Energy-efficiency optimization of the biomass pelleting process by using statistical indicators

F. Manca[1], E. Loiacono[2], G. L. Cascella[2*], D. Cascella[2]

[1] *Department of Education, Psychology and Communication - University of Bari Aldo Moro; fabio.manca@uniba.it*
[2] *Idea75 Srl - Via Guido de Ruggiero 1, Bari; e.loiacono@idea75.it; g.l.cascella@idea75.it; d.cascella@idea75.it*
[*] *Corresponding author*

Abstract. *Biomass pelleting process strongly depends on a number of variables hard to be simultaneously controlled. This paper suggests a method to ensure pellets moisture optimization and process energy saving. An experimental testbed was arranged in order to validate the performance of the proposed strategy. It is based on a closed-loop control system that regulates material moisture and flow rate, but its robustness is affected by the control-loop delay (the actuator delay is about 10 minutes) and by the random arrangement of the pellets inside the cooler that strongly affects product moisture (the measurement errors are not negligible). To overcome those problems, a robust statistical approach was adopted to reach the best tradeoff between estimation accuracy and computational effort. It was derived by the well known Random Close Packing model and statistical estimator. Experimental results prove the effectiveness of the proposed approach that provides moisture errors less than 7.2% with a continuous limitation of energy consumption.*
The present work is part of Idea75's project - SEI Smart supervisor for Energy efficiency optimization of Industrial processes - funded by Regione - PO FESR 2007-2013, Asse I, Linea di Intervento 1.1. Azione 1.1.3 - Aiuti alle piccole imprese innovative di nuova costituzione.

Keywords. *Biomass pelletizing; Energy saving; Robust optimization; System identification; Closed-loop control system.*

---

1 Introduction

Focusing on economical and environmental advantages, biomass pelleting process represents a well known solution for the molding of waste organic materials addressed to be used as biofuels, compost, or animal feed depending on their composition. In order to ensure certain pellets requested characteristics with the lowest energy consumption, an accurate characterization of all factors that influence pelleting process is needed. Due to the presence of several input, output and system parameters, extrusion is a multiple input and multiple output process that needs an appropriate method for prediction of processing results[1]. In literature, the identification of factors affecting quality and energy consumption in pellets production is conducted for example by means of: dynamic modeling and steady state modeling[2]; statistical approaches for data processing, correlation and regression analysis[3]; Genetic Algorithms (GAs), Artificial Neural Networks (ANNs)[4, 5] and Response Surface Method (RSM)[6] for establishing mathematical relationships between input variables and product properties.
This paper focused on two different but highly correlated aspects in pellets production: moisture content and energy consumption controls. They are generally influenced by several dependent and independent

variables that cause their monitoring modestly accurate; this paper proposed a statistical approach to reduce errors and complications due to variables complexity, so allowing the system identification and the robust optimization of the used pelleting process.

2 Experimental testbed

Pelleting process synthetically consists of an initial phase in which waste materials are mixed together and then softened by addition of water and heat. The so formed mixture is conveniently compressed, dried, and cooled in order to reach a sufficiently mechanical strength and preserve pellets quality.
The used experimental testbed was based on a closed-loop control system and mainly consisted of: screw and valve respectively for raw materials and water introduction, chamber in which they are mixed, pelletizer, cooler, sensor for motor current control, microwave moisture sensor and PLC for actuators management. Also an inverter is connected to screw motor ensuring variable rotation speed and material flow rate.
Pellets to be dried and cooled are randomly dropped into a chamber and are exposed to the microwave sensor for their moisture content measurements: values are measured on different incoming product volumes before to be moved into a storage tank. Pellets random packing density strongly affects moisture values. Moreover delays in feedback measurements generates error in process control. In order to reduce these errors firstly density-moisture dependency was estimated, then a statistical method for the reduction of delay-related errors was applied. The automated experimental testbed was firstly modeled and related output were properly manipulated by using a statistical approach.

3 Model description

Process control consisted in monitoring of product moisture and motor current, respectively by means of moisture and current sensors. Those generate the feedback for the water and raw material regulation in order to reach the desired reference. The energy efficiency of the process is estimated by the following ratio: amount of processed material divided by motor current. The higher this ratio, the higher the process energy efficiency. The used testbed is reported in Figure 1.

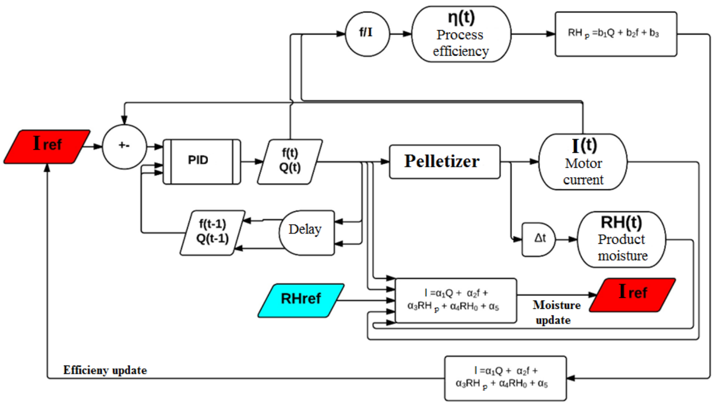

Figure 1 : Experimental testbed and related closed-loop control system.

