PROCESS TRANSFER FUNCTION DEVELOPMENT FOR OPTICAL MEDIA MANUFACTURING

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Multiple staged experiments enable optimization of manufacture of digital video discs.

ABSTRACT

In injection moulding, complex systems are typically characterized by numerous input and output parameters. This complexity limits the immediate use of Design of Experiments, DOE, without prior understanding of the critical parameters to be evaluated. To properly apply the principles of designed experiments a systematic decomposition of the system is required in order to develop controllable experiment run lengths and gain beneficial information. With application to Digital Video Discs, DVDs, this paper decomposes the moulding system to develop detailed and fundamental qualitative and quantitative transfer functions using DOE data to provide specific processing conditions for optimal productivity and media quality.

KEYWORDS

Optical Media, DVD Substrate, Design of Experiments, Injection Moulding, Polymer Processing, Process Window, Manufacturing Process Optimization.

INTRODUCTION

The instant success of the digital video disc (DVD) in the marketplace has required manufacturers to have high yield, robust, tunable processes at startup. Further complicating production is the relatively recent introduction of small quantity, short run orders that require the understanding of process changes on quality in order to compensate for differences in stampers, moulds, machines, etc [4]. The result is an ultra competitive market that requires the minimization of production costs and maximized optical media production.

Traditional process optimization consists of "trial and error" with limited operator experience. In this approach, the processing engineer "picks" the starting process conditions based on limited experience, after which discs are made and then measured. An interactive process ensues with process changes made with the expectation of improved disc quality. This process must continue until all quality characteristics are met. Unfortunately there are many quality measurements for DVDs, with most processing parameters affecting multiple product attributes. For example, increased cooling time has a desirable effect on most quality characteristics yet negatively impacts production efficiency. The result is a complex process space that is difficult to visualize and hence utilize without some statistical tools. In fact, the time consuming process of optimizing machine parameters to maximize yield and minimize cycle time is rarely performed. Previous research has focused on optimization of only few quality characteristics [1,2]. Thus, great opportunities abound in yield improvements and cycle time reduction if a design of experiment (DOE) statistical optimization approach could be developed [3].

This paper develops a methodology for process characterization through empirical models termed transfer functions. The empirical models can then be used to optimize a process, compare different processing systems, or predict output quality performance from input processing conditions. As a result, DVD manufacturers can increase productivity through cycle time reduction, improve quality, compare materials, or compare different machine and mould manufactures.

DIGITAL VIDEO DISC REQUIREMENTS

The disc is composed of an optically transparent substrate (typically polycarbonate), with injection moulding as the primary manufacturing process. For prerecorded media, the data stored on a disc, in the form of pits, is moulded into the disc during the injection moulding process. Shown in figure 1 is schematic of a typically mould. Depicted in the figure are the mould halves, disc, sprue, mould cooling channels, and stamper. It is the stamper that contains the data pits and is removable from the mould, thus allowing quick changeover from recording to recording.

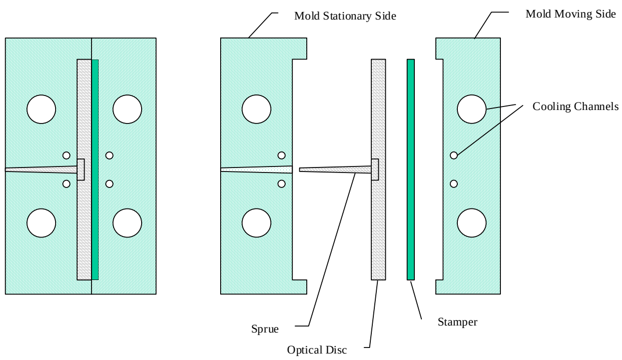


Figure 1 Schematic of a typical DVD mould

Current DVD formats have a relatively large range in storage capacity. All formats of DVD require bonding of two 0.60mm polycarbonate substrates together (Figure 2). This requirement combined with the small definition of data pits requires stringent flatness specifications of each DVD substrate. In addition, substrate thickness and birefringence play significant roles in the ability of the DVD laser to properly read the optical media [5,6,7].

