Korean J. Chem. Eng., 39(12), 3179-3189 (2022)
DOI: 10.1007/s11814-022-1294-x
pISSN: 0256-1115
eISSN: 1975-7220

INVITED REVIEW PAPER

Objectives, challenges, and prospects of batch processes: Arising from injection molding applications

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(*Received 29 June 2022 • Revised 3 September 2022 • Accepted 15 September 2022*)

Abstract−Injection molding, a polymer processing technique that converts thermoplastics into a variety of plastic products, is a complicated nonlinear dynamic process that interacts with a different group of variables, including the machine, the mold, the material, and the process parameters. As injection molding process operates sequentially in phases, we treat it as a batch process. The review paper discusses the batch nature of injection molding and identifies the three main objectives for future development of injection molding: higher efficiency, greater profitability, and longer sustainability. From the perspective of system engineering, our discussion centers on the primary challenges for the batch operation of injection molding systems: 1) Model development in face of product changes, 2) Control strategies in face of dynamic changes, 3) Data analysis and process monitoring, and 4) Safety assurance and quality improvement, and the current progress that has been made in addressing these challenges. In light of the advancement of new information technologies, this paper provides several opportunities and encourages further research that may break existing capability limits and develop the next generation of automation solutions to bring about a revolution in this area.

Keywords: Injection Molding, Batch Process, Process Modeling, Process Control, Process Monitoring, Quality Optimization

INTRODUCTION

Currently, injection molding accounts for more than a third of all polymer materials processed [1], while polymers have surpassed steel, copper, and aluminum as the most popular materials on Earth [2]. To advance scientific understanding and technological innovation in polymer processing, a number of polymer processing-related societies have been established, such as the Society of Plastics Engineers (SPE), founded in 1942 in the US, the Society of Advanced Molding Technology (SAMT), founded in 2005 in Asia and currently under the presidency of the corresponding author, and the Polymer Processing Society (PPS), founded in 1985 in Akron, Ohio, US. As the polymer processing industry continues to grow, injection-molded parts find more and more applications in everyday lives, such as automobile parts, furniture, toys, packaging, polymer implants, and medical devices [3], which increases the need for fast and efficient manufacturing of complex parts with tight tolerances and superior finishes. When it comes to large-scale applications, it is imperative to facilitate safety, ease of use, and environmental harmony with energy- and space-saving features.

Unlike other processes, injection molding is a complex nonlinear dynamic process that involves the interaction of machine parameters, material properties, and process variables [4,5]. Fig. 1 shows

Fig. 1. Photo of the injection molding machine at HKUST's Advanced Materials Lab.

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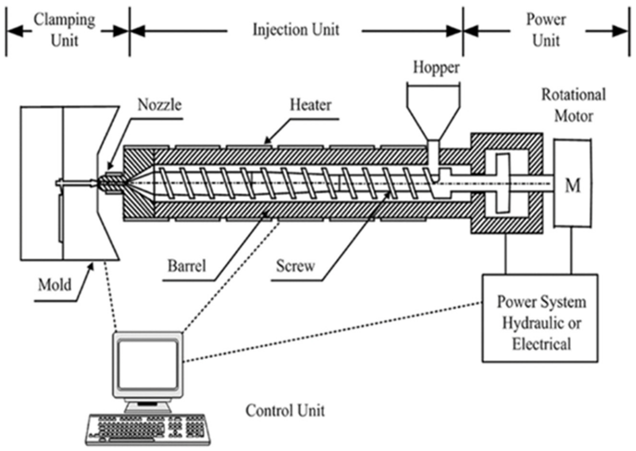

Fig. 2. Simplified schematic diagram of the injection molding machine.

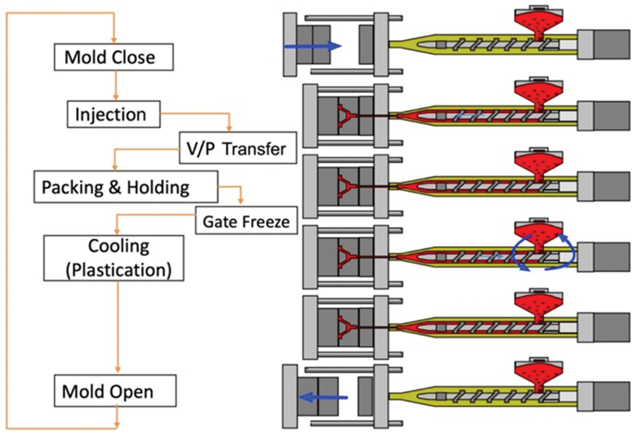

Fig. 3. Illustration of the injection molding process in phases.

the reciprocating-screw injection molding machine at the Advanced Materials Laboratory at the Hong Kong University of Science and Technology (HKUST). A simplified schematic diagram of this machine is shown in Fig. 2. Fig. 3 illustrates how injection molding works sequentially in phases [6], including the following steps:

1) First, material granules from the hopper are fed into the heated barrel and rotating screw;
2) Second, the plastic material is heated and injected under pressure into a closed metal mold tool;
3) Third, the tool is held closed under pressure until the molten plastic cools and hardens into the shape inside the mold tool, which is the most time-consuming part of the injection molding process; meanwhile, the machine plasticizes by rotating the screw and moving it back to prepare for the next cycle;
4) Fourth, the mold is opened so that the molded parts can be ejected or removed for inspection, shipment, or secondary operations;
5) The whole process is repeated again by moving to (1).

