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Control for Intelligent Manufacturing: A Multiscale Challenge

Han-Xiong Li *, Haitao Si *

Department of Systems Engineering and Engineering Management, City University of Hong Kong, Hong Kong, China

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ABSTRACT

The Made in China 2025 initiative will require full automation in all sectors, from customers to production. This will result in great challenges to manufacturing systems in all sectors. In the future of manufacturing, all devices and systems should have sensing and basic intelligence capabilities for control and adaptation. In this study, after discussing multiscale dynamics of the modern manufacturing system, a five-layer functional structure is proposed for uncertainties processing. Multiscale dynamics include: multi-time scale, space-time scale, and multi-level dynamics. Control action will differ at different scales, with more design being required at both fast and slow time scales. More quantitative action is required in low-level operations, while more qualitative action is needed regarding high-level supervision. Intelligent manufacturing systems should have the capabilities of flexibility, adaptability, and intelligence. These capabilities will require the control action to be distributed and integrated with different approaches, including smart sensing, optimal design, and intelligent learning. Finally, a typical jet dispensing system is taken as a real-world example for multiscale modeling and control.

1. Introduction

In Germany, Industry 4.0 is the term for the next industrial revolution [1]. In the United States, General Electric is promoting a similar idea under the name of the Industrial Internet. In China, the central government has established the Made in China 2025 initiative for future industry. All these ambitious plans indicate the beginning of the Fourth Industrial Revolution—a revolution that will merge real things with the virtual world for greater efficiency. Three other industrial revolutions have occurred in human history. The First Industrial Revolution employed mechanical production facilities; it started in the second half of the 18th century and lasted throughout the entire 19th century. Mass production using electrification led to the Second Industrial Revolution, which started around the end of the 19th century. The "digital revolution" that occurred in the 1970s can be defined as the Third Industrial Revolution, as information technology began to be used for the automation of production processes. Unlike all previous revolutions, which only released human physical power for linear changes, the Fourth Industrial Revolution will free the human thinking power that is "intelligence" and will create nonlinear changes beyond what we can imagine.

The core of Industry 4.0 is intelligent manufacturing, which can be considered as the cyber-physical system (CPS) within the manufacturing environment, in order to achieve full automation of both materials and information. The CPS is an Internet environment in which all users, hardware, and software are integrated, regardless of time and location, in order to adapt to different working conditions through good coordination and enhanced ability [2]. Examples of CPSs include smart grids, automated vehicle systems, medical monitoring, and intelligent manufacturing [3]. The differences between an embedded system and a CPS are as follows: An embedded system focuses on developing algorithms, while a CPS focuses on the connection and coordination between physical elements and computational software [4].

Over the past decades, consumable products have become increasingly advanced and intelligent, making manufacturing systems increasingly complex. From an academic point of view, the manufacturing industry is a nonlinear multiscale complex system. No single solution exists for such a complex system. Due to the human way of linear thinking, nearly all the theories and methods developed

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* Corresponding authors.
 E-mail addresses: mehxli@cityu.edu.hk; haitaosi2-c@my.cityu.edu.hk

so far are linearly dominated, making it difficult to apply them directly to nonlinear systems. The principle of systems engineering is to decompose a complex system into simpler ones, solve them separately, and then integrate all separate solutions in order to meet a global objective. In a manufacturing plant, each product is produced through a series of complex operations, each of which can be further decomposed into multiple basic actions. Obviously, uncertainties will appear at all of these stages and affect the overall quality.

This paper briefly discusses the multiscale complexity of the manufacturing process, presents modeling and intelligence that may be required in a manufacturing environment, and examines a case study for jet dispensing control for the integrated circuit (IC) packaging industry.

2. Multiscale complexity and uncertainty processing

A whole factory or plant usually has more than one production line containing many different types of processes. Each process may integrate multiple machines or pieces of equipment. Manufacturing operations in a factory can be classified into three different levels: the machine level, the production level, and the plant-wide level. The whole manufacturing process can be considered as a hierarchical structure: from machine control at the bottom layer, through mid-level supervisory control and production scheduling, and up to business management at the highest level. Different properties are exhibited at different levels, as shown in Table 1.