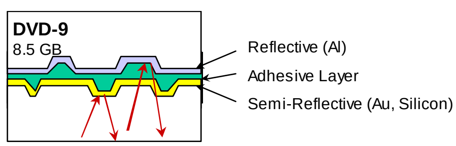


Figure 2 DVD capacities and configurations

Optical quality characteristics, as explored in this work, are limited to birefringence. Birefringence is the refraction of light, as it passes in a material, into two different components. This occurs when a material has two different refractive indices. The different refractive indices are dependent on the direction of the light propagation, which result in the transmission of light at two distinct speeds. In relation to an optical disc, this means the speed of light traveling through the disc perpendicular to the surface is different than the speed of light traveling through the disc parallel to the surface. Material properties and the moulding process cause the difference in refractive indices.

During moulding molecular orientation and residual stress contribute greatly to birefringence. In-plane birefringence, *IBR*, is defined by equation 1, where n_θ and n_r is light wavelength tangential and radial to the disc respectively, and t is a proportionality constant [8].

$$IBR = t(n_\theta - n_r) \qquad (1)$$

Physical quality characteristics are necessary to ensure proper positioning and control of the optical media during subsequent manufacturing stages as well as end-use. Physical characteristics usually controlled are: 1) disc weight, 2) substrate thickness, 3) radial tilt as defined by the slope of substrate surface measured in the radial direction of the disc, 4) tangential tilt as defined by the change in disc height, at a constant radius, measured through 360 degrees of revolution, 5) dishing as defined by the maximum change in height from the inner to outer radius measured in micrometers, and 6) outer diameter deviation as defined by the change in height from the lowest point to the highest point on the disc surface, measured at the outer most diameter.

Electrical measurements are the ultimate measure of data storage on the optical media. These measurements can be thought of as quality control for how well the pit data was replicated on the disc. However, this can be misleading since other factors affect electrical measurements, such as the quality of the original stamper or any contamination in the polymer. Typical electrical measurements are: 1) block error rate (BLER) as defined by the number of errors that were corrected by error correction methods embedded into the disc while the disc was played, 2) jitter which is a measurement of pit length variation, 3) tangential push which gauges the controller reactions when the laser is off center of the data pit, 4) asymmetry which is a comparison of the shortest, or fastest, data pit to the longest, or slowest, pit, and 5) cross talk which is a measure of channel separation.

SYSTEM MODELLING

Topology Assumptions

It may not be feasible to characterize extremely complex systems given limited resources. For example, in figure 3 a non-monotonic system is depicted with several model representations. In this figure the curve, titled *Actual Process*, is the true response of the system. In figure 3, a complex system is modeled using three experimental data points. Using three data points, quadratic as well as linear models can be fitted to the data. Such data points are typical in a response surface or three level designed experiment [9, 11]. The model created by the experimental data misrepresents the actual process. In both potential models depicted, linear and quadratic, the response of the system to processing conditions is shown to have a small affect on the quality characteristic, when in fact the system is extremely dynamic. Such models cannot appropriately predict the behavior of the system, and in some cases lead to incorrect conclusions.

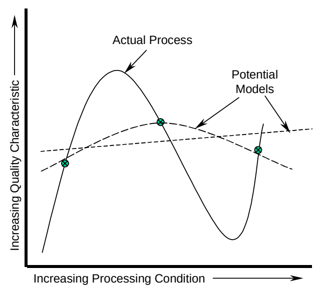


Figure 3 Non-monotonic system and potential modeling representation

The curves in figure 3 are hypothetical, however, they illustrate why highly complex systems cannot be modeled using simple designed experiments. Complex systems could be modeled using a large number of different experimental run conditions. Unfortunately time and resources frequently do not allow for such large undertakings. As a result, assumptions are made from initiation of the designed experiments that the system is at most quadratic, thus reducing the required number of different processing conditions [9]. Designed experiments typically will not provide information about third order and higher systems [10]. Confirmation of the modeling assumptions can be accomplished with a few validation runs, where each validation run condition is at locations not originally evaluated in the design of experiments, thus ensuring the behavior of the system to be represented by the model.

