

# **Investigation of Advanced Process Control Methods for Exposure Controlled Projection Lithography**

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## **Abstract**

The DMD based Exposure Controlled Projection Lithography (ECPL) process has promising applications in fabrication of microfluidics and micro optics components. Unlike a conventional layer-stacking projection stereolithography process, ECPL cures a 3D feature by projecting radiation through a stationary, transparent substrate by varying exposure patterns and durations implemented by a sequence of DMD bitmaps. Due to the unavailability of an in situ metrology for cured part dimensions, unmeasurable time-varying disturbances such as oxygen inhibition and light source fluctuations, and the complex chemical & physics interactions in photopolymerization, a common practice in stereolithography process planning is to use experimental characterization and statistics models in an open-loop mode, which yields poor accuracy. This paper reviewed existing process control methods for ECPL and defined a need for advanced control methods. As a first proposal for advanced control methods to mask projection stereolithography, the paper surveyed relevant processes and put forward a hierarchical framework of advanced control methods for ECPL, including evolutionary cycle-to-cycle (EC2C) and adaptive neural network (ANN) backstepping control methods. The goal is to identify some advanced control methods, which are capable of tracking the process dynamics by online updating the model parameters with real-time measurement feedback. Such closed-loop control methods are promising to be able to improve the process precision and robustness.

## **1 Introduction and Motivation**

### **1.1 ECPL System Overview (need to correct the left margin on your headings)**

Various micro fabrication applications in microelectronics, micro-optics, micro-fluidics, MEMS and MEMOS demand smaller and smaller devices. Driven by the trend, micro stereolithography ( $\mu$ SL) is required to deliver photo-curable micro structures with decreasing feature sizes. Improved control of  $\mu$ SL is critical in realizing better manufacturing resolution and reproducibility.

A prototypical  $\mu$ SL process consists of the following basic steps - substrate and chamber setup, photopolymerizable material preparation, photo exposure curing, post-developing and washing.  $\mu$ SL machines can be classified into two main categories: laser scan and mask projection. The Digital Micromirror Device (DMD) based Exposure Controlled Projection Lithography (ECPL) system falls into the category of non-stacking mask projection stereolithography apparatus. It has promising applications in fabrication of microfluidics and micro optics components for biomedical devices. Different from a conventional laser scan stereolithography process, ECPL cures a 3D feature by projecting radiation through a

stationary, transparent substrate and by varying exposure patterns and durations with a timed sequence of DMD bitmaps. As illustrated in Figure 1, in the ECPL process, when the resin is exposed to a patterned light beam from DMD for certain time, photopolymerization takes place and a layer of liquid resin is cured. Each layer has a target cured height, and the cumulative layers form the final cured part.

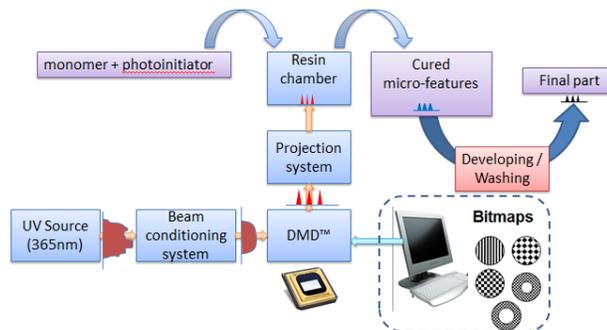


Figure 1: Exposure Controlled Projection Lithography Process Overview [1]

## 1.2 Motivation

ECPL systems have been evolving since our first generation prototype in 2008, and the process has been continuously improved, resulting in a smaller and smaller fabrication error, from 25% [2] to 15% [1] to recently 10% [3]. However to become a more capable micro manufacturing method for wider applications, ECPL still has limited process accuracy, which sparks a new study area of interest - advanced process control methods as will be investigated in this paper.

Another motivation is the development of an in-situ measurement system - , the interferometric curing monitoring (ICM) system, proposed by Jariwala et al. ([4], [5]) in an attempt to build a more precise ECPL system. The plateau of current open-loop process accuracy might be changed with a more mature ICM, which will be able to provide real-time measurement output enabling a closed-loop control. It is reasonable to think that advanced control methods with real-time closed-loop feedback could improve significantly ECPL process accuracy.

This paper initiates a preliminary investigation about advanced control methods, which are defined under this particular scenario as closed-loop real-time feedback control, and identifies some potential control methods applicable to ECPL.

## 2 Existing ECPL Process Control

Primarily due to the complicated nature of photopolymerization and stereolithography process, so far no comprehensive control strategy exists yet except for some basic use of offline open-loop process control technology. This technique relies on characterization experiments, which are used to quantify the effects of exposure dose on the cured heights. Our group has worked extensively in an effort to realize an automated and precise ECPL system.

## 2.1 Process Control Method Developed by Zhao

Zhao (2009) [2] built a process model (Equation 1) relating the exposure dose  $E$  to the final cured height  $Z$  by curve fitting of measurement data from many cured parts. Experiments were performed beforehand to determine the values of critical exposure  $E_c$  and penetration depths of liquid ( $D_{pL}$ ) and of solid resin ( $D_{pS}$ ). This model was an analytical solution of the ordinary differential equation of a transient layer curing model developed by Limaye and Rosen (2007) [6], which was based on Beer-Lambert's Law ( $E_c$ - $D_{pS}$ , i.e., threshold exposure model). Before solving, it was simplified by applying Taylor series expansion with higher order terms omitted.

$$Z(E) = D_{pS} \ln \left[ \frac{D_{pL} E}{D_{pS} E_c} + 1 - \frac{D_{pL}}{D_{pS}} \right] \quad (1)$$

Based on the process model above, an open-loop process control for ECPL was developed and the control scheme is summarized as shown in Figure 2. Given a 3D part profile, based on the inverse process model, a timed sequence of bitmaps was generated to minimize the mean squares of errors between all voxels' actual exposure dose to their required dose in order to cure the desired part.

The process control method was implemented on a few examples of lenses fabrication by Jariwala [1]. The desired diameter was 200  $\mu\text{m}$  and the sag height was 120  $\mu\text{m}$ . It was observed that the process control failed to adequately cure the heights and the overall diameter of the part. The height was under-cured by almost 20  $\mu\text{m}$  and the diameter mismatch was up to 50  $\mu\text{m}$ , which corresponded to around 30%.

This process control has a virtue in terms of process automation development, but could not achieve good accuracy due to an over-simplified process model and process inherent challenges. This is a common problem of open-loop control.

