Auto-monitoring system of grainy biomass comminution technology

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Abstract. The work discusses the basics of active monitoring, creative and cognitive machinery process, technical systems, energy processing technologies, and control. The aim of this study was to describe, analyze and assess the idea and techniques of auto-monitor of the grainy biomass processing environment illustrated with an example of comminution technology. In order to achieve the purpose, a problem was identified and solved: what technical conditions of measures and ways of active auto-monitoring supported with active cognition of temporary states and changes in comminution properties are required for autonomous completion of the process with regard to the proposed states: a top product quality, high efficiency of the process, low impact of a product and the process of grain comminution for energy purposes? To resolve the problem created structure of auto-monitoring system and conducted simulation on multi disc mill. It was assumed that by applying genetic algorithms in the process of auto-monitoring it is possible to increase a particle-size quality of a product, improve process performance by 25.5% and ensure product harmlessness (elimination of dust contamination). It is desirable to use auto-monitoring (self-cognitive) systems to control comminution processes in power plants (also chemical and food plants) or to monitor biomass processing chain.

1. Introduction
Auto-monitoring — cognitive monitoring of engineering methods of the processing of, for example, energy media, is synonymous with advanced development today. For a creative engineer, protecting and shaping the environment is not enough nowadays. Advanced engineering work constitutes autonomous processing and autonomous improvement, perfection, and nurturing of the environment of the processing and the broadly defined technology. Engineering development of the autonomous, active environmental monitoring and goods processing — one that is advanced through optimisation and instrumentalisation of the processing and improves the environment — is purposeful. The current level of development of auto-monitors, active monitoring that uses cognitive systems, is certainly insufficient to allow such implementations which would fully take the role of research, cognition, and creation of process variables in actual, progressive industrial applications [1-5].

Such solutions are naturally adapted for launching in large and uncertain environments, e.g. in computer networks, where connection failure, computer failure or an interruption of computing by wrong data may occur. However, the number of unpredictable situations in such an environment is significantly lower than the number of potential failures in large energy or chemical industrial plants [6-8].
Besides the multitude of potential failures, their variety is more significant — which constitutes one of the main assumptions for the formulation of problems inhibiting the deployments of the autonomous monitoring with cognitive control systems (AUTO-MONITOR) [2].

The assumption for the formulation of — and consequently, for a solution to — the problem that must be adopted by authors of such solutions is to ensure operational determinism, and hence, safe operation of an autonomous system. It may be argued that currently known methods and algorithms are not sufficiently developed to be deemed cognitively active, complete systems of cognitive control, although they do have some features that such systems should possess [2].

The purpose of this paper is description, analysis and assessment of the idea and technology behind the auto-monitoring of granulated biomass processing environment based on its grinding technology. In order to achieve the goal, the following problem needed to be formulated and solved: what technical conditions WT of the means and methods of active auto-monitoring supported by active cognition of transient states and changes of grinding characteristics H₀ are necessary for autonomous process performance towards expected states: high-quality of product SPₚ, high process efficiency SPₑ, and high harmlessness of product and process influence SPₚₑ? 

2. Methods

2.1. Idea, structure, functions of cognitively active monitoring

A monitor in Medieval England was a very advanced student who taught their colleagues, substituting the teacher. For technical facilities, the “auto-” prefix has been added that emphasises the role of self-control, automation and robotics in replacing an engineer, a creator, and an observer of technology [9].

Auto-monitor is the evolution strategy (border zone), still alive, documented through observations from such fields as palaeontology, biochemistry, molecular biology, genetics, comparative anatomy, embryology, and biogeography. The theory explains the mechanisms of the development of new species and the reasons for the diversity of biological forms and, at the same time, their uniformity that is demonstrated by the prevalence of nucleic acids [10-11].

Suggested architecture of cognitive active auto-monitoring and its key elements and relations are:

- **Perception.** A module responsible for collecting and processing data from sensors. Sensor measurement data constitute information for the learning module and allow the control module to make decisions that are subsequently sent to the object on an ongoing basis.

