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Injection Speed Optimization Based on Improved Generalized Predictive Control

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Abstract: Injection molding is a typical nonlinear system, in which there is a need for high-precision control of injection velocity to produce sophisticated products. In view of the shortcomings in control precision of existing control systems, this paper proposes an improved generalized predictive control (GPC) model for high-precision injection velocity control. The velocity response curves are studied and corresponding control action coefficients under step disturbance with different velocity constants are determined based on the characteristics of curves. To overcome large overshoot and insufficient accuracy when controlling large delay processes, the softening factor is changed to a dynamic softening factor and the initial value of reference trajectory is determined with a new manner. To verify the performance of the propsed model, extensive simulation and experimental analysis are conducted considering parameters including horizon length, prediction horizon length, control horizon length, control weighting factor and softening coefficient. The resultsreveal that the improved GPC model achieves fairly high accuracy for the control of injection velocity, the errors is controlled within 0.05 cm/s, which can meet the injection precision requirement of actual injection molding machines. Moreover, the model can guarantee the starting and finishing ends of prediction horizon to overcome the over-regulation occurring in high precision control with other algorithms, meanwhile, the model also improves the control response velocity.

Keywords: Generalized Predictive Control, Nonlinear System, Velocity Control, Control Precision

1. Introduction

With the rapid development of industries such as electronics, telecommunications, medicine and automobile, the international market's requirements for high-precision, high-performance plastic molding process have been increasing [1-5]. R&D of more advanced injection molder control system and realization of ultra-high precision injection molding are of very high engineering significance and economic value.

Injection molding is a major production process in the plastics industry [6, 7], which can generally be divided into four stages: melting, injection, holding and cooling [8]. To obtain sophisticated, consistent products, it is important to control the process parameters at each stage, of which the control of injection velocity is the most important for the product quality [9-11]. In particular, for precision injection molding products with extremely high requirements on dimensional accuracy and internal quality, the requirement on velocity control accuracy is higher [12, 13].

Velocity control of injection molding machine is rather complicated, and extensive analytical research has been done on this model. K. K. Tan and Huang [14] used the polynomial approximation approach to avoid the high-order components in the system model, which yielded fairly ideal simulation results. The approach must first implement off-line identification, so that the initial values of system parameters cover the operating point. Gao F et al. [15] proposed robust learning control on the basis of optimal learning control and conducted relevant experiment. S. N.

Huang et al. [16] combined neural network with learning control and presented the simulation results of system by assuming the presence of repetitive interference. Tsai Ching-Chih [17] proposed a method combining gain mechanism PI controller with fuzzy PI controller for optimization of velocity control curves. However, due to numerous nonlinear factors such as back pressure, hydraulic pressure, material property, melt temperature, nozzle pressure and mold cavity geometry in the injection process, the mathematical model was always flawed.

Generalized predictive control (GPC) [18, 19] is an optimal control algorithm that is based on predictive model. The GPC algorithm controls the target by using strategies such as multistep prediction, rolling optimization and feedback compensation, which can effectively overcome the influences of imprecision, nonlinearity and time-dependence of model in the industrial process control and is thus applied to multiple fields [20-22]. However, actual application has found that the algorithm often has large overshoot when controlling large delay process; besides, its control accuracy is still somewhat insufficient.

To solve the above problems, this paper focuses on studying the application of optimization-based generalized predictive algorithm in the injection velocity control for injection molding machines. The velocity response curves and corresponding control action coefficients under step disturbance with different velocity constants are analyzed by establishing Improved predictive control algorithm based on its characteristics. Finally, simulation and experiment verify that the method can highly precisely control the injection velocity of injection molding machine under different processes.

2. Typical Injection Velocity Curves and Injection Velocity Model

2.1. Typical Injection Velocity Curves

Injection velocity refers to the displacement of injection screw per unit time, whose magnitude directly influences the quality and production efficiency of plastic products. Figure 1 presents the injection molding system of the injection molding machine, where the controller controls the servo motor and servo valve based on feedbacks through analog quantity and then controls the injection unit for injection molding. Empirically, there are two typical injection velocity curves.