It is important to understand that the quality of the final molded part, which is characterized by its weight, dimensions, appearance, and mechanical properties, cannot be measured online. It is widely accepted that quality is a function of the processing conditions [4]. Further, the three critical phases of the injection molding process are the filling phase, the packing phase, and the cooling phase, which largely determine the quality of the end product [7].

Recently, there has been an increasing interest in the control, monitoring, and optimization of batch processes [8-11]. As a typical manufacturing method, batch process refers to a production process in which raw materials are processed through orderly phases to produce final products, and the procedures are repeated to form more of the same products [12]. Unlike continuous-time processes, batch processes can change the shape and quality of the final product by adjusting the conditions and sequences of the processes. Therefore, batch production can quickly respond to changes in customer demand, adapt to the diversity and variability of the market, and meet the requirements of the current customized production method. Because of its high flexibility and versatility, it has found wide application in industries, such as semiconductor manufacturing, polymer processing, and pharmaceutical production [13].

Based on the characteristics of injection molding and batch processes, it is evident that injection molding can be seen as a batch process, and many methods developed for injection molding may be equally well used for other types of batch processes, as reported in many articles [6,7,14-17]. In fact, the injection molding system works the same way as the batch process in chemical engineering [12]. It is now widely accepted that injection molding is a batch process in both academia and industry. The batch control of injection molding has undergone significant development over the past three decades [13]. Meanwhile, efforts have been made to optimize the design of molds and parameter settings for injection molding systems [5]. Yet, there remain many challenges for injection molding applications, due to their complexity and increasing requirements on safety and quality [18]. With the advent of Industry 4.0, the manufacturing industry faces numerous challenges and opportunities [19]. The injection molding industry is no exception, as it now faces new challenges and can reach new goals. With the development of information technology, injection molding has become more efficient, resulting in shorter turnaround times; with new sensing technologies, the collection of process data online has become easier and more convenient. It is possible to use those data to improve injection molding safety and quality [16]. However, more work is needed. Dynamic models are crucial for injection molding because their high accuracy and robustness enable efficient process monitoring and control [20]. Analyzing data effectively allows us to better understand the molding process and its relationships with parameters. For example, it has become easier to monitor and control previously mysterious phenomena associated with injection molding systems (such as warpage and sagging) [6]. Furthermore, traditional injection molding processes are often checked and updated via trial-and-error methods after each batch is completed. Developing an online process monitoring system and an online method of optimizing product quality at the lowest cost is also critical for online parameter adjustment and real-time quality prediction. In general, modern information and sensing technologies have now made it possible to develop more effective computer-aided process automation strategy, and to implement the rapid updates of batch processes, automated production, real-time monitoring, and on-line quality improvement. In every aspect of analysis, design, simulation, optimization, control, and monitoring, we can improve our advantage when we use the information tools of modern industry. Finally, it will boost productivity, profitability, and sustainability for injection molding industries.

It is important and interesting to study injection molding systems from the perspective of their batch process nature theoretically and systematically. In this paper, we examine batch process challenges, review engineering strategies, analyze several control and monitoring algorithms, and discuss the future development of the batch process. Operation safety and quality are addressed by analyzing the batch process nature of injection molding systems. To achieve higher efficiency, greater profitability, and longer sustainability, injection molding systems will be examined in terms of their goals, challenges, and prospects. Finally, this paper provides opportunities and motivations for future research on the next generation of injection molding automation. Our objective in this paper is to summarize the objectives, challenges, and prospects of injection molding systems from the point of view of batch process. The key contributions of this paper are threefold. First, we review recent advances, point to relevant literature, and discuss new injection molding objectives. Second, we analyze four main challenges and how we advance in each based on the batch process nature. There is no attempt in this paper to provide a comprehensive review of versatile methodologies. Third, by exploring some promising directions for further research, we aim to use emerging technologies and tools to push the boundaries of existing capabilities and develop the next generation of automation solutions.

The outline of this paper is as follows. In Section II, we explore the objectives, challenges, and advancements for injection molding systems, focusing on four aspects. In Section III, we provide an overview of four emerging technologies and tools that can be used to develop the next generation of injection molding systems. Finally, we draw conclusions in Section IV.