In addition to the issues of modeling, complex systems are also susceptible to poor optimization do to multiple local extrema. For example if the optimization objective is to minimize a function, each of local minima could be interpreted as the optimized processing condition. Unfortunately, iterative methods frequently find a local minimum instead of the global minimum [9,12].

One of the simplest models that can be developed is a linear model, equation 2. As with any mathematical representation of a natural system, these models have several limitations. However the simplicity and inexpensive development costs of linear models frequently offset the shortfalls of such an unsophisticated model. Linear models provide the advantage of minimizing the amount of experimental data required for model development. The linear model of equation 2 only models the main effects of the processing conditions, x_n, for a particular quality characteristic Y_1. As a result such models can be developed from designed experiments as simple as a Main Effects designed experiment, or more involved designs, such as a 2^k factorial design [9,11].

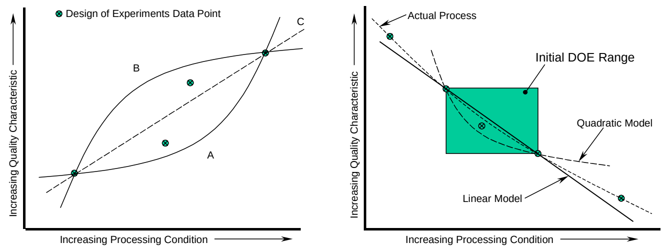
$$Y_1 = a_0 + a_1x_1 + a_2x_2 + a_3x_3 + \ldots + a_nx_n \qquad (2)$$

Nonlinear models, such as the quadratic model of equation 3, are critical for describing non-monotonic systems. Higher order models do require more experimental run conditions in comparison to a linear model, however they can reveal critical behavior characteristics of a system. Frequently, nonlinear models are developed from experimental data created from response surface designed experiments [9,11].

$$Y_1 = a_0 + a_1x_1 + a_2x_1x_2 + a_3x_1^2 + \ldots \qquad (3)$$

Linear models can frequently predict a more accurate system response compared to an over constrained quadratic or higher-order model. For example, two different systems are depicted in figure 4 with both linear and quadratic models. In systems with significant variance and few replicates, force fitting a quadric model can misrepresent a system. In figure 4a, a system is shown with empirical data at four different processing conditions. For this example, suppose the two extreme data points, i.e. the data points at the minimum and maximum processing condition, have multiple replicates, while the data points in between are single data points. For this example, the least squares approach will force the system model to contain the minimum and maximum data points. Therefore, if a quadratic model is assumed, the correct curvature of the model represented by curves A and B remains unresolved. The single replicate data points in between the data endpoints will dictate the curvature.

If noise and variation in the data set are large enough, the least squares approach might fit a curve that misrepresents the system. In particular, the slope at the experiment endpoints is very misleading depending on which curve, A or B, is used. For the linear model line C, the direction and trend of the system is potentially more representative of the true system if the data is scattered around the linear model due to system noise. This is particularly important in a monotonic system where curves A and B misconstrue the true processing trend. However if the system is non-linear, more experimental data might be required to determine the actual curvature of the system.



a *b*

Figure 4 Comparison of linear and quadratic system representation

Linear models can potentially predict more accurate information outside the designed experiment window when compared to a nonlinear model. Though prediction outside of a DOE range is not recommended, frequently an initial experimental setup does not reveal the desired outcome. Therefore secondary experiments must be conducted by moving the experiment window to a new location in the processing space. In figure 4b, a system is depicted with an initial DOE range and the corresponding developed models, linear and quadratic. If the desired outcome is a reduction in the quality characteristic value, the results of the quadratic model might suggest only a small improvement in quality for an increase in processing conditions. As a result, the experimenter might consider looking to other processing conditions to optimize the system. However, the linear model suggests that further increasing of the processing condition will result in the desired outcome [9]. For this particular example the linear model better represents the true system. The correct conclusions as to the system trends outside the original DOE window are demonstrated in the linear model and a new experiment might be conducted by shifting the experiment window to higher processing condition values.

The most significant disadvantage of a linear model is over simplification. In figure 5 a non-monotonic process is shown with several linear models. The lines labeled as A, B, and C represent potential linear models for this system. Obviously each of these linear models incorrectly represents the quality characteristic output as a function of processing condition. In this example a simple quadratic model accurately represents the system. Knowledge of the system complexity is important when applying linear models, therefore, such simple models should be considered where appropriate.