The characteristics and dynamics at different levels differ such that different control actions, from continuous to discrete, are required. Different processes may have different types of dynamics and a different scale of complexity. Some typical processes may include:

- **Multi-time-scale processes.** This is the most common scenario in manufacturing, in which a single part is manufactured within a short time, whereas parts in batches are produced over a long time period. The consistency of production is hence a primary concern, and involves the integration of various methods, such as robust system design, feedback control, and statistical process control.
- **Space-time dynamic processes.** Temperature fields, pipe fluid, and flexible robotic arms belong to this space-time dynamic system. Here, the performance changes not only in time but also in spatial location, and is therefore extremely difficult to model and control.
- **Multi-level hybrid processes.** The integration of systems at different levels results in hybrid systems that may be continuous, discrete, fuzzy, probabilistic, and so forth. The modeling and control of these types of systems are difficult because no mature methods are available. In general, the lower the level, the more dynamic property is required, such that dynamic control is needed. Uncertainty exists everywhere, in all levels of the manufacturing hierarchy. The higher the level, the larger the uncertainty, such that more intelligence is required for the

control system.

In terms of control engineering, several types of control can be defined, as follows:

- **Logic control.** This involves discrete action with two discrete states: on/off. No dynamics are involved.
- **Loop control.** This requires dynamic control because it entails the handling of physical dynamics. It involves continuous action at the machine level. Since machine dynamics can be expressed quantitatively, the control action can be optimized.
- **Supervisory control.** This involves nest control action, which is of a hybrid discrete/continuous nature.

All of the abovementioned low-level types of control are widely used in process control. High-level control involves a more decision-making type of action, which requires more intelligence-based methods, such as the following:

- Operation scheduling at the production level; and
- Business management of the plant-wide operation.

Regarding intelligent manufacturing, the five-level pyramid structure shown in Fig. 1 can be useful in effectively processing uncertainties and improving the overall quality [5]. The first step is to place sufficient sensors appropriately in order to collect data from the physical process. If everything can be measured and connected, physical uncertainty can be minimized. Once data is obtained, it should be converted into useful information for higher level analysis and processing. Many mature modeling and learning methods can be used to help reduce information uncertainty. Since manufacturing involves the integration of many different types of equipment and functional devices, hybrid modeling and learning is required for system-level coordination. Decision-level coordination involves human-machine interaction, which requires processing ability between human linguistic language and machine computational algorithms. In order to achieve full automation, knowledge-level decisions should be able to process unexpected events, which will continue to be a long-term challenge.

In summary, different types of processes require different control actions.

- More design is required at the fast time scale, and more control is needed at the slow time scale. The jet dispensing system for packaging is a good example that will be discussed in detail in Section 4.
- More quantitative action is required at low-level operations because machine dynamics can be expressed mathematically; in contrast, more qualitative action is needed in high-level supervision because that system cannot be described quantitatively.

Systematic work in this area should be built step by step using a bottom-up approach: from dynamic modeling, system design, process control, and intelligent supervision, up to plant-wide management control, and so forth. This is a large-scale challenge.

3. Modeling and intelligence in manufacturing

The multiscale complexity of the intelligent manufacturing process

Table 1
Multiscale properties of the manufacturing industry.

| Property	Machine level	Plant-wide level
Characteristics	Local (product oriented)	Global (business oriented)
Dynamics	Fast	Slow
Complexity	Small scale (linear dominant)	Large scale (nonlinear multivariable)
Uncertainty	Small	Large
Control	Dynamics-driven (continuous, instinct)	Knowledge-driven (discrete, logic)
Evaluation	Accuracy/precision	Profit
Intelligence	Low (adaptation)	High (decision)
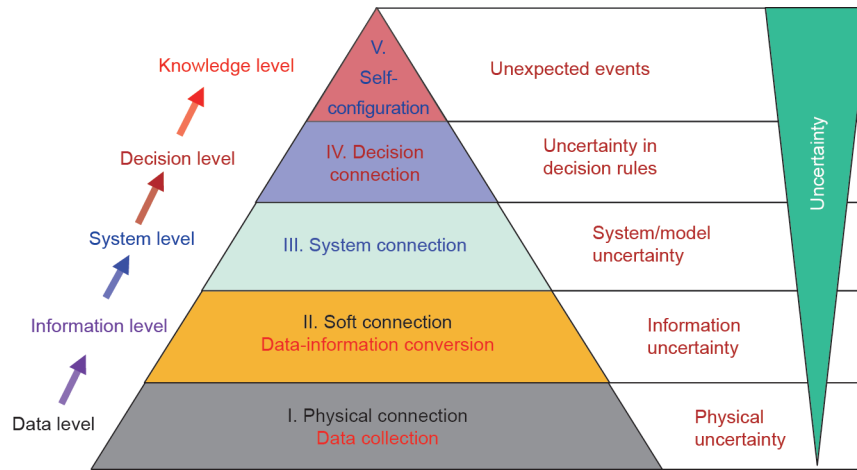
Fig. 1. Functional layers for uncertainty processing.

makes process modeling difficult. Process modeling is an essential step toward engineering control. System modeling in the field of control and machine learning in computer science actually perform similar work, albeit with different technologies and in different environments:

- System modeling relies more on the physics of the process because it usually operates in an environment with a low degree of uncertainty that does not affect the dominance of the process dynamics. In this case, a deterministic solution will exist. Under this relatively certain environment, physical dynamics play a major role, while external disturbance and nonlinearity have a smaller influence. Since classical quantitative methods can be used for optimization, the modeling performance is fairly deterministic and can be used for online prediction. Since the process dynamics can be quantitatively modeled, quantitative control or design can be performed.

