THE FOUNDATIONS OF INTELLIGENT PROCESS CONTROL FOR INJECTION MOLDING

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ABSTRACT

Modern injection molding machines utilize sophisticated systems for control of machine parameters and plastic process variables. The relationships between these variables and selected aspects of molded part quality has been widely studied. While these approaches have produced some interesting correlations regarding molded part quality, they can not generally or reliably guarantee satisfactory parts without time consuming and uneconomical application-specific research. The system described in this paper has been commercially implemented but not widely understood [1]. This system is composed of: 1) an initial input utilizing flow simulation for product and process optimization, 2) an expert system developed for defect elimination on the production floor, 3) a design of experiments approach to verify process stability and model the quality dynamics which provides information to 4) a continuous and automatic production quality monitor and controller. This paper discusses the design foundations, implementation, and benefits of this on-line quality monitoring system.

INTRODUCTION

Injection molding of thermoplastics is increasingly regarded as the preferred method for delivering high quality, value added commercial parts to the marketplace. This process allows for high volume production of complex three-dimensional parts, but is plagued by complex process dynamics and material properties, which make it difficult to understand, predict, and control the molded part quality. The molded part quality has been traditionally ensured by setting up the closed-loop controls of some important process/machine variables such as barrel heater temperatures, injection velocity profile and packing pressure profile. The correlation of these process conditions to the molded part's final quality has been widely studied both experimentally and theoretically. These studies have enhanced the physical understanding of the injection molding process. However, they only relate the process conditions to a few molded part qualities for the examined application's specific mold geometry, material properties, and machine dynamics.

Fundamentally, the difficulties associated with injection molding arise from the lack of simple and consistent relationships between the machine inputs, part geometry, material properties, and molded part quality. In product and tool design, hybrid finite element/difference simulations can aid the design engineer [2]. In tuning and regulation of injection molding, however, no method has had similar success in aiding the process engineer. Setting and control of the injection molding process is unique in that quality is multi-dimensional and discrete (not continuous), the process is stochastic (not deterministic), and that quality data is both non-uniform and sparse. The objective of this research is to fill this gap by introducing an efficient method of intelligent process control for the injection molding process.

RELATED APPROACHES

Quality control for injection molding is inherently a two-stage process. The first stage consists of process tuning, in which acceptable process dynamics and molded part quality are achieved. The second stage consists of some form of continuous quality monitoring and control during production. For each stage, several fundamentally different approaches have been proposed for locating and/or ensuring molded part quality.

Process Tuning

The traditional approach to machine input selection (tuning) in the plastics industry has been based on "trial and error". For this, shots are usually taken during start-up, and part quality attributes are measured after each shot to evaluate the quality of produced parts. A human expert then uses their knowledge of the process to select the machine inputs in such a way as to improve the quality of the part from shot to shot. This tuning exercise is repeated until the specifications for part quality are satisfied. The main drawback of the traditional tuning approach is its inefficiency, which arises from its "ad hoc" nature. Humans usually use linear relationships to relate machine inputs to quality attributes, therefore, they often have difficulty adjusting the inputs over large ranges [3]. Furthermore, they tend to treat the various attributes as independent, and so ignore the couplings among the attributes. The complexity of the molding process, and the added difficulty of coping with noise, often lead to time-consuming tuning sessions and considerable waste.

An alternative to the traditional trial and error approach has been the use of expert systems. These expert systems, which have attracted considerable attention in recent years, represent corrective guidelines in the form of "if-then" rules [4, 5, 6], so they have the appeal of replacing the human expert in providing trouble-shooting knowledge. However, expert systems have the limitations of being non-quantitative, and unable to cope with quality issues not addressed in the rule base. Ongoing research [7] is developing special learning capability to upgrade performance during usage by changing certainty factors and, therefore, adjusting an order of a priority list of recommended fault-removing remedies.

A more methodical approach to tuning is provided by Taguchi analysis and Design of Experiments (DOE) [8, 9] where an empirical model is formed based on data obtained from a set of designed experiments. Based on this model, the objective function of an unconstrained optimization problem is defined in terms of the part quality attributes, and the set of inputs that produce the best quality attributes are obtained as the "optimal" point of this optimization problem. While DOE based methods offer a methodical approach to tuning that can also be used for mold qualification [10, 11, 12, 13, 14, 15], they have only been practical for large scale injection molding applications where the high cost associated with constructing a comprehensive empirical model can be justified.