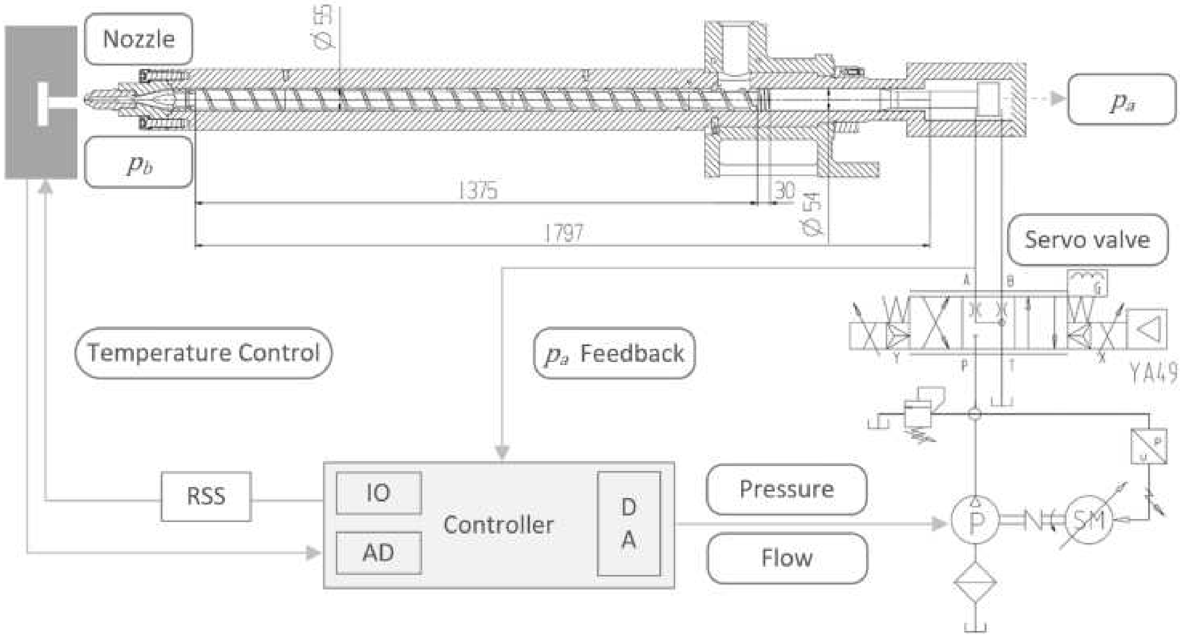
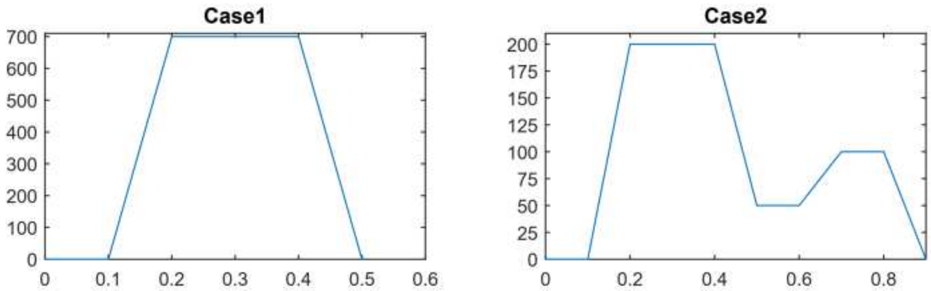


Figure 1. *Injection molding system.*

One is the velocity curve for rapid molding products as shown in Figure 2a. After the molten resin enters the mold through the nozzle, it begins to cool down. To timely fill the mold cavity with melt and to obtain high precision products with uniform density, rapid mold filling is necessary in a short period of time. If the injection is slow, the time to fill the mold will be extended correspondingly, so that the manufactured product easily has defects such as cold joints, uneven density and large stress. The use of high-velocity injection can reduce the melt temperature difference within the mold cavity and improve the pressure transfer effect, so that precision products with uniform density and small stress can be obtained. However, if the injection velocity is excessively high, it will be unfavorable to the control, so that irregular flow of melt is highly likely at places like gate, and material scorching as well as poor suction and exhaustion of gas will be caused, which will affect the surface smoothness of products as well.