- Machine learning mainly works in an environment with a high degree of uncertainty; plant-wide management is an example of such an environment. Multi-level hybrid solutions also accumulate uncertainty. Since the model structure is difficult to obtain, it relies more strongly on process data. Rather than a deterministic solution, a statistical solution will exist in this case. Non-traditional methods such as computational intelligence can be used to explore a better solution; therefore, the performance in this case is usually optimized using statistical or experiential data. Since the process dynamics cannot be quantitatively estimated, a qualitative decision is made instead of performing quantitative control.

3.1. System modeling

Many processes in the manufacturing industry, such as thermal processes, fluid/flow processes, and flexible robotic arm processes, belong to space-time dynamic systems, which are also called distributed parameter systems (DPSs). The dynamics of a DPS are described with partial differential equations (PDEs) and exhibit a strong space-time coupled nature. For example, the cure oven, or the reflow oven, that is used in the IC packaging industry requires a uniform temperature field because an equal heating effect is expected at every spatial location of the cured object.

3.1.1. Modeling classification

System modeling is very important in manufacturing control because it can help to determine the physical process well before any control action or decision is made. Different modeling is required for different functional purposes. System modeling can be classified as follows:

- **Modeling for process simulation.** This is physics-based modeling, in which every aspect is considered to reflect the true situation. Since most of such processes are DPSs, if first-principle knowledge of the DPS is accurately known, the model can be precisely derived and then solved using computational methods such as the finite difference method (FDM) [6] and the finite element method (FEM) [7]. This type of physics-based modeling requires heavy computation and is suitable for offline process analysis.

- **Modeling for control design.** Most control theories are linearly dominated, so a linear model structure is required for control design.

- **Modeling for online prediction.** An analytical model is required with parameters calibrated from experimental data. The dominant dynamics are considered in terms of ordinary differential equations (ODEs).

- **Modeling for process design.** Because this is function-based modeling, only important dynamics are considered for optimal design.

- **Modeling for decision-making.** Since decisions are based on important features and have a discrete nature, this is feature-based modeling.

When modeling, an appropriate model structure must be selected, along with optimal calibration of parameters under appropriate training signals (i.e., persistently exciting signals), and so forth.

3.1.2. Analytical modeling for space-time dynamic processes

The modeling of DPSs has been widely studied in the process industry [8]. The following PDE is provided as an easily understood illustrative example:

$$\frac{\partial y(x,t)}{\partial t} = \alpha \frac{\partial^2 y}{\partial x^2} + \beta \frac{\partial y}{\partial x} + f(y) + wb(x)u(t) \tag{1}$$

where x is the spatial variable; y is the process output; t is time; α, β, and w are coefficients; $f(y)$ is the nonlinear function representing other unmodelled dynamics; $b(x)$ is the spatially distributed function; and u is the control signal to the process. The boundary conditions are $y(0, t) = 0$ and $y(\pi, t) = 0$, and the initial condition is $y(x, 0) = y_0(x)$.

Because extensive computing power is required to solve a PDE, lumping techniques are used to approximately reduce the PDE into a finite-dimensional ODE using the space-time separation method [9] shown in Fig. 2. This ODE-based model is computationally efficient

and can be applied for online performance prediction; for example, it would be a challenge to estimate a temperature distribution over space using just a few sensors.

Many studies have been performed on this kind of space-time modeling, including studies on the spectral method and the approximate inertial manifold [10]. If the PDEs of a DPS are unknown due to process uncertainties, data-based model identification must be used. When the nominal PDE is unknown, neural networks can be used with the spectral method [11] to model the unknown nonlinearities. Neural networks can also be used with the Karhunen-Loève (KL) method [12] to model a completely unknown nonlinear DPS with the help of multiple sensors. Many different variations have been developed, and are systematically discussed in a literature survey paper [10].

3.1.3. Model-based integrated design and control

An integrated design and control approach is proposed for manufacturing control in three phases, as shown in Fig. 3.