- **Learning.** A module responsible for constant update of knowledge on environment and adaptation to current conditions.

- **Knowledge.** This module constitutes a fundamental feature of cognitive control systems. It is a system’s memory where knowledge on the object is stored.

- **Decision-making.** A decision-making module is responsible for determining actions that must be applied to the object. The module make decisions on the basis of current measurements from sensors and experience (recorded in the knowledge module). The decisions are sent to the executive and learning modules.

- **Execution.** The execution module is responsible for transferring a control signal (determined by the decision-making module) to the object, e.g. drive settings update.

The purposes of auto-monitoring of grainy biomass processing technology environment are: cognition, modelling, and explanation of thinking processes and modelling the intelligence, its computer simulation, development of various more or less “intelligent” states and transitions of devices.

2.2. Grainy biomass processing environment

Overall, for postulated states λ: efficiency of action, harmlessness of influence and product quality of a selected process of grainy biomass processing, there is a fragmentary cognitive relationship [12-14]:

\[ \lambda = \lambda [IS, IW, ISW] \] (1)
Test results exactly in these areas are significant in the development of the auto-monitors, as they may allow learning the mechanisms of the system, process, product, and consequences to such an extent that it is possible to create their artificial counterparts — models that would be able to imitate processes of understanding, decision making, and learning; they may also allow better understanding of the human (active creator) — machine cooperation and design of machines with cognitive functions that will allow people to perform their tasks in a more efficient way.

It is not possible to develop the cognitive concept of auto-monitor in isolation from the classic theory of control/observation. Controllability of dynamic linear, stationary, continuous, (DLSC) systems occurs when it is possible to bring this system from the initial state $x(t_0)=0$ to any final state $x(t_k)$ in a finite period of time $t_k-t_0$ (e.g. change of charge supply, location, velocity, etc.) [15]. Observability of DLSC systems — a property of a control system that shows whether it is possible to determine an internal state of an object, and more specifically — necessary changes of conditions, on the basis of the readout of a control signal and the readout of an output signal $\bar{W}$. Object (operator-related) control transmittance — it is the ratio of the Laplace transform of an input signal to the Laplace transform of an output signal at zero initial conditions [15]:

$$G(s) = \frac{Y(s)}{X(s)} = \frac{b_n s^n + \ldots + b_0}{a_m s^m + \ldots + a_0} \tag{2}$$

Cognitive compensation of postulated states of grainy biomass processing, e.g. grinding, is a method of reduction (of impacts), but especially elimination of interference causes, where (interference) measurement results and descriptions are used for the impacts on control variables, which eliminates or reduces the impact of known interference (states $\delta \lambda$) on the stabilised output variable of the object (Figure 1 and Figure 2). For a discrete DLSD system [15]:

$$y(i) = \frac{B(z^{-1})}{A(z^{-1})} z^{-p} u(i) + \frac{C(z^{-1})}{D(z^{-1})} z^{-k} d(i) + m(i) \tag{3}$$

where:

- $d(i)$ – measurable interference;
- $m(i)$ – unmeasurable interference;
- $p$ – delay time in the interference circuit;
- $k$ – delay time in the circuit of auto-monitor, cognitive control.

![Figure 1.](image) Flow chart of the method of reducing (the impact) and eliminating interference [own work].

![Figure 2.](image) Flow chart of the auto-monitor, cognitive, intelligent, automatic regulation with compensation [own work].

