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Control of mineral wool thickness using predictive functional control

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ABSTRACT

The production process of mineral wool is affected by several constantly changing factors. The ingredients for the mineral wool are melted in a furnace. The molten mineral charge exits the bottom of the furnace in a water-cooled trough and falls into a fiberization device (the centrifuge). The centrifuge forms the fibers. At this stage binders are injected to bind the fibers together. To ensure the quality of the end product (the consistent thickness) the flow of the bounded fibers must be as constant as possible. One way to ensure that is to control the speed of the conveyor belt that transports the bounded fibers from the centrifuge to the curing process. Predictive functional controller and PID controller are considered to replace an existing algorithm. Both can easily replace an existing one as they do not require any new sensor installation. All three algorithms are presented and tested on a developed plant model. The study showed that the predictive control gives better results than the existing and PID controller.

1. Introduction

The conveyor belt is one of the key components for most manufacturing processes. The speed of the conveyor must be in most cases adapted depending on some criteria. Despite a wide use of the conveyor belt only a few papers (to our knowledge) were published concerning the control problem of adapting the speed. Some propose model predictive controllers [18] or fuzzy controllers [23], others still prefer the PID controllers [9,24].

In our study the conveyor belt is used in a stone wool production company to transport the material from the centrifuge to the curing oven. Because of the changing mass flow from the centrifuge to the conveyor belt, speed must be controlled to ensure homogenous thickness of the wool blanket. The existing control is very slow. Both the disturbance rejection and the transition to new wool grade (thicker wool blanket) are slow. Therefore, the company has more rejected product as necessary. To improve the speed control of the conveyor belt, a PID and PFC algorithms were considered and compared against the existing algorithm.

The PID controller is well known and probably the most widely used controller in the industry [20,13,15,1,2,25]. Despite its simplicity and wide use, it does not always perform very well, especially with processes that have delays [10,12]. Since the studied process has a variable delay and therefore a predictive functional control was also considered as a replacement for an existing control algorithm. The principle of the predictive functional controller is very simple to understand and the controller is easy to tune [16,4]. It is based on the prediction of the process output signal at each sampling instant. The prediction is obtained implicitly or explicitly according to the model of the controlled process. Using the predictive control law, a control signal is calculated which forces the predicted process output signal to follow the reference signal in a way that minimizes the difference between the reference and the output signal in the area between certain time horizons. Originally, the algorithm was developed for linear systems, but the basic idea of prediction has been extended to nonlinear systems [3,8,22]. In Clarke [5] and Doyle III et al. [6] an adaptive fuzzy PFC is proposed using recursive clustering method [7]. Because of PFC's good performance, its use in industrial and other applications is beginning to increase [16,11,21,14].

In this paper, a conveyor belt speed control problem is studied for a stone wool production process. The model of the process is derived based on real plant data. PID and PFC control algorithms are presented and tested on a plant model. Comparison with the currently used control algorithm is made. The results show advantage of using the PFC for speed control.

The paper is organized in the following fashion. First the process is briefly described. Then the model is built using the real plant data. Following that the existing control algorithm, PID and PFC algorithms are derived. Simulation results are shown and a conclusion is made.

2. Process and model description

Mineral wool is made from natural or synthetic minerals or metal oxides. It is widely used for thermal insulation, filtration and soundproofing. The production process has three primary

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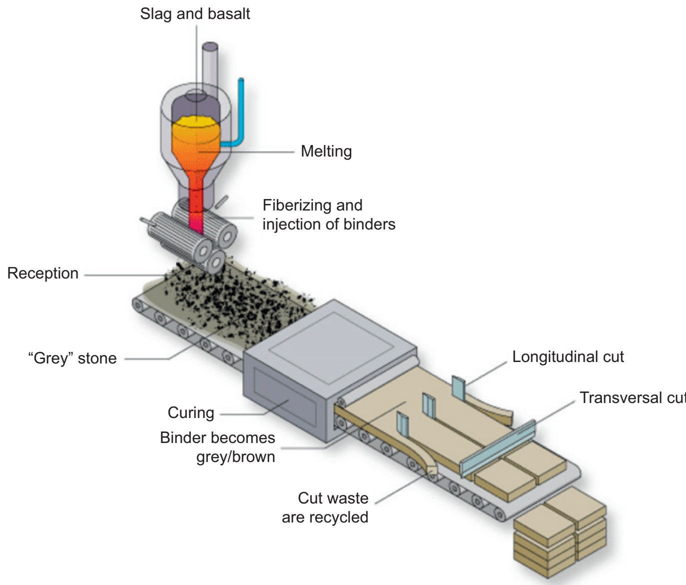

Fig. 1. The mineral wool process.