The other is the injection curve for general products as shown in Figure 2b. Such products are not demanding on the injection velocity, but are highly demanding on the velocity following feature. In the actual production of such products, injection velocities at the gate and various points on the mold cross-section are non-uniform. In part one where the injection just begins, the melt passes through the runner, and the velocity accelerates very quickly, then the injection proceeds at a relatively stable velocity. In part two, injection velocity declines rapidly, and the main purpose of doing so is to eliminate the radial lines at the gate. Afterwards, in part three, injection velocity again rises to a relatively high value and holds for a certain period of time since the molten material should be filled onto the surface of mold. Finally, velocity must be rapidly reduced to a very low value in order to eliminate the flash and overfill.



(a) (b)

Figure 2. *Typical injection velocity curves; (a) is the velocity curve for rapid molding products; (b) is the injection curve for general products.*

2.2. Injection Velocity Model

K. K. Tan established a linear system equivalent to a typical inertial loop for injection model and performed simulation on this basis. However, his model is not universal as it is linear and too simple. C. P. Chiu, J. H. Wei, M. Rafizadeh established nonlinear models of injection molding process, respectively. This paper also uses the M. Rafizadeh model as the main simulation target to perform verification.

$$\begin{cases} \mathrm{d} = v_d \\ p_a = \frac{\beta_1}{v_{10} + a_{1d}}(\mu - a_1 v_d) \\ p_b = \frac{\beta_2}{v_{20} + a_{2d}}\left(a_2 v_d - q_p\right) \\ v_d = \frac{1}{m}\left[p_a a_1 - p_b a_2 - 2\pi\eta r^{1-n}(l_0 + d)\left(\frac{(s-1)v_d}{k^{1-s}-1}\right)^n\right] \end{cases} \quad (1)$$

Where d is the injection position; v_d is the injection velocity; p_a is the hydraulic pressure; p_b is the nozzle pressure; q_p is the polymer flow rate; u is the hydraulic oil flowing into injection cylinder; v_{10} is the oil capacity of injection edge; a_{1d} is the sectional area of oil cylinder; β_1 is the volume modulus of liquid; v_{20} is the volume of polymer in drum; a_{2d} is the sectional area of drum; m is the weight of screw; *r* is the radius of nozzle; *n* is the power exponent of polymer melt; η is the viscosity coefficient of polymer; *k* is the ratio of screw radius to nozzle radius; *s* is *1/n*; and l_0 the length of screw.

3. GPC-Based Injection Velocity Control Model

3.1. Standard GPC Algorithm

The prediction model in GPC predicts the output of object at future P moment based on the historical information (system's output and control action) and the future input information of the system. Where P is the prediction step size. The model gets rid of the previous requirements that are based on rigorous mathematical model, which has the function of predicting the system's future dynamic behavior. Thus, we can use the prediction model to gain priori knowledge of the optimization of predictive control, thereby deciding the control input that we will use, therefore the output variation of the future controlled object is in line with the expected goal. That is, control quantity $\mathrm{u(k)}$ at present and future L moment are calculated according to the deviation $\mathrm{e(k) = y(k) - yM(k)}$ between the actual output $\mathrm{y(k)}$ and the predicted output $\mathrm{yM(k)}$ of the system to minimize the deviation $\mathrm{e(k)}$. Where L is the control step size. Assuming that the controlled object can be described using the following discrete difference equation:

$$A(z^{-1})y(k) = B(z^{-1})u(k-1) + \xi(k)/\Delta \quad (2)$$

Where $y(k)$, $u(k-1)$ and $\xi(k)$ are the output, input and interference information of the system, respectively, and Δ is the differential operator.