In order to avoid the impact of interference $d(i)$ on the output $y(i)$, the variable $u(i)$ should be cognitively controlled in a way to fulfil the condition [1], [15]:

$$G(s) = \frac{Y(s)}{X(s)} = \frac{b_n s^n + \ldots + b_0}{a_m s^m + \ldots + a_0} \tag{2}$$

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- $m(i)$ – unmeasurable interference;
- $p$ – delay time in the interference circuit;
- $k$ – delay time in the circuit of auto-monitor, cognitive control.
\[
\frac{B(z^{-1})}{A(z^{-1})} z^{-k} u(i) + \frac{C(z^{-1})}{D(z^{-1})} z^{-p} d(i) = 0
\]  

(4)

The condition is called the condition of absolute invariance of the output values \(y(i)\) against the interference \(d(i)\). The following compensation algorithm arises from the condition:

\[
u(i) = \frac{A(z^{-1})}{B(z^{-1})} C(z^{-1}) z^{-(p-k)} d(i) = \frac{A(z^{-1})}{B(z^{-1})} D(z^{-1}) d(i-(p-k))
\]  

(5)

For the technical performance of an auto-monitor, there is a variant, when \(p \geq k\), of cognitive, intelligent, automatic regulation with compensation (Figure 2).

The use of artificial intelligence algorithms in the systems of scientific research, processing environment (e.g. grainy biomass grinding) compensation, where decisions are strictly dependent on the process dynamics and are mainly based on feedback loop from the state or output, is limited. Therefore, the existing algorithms must be developed on the basis of dynamic system properties [16-20].

In the integrated auto-monitoring, e.g. grinding, the following areas must be considered: (i) the theory of reasoning in the conditions of uncertainty, inference, and rule-based systems, (ii) representation of knowledge, exploration of knowledge, (iii) the theory of development, reengineering, machine learning, probabilistic method of learning, reinforcement learning.

2.3. Grainy biomass grinding environment research and development

Figure 3 and 4 demonstrate the examples of cognitive control of a five-disc multiple hole grinder of granulated biomass in air.

Figure 3. New-generation grinder: 1-, 2-, 3-, 4-, 5- electric motor, 6- grinding unit made up of multiple hole discs, 7- feeder of the input material to the grinder, 8- output, reception of the finished grinding product [own work].

Figure 4. Example of the structure of auto-monitoring system of grainy biomass processing for energy purposes [own work].

The application operates autonomously on temporary values of runs in the following sequence: perception — learning — decision-making — execution.

**Perception:** The runs of outcome variables, such as: energy demand \(P_{\theta=f(n)}\), grinding degree \(\lambda=f(n)\), mass target efficiency \(Q_{m=f(n)}, Q_c \leq Q_m\), depending on: rotational, angular, linear speed of the grinding element \(n, o, v=f(n)\); feeding (volume and mass of the charge) \(q(0;1)\), were called the characteristics of state and transitions of granular material grinding, (Table 1) [21-23]. Relations, states and transitions of the movement of particles being ground and grinding elements, their displacement \(p\), mixing \(m\), grinding \(r\) of a granule and its particles \((p-m-r)\) in grinding machines depend on such factors as: conditions of friction, collisions, cutting, structural properties of the discs and distribution of holes in the discs [23-24].
Learning: A feature identical for states and transitions of all multiple hole spaces of multi-disc grinding units is variable energy demand \( P_{Rjm} \) depending on rotational speed of grinder units and elements \( n_m \) (characteristics of machine idle running) – without the ground material (6), (Table 1), which, depending on linear velocity of the grinding element \( v_R \) has a form of (6a), (Table 1). Similarly, power \( P_{Rj(m+z)} \) for machine idle running with granules (granule feeding \( q \), movement of machine elements and granules with a velocity of \( n_{m+z} \), without grinding) (7), (Table 1), which leads to a relationship that takes into account the volume of granules \( V_g \) moved between the discs (7a), (Table 1).

