12th IFAC International Symposium on
Advanced Control of Chemical Processes
July 14-17, 2024. Toronto, Canada

Utilizing Neural Networks for Image-based Model Predictive Controller of a batch Rotational Molding process

Aswin Chandrasekar, Hassan Abdulhussain, Michael R. Thompson, Prashant Mhaskar

McMaster University

Abstract: We present a data-driven modelling and control approach for batch processes utilizing information from thermal images for feedback control. This work is driven by the requirement of utilizing the thermal image data that is the sole output of the system for feedback control. The overall goal here, like in many batch processes, is to obtain products with quality variables which match the user's specifications. The quality variables of the product cannot be measured online and is only measurable after the batch has terminated. The control problem is therefore not a setpoint tracking problem. We propose a multi-layered modelling approach. We first have a dimensionality reduction technique to reduce the high dimensional image to a set of few representative outputs. Then, we apply subspace identification (SSID) to identify a Linear Time Invariant (LTI) State space (SS) model between the inputs and the reduced outputs, and finally we construct a Partial Least Squares (PLS) model between the terminal states of a batch (identified using SSID) and the product qualities obtained for that particular batch. This model is utilized in a Model Predictive Control (MPC) formulation. We demonstrate the working of the MPC by showing its ability to achieve products with good quality.

Keywords: Image-based Model Predictive Control, Batch Process Control, Quality Control

1. INTRODUCTION

Most industrial processes, regardless of the field, share the common goal of producing high-quality products. Occasionally, batch operations are favored, as seen in pharmaceutical or biochemical applications, prioritizing quality over quantity. However, this emphasis on quality necessitates the development of a suitable control routine for the process, a critical task for maintaining consistent product quality. Model Predictive Controllers (MPC) have traditionally found use in various industrial applications. An MPC relies on an underlying dynamic process model, empowering the controller to forecast future process states and take optimal control actions. It's worth noting that constructing an effective model poses a challenge, particularly in processes lacking a first-principles model. An even more formidable challenge, and opportunity, arises with the integration of non-traditional sensors like sound or image data. In such instances, the model development and the resulting MPC framework must be adapted to preprocess and accommodate high-dimensional output data before being deployed in a closed-loop system.

There have been some work in utilizing high dimensional data effectively for feedback control but most of the image based modelling has been done in the context of soft sensing applications like monitoring and fault detection (Gopaluni et al. (2020)). Narasingam and Kwon (2017) have applied Dynamic Mode Decomposition (DMDc) directly on spatial CFD (Computational Fluid Dynamics) data to construct the dynamic between the inputs and the outputs, which are known specific points in the spatial data. They design an MPC to track the desired setpoint concentrations at these specific locations. In this case, it is safe to assume that the states of the process are present in the high dimensional CFD data, and moreover the mapping between the states and the output is known to the authors (i.e., data at specific locations). In most cases, these two assumptions may not hold true. Likewise Lu and Zavala (2021) have used DMDc on thermal images on a system with multiple heating inputs spread across the spatial field. In particular they work with a desired reference thermal image as a setpoint for the MPC. Often in processes, one might not have a high dimensional setpoint available for MPC implementation, and moreover, the desired target might not be in the form of a setpoint in the first place, but rather for the processed product to meet a certain quality demand. There are other work (Masti and Bemporad (2021)) which combine the reduction of high dimensional data and constructing the dynamic model into one Neural Network model, but these approaches assume high volume of available data. In our case, and in most batch processes, we deal with limited amount of experimental data and might not have the luxury to run too many experiments considering the material and the energy costs.

Considering these issues, we present a general modelling approach to model the process and specifically the quality variables associated with batch processes. This work focuses on designing an MPC for a Bi-axial Rotational Molding setup which is a batch process used for manufacturing hollow plastics. The system has only one heater as the input. The mold rotates biaxially inside the oven and a thermal imaging camera is placed outside the oven to capture the image of the mold, which is the only continuously measured output of the system, through a window slit. Although the rotation speed is given along with the equipment, the rotation is not perfect and hence the camera cannot be hard-coded to take images at particular instances to get the mold in the frame perfectly. Furthermore, there are two quality variables associated with the molded product; the sinkhole area percentage and the impact strength, which can be measured only through destructive means, only after the experiment is done. It is essential that the MPC is designed taking into consideration the aforementioned challenges.

