3D-Surface-Model for Injection Speed Process

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ABSTRACT

Injection velocity control in plastic injection molding is challenging as this process is inherently nonlinear, requiring an adaptive control strategy for good tracking of complex velocity trajectories. In this paper, a surface based model approach is developed tracking complex trajectories of injection velocity. This technique employs a 3-dimensional (3D) nonlinear surface model of the controlled variable (injection velocity) in the overall control architecture to calculate the manipulated variable or control action to a hydraulic servovalve. The strategy uses the controlled and manipulated variables as inputs to the 3D surface to update the nonlinear plant and controller parameters while the closed-loop control is executed, thereby handling the nonlinear characteristics of the plant being controlled.

Keywords: Predictive Control, Modeling, Nonlinear Systems, Injection Molding Machine.

1. INTRODUCTION

The application of injection molding for plastic part manufacturing is best suited for producing high quality plastic components associated with electronic devices, household tools, automobiles aerospace applications and others [1,2]. The molten polymer is injected into a mold, cooled and solidified, taking the shape of the mold cavity [3]. The injection mold filling process starts with the axial movement of an injection screw at a predetermined velocity. This process or system contains a hydraulic servovalve that receives an analog control signal which is evaluated by a control algorithm [4].

It is well known that to obtain tight performance when controlling a process, good knowledge of that process is necessary. Several models for the injection velocity process have been developed [5,6,7]. Paul et al. [6] developed a dynamic model for the filling phase by solving the continuity and momentum equations of the hydraulic unit and the continuity and energy equations of the polymer inside the barrel and the mold cavity. While these models are reasonable accurate, the main drawback of these approaches is that the cavity pressure was assumed to be zero and the melted plastic flow rate was assumed to be at a steady state [8]. Furthermore, these models are generally for a specific polymer, which are not readily solved and not suitable for integration in real time process control [8].

A predictive based controller for the screw velocity in injection molding was developed by Huang, et al. [9] by selecting a state model and considering the process disturbances to design the predictive controller. Also, this controller used a steady state Kalman filter to predict the future state of the screw velocity in an injection molding machine. An adaptive predictive control scheme was developed in injection molding by Hernandez et al. [10] for controlling the part average surface temperature within the mold cavity. In this approach, the controller and plant parameters were updated every control timestep.

Dubay et al. [11] used a multi-model approach Model Predictive Control (MPC) [12] to overcome the nonlinearity effects of screw injection velocity with improved results in comparison to the original controller form. The drawback on the multi-model controller is that there was no criterion for selecting the dynamic matrices during closed-loop control. Furthermore, the selection of the models was based on step changes in setpoint profile which is not suitable for tracking setpoint trajectories.

Recently, Dubay et al. [13] developed a continuous form of a model predictive controller which is constructed from the actual nonlinear behavior of the injection velocity process. In this method, the controller dynamic matrix is formulated from continuous nonlinear functions of the manipulated variable. At each sampling instant, the dynamic matrix is re-evaluated from these functions and then used to determine the control move. This controller approach provided better closed-loop performance than the multi-model approach [10]. However, it only considers the nonlinear behavior of the system as a function of the manipulated variable only without considering the state of the controlled variable especially when the plant is moving from one nonlinear state to another.

Based on the above mentioned investigations, developing an advanced controller for nonlinear systems is a considerable challenge, and an important area of research. This work is aimed at developing a nonlinear control strategy for injection velocity tracking control. The proposed method uses the controlled and manipulated variables as inputs to a 3D surface process model to update the several nonlinear parameters while closed-loop control is executed. The performance of the enhanced control algorithms are tested and implemented on a 150-tonne injection molding machine (IMM).

2. THEORITICAL FORMULATION

In this section, the procedure for obtaining a multi-dimensional surface model of the nonlinear system (injection velocity) will be presented.

