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DEVELOPMENT OF A MODEL CONTROL STRATEGY FOR PREDICTING THE GRANULATION PROCESS IN AMMONIA-UREA PRODUCTION

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Abstract. This paper presents a Model Predictive Control (MPC) strategy for a multivariable, strongly coupled, and time-delay continuous granulation process in ammonia–urea production. The study focuses on the granulation stage, where product quality is primarily determined by bulk density and particle size distribution. An asymmetric control formulation is proposed, in which bulk density is required to track a predefined reference trajectory, while particle size indicators are maintained within specified bounds rather than fixed setpoints. A linear discrete-time model with input–output delays is employed to represent process dynamics. At each sampling instant, a constrained quadratic optimization problem is solved to compute optimal control actions. The performance of the proposed MPC approach is evaluated through simulation and compared with conventional PID control. The results demonstrate that MPC significantly improves tracking performance, reduces overshoot, and shortens settling time. In particular, the Integral Squared Error (ISE) is reduced by approximately 70-75%, while overshoot is limited to 2–3%, which is considerably lower than that achieved with PID control. Moreover, MPC effectively enforces constraints on particle size distribution, whereas PID control leads to noticeable constraint violations. Overall, the proposed control strategy provides a robust and efficient solution for improving product quality, maximizing yield, and enhancing operational performance in industrial granulation systems.

Keywords: Model Predictive Control, granulation process, urea production, multivariable control, particle size distribution, constrained optimization

Annotatsiya. Ushbu maqolada ammiak–karbamid ishlab chiqarish jarayonining uzluksiz granulyatsiya bosqichi uchun ko'p o'zgaruvchili, kuchli bog'langan va vaqt kechikishlariga ega tizimni boshqarishga mo'ljallangan Model Predictive Control (MPC) strategiyasi taklif etiladi. Tadqiqot granulyatsiya bosqichiga qaratilgan bo'lib, bunda mahsulot sifati asosan massa zichligi va zarracha o'lchami taqsimoti bilan belgilanadi. Ishda boshqaruv masalasi assimetrik shaklda qo'yilgan: massa zichligi berilgan referens trayektoriyani kuzatishi talab etiladi, zarracha o'lchami ko'rsatkichlari esa qat'iy qiymatlar o'rniga berilgan chegaralarda ushlab turiladi. Jarayon dinamikasini ifodalash uchun kirish–chiqish kechikishlariga ega chiziqli diskret model qo'llanilgan. Har bir diskret vaqt momentida optimal boshqaruv signallarini aniqlash uchun cheklovli kvadratik optimallashtirish masalasi yechiladi. Taklif etilgan MPC yondashuvining samaradorligi simulyatsiya orqali baholanib, an'anaviy PID boshqaruv bilan solishtiriladi. Natijalar shuni ko'rsatadiki, MPC kuzatish aniqligini sezilarli darajada oshiradi, ortiqcha oshib ketishni kamaytiradi va tizimning barqarorlashish vaqtini qisqartiradi. Xususan, kvadratik xatolik integrali (ISE) taxminan 70–75% ga kamayadi, ortiqcha oshib ketish esa 2–3% darajada bo'lib, bu PID boshqaruvga nisbatan ancha pastdir. Bundan tashqari, MPC zarracha o'lchami taqsimoti bo'yicha cheklovlarni samarali saqlab turadi, PID boshqaruvda esa bu cheklovlar buzilishi kuzatiladi. Umuman olganda, taklif etilgan boshqaruv strategiyasi mahsulot sifatini oshirish, chiqimni maksimal darajaga yetkazish va granulyatsiya jarayonining umumiy samaradorligini yaxshilash uchun samarali va ishonchli yechim hisoblanadi.

Kalit so'zlar: Model Predictive Control, granulyatsiya jarayoni, karbamid ishlab chiqarish, ko'p o'zgaruvchili

Аннотация. В данной работе представлена стратегия модельно-прогностического управления (MPC) для многомерного процесса непрерывной грануляции с сильными взаимосвязями и запаздыванием в производстве аммиака и карбамида. Исследование сосредоточено на стадии грануляции, где качество продукции определяется преимущественно насыпной плотностью и гранулометрическим составом. Предложена асимметричная формулировка управления, при которой насыпная плотность должна отслеживать заданную эталонную траекторию, в то время как показатели размера частиц удерживаются в определенных границах, а не на фиксированных уставках. Для описания динамики процесса используется линейная дискретная модель с задержками по входу и выходу. На каждом шаге дискретизации решается задача ограниченной квадратичной оптимизации для расчета оптимальных управляющих воздействий. Эффективность предложенного подхода MPC оценивается с помощью моделирования и сравнивается с традиционным ПИД-управлением. Результаты показывают, что MPC значительно улучшает качество отслеживания, уменьшает перерегулирование и сокращает время установления. В частности, интегральная квадратичная ошибка (ISE) снижается примерно на 70–75%, а перерегулирование ограничивается 2–3%, что значительно ниже показателей ПИД-регулятора. Кроме того, MPC эффективно обеспечивает соблюдение ограничений на гранулометрический состав, тогда как ПИД-управление приводит к заметным нарушениям границ. В целом, предложенная стратегия управления представляет собой надежное и эффективное решение для повышения качества продукции, максимизации выхода и улучшения эксплуатационных характеристик промышленных систем грануляции.