The proposed modelling strategy is as follows. First a neural network-based classifier is trained on all the images of a batch, to detect whether or not the box is in the camera frame. For the images for which the box is detected, we need a way to reduce the high dimensional image data to a representative (lower dimensional) set of variables which reasonably represent the dynamics of the mold temperature- and/or even more importantly, captures the information necessary to estimate the final product quality. To achieve this, we fit a Principal Component Analysis (PCA) Model on only the images containing the box, to acquire a set of these latent variables. A Linear Time Invariant State Space (LTI SS) model is built between the input and the previously obtained latent variables and a Partial Least Squares (PLS) model is built between the latent variables and the quality measurements. This entire model is integrated with an MPC designed to achieve products with user specified qualities subject to certain input constraints. The framework is demonstrated by closed-loop experiments on the rotational moulding setup.

2. PRELIMINARIES

2.1 Rotational Molding

A laboratory-scale bi-axial rotational molding machine is employed for the production of plastic molded items. The system's single heater coil inputs and the resultant images from the rotational molding setup are both monitored and manipulated using LabVIEW and MATLAB programs. Positioned outside the oven, a camera captures images inside through a narrow slit. High-density polyethylene powder is introduced into the mold at room temperature, while the oven is pre-heated to 300°C. Once prepared, the mold is inserted into the oven and set to rotate at a constant speed of approximately 8 RPM. Following the heating phase, the mold is transferred to a cooling chamber, and the product, still in the mold, undergoes air cooling before being removed for quality testing. During this process, the sinkhole area and impact strength of the product are evaluated. It's crucial to highlight that the camera's field of view doesn't always encompass the mold containing the polymer, given the continuous rotation of the mold, while the camera remains fixed outside the oven. Sample images from the process are shown in Figure 1.

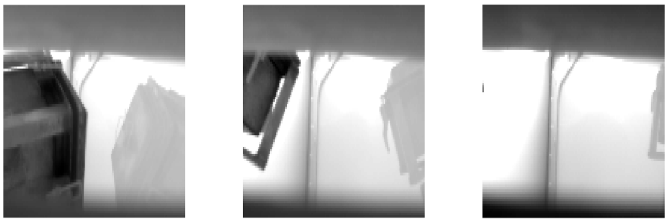

Fig. 1. Sample images from a Rotomolding batch. Leftmost image shows an image with the mold in the frame. As the mold always undergoes constant rotation, the mold doesn't always sit in the frame of the image, as shown in the middle and the rightmost images.

In rotational molding, the extent of sintering is gauged by assessing surface voids. In instances where polymer particles don't fully undergo sintering during the process, the resulting product often exhibits a noticeable number of surface voids. ImageJ is employed for the analysis of surface voids, utilizing images of the mold captured by a digital camera. Additionally, the strength of the product needs quantification, and one method for this is pendulum impact testing. Samples were cut into 63.5 x 12.7 mm strips (2.5 x 0.5 in) and impact testing was done on an HIT25P pendulum impact Tester with a 5 J hammer from Zwick/Roel to get the impact energy of the samples according to ASTM D256. The key objective in the process is to determine (and adjust under closed-loop control as appropriate) the heating provided to the mold to achieve the desired product quality at batch termination.

2.2 Dimensionality Reduction Techniques (Principal Component Analysis)

These techniques help the user analyze the level of redundancy in a high dimensional data set. PCA in particular is a linear reduction technique where the data is transformed into a different coordinate system through scaling and rotations so that maximum variation in the data can be explained through fewer dimensions. The following equation represents the relation between different matrices encountered in a PCA model:

$$T = X * P \tag{1}$$

where T is the score matrix, which represents the transformed dimensions, X is the original data matrix and P is the transformation matrix which transform the data to the score.