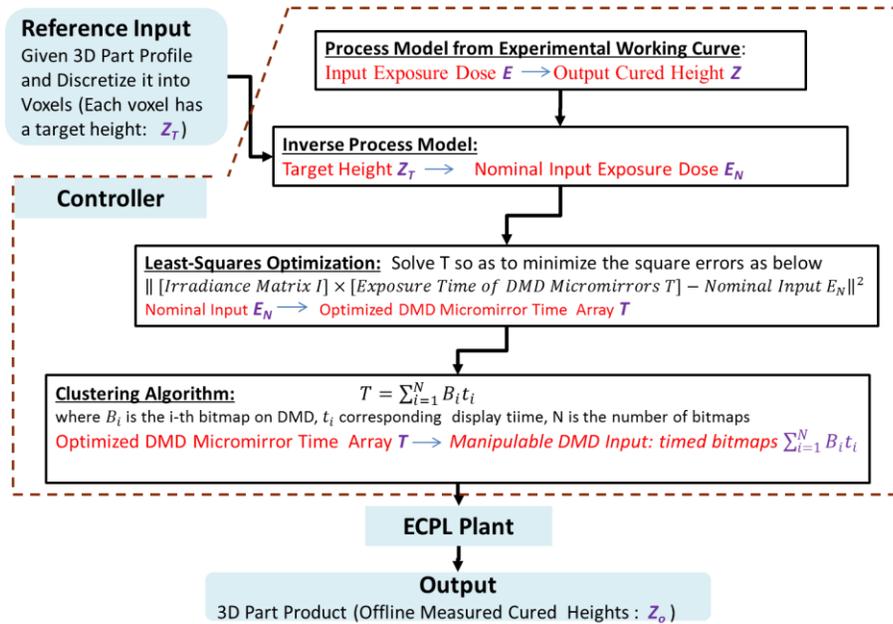


Figure 2: ECPL Open-loop Process Control Scheme by Zhao [2]

## 2.2 Process Control Method Developed by Jariwala

To come up with a more accurate process model, Jariwala (2013) [1] investigated the photopolymerization chemical reaction kinetics and conducted both 1D and 2D simulations in COMSOL Multiphysics® to generate a semi-empirical material model based on the well-known Beer Lambert's law of attenuation. This chemical kinetics based material model was validated to be able to estimate better the shape of a cured part than the experimental working curve above, because it added oxygen inhibition and diffusion effects.

The semi-empirical model, still based on the basic threshold exposure model, was revised by incorporating the idea that both  $E_c$  and  $D_p$ , rather than remain constant, could actually change with the distance between substrate pixel and substrate center. In order to find out the functions of  $E_c$  and  $D_p$  with the substrate pixel's distance away from the substrate center, a response surface named as material model was generated with COMSOL simulation data (note: not physical experiment, which was verified to agree with COMSOL simulation result with some acceptable errors).

The final form of this process model is as shown in Equation (2), where  $R$  is the maximum radius ( $\mu\text{m}$ ) of the part to be cured,  $r$  is the distance ( $\mu\text{m}$ ) of the point of interest from the center,  $E(r)$  is the irradiance energy ( $\text{mJ}/\text{cm}^2$ ) incident at the point of interest and is obtained from the material parameter database and  $Z$  is the cured part height at the point of interest.

$$Z(r, R) = \begin{cases} 0, & \text{for } E(r) < E_c(r, R) \\ D_p(r, R) \times \ln\left(\frac{E(r)}{E_c(r, R)}\right), & \text{for } E(r) \geq E_c(r, R) \end{cases} \quad (2)$$

With the process model in the equation above, a process control scheme was formulated by interplaying the empirical response surface with COMSOL simulation of polymerization reaction kinetics to estimate the manufacturing process input required to cure a part with desired shape and dimensions.

The process-planning problem, which was actually also an open-loop control, was split into two steps – estimating first bitmap and exposure time using material model database, and estimating subsequent bitmaps and exposure time based on simulated slicing techniques. Figure 3 shows the flow chart for estimating the subsequent bitmaps and exposure times.

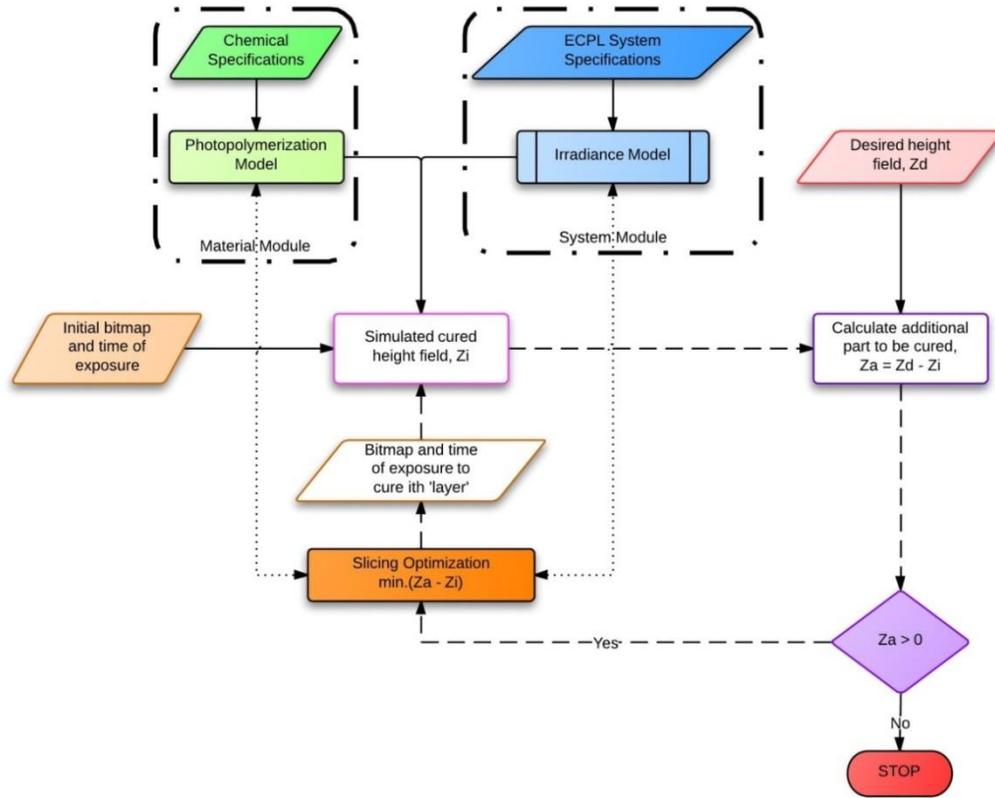


Figure 3. ECPL Open-loop Process Control Scheme by Jariwala [1]

In micro-lens curing experiments, Jariwala's process control method yielded an error of about 15% between the cured part geometry and the desired part geometry, both in sag height and diameter.

However, because the time-consuming COMSOL simulation could not provide in-situ feedback, the controller calculated the input offline which was later implemented in an open-loop mode. Consequently, such kind of controller is incapable of dealing with process variations and disturbances.