OBJECTIVES, CHALLENGES, AND ADVANCEMENTS FOR INJECTION MOLDING SYSTEMS

Due to the importance of the products by injection molding systems in our lives, research on these systems is crucial. The versatile injection molding technique can manufacture, repeatedly and at high speeds, products with complex shapes, micro to large sizes, layers and colors, with or without inserts [7]. Products made by injection molding must meet a multitude of specifications, such as shape, size, dimensional stability, strength, surface characteristics, and other requirements associated with functionality and the intended use. As a general summary, the three main objectives of injection molding systems are 1) higher efficiency; 2) greater profitability; and 3) longer sustainability. The efficiency of injection molding is directly related to productivity, so re-examining the working processes and updating the procedures will make injection molding easier to operate and more efficient. Reduced energy consumption and increased space efficiency will help the industry achieve higher profitability. While producing the needed product, it is also important to ensure that the entire process is environmentally friendly. Due to higher energy costs and stricter environmental regulations, as well as increased competition for prices and quality on the global marketplace, the injection molding industry has seen significant changes in recent years.

To achieve the above three objectives, we need to gain knowledge and control over the injection molding process, analyze the sensing data that the polymer experiences during the process, and predict the effects of the data on the final product. Many of these interactions and concepts are complex, so it is important to develop modeling and monitoring strategies that identify the status and potential responses of the critical process key variables, as well as a control strategy for monitoring their profiles. Overall, a successful injection molding process requires a great deal of modeling, control, monitoring, and optimization. To ensure a successful injection molding process, the following four challenges must be addressed:

1) Model developments in face of product changes;
2) Control strategies in face of dynamic changes;
3) Data analysis and process monitoring;
4) Safety assurance and quality improvement.

These categorizations of the main challenges for injection molding systems summarize the discussion in this section and highlight the main points in this paper. Analysis of those challenges, from the point of view of batch process nature, is extremely important in the injection molding community. Therefore, they will be discussed in greater detail below.

1. Model Developments in Face of Product Changes

For process automation, modeling and process identification play an important role since we do not have all the information about complex processes, and we are only mathematically modeling processes approximately. Typically, the majority of parameter tuning and profile setting in injection molding systems is accomplished by experience or prior knowledge. However, for highly automated processes, such as decision-making, optimization, and predictive analytics, having the ability to build accurate models from online or offline process data is essential [21]. A sufficiently accurate model is required for applications such as control strategies, process monitoring methods, and quality optimization. To construct a model, process data is required. Data collection in injection molding systems has historically been challenging and resource-intensive due to its time-consuming, expensive, and computational nature. Today, collecting data online or offline is easier than ever thanks to advances in information technology. Additionally, data required to construct accurate models that reflect the regulation of key variables is often limited, which simplifies the data collection process.

Industrial process models consist of a model structure associated with key variables and a set of parameters defined according to that structure. Fig. 4 shows a general framework of how data-driven models are developed for industrial processes. In the development of an application model, there are three steps:

- First, identify key variables using various methods, such as principal component analysis (PCA), independent component analysis (ICA), partial least squares (PLS) analysis, or slow feature analysis, etc.
- Second, choose a model structure associated with those key variables that closely matches the dynamics of the process, such as a time-domain evolution or frequency-domain description of the process, and model orders, etc.

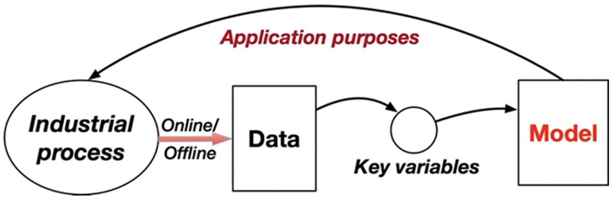

Fig. 4. A general framework of how data-driven models are developed for an industrial process.

- Third, use the key variables to fit the model structure, determine the involved parameters, and analyze their impacts on the model.

When modeling injection molding, the model structure can differ from the process dynamics because material (morphological) structure changes can occur. The determination of model orders will also have a significant impact on model accuracy.

When we identify key variables for the injection molding process, we must emphasize that it consists of many phases [15] and that each phase has its own set of key variables. During the filling phase, the speed of the polymer flow entering the cavity strongly influences the surface quality of the molded part. The filling rate can be described as the ram injection velocity (or simply injection velocity), which can be measured directly. During the packing phase, the packing pressure is critical because it determines how many materials will be packed into the mold. During the cooling phase, the cooling temperature is the most important variable, since it affects cooling rate and, consequently, cycle time. The cooling rate is related to solidification, and in the case of semi-crystal materials the crystalline percentage and, hence, the mechanical properties of the part. Concurrent to the cooling, the machine undergoes plastication, which prepares the melt for the next shot by shear heating generated by screw rotation and back pressure. This makes the screw rotation speed and the back pressure the most important key variables during the plastication. Throughout the injection molding process, several key variables must be carefully monitored, including the barrel temperature, the cavity pressure, and the mold temperature. These variables are easy to measure.

When selecting a model structure for different phases of the injection molding process, the discrete time autoregressive with external input (ARX) model can be used [22]. Besides, a standard open-loop step response method can also be used to analyze the injection dynamics. To determine the delay, an ARX model can be fitted with different delay orders to the response [23,24]. In optimal ILC design, a linear time-invariant model is used to approximate the dynamics of injection velocity [25], which is actually nonlinear and time-varying, so there will inevitably be a significant model mismatch. In fact, the fitting of a model structure will smooth out some of the modeling errors that cannot be avoided. The injection molding dynamics during early injection may not change significantly for two consecutive cycles [6]. As a result, the current model parameter estimation can be adjusted based on the information from the previous cycles. To warm up and stabilize an injection molding machine takes about 50 cycles, so during this warm-up period, process dynamics may change significantly.