The closed-loop control system was approximated to a linear model mainly based on current control according to relation (1).

$$I = \alpha_1 Q + \alpha_2 f + \alpha_3 RH_p + \alpha_4 RH_0 + \alpha_5 \qquad (1)$$

where I [A] is the motor current, Q [kg/s] is the raw material flow rate, f [Hz] is the frequency of the inverter connected to the screw, RH_p and RH_0 [%] respectively are pellets and raw material relative moisture contents, α_n are experimentally determined coefficients. The control system aims to keep the current as close as possible to $I_{setpoint}$. Frequency and flow rate are properly adjusted according with the feedback from final product moisture and motor current. The feedback measurements are affected by delays, consequently control errors are generated. Moisture measurements are average values between product moisture and air humidity in the empty spaces, as quantified by relation (2). Also actual product moisture is strongly affected by pellets random packing density inside the cooler. For these reasons, pellets random density and moisture-density dependency were firstly estimated.

$$RH_{sensor} = \phi RH_p + (1-\phi) RH_{air} \qquad (2)$$

Both product density (established through the Random Close Packing model for cylindrical pellets density randomly gathered in a certain volume) and product moisture distribution are Gaussian functions. In order to reduce error on moisture measurements a statistical estimator, based on the mean value of the last n measures instead of punctual ones, was used. Variance mean value is expressed as:

$$\sigma^2 = \left[\overline{RH}\right] = \frac{\sigma^2 [RH]}{(n-1)} \qquad (3)$$

Therefore increasing the number of samples, both variance and standard deviation decreased, as shown in Figure 2. Samples are the moisture contents measured on different product volumes inside the cooler; after that the product moves to the storage tank. The collection of several values is required for a more accurate estimation of actual final moisture content.
Distributions were built through Matlab fit probability distribution tools.

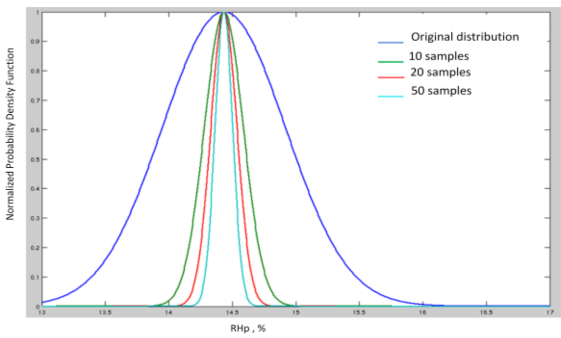

Figure 2 : Normalized error distribution plotted for different number of samples.

In order to reduce the measurement error a large number of sample is recommended; on the other hand this implies a larger delay in feedback calculation. Therefore error function on moisture measurements ξ_m decreases, error function on the process control ξ_c increases during the period between moisture calculation and action on actuators. Moreover according with Nyquist criterion for the stability determination of closed-loop systems, delay increasing over a critical value makes the loop system unstable, thus samples collection has to be properly limited.
A robust optimization technique was used to find the best number of samples for the feedback calculation. This strategy outstands results obtained by the following standard method. Both ξ_m and ξ_c depend on sample time t_s, their sum can be approximated with a continuous-time function: the best tradeoff between measure accuracy and control dynamics can be simply found by determining the

minimum of (4).

$$\frac{d}{dt_s}[\xi_m(t_s) + \xi_c(t_s)] = 0 \qquad (4)$$

4 Experimental results and conclusions

During each run of control, the use of the here presented approach guaranteed a continuous control on process variables for pellets moisture control and thus energy consumption. In fact, as shown in Figure 3, by properly regulating process variables (f and Q) into a certain convenient range, obtained moisture oscillated around the desired value RH_p = 15.2% with slight deviations only up to 7.2%.

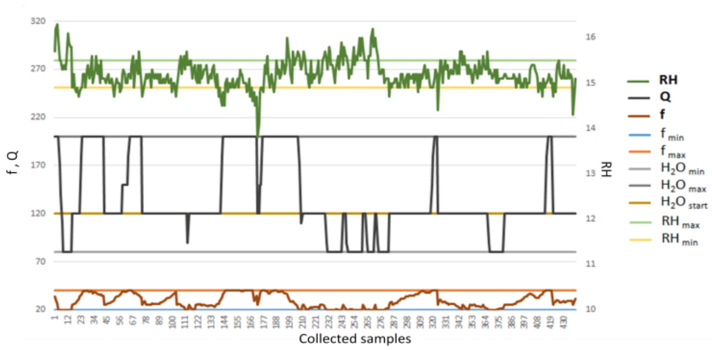

Figure 3 : Moisture trend.

This innovative statistical approach successfully faces this problem. The proposed technique minimizes errors control and guarantees more repeatability and accuracy of the process conditions. This optimized closed-loop system also ensures a convenient control of energy consumption.

References

[1] Ganjyal, G.M., Hanna M.A., Jones D.D. (2003). Modeling selected properties of extruded waxy maize cross-linked starches with neural networks. *Journal of food science*, **68**(4).

[2] Levine, L., Symes, S., Weimer, J. (2008). A simulation of the effect of formula and feed rate variations on the transient behavior of starved extrusion screws, *Biotechnology Progress* **3**, 212-220.

[3] Vigants, H., Uuemaa, P., Veidenbergs, I., Blumberga D. (2014). Cleaner pellet production – an energy consumption study using statistical analysis. *Agronomy Research* **12**(2), 633-644.

[4] Zafari A., Kianmehr M. H., Abdolahzadeh R. (2013). Modeling the effect of extrusion parameters on density of biomass pellet using artificial neural network. *International Journal of recycling of Organic waste in Agriculture* **2**(1), article No. 9.

[5] Shankar, T.J., Bandyopadhyay, S. (2004). Optimization of extrusion process variables using a genetic algorithm, *Food Bioproducts Process* **82,** (C2), 143 – 150.

[6] Shankar, T.J., Sokhansanj, S., Bandypadhyay, S., Bawa, A.S. (2010). A case study on optimization of biomass flow during single screw extrusion cooking using genetic algorithm (GA) and response surface method (RSM). *Food Bioprocess Technology* **3**, 498- 510.