### 2.3 Process Control Developed by Jones

Jones [3] experimented with a real-time sensor, an interferometric curing monitoring (ICM) system, to fit a model relating time ( $t$  in seconds) and phase angle ( $\Phi$  and  $\Phi_c$  in degrees) with part height ( $Z$  in  $\mu\text{m}$ ) so that a comparison between the direct control of time and the control with measured phase angle could be performed. The time to part height relationship, Equation. (3), was experimentally determined by curing a single square for a known amount of time, washing the sample, and then measuring its height.

$$Z(t) = 36.85 \times \ln(t) + 22.707 \quad (3)$$

The relationship, as shown in Equation (4), between phase angle and part height was also found using the same dataset.

$$Z(\phi_c) = 30.144 \times \ln(\phi_c) - 159.83 \quad (4)$$

Corresponding to model in Equation (3), a simple controller, working like a stopwatch, was used to control the curing time so as to achieve a desired height. A second control method was proposed based on Equation (4) with the aid of ICM which could provide in-situ measurement. Equation (4) maps the in-situ measurement of interferogram phase angle with the ICM to the off-line measurement of cured part height with microscopy. The objective was that after characterizing the in-situ ICM measurement, real-time inference of cured height would be available to advance the controls towards real-time closed loop feedback control, which was proposed in Figure 4. This controller aimed to achieve real-time control by turning bitmaps on and off in response to ICM measurements of phase angle.

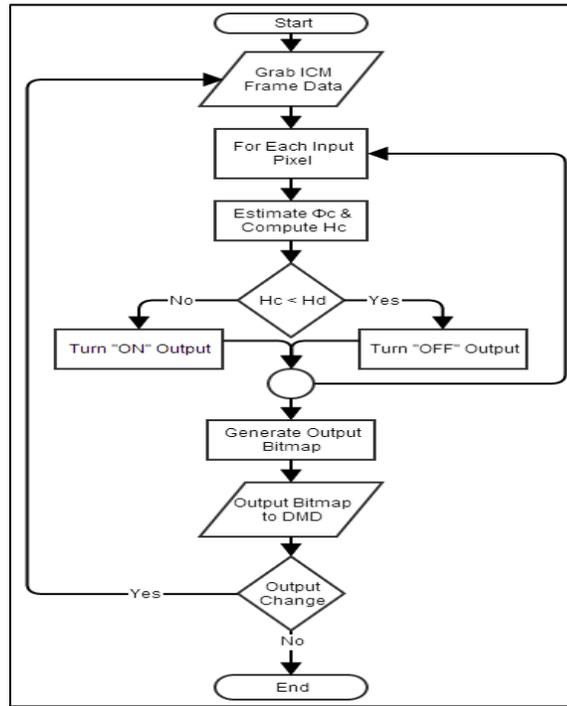


Figure 4: Flow Diagram of the Control System Proposed by Jones [3]

The stopwatch type of control is simple and straightforward, and its accuracy depends on the model accuracy in Equation (3).

As to the proposed control scheme in Figure 4, it is a quasi closed loop controller because it compares feedback with a set-point just to decide when to stop displaying the given bitmap, but can not adjust accordingly the exposure intensity or pattern. Another limitation is that it achieves control only in a conditioned scenario where the bitmap is known and all that needs control is just the bitmap's display time. Simple examples of squares curing using only single or two bitmaps were conducted experimentally and the results demonstrated better accuracy than the use of open-loop, time-based control. However, more complete closed-loop feedback control across the entire build chamber for a 3D part is still needed. Furthermore, the controller performance depends heavily on the accuracy of the empirical model, and was constrained by a lack of well-developed analysis of real time measurement data.

### 3 Need for Advanced Control of ECPL Process

#### 3.1 Summary of existing ECPL controls

The existing ECPL process control methods introduced above are summarized in Table 1.

Table 1. Summary of Existing Process Controls

Control Methods		Zhao (2009)	Jariwala (2013)	Jones (2014)
Process Model	Measurement	Offline (Microscopy)	Offline (Microscopy)	Offline (Microscopy), <b>Online (ICM)</b>
	Operation	<b>Offline</b>	<b>Offline</b>	<b>Offline</b>
	Methods	<b>Physical</b> (Analytical Transient Layer Curing Model) + <b>DOE</b> (to build Working Curve)	<b>Physical</b> (Revised Exposure Threshold Model) & <b>Chemical</b> Kinetics COMSOL Simulation + <b>DOE</b> (to build Material Database)	<b>DOE</b> (Purely Experiments Data Curve Fitting using Logarithmic Regression)
	Process Knowledge	<b>Preliminary</b>	<b>Intermediate</b>	<b>None</b>
	Parameters	1. Offline Preset. 2. Uniform all across time and space. <b>No variation or dynamics considered.</b>	1. Offline Preset. 2. Changing radially. <b>Spatial variation but no dynamics considered</b>	1. Offline Preset. 2. Constant Curve slope and interceptions (No physical meaning). <b>No variation or dynamics considered.</b>
	Variables	<b>Exposure dose E</b> (both bitmap and exposure time)	<b>Exposure dose E</b> (both bitmap and exposure time)	Requiring Bitmap be given, Model #1: <b>exposure time t</b> ; Model #2: <b>exposure time t</b> (by comparing measured and desired Phase angle $\Phi$ )
Equations	$Z(E) = D_{pS} \ln \left[ \frac{D_{pL} E}{D_{pS} E_c} + 1 - \frac{D_{pL}}{D_{pS}} \right]$	$Z(r, R) = \begin{cases} 0, & \text{for } E(r) < E_c(r, R) \\ D_p(r, R) \times \ln \left( \frac{E(r)}{E_c(r, R)} \right), & \text{for } E(r) \geq E_c(r, R) \end{cases}$	Model #1: $Z(t) = 36.85 \times \ln(t) + 22.707$ Model #2: $Z(\theta_c) = 30.144 \times \ln(\theta_c) - 159.83$	
Controller	Algorithms	1. Offline 2. Optimization & Clustering to calculate process input from the model	1. Offline 2. Incremental Trial and error based on simulation feedback	<b>Controller #1:</b> Simple stopwatch type of time control using Model #1. <b>Controller #2:</b> Feedback time control using Model #2.
	Implementation Mode	implement the pre-calculated input in an <b>open-loop</b> mode	implement the pre-calculated input in an <b>open-loop</b> mode	Controller #1: Open-loop Controller #2: <b>Quasi Closed-loop</b>
Fabrication Error		~ 25%	~ 15%	~ 10%
Notes		1. "Offline" means the model parameters or controllers inputs are calculated ahead of the process. Oppositely, "Online" means the calculations are done during the process. 2. "DOE": Design of Experiments 3. Parameter "Dynamics" means its changes or evolution with time.		

Despite their effectiveness to some extent, the existent process controls suffer noticeable loss of accuracy because they cannot track the changes in process, material and equipment. The techniques have some common limitations of the inherent weakness of the offline process model and non-closed-loop control mode.

#### 1) Offline process model

It is noted that all the existent process controls are based on offline process model, which couldn't address the online process variations and disturbances. The process input has been preset by the process model, whose parameters are obtained offline and prone to become oversimplified or obsolete due to the varying material properties and equipment conditions along with some stochastic phenomena present in the photopolymerization. Thus, offline static process model would undermine a desired accurate process control.

