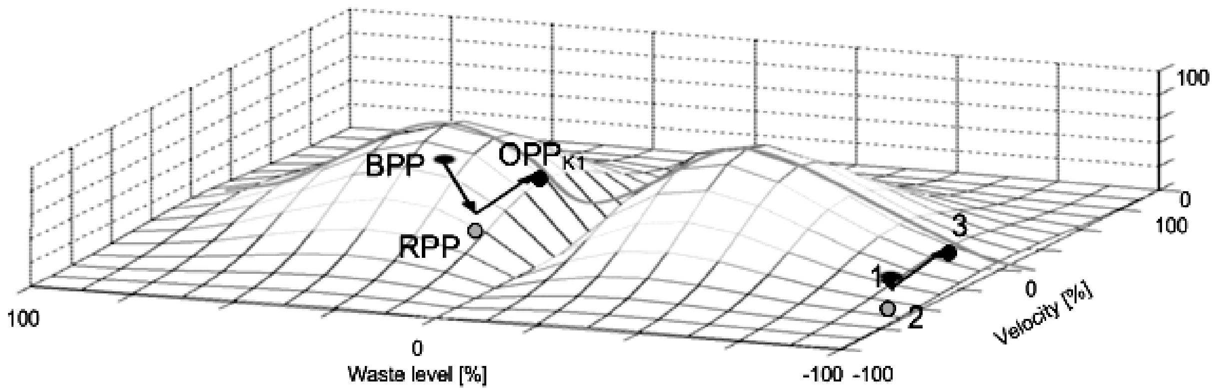

Fig. 4. STG algorithm block chart

Lemma 2. It is possible when the slicing process distribute is lead so that one slicer works in optimum point of work vicinity (OPP_{K1}) and the second - compensate the supply, being at the lowest admissible point of work (PP_{K2}). Keeping solid distance the d between these points allow the process to be lead so that, when the productivity of the first device decrease, the other is forced to increase in OPP_{K2} direction.

Measured drum velocity from both devices are snapped to the grid (surface function) and mentioning estimated knives waste level for each of the slicer, new control values are calculated (as close as possible to the optimal points of work trace).

The simulation results of Snap-To-Grid algorithm are presented in the Fig.5.

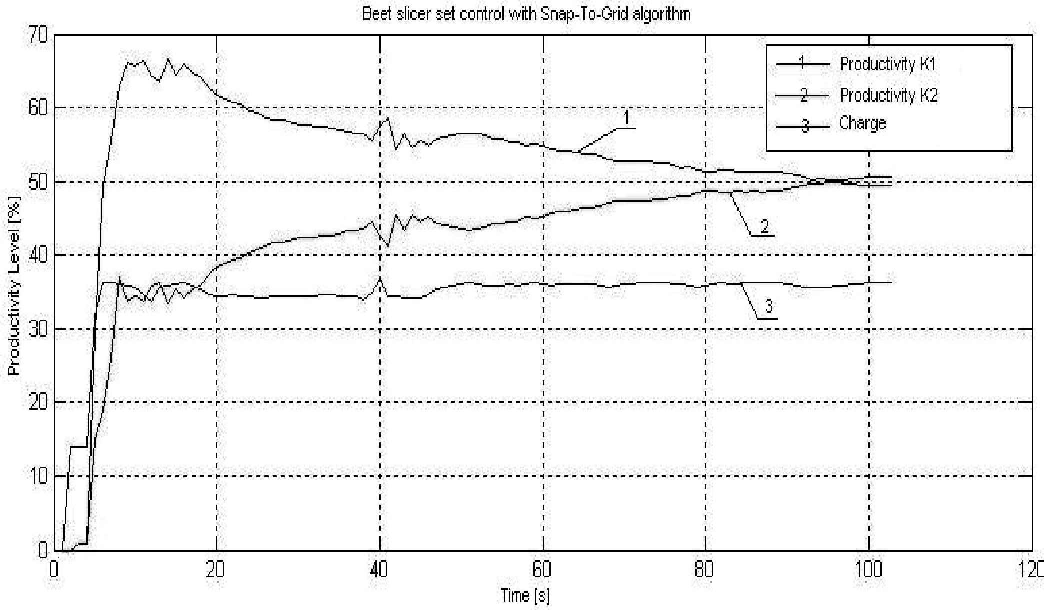

Fig. 5. STG algorithm simulation results

It is perceptible, that with worsen productivity of the first slicer (curve 1), becomes successive compensation of demand by the second slicer (curve 2), with charge level given by curve 3.

6. Conclusions

The beet slicer set, thanks to hierarchical control approach, allows usage of new algorithm for fluent productivity compensation, embedded in the adaptive layer. Regarding to many factors influencing the process, solving optimization task is needed. Solving nonlinear optimization task for nonlinear object is rather difficult task and do not guarantee the solution during specified time, even using constraints.

For faster and credible computation, steady-state optimization approach, with referential surface description was used. Parameters of this mathematical model are sequentially computed and then updated, using nonlinear least squares method. This also gives additional information about individual beet slicers.

Simulations have proved, that this approach fulfils set up expectations under the computation speed as well as control task completion. It allows for soft productivity management, contribute to expensive standstills leveling and raise the final product quality.

1. Tatjewski P., Sterowanie zaawansowane obiektów przemysłowych. Struktury i algorytmy, EXIT 2001, Warszawa

2. Duda J.T., Modele matematyczne, struktury i algorytmy nadrzędnego sterowania komputerowego, Uczelnianie Wydawnictwa Naukowo-Dydaktyczne, Kraków, 2003.

3. Roberts P.D. , An algorithm for steady-state optimization and parameter estimation, Int. Journal of system science, 10: 719–734, 1979.

4. Tao G., Adaptive control design and analysis, New Jersey, 2003.

5. Becerra V. M., Roberts P. D., Griffiths G. W, Novel developments in process optimization using predictive control, Journal of Process Controll, v. 8: 117–138, 1998