Developing an Effective Control Strategy for Granulation Processes

A. Adetayo, B.A. Ogunnaike and M. Pottmann

E.I. duPont de Nemours and co.*

Abstract

The main objective of granulation processes is to produce granules with specific physical properties based on the end usage. The numerous disturbances associated with most granulation processes causes significant variations in first pass yield. Development and application of a yield based on-line control strategy is essential to maintaining consistent product quality. This paper highlights the problems associated with, and the need for, the development and online implementation of a yield based control scheme that controls appropriate physical properties of the granules exiting the granulator. A multi-level control scheme using process models of varying complexity is proposed. This paper discusses some of the results from online implementation of a section of this control scheme on a continuous granulation unit.

Introduction

Granulation is a particle size enlargement process that is widely used in the agricultural, pharmaceutical, food, metallurgical and ceramic industries. Granules have better handling properties, are free flowing, less dusty and have significantly lower explosion potential.

In a typical industrial granulation process, the objective is to produce granules with consistent product quality. For Agro-chemicals, these physical properties include attrition, bulk density, breakage resistance, size uniformity and dispersion rate. These properties are related directly or indirectly, to two fundamental quantities: particle size distribution and bulk density. Maximizing the product yield defined as the percentage of manufactured product having the required physical property is the main economic objective.

Although product specification on granule size may vary from product to product and from plant to plant, they are typically of the form of an upper limit $d_u$ and a lower limit $d_L$ as specified by the screen sizes used in product classification. Granules exceeding $d_u$ in size are classified as oversize while those below $d_L$ are classified as undersize. Acceptable product granules are those within these size classes that have the desired physical properties. As a result of this strict product specification, a first pass yield of less than 40% is not uncommon.

Up until now, online control of granulation processes has been restricted to stabilizing process flow rates. Quality control is typically achieved by adjusting the liquid flowrates through the different nozzles, the point of liquid addition and the specific amount of liquid introduced at each location. Product quality control is performed manually with particle size measurements taken rather infrequently, typically via sieve analysis. On-line size characterization of wet granules is desirable for many reasons. Firstly, granule densification, breakage and coalescence that occur on the sieves and in the drier are eliminated from the analysis. Secondly, measurement dead time is significantly reduced from approximately 60 minutes (depending on the size of the drier) to less than 2 minutes making it easier to monitor the response of the process to changes in the operating variables. Recent advances in light scattering technology makes on-line size characterization of free-flowing granules possible. Commercially available instruments like the Sympatec Helos® can now measure granule sizes up to 3.5mm in diameter paving the way for the development and on-line implementation of advanced process control schemes.

In addition to the challenges of obtaining reliable online particle size measurements, there are many factors that make implementation of online particle size
control difficult [4]. For most granulation processes, especially those involving recycle streams, a complex interaction exists between the operating variables, the unit operations and the product yield [1]. For such systems, a plant-wide control strategy is desirable. Prior to designing a plant-wide control scheme, one needs to be able to control the granulation unit.

This paper presents a summary of the development and successful implementation of a yield based model predictive control (MPC) scheme on a pan granulation unit. Results from on-line characterization of both the size distribution and, the bulk density of the granules exiting the pan are used in the feedback loop of the MPC. For the feed-forward/feedback analysis, the feedrate is taken as the measured disturbance. Note, this yield-based scheme is applicable to other granulation processes: In the drum granulation circuit [1], the optimization section might use a model that accounts for the effects of drum speed, drum angle and spray zones while the control section uses the liquid flowrate as the manipulated variable. Similarly, in a fluid bed granulation unit, the optimal section can be used to optimize nozzle location, air velocity, liquid droplet size etc. while the control section uses the liquid flowrates to achieve the desired control objectives.

The Pan Granulation Process

In the pan granulation process, powder feed, 10±8μm in diameter, is continuously fed into a rotating pan. Liquid binder (e.g. water) is introduced into the pan from one or more strategically chosen position(s). The liquid binder contacts the premix powder forming small particles known as nuclei which subsequently grow by layering/coalescence [2]. The flowrates through the nozzles can be used to adjust both the size and bulk density of the granules thus produced. The experimental setup is schematically depicted in Figure 1.

Representative samples of the wet granules exiting the pan are collected at regular intervals for online size measurement using a forward laser scattering instrument. With the help of a data acquisition program, information on \(d_5\), \(d_{50}\) and \(d_{90}\) is transmitted to and graphically displayed on a computer screen. The terms \(d_5\), \(d_{50}\) and \(d_{90}\) represent the 5th, 50th and 90th percentile of the granule size distribution respectively. With this setup, it is easy to quantify the effect of the total moisture content and its distribution in the pan on the sizes of the granules produced. Figure 2 shows an example of how results from the online size analyzer compares with off-line classification by the sieving of the same sample. There is a good agreement between the two methods for a broad granule size distribution typically obtained in a process like this.
The Bulk Density

Figure 3 is an indication of the strong correlation that exists between the bulk density of the wet granules and that of the product. The product's bulk density lags behind the wet one by the estimated average residence time of the granules in the drier. An indirect control of the product's bulk density can therefore be achieved by controlling the bulk density of the wet granules.