#### 2) Open-loop control mode

Under the existing strategies it is common practice to operate the ECPL process in an open-loop mode. The fabrication process would go thru without adjusting the process input according to online process variations and disturbances.

### **3.2 Issues of Controlling ECPL Process**

Like all other complex polymerization processes, ECPL also faces challenges on both issues of model formulation as well as control computation.

Foremost, process knowledge, preferably in-depth, is very important in controller design. However, the nonlinear process involves multi-physics such as photonics, chemistry and mechanics, which interact in a complex and unknown way. Consequently, no process dynamics has been modeled yet, not to mention control it.

Another factor detrimental to process control is unmeasured or unmeasurable process variations including exposure UV light source intensity fluctuation, batch-to-batch inconsistencies in photo material formulation, etc. Worse still, ECPL is vulnerable to external disturbances such as oxygen inhibitor distribution, and unquantified effects on cured thickness and shape caused by downstream operations such as post-curing developing and washing.

Therefore, it is difficult to control the ECPL process because of the specific issues described above, which become motivations for new research. The study aims to find some controls of the corresponding unknown process with adequate design and appropriate measurements.

### **3.3 Research Objective**

Many of the limitations of the existing ECPL controls mentioned stem from the fact that fundamental understanding of photopolymerization based stereolithography is still incomplete; therefore an open-loop control cannot effectively address all the process control problems of concern. An advanced method for controlling processes, which are only partially understood, is closed-loop control where input and output variables are linked through information feedback [7].

Specifically, to address the challenging issues in previous section, an advanced control method should be able to conduct online adaptive learning and dynamics control with real-time measurement.

In this study, we define advanced control methods as these with the characteristics in Table 2. To be clear, advanced control means online closed-loop control system with real time feedback and online parameter estimation. There are various embodiment designs based on different schemes and algorithms. The research aims to identify some applicable advanced control methods for the ECPL system.

Table 2. Research Gaps Identification for ECPL Control

Control Methods	Process Model		Measurement	Controller				Actuator		
	Mode			Method	Operation Mode		Algorithms		Manipulated Input (DMD Bitmaps)	
	Offline	Online	Offline		Online (Real-time)	Open-loop				Closed-loop
Zhao (2009)	✓		DOE & Simple Physical Model	✓		✓		Optimization & Clustering	1. Binary Bitmaps 2. Display time of Each Bitmap	PowerPoint
Jariwala (2013)	✓		DOE & Chemical Kinetics with COMSOL 2D Finite Element Simulation	✓		✓		Incremental Trial and error based on simulation feedback	1. Binary Bitmaps 2. Display time of Each Bitmap	PowerPoint
Jones (2014)	✓		DOE & Logarithmic Curve Fitting	✓	✗ (Immature)		✗ (Quasi)	Compare feedback with setpoint just to decide when to "stop", can NOT adjust accordingly the exposure intensity or pattern.	1. Only Display time of Bitmap (Binary Bitmap Given)	MATLAB
Advanced (Proposed to Fill Gaps)		✓ (Online Estimation & Update)	DOE, Advanced Multi-Physics Models, System Identification	✓	✓	✓	✓	Advanced control algorithms with measurement feedback e.g. digital control, adaptive, neural network.	1. Greyscale Bitmaps 2. Display time of Each Bitmap	Not decided

#### 4 Literature Review on Controls of Manufacturing Processes Relevant to ECPL

Very few literature reports application of advanced control methods to micro stereolithography ( $\mu$ SL) process, not to mention to the specific kind of non-stacking DMD-based uSL process as is the ECPL case. Nevertheless, there is quite a lot of research effort on control technologies in other manufacturing processes which are similar to ECPL in one or another way. Perusing literature in these process control methods could shed some light onto the guidelines or approaches of developing an improved ECPL control system. Figure 5 depicts the surveyed control strategies in a wide spectrum of processes linked to the ECPL process of our interest. The literature review started from the properties space of ECPL and reached out to similar processes in terms of a particular property. We wish to learn various controls and identify these suitable to ECPL.

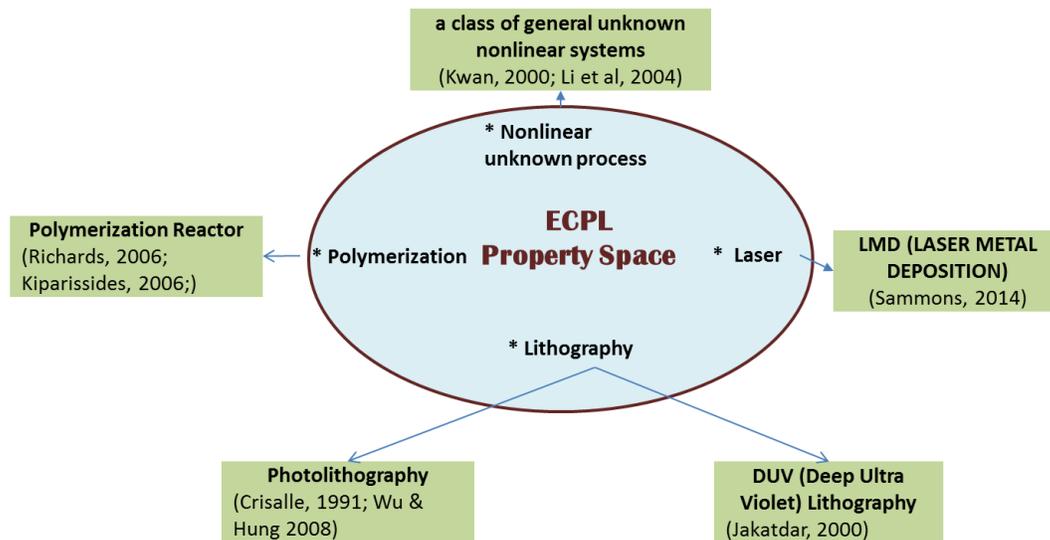


Figure 5. Literature Survey on Controls of Processes Relevant to ECPL

## 4.1 Controls of Polymerization

First of all, ECPL could be deemed as a miniature polymerization reactor, specifically, a free radical chain-growth photo-polymerization process, which is one of various polymerization kinds. A polymerization process usually undergoes disturbances, which move the process away from the desired trajectories. In order to obtain in-specification end-use polymer properties such as final form and shape, for the intended application, process measurement and control systems must be designed and implemented.

### 4.1.1 Challenges in polymerization modeling and optimization: A population balance perspective

Kiparissides (2006) [8] surveyed a unified population balance approach to follow the time evolution of molecular and morphological polymer properties in batch and continuous polymerization reactors. The numerical methods as well as the computational issues related with the solution of the dynamic population balance equation were critically assessed. The orthogonal collocation on finite elements (OCFE) method and the fixed-pivot technique (FPT) are then applied to a free-radical batch polymerization reactor to calculate the dynamic evolution of the molecular weight distribution (MWD). Moreover, theoretical and experimental results were shown on the dynamic evolution of particle size distribution (PSD) in a suspension polymerization reactor.