To meet the diverse needs in life, injected products have changed

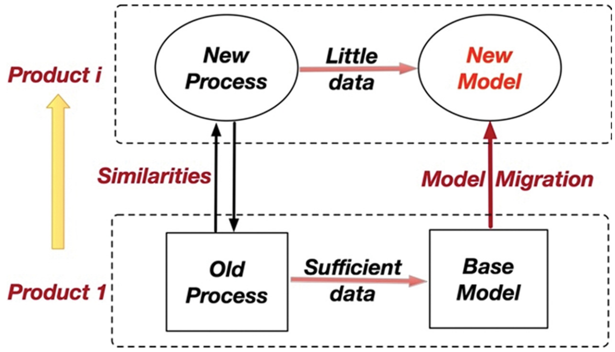

Fig. 5. Model migration from an existing (or, old) process to a new process.

rapidly, resulting in frequent model changes in injection molding systems. To achieve smart injection molding, modeling methods that can deal with a wide range of products are important. It has been found that robust data-driven modeling techniques based on input-output data are more effective for injection molding [20]. Due to the increased frequency of product changes, intelligent modeling development method that can deal with problems arising from producing one product to another products, from converting an existing mold to a new mold, from changing a conventional phase to a more efficient phase, is becoming increasingly necessary. Therefore, the concept of *model migration* is proposed and defined in [26], which allows a model developed for one injection molding product to be migrated efficiently to a new product [27-30]. As shown in Fig. 5, a new model corresponding to the new process of product *i* is developed by migrating the base model of the old process of product 1 with little training data. The concept of *process similarity* and *attribute similarity* has been discussed by the previous work presented in [28]. Due to the similarity in processes, training data attributes are reduced between the new and old processes. Several key challenges on model migration from an existing process to a new process are examined in [27], along with an application example on the injection molding process. The concepts of process similarity and *model migration* allow us to build efficient models that can serve both process monitoring and control. The high-level representation is designed for similar products, such as updating procedures for one kind of product, or similar processes in terms of process attributes.

2. Control Strategies in Face of Dynamic Changes

A batch process, like the other two types of industrial processes, namely continuous and discrete, suffers from common process control issues, such as uncertainty handling, constraints satisfaction, and performance optimization [31]. However, the batch process involves repeated execution of cycles [12], where repeatability provides an opportunity to learn from historical process data, thus enabling batch processes to improve control performance from cycle to cycle [11,32]. Essentially, the run-to-run method can monitor and improve the performance of subsequent cycles by using the results from previous cycles [33].

In batch processes, there are two time variables, the time index t and the cycle index k, which evolve in two different directions, called two-dimensional (2D) framework [34]. The 2D framework

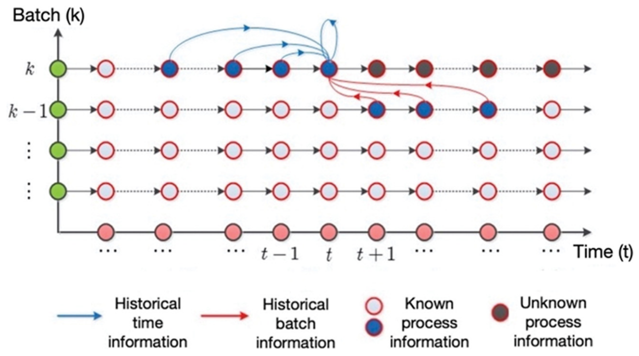

Fig. 6. Illustration of the 2D control framework for batch processes.

has provided many opportunities and advantages for monitoring and controlling batch processes [35]. Fig. 6 below provides an illustration of the 2D control framework for batch processes. Here, the 2D control framework can take advantage of historical time information, historical batch information, and known process information to optimize the current to-be-designed control input. This provides additional degrees of freedom for meeting control objectives when these objectives do not necessarily have to be completed in a single batch, but can be distributed over several successive batches. It offers batch processes a number of advantages when it comes to handling dynamic change [36].

To exploit the repetitiveness of batch processes, iterative learning control (ILC) has been extensively studied [37-39]. The biggest strength of ILC is that it has learning capability from its historical experience [37], where the ability to modulate input signals by integrating the input and output information from past iterations/cycles/batches leads to gradual improvement in control performance [33,40]. For example, a simple 2D feedback ILC strategy can be designed as follows [41,42]:

$$\begin{aligned}\Delta_t\Delta_k \mathrm{u}(\mathrm{t},\mathrm{k}) = {} & \mathbf{K}_1\Delta_t\mathbf{e}(\mathrm{t}|_{t+n_1}^{t+1}, \mathrm{k}-1)\\ & +\mathbf{K}_2\Delta_k\mathbf{u}(\mathrm{t}|_{t+n_2-1}^{t}, \mathrm{k})\\ & +\mathbf{K}_3\Delta_k\mathbf{y}(\mathrm{t}|_{t+n_2-1}^{t}, \mathrm{k})\end{aligned} \tag{1}$$