- **Phase I:** This is a real-time experiment; a multi-sensing experimental platform is needed for the collection of real-time data for analysis.
- **Phase II:** This involves a physical simulation for offline analysis; a physical model in the form of a PDE is usually developed for physical simulation. Collected experimental data is used for model calibration. This physics-based simulation provides detailed information about the real process. Many commercial software packages, such as Fluent and Comsol, can provide basic functions. However, parameter selection and calibration are extremely difficult, and no mature solutions exist. After simulation,
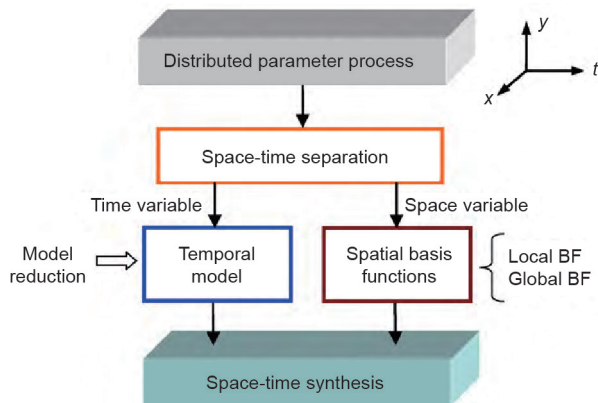
the system design can be carried out and tested at this stage.
- **Phase III:** This involves online prediction and control design; the analytical model, which is simplified as an ODE, is needed for control design or for online performance prediction. Optimal performance is expected to be achieved at this stage.

3.2. Intelligence for uncertainty processing

Uncertainty exists everywhere, and greatly affects manufacturing quality. There are two types of uncertainty: deterministic vagueness and stochastic variation.

- Deterministic vagueness usually comes from coarse measurement or imprecise perception of a process due to a harsh industrial environment. It has a fuzzy nature and can be properly modeled using a fuzzy system.
- Stochastic variation usually comes from missing dynamics (i.e., critical dimensions and factors) and from insufficient sampling data. Statistics or probability-based methods are needed to deal with this kind of random variation.

If uncertainty can be modeled using a traditional quantitative approach, it is classified as deterministic vagueness. If uncertainty cannot be modeled deterministically, it can be described probabilistically.

3.2.1. Computational intelligence

Artificial intelligence (AI) is the intelligence exhibited by machines in mimicking "cognitive" functions that humans associate with other human minds, such as "learning" and "problem-solving." An intelligent system can be classified according to its intelligence level, as follows:

- **Skill-based systems.** These systems learn from action mimicking, in a process that is somewhat like riding on bike; the intelligence level is similar to classical modeling, and the system only works for trained behavior.
- **Rule-based systems.** These systems involve decision-making according to defined regulations, in a process that is somewhat like driving a car; although they perform similarly to expert systems, they cannot make correct decisions in response to unknown symptoms.
- **Knowledge-based systems.** These systems make judgements in response to unexpected events. Such systems will continue to be challenging, as they require the highest possible intelligence level to predict forthcoming events that have not happened before.

All current AI solutions come from a set of computational methods and techniques, instead of from a single method or technique. There are four basic methodologies for computational optimization,
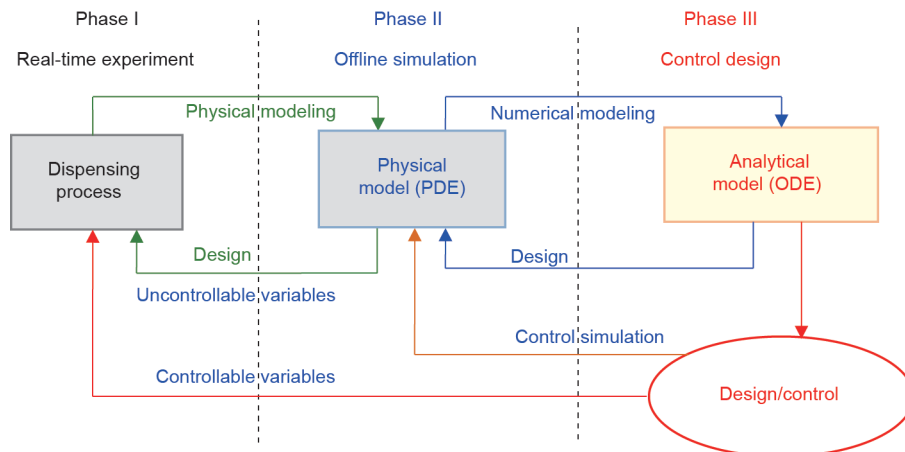
Fig. 2. The framework of space-time separation method. BF: basis function.