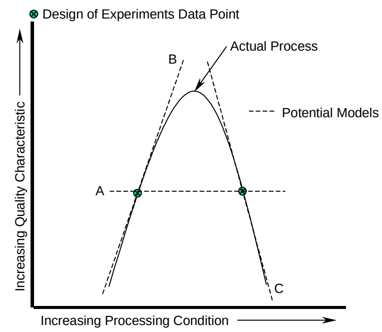


Figure 5 Higher order process with over simplification of the linear model

Regression models may not properly represent the true behavior of the system. For example, certain quality characteristics may approach an asymptotic limit as a processing condition is increased or decreased. Such a system is shown in figure 6. The figure also shows a possible quadratic model representation. The quadratic model fails to represent the system at high processing conditions; as such optimization of the system based on the quadratic model would not represent the true ideal processing conditions.

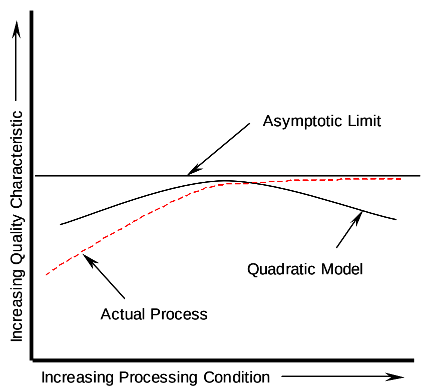


Figure 6 Depiction of exponential system with a quadratic model

System Decomposition

In the processing of optical media there are numerous processing parameters that affect the quality characteristics of the media substrate. Typically the number of parameters that affect one or more quality attributes can exceed twenty. Many of the processing conditions are known to have nonlinear and quadratic effects on quality, and include numerous processing interaction effects. The system could be completely mapped, or characterized, using a full factorial Design of Experiments, DOE, with three levels. However, such a DOE with 20 parameters would require nearly 3.5 billion unique run conditions. This is not a feasible means of understanding the process. There are methods of reducing the total number of runs while still mapping the system, such as half-fraction factorial, central composite designs, Box-Behnken, etc. However, these designs still require an unmanageable number of different processing conditions. As a result, the system is too large to treat as a whole and must be decomposed into smaller subsystems.

The process of system decomposition can be visualized by figure 7. The system starts with the unknown, un-optimized process and proceeds, through main effects design of experiments, to develop underling trends and behaviors. Using the knowledge learned in the main effects experiments, significant processing parameters are then identified and categorized into different experiments. Each of these subsequent experiments is termed a "stage" in a multi-stage design of the experiments. As the system is broken down into smaller components, more and more detail is defined and modeled. Finally a select group of the most critical process parameters are assembled for an optimization design of experiments. Selection and identification of parameters for each phase of the optimization process are described in their respective subsequent sections below.

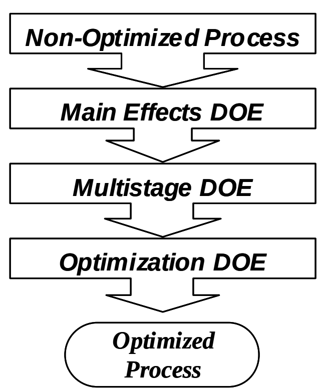


Figure 7 Decomposition of experimental methodology

Main Effects DOE

The main objective of the high level model is to define the global system behaviors for sub-system specification and analysis. However, the quality characteristics to examine must first be completely defined. Adding quality characteristics in subsequent stages is a futile task since important processing parameters might have already been eliminated after the main effects DOE. Second, identifying which parameters to evaluate can be a nontrivial process with considerable consequences to the significance of the system models. Failure to identify the importance of a parameter in the early phase of the system decomposition might completely eliminate it from further exploration. Thus it is critical to evaluate as many parameters as possible to determine which are significant and warrant further investigation.