where Δ_t and Δ_k denote the time-wise and cycle-wise backward difference operator, respectively; $\mathbf{f}(\mathrm{t}|_{t_1}^{t_2}, \mathrm{k})=[\mathrm{f}^T(\mathrm{t}_1, \mathrm{k}), \cdots, \mathrm{f}^T(\mathrm{t}_2, \mathrm{k})]^T$, $\mathrm{t}_1 \le \mathrm{t}_2$, $\mathbf{f} \in \{\mathbf{u}, \mathbf{y}, \mathbf{e}\}$, where u(t, k), y(t, k), and e(t, k) represent the input, output, and tracking error, respectively; $\mathbf{K}_1$, $\mathbf{K}_2$, and $\mathbf{K}_3$ are the gain matrices to be designed or optimized. By combining feedback control and ILC as the form of (1), the issue of integrated design and coordinated optimization for batch processes is resolved. This design method takes advantage of the 2D information to deliver enhanced control performance both in the batch and time direction, even if there are significant dynamic changes in the time direction.

When automating batch processes, the first priority is to establish the set-point profile of the process parameters based on economic considerations and/or the requirements of the final product quality, known as recipe optimization [8]. The following objective is to ensure that the process operation meets the precise tracking of the optimal values or trajectories while satisfying the path constraints. Batch automation is heavily dependent on optimized recipes and subsequent sequence control. The product quality largely depends on the control of production process and process parameters, often under a set of constraints to ensure process safety [43]. For batch processes, constraint and uncertainty are always present [44-46]. For example, there are physical constraints carried by the system or human-defined constraints based on safety or economic considerations [47,48]. To handle such constraints, several constrained ILC methods are proposed, such as using projection operations [49] and solving constrained optimal control problems [50, 51]. Besides, integrating ILC with model predictive control (MPC) is another popular control strategy, since MPC is good at solving constrained optimal control problems [52,53] and the combination stands out with clear and effective advantages of both methods [54,55]. The uncertainty usually arises from model mismatch or process disturbance, since it is generally impossible or impractical to accurately model physical plants. These issues can deteriorate system performance or stability. To deal with uncertainty, several robust methods are proposed in [7,25] for injection molding systems. Additionally, closed-loop control of key process variables in injection molding systems, such as barrel temperature, is also essential [56].

Under the 2D framework, batch process control strategies can be implemented online or run-to-run, according to two different control objectives, which correspond to the set-point references, i.e., the desired values of the run-time outputs or the run-end outputs. By switching between the implementation methods and the control objectives, we can obtain four types of control strategies as [12]:

- Online control of run-time output;
- Online control of run-end output;
- Run-to-run control of run-time output;
- Run-to-run control of run-end output.

Typical control approaches for each type include time-varying feedforward control or PID feedback control [31] for the first type, model predictive control (MPC) [52,57] for the second type, ILC [39,58] for the third type, and run-to-run control [33] for the fourth type. With the advancements in batch process control, many different complex control strategies are developed, such as robust ILC [34,41,59], normal optimal ILC [60-62], real-time-feedback-based ILC [63-65], data-compensated ILC [11,16,43,66,67], model-free ILC [68-72], run-to-run ILC-MPC [73-77], and real-time-feedback-based ILC-MPC [64,65,78]. Therein, several design approaches under the 2D framework are outlined in [55,59,79], which take advantage of the repeatability of the cycle information into improving the control performance. For batch process control, a number of books are available [80-82]. However, batch process facilities often have more complex control configurations than continuous process plants, especially when objectives like minimizing energy and material consumption are involved.

3. Data Analysis and Process Monitoring

In past decades, process monitoring has received considerable attention for maintaining favorable operating conditions and avoiding the effect of faults. In the batch process, safety, reliability, and quality are important issues of primary concern, with process monitoring being the most widely used method [83]. Although the batch process has become a common practice in industrial manufacturing, it has not benefited as much from advanced monitoring technologies as the continuous process.

Modeling and interpreting the process data is the most important step of data-based process monitoring, and this is also known as data analysis. In recent years, significant improvement has been made in data mining and processing, providing many new methodologies for data-based process monitoring, from univariate models to multivariate models, from linear to nonlinear and dynamic issues, and from continuous to batch applications [84-87]. Statistical process monitoring strategies cannot be successful without high-quality data. Ideally, the data used for modeling and monitoring should be accurate representations of real-world processes. In the statistical sense, the modeling data should be complete, which means they should cover all the in-control conditions. During the data collection step, it is important to account for all normal process variations. In this way, we can accurately distinguish between normal and abnormal processes. To ensure that data is accurate, correct, and consistent, data cleansing activities are performed such as filtering noises, mitigating attacks [88], removing outliers, and filling in missing data [20].