The Model Development

Model identification was done by making step changes to the liquid flowrates through each nozzle while keeping all other process variables constant. Open loop response data shows that while the 90th and 50th percentiles of the exiting granule size distribution go through a minimum as binder content increases [2, 3], the 5th percentile, an indication of the amount of 'fines' produced increases monotonically with liquid content [2]. This indicates the existence of an operating region where the granule size distribution has the lowest spread. Day-to-day variations in the attained steady states under otherwise constant operating conditions were also noticed. These factors present significant challenges to the development and online implementation of an effective control strategy. A yield based multi-level, model predictive control scheme is proposed for optimal operation of this process. Figure 4 shows the block diagram of the proposed control scheme which has two sections; the optimization and control sections.

The Model Predictive Control Scheme

A dynamic non-linear model that accounts for the significant interactions among the variables such as pan angle, pan speed and nozzle positions affect the product properties is required at the optimization level. The effectiveness of this level depends on one's understanding of the process and, the model's accuracy. This level can be used to specify the optimal pan speed, pan angle, nozzle position for a given formulation during startup. The optimization level can also be called upon when the control section cannot achieve the desired control objectives at the current operating condition. Online comparison of the non-linear model prediction and the measured size distribution is used to determine the accuracy of the model and the effect of unmeasured disturbances.

At the control level, liquid flowrates through the nozzles, \( N_i \), are manipulated by the control scheme to achieve the control objectives outlined below. Depending on the process dynamics, a linear or multi-linear (to take care of the negative steady state gain of the \( d_{90}-\)liquid content relationship) empirical model is sufficient. A summary of the linear first order transfer function model with time delay used for this application is given below. Detailed description of the control scheme and model development is presented elsewhere [5, 6].
**The Linear Model**

Introducing model inputs and outputs as deviations from their nominal respective values,

\[
\begin{align*}
U_i &= N_i - N_i^0, \quad i = 1, 2, 3 \\
Y_1 &= \rho_B - \rho_B^0 \\
Y_2 &= d - d^0 \\
Y_3 &= d - d_0^0
\end{align*}
\]

where \( N_i \) represent the liquid flowrates through nozzle \( i \). This granulation process is equipped with three spray nozzles. \( \rho_B \) represents the granules bulk density and the superscript 'o' represents the nominal (steady state) values of the variables. The linear discrete-time model is of the form:

\[
\begin{bmatrix}
Y_1(z^{-1}) \\
Y_2(z^{-1}) \\
Y_3(z^{-1}) 
\end{bmatrix} =
\begin{bmatrix}
g_{11}(z^{-1}) & g_{12}(z^{-1}) & g_{13}(z^{-1}) \\
g_{21}(z^{-1}) & g_{22}(z^{-1}) & g_{23}(z^{-1}) \\
g_{31}(z^{-1}) & g_{32}(z^{-1}) & g_{33}(z^{-1})
\end{bmatrix}
\begin{bmatrix}
U_1(z^{-1}) \\
U_2(z^{-1}) \\
U_3(z^{-1})
\end{bmatrix}
\]

Here, \( y_i^* \) represents the model prediction which is different from the actual process data, \( y_i \). The experimental step response data indicate that simple first-order plus time-delay transfer functions, \( g_{ij} \), are adequate to represent the behavior observed in each of the responses, at least for moderate deviations from the nominal operating point.

\[
g_{ij}(z^{-1}) = \frac{k_{ij}z^{-\delta_{ij}}}{1 + \tau_{ij}z^{-1}}
\]

\( k_{ij} \) and \( \tau_{ij} \) are the gain and time constants respectively.

**The Model Predictive Control Scheme**

Due to the limited capacity of the nozzles, lower and upper bounds are imposed on their flowrates. The overall yield based process control strategy adopted for this study is:

1. Monitor and control the bulk density, \( \rho_B \) around its setpoint, \( \rho_B^* \)
2. Maintain \( d \), the 90th percentile of the granule size distribution below the upper limit, \( d_u \)
3. Maintain \( d_L \), the 5th percentile of the size distribution above the lower limit, \( d_L \).

The control objectives at every sampling instance can be represented mathematically as,

\[
\begin{align*}
\rho_B(t) &= \rho_B^*(t) \pm \varepsilon_B \\
d(t) &= d_L(t) \geq d_L \\
d(t) &= d_L(t) \leq d_U
\end{align*}
\]

subject to

\[
N_i^\text{min} \leq N_i(t) \leq N_i^\text{max} \quad i = 1, 2, 3
\]

\( \rho_B' \) is a reference trajectory for the granule's bulk density and \( \varepsilon_B \) is the allowable deviation in \( \rho_B \).