Table 1. List of mathematical depending.

| Parameter | Relationship | No. |
|-----------|--------------|-----|
| Power \( P_{Rjm} = f(n_m) \), \( q(0) \) | \( (6) \) |
| Power \( P_{Rjm} = k_{lm} \cdot v_T \), for \( q(0) \), \( Q_m = 0 \), \( Q_c = 0 \) | \( (6a) \) |
| Power \( P_{Rj(m+z)} = f(n_{m+z}) \), \( q(0;1) \) | \( (7) \) |
| Power \( P_{Ro} = P_{Rj(m+z)} + P_{Rc} + P_{Rd} \), for \( q(0;1) \), at \( \lambda = f(n,\Delta n) \neq 1 \), \( Q_m = f(n,\Delta n) \), \( Q_c \neq 0 \) | \( (7a) \) |
| Power \( P_{Ro} = \left(k_{2(m+z)} \cdot v_T + \tau \cdot f\left(S_n,\rho_n^{m+1},V_g\right) + \epsilon_\lambda \cdot f\left(S_n,\lambda_n^{m+1},\rho_n^{m+1}\right)\right) \cdot v_R \) | \( (8a) \) |
| Performance \( q(0;1) \), at \( \lambda = f(n,\Delta n) \), \( Q_m = f(n,\Delta n) \) | \( \left(\frac{dm}{dt}\right) \Rightarrow \max, Q_c \neq Q_m \) | \( (9) \) |
| Performance \( q(0;1) \), at \( \lambda = f(n,\Delta n) \), \( Q_m = f(n,\Delta n) \) | \( \left(\frac{dm}{dt}\right) \Rightarrow \max, Q_c \neq Q_m \) | \( (9a) \) |
| Performance \( q(0;1) \), at \( \lambda = f(n,\Delta n) \), \( Q_m = f(n,\Delta n) \) | \( \left(\frac{dm}{dt}\right) \Rightarrow \max, Q_c \neq Q_m \) | \( (10) \) |
| Energy \( E_j = \frac{P_h\left(\tilde{\rho}_n^{m+1},S_n,\lambda_n,\Delta n\right)}{Q\left(\tilde{\rho}_n^{m+1}\right)} \Rightarrow \min \) | \( \text{where } Q_c = \text{const} \) and \( Q_m \Rightarrow Q_c \) | \( (10a) \) |
| Performance \( q(1) \), at \( \lambda = \text{const} \) \( \lambda \neq 1 \), \( Q_m = Q_{m_{\text{max}}} = \text{const} \), \( Q_m = Q_c \) | \( (11) \) |
| Energy \( E_j = \frac{P_{\rho}\left(\tilde{\rho}_n^{m+1},q_n,\Delta n\right)}{Q_{\rho_{\text{max}}}} \Rightarrow \min \) | \( \text{where } Q_c = \text{const} \) and \( Q_m \Rightarrow Q_c \) | \( (11a) \) |
| Performance \( q(0;1) \), at \( \lambda = \text{const} \), \( Q_m = Q_{m_{\text{max}}} = \text{const} \), \( Q_m = Q_{m_{\text{c}}} \) | \( (12) \) |
| Energy \( E_j = \frac{P_{\rho}\left(\tilde{\rho}_n^{m+1},q_n,\Delta n\right)}{Q_{\rho_{\text{max}}}} \Rightarrow \min \) | \( \text{(12a)} \) |

Relationships from (6) to (7a) require research within determination of idle running modules and calculations of functional volume of moved material \( k_{lm}, k_{2(m+z)}, f(V_g) \). This way we obtain power model for the movement of machine elements: without granular charge or with granular charge (without grinding, the sole movement of granules), it depends on rotational speed at zero or stable feeding without granule size change, without grinding performance and zero target performance \( (Q_c=0) \), but with movement performance or performance the same as feeding without grinding \( Q_m=\infty \text{dm} \cdot \text{dt}^{-1} \). For the purposes of learning, idle running characteristics is a particular case of load characteristic family. Its run corresponds to the granule mixing power characteristics \( P_R=P_m \) in the hole and disc unit.

Knowledge: For various rotational speeds of discs (linear velocity \( v_R \) on radius vectors of the edges of straight through and grinding holes), variable feeding/dosing of granules \( q(0;1) \), we obtain variable
grinding degrees, mass and target performances (full grinding loads), definitely different mass \( Q_m \) and target performances \( Q_t \) (chemically and geometrically desirable product).

Power for grinding includes the components of idle, grinding, and dynamic increase loads — depending on the complexity of phenomena (8), (Table 1).