In addition to predicting the model, the GPC algorithm also needs to perform rolling optimization of the model. However, there are many differences between the optimization of the predictive control and the usual optimal control algorithm, which is reflected in the way that it uses a rolling, usually finite horizon optimization strategy rather than a constant global optimization goal. At each sampling time, the optimal performance index generally involves only a finite time in the future, and at the next sampling time, such an optimal horizon moves forward at the same time. The prediction model should be corrected by the deviation between the actual output at this time and the output predicted by the model, then new control action should be produced through a new optimization. A currently common objective function for rolling optimization is shown in (3) below:

$$J = \sum_{j=N_0}^{N_l}[y(k+j) - y_r(k+j)]^2 + \lambda\sum_{j=1}^{N_u}[\Delta u(k+j-1)]^2 \quad (3)$$

Where N_0 is the minimum prediction horizon; Nu is the maximum prediction horizon; Nu is the control horizon; and λ the control weighting factor. To ensure the system output y (k)'s tracking stability of set value w, the following flexible processing is generally performed on the set value, where yr is called the reference trajectory.

$$y_r(k) = y(k) \tag{4}$$

$$y_r(k+j) = ay_r(k+j-1) + (1-a)w \tag{5}$$

Where j = 1, 2...; and a is the softening factor, $0 \leq a \leq 1$;

Hence, GPC is actually to solve the control increment $\Delta u(k)\ldots\Delta u(k+N_u-1)$ and to minimize the objective function J.

Since predictive control is a closed-loop control algorithm, the optimization base point should be consistent with the system reality during rolling optimization. However, as a basic prediction model, it only roughly describes the dynamic characteristics of object. Due to the nonlinear, time-varying, model mismatch and interference factors present in the actual system, the invariant model-based prediction cannot agree completely with the actual situation. Therefore, addition of feedback compensation process is needed into the GPC algorithm aside from the above prediction model and rolling optimization.

Feedback compensation is the prerequisite for rolling optimization. So after determining a series of future control actions through optimization, the control tend to deviate from ideal state under the predictive control algorithm, with the aim of preventing model mismatch or environmental interference. At the next moment, the algorithm monitors the actual output of object first, then corrects or compensates for the prediction model through various feedback strategies, followed by a new optimization. There are diverse ways to achieve feedback compensation. For example, we can predict and compensate for future errors while keeping the model unchanged; we can also modify the prediction model with on-line identification. Therefore, the optimization in predictive control is based on model and feedback information so as to form closed-loop optimization.

3.2. An Improved GPC Algorithm

Despite many advantages, the GPC algorithm has been found to have large overshoot and somewhat insufficient accuracy when controlling large delay processes in the actual application. The control increment u of the algorithm is directly proportional to the value of polynomial $y_r - H\Delta u(k-1) - Fy(k)$. y_r is the reference trajectory, while $H\Delta u(k-1) - Fy(k)$ is the optimal predicted value at a control increment of 0. With the increase of j, the deviation between the reference trajectory and $H\Delta u(k-1) - Fy(k)$ also increases. When the controlled object has no pure delay, reference trajectory and $H\Delta u(k-1) - Fy(k)$ have the same value y(k) at the starting and finishing ends of prediction horizon, and $y_r - H\Delta u(k-1) - Fy(k)$ is not excessively large, so the control will be relatively smooth. When the controlled object has large delay, reference trajectory and $H\Delta u(k-1) - Fy(k)$ have large error at the starting and finishing ends k+N0 of prediction horizon, so that the control increment is excessively large, which affects the stability of the control system.

Therefore, this paper proposes an improved GPC algorithm based on $H\Delta u(k-1) - Fy(k)$, so that the reference trajectory value at each time on the prediction horizon is always the weighted sum of $H\Delta u(k-1) - Fy(k)$ and set value at this time, as shown in (6) below:

$$y_r(k+j) = a[H_j\Delta u(k-1) + F_jy(k)] + (1-a)w \tag{6}$$

Where $j = N_0\ldots N_l$.