Ключевые слова: модельно-прогностическое управление (MPC), процесс грануляции, производство карбамида, многомерное управление, гранулометрический состав, оптимизация с ограничениями.

Introduction

The granulation process is considered one of the important stages in the chemical industry, especially in ammonia–urea production. In this process, fine powder particles stick together with the help of a granulation liquid and form larger granules. As a result, the physical properties of the material improve, dusting decreases, and it becomes easier to use in subsequent technological processes [1,2]. Therefore, the granulation stage not only determines the product quality, but also significantly affects the efficiency of the entire production process.

Despite its simple appearance, granulation is internally a rather complex process. In it, solid, liquid, and gas phases simultaneously participate. Liquid bridges are formed between particles, through which the particles bond and grow. How this process proceeds depends on many factors — equipment parameters, technological conditions, and material properties [3–5].

From a practical point of view, product quality is mainly evaluated by two indicators: bulk density and particle size distribution. Maintaining these indicators within the required limits is necessary to increase production yield and ensure stable quality.

In recent years, various studies have been carried out to understand and control granulation processes. In some works, the physico-mechanical properties of the process and particle growth mechanisms have been studied [9], while other studies have focused on control issues [10–12]. Nevertheless, in practice, control of granulation processes is often carried out using experience-based methods. In many cases, the system is controlled not on a fully mathematical basis, but relying on operator experience and experimental results.

One of the most widely used control methods in industry is the PID controller. It is widely applied due to its simplicity and reliability. However, in multivariable and interconnected systems such as the granulation process, PID does not always provide good results. This is because several input signals simultaneously affect multiple outputs. As a result, improving one parameter may lead to the deterioration of another. In addition, it is difficult to precisely control particle size constraints using PID [10,11].

From this point of view, one of the modern control methods, Model Predictive Control (MPC), is attracting great interest. This method predicts the future behavior of the system based on its model and selects the optimal control signal at each time instant. Its most important feature is that MPC simultaneously considers multiple parameters and directly incorporates input and output constraints into the control strategy [16,17]. Therefore, it is suitable for complex processes such as granulation.

However, in most existing works, classical control problems are considered where exact target values are specified for all outputs. In practice, the situation is somewhat different. For example, bulk density needs to be maintained around a specific value, but for particle size indicators it is sufficient to remain within certain limits. That is, not all parameters are controlled with the same priority. This complicates the control problem and requires determining which parameter is more important [11,12].

In this work, such an approach is proposed. That is, the control problem for the granulation process is formulated in an asymmetric form: bulk density is taken as the main control objective, while particle size indicators are maintained within specified limits. For this purpose, a control algorithm based on Model Predictive Control is developed. The effectiveness of the proposed method is tested through simulation, and the results are compared with conventional PID control. The obtained results show that the MPC approach operates more stably, accurately, and efficiently in controlling granulation processes.

Methodology

The ammonia–urea production process is a complex, multi-stage technological system, which includes synthesis, separation, concentration, and granulation stages. The overall technological flow diagram of this process is presented in Figure 1.

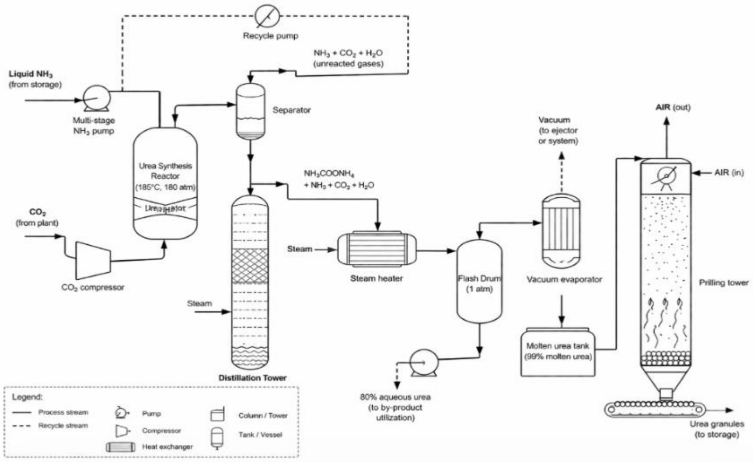

Fig.1 Technological scheme of the ammonia–urea production process.

This scheme shows the main stages of urea production based on ammonia and carbon dioxide, including synthesis, concentration, drying, and granulation processes.

The urea production process is based on the chemical interaction between ammonia (NH_3) and carbon dioxide (CO_2). This process is carried out under high pressure and temperature conditions and includes the formation of ammonium carbamate as an intermediate stage. Subsequently, this compound undergoes dehydration, resulting in the final product — urea.

The process consists of two main reactions:

$$2NH_3+CO_2 \rightarrow NH_2COONH_4$$

$$NH_2COONH_4 \rightarrow (NH_2)_2CO+H_2O$$

These reactions are thermodynamically equilibrium-limited, and in order to increase urea formation, ammonia is supplied in excess. This approach makes it possible to shift the reaction toward the desired direction.