As knowledge, we may propose an experimental description of power taken under load related to granule mass sections in grinding holes \( S_c \) and on areas between discs \( S_H \), as a general dependency, depending on grinding edge velocity \( v_k \) (8a), (Table 1).

Dependencies (8) and (8a) require research within determining the module of dynamic increase and calculations of probable sections participating in material grinding: \( \varepsilon_d, S_c, S_H, P_{Ri}^{mm+1} \).

**Decision-making:** For uneven, variable feeding with mass, power, information (Table 2) in the grainy biomass processing, there are inversion conditions of the movement of motors driving particular discs (from first to fifth), variable (irregular) rotational (angular, linear) speeds of particular discs (\( \Delta n_\neq \text{const} \)) and variable torques within balancing the grinding power (\( P_R = f(\Delta n_\neq) \)). They lead to the necessity of maintaining a minimum power for grinding (\( P_R = P_{\text{Reach}} \)), maximum mass performance (\( Q_m = Q_{mm\text{a}n} = \text{const} \)), often — random performance runs of target energy product (\( Q_t \neq Q_m \)).

| No. | Type of measurable interference, \( d(i) \) | Acceptable value, % |
|-----|----------------------------------------|---------------------|
| 1.  | Power irregularity \( \delta P \)       | 2.0                 |
| 2.  | Output irregularity \( \delta Q_{2,10} \) | 20.0                |
| 3.  | Output irregularity \( \delta Q_{2,35} \) | 6.0                 |
| 4.  | Dynamic irregularity \( \delta \delta K \) | 10.0                |
| 5.  | Kinematic irregularity \( \delta K \)    | 10.0                |

Power for grainy biomass grinding includes the components of idle, grinding, and dynamic increase loads — depending on the complexity of phenomena (according to the equation (8a)), for equation (9), (Table 1). In order to elaborate on the presented dependency, we may propose an experimental description for variable power supply with grinding velocity, e.g. according to equation (8a). It requires additional research within determining the module of dynamic increase and calculations of probable sections participating in the reality of grinding of granulated material — just as for equation (8a).

Mass performance of grinding \( Q_m \), maximised from the nature of external conditions, is described by the dependence on the grinding time \( t_\xi \), sections and volumes \( S_c, S_H, V_\xi \) as well as on rotational speeds of discs and speed differences between the discs \( n, \Delta n_\xi \) (9a), (Table 1).

**Execution:** For irregular, variable mass supply, variable processing stream, performance of inversion conditions of movement of engines that drive particular discs with straight-through grinding holes, the answer is variable rotational (angular, linear) speeds of the discs (\( \Delta n_\neq \text{const} \)) and variable torques, grinding powers (\( P_R = f(\Delta n) \)), mass performances as functions of variables dependent on the difference of rotational speed of working discs \( Q_m = f(n, \Delta n_\xi) = dm \cdot dt^{-1} \), for set target product performance (\( Q_t \leq Q_m \)).

The auto-monitor of grinding process compares the input variable of the initial state of technical conditions \( W_{t_0} \) of feeding, speed, product quality, effectiveness and harmlessness of the process \( S_{P_0} \) with the values of a subsequent state \( W_{t_1}, S_{P_1} \), obtaining a quality function \( Q_{u_1} \), deviation — and on that basis (cognition), it creates a control signal providing appropriate modification or stabilisation of the processing. Generation of quality and deviation functions takes place for a chosen type of artificial intelligence — in this case genetic algorithms AI-AG with very high frequency and fixed amplification factors. Due to variable grinding conditions (changing charge mass, phenomena related to the change of humidity, e.g. unstabilised grains), it is necessary to use an adaptive system (Figure 4) that forms optimum states and transitions of actuators, feeding speed set points, angular speed of each disc (which most often are the function of humidity, form, and dimensions of grains) for
current states of the processing variables. The grinding environment auto-monitor consists of monitoring sensors of: speed, acceleration, force and torques, forms and dimensions of the product; controllers that allow switching performance characteristic; photo-optical electronic systems for calculating modulations and demodulations, amplifications, signal switching, comparing and logical operations of control, regulation and compensation.