Fig. 3. Methodology for integrated design and control.

as follows:

(1) Traditional optimization for modeling. This math-oriented optimization can accurately identify the optimum point for a well-defined mathematical problem. It has the lowest intelligence level, as it may not be able to work under larger uncertainty if a mathematical expression does not exist.

(2) Statistics-based machine learning. This statistical learning is widely used in environments where a problem cannot be defined well mathematically. It searches for a nearly optimal solution through data-based learning.

(3) Experience-based reinforcement learning. This method mimics human decision-making through reward/penalty action. It is an offline solution that operates with the help of extensive computational trials.

(4) Nature-inspired evolutionary computation. A typical example of this method is the genetic algorithm. This is a kind of random search that can work globally. It is an offline solution with the heaviest computational load.

Different methods work for systems with different uncertainties and different intelligence levels, as illustrated in Fig. 4. The larger the uncertainty a method can handle, the more global and less optimal solution it will have. The best optimal solution still comes from a traditional optimization method under the lowest degree of uncertainty. This is the nature of the universe. In practice, higher level methods can locate a possible zone for optimal solutions; next, the lo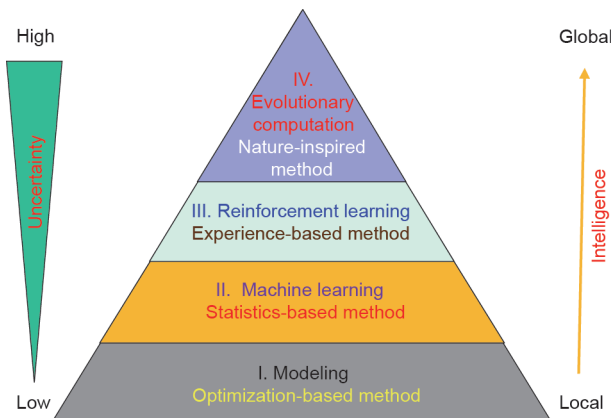wer level method finds the most concrete solution with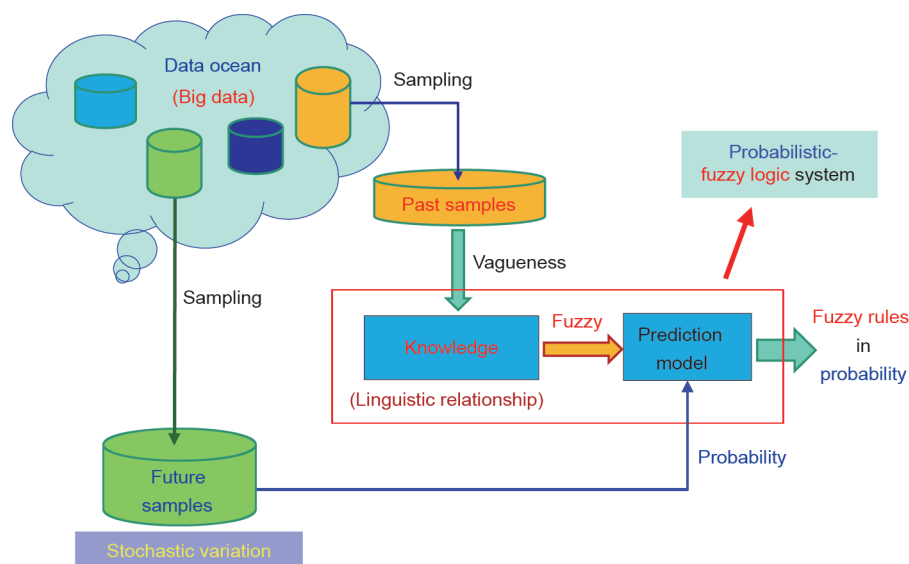in the identified zone. The optimal solution for a multiscale nonlinear process must come from an appropriate integration of multiple methods at different levels.

3.2.2. Probabilistic-fuzzy modeling for decision-making

A high-level control involves human decision-making. Human knowledge has a qualitative nature that is very suitable for modeling a fuzzy system. A future prediction for a fuzzy system will involve stochastic variation that comes from missing dynamics, and should be suitable for a probabilistic method to process. Thus, the two types of uncertainty—deterministic vagueness and stochastic variation—will always exist in real-world applications, as illustrated in Fig. 5.

A traditional fuzzy logic system is good at performing knowledge extraction, but cannot simultaneously handle stochastic variation. A probabilistic-fuzzy logic system is developed to merge fuzzy reasoning with probabilistic processing for the modeling of complex stochastic processes [13], and with data classification for decision-making [14]. However, the probabilistic-fuzzy logic systems developed so far have many shortcomings to overcome. One of the major remaining problems is difficult parameter calibration due to the complexity of the system configuration. Extensive efforts are still needed in this aspect for decision-making under large uncertainties.