According to the technological scheme, liquid ammonia is compressed to high pressure using a multistage pump and fed into the synthesis reactor. At the same time, carbon dioxide is compressed by a compressor and supplied to the reactor. The synthesis process is usually carried out under high temperature and pressure conditions, which increases the reaction rate and conversion degree.

The mixture formed as a result of the reaction is then sent to a separation (distillation) unit in the next stage. Here, unreacted ammonia and carbon dioxide are separated and recycled back to the synthesis stage. The implementation of such a closed cycle serves to reduce raw material consumption and increase process efficiency.

After distillation, the remaining solution is processed in a flash drum by sharply reducing the pressure. At this stage, the gas phase is separated, and a urea solution of medium concentration is obtained [3–5]. In the next stage, the solution is treated in a vacuum evaporator, where excess water is removed and a highly concentrated molten urea is obtained. In the granulation stage, molten urea is sprayed from the top of a special tower, while a cooling air flow is supplied from the bottom. As a result, the droplets cool down and form solid granules. The formed granules are transferred via a conveyor system to the next processing or packaging stage. The recycling of separated NH_3 and CO_2 components in the process ensures a closed cycle and significantly reduces overall energy and raw material consumption. The granulation process is often carried out in industry using fluidized bed granulators. A simplified schematic representation of this device is shown in Figure 2.

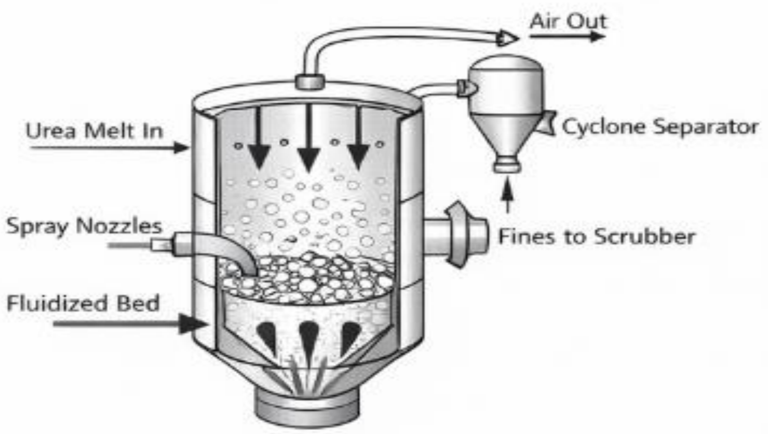

Fig.2 Simplified schematic representation of an industrial fluidized bed urea granulator.

The granulator fluidizes the particles by means of an on flow supplied from the bottom, while the urea solution sprayed from the top or from the side solidifies on the surface of the particles and leads to their growth. The granulator consists of the following main elements: spray nozzles, fluidized bed, cyclone separator, and exhaust gas flow system.

Particles grow as a result of spraying, evaporation, and cooling processes, which directly affect the particle size distribution and bulk density. The granulation process and the circulation flows within it are shown in Figure 3.

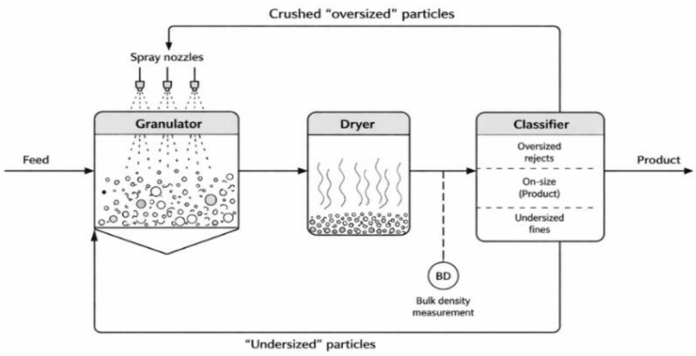

Fig.3 Schematic representation of the granulation process

This scheme shows the recycling and return of course and fine granules to the process.

The process operates as follows: coarse granules are crushed and returned to the process, fine granules are directly recycled, and only granules within the specified size range are taken as the final product.

This mechanism plays an important role in controlling product quality.

In a continuous granulation process, raw materials are continuously fed into the granulation apparatus, where particle formation and growth processes take place. Such equipment typically includes drum, pan, or mixer-type granulators. Inside the granulator, several spray nozzles are installed to introduce moisture and binding agents into the particle bed, and these are considered the main controllable elements of the process.

The formed granules are dried in the next stage and then classified according to their size. As a result of classification, particles that do not meet product specifications are returned to the process for reprocessing. In particular, oversized granules are first crushed and then recycled, while smaller particles are directly returned to the recycle loop. This closed-loop structure is schematically illustrated in Figure 1.

The main objective of industrial granulation processes is to produce granules with stable quality characteristics. These quality criteria include indicators such as mechanical strength of particles, uniformity of size, and resistance to breakage. In practice, these characteristics are mainly defined by two key parameters: particle size distribution and bulk density.