In many control applications, the plant can be approximated as a first order plus dead time (FOPDT) model [14] expressed as

$$\Theta(s) = \frac{K_p e^{-T_d s}}{\tau_p s + 1} \qquad (1)$$

where K_p is the process gain, τ_p is the time constant and T_d is the dead time. In this paper, the premise of this work is based on the assumption that a FOPDT model structure can be used to model open-loop dynamic behaviour of a nonlinear system from timestep to timestep during closed-loop control. Consequently, the plant is piecewise linear during the sampling interval or timestep. Also, the open-loop dynamics of the plant can be obtained at any state during closed-loop control using the 3D surface model.

The general discrete FOPDT model as in Eq. (1) can be expressed as [14]

$$\Theta(z^{-1}) = \frac{B(z^{-1})}{A(z^{-1})} z^{-D} = \frac{\beta z^{-1}}{1 - \alpha z^{-1}} z^{-D} \qquad (2)$$

The polynomials $A(z^{-1})$ and $B(z^{-1})$ contain coefficients associated with the controlled and manipulated variables respectively. The parameter D is assumed to be an integer constant in this investigation and can be calculated as $(D = \frac{T_d}{\Delta t})$ where the timestep Δt is much smaller than τ_p. The enhanced control strategy incorporates the manipulated and controlled variables (u, y_m) at every Δt into the design of the controller.

The nonlinear plant parameters (gain and time constant) are expressed as functions of (u, y_m)

$$\begin{aligned} K_p &= f(u, y_m) \\ \tau_p &= f(u, y_m) \end{aligned} \qquad (3)$$

The FOPDT model variables (α, β) in Eq. (2) are directly related to the controlled variables (u, y_m). Using Eq. (3), (α, β) are

$$\begin{aligned} \alpha(u, y_m) &= e^{-\frac{\Delta t}{\tau_p}} \\ \beta(u, y_m) &= K_p \left[1 - e^{-\frac{\Delta t}{\tau_p}} \right] = K_p [1 - \alpha] \end{aligned} \qquad (4)$$

The model variables (α, β) are calculated every from nonlinear functions in Eq. (4). The usefulness and applicability of Eq. (4) can be better understood as a three-dimensional (3D) workspace or surface plot. The 3D surface can provide graphical information on plant nonlinearities such as saturation, unstable and unbounded regions, discontinuities and the nonlinear variations in the process parameters (K_p, τ_p). This 3D relationship for injection velocity will be illustrated later and the steps required obtaining this surface presented.

3. 3D NONLINEAR SURFACE

The 3D surface of the FOPDT model variables (α, β) are generated for injection velocity process by conducting several groups or sets of open-loop tests as shown in Figure 1-5. Using several DC voltage inputs $u(t)$ (which is a negative voltage in this study) with the hydraulic servovalve noted that each open-loop test commences from a state y_m which is zero initially and nonzero throughout. From these tests and results, valuable information is obtained about the plant, indicating its nonlinear dynamic behavior in relation to (u, y_m).

The process parameters (K_p, τ_p) are extracted from these tests using standard gain and time constant equations, and the results are depicted in Figure 4. Using Eq. (4), the model variables (α, β) are presented as a 3D surface as shown in Figure 5. Regions of high nonlinearity of the process gain K_p can be observed for high input $u \in [-3, -5]$. Moreover, within this *u* range, K_p becomes severely nonlinear for high speeds where the measured value $y_m \geq 60$ mm/sec. On the other hand, the process parameter τ_p shows a linear behaviour for high speeds where τ_p is almost constant around 0.08 sec indicating that the process has a very fast response. These observations are clearly demonstrated in the open-loop tests Figure 1, Figure 2, and Figure 3.