The numerical solution of the dynamic population balance equation (PBE) for a particulate system, especially for a reactive one, is a notably difficult problem due to both numerical complexities and model uncertainties regarding the particle nucleation, growth, aggregation and breakage mechanisms that are often poorly understood. Usually, the numerical solution of the PBE requires the discretization of the particle volume domain into a number of discrete elements that results in a system of stiff, nonlinear differential or algebraic/differential equations that is solved numerically.

Recent advances in on-line monitoring of “polymer quality” were briefly discussed in the context of available hardware and software sensors. The problem of real-time optimization of polymerization processes under parametric uncertainty is also examined. Finally, new issues related with the modeling, numerical solution and control of multidimensional population balance equations were conferred.

### 4.1.2 Measurement and control of polymerization reactors

Richards and Congalidis (2006) [9] presented a hierarchical approach to the control system design and reviewed traditional regulatory techniques as well as advanced control strategies for batch, semi-batch, and continuous reactors. The paper focused on process control in a complex industrial environment of free radical copolymerization reactor with environmental conditions (Pressure, Temperature, Level, and Flow) regulation, and material property (viscosity, MWD and PSD) measurement. This process had been used as a benchmark to test various control and estimation schemes. It represents a wide class of free radical polymer reactors with no less challenge in general polymer industry than in ECPL. The logic is that if the control methods introduced in the literature could address the polymerization with more complex issues, they or their variations might also be applicable to ECPL, because the polymerization process is more aggressive than ECPL in terms of high nonlinearity, multiple inputs-outputs, multiple sensors and deadtime issues.

The industrial measurement techniques are not applicable to ECPL micro process, however, as rationalized above, the controls methods might be leveraged to ECPL.

Richards [9] started reviewing controls with a comparison of generic control methodologies as below.

1) PID feedback control

Very widely used because it requires minimal process knowledge. In particular, it doesn't require a mathematical model of the process. If properly tuned, the PID controller can be quite robust in maintaining good steady state in the face of unmeasured disturbances. However, it has a serious limitation: the PID controller requires control variables to be measured online so that the control action can occur after detecting a deviation between the set point and the measured variable. Perfect control is not possible because PID feedback control is reactive and compromising.

2) Feedforward control

It relies on the fidelity and accuracy of the process model, based on which it compensates the measured disturbances.

3) Feedforward - feedback control

A combination of feedforward and feedback control utilizes the best of both approaches by being able to provide compensation for both measured and unmeasured disturbances as well as model inadequacy and measurement inaccuracies.

As expected, the authors recommended feedforward-feedback control, which includes distinct control schemes based on different control algorithms. Academic researchers have established prominent nonlinear MPC (Model Predictive Control) technology for tough control problems in polymerization reactors. A nonlinear MPC control might be designed for ECPL, given real-time measurement and based on a reasonably accurate process model that can capture the interactions between input, output, and disturbance variables. The scheme of MPC is shown in the block diagram in Figure 6. If Jariwala's [1] output prediction with COMSOL simulation could be fast enough to be in pace with real-time ICM measurement, a nonlinear MPC model might be interesting and applicable.

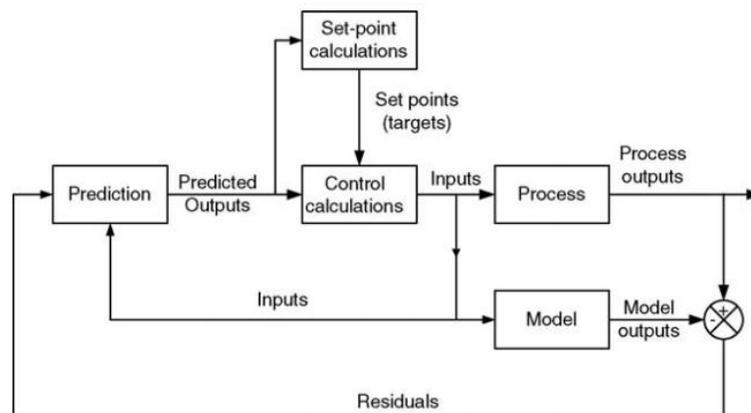


Figure 6. MPC block diagram (Seborg, Edgar (2004) [10])

## 4.2 Controls of Lithography

Lithography such as photolithography, DUV lithography and electronic beam lithography in semiconductor manufacturing all have some commonality with micro stereolithography in that they involve photo induced chemical process and need exposure dose control.

### 4.2.1 Model-based Adaptive Control of Photolithography [7]

Adaptive control techniques, with their capability for providing satisfactory control even when the process changes with time, are promising candidates for dealing with common problems encountered in photolithography processing such as batch-to-batch variations in resist properties, inconsistencies in resist curing, etc. Crisalle, Soper (1991) [7] proposed and evaluated an adaptive control strategy for the photolithography process. The design utilizes a reduced-order lithography model, an on-line parameter estimator, and a nonlinear model-inversion controller (NMIC).

A crucial output of photolithography - the width of the printed resist lines - was controlled by automatically adjusting the exposure energy. In the calculation of the appropriate exposure adjustment, the controller uses both measured critical dimensions as well as estimated values produced by the process model. The control system is capable of tracking changes in the photolithography process by automatic updating of key model parameters as the process evolves in time. Simulation studies of the closed-loop adaptive control strategy using the PROLITH simulation package to represent the lithography process demonstrate the feasibility of this approach.

The lumped-parameter model (LPM) of Hershel and Mack defines an explicit relationship between the critical dimension (a controlled variable) of the line or space feature, and the exposure energy (a manipulated input variable) by means of the integral equations.

$$\left[ \frac{E}{E_0} \right]^{\gamma_e} = 1 + \frac{1}{D_e} \int_0^x \left[ \frac{I(\xi)}{I(0)} \right]^{-\gamma_e} d\xi$$

where, CD = critical dimension (nm), E = exposure energy (mJ/cm<sup>2</sup>), E<sub>0</sub> = effective photosensitivity (mJ/cm<sup>2</sup>), D<sub>e</sub> = effective film thickness (nm), γ<sub>e</sub> = effective resist contrast (dimensionless), I(ξ) = aerial intensity distribution (mW/cm<sup>2</sup>), and ξ = horizontal location on the mask (nm).

The model-based adaptive control strategy proposed for photolithography consists of the concerted operation of the parameter estimation technique, the nonlinear controller, and the LPM equation. The relationship between these three elements is shown in the block diagram of Figure 7. At a given sampling instant the estimator first makes use of the measured input-output data N-tuples to calculate updated values of three model parameters D<sub>e</sub>, γ<sub>e</sub> and E<sub>0</sub> which minimize the least-squares error. Next, the updated LPM parameters are used to calculate the estimated critical dimension CD (t). Finally, the nonlinear controller makes use of all available information— the updated LPM parameters, the estimated critical dimension, the desired set point, and the actual critical dimension measurement— to calculate the prescribed exposure energy according to inverse of LPM.