components: molten mineral generation in the furnace, fiber formation and collection, and final product formation. In the first step, the mineral feed is molten in the furnace. The raw material is loaded into the furnace in alternating layers with coke. The molten mineral charge exits the bottom of the furnace in a water-cooled trough and falls into a centrifuge. The centrifuge forms fibers. At this stage, chemical agents and binders are injected for structural rigidity. The mixture is then transported by the conveyor belt to the curing oven where the mixture is cured. The speed of the belt is set depending on the desired thickness of the blanket. At the curing oven, the wool blanket is compressed to appropriate density and the binder is baked. At the end of the process line the mineral wool is cut to a desired length. Fig. 1 shows the schematic of the process. Because of unpredictable flow of molten mineral charge from the furnace and from the centrifuge to the conveyor, the speed of the conveyor must be controlled in order to ensure a homogenous desired thickness of the mineral wool. The thickness is defined by the reference mass of the mineral wool, which is measured at the end of the belt.

Mass is measured with four measuring elements distributed over the last meter of the conveyor belt. The length of the conveyor in the studied case is 9 m. The reference speed is 3.5 m/min. In an ideal case, the mass of the wool at the end of the conveyor should be about 120 kg (conveyor moves with the reference speed). The relation of mass and speed is shown in Fig. 2.

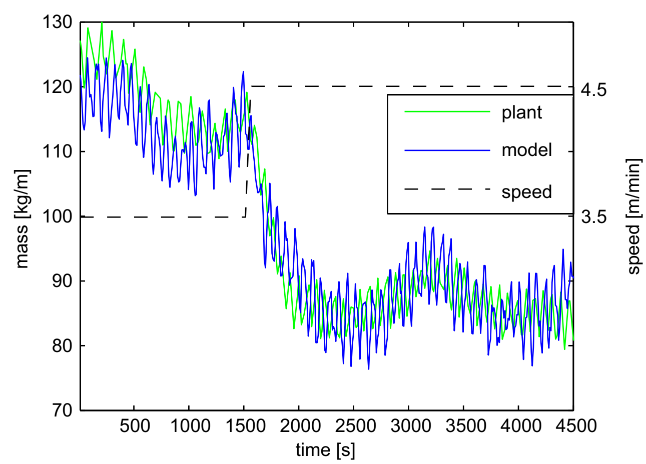

Fig. 2. Mass of the mineral wool and speed of the conveyor.

2.1. Model of the process

In order to compare and test the control algorithms a simulation model of the process was developed. The available measurements of the system are mass at the end of the conveyor belt, speed of the belt and electric current of the centrifuge. Data from the SCADA system are sampled with sampling time 10 s ($t_s = \Delta t = 10$ s).

Transport of material with the conveyor belt was simulated using an object-oriented approach. At each time sample a new object named *segment* was created. The *segment* holds information about the mass that is transferred to the belt (Δm), which depends on mass flow (Φ_m), position of the segment on the conveyor belt (x) and length of the segment (Δx), which depend on the speed of the belt (v):

$$t_k = t_{k-1} + \Delta t \quad (1)$$

$$\Delta x = v(t_k)\Delta t \quad (2)$$

$$\Delta m = \Phi_m(t_k)\Delta t \quad (3)$$

$$x(k_i) = x(t_{k-1}) + \Delta x \quad (4)$$

Mass at the end of the belt is calculated with the sum Δm of the *segments*, which are between eighth and ninth meter (the position of measuring element). The *segment* is deleted when its position ($x(t_k) - \Delta x$) is greater than 9 m. The assumption made here is that the speed of the belt can only be positive. A sinus signal ($5\sin(0.08t_k)$) and an uniformly distributed noise (from interval $[-0.2 \ \ -0.2]$) were added to the model output. The noise level was estimated from real plant data.

The relation between the conveyor speed and voltage input to the motor was estimated as a first-order transfer function with a gain of one and a time constant of 180 s.

Mass flow from the centrifuge is not directly measured. It was estimated from mass and speed data (Fig. 2) in steady state from equation:

$$\Phi_m = mv \tag{5}$$

The average mass flow was estimated to be approximately 6.7 kg/s. Since the real data are very noisy, noise was added to the mass flow. A sinus signal and an uniformly distributed noise from interval $[-0.3\ 0.3]$ was added to the mass flow by trial and error:

$$\Phi_m(k) = 6.7 + 0.6\left|\sin\left(2\pi\frac{1}{3000}t_k^3\right)\right| + (-0.3 + (0.3+0.3)rand) \tag{6}$$

The comparison between model and plant output is shown in Fig. 2.

Inspection of the available data showed that the centrifuge current is in a strong relationship with the mass of the mineral wool. Therefore it is correlated with the mass flow from the centrifuge. This information is very useful for predicting the mass flow and can be incorporated into the control algorithm to better cope with variations of the mass flow from the centrifuge. The relation between mass flow and the centrifuge current was identified by comparing the real data with the model described above.