The economic efficiency of the process is evaluated by product yield, meaning that maximizing the fraction of granules that meet the specifications is essential. Particle size requirements are usually defined by upper (d_u) and lower (d_l) limits. Particles larger than the upper limit are classified as coarse, while those smaller than the lower limit are classified as fine fractions. Only granules within this specified range are accepted as the final product.

In the granulation process, quality control is mainly achieved by adjusting the flow rates supplied through the spray nozzles. The location and amount of moisture and binding agents introduced into the granule bed significantly affect the particle formation mechanism and their growth kinetics. In practice, the positions of the nozzles are determined by the design, and control is mainly carried out by adjusting their flow rates.

The system under consideration is equipped with three spray nozzles, and their flow rates are denoted by, n_1 , n_2 and n_3 , respectively. These variables are considered control inputs and are subject to physical constraints. In controlling process quality, the main focus is on maintaining bulk density (ρ_B) around a specified value, while the indicators representing particle size distribution, d_5 and d_{90}, are required to remain within given limits.

Practical experience shows that if ρB is maintained close to its specified value and at the same time the conditions and are satisfied, a high product yield (approximately 85% or more) is achieved. This process and the corresponding control objectives are presented in the form of a block diagram in Figure 2.

Among the typical challenges of granulation systems are high recycle flows and external disturbances, which complicate process control. In addition, the following important features create additional difficulties in control system design:

1. Although the system has three control inputs, the output parameters d_5 and d_{90} are strongly coupled, and $d_5 \leq d_l$ their independent control is limited.

2. There is a specific target value (ρ_B^*) for bulk density, whereas no strict setpoints are defined for particle size indicators; only their limits must be satisfied.

3. Measurement acquisition and processing in granulation processes are more complex and less standardized compared to conventional chemical processes.

Although the granulation process is inherently nonlinear, for the purpose of control system synthesis it is considered appropriate to use a simplified linear model that represents the relationship between three control inputs (n_1, n_2, n_3) and three main outputs (ρ_B, d_5, d_{90}). The structural scheme of the granulation process as a control object is shown in Figure 4.

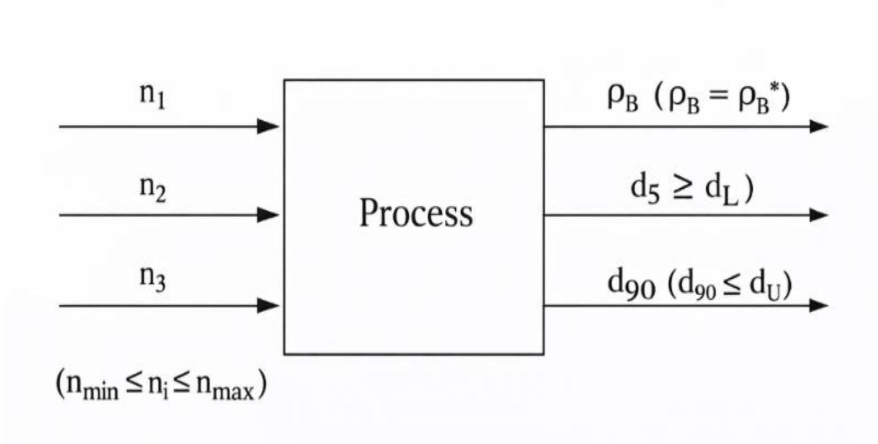

Fig.4 Analysis of the granulation process as a control object

This scheme shows the inputs, outputs of the control system, and the role of the MPC controller. In the process, three spray flow rates are selected as the controlled input variables:

$$u(k) = \begin{bmatrix} n_1(k) \\ n_2(k) \\ n_3(k) \end{bmatrix}$$

The output variables represent the product quality:

$$y(k) = \begin{bmatrix} \rho_B(k) \\ d_5(k) \\ d_{90}(k) \end{bmatrix}$$

where: ρ_B — bulk density; , d_5, d_{90}— particle size distribution indicators.

Despite the nonlinear nature of the process, a linearized discrete model was used for MPC design. The model was expressed in terms of deviations around the nominal operating point:

$$\Delta y(k) = y(k) - y_0 \, , \; \Delta u(k) = u(k) - u_0$$

The linear model is expressed as follows:

$$\Delta y(k+1) = A\Delta y(k) + B\Delta u(k-\theta)$$

where: A— system dynamics matrix; B — control influence matrix; θ— time delay.

For each input–output pair, a first-order time-delay model is assumed:

$$G_{ij}\left(z^{-1}\right) = \frac{b_{ij} z^{-\theta_j}}{1 + a_{ij} z^{-1}}$$

where: $i = 1, 2, 3$, $j = 1, 2, 3$

The control objectives of the considered granulation process differ from conventional multivariable tracking problems. In this case, it is not required to define strict target values for all output variables. Instead, a specific reference trajectory is assigned for bulk density ρ_B, which is the main quality indicator, while the particle size distribution indicators d_5 and d_{90} are formulated in the form of constraints.

Therefore, the control objectives are defined as follows:

$$\rho_B(k) = \rho_B^*(k)$$

$$d_5(k) \geq d_L$$

$$d_{90}(k) \leq d_U$$

where: $\rho_B^*(k)$ — the required trajectory of bulk density; d_L — the lower bound of particle size; d_U — the upper bound of particle size.