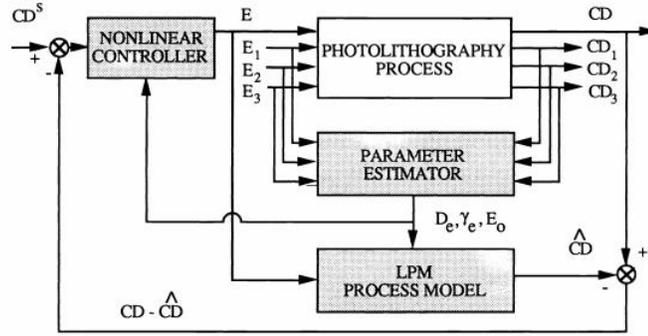


Figure 7. Adaptive control of photolithography using the nonlinear model [7]

The performance of the overall adaptive control structure is enhanced by including the data filtering operations and by adopting the deadband policy. Since commercial projection step-and-repeat steppers have a bound on the fastest reproducible shutter speed (typically of the order of 3 msec), exposure adjustments less than this limit are therefore not possible. This limitation in the control action is expressed in terms of a deadband variable,  $E_{min}$ , the minimum allowable exposure energy change. No attempt is made to adjust the exposure dose when this threshold is violated. The control policy is then ruled by the logical condition as below.

$$\text{If } |E(t_k) - E(t_{k-1})| \leq \Delta E_{min}, \text{ then } E(t_k) = E(t_{k-1}).$$

The control deadband  $\Delta E_{min}$  may be arbitrarily set to values greater than the resolution of the optical shutter. Such a choice prevents the controller from making small exposure adjustments that would have only a minor effect on the critical dimensions. The performance of the control loop is thus markedly enhanced.

Similarly in ECPL, the UV light shutter and DMD flip time also limit exposure adjustment. This limitation in the control action could be expressed in terms of a deadband variable,  $\Delta E_{min}$ , the minimum allowable exposure energy change.

Deadband consideration can be an improvement in our proposed control method of ECPL compared with Jariwala's method [1].

It is necessary to clarify that “adaptive” control in this paper [7] is actually a recursive least squares digital control. By the term “adaptive,” the paper meant online parameter estimation. There are different forms of adaptive control, which is generally a broad class.

#### 4.2.2 Run-to-run control of DUV lithography [11]

To achieve enhanced predictive model as well as to facilitate control of deep ultra violet (DUV) lithography, Jakatdar (2000) [11] presented a framework that integrates the metrology of wafer level observables with a physical model. For simulation, he proposed a dynamic physical model for volume shrinkage in chemically amplified photo resists. He also designed an in-line run-to-run control with sensors. A static model of the DUV (Deep Ultra Violet) lithography process was obtained using regression on a design of experiment to predict the output CD (critical dimensions) in terms of exposure dose and bake time. Based on the static model, a process drift model was developed to attribute CD variability to wafer reflectivity variation, batch to batch resist variation and exposure and thermal dose variation, as well as measurement noises.

In a scenario with one sensor, the in-line reflectometer measures the resist thickness before and after the exposure and baking steps, in order to calculate the deprotection induced thickness loss (DITL). This DITL value is used to estimate the post-develop CD which is then used in conjunction with a standard RtR control algorithm, to prescribe a recipe for the subsequent wafer. A schematic of the control architecture and notation is shown in Figure 8.

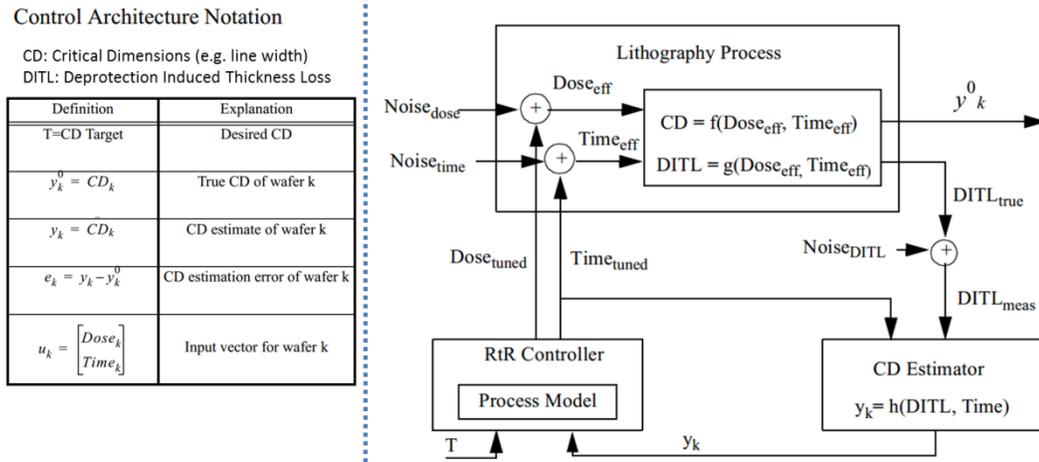


Figure 8. Run to Run Control Architecture for DUV Lithography [11]

The controller uses a Kalman Filter to provide estimates of the noise and uses process models based on a statistical design of experiments technique. Two scenarios were considered, differing in the type of metrology as well as the frequency of measurements available. The simulation results indicate the efficacy of using such a scheme for a real-world lithography sequence.

#### 4.2.3 Run-to-run controls of Photolithography [12]

Wu, Hung (2008) [12] described two run-to-run controllers, a nonlinear multiple exponential-weight moving-average (NMEWMA) controller and a dynamic model-tuning minimum-variance (DMTMV) controller, for critical dimensions (CD) control in photolithography processes. The experimental design and a multiple regression analysis were used to form relationships between the factors (exposure dose and focus) and the output quality property (critical dimension). Both controllers could easily update the dynamic model and obtain the optimal inputs for the next run. The simulation results demonstrated that the DMTMV controller was more powerful than the NMEWMA controller for rejecting disturbances and increasing yields. Quantified improvements were obtained from simulations and real photolithography processes.

#### 4.3 Frequency Domain Control of Laser Metal Deposition [13]

Also using laser to deposit material as ECPL does, the Laser Metal Deposition (LMD) process is an established additive manufacturing process which is comprised of melting powdered metal material with a laser to fabricate metal structures. While the process is usually modeled and controlled via pure temporal models and algorithms, the process is more aptly described as a repetitive process with two sets of dynamic processes: one that evolves in time and one that evolves in part layer. Therefore, it is advantageous to derive a

model of the LMD process that captures these two dominant phenomena. Although first principles models are capable of capturing both phenomena, simpler models can be derived and characterized using system identification methods. Therefore, a Hammerstein model describing the LMD process is derived in this paper which captures the two dominant aspects of the process and reproduces a common description of the melt pool shape. The model is then transformed into the frequency domain and the unknown dynamics are identified and validated using system identification techniques. The phase and magnitude properties of the model are also examined.