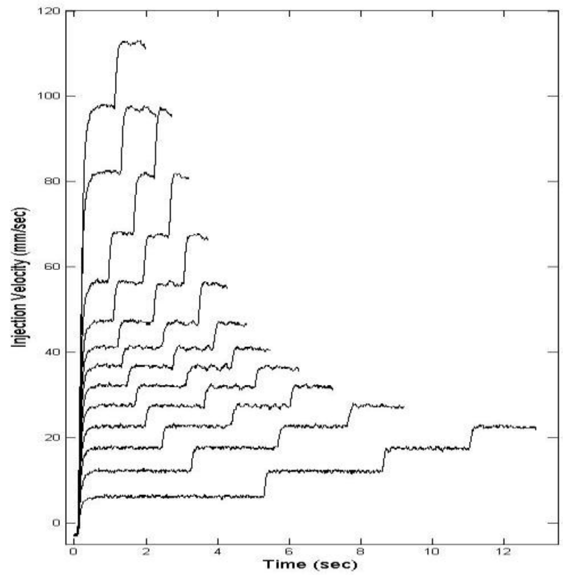

Figure 1 Open-loop tests (group 1) of the injection velocity process

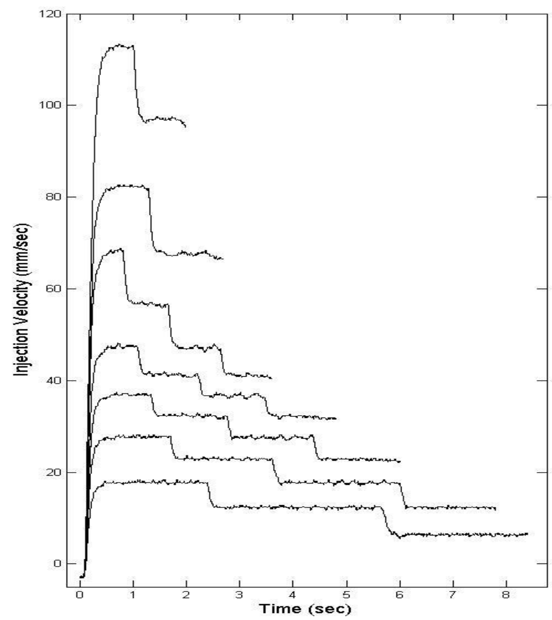

Figure 2 Open-loop tests (group 2) of the injection velocity process

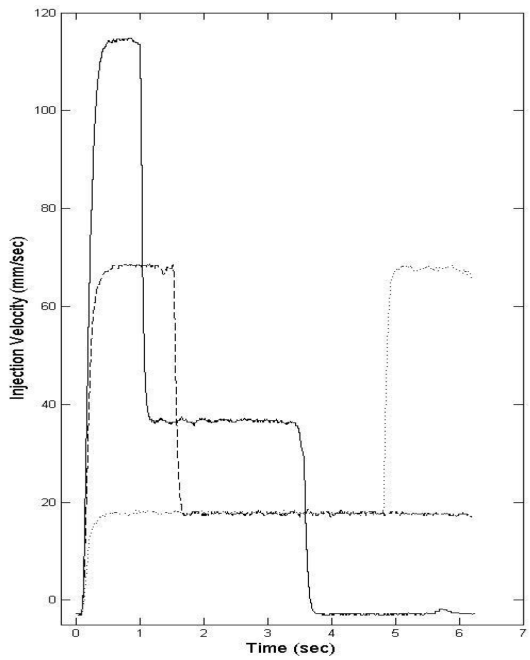

Figure 3 Open-loop tests (group 3) of the injection velocity process

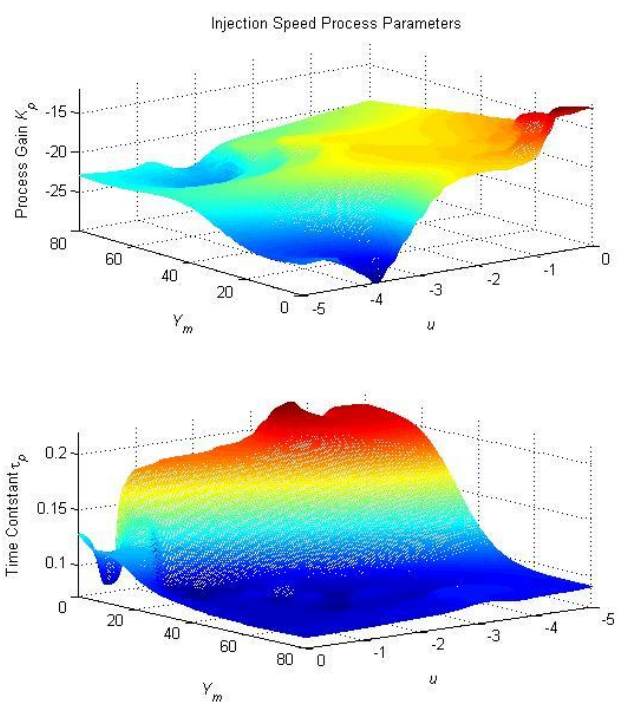

Figure 4 The process parameters (K_p, τ_p) as functions of (u, y_m)