In this work, determining which parameters to evaluate was based on a variety of sources. These sources included previous experimental work, customer input, machine operator knowledge, developed phenomenological models, and brainstorming parameters of potential interest that were historically overlooked. The final list of main effects parameters were determined by a committee consisting of machine operators, manufacturing specialist, material development specialist, and injection moulding processing engineers. In the main effects experiment, the main, or linear effect of a particular processing parameter is quantitatively described. Such a designed experiment simply develops a linear model for the affect of any processing parameter on a particular quality characteristic. Using such a model, the number of runs is defined by equation 4 and the resulting transfer function for a quality characteristic can be generically written as equation 5.

$$\#\ Runs = 1 + number\ of\ parameters \qquad (4)$$

$$Y_1 = a_0 + a_1x_1 + a_2x_2 + a_3x_3 + \ldots + a_nx_n \qquad (5)$$

The greatest advantage of this experiment design is its simplicity. The structure of the experiment consists of one base run condition where each parameter is set to either a high value or a low value. Then each subsequent run changes only one processing parameter at a time either to a low value or a high value, i.e. opposite to the base run conditions. For some processing conditions it is physically impossible for the machine to manufacture a disc. Under such conditions the machine may significantly short shot, the disc may stick in the mould, the sprue might stick, or otherwise prohibit the disc from being removed by the machine robot. If the feasible processing range is unknown, the experiment can be advantageously changed at the machine with no adverse effects. In other words, the parameters of interest for that run can be changed until a feasible condition is reached without impacting prior experimental validity. In addition, subsequent runs after the base run need not fall all above or all below the base condition. Each run can independently be picked either above or below the base run conditions, ideal if the feasible processing window is unknown.

For very complex systems the main effects of a particular processing parameter may be nonlinear. For such systems a second order main effects model can be generated. In such an experiment the number of runs is defined by equation 6. The general resulting model is described in equation 7 [9].

$$\# Runs = 1 + 2(number\ of\ parameters) \qquad (6)$$

$$Y_1 = a0 + a_1x_1 + a_2x_1^2 + \ldots + a_{2n-1}x_n + a_{2n}x_n^2 \qquad (7)$$

The main effects methodology is very powerful. There are a very low number of run conditions required for the amount of process knowledge learned about system. These experiments are very inexpensive compared to central composite or factorial designs in terms of machine processing time, testing time, and labor. Though quality prediction is not very accurate, these trends can be used to tune a process. Unfortunately, a main effects experiment does not model interactions. This is of particular importance in the prediction of quality characteristics and the optimization of a process. Without modeling these interactions and higher order curvature, the true optimum processing condition cannot be predicted. The models can only be used to indicate trend and processing direction.

Multi-Stage DOE

The main effects experimentation identified the set of critical processing parameters that have the greatest effect on quality characteristics. However, additional experiments are needed to define the system models with respect to curvature, monotonicity, interaction effects, consistency, and confidence. Parameters of each stage were categorized based on two criteria. The first criterion was to select parameters and stages such that interaction between stages would be minimized. The second criterion was based on simplifying and reducing experimental complexity and laboratory time. Processing changes that involve long transients and settling times, such as a melt or mold temperature change, need to be minimized to reduce experimental time. Therefore, melt and mould temperature changes where confined to one experiment stage.

The use of multi-stage designed experiments can map a large process in a feasible number of run conditions. In a hundred or so experimental run conditions the process is mapped compared to the millions of runs required if one experiment was conducted. In addition, these experiments yield interaction affects within each design. Unfortunately, no interaction information between each stage system can be determined. Therefore the system is not fully quantified. However, if the multiple experiments are setup with forethought a global model can be developed.

Optimization DOE

Once the system was understood in terms of the main effects and multi-stage designed experiments, a single process optimizing experiment was designed and conducted. The purpose of this experiment was to validate the behavior of the most critical five or six processing parameters that had the greatest effect on quality characteristics. Typically these parameters were composed of one or two parameters from each part of the multi-stage experiments. Using the optimal conditions based on the multi-stage experiments, these critical processing parameters were used to finish the optimization process. The model transfer functions developed from this experiment could then be used to compare the response of multiple materials, or for process optimization at DVD manufacturers. Moreover, this optimization DOE also quantified any significant interaction terms previously disregarded during the multistage evaluation.