Continuous Quality Control

Many forms of continuous quality control have been implemented commercially. Most common are simply statistical process control (SPC) techniques of critical process variables, such as average melt temperature, maximum injection stroke, peak injection pressure, etc. With SPC, process specification limits are defined which are known to produce acceptable molded parts. Significant process disturbances should appear as random variation or trends, permitting the molded parts to be identified as defective. Initially developed by Shewhart in the 1920s for quality assurance of communication equipment using statistical sampling and analysis techniques [16, 17], such systems have only recently been internalized within many molding machines.

There have been many related technologies which mirror the SPC architecture. For instance, quality controllers have been proposed to utilize process data for cavity pressure [18,19], infrared melt temperature [20], hydraulic pressure ratios [21], or a host of other signals [22, 23]. All of these systems fundamentally rely upon the use of statistical process control to extrapolate molded part quality from the measured process signals, e.g. assessing part dimensions from measured weight or observed cavity pressure.

There are two significant difficulties with SPC approaches. First, the correlation between the measured process signals and specific attributes of molded part quality are not known precisely. In fact, there is no guarantee that the selected process signals will even have a significant correlation. For instance, peak cavity pressure may have a very poor correlation to part gloss for many molding applications. The second major difficulty is the effect of external process disturbances on the quality system. In such instances, these disturbances may result in perturbations in the process signals which should not be corrected using the embedded SPC rules. These difficulties have prevented the commercial success of SPC systems in ensuring molded part quality during production.

Different have proposed utilizing artificial neural networks [24, 25] and fuzzy logic [26, 27] for quality control. While these approaches are fundamentally different, both rely upon developing a relevant quality model for the specific application. Once a neural network has been trained or a fuzzy model developed, the quality characteristics of the molded product are typically forecasted from the measured process data in during production. The input to these models usually corresponds to the process parameters and the outputs to the quality characteristics. Both neural networks and fuzzy models can provide values for the quality characteristics rather than simple good or bad.

The creation of the internal forecasting model can be performed either on the basis of a test plan or historical process observation. In either case, the forecasting model is valid only within the tested regime of the process. As such, the models can be extremely inaccurate in the presence of external variation or other process changes.

OBJECTIVES OF INTELLIGENT PROCESS CONTROL

The vision of intelligent process control for injection molding is to enable accelerated production of higher quality molded products at lower total cost, i.e. "faster, better, cheaper." As such, there are several objectives which, if met, will enable the fulfillment of this vision. These objectives may be grouped into two broad categories: 1) attainment of acceptable molded parts, and 2) improved production of molded parts.

An operations manager of a well-known appliance manufacturer recently testified that their company's product development process is capable of being compressed from twenty-four months to twelve. However, the mold commissioning and manufacturing start-up requires another six months, with further reductions quite difficult [28]. To address this need, the described approach facilitates assessment of molded part quality prior to tooling and molding trials. This enables optimization of the product concept and mold geometry to reduce the difficulty of manufacture. After mold designs have been approved and built, this same analysis system provides guidance to the molding operation to reduce mold commissioning times. This information may include molding set-points and profiles in machine-readable format as well as quality models for quickly eliminating defects. The described approach should then automatically and efficiently adjust the machine settings to produce acceptable moldings. This is made feasible given reasonable mold designs and advanced process knowledge as inputs. If successful, this objective will result in the production of one acceptable molded part with reduced product development time and cost.

The second objective of intelligent process control, improved production of molded parts, is to then continuously manufacture high quality molded parts at minimal cost. To achieve this objective, the described approach will investigate the process space around the set-point to verify the process stability. As will be described, the system will automatically move the operating point to an area of higher quality and lower cost. At the same time, quality models will be developed on-line which can be used for quality assessment and control during automatic production. If successful, the objective to maximize the yield of high quality parts at minimal production costs will be achieved.

ASSUMPTIONS OF INTELLIGENT PROCESS CONTROL

There are two primary assumptions regarding the design of intelligent process control. Both these assumptions are extremely conservative, meaning that the system must be designed with fundamental and robust methods to cope with the complex dynamics and unexpected occurrences which the injection molding process presents.

The first assumption is: **simulation technology is not currently capable, and may never be capable, of precisely producing optimal machine settings in a reliable manner**. This assumption is necessitated by several significant sources of error. For instance, the simulation may not model some fundamental process phenomena such as three dimensional flow effects, complex material behavior, etc. Even assuming a perfect simulation, moreover, there are many physical aberrations which can induce error. Such instances may include unmodelled mold geometry, shut off and leakage of the check ring, tuning-dependent molding machine dynamics, etc. This counter-assumption requires that the developed system must be able to automatically correct the molding process for potentially inaccurate results.