3. Results and discussion

Power used in the grinding technology with controlled, powered energy, mass, and information inputs with target function performance includes the components of: idle, grinding, and dynamic increase loads — depending on the complexity of phenomena (according to dependency (8a)) for targets specified as (10), (Table 1).

Values of temporary runs for determining detailed irregularity of total irregularity ($\delta Q$) and granulometric irregularity of the flow of dimensional fractions of product ($\delta Q_{2,10}$, $\delta Q_{2,25}$, $\delta Q_{2,40}$, $\delta Q_{2,70}$, $\delta Q_{2,85}$, $\delta Q_{3,00}$), total power ($\delta P$) and individual power of five motors driving the five grinding discs ($\delta P_1$, $\delta P_2$, $\delta P_3$, $\delta P_4$, $\delta P_5$), as well as the assessment of the quality of reaction to interference are shown in Table 3.

Table 3. Temporary runs of the indicators of postulated states of product (quality $Q$) and the grinding process (unit power (1-5) along with the assessment of auto-monitoring [own studies].

| Q | Unit Power, kW | Productivity | Power, kW | Rate |
|---|----------------|--------------|-----------|------|
| 2,10 | 2,25 | 2,40 | 2,55 | 2,70 | 2,85 | 3,00 | 1 | 2 | 3 | 4 | 5 |
| 16 | 11 | 3 | 27 | 11 | 10 | 16 | 0.678 | 0.689 | 0.374 | 0.157 | 0.236 | 3 | 2,251 | 0.444 |
| 28 | 5 | 19 | 25 | 1 | 30 | 5 | 0.126 | 0.317 | 0.863 | 0.568 | 0.952 | 4 | 2,507 | 0.604 |
| 29 | 23 | 7 | 30 | 24 | 7 | 0 | 0.598 | 0.341 | 0.22 | 0.510 | 0.343 | 13 | 2,597 | 1.669 |
| 4 | 4 | 7 | 22 | 2 | 22 | 23 | 0.855 | 0.173 | 0.015 | 0.779 | 0.011 | 19 | 2,653 | 2.387 |
| 2 | 12 | 2 | 19 | 24 | 0 | 29 | 0.225 | 0.029 | 0.076 | 0.791 | 0.214 | 28 | 2,886 | 3.235 |
| 14 | 13 | 18 | 23 | 28 | 4 | 12 | 0.307 | 0.106 | 0.103 | 0.829 | 0.682 | 13 | 2,703 | 1.603 |
| 14 | 18 | 28 | 28 | 7 | 13 | 22 | 0.808 | 0.128 | 0.323 | 0.151 | 0.67 | 23 | 2,144 | 3.575 |
| 17 | 30 | 5 | 9 | 20 | 2 | 26 | 0.464 | 0.007 | 0.984 | 0.480 | 0.652 | 23 | 2,706 | 2.833 |
| 24 | 8 | 8 | 29 | 15 | 26 | 12 | 0.883 | 0.642 | 0.122 | 0.443 | 0.973 | 5 | 1.465 | 1.137 |
| 14 | 3 | 5 | 25 | 7 | 3 | 10 | 0.473 | 0.237 | 0.767 | 0.366 | 0.319 | 27 | 2,966 | 3.034 |
| 27 | 28 | 29 | 16 | 28 | 4 | 21 | 0.027 | 0.762 | 0.321 | 0.851 | 0.034 | 4 | 2.08 | 0.641 |
| 17 | 10 | 3 | 24 | 2 | 20 | 28 | 0.884 | 0.626 | 0.272 | 0.610 | 0.338 | 3 | 1.901 | 0.526 |
| 1 | 13 | 27 | 17 | 3 | 21 | 16 | 0.042 | 0.755 | 0.709 | 0.083 | 0.859 | 22 | 2,335 | 3.141 |
| 19 | 2 | 21 | 17 | 8 | 9 | 5 | 0.105 | 0.751 | 0.324 | 0.865 | 0.638 | 13 | 3.639 | 1.191 |
| 30 | 25 | 11 | 29 | 23 | 1 | 2 | 0.912 | 0.381 | 0.815 | 0.551 | 0.779 | 6 | 2.559 | 0.782 |
| 17 | 28 | 27 | 2 | 3 | 16 | 25 | 0.608 | 0.343 | 0.364 | 0.224 | 0.796 | 19 | 2,139 | 2.96 |
| 21 | 8 | 29 | 9 | 24 | 28 | 23 | 0.134 | 0.608 | 0.191 | 0.051 | 0.193 | 3 | 2.534 | 0.395 |
| 13 | 25 | 3 | 0 | 5 | 20 | 7 | 0.699 | 0.366 | 0.423 | 0.653 | 0.266 | 22 | 2,684 | 2.733 |