APPLICATION RESULTS

Experimental Methods

Optical media experiments were conducted on a Sumitomo SD30 injection-moulding machine. All laboratory experimentation was conducted at General Electric Plastics’ Polymer Processing Development Center (Pittsfield, Massachusetts) in the Optical Media Development Center (OMDC). In the OMDC, the Sumitomo SD30 is configured as a batch process. Technically, the Sumitomo is a 30-ton hydraulic machine with a mechanical clamp. Sumitomo advertises the machine as capable of producing quality CD substrates with cycle times of less then 3 seconds. The Sumitomo mould is configured with four independent zones of mould cooling, which translates to two independent zones per mould half. The robotic disc take-out arm is quite advanced using vacuum to secure the disc during removal and small gripping fingers to remove the sprue.

In addition, the Sumitomo has an expanded injection compression moulding (ICM) control sequence. The Sumitomo uses clamp pressure profile triggered by timing delays from injection start. Therefore, an initial clamp pressure can be specified followed by up to three different pressure stages at different delay times during moulding. In addition, the transition time between stages is controllable allowing for a clamp pressure ramp profile between stage tonnage's. The injection moulding machines at the OMDC are equipped with a data acquisition system used to monitor the performance of the moulding machine and process. The system acquires moulding machine signals generated by the machine's internal process measurement devices including clamp pressure, melt pressure, melt temperature, ram velocity, shot size, etc. In addition, the machine is instrumented to measure mould displacement, disc temperature, and static level after ejection.

Disc handling and testing procedures were uniformly maintained. The entire cross-section of the disc may not be below the glass transition temperature, T_g, hence handling must be minimized until cooling is complete. In the laboratory, all discs were handled by a pneumatic robot that secures the disc by means of a vacuum around the center hub. As a standard practice, discs were stacked in batches by robotic means and allowed to cool for 24 hours before testing. The substrate testing equipment at the OMDC included an atomic force microscope (Topometrix) and optical disc scanner (Dr. Schenk). After the necessary unsputtered measurements, the substrates were batch processed for sputtering and bonding, and final testing of the sputtered discs was completed with the appropriate player signal analyzers (CD Associates).

Main Effects DOE

Using the described methodology, a three level main effects designed experiment was conducted to evaluate 24 input processing parameters. These experiments provided invaluable amounts of information, including dispelling a few myths and uncovering some frequently over-looked processing parameters. The testing window for each parameter was determined with the intention of creating the largest processing window possible. This experiment alone contributed to the general optical media processing knowledge in the industry [16].

Multi-Stage DOE

Stage I

To begin system de-coupling, the processing system was broken into two major control components; injection and clamping. As such, two designed experiments were created to characterize the system, Stage I and Stage II. Shown in table 1 is a listing of the Stage I DOE parameters. These parameters are mostly concerned with the thermal aspects of the process. The parameters *Melt, Mould*, and *Offset* temperatures are the machine control set points and not the actual melt or mould temperatures. The results of the Stage 1 DOE provided the base line for the development of future experiments.

Table 1 Stage I DOE parameters

Process Parameter	*Description*
Melt Temperature	Barrel Temperature Preset
Mold Temperature	Mold Coolant Temperature
Offset Temperature	Coolant Temperature Offset between Moving and Stationary Side
Cooling Time	Duration of the Cooling time

Stage II

The Stage II DOE complements Stage I in the decomposition of initial processing parameters. The focus of Stage II is the control of the clamping profile during injection, which largely determines the propagation of the polymeric melt through the mold cavity and initial surface replication. Table 2 lists the factors of the Stage II DOE.

Table 2 Stage II DOE factors

Process Parameter	*Description*
Stage 1 Pressure	First Clamping Pressure
Stage 2 Pressure	Second Clamp Pressure
Clamp Time 1	Duration of Stage 1 Clamp Pressure
Clamp Time 2	Duration of Stage 2 Clamp Pressure
Cooling Time	Duration of the Cooling time

Simplification is a key to process understanding. Failure to determine which parameters have zero effect will only complicate an already complex system. In addition to simplification, the Stage II results also revealed some of the factors that have little effect on many of the quality characteristics. For example, clamp time two was found to negligibly affect most of the quality parameters. Therefore, this process parameter doe need not be considered for the Optimization DOE. In addition, for subsequent experiments this Stage II processing condition should be set at an optimum value which maximizes quality and yield.