In this work, PCA will be used to reduce the high dimensional image (90 x 120 = 10800 variables) and finally only one principal component (or latent variable) will be taken and used as the output variable representing the dynamics of the system. For the present implementation, one latent variable ended up being chosen since it was able to capture the most variance in the data.

Remark 1. In this work, the focus was to develop a general modelling framework that allows for images to be used under feedback control especially for batch processes. One can improve the modelling by including more latent variables or even changing PCA to autoencoder for better accuracy. The overall modelling accuracy (including the LTI SS model and eventually the quality model) was found to be better while using one latent variable as opposed to more. The latent variable is meant to capture the key information available in the thermal image, which in turn is expected to contain 'more' information than a point value of a temperature. The behaviour of the latent variable therefore would be expected to align with that of a representative temperature of the mold. The latent variable is meant to capture the key information available in the thermal image, which in turn is expected to contain 'more' information than a point value of a temperature. The behaviour of the latent variable therefore would be expected to align with that of a representative temperature of the mold.

2.3 Subspace Identification and Partial Least Squares for Dynamic Quality Modelling

To consistently achieve the desired product quality, it's crucial to have a robust process model that captures system dynamics and reasonably predicts the evolution of process and quality variables. The model development follows a two-step process. Initially, a dynamic model's state space is constructed, linking the sole heater as the input to a representative latent variable (obtained in the previous section) as the output. This dynamic model is then enhanced with a static model, establishing connections between the final product qualities (from training batches) and the endpoint state predictions of the dynamic model.

To derive this dynamic state space process model, a deterministic subspace identification technique, specifically tailored for batch processes, is employed. This identification process entails determining the system order n and the system matrices of the previously mentioned state space model using input-output batch data.

The identified model takes the following form :

$$x^d_{k+1} = Ax^d_k + Bu_k, \tag{2a}$$

$$y_k = Cx^d_k + Du_k, \tag{2b}$$

where $A \in \mathbb{R}^{n\times n}$, $B \in \mathbb{R}^{n\times m}$, $C \in \mathbb{R}^{l\times n}$, $D \in \mathbb{R}^{l\times m}$ are the associated system matrices and x^d_k denotes the state vector.

In contrast to classical system identification Raghavan et al. (2006), subspace identification methods are non-iterative, employing matrix algebra with decomposition techniques and/or projections for computing unknown parameters Tangirala (2014); Qin (2006). Various subspace algorithms exist, such as canonical variate analysis (CVA) Larimore (1990), numerical algorithms for subspace state space system identification (N4SID) Overschee and Moor (1992), and multivariable output error state space algorithm (MOESP) Verhagen and Dewilde (1992). These algorithms differ mainly in the weighting matrix used in the singular value decomposition step Van Overschee and De Moor (1995). However, they were originally designed for continuous processes Wang and Qin (2002); Qin et al. (2005); Pour et al. (2010).

Batch process data, being a collection of multiple independent trials exploring process transients, requires adjustments in the subspace algorithm. The current implementation employs a single pseudo-Hankel matrix for both input and output data, recognizing the batch nature of the data Corbett and Mhaskar (2016). Once these pseudo-Hankel matrices are formed, the deterministic algorithm presented in Moonen et al. (1989), and suitably adapted in Corbett and Mhaskar (2016), is used for process identification.