The second assumption governs the use of process sensors to automatically estimate and control the molded part quality during production. This assumption states: **there is not one single sensor technology which is currently capable of consistently indicating every aspect of molded part quality**. This assumption is necessitated by the vast array of material properties, mold geometries, machine dynamics, and product specifications. While there are some technologies which may yield estimates of gross part properties consistently, no one technology can predict a diverse set of part properties given pre-defined rules or parameters. For instance, cavity pressure is a very valuable source of process data which is being increasingly utilized to predict the consistency of molded parts. An increasingly common assumption, which the described approach does not use, is that molded parts will be identical if cavity pressure traces are identical. However, given viscosity or temperature changes, consistent cavity pressure traces may not result in consistent molded parts. As such, the described approach will develop the relationships between the molded part quality and process data on-line rather than relying on any single heuristic.

FOUNDATIONS OF INTELLIGENT PROCESS CONTROL

The described assumptions are warranted to ensure a robust and capable process. However, these assumptions make the development of an intelligent process control system very difficult – no existing quality control system fulfills the described objectives and assumptions. This section describes the methods which have been implemented to meet the objectives of intelligent process control.

Simulation

Computer simulation employs physical laws (i.e. the continuity equation, momentum equation, and energy equation) to simulate the machine and plastics behavior [29, 30, 31]. Simulation technology has advanced rapidly in the last decade. In fact, process simulation has become an integral tool in many firms' plastic part design processes. However, molders and end-users do not normally specify the products requirements based on physical properties such as melt-front velocity, pressure and temperature histories, fibre orientations, etc. They normally examine the parts to see if they are 'fit for purpose.' Each customer has a different part quality requirement. For example, the surface quality for a visible external part might be extremely important. However, this requirement for an internal automotive component can be significantly reduced or eliminated. As such, the process simulation technology has been extended to predict molded part quality attributes rather than raw process data. Table 1 lists a few of the predicted part attributes. This allows the designer to better understand the molding application and develop more robust part and mold designs.

The process simulation also provides new functionality not previously available: machine-optimal process settings in a shop-floor format, e.g. molding profiles and set-points for mold commissioning. These outputs reflect the advanced process and material knowledge which is available within the simulation. For instance, the filling stage profile will be selected to minimize fill time while trying to maintain uniform melt front velocity, provide uniform melt front temperature, and avoid excessive shear. The result will be maximal homogeneity of the injected material with minimum frozen layer formation and pressure drop across the cavity. To ensure a feasible profile, a set of machine properties, including number of steps per profile, machine response time, barrel diameter, maximum ram velocity, etc., is input to the simulation.

The filling to packing stage transition is selected such that the polymer melt in the cavity experiences a controlled transition. To successfully achieve this goal, the simulation must consider the dynamics of the molding machine and compressibility of material in the feed system and cavity. The resulting dynamics are shown in Figure 1. At point (a), the ram begins moving forward and compresses the material in the barrel. At point (b), the ram is forcing compressed material into the cavity. At point (c), the ram stops moving even though the cavity is incompletely filled. However, the decompression of the melt completes the filling of the cavity as shown in (d).

During the packing stage optimization, the simulation selects a packing profile to attain uniform volumetric shrinkage and part dimensions without sink marks or flash. There are three primary steps in the algorithm. First, a level of packing pressure is selected to minimize the variance of the volumetric shrinkage. This pack pressure is maintained until a freeze front develops. Then, the packing pressure is decayed as the freeze front converges back to the gate at which time the packing stage is terminated. As will be demonstrated later, the use of simulation is both warranted and advantageous – the simulation consistently produces initial set-points and process knowledge which no process expert can approach.

Process Tuning

The injection molding processing space is multi-dimensional and relatively unknown for a given application prior to mold commissioning. As such, it is desirable to quickly locate a region within the process space in which the quality of the molded parts are acceptable. In order to establish an acceptable set of processing conditions, an expert system utilizes a set of rules that combines an expert knowledge of the process with some realistic process limits that are predicted by the CAE optimization analysis. These heuristics are used to modify the injection and packing profiles in order to get an acceptable quality part. This process is not fully automatic – the previously described assumptions prohibit automatic judging of molded part quality in isolation. Thus, the expert system does require the operator to assess the molded part quality. However, all inferences related to process faults and changes to machine parameters are performed automatically.

The knowledge base of the expert system was designed with two intents. First, the system should utilize conservative process changes to safeguard against damaging the mold or machine. Second, the system should utilize a set of rules only if they were previously effective. The mold start procedure begins by molding a shot with a simulation-provided or user-specified set of operating conditions as shown in Figure 2. After a shot has been molded, two levels of heuristics are applied. First, the quality of the process dynamics are judged automatically using process knowledge from the simulation. For instance, excessive screw displacement during the packing stage indicates mold filling during pack, which potentially represents that a short shot has occurred. As such, the injection stroke would be automatically increased by an appropriate amount without requesting any input from the operator. This is one of many rules which have been embedded in a capable expert system shell, CLIPS [32], to diagnose the process quality.