However, the initial state of interference (process irregularity), time of evolution towards interference elimination (according to conditions set) and value of interference after auto-compensation of chosen performance characteristics — are shown in Table 4. Taking into account the delay time in the interference circuit $p$, delay time $k$ in the auto-compensation circuit, in order to remove the influence of measurable interference $d(i)$ on the output $y(i)$, the variable $u(i)$ must be controlled (by genetic algorithm) in such a way that the condition of absolute regularity (invariance) of output values $y(i)$ is fulfilled in relation to the interference $d(i)$. The above task turned out to be quite difficult in the conditions of genetic algorithms, mainly because of quite a long time of auto-
compensation \((k=346\ \text{s})\) of technical conditions: feeding, angular speed and other to the acceptable state (from the rational range: \((1.44-18.36)\%)\), but not absolute irregularity.

For full, stable granular mass feeding, variable stream of external information and data processing on input and output of the machine, towards the performance of inversion conditions of the movement of motors driving individual working discs, there are tasks performed at a variable rotational (angular, linear) speed of individual discs \((\Delta n_{ij}\neq\text{const} \text{ and } q=\text{const})\). Characteristics are created in the conditions of variable torque, grinding power \(P_{\text{R}}=f(n,\Delta n_{ij})\), towards its minimisation \((P_{\text{R}}=P_{\text{Rmin}})\), as well as regulation of the process of obtaining the postulated granulometric state of grinding, time-constant level of grinding \((\lambda=\text{const} \text{ and } \lambda\neq1)\) with simultaneous maintenance of stable maximum mass performance \((Q_{\text{m}}=Q_{\text{max}}=\text{const})\) and its compatibility with the target product performance \((Q_{\text{m}}\approx Q_{\text{c}})\) through elimination of the influence of the grinding interference.

Power used for grinding with the performance of the process regulation function, according to (8a), consists of the components of idle, grinding, and dynamic increase loads — depending on the complexity of phenomena of the regulation of the disc and grain charge feeding speeds (11), (Table 1). Regulation characteristics allow determining the state of the set points of the basic machine and process operation parameters, which in turn allows the process to be performed in a way to obtain the postulated target despite interference. The term interference refers to any inaccuracies (irregularities) of cutting cross-sections and volume flows that do not lead to the set fixed product grinding level. They lead, then, to the postulated, uninterrupted state:

\[
\lambda=\text{const} \text{ and } \lambda\neq1
\]

and

\[
\begin{align*}
S_y &= \text{const} \\
V_{\text{g}max} &= \text{const}
\end{align*}
\]

meaning the minimum unit energy consumption, independent from the area, volume \(S_y, S_T\) and \(V_{\text{g}}\), and dependent on grain feeding and disc speed \(q, n\) and \(\Delta n_{ij}\), which determines dependency (11a), (Table 1 and Table 2).