In addition, the control signals are constrained by the technological and physical limitations of the equipment:

$$n_i^{\min} \leq n_i(k) \leq n_i^{\max}, \quad i = 1, 2, 3$$

From this formulation, it can be seen that the given problem may have multiple solutions, since several control combinations can simultaneously ensure tracking of ρ_B and satisfy the constraints on ρ_B^* and d_5 d_{90}. Therefore, the problem is reformulated as an optimization problem and an optimal solution is selected.

From a practical point of view, the control system should ensure the following priorities:

1. Tracking the prescribed trajectory of bulk density is considered the primary objective.

2. If the particle size indicators are within the allowable region, the control signals should be kept close to their nominal values.

3. If or approaches the constraint boundaries $d_5 . d_{90}$, preventive corrective action should be taken to avoid violation.

4. If a constraint is violated, the system must be returned to normal operating conditions as quickly as possible.

In the proposed MPC algorithm, at each discrete time instant, a cost function is minimized based on predictions of future outputs. This function combines two main requirements: keeping the outputs close to their desired values and limiting excessive changes in the control signals.

The objective function is written as follows:

$$J(k) = \sum_{i=1}^{P} \left(y(k+i|k) - y^{ref}(k+i) \right)^T W \left(y(k+i|k) - y^{ref}(k+i) \right) + \sum_{i=0}^{C-1} \Delta u(k+i)^T Q \Delta u(k+i)$$

where: P — prediction horizon; C — control horizon; $y(k+i|k)$ — predicted outputs for the time instant based on information at time ; k — desired output vector; $k+i$ — increment of the control signal; $y^{ref}(k+i)$ — weighting matrix for output errors; $\Delta u(k+i)$ — weighting matrix for control inputs.

The first term of this objective function minimizes output errors, while the second term prevents excessively rapid changes in the control signals. As a result, stable and technologically feasible operation of the system is ensured.

An important aspect of this work is the asymmetric nature of the control objectives. In particular, only bulk density has a defined reference trajectory, whereas the indicators and do not have fixed target values but are instead defined by allowable bounds.

Therefore, the desired output vector is defined as follows: Therefore, the desired output vector is chosen in the following form:

$$y^{ref}(k+i)=\begin{bmatrix}\rho_B^*(k+i)\\ d_5^0\\ d_{90}^0\end{bmatrix}$$

where d_5^0 and d_{90}^0 denote the nominal operating points. These values do not need to be strictly tracked; however, using them in the objective function helps keep the system outputs within the allowable region.

The output weighting matrix is chosen as follows:

$$W=diag(w_\rho,w_5,w_{90}),$$

$$Q=diag(q_1,q_2,q_3)$$

and the following relation is typically satisfied:

$$w_\rho \ ? \ \ w_5,w_{90}$$

This ρ_B prioritizes tracking of as the main objective, while d_5 and d_{90} are mainly handled through constraints.

In the optimization process, constraints on inputs and outputs are explicitly taken into account. The input constraints are written as follows:

$$u_{\min}\le u(k+i)\le u_{\max}\,,\quad i=0,1,\ldots,C-1$$

or in terms of components:

$$n_i^{\min}\le n_i(k+i)\le n_i^{\max}\quad i=1,2,3$$

In practical processes, it is not always possible to strictly satisfy all constraints at all times. For example, due to external disturbances or unexpected changes in raw materials, the outputs may exceed the allowable limits for a certain period of time. In such cases, soft constraints are introduced to prevent the optimization problem from becoming infeasible.

For this purpose, additional slack variables are added to the output constraints:

$$d_5(k+i)+\varepsilon_1(k+i)\ge d_L$$

$$d_{90}(k+i)+\varepsilon_2(k+i)\ge d_U$$

where $\varepsilon_1\ge 0$ and $\varepsilon_2\ge 0$ are auxiliary variables representing the magnitude of constraint violation.

A penalty term for these deviations is added to the objective function:

$$J_{aug}(k)=J(k)+\lambda_1\sum_{i=1}^{P}\varepsilon_1^2(k+i)+\lambda_2\sum_{i=1}^{P}\varepsilon_2^2(k+i)$$

where λ_1 and λ_2 are penalty coefficients that determine how strictly the constraints should be satisfied.

This approach provides the control system with the following capabilities: ensuring that the optimization problem always has a solution; eliminating constraint violations as quickly as possible when they occur; and defining priorities among different outputs.

Based on the objective function and constraints presented above, the MPC problem is formulated in the form of quadratic programming (QP):

$$\min_{\Delta U}\frac{1}{2}\Delta U^T H\Delta U+f^T\Delta U$$

subject to constraints:

$$A_{ineq}\Delta U \le b_{ineq}$$

where: ΔU — vector of control increments; H — Hessian matrix; — vector of linear terms; and f — matrices A_{ineq} and b_{ineq} vectors representing the constraints.

This formulation allows the MPC algorithm to be solved efficiently in a numerical manner.