#### **4.4 Adaptive Neural Network Control of a Class of Unknown Nonlinear System [14]**

Kwan and Member (2000) [15] proposed a robust controller for backstepping control of a class of general nonlinear system using neural network (NN). All errors and weight are guaranteed to be bounded. The tracking error can be reduced to arbitrarily small values by choosing certain gains large enough. Several practical systems, including an induction motor and a RLFJ robot, were used to demonstrate the effectiveness of the proposed controller. The method does not require the system dynamics to be exactly known or require any off-line learning phase.

A similar but more powerful control algorithm was presented by Yahui Li (2004) [14]. Two different backstepping neural network (NN) control approaches were presented for a class of affine nonlinear systems in the strict-feedback form with unknown nonlinearities. By a special design scheme, the controller singularity problem is avoided perfectly in both approaches. The closed loop signals are guaranteed to be semiglobally uniformly ultimately bounded and the outputs of the system are proved to converge to a small neighborhood of the desired trajectory. The control performances of the closed-loop systems can be shaped as desired by suitably choosing the design parameters. Simulation results obtained demonstrate the effectiveness of the approaches proposed.

Although it still requires further research to check if ECPL could be really modeled into a backstepping system with a particular form of equations as described in literature [14] and [15], the salient feature of such model and robust adaptive neural network control algorithm for a class of general unknown nonlinear system is very interesting.

#### **4.5 Summary**

The literatures, as summarized in Table 3, have relevance to aspects of ECPL process control, but could not be applied directly due to the differences in material, equipment and approach. For example, the traditional lithography control design cannot be directly used for ECPL because the processes are fairly different in nature - the former is subtractive while the latter is additive.

Actually, system control is challenging and requires careful development across several levels of detail. There is no panacea control method and each class of system might have its own unique characteristics that require a special algorithm for stability and robustness. Hence, there is still no handy solution to ECPL advanced process control, which demands further research work on both the real-time measurement and process modeling. Even so, the literature review has tremendous value in providing inspirational insights into feasibility of advanced control for ECPL.

Table 3. Summary of Literature Review on Controls of Processes Relevant to ECPL

Literature Process	Process Measurement	Process Model	Controller	Enlightenment to ECPL
<b>Polymerization Modeling &amp; Optimization</b> (Kiparissides, 2006)	Online Hardware Sensors (e.g. spectroscopy) and Software Sensors (e.g. Nonlinear State Estimator)	Dynamics of population balance equations (PBE): nonlinear, high-dimensional	Dynamics optimization and control of particulate polymerization processes	1. A PBE (Population Balance Equation) approach of ECPL model and optimization might be possible. This might provide more insight of the photopolymerization mechanisms. Challenges are huge in mathematical formulation and solution algorithms. 2. State observer (i.e. estimator) might be needed and could be designed based on PBE model to complement with the insufficient in-situ metrology.
<b>Polymerization Reactor</b> (Richards, et al, 2006)	1. Environmental conditions: Pressure, Temperature, Level, and Flow. 2. Material property: viscosity, MWD and PSD Note: many still offline.	Not specifically given. Could be DOE or Chemical Kinetics and Dynamics	Nonlinear Model Predictive Control (MPC)	If Jarivala's [1] output prediction with COMSOL simulation could be fast enough to be in pace with real-time ICM measurement, a nonlinear MPC model might be interesting and applicable.
<b>PhotoLithography</b> (Crisalle, et al, 1991)	PROLITH simulation only	Reduced order Lumped Parameter Model	Run-to-Run: Model Parameters online estimation	1. Run-to-Run controller could be adapted for ECPL. 2. Deadband: minimum allowable exposure dose change. 3. Data filtering to reduce the measurement error effect.
<b>PhotoLithography</b> (Wu, et al, 2008)	Offline measurement	DOE (factorial design of experiments: two factors, seven levels)	Two Run-to-Run controllers: 1. exponential-weight moving average 2. recursive least squares (RLS)	1. Both Simulation and Experiments demonstrated Run-to-Run control could automatically regulate the model coefficients and could be applied to nonlinear models to reject disturbances and increase yields. 2. Double confirmed that Run-to-Run controller might be applicable to ECPL, especially a variation of Run-to-Run controller with RLS system identification.
<b>Deep Ultra Violet (DUV) Lithography</b> (Jakatdar, 2000)	in-line Reflectometer	Dynamic physical model for volume shrinkage, DOE	Run-to-Run controller uses a Kalman Filter to provide estimates of the noise and uses process models based on a statistical design of experiments technique.	1. Suggest that Run-to-Run controller with Kalman Filter could work for ECPL.
<b>Laser Metal Deposition</b> (Sammons, 2014)	Offline measurement	a Hammerstein model: a combination of a static nonlinear process in series with a linear dynamic process.	No controller design, but only Frequency Domain System Identification techniques.	Indicate possibility of applying frequency domain techniques in system identification for ECPL process dynamics, based on which a controller could be designed.
<b>a class of general unknown nonlinear systems e.g. robot, motor</b> (Kwan, 2000; Li et al, 2004)	simulation only, no experiments done.	1. No preliminary dynamical analysis is needed. 2. No need for the off-line experimental learning phase.	Adaptive Backstepping using Neural Network	This general adaptive neural network controller for robust backstepping control of a class of unknown nonlinear systems, which might include ECPL as long as it could be fit into such a backstepping model.

As we could see from the literature, Run-to-Run (R2R) control has been used extensively in lithography processes and actually other semiconductor processes as well. The R2R control literature is based on the processes where fundamental or first principles model are not available or are very difficult to obtain. In addition, large numbers of off-line experiments are required for the generation of linear or nonlinear empirical models from experiments. All the features enable R2R to be a good candidate for ECPL because currently we lack a first principles model for ECPL but already did lots of experiments and have empirical models. Obviously, considering the unique constraints of ECPL, we need a variation of R2R; one candidate variant has been developed, called evolutionary cycle-to-cycle (EC2C) control, which will be introduced in the next section.

Additionally, adaptive neural network (ANN) methods also appear to be promising, based on their successful application in other process governed by unknown nonlinear systems. Hence, it seems that applying advanced control technologies, such as EC2C and ANN, to ECPL is promising but requires further conclusive investigation and more specific detailed design of the control system. In the following section, we will explore more about the ECPL process control.

## 5 Proposed Advanced Process Control Schemes

The overall objective of an ECPL control system is to ensure that the final outputs of the process (i.e. the cured height and shape) conform to established specifications. Although all the final outputs are important, the cured height has been a most prominent concern because cured heights of discretized voxels define the shape.

Considering the process control issues above, we focus the search space of advanced control methods on these which could update online process dynamics modeling and thus track the process evolution with various disturbances more accurately.