From the methodological point of view, methods for process monitoring can be divided into three categories: model-based methods, knowledge-based methods, and data-based methods [84]. Due to data-driven and multivariate nature, data-based process monitoring and diagnosis is widely accepted in industrial practice. With the advancements in machine learning methods, unsupervised learning [89] has become popular in the process monitoring field. By facilitating unsupervised learning, dimension reduction methods can be used as analytical methods for fault diagnosis, such as PCA, manifold learning, factor analysis, random projections, and autoencoders [90-92]. Fig. 7 illustrates the general framework for data-based process monitoring of dynamic process systems, which consists of two stages: offline training stage and online monitoring stage [93]. During the offline training stage, we need to determine the mapping function $\mathbf{f}(\cdot)$ from the data matrix $\mathbf{X}$ to the feature matrix $\mathbf{F}$ (i.e, the dimension reduction function), the demapping function $\mathbf{g}(\cdot)$ from $\mathbf{F}$ to the reconstructed data matrix $\hat{\mathbf{X}}$, and an appropriate diagnostic threshold for the residual space. During the online monitoring stage, we need to perform the mapping $\mathbf{f}(\cdot)$ and the demapping $\mathbf{g}(\cdot)$ on the new data matrix $X^{(test)}$, yielding the new feature matrix $F^{(test)}$ and (after subtraction) the new residual matrix $E^{(test)}$. The diagnostics for feature space and residual space are then calculated and compared with the thresholds to determine if a fault has occurred. Note that data imputation or the *model migration* of existing known processes can also be used to generate the training data matrix $\mathbf{X}$ for the new process. The author in [83] presents a state-of-the-art review of data-driven process monitoring methods. The author in [94] reviews recent developments on data-driven approaches for process monitoring, with a focus on principal component analysis (PCA) and partial least squares (PLS). The author in [95] provides review and perspectives of data-driven distributed monitoring for industrial plant-wide processes. For more reviews and perspectives on the design of process monitoring systems, readers can see the papers [96-99].

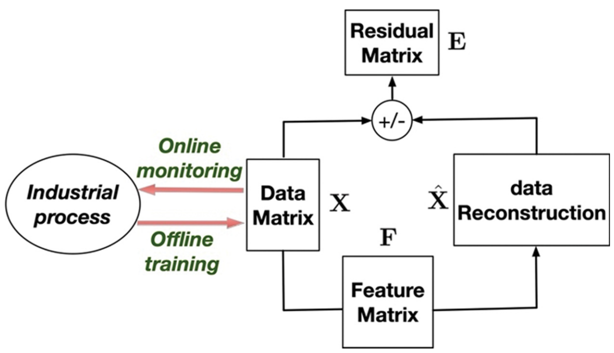

Fig. 7. A general framework for data-driven process monitoring of industrial process.

Our opinion is that process monitoring research in process industry falls into two categories:

1) Fault-related research. The main objective of fault-related process monitoring is to detect, identify, locate, or reconstruct the faults so that the system will not be greatly affected by the fault, and it can function normally.
2) Quality-related research. Studies of quality-related process monitoring mainly focus on the standard operating system free of faults and investigate the factors that decrease or improve the process quality in order to propose frameworks and methods for improving process quality.

Currently, most data-based process monitoring is focused on fault-related monitoring, which includes: (i) fault detection; (ii) fault identification or diagnosis; and (iii) fault reconstruction that estimates the magnitude of the fault and the fault-free value. The authors in [83,84,100] provide surveys on data-driven industrial process monitoring and diagnosis, which mainly focus on fault aspects. However, the author in [83] considers quality monitoring and control as the part of process monitoring research, effectively igniting the fire on quality-related process monitoring methods.

For injection molding processes, identifying phase divisions and extracting key information are the key challenges in monitoring and analysis [101,102]. Injection molding processes typically have multistage/multiphase characteristics [103]. Multistage/multiphase batch processes have variable correlations, making conventional multivariate statistical process control (MSPC) ineffective at capturing the multiphase characteristics. Examples include multiway principal component analysis (MPCA), an extension of PCA, and multiway partial least squares (MPLS), an extension of PLS. MSPC strategies that rely on MPCA/MPLS methods ignore time-varying factors or dynamics changes, resulting in difficulty in understanding processes and affecting monitoring efficiency. Then, for batch processes, different phase-division methods have been proposed [104-108], and different modeling methods that consider phase effects have been developed [109-112]. There are three primary methods for dividing batch processes into phases: process knowledge-based phase division, process analysis-based phase division, and data-based automatic phase division, which can be used to model and analyze different types of multistage/multiphase batch processes [103]. To model multistage/multiphase batch processes, various techniques have been developed, such as multiblock and phase-separated techniques, while guidelines are still needed to choose the best modeling method for specific monitoring applications. It has now been shown that dividing a batch process into phases based on the time-slice correction changes, and implementing multi-phase monitoring and analysis strategies accordingly are effective steps for many multistage/multiphase batch processes, especially for the injection molding systems [104,113].