The transfer function between mass flow and current can be estimated from the starting period of the process. Mass flow from the centrifuge can approximated from mass and speed data. Comparing the approximated mass flow with the measured centrifuge current the transfer function between them is estimated as:

$$I_c(s) \approx \frac{16.216}{(40.219s+1)}\Phi_m(s) + 37.017 \tag{7}$$

An uniform noise from interval $[-2\ 2]$ was added to the current to better match the real data. The comparison between real and modeled current at the startup is shown in Fig. 3. The comparison during the operation is shown in Fig. 4.

It can be seen that the plant has a dead zone at the startup and therefore the real response is a bit different than that of the model.

3. Control

The control is done based on the measured signals: speed of the belt, mass at the end of the belt and centrifuge current. The thickness of the mineral wool must be kept as constant as possible by changing the belt's speed. In this section the existing control algorithm and possible replacement are described.

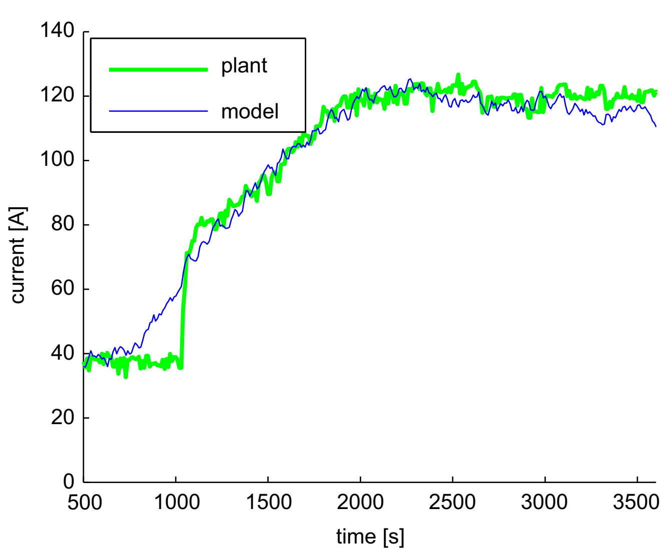

Fig. 3. The centrifuge current at the startup.

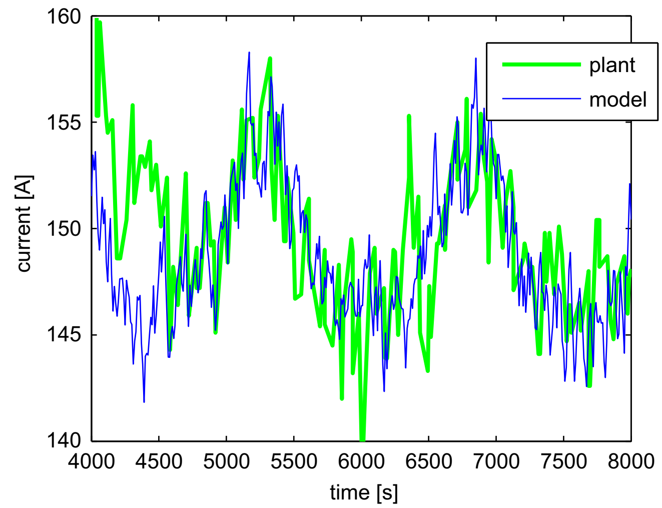

Fig. 4. The centrifuge current during operation.

3.1. Existing control

The existing control is a very simple and intuitive algorithm that does not perform very well compared to modern control algorithms that can be used instead. The algorithm is very similar to PID control algorithm. The startup of the process is made by setting the conveyor speed to constant reference speed $v_{start} = 3.5$ m/min. When there is available data of mass at the end of the conveyor the control algorithm is turned on. The speed is changed depending on the error:

$$e(k) = m_{ref}(k) - m(k)$$

$$d(k) = e(k) - e(k-1) \tag{8}$$

if $d(i)$ is positive, the speed is changed as:

$$K_{2e} = e(k)\ K_2$$

$$K_{3d} = K_3\ d(k)$$

$$\Delta v(k) = \frac{(K_{2e}+K_{3d})K_1}{m(k)}\ v_{start}$$

$$u_{in}(k) = v(k) + \Delta v(k) \tag{9}$$

if $d(\mathrm{i})$ is negative, the speed is changed as:

$$K_{5e} = e(k)/K_5$$

$$K_{6d} = d(k)\ K_6$$

$$\Delta v(k) = \frac{(K_{5e}+K_{6d})K_4}{m(k)}v_{start}$$

$$u_{in}(i) = v(k) + \Delta v(k) \tag{10}$$

Values of constants are $K_1 = 0.15$, $K_2 = 0.7$, $K_3 = 5$, $K_4 = 0.2$, $K_5 = 3$ and $K_6 = 3$, $v(i)$ is the current speed of the conveyor, $u_{in}(i)$ is the input to the motor, $m_{ref}(i)$ is the reference mass of the mineral wool at the end of the conveyor and $m(i)$ is the actual mass.