### **5.1.1 Evolutionary Cycle-to-Cycle Control**

We proposed a digital control method – evolutionary cycle to cycle (EC2C) control method- based on the R2R literature. The name, changed from “Run” to “Cycle”, clarifies that the proposed controller works per measurement cycle instead of per experiment run. There is an essential difference between our EC2C approach and traditional R2R approaches. In semiconductor processes, run-to-run usually means wafer-to-wafer, lot-to-lot or batch-to-batch, which is more of a statistical process control, even though there are a broader classification of R2R including statistics, estimation and artificial intelligence [16]. In our proposed cycle-to-cycle control, we dive into a smaller scale and smaller time step, and focus on a single part fabrication process, that is, to control a single “Run” of process instead of “Run-to-Run” in a batch process.

The EC2C control will inherit the advantages of present R2R control methodologies and adapt well to our ECPL process special issues. Furthermore, if physical (first principles) models can be developed, EC2C control might be extended by synthesizing both physical and empirical models for optimization to overcome the limitations and disadvantages of classical R2R. A recursive least squares (RLS) system identification and Kalman filters could be used in the EC2C for ECPL to enhance the controller performance.

### **5.1.2 Hierarchical Framework of Control Methods for ECPL**

We already looked into a search space of ECPL-like process control methods. There is no panacea or all-purpose control method, but only myriad control methods dealing with various types of systems. Worse still, terminologies and definitions of various control methods seem to clutter in vast literature. It is confusing that there are a number of control methods which differ despite similar name or resemble despite different names. For example, in some paper adaptive control might mean a run-to-run control, which again could also be called as a cycle-to-cycle control or recursive least square digital control. Hence, we need clarify our candidate control methods.

Furthermore, under the scenario of ECPL, which kind of control is suitable totally depends on the process model and measurement capability. It is always easier to start with a simple model and develop a baseline control. As our knowledge of the process develops along with improved in-situ measurement to provide real-time feedback, we might be able to progress towards a more and more complex process model based on which a more advance control algorithm will become enabled. Hence, it is better to summarize the candidate methods in a hierarchical manner.

Inspired by literature, tailored for ECPL, a hierarchical framework of control methods is put forward for different stages. The development stage of control methods is defined in two status coordinates: degree of process knowledge and degree of measurement capability. The hierarchical framework of control methods, both existing and potential in our research scope, is presented in Figure 9.

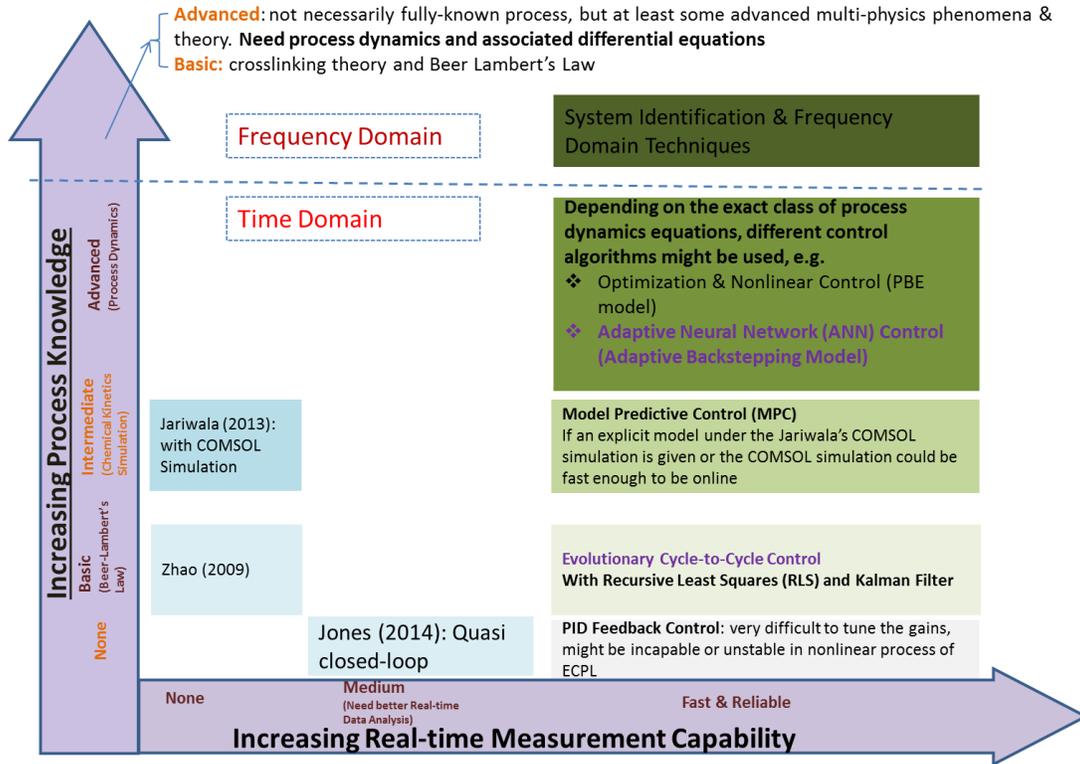


Figure 9. Hierarchical Framework of Control Methods for ECPL

As shown in the control methods hierarchy in Figure 9, only when the in-situ, real-time measurement capability is fast and reliable can we attempt, in increasing order of complexity, the implementation of more advanced control strategies, dynamics model based control algorithms, and on-line optimization strategies to compute input recipes for the ECPL.

Considering current development of ECPL and ICM, we will investigate two most viable candidate controls, evolutionary cycle-to-cycle (EC2C) control and adaptive neural network (ANN) control, which are mostly likely to satisfy the search criteria - capability of adaptive learning and control of unknown or uncertain process.

As shown in the hierarchical framework, the two proposed control methods adopt different theory and architecture, and can be applied under different development stages depending on the knowledge of the process dynamics. EC2C is basically a kind of digital control based on recursive least squares estimates. It can be used at the initial stage when we still have no good fundamental knowledge of the physical relationships among the ECPL photopolymerization variables. The EC2C digital control is envisioned as a baseline controller, which serves as both a guideline for controller tuning and a system identification tool for modeling the ECPL process dynamics in forms of sophisticated differential equations. As the research moves forward with better knowledge of the photopolymerization mechanism and ECPL process dynamics, a more advanced control strategy – adaptive neural network control- with developed process ordinary differential equations could be designed to manipulate the process input directly.

## 6 Conclusion

Investigation of instrumentation and control methodologies, which will be needed to meet the evolving needs of photopolymerization based processes and other additive manufacturing processes, could be a challenging and vibrant area for academic researchers and industrial practitioners alike.

The study reviewed existing control methods for ECPL and identified research gaps. Advanced control methods for the ECPL process were identified and a search space of relevant literature was surveyed to reveal promising techniques. Inspired by literature, tailored for ECPL, a hierarchical framework of control methods is proposed. Candidates include evolutionary cycle-to-cycle control, model predictive control, adaptive neural network control, and frequency domain techniques.

Future work includes detailed design and physical implementation of advanced control systems onto the real ECPL system to further verify and explore their capability.

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