As product quality measurements are unavailable online during experiments, the identified process model alone is insufficient for predicting sample quality. This approach relies on the understanding that the 'states' of the state-space model effectively capture the essence of the process. Hence, the dynamic model is augmented with a partial least squares-based linear quality model obtained by relating the terminal states of the state-space model to the product quality measurements of the training batches. The product quality measurements are obtained as described in Section 2.1. This augmentation establishes an indirect model between product qualities and the process inputs, enabling quality control during the implementation of the predictive controller. The quality model takes the form shown below:

$$Q_{t_{f_{heat}}} = \hat{R}_m + \hat{P}_m x[t_{f_{heat}}] + e \tag{3}$$

where $Q_{t_{f_{heat}}}$ denotes quality measurements at the termination of batch at time $t_{f_{heat}}$, $\hat{P}_m$ and $\hat{R}_m$ are the linear quality model parameters, $x[t_{f_{heat}}]$ are terminal states of the subspace model (i.e., at completion of the heating cycle at time $t_{f_{heat}}$) and e represents white noise.

2.4 MPC Formulation

The subsequent phase in achieving economical control while meeting product specifications involves integrating the data-driven model (state-space model augmented with a linear quality model, as detailed in the previous section) into an Economic Model Predictive Control (EMPC) scheme. This integration aims to produce a product with user-specified qualities. It's crucial to note that for a model to synergize effectively with a predictive controller, it must accurately capture and predict the process evolution based on an input sequence, as illustrated in the preceding section.

It's worth recalling that the control objective and the evolution of the control horizon differ significantly between batch and continuous processes. To attain a low-energy-intensive solution that satisfies product quality constraints, the objective function is the sum of the input sequence (heater power) over the control horizon (4a). Other, more detailed and alternative representations of the cost can be readily included. The rest of the constraints remain consistent for both manifestations of EMPC. Additionally, the duration of the heating cycle in the rotomolding process is a decision variable and must be appropriately considered when designing the optimization scheme.

In implementing the proposed control scheme on the lab-scale rotomolding setup, MATLAB is linked with LabView, which, in turn, interfaces with sensors and actuators, serving as a data acquisition system. The control action is computed and implemented approximately every 7.5 seconds through the MATLAB-LabView interface. At a sampling instance l, the optimal input trajectory till the end of the batch is obtained through solution of the following optimization problem, using Equation (4e) to compute the state estimate at the l^{th} instant:

$$\min_{U_f, l_f} \sum_{k=0}^{k=l_f-l} u_f[k] \tag{4a}$$

$$s.t.\ U_{j,min} \le u_f[k] \le U_{j,max},\ \forall\ 0 \le k \le l_f - l \tag{4b}$$

$$|u_f[0] - u[l-1]| \le \delta, \tag{4c}$$

$$|u_f[k] - u[k-1]| \le \delta,\ \forall\ 1 \le k \le l_f - l \tag{4d}$$

$$\hat{x}[0] = \hat{x}[l] \tag{4e}$$

$$l_f \in \{k_{switch} + 85, k_{switch} + 100, k_{switch} + 115\} \tag{4f}$$

$$\Lambda \hat{Q}_{t_f} \le \Gamma \tag{4g}$$

$$\hat{x}[k+1] = A\hat{x}[k] + Bu_f[k] \tag{4h}$$

$$\hat{y}[k] = C\hat{x}[k] + Du_f[k]\ \forall\ 0 \le k \le l_f - l \tag{4i}$$

$$\hat{Q}_{t_f} = R_m + P_m \hat{x}[l_f] \tag{4j}$$

with,

$$\hat{Q} = \left[\hat{Q}_1 \;\; \hat{Q}_2\right]^T \tag{5a}$$

$$\Lambda = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \tag{5b}$$

$$\Gamma = \begin{bmatrix} 2 \\ -0.3 \end{bmatrix} \tag{5c}$$

where, $U_f = [u_f[0], u_f[1], \ldots u_f[l_f - l]]$ are the set of decision variables consisting of the heater input at each sampling instance over the control horizon and l_f denotes the heating cycle termination time. The set of possible batch termination times, l_f is specified in Equation (4f) based on experience. The MPC is solved three times with each of the batch times, and the MPC with the best objective function would be implemented at each iteration. $\delta = 0.5$ is the allowed rate of input change specified through Equations (4c) and (4d), and $U_{j,min}$ and $U_{j,max}$ are the lower and upper bounds on the input variable (Equation (4b)) with $U_{j,min}$ and $U_{j,max}$ being 0 and 5 respectively. In addition, k_{switch} denotes the time instance at which the controller switches to MPC from PI controller. This is set to 30, which is roughly 30% of the batch time. The images and the input data are being collected during the PI phase. During this phase, each of the images are reduced by the PCA eventually, to a representative output. The Luenbeger observer is then used on the input and output trajectory upto this point with an initial guess for the state, so that the states of the LTI SS model converge. At each MPC iteration, the current state estimate is fed as the initial condition through Equation (4e).