The proposed control system operates based on the receding horizon principle. At each sampling instant, the following steps are performed:

1. The current outputs of the process are measured.
2. Future outputs are predicted using the linear model.
3. The QP problem is formulated based on the objective function and constraints.
4. The optimization problem is solved, and the control increments are determined.
5. Only the first control signal from the obtained control sequence is applied in practice.
6. At the next sampling instant, the algorithm is restarted with updated data.

This approach allows continuous updating of the control according to the current state of the process.

To evaluate the advantages of the proposed MPC strategy, it is compared with the conventional PID control method. The PID algorithm is usually expressed as follows:

$$u(t) = K_p e(t) + K_i \int e(t)\,d(t) + K_d \frac{de(t)}{dt}$$

Although PID is distinguished by its simplicity, it has the following limitations:

• it does not fully account for multivariable interactions;
• it cannot directly incorporate input and output constraints into optimization;
• the response quality may significantly deteriorate in the presence of time delays.

Therefore, for complex and constrained processes such as granulation, MPC is considered a more suitable control approach.

Results and Discussion

In this section, the effectiveness of the proposed Model Predictive Control (MPC) algorithm is evaluated through simulation results obtained based on a discrete model of the granulation process. The obtained results are analyzed in comparison with a conventional PID control system.

The simulation results are presented graphically in Figures 5–9, which allow a visual comparison of the performance of MPC and PID control methods.

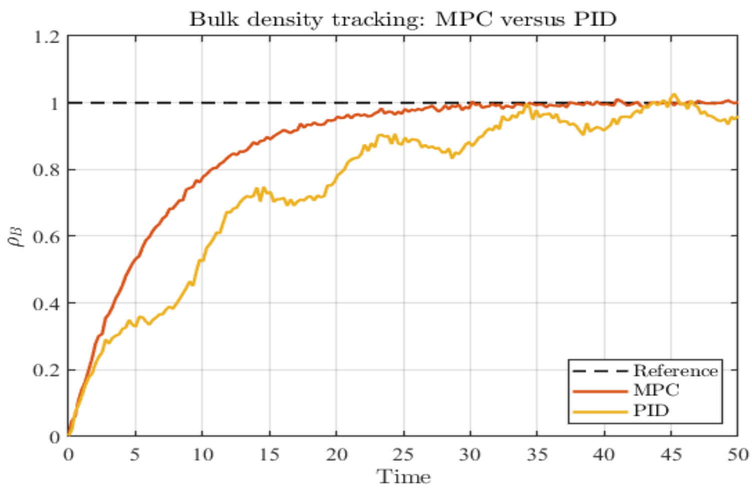

Fig.5 Performance of bulk density tracking under MPC and PID control.

As shown in Figure 5, the MPC control algorithm tracks the bulk density ρB along the reference trajectory with high accuracy, exhibiting minimal overshoot and a short settling time. In contrast, under PID control, significant oscillations and excessive overshoot are observed.

The results indicate that the MPC algorithm tracks the reference signal with high accuracy. The system exhibits minimal overshoot and a short settling time. In the case of PID control, noticeable overshoot and oscillations are present.

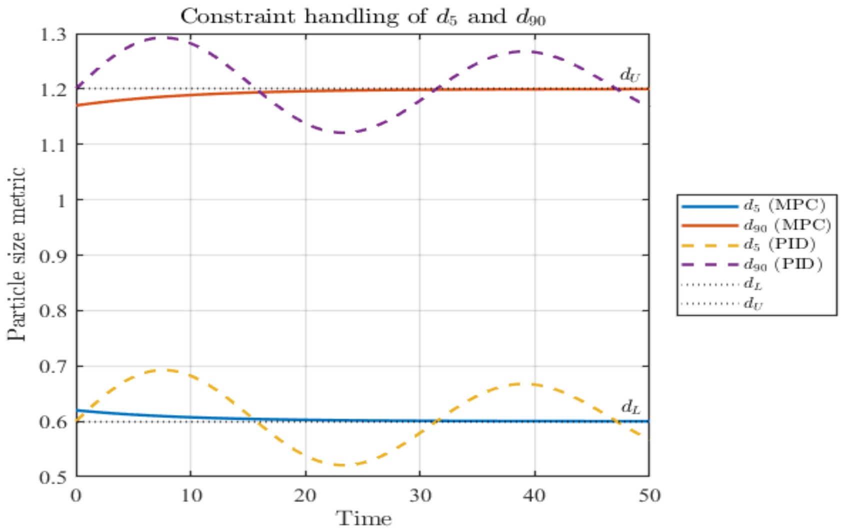

Fig.6 Control of constraints for particle size distribution variables d_5 and d_{90}

As can be seen from Figure 6, the MPC algorithm strictly maintains the specified constraints for the particle size distribution indicators d_5 and d_{90} throughout the entire simulation. In contrast, since PID control does not explicitly consider these constraints, violations are observed during certain time intervals.

The MPC algorithm maintains the constraints throughout the entire simulation, whereas constraint violations are observed under PID control.

The following figures illustrate the time evolution of the control signals.