Therefore, the initial value of reference trajectory is modified in the above manner to overcome the defect of excessively large $y_r - H\Delta u(k-1) - Fy(k)$ at the starting end of prediction horizon in controlling the large delay process. That is, excessively large overshoot resulting from excessively large control increment can be avoided. Meanwhile, to meet the rapidity requirement, softening factor is also optimized to some extent here, which is changed to a dynamic softening factor. Accordingly, the complete reference trajectory selected is as shown in the following formula (7):

$$\begin{cases} a_1(j) = a - a(j-N_0)/(N_l - N_0) \\ y_r(k+j) = a(j)[H_j\Delta u(k-1) + F_jy(k)] + (1-a(j))w \end{cases} \tag{7}$$

Where $j = N_0\ldots N_l$.

Through the above optimization, the proportion of $H\Delta u(k-1) - Fy(k)$ in the reference trajectory is in a progressively declining trend. This not only can ensure the initial end of prediction horizon, but also avoids overshooting while ensuring the rapidity of control system, so that the control quantity follows the set value timely.

4. Simulation and Experimentation

4.1. Selection of Control Parameters

The control performance of GPC is greatly related to the selection of model control parameters [23, 24]. The selection of different model parameters will affect the quality of control. The function and selection of GPC parameters generally comply with the following principles:

(1) Horizon length (T): In GPC, selection of sampling period is very important. Excessively large T is conducive to the system stability, but will ignore some interference to result in inaccurate model and reduced control performance. Excessively small T will increase the computational burden of system. Generally, selection of T should follow the Shannon theorem while taking into account the interference requirements.

(2) Prediction horizon length (N): The prediction length N is related to the stability of system. The greater the N, the better the system stability, the complex the computation, and the slower the response. The less the N, the more unstable the system, and the faster the response. Generally, N is selected between 5-15.

(3) Control horizon length (Nu): The control length Nu also has a significant impact on the stability of system. The less the Nu, the stronger the constraint on control, and the more conducive to the system stability. The greater the Nu, the larger the change in control increment, and the higher the rapidity and flexibility of system. Generally, Nu is taken between 1-3. Of course, the greater the Nu, the longer the computation time.

(4) Control weighting factor (λ): In the objective function of rolling optimization, it is necessary to prevent the system overshooting or oscillation in order to suppress the excessive change of control quantity. Excessively large λ decreases the output of control quantity and slows down the system response, but is conducive to the system stability. If $\lambda = 0$, there will be no constraint on the control quantity.

(5) Softening coefficient (α): Softening coefficient α is related to the robustness of system. If α is very small, the reference trajectory will reach the set value very quickly, which is not conducive to enhancing the system robustness. If α is too large, the system will change slowly, and robustness will be enhanced. Thus, selection of α should trade off between system dynamics and robustness, which is generally between 0-1.

(6) It is also found through practical application that the maximum prediction horizon N and the control horizon Nu are not only two important parameters influencing the control effect, but are also mutually influential. When increasing the maximum prediction horizon, the control horizon must be increased accordingly, otherwise it will easily cause instability of the control system.

4.2. Model Simulation Results

According to the above selection of relevant control parameters for the generalized predictive algorithm, the model parameters used in the simulation herein are listed in Table 1.

By corresponding the injection velocity V_z of M. Rafizadeh model to $y(k)$ of the GPC algorithm, the process of simulation is basically set within 2 sec because the injection molding machine can complete a full injection molding motion in about 2 sec.

Table 1. *GPC algorithm related control parameters.*

Model system parameter	value
Horizon length (T)	10
Prediction horizon length (N)	3
Control horizon length (Nu)	3
Control weighting factor (λ)	0.1
Softening factor (α)	0.01

Simulation 1: To better reflect the effectiveness of the present model algorithm, the first simulation aims to observe the model's controllability over a single object by giving a basic object. The results are shown in Figure 3 below:

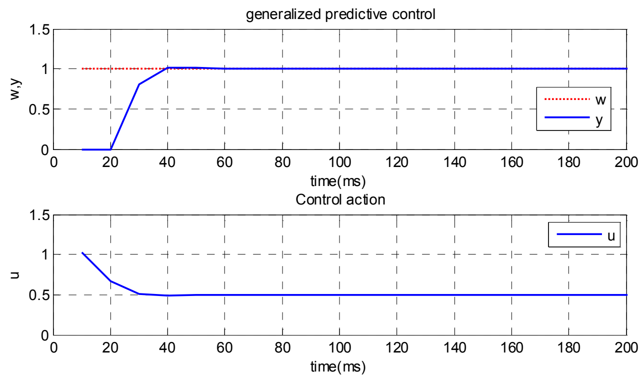
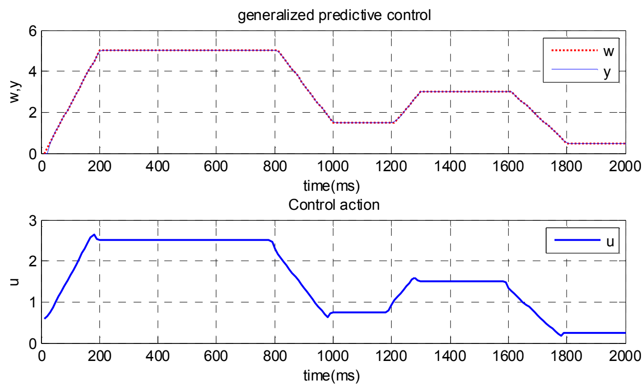


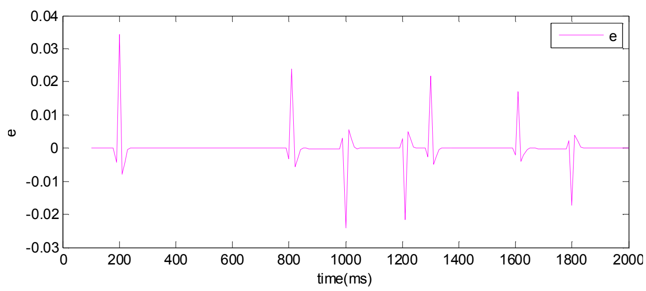
Figure 3. *Results of object control process for GPC algorithm.*

It can be seen from the simulation results in Figure 3 that the improved GPC algorithm proposed herein basically controls the output value within an allowable target value range at 60 ms and can quickly achieve the tracking and control of target value. Meanwhile, the variation of control effect coefficient u shows that the control action also gradually decreases over time and reaches a stable value at 40 ms. This value remains stable over time.

Simulation 2: The injection velocity V_z of M. Rafizadeh model is taken as the control object of model. The velocity tracking curves obtained are shown in Figure 4 below:



(a)

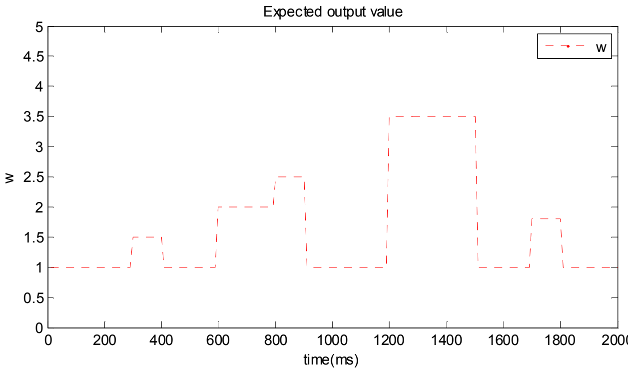


(b)

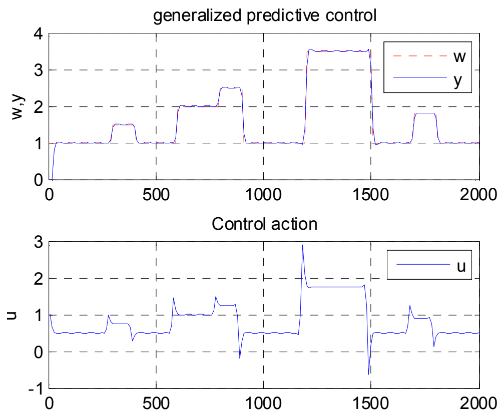
Figure 4. *Results of injection velocity control response; Figure a Injection velocity control curves at different time periods; Figure b Errors between control and expected values.*