Further, Equation (4g) represents the user-specified constraints on the quality variables. Finally, Equation (4j) represents the quality model which the MPC uses to predict the terminal product quality using the terminal states (of the heating cycle) which in-turn are produced by the dynamic state-space model as specified in the Equations (4h)-(4i). In Equation (5a), $\hat{Q}_1$ and $\hat{Q}_2$, refers to the estimated values of the two quality variables namely, sinkhole area percentage (%) and impact strength respectively.

3. PROPOSED MODELLING APPROACH

In this section, we put together all the techniques discussed in the previous section along with additional necessary Neural Network tools to make the approach implementable on the current Rotational Molding setup. The overall modelling approach is shown in Figure 2. In particular, first we use a Convolutional Neural Network (CNN) based classifier to classify whether an image has the mold. The classifier classifies the images and lets the other models use only those images which contain the mold. For example, in Figure 1, the classifier only allows the left most image to be further processed by the rest of the models like PCA, and the latent variables used in the state space models correspond to images where the mold is present.

Once the CNN classifies an image with the mold, a pre-trained CNN based object detection model (YOLOv3, *You Only Look Once* by Redmon and Farhadi (2018)), is used to further detect only the portion of the image which contains the mold and discards the surroundings. For consistency, the frame of this portion of the detected image is kept constant (40x40) for the image at every time step. The working of the CNN classifier along with a CNN-based object detection model is shown in Figure 3 on the left. Furthermore this 40x40 image is reduced by PCA to a single latent variable which is then used as an

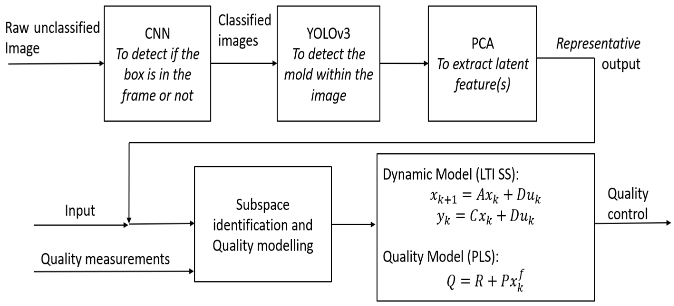

Fig. 2. Proposed layered modelling strategy

output variable along with the heater input while constructing an LTI SS model (Equation (2)) of an order 2. Finally, a PLS based quality model (Equation (3)) is constructed to link the product qualities to the dynamics of the process.

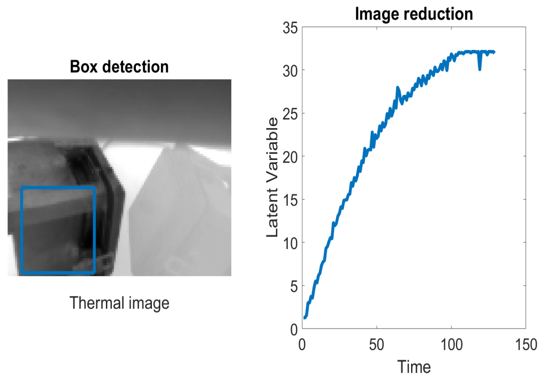

Fig. 3. (Left) shows the working of the CNN based classifier in detecting the image with the box and another CNN based model (YOLO) in detecting the mold within the image. (Right) shows the evolution of latent variable obtained by applying PCA on the highlighted portion on the left image, throughout the batch time.