4. Safety Assurance and Quality Improvement

Over time, the operational condition for injection molding systems will gradually deteriorate as a result of machine aging, production environment changes, and abrasive tool changes, etc. This results in a serious concern regarding safety assurance and quality improvement in the systems. As with any industrial system, safety and quality are the top priorities of modern industries [114,115], and batch processes are no different, nor are injection molding systems different either [104].

Traditionally, safety was addressed through decisions regarding process design (e.g., designing the process to be inherently safe) and control and safety system design (e.g., adding sensors that trigger an alarm when a measurement exceeds a desired range) [116]. Complete control and safety systems in process industries should include the following four systems: 1) Basic process control systems, 2) Alarm systems, 3) Emergency shutdown systems, and 4) Safety relief devices. The basic process control systems should regulate process variables to their set-points, while the layers of the safety system should not be activated regularly. For example, during the packing stage of an injection molding system, the nozzle pressure should be adjusted to a specific profile, while the layers of the safety system should not be activated frequently, because it is a slow-time varying process. When the basic process control system fails to maintain process variables within acceptable ranges due to equipment faults or unusually large process disturbances, alarms are triggered to alert operators so they can take preventative measures to avoid further unsafe deviations. If the process variables continue to exceed the allowable values, the emergency shutdown system is triggered, which takes automatic and extreme actions, such as forcing a valve to its fully open position, to stabilize the process. Safety relief devices, such as relief valves, are used to prevent explosions in vessels that become highly pressurized quickly.

Process monitoring and process control are also closely related to safety assurance. Process monitoring is primarily concerned with ensuring the safety of processes. Therein, the techniques of fault isolation and fault identification, which are active process monitoring techniques, can be used to locate and extract fault information that could impact the safety of the process. In terms of basic process control, every industrial process has its own set of constraints, and keeping the key variables within those constraints is a conventional method of maintaining the safety of the industrial processes. It has been developed to control the V/P transfer in a timely manner using a fuzzy system technique [117] that exploits the process characteristic that the nozzle pressure significantly increases at the end of the filling stage. Moreover, we always use a more conservative constraint for the operational safety of the machine, so that the closed-loop system has enough redundancy to ensure its safety. Optimization-based control schemes, such as MPC [77,118], can incorporate safety considerations and safety control actions. It has been widely used in the real-time operation of industrial plants to optimize process performance, which takes into account closed-loop stability and actuator constraints [52,119].

Aside from safety assurances for injection molding processes, another concern is product quality [104,120,121]. Finding solutions to optimize the variation of end-product quality and improve quality consistency are very important questions, which are directly related to the profitability. Those problems will be solved as long as a method for predicting the quality of the end product is developed with high efficiency and accuracy. It is, however, difficult to predict product quality for batch processes in an online way. The main reasons are that:

1) End-product quality attributes are only available after a batch operation is finished, and
2) Most quality attributes are difficult to measure instantly after a product is produced.

Nowadays, some indirect product quality monitoring methods have been developed by inferring end-product quality from the process behaviors that were discussed in the previous section. Using offline quality information for safety monitoring and quality prediction along with online process measurements is very attractive for batch processes, where quality measurements are obtainable offline. Online quality prediction is more reliable since it can reveal the relationship between online measurable process variables and offline measurable quality attributes. For online measurements, sensor development should focus on tracking changes in material structure during online injection molding processes, since end-product quality is often determined by, or highly correlated with, changes in material structure. Using the correlation between structural changes and product quality, the first in-mold quality sensor for injection molding was developed that can detect multi-period and multiquality parameters online in our lab at HKUST. So, it has been a challenge to develop methods for online quality prediction, among which multivariate statistical models are the most popular [102], since they can be derived directly from historical data with little prior process knowledge, and also handle data sets with high dimensionality and correlation.

For injection molding systems, there are two types of quality variables: variables determined by only one phase and variables determined by more than one phase. The two types of quality variables in injection molding systems are generally defined and categorized similarly to the key variables of the model development presented in Subsection II-A, based on their coupling or not within their three different phases: filling phase, packing phase, and cooling phase of the process. Thus, to improve the quality for injection molding systems, several topics need to be addressed, such as quality modeling, quality analysis, and quality prediction. Since injection molding is a multiphase batch process, each process variable has an impact on quality at a specific time. Therefore, MPLS is ineffective at revealing these relationships. By introducing intermediate quality measurements, a pathway multiblock PLS algorithm was developed in [122] to isolate the local effects of process variables on the final product quality. By utilizing the VIP (Variable Importance in the Projection of MPLS), a bootstrapping improved MPLS [123] can isolate the local effects of process variables on the final quality. PLS models of the critical-to-quality phases can be used directly for online quality prediction in [104] without any modifications. The predicted deviations in earlier critical-to-quality phases may be compensated for in current or future critical-to-quality phases [124]. Stacking modeling methods [125] can be used to weight each phase of a PLS model in a multiphase PLS model. However, phase PLS models are linear and average time-slice PLS models, so the predicted quality can vary slightly across phases due to measurement noise and model errors. Overall, quality improvement for injection molding remains a challenge when it comes to measuring and predicting online quality of the end product.