4. Integrated modeling and control for multi-time-scale processes

The multi-time-scale process is a typical problem encountered in the manufacturing industry. As mentioned in Section 2, a single product is made in a short time period, but volumes of products in batches are produced over a long period. Production consistency is the primary concern for manufacturing quality. A typical example involves the jet dispensing system that is commonly used in the IC packaging industry; the jetting quality has become a bottleneck in this fast-developing industry.

A schematic drawing of one kind of jet dispensing system is shown in Fig. 6; this can be simplified into a system consisting of a needle, a chamber, and an adhesive supply. When the system begins to function, compressed air pumps the adhesive into the chamber, and a stiff spring is released to rapidly drive the needle, thus pushing the adhesive out of the chamber and onto the substrate. This is a multiscale (fast/slow) complex process, as shown in Fig. 7. A single droplet can be jetted out of the chamber in milliseconds (ms), and several thousand droplets can be jetted within a dozen minutes.
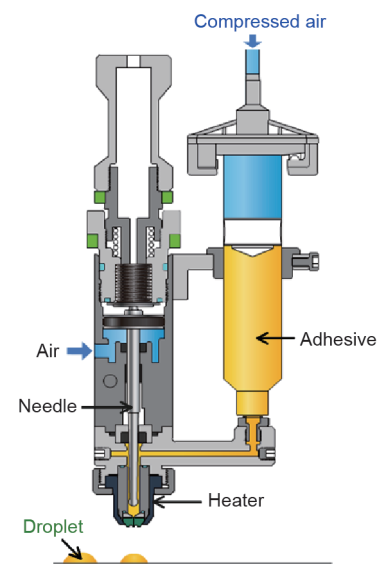

Fig. 4. A pyramid of intelligent methods.

Fig. 5. Probabilistic-fuzzy modeling.

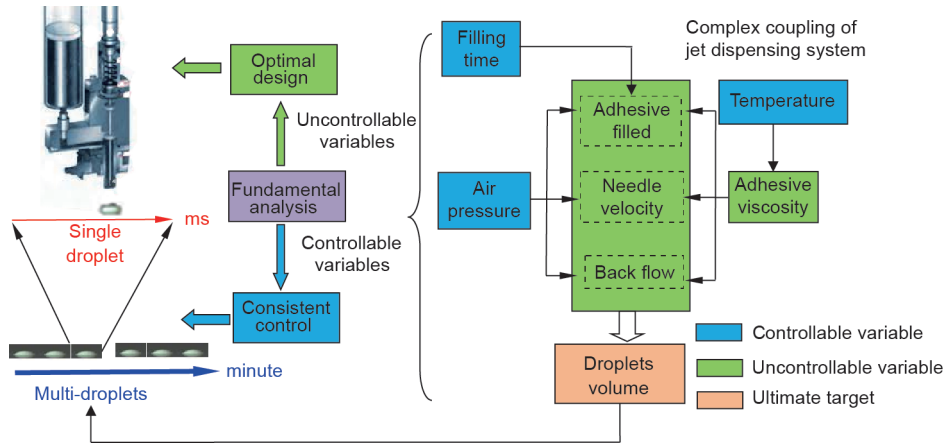**Fig. 6.** A jet dispensing system for electronics packaging.

Fig. 7. The dual-scale property of the jetting process.

Highly consistent droplets are required for high-speed dispensing. Long operation deteriorates the jet performance because the viscosity of the adhesive has a nonlinear and time-varying nature. The following difficulties with consistent dispensing are encountered:

- For fast-scale single-droplet dispensing, a disturbance cannot be captured in such a short instant, so no control can be designed to manipulate the flow rate.
- For slow-scale long-term operation, it is difficult to perform adjustments to suppress disturbances because there is no online measurement of the internal operation of the device.

Design and control should be effectively integrated in order to achieve consistent dispensation. For the fast-scale performance, only design can be applied to optimize the jet dispensing system; in contrast, for the slow-scale performance, consistent control can be applied once online sensing is implemented.

4.1. Optimal design for fast-scale performance

There is a strong interaction between the adhesive and the jet dispensing system. The design of the system includes material handling and jet valve design. This involves both real-time experimentation and physical simulation.