3.2. PID control

For conveyor control, a PID controller was designed. The controller was designed to control the speed of the conveyor around a working point ($m_{ref} = 120$ kg, $\Phi_m = 6.7$ kg/s, $v = 3.5$ m/min).

The control algorithm is given by the following equations:

$$e(k)=(m_{ref}(k)-m(k)) \quad (11)$$

$$d(k)=e(k)-e(k-1) \quad (12)$$

$$K_p=-6.3\times10^{-4} \quad (13)$$

$$K_d=-0.003 \quad (14)$$

$$K_i=0.2 \quad (15)$$

$$I(k)=I(k-1)+1\times10^{-4}e(k) \quad (16)$$

$$u_{in}(k)=3.5/60+(K_p\ e(k)+K_d\ d(k)-K_i\ I(k)) \quad (17)$$

The startup of the process is the same as with PFC and the old algorithm.

3.3. Predictive functional control

MBPC stands for a collection of several different techniques all based on the same principles. In this study, the basic principles of predictive functional control (PFC) are applied. In this case, the prediction of the process output is given by a process model. The fundamental principles of predictive functional control [16,17] are very strong and easy to understand since they are natural and can be rapidly grasped.

Model-based predictive control (MBPC) is a control strategy based on the explicit use of a dynamic model of the process to predict the future behavior of the process output signal over a certain (finite) horizon and to evaluate control actions to minimize a certain cost function. The predictive control law is generally obtained by minimization of the following criterion:

$$J(u,k)=\sum_{j=N_1}^{N_2}(y_m(k+j)-y_r(k+j))^2+\lambda\sum_{j=1}^{N_u}u^2(k+j) \quad (18)$$

where $y_m(k+j)$, $y_r(k+j)$ and $u(k+j)$ stand for j-step ahead prediction of the process output signal, reference trajectory, and control signal, respectively. N_1, N_2 and N_u are minimum, maximum, and control horizon, respectively, and λ weights the relative importance of control and output variables. The predictive control law adopts a receding policy, which means that at each time instant, the optimal control sequence according to the criterion under Eq. (18) is obtained, but only the first element in this sequence is applied to the plant. The procedure is repeated in the next time instant.

The plant can be approximated by a first order model, described by the following difference equation:

$$y_m(k+1)=a_my_m(k)+b_mu(k) \quad (19)$$

Closed-loop behavior of the system is defined by a reference trajectory given in the a form of reference model. The control goal is to determine the future control action so that the area between the predicted output and reference trajectory over a certain prediction horizon ($N1$, $N2$) is minimized. The reference model in the case of a first-order system is given by the following difference equation:

$$y_r(k+1)=a_ry_r(k)+b_rw(k) \quad (20)$$

where the reference model parameters should be chosen to fulfill the following equation:

$$\frac{b_r}{1-ar}=1 \quad (21)$$

This choice ensures that reference-model output tracks a constant reference signal ($w(k)$) and it enables the reference trajectory tracking. According to this it follows that:

$$y_r(k+1)=a_ry_r(k)+(1-a_r)w(k) \quad (22)$$

In the case of predictive functional control, one single horizon called coincidence horizon ($N_1=N_2=H$) is assumed. At this horizon the predicted output value coincides with the reference trajectory. In order to derive an analytical control law the constant future manipulated variable $u(k)=u(k+1)=\ldots=u(k+H-1)$ and $\lambda=0$ has to be taken into account. The H-step ahead prediction of the process output based on first-order model is given by Eq. (23). Taking into account the constant future control and Eq. (24) the H-step ahead prediction can be expressed by Eq. (25):

$$y_m(k+H)=a_m^Hy_m(k)+a_m^{H-1}b_mu(k)+\cdots+b_mu(k+H-1) \quad (23)$$

$$(1+a_m+\cdots+a_m^{H-1})(1-a_m)=(1-a_m^H) \quad (24)$$

$$y_m(k+H)=a_m^Hy_m(k)+\frac{b_m}{1-a_m}(1-a_m^H)u(k) \quad (25)$$

The reference trajectory prediction is given by the following equation:

$$y_r(k+H)=a_r^Hy_r(k)+(1-a_r^H)w(k) \quad (26)$$

The main idea of PFC is the equivalence of the objective increment of the process and the model output increment. The objective increment Δ_p is defined as the difference between the predicted reference trajectory ($y_r(k+H)$) and actual process output signal ($y(k)$):

$$\Delta_p=y_r(k+H)-y(k) \quad (27)$$

Assuming (Eq. (26)) the objective increment is defined as follows:

$$\Delta_p=a_r^Hy_r(k)+(1-a_r^H)w(k)-y(k) \quad (28)$$

The model output increment is defined in the same manner:

$$\Delta_m=y_m(k+H)-y_m(k) \quad (29)$$

$$\Delta_m=a_m^Hy_m(k)+\frac{b_m}{1-a_m}(1-a_m^H)u(k)-y_m(k) \quad (30)$$

From the above equations and the goal of PFC, which is described with the following:

$$\Delta_p=\Delta_m \quad (31)$$

the control law of the PFC is obtained:

$$u(k)=\frac{(1-a_r^H)(w(k)-y(k))}{\frac{b_m}{1-a_m}(1-a_m^H)}+\frac{y_m(k)}{\frac{b_m}{1-a_m}} \quad (32)$$

If the process has a time delay, the control law is modified according to Smith's predictor principle [19]:

$$u(k)=\frac{(1-a_r^H)(w(k)-y(k)-y_m(k)+y_{md}(k)))}{\frac{b_m}{1-a_m}(1-a_m^H)}+\frac{y_m(k)}{\frac{b_m}{1-a_m}}, \quad (33)$$

where y_{md} is the delayed model output.

The transport with the conveyor belt is a process with a variable time delay. The delay changes depending on the speed of the conveyor. Because of this, the PFC controller was considered to be the best choice for control of this process. To construct the PFC we need a first-order model that approximates the process. In our case the output of the process is mass at the end of the conveyor belt and the input is the input voltage to the motor drive of the conveyor belt. Since the mass correlation to speed (input voltage) is not very (Eq. (5)) convenient for a first-order model a coefficient, on which the control is based, was introduced (Eq. (34)). This enables us to derive the first-order model of the process. The introduced coefficient is an inverse length density:

$$\rho^{-1} = \frac{dl}{dm} \quad (34)$$

Because the length of the measurement element is 1 m, the measured coefficient can be defined as:

$$\rho^{-1} = \frac{1}{m} \quad (35)$$

and in the same manner the reference coefficient is defined:

$$\rho_{ref}^{-1} = \frac{1}{m_{ref}}. \quad (36)$$

The approximation of the process dynamics can be made from following assumptions:

$$\rho^{-1} = \frac{dl}{dm} \approx \frac{v}{\Phi_m} \quad (37)$$

The speed of the conveyor depends on the input voltage of the conveyor motor. The dynamics of the speed are approximated by a first-order transfer function:

$$V(s) = \frac{K_v}{T_v s+1} U_{in}(s) \quad (38)$$

From this we can derive the model for the coefficient:

$$\rho_m^{-1}(s) = \frac{\frac{K_v}{\Phi_m}}{T_v s+1} U_{in}(s) \quad (39)$$

As the information for Φ_m is not available, its approximation from the centrifuge current must be done:

$$\hat{\Phi}_m(k) = \frac{i_c(k)-45}{15} \quad (40)$$

For the parameters in Eq. (40) gain and offset from Eq. (7) could be used. In this paper different values were used to test the robustness of the algorithm. The model for the inverse length density can be rewritten in the discrete form:

$$\rho_m^{-1}(z) = \frac{b_m}{z-a_m} U_{in}(z) \quad (41)$$

$$a_m = e^{-t_s/T_v} \quad (42)$$

$$b_m = K_m(1-a_m) \quad (43)$$

$$K_m = \frac{K_v}{\hat{\Phi}_m} \quad (44)$$

and represented by a difference equation as Eq. (19):

$$\rho_m^{-1}(k+1) = a_m \rho^{-1}(k) + b_m u(k). \quad (45)$$

The actual prediction of the process output is the average value of the inverse length densities, which are at current time moment between at beginning of the belt and first meter. The delayed model output is the average of the inverse length densities between eight and ninth meter at current time sample. To calculate the prediction outputs, the delays at each time sample are estimated as:

$$D_1 = \left\lceil \frac{l_1}{v t_s} \right\rceil \; D_2 = \left\lceil \frac{l_2}{v t_s} \right\rceil \; D_3 = \left\lceil \frac{1}{v t_s} \right\rceil \quad (46)$$

where l_1 is the length from the beginning of the belt to the measuring instrument and l_2 is the length of the conveyor belt. Delay D_3 is the delay for the length of 1 m. The output of the model and the delayed output are then calculated as:

$$y_m(k) = \frac{\rho_m^{-1}(k) + \cdots + \rho_m^{-1}(k-D_3)}{D_3} \quad (47)$$

$$y_{md}(k) = \frac{\rho_m^{-1}(k-D_1) + \cdots + \rho_m^{-1}(k-D_2)}{D_2-D_1} \quad (48)$$