Remark 2. The "temperature" of the mold, or rather, the set of temperatures obtained from the image of the mold, acts as the only dynamic output information from the process, with which the modelling strategy is devised to relate the quality variables. The infrared camera directly gives a thermal image to MATLAB, which is a 2-dimensional array containing temperature at each pixel. The dimensionality reduction is performed on this thermal image. The oven temperature is not taken into account explicitly and the proposed modelling strategy solely relies on the thermal image readings.

Remark 3. The LTI SS model is identified with 2 states, which is also set by the user, since this is a complete black-box model. Since it is a black-box / data-driven model, the states themselves do not have physical meaning but the idea of a state space model is that the states capture the essence of the dynamics of the process. Hence, when the number of states is tuned appropriately to achieve good prediction accuracy, it is expected that the identified states capture the key variables of the process.

4. CLOSED LOOP IMPLEMENTATION RESULTS

We present the closed loop results in this section. It must be noted that although we have many models in our many-layered modelling strategy as one can notice in Figure 2, only the LTI

SS and the PLS models play a direct role in the MPC calculations, and the rest of the models exist to process the feedback images for the MPC to function. These auxiliary layers can be thought of as an observer/filter, that help in processing the high dimensional output and estimating the states of the system. Before we present the closed loop results, we show the efficacy of the proposed modelling approach by showing the performance on the quality variable predictions in Figure 4. We can see that though the predictions are not satisfactory in the beginning of the process, as the batch progresses, the quality predictions get better.

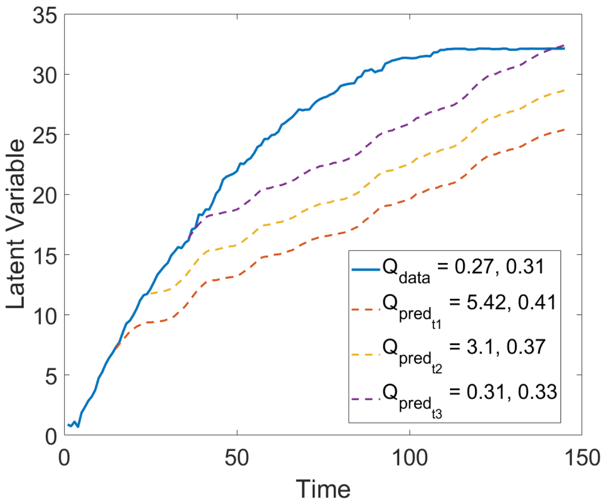

Fig. 4. Figure shows the evolution of the latent variable in a batch, and the open loop predictions of the same using the state space model, with a Luenberger observer run till times t_1, t_2 and t_3. The legend shows the final quality variable predictions as seen from times $t_1 = 15$, $t_2 = 25$ and $t_3 = 35$ compared with the quality measurement for this particular batch.

The overall summary of the quality predictions is shown in Table 1. Each of the errors in the table has been calculated for all the 6 available batches of data. It must be noted that the quality variables do not exist during the batch, and hence we compute the performance of the predictions of the quality variables as seen from particular times during a batch. Three equally spaced times during a batch are chosen for this purpose and the respective RMSEs (calculated across all batches) are tabulated in Table 1. Additionally, Figure 5 shows the performance of the quality model on the two quality variables.

Table 1. Summary of Quality modeling results

Open loop predictions from time t_i	$t_1 = 40$	$t_2 = 90$	$t_3 = 130$
Quality Error (across all batches) RMSE	2.45	2.07	2.06

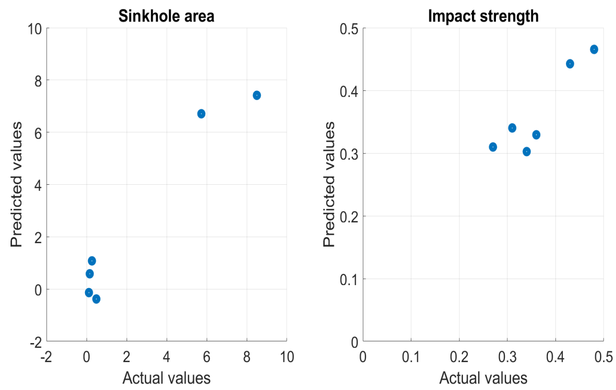

Fig. 5. Figure shows the prediction performance of the quality model on the two quality variables namely, the sinkhole area percetage and the impact strength.