Specification of auto-compensation determines basic parameters of the machine operation and the process with simultaneous compensation of interference and deformation of cutting cross-sections and volume flows for obtaining the postulated target \(\lambda=\text{const} \text{ and } \lambda\neq1\) and \(Q_{\text{m}}\Rightarrow Q_{\text{max}}=\text{const}\). Unit energy demand is determined by dependency (12a), (Table 1). Each of the states and transitions of the characterised grinding arose due to other operation-related properties of the machine, granular material; the process, then, required specialist calculations, simulations, research, analyses and assessment of phenomena and processes.

Substantially, the systems of auto-monitoring of granular material processing environments operate online: recognising, learning, building knowledge, making decisions and performing controls, regulations or compensations in the processing system, monitored process. Their operations — through primary knowledge/cognition, its possible and fragmentary exploitation/use — lead, as a consequence, to innovative development of the system.

**Table 4.** Result of auto-compensation of the irregularity of biomass grain five-disc grinding with the use of the auto-monitoring [own studies].

| No. | Type of measurable interference, \(d(i)\) | Value before self-compensation, % | Acceptable value, % | Time of self-compensation, s | Value after self-compensation, % |
|-----|----------------------------------------|----------------------------------|-------------------|-----------------------------|----------------------------------|
| 1.  | Power irregularity \((\delta P)\)      | 6.240                            | 2.0               | 15                          | 1.44                             |
| 2.  | Output irregularity \((\delta Q_{2,10})\) | 83.82                           | 20.0              | 256                         | 18.36                           |
| 3.  | Output irregularity \((\delta Q_{2,55})\) | 17.09                           | 6.0               | 178                         | 5.53                            |
| 4.  | Dynamic irregularity \((\delta u_k)\) | 32.97                           | 10.0              | 309                         | 9.90                            |
| 5.  | Kinematic irregularity \((\delta u_k)\) | 17.78                           | 10.0              | 346                         | 10.02                           |
4. Conclusions

Engineering of auto-monitoring, cognitively active processing of granulated biomaterials, is a broad subject that is based on fragmentary experience of technical sciences and cognitive science developments. In the conditions of granulated biomaterials grinding engineering, premises and possibilities of solving broad problems of autonomous compensation of performance characteristics irregularities. The aspect of cooperation between creators and producers of grinders and measuring devices in database standardisation, coherent methodology/technique of measurement and research may be developed on the basis of the cooperation with the producer of measurement and research apparatus for the energy industry. Using genetic algorithms, we may find the following technical conditions in the auto-monitoring process: charge feeding intensity \( q_{\text{pk}} \), with specified parameters: mean size \( d_{\text{pk}} \), humidity \( w_{\text{pk}} \), angular speeds of grinding discs \( \omega_{1-\omega_{5}} \), such that irregularity indicators reach values from the acceptable range: \( (1.44-18.36)\% \).

Developed mathematical apparatus, methods of analysis and synthesis of regulation structures working in the feedback loop, algorithms of modelling and identification, theory of stability, theory of optimisation — all the subjects constitute the core of the proposed solutions.

Classic theory of controlling a human being should play a leading role in the intelligent development based on knowledge and innovation, future, modern systems, as it is in this way that one can fulfil the safety condition which is fundamental for the control systems – input feeding, interference inflow regulation, and compensation of the same interference, also target performance and susceptibility of the conditions of energy media processing.

We may say with high probability that future auto-monitors, systems of cognitively active monitoring, will strongly integrate the process of conclusion drawing, planning, learning – thereby creating knowledge which allows their application to be significantly expanded. Cognitively active monitoring may be one of the main stimuli for new, autonomous technologies in many different areas.

Robotics may serve as an example, where control systems of, for example new generation unmanned vehicles may allow achieving a higher level of autonomy, thanks to which it will be possible to perform task that today cannot be performed without a human.

It is especially important when it comes to the processing environment – dangerous or even unavailable to humans – e.g. contaminated, irradiated or potentially explosive. The use of auto-monitoring systems (self-cognitive) is also desirable for controlling processes in energy plants (also: chemical and food plants) or for controlling the flow of grainy biomass, transport logistics for raw materials, components and finished product, waste.

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