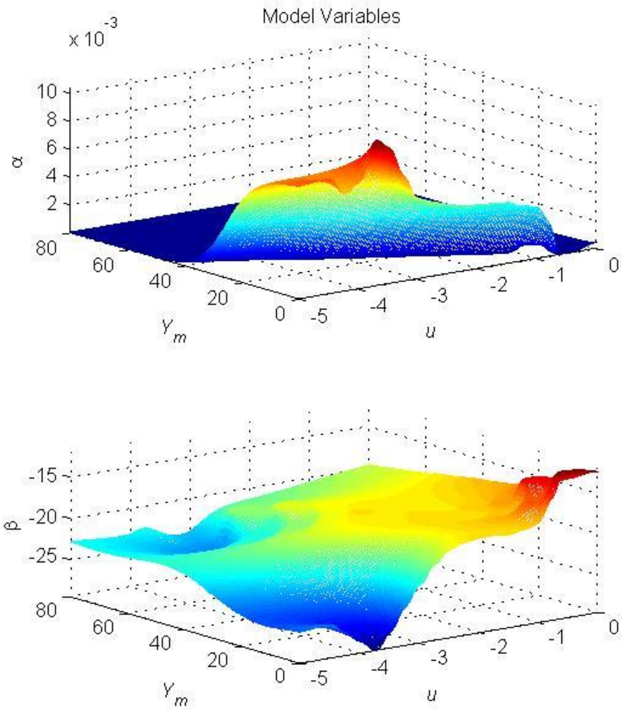

Figure 5 The 3D surface for the injection velocity process

A general diagram of the IMM is shown in Figure 6 where the controlled variable is the translational screw velocity as it injects molten plastic into a mold cavity. A 16-bit data acquisition (DAQ) board is used to monitor the velocity transducer output (DC voltage) which provides the control. The hydraulic servovalve receives analog control signals from the DAQ which is generated by the derived control algorithms using a C-based language programming software, LabWindows CVI. More details on the injection velocity process can be found in [15].

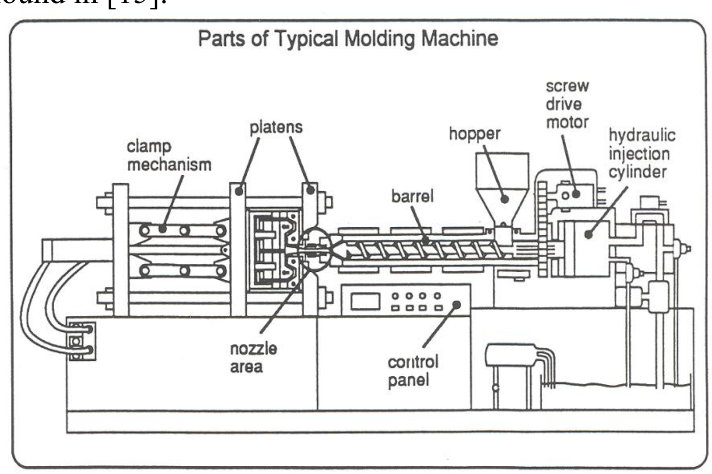

Figure 6. 150-tonne injection molding machine

4. CONCLUSIONS

A unique modeling technique for injection speed process is presented in this paper. The methodology requires large number of open loop tests of the process to capture the dynamic characteristics of the plant. Sufficient open loop tests of the injection speed were conducted and the process gain and time constant parameters were extracted and presented in a 3-dimensional surface covering the ranges of the control signal and injection speed. The proposed method was tested in simulation with improved closed loop performance. A future work using the surface model of the injection speed will be implemented in real time application for controlling the speed of 150-tonne injection molding machine.

5. REFERENCES

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