We implement the Model Predictive Controller, formulated in Section 2.4 on the Bi-axial Rotational molding setup (Section 2.1). The MPC is compared with an open-loop operation strategy, where a PI controller is designed to regulate the oven temperature at 300°C and the only decision variable with the operation is the batch time. The approximate batch time was selected according to the recommendation from the industrial partner, and we changed it by few minutes to compare the performance. Moreover, the MPC formulation accommodates different batch times so that the operator would not have to choose manually, as it is in the case of the PI control. In the table 2 we can see that MPC batch 1 performs better in terms of the overall input consumption when compared to both PI runs. Furthermore, it is also able to successfully produce a product that meets the quality constraints given in the MPC formulation. For MPC batch 2, we tried to tighten the quality constraint on Q_1 and reduce the maximum batch time to 17 min to check for the MPC performance. The MPC tried to push the system with more heat and hence resulted with a ‘more expensive’ input profile. Moreover, due to excess heat, the quality actually degraded a bit, affecting the impact strength, Q_2. We conclude that the MPC performance can be further enhanced by training the state space and the quality models with an adequate range of data.

Table 2. Summary of Closed loop results

Batch	Batch time (min)	MPC Quality Constraints $Q_1 \leq 2, Q_2 \geq 0.3$	Product Qualities	Total input power
PI 1	18	~	0.27, 0.31	250.3
PI 2	16	~	0.16, 0.36	214.8
MPC 1	18	2, 0.3	0.49, 0.34	189.9
MPC 2	17	1, 0.3	0.12, 0.27	279.6

This is an ongoing work and the results will be improved in due time but the goal a working image based MPC has been achieved. Furthermore, with a sufficiently trained model and a well performing MPC, we will develop a case study and demonstrate the superior performance of MPC over regular

PI control. Nevertheless, we have presented a working image based MPC scheme for quality control in batch processes.

5. CONCLUSION

In this manuscript, a layered modelling strategy combining the concepts of partial least squares regression, principal component analysis, subspace identification for linear state space models, and neural network models, is proposed for modelling process dynamics with high dimensional output data. In particular, a CNN based classifier along with a CNN based object detection model is used to detect the portion of the image that contains the mold. A PCA model is then used to reduce this smaller image into a single latent variable which is then used as an output for the subspace-based state space model. Finally a PLS model is used to relate the product qualities to the final states of a batch, obtained from the state space model. The open-loop quality prediction results show that the proposed modelling approach is able to predict the qualities well and hence it can be inferred that the dynamics of the system is also reasonably captured. The MPC's ability to drive the product qualities close to the user's requirements demonstrate the working of the proposed approach under a closed-loop setting.

ACKNOWLEDGEMENTS

Financial support from the McMaster Advanced Control Consortium (MACC) and the Natural Sciences and Engineering Research Council of Canada (Collaborative Research and Development Grant) is gratefully acknowledged. Authors thank Imperial Oil and Ron Cooke for the donation of polyethylene and technical advice on rotomolding process.

REFERENCES

Corbett, B. and Mhaskar, P. (2016). Subspace identification for data-driven modeling and quality control of batch processes. *AIChE Journal*, 62(5), 1581–1601. doi:10.1002/aic.15155.

Gopaluni, R.B., Tulsyan, A., Chachuat, B., Huang, B., Lee, J.M., Amjad, F., Damarla, S.K., Kim, J.W., and Lawrence, N.P. (2020). Modern machine learning tools for monitoring and control of industrial processes: A survey. *IFAC-PapersOnLine*, 53(2), 218–229. doi: https://doi.org/10.1016/j.ifacol.2020.12.126. 21st IFAC World Congress.