It can be seen from the simulation results in Figure 4 that the improved GPC algorithm proposed herein achieves fairly high accuracy for the control of injection velocity, with some errors present only during the step disturbance of each stage. Nevertheless, the magnitude of these errors is controlled within 0.05 cm/s, which can meet the injection precision requirement of actual injection molding machines. From a complete injection process perspective, the control model can control the velocity within the allowable error range, which has higher control precision than other model algorithms.

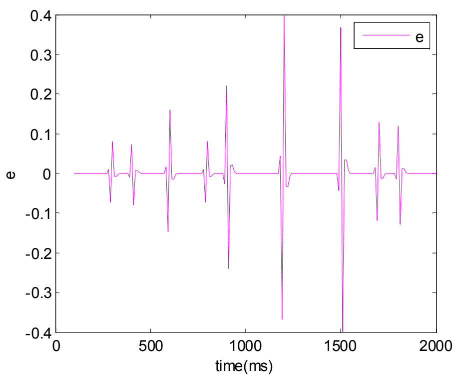
Simulation 3: To more fully reflect the advantages of the present model, it is used in the process of velocity control with multi-stage step disturbances. The simulated desired target value and the results of velocity control tracking simulation are shown in Figure 5 below:



(a)



(b)



(c)

Figure 5. *Velocity control response results during step disturbance; Figure a Target step disturbance values at different time periods; Figure b Control curve in which multiple step disturbances occur at different time periods; Figure c Errors between control and target values.*

It can be seen from the simulation results in Figure 5 that the improved GPC algorithm proposed in this paper still has high precision when used in the velocity control process with step disturbances. The model only has a certain error in each step disturbance, which is only 10% of the change in step disturbance velocity. From the perspective of a complete control process with multi-stage step disturbances, the model can well control the velocity within a stable range. Besides, it can be seen from the variation of control coefficient that the control coefficient of the model can respond quickly.

4.3. Experimental Results

Figure 6 presents the experimental setup and control flow. The main experimental equipment is an injection molding machine with 380 t hydraulic toggle mechanism, whose injection unit parameters are listed in Table 2. DELL Vostro 14 3000 Series PC with 1.9 GHZ dual-core frequency and 4G DDR3 memory is used for simulation and data processing. KEBA CP032 controller is used, which controls the servo drive and servo valve through 0-10 V analog quantity and controls the opening and closing of magnetic exchange valve through the IO point output. Servo drive uses the Inovance 1 IS580T080-R1-1; motor uses the Inovance 1 ISMG2-48D17CD-R131F with a maximum speed of 2000 r/min; and servo valve uses the ATOS DPZO-T-373 S5/D. During experiment, the actual position is fed back via electronic scale, which is the MTS magnetostrictive sensor with an accuracy of ±0.002 mm.

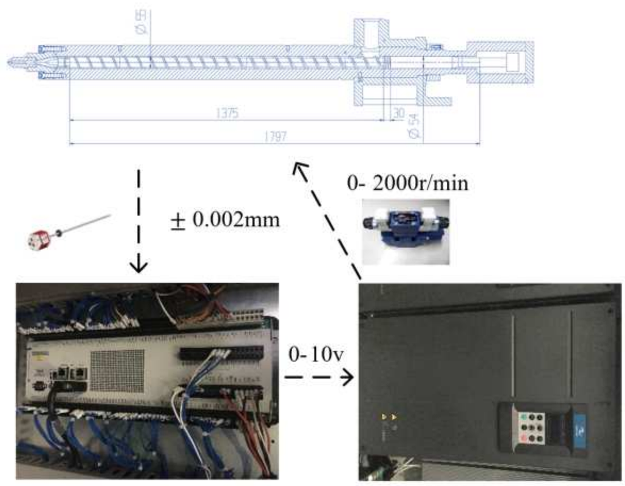


Figure 6. *Experimental setup and control flow.*

Table 2. *Machine parameters.*

Parameter	value
Screw diameter (mm)	55.0
Screw length to diameter ratio (L/D)	25.0
Theoretical capacity (cm^3)	601
Injection pressure (Mpa)	187.4
Maximum empty injection velocity (cm^3/s)	857
Injection stroke (mm)	253
Screw speed (rpm)	300
Maximum pump pressure (Mpa)	17.5
Pump motor power (kw)	97