The incompressible polymeric adhesive motion can be described with the continuity equation (Eq. (2)) and the modified Navier-Stokes equation (Eq. (3)) [15].

$$\nabla \cdot (\boldsymbol{u}) = 0 \qquad (2)$$

$$\frac{\partial(\rho\boldsymbol{u})}{\partial t} + \nabla \cdot (\rho\boldsymbol{uu}) = -\nabla p + \nabla \cdot (\boldsymbol{\tau}_s + \boldsymbol{\tau}_p) + \rho\boldsymbol{g} \qquad (3)$$

where $\boldsymbol{u}$ is the fluid velocity; $\boldsymbol{\tau}_s$ is the solvent stress tensor; $\boldsymbol{\tau}_p$ is the polymeric stress tensor; ρ is the fluid density; p is pressure; and g is the gravitational acceleration. The generalized power law (Eq. (4)) is used to model the solvent stress [16], and the Oldroyd-B constitutive equation (Eq. (5)) is used to model the polymeric stress.

$$\boldsymbol{\tau}_s = \boldsymbol{\tau}_0 + \eta_s \dot{\gamma}^n \qquad (4)$$

$$\boldsymbol{\tau}_p + \lambda \overset{\triangledown}{\boldsymbol{\tau}}_p = 2\eta_p(T, \dot{\gamma}, t)D \qquad (5)$$

where τ_0 is the yield stress; η_s is the solvent viscosity; $\dot{\gamma}$ is the shear rate; n is the power-law constant; η_p is the polymeric viscosity, which has a nonlinear time-varying nature; λ is the relaxation time; $D = \frac{1}{2}\left(\nabla\boldsymbol{u} + (\nabla\boldsymbol{u})^T\right)$; $\overset{\triangledown}{\boldsymbol{\tau}}_p$ is the upper convected time
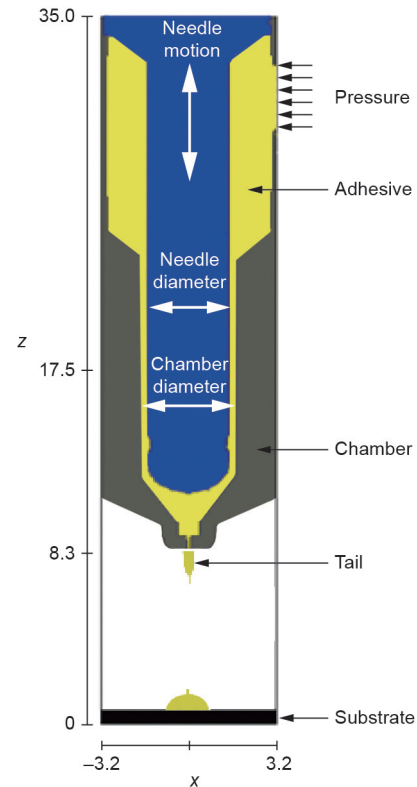

Fig. 8. A simulation of the jetting process (unit: mm).

derivative of $\boldsymbol{\tau}_p$; and T is the adhesive temperature.

The adhesive viscosity, η, can be derived experimentally using a rheometer. The simulation model is calibrated with the experimental data. A simulation of the jetting process, as shown in Fig. 8, can provide more information that may be difficult to observe from an experiment in real time:

- The hidden mechanism for droplet formation and breakup is disclosed, and the coupling relationship between different variables is discovered [17].
- Data generated from the simulation can help to develop the analytical relationship between critical parameters and the jetting performance.

Next, these design guidelines should be followed for performance improvement:

- The rules for proper handling of the adhesive materials before dispensation, provided in Ref. [18], ensure that the adhesive materials are in the best state for dispensing.
- The optimal design of the critical parts of the jet valve, provided in Ref. [19], maximizes the dispensing capability for a single droplet.

4.2. Consistent control for slow-scale performance

In a slow-scale long operation, the performance drift should be identified in order to enable system control by means of the following actions:
- Establishing integrated sensing for the real-time estimation of the jetting performance at every cycle (i.e., the fast scale); and
- Determining the cross-scale multivariable compensation for consistent jetting in batches (i.e., the slow scale).

4.2.1. Integrated sensing for real-time estimation

A measurement device [20] was added onto the existing valve of the jet dispensing system in order to sense the needle displacement x. With this measurement device, the volume V pushed out of the nozzle at every cycle (i.e., the fast scale) can be estimated by integrating the flow rate over the cycle period. Since the adhesive is a non-Newtonian fluid, the flow rate is unknown. Calibration with the experimental data is needed with the help of a camera and a high-precision balance.