FUTURE PROSPECTS FOR INJECTION MOLDING

Powered by Industry 4.0 technologies, manufacturing plants have been transformed into smart facilities to meet the challenge of manufacturing smart products [19,126]. To avoid being left behind, the injection molding industry must adapt to such changes. In recent years, new technologies and tools have been developed that may help us develop next-generation automation solutions that break the limitations of existing capabilities. The following are a few technologies that may improve automation and trigger a revolution in the near future.

1. Machine Learning Methods

Machine learning (ML) is one of the fastest growing technical fields, with numerous successes in health care, education, robotics, and so on [89]. Generally, ML techniques can be divided into three categories: unsupervised learning, supervised learning, and reinforcement learning (RL) [127,128], where RL is becoming more popular in batch process applications [129,130]. In the field of system engineering, many efforts have been made to apply ML techniques to process modeling, control, monitoring, and optimization [131,132]. For injection molding systems using ML methods, the model development could be made easier by showing examples of desired input-output behavior; the control strategies can become more intelligent by combining online data and low-cost computation with new learning algorithms and theories; process monitoring can capture dynamic features in the data, making interpretation and visualization easier; quality optimization can be more effective in various product-changing and dynamical-changing environments, explicitly letting engineers handle trade-offs among different resources. Since ML methods rely on data, they are ideally suited for modeling, controlling, monitoring, and predicting batch processes [8], which will result in more efficient automation of batch process machines. However, the application of advanced ML methods to the injection molding systems in practice still requires a great deal of effort.

2. Big Data Analytics

Big data analytics is used to identify trends, patterns, and correlations in vast amounts of raw data in order to make data-driven decisions [133]. Through the use of newer tools, batch processes apply familiar statistical analysis techniques, such as clustering and regression, to more extensive datasets. Plastic injection molding has been the most versatile, flexible, and dynamic manufacturing process for almost 40 years. As companies use sensors and wireless technologies to capture images, videos, process data, and analyze data at every phase of their products' lifecycles, they generate more than ten exabytes of data each year. However, except for a small portion of the data used for modeling and monitoring, most companies have no idea how to use valuable data, such as long-term planning data for ordering raw materials and short-term scheduling data for unloading orders [134], let alone how to interpret them to improve processes and products. Injection molding big data analysis can help us gain a better understanding and control of the various steps of the process, the thermo-mechanical secret experienced by the polymer throughout the process, and the impact of this history on the characteristics of the final product [6]. Overall, the injection molding industry can benefit and be transformed by big data analytics [126], but a great deal of work still needs to be done.

3. Internet of Things

The internet of things (IoT) refers to a system of computing devices, mechanical and digital machines, objects, and people that exchange data over a network without human or computer interaction [135]. IoT ecosystems consist of web-enabled smart devices that use embedded systems, such as processors, sensors, and communication hardware, to collect, send, and process data. The IoT devices share sensor data by connecting to an IoT gateway or other edge device, which sends the data to the cloud or analyzes it locally. The devices do a significant amount of their work without human intervention, although they can be set up, instructed or accessed by people. Using IoT, injection molding companies can improve decision-making, improve customer service, and increase the value of their business, especially when using multiple machines and peer-to-peer sharing to enhance efficiency and profitability [136-140]. Overall, injection molding systems will become more intelligent with IoT.

4. Digital Twin Technology

Digital twins are digital representations of physical objects, processes, or services [141]. A digital twin can be a digital replica of an object in the physical world, such as a jet engine or wind farm. In addition to physical assets, digital twin technology can be applied to replicate processes in order to collect data that can be used to predict how they will perform. A digital twin is, in essence, a computer program that uses real-world data to create simulations that predict how a product or process will perform. For example, injection molding companies can create digital representations of products quickly and adapt them to customer needs prior to production. Programs like this can integrate IoT (or Industry 4.0), artificial intelligence, and software analytics to improve output. With the advancement of ML and big data, virtual models have become a staple in modern engineering to drive innovation and improve performance. By leveraging digital twin technologies, we can enhance strategic technology trends, prevent costly failures in physical objects, and test processes and services through advanced analytical, monitoring, and predictive capabilities [142].

CONCLUSIONS

Intelligent automation of injection molding processes has proven to be a challenging but very compelling endeavor based on real-world applications and key stakeholders. We have identified and analyzed several challenges at the model, control, monitoring, and quality levels to understand its existing limitations. To take advantage of the full potential of information technology, intelligent automation requires a high-performance computing platform. For specific application purposes, data collection and analysis must be secure, complete, and appropriate. It is important for systemic frameworks to examine the relationships between samples, models, and data sources, as well as their changes over time, batches, products, and other factors. As information technologies advance, we hope to be able to give you the latest advancements and most promising innovations to better understand injection molding's future.

ACKNOWLEDGEMENTS

This work was supported in part by the Hong Kong Research Grant Council under grant 16208520; in part by the Foshan-HKUST Project under grant FSUST19-FYTRI01; in part by the Guangdong scientific and technological project (202002030323 and 2014B 050505002); and in part by the SJTU Global Strategic Partnership Fund (2021 SJTU-HKUST).

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