Figure 7 presents the control status of two typical injection curves at different velocities and injection amounts under GPC. (a) and (b) show the velocity control status at maximum injection velocities of 200 mm/s and 400 mm/s under a 60 mm injection amount. (c) and (d) show the velocity control status at maximum velocities of 300 mm/s and 200 mm/s under a 90 mm injection amount.

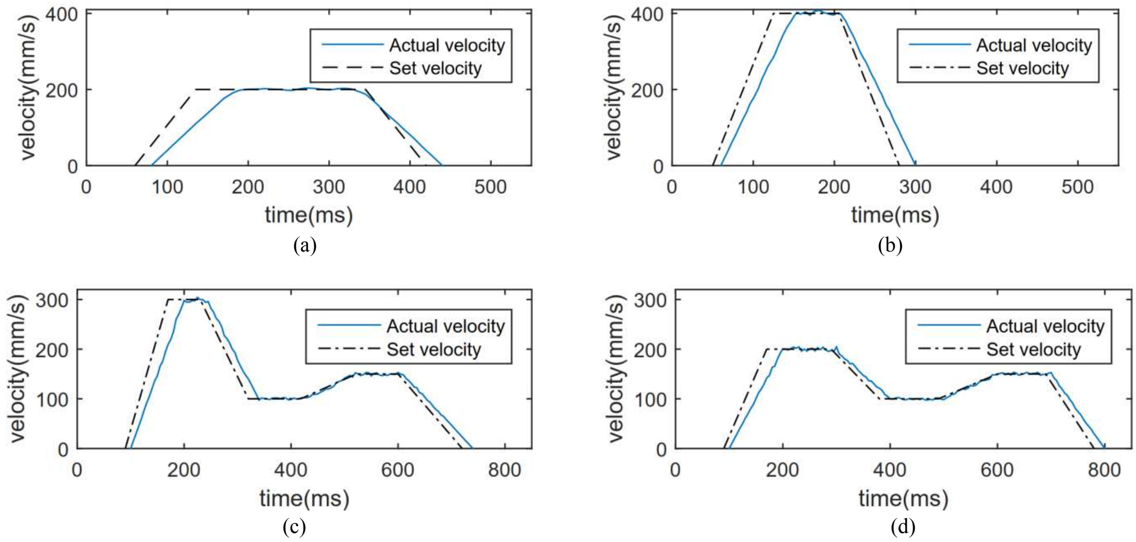


Figure 7. *Control status of two typical injection curves at different velocities and injection amounts under GPC. (a) and (b) present the velocity control status at maximum injection velocities of 200 mm/s and 400 mm/s under a 60 mm injection amount. (c) and (d) present the velocity control status at maximum velocities of 300 mm/s and 200 mm/s under a 90 mm injection amount.*

5. Conclusion

In this paper, an injection velocity control model based on the Improved generalized predictive algorithm is proposed on the basis of studying the typical injection velocity curves and injection velocity model of injection molding machine, in order to overcome the accuracy defects of existing control systems. According to the characteristics of the algorithm, relevant parameters used in the model control process are determined. Meanwhile, to better reflect the effectiveness of the present model algorithm, the injection control effect of typical injection curves is simulated separately. Finally, effectiveness of the method is verified through experimentation. The results show that: (1) The model can guarantee the starting and finishing ends of prediction horizon to overcome the over-regulation occurring in high precision control with other algorithms. Besides, it also improves the control response velocity. (2) The improved GPC algorithm proposed herein can be applied to a variety of injection molding processes.

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