4.2.2. Cross-scale multivariable compensation

Both the experiment and the simulation have shown that the jetting performance is coupled with the pressure P and the adhesive viscosity η. The inverse models $T(\eta, t)$ and $P(V, t)$ should be developed for the purpose of decoupling control. Here, we propose a novel cross-scale multivariable control strategy for the jetting process, in which the pressure P and temperature T are handled separately in two control loops, as illustrated in Fig. 9:

(1) Temperature control in the auxiliary loop for viscosity compensation. The steady viscosity η should be maintained in order to minimize the coupling effect between P and T. The viscos-ity changes slowly during the operation and is compensated for by adjusting the adhesive temperature.

(2) Cross-scale compensation control [21] in the dominant loop. The dominant loop has two functional loops: disturbance compensation for coupling suppression and feedback control for set-point tracking.

The disturbance compensation has three major components:
- **Fast-scale estimation.** The jetted volume V_f is estimated at each cycle through the online sensing of the needle motion. This fast-scale data (i.e., V_f) must be transformed into slow-scale information V_s with all the stochastic variation minimized through the fast-slow conversion.
- **Batch measurement.** The actual jetted volume in the batch is periodically weighed and statistically processed. Using the statistical method, the volume distribution information can be obtained and properly processed.
- **Slow-scale compensation.** The inverse model $P(V, t)$ is used to convert the process deviation ΔV into the appropriate adjustment ΔP in order to eliminate any prediction error.

A simple feedback controller can be sufficient to maintain good set-point, V_r, tracking if the disturbance can be well compensated for. Calibration is needed to adjust both the fast-scale estimation and the slow-scale compensation if the process is strongly time-varying.

5. Conclusion

Manufacturing processes have many different types of equipment and systems that are integrated to exhibit multiscale dynamic features with a hierarchical structure. Manufacturing control is a multiscale task: from smart sensing of the process at the lowest level, to optimal design of the system offline, to multivariable process control online, and further to intelligent learning for decision-making at the highest level. Multidimensional knowledge from nearly all engineering fields is needed, such as physics and material engineering, control engineering, mechanical and electrical engineering, and computer engineering. Systematic work in this area should be built
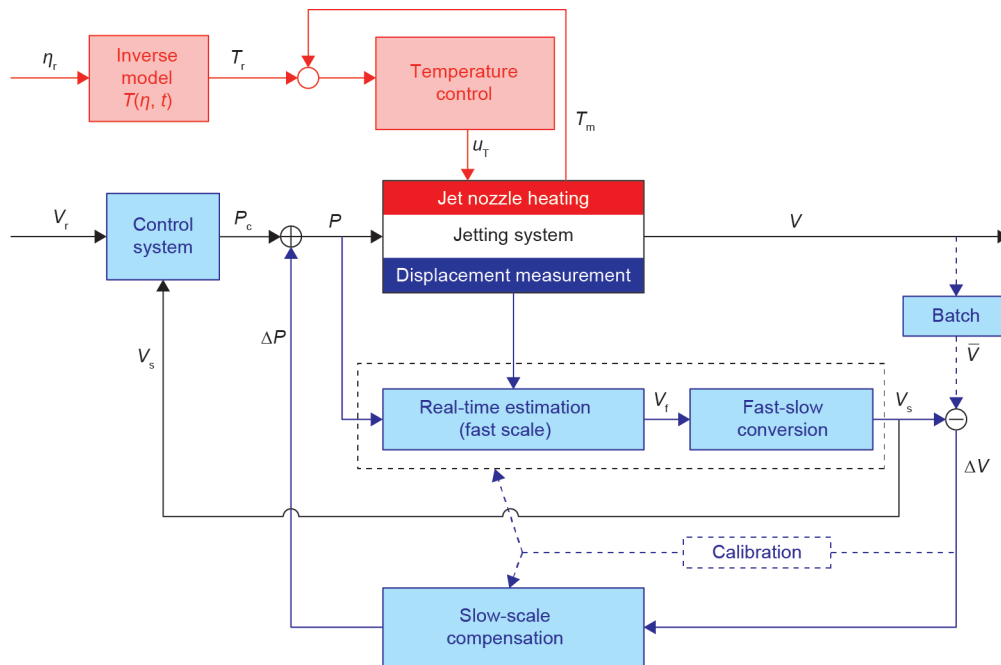

Fig. 9. Cross-scale multivariable compensation. η_r: viscosity setpoint (required value); T_r: temperature setpoint (required value); V_r: pressure setpoint (required value); $\overline{V}$: average of volume in batch; P_c: pressure output from controller; T_m: measured temperature; u_T: output signal from temperature controller.

up step by step using a bottom-up approach, from dynamic modeling, to system design, to process control, to intelligent supervision, and up to plant-wide management control. This development will be a long-term challenge.

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Compliance with ethics guidelines

Han-Xiong Li and Haitao Si declare that they have no conflict of interest or financial conflicts to disclose.

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