Using these equations, the control law under Eq. (33) is written as:

$$u(k) = \frac{(1-a_r^H)(\rho_{ref}^{-1}(k) - \rho^{-1}(k) - y_m(k) + y_{md}(k))}{K_m(k)(1-a_m^H)} + \frac{y_m(k)}{K_m(k)} \quad (49)$$

$$a_r = e^{-t_s/T_r} \quad (50)$$

$$K_m(k) = \frac{K_v}{\hat{\Phi}_m(k)} \quad (51)$$

where y_m is the model output (Eq. (47)), y_{md} is the delayed output of the model (Eq. (48)), ρ_{ref}^{-1} is the reference length density (Eq. (36)), ρ^{-1} is the measured length density (Eq. (35)), a_m is the parameter of the model (Eq. (42)) and K_m is the gain of the process which depends on the current mass flow and gain of the motor transfer function (Eq. (38)). Parameter H denotes a coincidence horizon and was set to 5. T_r defines the time constant for reference model response and was set to 20 [16,22,4].

For the starting period, the speed is set the same as with the existing algorithm to 3.5 m/min. When the information for mass at the end of the belt is available, the control algorithm is turned on.

3.4. Results

The mass flow during the experiment was as shown in Fig. 5.

The output of the process controlled with the PFC algorithm is shown in Fig. 6, the output with a PID controller is shown in Fig. 7 and the output of the process controlled with the old control algorithm is shown in Fig. 8. The speed of the conveyor for compared control algorithms is shown in Fig. 9. Fig. 10 represents the input to the motor for compared algorithms. The result of the study was expected. Control with the predictive functional controller is far better than with the PID and the old control algorithm. The sum-squared errors for the experiment are given in Table 1. The old algorithm is slow and can not cope with disturbances very well. Both PID and PFC algorithms are much better than the old control algorithm. Around the working point, the PID controller and the PFC controller have comparable performance. The problem of the PID controller is that it does not use the prediction of the mass flow as does the PFC. Therefore the PFC performance is better than PID's. PFC is able to control the

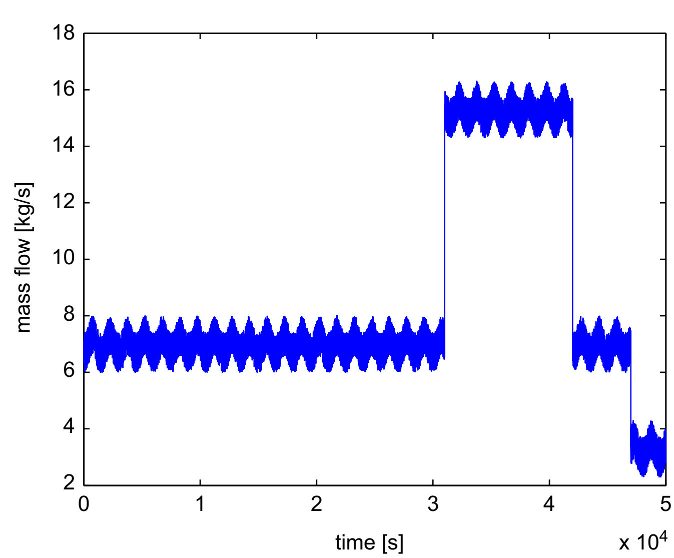

Fig. 5. The mass flow in the experiment.

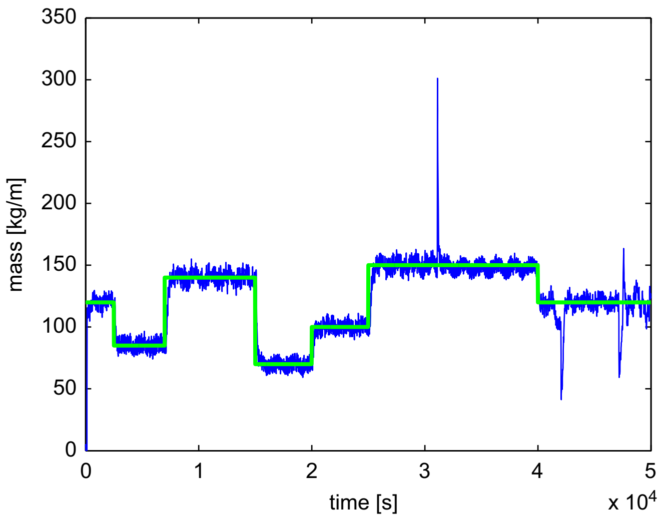

Fig. 6. The output of the process controlled with the PFC.