Note that this strategy guarantees a product yield of at least 85%. The decision on the percentiles of interest depends on one's knowledge of the physics of the process, the material being granulated, the reliability of the measuring instrument and the targeted yield increment. It is practically impossible to control a size distribution. Granulation processes do not have enough actuators to arbitrarily "shape" the particle size distribution. The approach taken here to control two points on the PSD requires at least two input variables that have a significantly different effect on the chosen percentiles.

**Results and Discussions**

Experiments were conducted with both the feedback-feedforward and feedback only control actions. For the feedback only control scheme, information on feedrate changes is not communicated to the controller. This simulates cases of unmeasured disturbances. The second scheme combines a feedforward action using a simple ratio controller that maintains a constant liquid flowrate to feedrate ratio and a feedback action using feedback information from online granule characterization. The performance of the controller using the combined feedback/feedforward action can be greatly improved if a better model is used.

**Feedback Control**

Figure 5 shows the closed-loop response to a change in the powder feed rate from 320 to 350 [MT-1] when feedback control alone is used. The response is rather sluggish because a small weight [5, 6] is used for density tracking, and neither \( d_L \) nor \( d_0 \) initially violates their constraints. Significant changes in the nozzle flowrates are initiated as \( d_L \) approaches and subsequently violates its lower bound at 400\( \mu \)m. Although the nozzles saturate at their upper bound, (i.e. the valves are fully opened), the control system returns the pan back to acceptable operating conditions.

**Combined Feedback/Feedforward Control Scheme**

Figure 6 shows the rejection of a step disturbance in the feed rate from 350 to 320 [MT-1] when the combined feedback/feedforward control scheme is used.
Liquid Flowrates

![Flowrates Graph]

Fig. 5 Feedback control rejection of a Feedrate disturbance [5]

![Density Graph]

![Percentiles Graph]

![d5 Filtered Graph]

![d90 Filtered Graph]

Fig. 6 Feedback/Feedforward rejection of a Feedrate Disturbance [6]
The arrow indicates the position of the step change. The feed-forward action is based on the premise of maintaining constant liquid flowrate to feedrate ratio. The drop in the feed rate causes an immediate step change in the nozzle flowrates of identical relative magnitude. However, this decrease is not sufficient to compensate for the decreased feed rate, as both $d_{15}$ and $d_{90}$ starts to increase considerably. Additional decreases in the nozzle flow rates are required to eventually return the pan to its nominal operating conditions.

This additional decrease in liquid flowrate shows the premise of a constant total moisture/feedrate ratio, on which the feed-forward control action is based on, is not a good approximation, at least not for the magnitude of feed rate changes implement here. The fact that the moisture content had to be reduced by more than the expected amount can be explained by the well known observation that a reduced feed rate results in a longer residence time in the pan. The particles then have more time to grow. For this reason, the total moisture has to be reduced even more to compensate for the additional factor that favors particle growth. Note, without these control actions, these disturbances would have resulted in a significant reduction in the first pass yield.

Conclusions

This report presents a successful demonstration of on-line granule size and bulk density characterization. With the on-line particle sizer, effects of process disturbance due to changes in input or disturbance variables can be monitored within a few minutes! This is a vast improvement over what is currently possible i.e. granule characterization after drying and screening, a process which, depending on the granule’s residence time in the dryer could take up to 60 minutes. In addition to the shorter dead time, the current approach eliminates the screen and dryer dynamics from the analysis.

A yield based multi-level control scheme that ensures a predefined yield is maintained is successfully implemented on a pilot plant granulation unit. This control scheme uses different models of varying complexities at its control and optimization section. This paper shows that effective control of key process variables using on-line particle size measurements is feasible.

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References

Anthony Adetayo

Anthony Adetayo is a Senior Research Engineer at DuPont’s Ag Enterprise. He received a degree in Chemical Engineering from the University of Lagos, Nigeria in 1988. He joined DuPont's Central Research and Development group after obtaining a PhD in Chemical Engineering from the University of Queensland, Australia in 1993. His research interests include granulation, material handling, granule segregation and, modeling, simulation and control of particulate processes.

Babatunde A. Ogunnaike

Babatunde A. Ogunnaike, B.S. (Chemical Engineering), M.S (Statistics), Ph.D. (Chemical Engineering), is currently a Research Fellow in the Advanced Control and Modeling group, DuPont Central Research and Development; he is also an adjunct professor in the Chemical Engineering Department, University of Delaware. His research interests include identification and control of nonlinear systems, modeling and control of polymer reactors and distillation columns, applied statistics, and biosystems analysis and control.

Martin Portmann

Martin Portmann is a Senior Engineer with DuPont DACRON. He received his doctoral degree from the University of Technology, Vienna, in 1993, and a M.S. degree in Chemical Engineering from the University of California at Santa Barbara in 1991. He joined DuPont’s Central Research and Development Department in 1993, and has been involved in a variety of research and application projects in process modeling and advanced control.