Once the molding process dynamics are acceptable, the same expert system is utilized to find the cause of molding defects and automatically invoke process changes for defect elimination. Working with detailed process information and simulation results, the expert system can efficiently correct several process parameters simultaneously. In the case of sink marks, for instance, the rule base may try to eliminate sink marks by increasing the pack time. However, if no more material enters the cavity, as measured by the ram displacement during packing, the expert system may reason that the pack time is sufficient (the gate has already frozen off) and attempt to increase the pack pressure if feasible. At the same time, the expert system will set a flag such that defects which require pack pressure reduction will be forced to take small steps so as to no cause sink marks to recur.

Process Characterization

The described process tuning method results in the confirmed molding of acceptable part(s). Producing one good part, however, does not ensure that the process is in a desirable operating regime. In fact, variation is inherent in the molding process and all molding applications may exhibit some consistency issues. For this reason, it is necessary to confirm that the process window around the suggested operating point is sufficient to tolerate these natural variations in the molding process without producing defects. The proposed approach consists of a five step methodology as shown in Figure 3.

The system begins by selecting an experimental design as appropriate for the molding application. As previously introduced, design of experiments has become an established field with well-understood methods and benefits. In establishing a Process Window, successive sets of experiments are utilized to verify production suitability of the current operating regime and move the process set-points to an improved area when possible. The design implementation utilizes a 'Plug and Play' architecture [33] whereby the number of process variables being investigated, resolution and order of models, and number of part quality attributes are specified from which an appropriate experimental design is developed. The flexibility of this approach permits the operator to specify a small set of process variables to investigate, such as injection speed, injection stroke, and pack pressure, or a much larger set which might include nearly all molding parameters. Naturally, there is a trade-off between number of process variables to include in the investigation and the time required to perform the set.

Before the determination of the Process Window begins, the requisite size of the window must be defined. The approach requires that the Process Window encompass the expected variation of the molding process. As such, the implementation examines the repeatability of the molding machine in terms of the critical process variables which will be included in the experimental design. Beginning in an equilibrium state, the process controller will mold several cycles at the nominal process set-points which have been determined to produce good moldings. Some process variation will always be present due to natural variation in the controller dynamics, errors in timing and switchover, slight temperature and material property fluctuations, etc. From the process examination, the behavior and distribution of each of the process variables will automatically be characterized. The required size of the Process Window is then calculated as representative of the process capability index, Cp [34]. The approach is robust in that the process variance is not assumed but rather measured for each application, i.e. representative of the actual material properties, mold geometry, and machine dynamics in the molding process. The more variation a given machine exhibits, the larger the size of the Process Window which musty be verified to produce good parts.

Given the experimental design and estimates of the process variation, a set of molding trials is automatically generated and executed about the nominal set-point which is known to produce a good part. A literal example is shown in Figure 4. In this case, the nominal set-points produced acceptable moldings. However, the process space around this operating point must be investigated to ensure that no defects would occur given natural process variation. The required magnitude of the horizontal and vertical perturbations is related to the measured process variation for stroke and pack pressure, respectively.

With the design of experiments fully specified, a series of molding trials are automatically executed. In this example, the system would ascertain that sink is caused by both low pressure and low injection stroke. Once the quality relationships are known, the process set-points are automatically modified to move the operating point to a better location. This would result in a new placement of the Process Window up and to the right of the previous location. Another set of molding trials would then be performed to validate that natural process variation would not result in defective moldings. If defects did occur, this process would continue until an acceptable process window is defined.

While this simple two-dimensional example was straightforward, the implementation of the described approach has access to volumes of data and multi-dimensional analysis which a human expert can not comprehend. Some of these issues are presented in Figure 5. In this case, there are multiple quality attributes, each of which has its own distinct process window. Within each attribute's process window, moreover, there is an optimal location whereby that quality attribute is optimal. As the process approaches the quality boundary, this quality attribute begins to decline. The decline may appear as either a reduction in the nominal part properties or a reduced probability of making acceptable parts. The implementation of the described approach considers these effects for multiple quality types.

This system is also able to handle multiple process parameters and quality attributes simultaneously, with no limit to the extension. Figure 5 shows four process parameters with the process window being represented by a hypercube. The described approach can analyze the results which could confound a process expert. The system is also able to resolve conflicting quality requirements through the use of a conflict resolution matrix.. Finally, the implementation is able to conclude when no Process Window exists for a given set of mold, material, and part quality requirements.