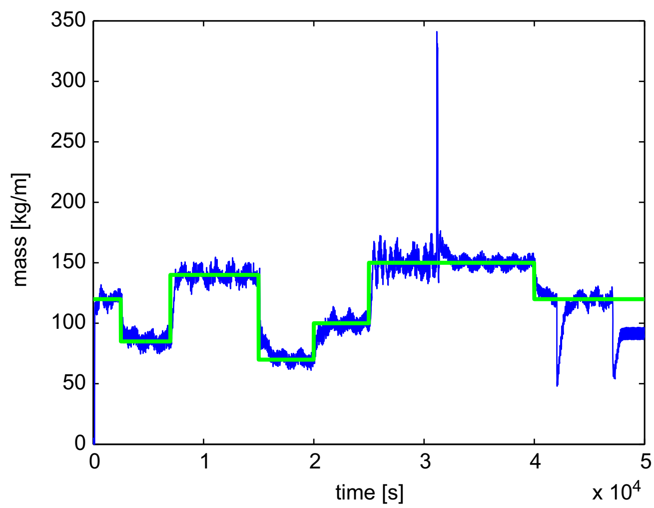

Fig. 7. The output of the process controlled with the PID controller.

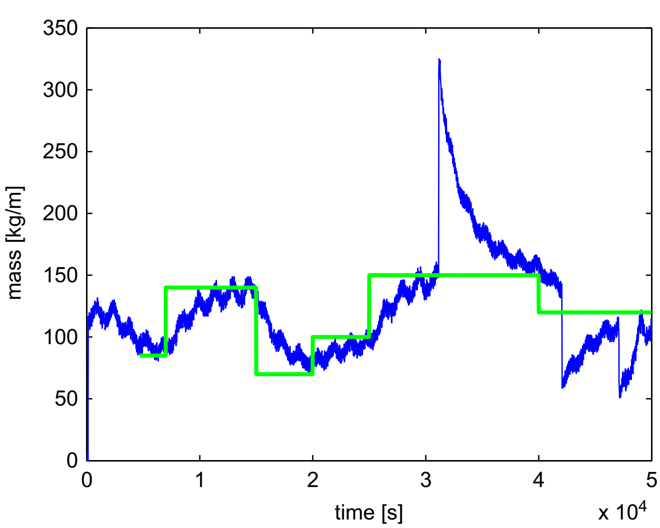

Fig. 8. The output of the process controlled with the existing algorithm.

process outside the working point. The PID controller faces another problem, because it lacks the prediction model. It can be seen from Fig. 9 that the conveyor stops at the end of the

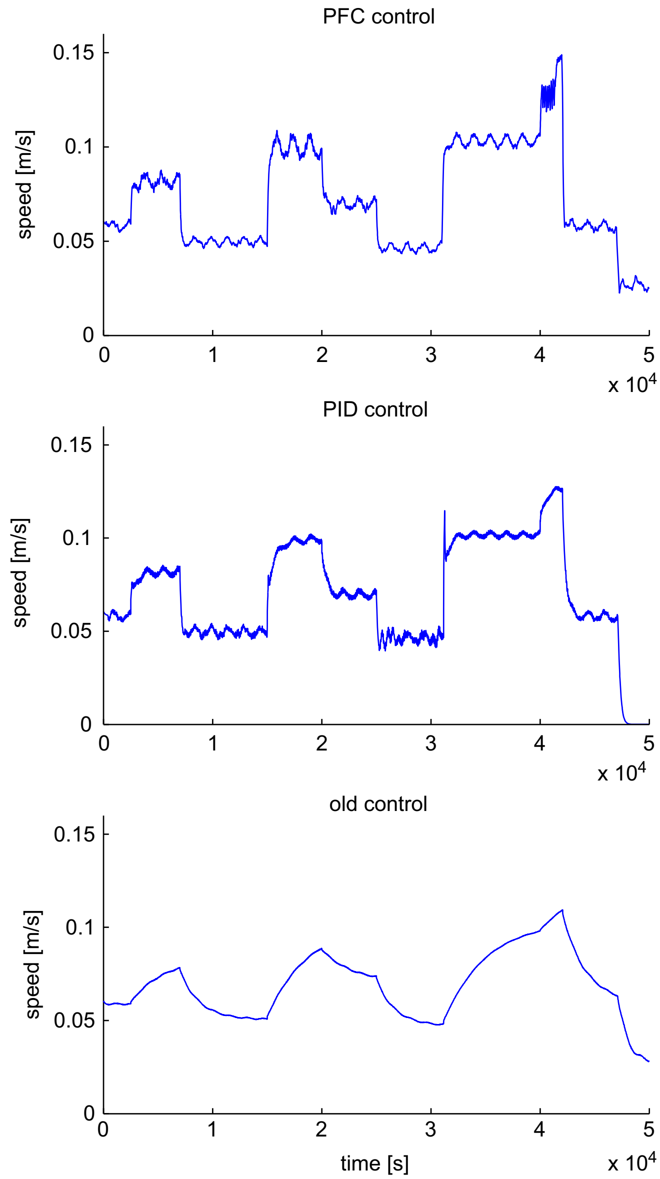

Fig. 9. The speed of the conveyor.