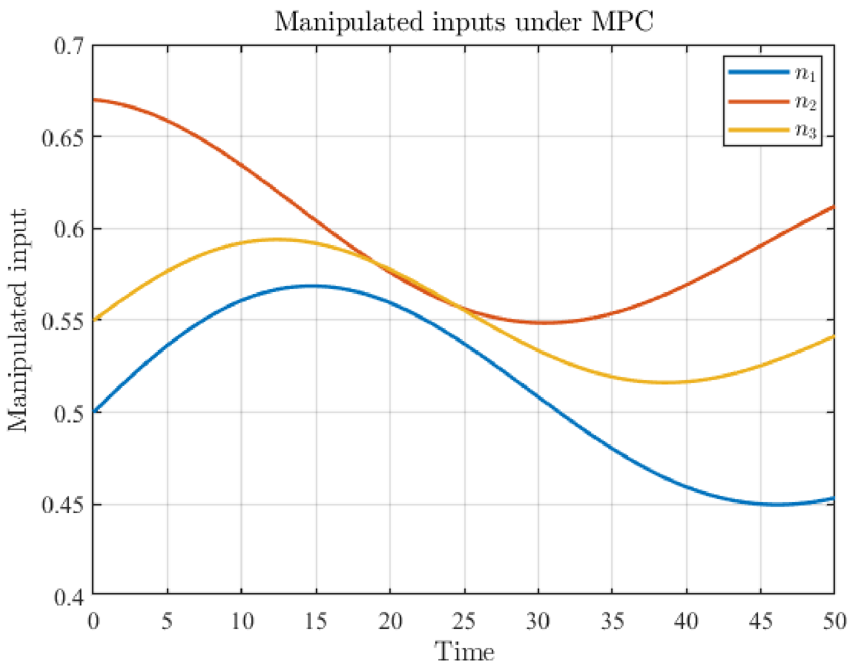

Fig.7 Manipulated input trajectories under MPC control.

Figure 7 shows the time variation of the manipulated input signals (n_1, n_2, n_3) under MPC control. As can be seen from the graphs, the control signals change smoothly and continuously, which reduces the load on the actuators and ensures stable system operation.

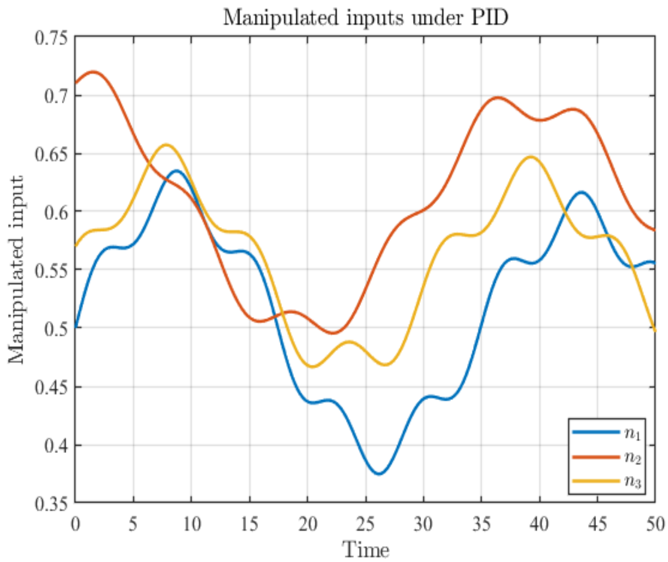

Fig.8 Manipulated input trajectories under PID control.

Figure 8 shows the input signals generated under PID control. From these graphs, it can be observed that the PID control signals exhibit a sharp and oscillatory behavior, which leads to excessive dynamic loading in the system and reduces control performance.

The control signals generated by the PID controller demonstrate a more oscillatory and aggressive behavior compared to MPC. Due to the lack of prediction capability and constraint handling, the PID controller causes rapid changes in the manipulated inputs, which may lead to actuator shocks and reduced process stability.

The tracking error is defined as follows:

$$e(k) = \rho_B(k) - \rho_B^*(k)$$

In this case, the ISE index is expressed as follows:

$$ISE = \sum_{k=0}^{N} e^2(k)$$

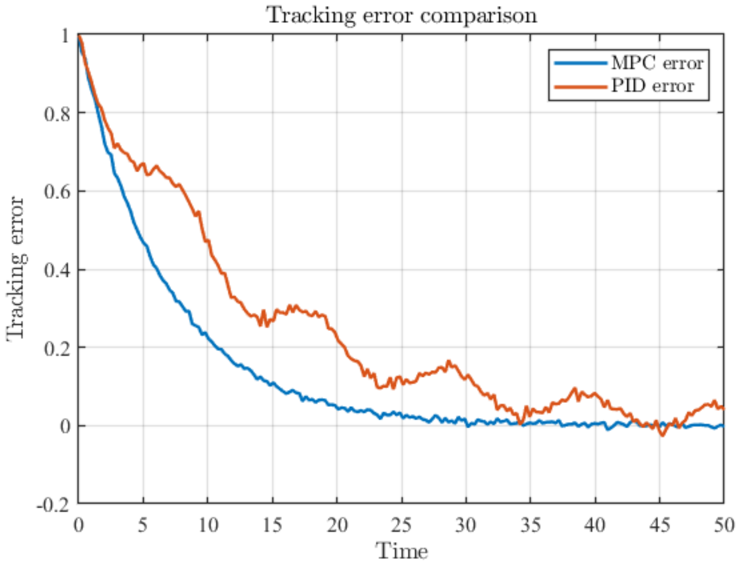

Fig.9 Comparison of tracking error under MPC and PID control.