The global behavior of the clamping profile in DVD production was still not completely understood after the main effects, Stage I, and Stage II designs of experiments. In order to characterize the complete clamping behavior, a Stage III DOE was created which investigated only the clamping control parameters.

Stage III

The Stage III DOE factors and description are listed in table 3. The experiment focuses on the parameters that control clamping profile during injection. These parameters include the duration and magnitude transition of clamp force and magnitude of clamp force two. In addition, the velocity control to pressure control transfer point was included. Mould cavity pressure, and hence clamp displacement, is significantly affected by the change in screw pressure, which is a function of velocity-to-pressure changeover. As a result, the shear-thinning behavior of the viscosity might be affected.

Table 3 Clamping DOE parameters

Process Parameter	*Description*
Clamp Force 1	First Clamping Pressure After Delay 1
Clamp Force 2	Second Clamp Pressure After Clamp Time 1
Clamp Time	Duration of Clamp Force 1
Change Time I	Clamp Pressure Ramp Time Between Intial Clamp and Clamp Force I
V/P Transfer	Velocity to Pressure Control Change Over Point

From the results a few conclusions could be reached, the first is parameter significance. The parameters *Change Time* and *V/P Transfer* are shown to have little significance on quality characteristics, and were not considered to be important parameters for the Optimization DOE. As such, optimum values for these parameters were determined based on experimental results and were held constant for subsequent experiments. The final result is the inclusion of *Clamp Tonnage I, Clamp Tonnage II, and Clamp Time* in the final Optimization DOE.

Optimization DOE

Using the information from the multistage and main effects experiments; the goal of the optimization DOE was to incorporate all of the major processing factors into one DOE. The intent was to create a base line experiment that would accomplish two goals. The first goal was to enable a direct comparison of different machines or materials. Having a standard experiment for comparison enables new materials to be tested and their performance compared to existing materials or other trial materials. The second was to create a standard, simplified experiment that could be conducted at a production site. The information obtained in the experiment at the production site could then be used to optimize the manufacturing process. Using such an approach, the information could be gathered and processed in a few days, instead of the weeks that are typically required at the OMDC.

The optimization DOE includes six factors determined from the information gathered during all of the initial experimental testing. Using the Main Effects experiment, the Multistage DOE, these six factors, shown in table 4, represent the most influential processing parameters for optimization based on the need to reduce cycle time and improve product yield.

Table 4 Optimization DOE processing parameters

Process Parameter	*Description*
Melt Temperature	Barrel Temperature Preset
Mold Temperature	Mold Coolant Temperature
Cooling Time	Duration of the Cooling time
Clamp Ton 1	First Clamping Pressure After Delay 1
Clamp Time 1	Duration of Clamp Ton 1
Clamp Ton 2	Second Clamp Pressure After Clamp Time 1

The results of the Protocol designed experiments are summarized quantitatively in figures 8 through 10. Each these figures were generated using empirically based quadratic system models, which include interaction effects. The ability of the model to represent the experimental data, described here as R-Squared, ranged from an impressive 98% for Maximum Birefringence to 65% for OD Deviation. As such lower R-Squared values for factors like OD Deviation suggest considerable un-modeled system variance leading to poor prediction confidence. This factor must be considered when predicted processing conditions are evaluated.

An initial review of the multiple response of figure 8 suggests a fairly complex system. The majority of the responses are quadratic and many exhibit non-monotonic response. In addition to system model coefficients and multiple response plots, it frequently is beneficial to use nteraction plots to visually quantify the system. The interaction plot depicted in figure 9 illustrates which processing parameters have an interaction effect on the quality characteristic Minimum Tangential Tilt. And finally, a feasible processing window is described in figure 10. In the figure the unshaded region depicts the feasible processing window for mold and melt temperature processing variables.