experiment (when the mass flow decreases). This is due to integral part of the controller and increased time delay of the process when the speed is lowered. This changes the process parameters so that the parameters of the PID controller are not adequate any more. The anti-windup loop would not solve the problem in this case. It can be seen that the speed is lowered till the conveyor stops. Even thou the conveyor is stopped the output of the process remains the same as there is the same mass of material on the measuring element as before. To prevent the PID to stop the minimum speed limit threshold should be added to the system. The PFC algorithm does not stop the conveyor as the control algorithm takes into account the output of the process model. In order to prevent the PID from stopping the conveyor some supervision logic must be implemented. The logic should reset the integral part of controller and decrease its gain if the speed is decreased under a certain threshold when the current from the centrifuge indicates that the mass flow from the centrifuge is not zero. To achieve better performance of the PID controller, its parameters should be adjusted depending on the operating range (delay and gain of the process change with speed of the conveyor and mass flow).

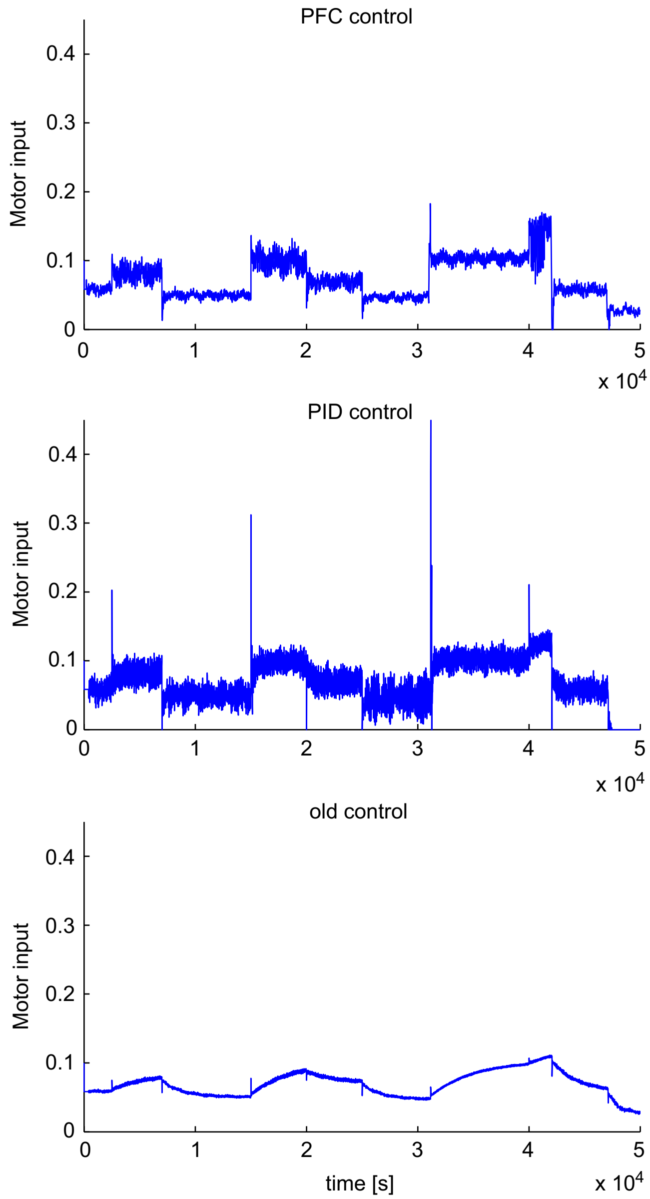

Fig. 10. The motor input.

Table 1
The sum squared values.

Control	SSE value
Old	5.93×10^6
PID	1.34×10^6
PFC	0.78×10^6

4. Conclusion

The paper presents the problem of conveyor belt speed control in a factory for producing stone wool. The model of the real plant was built and validated on a real plant data. Three different control algorithms were tested on the model: the existing control algorithm and the possible replacements of the existing control; the PID and the PFC control algorithm. The PID and PFC controllers were designed.

Evaluation of the control algorithms on the model showed the superior performance of the PFC algorithm. The problem with the PID controller is that it works well only around the working point. To achieve better performance of the PID the parameters should be adjusted depending on speed of the conveyor and mass flow. Additionally some supervision logic should be implemented to prevent stopping of the conveyor belt if the current from the centrifuge indicates that mass flow is not zero.

Both PID and PFC controller have better performance than the existing controller and are therefore suitable for replacing the existing one. But because of flexibility and quality of control PFC algorithm was recommended to use for the control of conveyor belt speed to ensure the right thickness of the stone wool. Better control quality will increase the quality of the product and smaller ejection of production.

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