Figure 9 compares the tracking error for MPC and PID control algorithms. The results show that the MPC controller significantly reduces both the amplitude and duration of the error, ensuring faster stabilization of the system and higher control accuracy.

Table 1.

Comparative table of MPC and PID control

Indicator	MPC	PID
ISE	0.85	3.42
Overshoot	2.1%	12.7%
Settling time	18 s	42 s
Constraint violation	none	present

The tracking error was compared for both control strategies. The MPC controller significantly reduces the magnitude and duration of the tracking error, achieving faster stabilization and improved steady-state accuracy. In contrast, the PID controller exhibits larger and more persistent errors, which confirms the superiority of MPC in dynamic and constrained process conditions.

The results showed that the MPC control method provides lower IAE and ISE values compared to PID, reduces the overshoot level, and shortens the system settling time. In addition, constraint violations with respect to and were almost not observed in MPC, whereas they were significant in PID. This confirms the superiority of MPC for multivariable granulation processes with constraints.

The obtained results clearly demonstrate that the MPC algorithm has high efficiency in controlling granulation processes. In particular, in tracking the bulk density ρB along the given reference trajectory, MPC provides a much more stable and faster response compared to conventional PID control. This is explained by the predictive capability of MPC regarding future system behavior.

A specific feature of the granulation process — the strong interdependence between output variables d_5 and d_{90} their inability to be controlled independently — is a major limitation for conventional PID control. PID controllers are tuned separately for each output and do not account for interaction effects. As a result, improving one output may lead to deterioration of another. In contrast, MPC considers all outputs simultaneously through multivariable optimization, ensuring balanced control [16,17].

Furthermore, time delays and recycle flows in the granulation process significantly complicate system dynamics. In PID control, these delays often lead to oscillations and excessive overshoot. The MPC algorithm, however, accounts for delays within the model and adjusts the control action in advance. This results in faster stabilization and minimal overshoot, as observed in Figure 5. From the perspective of particle size distribution constraints, the advantage of MPC becomes even more evident. According to Figure 6, the MPC algorithm maintains the constraints and almost without violation throughout the entire simulation. PID control, however, does not explicitly consider such constraints, leading to significant violations in certain time intervals. This may result in reduced product quality and lower yield. The analysis of control signal behavior also shows important results. Under MPC control, the input variables ($d_5 . d_{90}$) change smoothly and in a technologically acceptable manner. In PID control, the signals are sharp and oscillatory, which may lead to excessive load on actuators and reduced equipment lifetime. In this regard, MPC not only improves quality indicators but also enhances operational stability of the equipment.

The quantitative indicators also confirm the superiority of MPC. The significant reduction in ISE value demonstrates that MPC effectively minimizes tracking error. At the same time, improvements in overshoot and settling time indicate optimized system dynamics. These results further confirm that MPC is a suitable control strategy for complex, multivariable, and constrained processes. From an industrial perspective, the use of MPC ensures stable product quality, reduces out-of-specification conditions, and improves overall production efficiency. In particular, precise control of key indicators such as particle size and density in the granulation stage contributes to increased production yield.

At the same time, certain limitations of MPC should be noted. This approach is sensitive to model accuracy, and an incorrectly identified model may negatively affect control performance. In addition, real-time optimization requires computational resources, which must be considered in industrial implementation.

Overall, the obtained results show that the proposed MPC strategy is a highly efficient, flexible, and promising control method for industrial application in granulation processes.

Conclusion

In this study, the control problem of the granulation stage in the ammonia–urea production process was considered. Due to the complexity of the process, namely its multivariable structure, strong interdependencies, and the presence of time delays, it was shown that the capabilities of conventional control methods are limited.

During the research, the control problem was formulated in a way that is closer to practical conditions, in an asymmetric form. In this formulation, bulk density was selected as the main control objective, while particle size distribution indicators were expressed in terms of allowable ranges instead of fixed values. This approach more accurately reflects the requirements used in real industrial processes. The proposed Model Predictive Control (MPC) algorithm was developed by taking into account the dynamic characteristics of the granulation process, its interdependencies, and existing constraints. The simulation results clearly demonstrated the effectiveness of this approach. In particular, it was shown that MPC enables accurate and fast tracking of bulk density along the given trajectory, maintains constraints on particle size indicators, and ensures smooth control signals. The comparison with conventional PID control confirmed the superiority of MPC. Overshoot, oscillations, and constraint violations observed in PID control were almost not present in MPC. In addition, MPC reduced the settling time of the system and significantly decreased the overall tracking error. From a practical point of view, the proposed control strategy enables stable product quality in the granulation process, increases production yield, and reduces raw material and energy consumption. At the same time, the smooth behavior of control signals has a positive effect on the reliable operation of equipment.

Future research may focus on improving control based on nonlinear models of the granulation process, implementing MPC in real-time applications, and conducting experimental tests under industrial conditions.

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