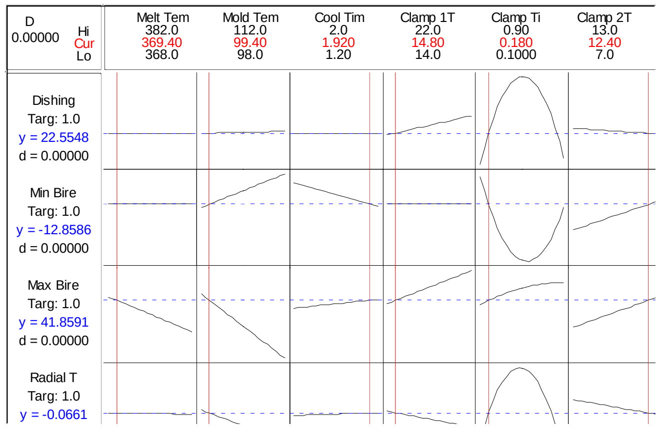


Figure 8 Quadratic response of Protocol DOE

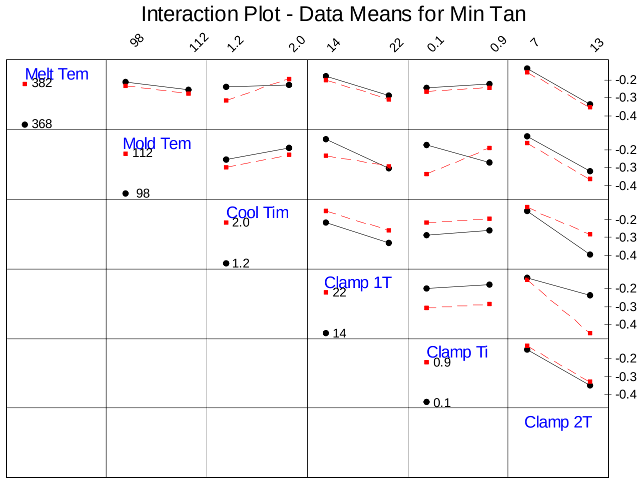


Figure 9 Interaction Plot of Protocol DOE

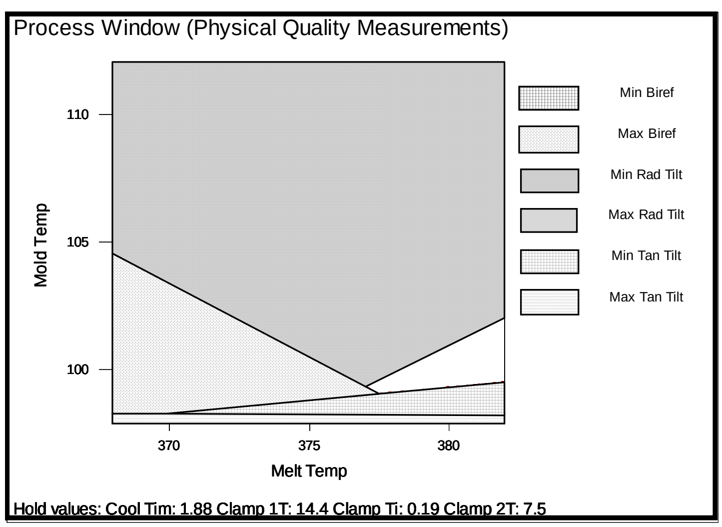


Figure 10 Process window developed from Protocol DOE

CONCLUSIONS

A rigorous experimental program was undertaken to characterize the transfer functions in optical moulding processes. The described approach consisted of a three-level main effects DOE to identify significant processing parameters, a multi-stage DOE to identify global processing behaviors without interactions between stages, and an optimization DOE to enable production optimization across multiple materials, molds, machines, and production sites.

This work demonstrates that useful process relations are created through design of experiments and statistical analysis, which may be used to optimize DVD production and increase productivity [15]. The mathematical relationships provide both quantitative and qualitative information about the process. Quantitatively, output process conditions can be predicted and optimized using traditional optimization techniques. Qualitatively, the process and interactions can be visualized and understood, thus helping to understand and control the process. Further work should develop a multi-objective optimization that that derives the most robust and cost effective process on-line.

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