Larimore, W. (1990). Canonical variate analysis in identification, filtering, and adaptive control. In *29th IEEE Conference on Decision and Control*, 596–604 vol.2. IEEE. doi: 10.1109/CDC.1990.203665.

Lu, Q. and Zavala, V.M. (2021). Image-based model predictive control via dynamic mode decomposition. *Journal of Process Control*, 104, 146–157.

Masti, D. and Bemporad, A. (2021). Learning nonlinear state–space models using autoencoders. *Automatica*, 129, 109666.

Moonen, M., De Moor, B., Vandenberghe, L., and Vandewalle, J. (1989). On- And Off-Line Identification Of Linear State Space Models. *International Journal of Control*, 49(1), 219–232.

Narasingam, A. and Kwon, J.S.I. (2017). Development of local dynamic mode decomposition with control: Application to model predictive control of hydraulic fracturing. *Computers & Chemical Engineering*, 106, 501–511.

Overschee, P.V. and Moor, B.D. (1992). Two subspace algorithms for the identification of combined deterministic-stochastic systems. *[1992] Proceedings of the 31st IEEE Conference on Decision and Control*, 311(I), 75–93. doi: 10.1109/CDC.1992.371682.

Pour, N.D., Huang, B., and Shah, S.L. (2010). Subspace Approach to Identification of Step-Response Model from Closed-Loop Data. *Industrial & Engineering Chemistry Research*, 49(18), 8558–8567. doi:10.1021/ie900972e.

Qin, S.J. (2006). An overview of subspace identification. *Computers and Chemical Engineering*, 30(10-12), 1502–1513. doi:10.1016/j.compchemeng.2006.05.045.

Qin, S.J., Lin, W., and Ljung, L. (2005). A novel subspace identification approach with enforced causal models. *Automatica*, 41(12), 2043–2053. doi:10.1016/j.automatica.2005.06.010.

Raghavan, H., Tangirala, A.K., Bhushan Gopaluni, R., and Shah, S.L. (2006). Identification of chemical processes with irregular output sampling. *Control Engineering Practice*, 14(5), 467–480. doi:10.1016/j.conengprac.2005.01.015.

Redmon, J. and Farhadi, A. (2018). Yolov3: An incremental improvement. *arXiv preprint arXiv:1804.02767*.

Tangirala, A.K. (2014). *Principles of System Identification: Theory and Practice*. Taylor & Francis.

Van Overschee, P. and De Moor, B. (1995). A unifying theorem for three subspace system identification algorithms. *Automatica*, 31(12), 1853–1864. doi:10.1016/0005-1098(95)00072-0.

Verhagen, M. and Dewilde, P. (1992). Subspace model identification Part 1. The output-error state-space model identification class of algorithms. *International Journal of Control*, 56(5), 1187–1210. doi:10.1080/00207179208934363.

Wang, J. and Qin, S.J. (2002). A new subspace identification approach based on principal component analysis. *Journal of Process Control*, 12, 841–855.

Appendix A. LTI SS MODEL

The matrices of the identified LTI SS Model are as follows:

$$A = \begin{matrix} 0.9901 & 0.0617 \\ 0.1411 & -0.1801 \end{matrix} \tag{A.1}$$

$$B = \begin{matrix} 0.0518 \\ -0.6362 \end{matrix} \tag{A.2}$$

$$C = 5.158 \;\; 0.4146 \tag{A.3}$$

$$D = 0.038 \tag{A.4}$$

Appendix B. PLS QUALITY MODEL

The matrices of the identified PLS based quality model are as follows:

$$R = \begin{matrix} 19.1083 \\ -0.7192 \end{matrix} \tag{B.1}$$

$$P = \begin{matrix} -3.1527 & 0.2706 \\ 0.9362 & -0.0645 \end{matrix} \tag{B.2}$$