Production Control

The mold start process, which includes the described method for process tuning and investigation, was developed to produce a robust set of molding conditions which will produce a minimal number of defects at low production costs. However, continuous quality monitoring is necessary throughout production to confirm and maintain the quality of molded parts at the 100% inspection level [35]. The quality system has been developed with the philosophy that:

- no bad parts should be accepted, and
- a minimal number of good parts should be discarded.

These two goals are competing in that an increasing number of good parts will be rejected as the quality criterion becomes more stringent. Therefore, the effectiveness of the system to assess the molded part quality is critical – the quality costs induced by poor quality prediction can quickly exceed the possible benefits of the quality control system [36]. To increase molder productivity, moreover, the system must operate fully automatic with no human intervention.

A production quality monitoring and control system has been developed and validated to accomplish these tasks. This approach utilizes a vector of quality indicators to monitor the molding process and determine if any quality changes have occurred. A partial list of quality indicators is listed in Table 2. Each quality indicator has been selected a-priori to correspond with possible process, material, and part property shifts. This knowledge has been gained through extensive molding experiments across several years.

Recalling the assumptions for intelligent process control, it should be noted that these quality indicators are not assumed to be indicative of molded part quality. Rather, the properties of each quality indicator is truly ascertained on-line during the previously described process investigation. Quality indicators with poor correlation to molded part quality are automatically discarded. The boundaries for the remaining quality indicators are then initially derived directly from the process investigation, and used to estimate the molded part quality.

The production monitoring and control process is shown in Figure 6. In this system, parts are molded continuously with two levels of quality diagnostics. The first level of diagnostics determines the quality of the shot just molded and ensures that the impact of random process variation is small. The second level of diagnostics examines trends in the molding process and eliminates defects due to systematic process disturbances. The system utilizes statistical process control and auto-regression techniques to assess the performance and stability of the system. If trends (due to material or mold temperature variation, for instance) are seen in the data, the production quality monitor will attempt to automatically correct the process to prevent molding defective parts, using regression coefficients which have been developed in the process investigation and later in production. If instabilities (due to barrel temperature cycling, etc.) or other trends occur which the quality monitor can not correct, the system will alert the molder of the difficulty before many possibly-defective parts are molded.

CAPABILITY OF INTELLIGENT PROCESS CONTROL

The foundations of intelligent process control have been described. While the technological implementation may be robust, it is the capabilities of the system to add value to the production operations which ultimately determine the system's value. This section quantifies some of the value which the system delivers by the development of more robust product and tool designs, better and faster mold commissioning, and higher quality, lower cost molded parts during production.

Robust Mold Design

As previously noted, process simulation has become an integral tool in many firms' plastic part design processes, largely due to the fact that the methods and benefits of such simulations have become well understood. The ability of simulation to facilitate more robust mold designs has been well documented [37, 38, 39] and will not be reviewed here. The implemented approach supersedes these technologies by deriving the optimum process conditions and evaluating the molded part quality at those conditions. As such, this "optimum" simulation provides improved estimates of the molded part quality as well as more explicit guidance for enhancing the part properties.

It should be mentioned that the potential gains which can be made during the part and mold design usually far outweigh cost reductions that can be made during part production [40]. Some of the benefits of the described approach are quantified in Table 3 for previously analyzed applications. The more robust mold design has a 50% reduced likelihood for tool modifications during mold commissioning compared to applications without analysis. Given that each tool modification requires separate molding trials, mold transport and disassembly, mold modifications, mold re-assembly and transport, the proposed approach can reduce the mold development time by 20%. There are further material and cycle time savings which can be obtained through improved mold design made possible by the improved product and process performance of the described approach.

Faster Mold Commissioning

The described system brings value to the molder by enabling faster mold commissioning and lowering the barriers to advanced process set-up techniques. Many industry practitioners have testified that their typical mold commissioning involves three molding trials, each with a duration of four hours. This does not include a process investigation to establish a Process Window. Assuming that the process is done correctly, the methods for establishing a Process Window require molding process expertise, knowledge of statistics and experimental design, proper experimentation techniques, and results analysis and interpretation. The amount of time required to manually develop and execute the tasks for proper mold commissioning is significant, as summarized in Table 4.

All these skills have been imbedded within the described system architecture. Since many of the tasks have been automated, the implementation times have been eliminated or significantly reduced. Moreover, the skill level required to utilize these techniques have been reduced from the level of specialist to a trained technician. As such, the time and cost of mold commissioning have been reduced by several order of magnitudes. Moreover, the described approach provides a better result than could be obtained manually and also provides vital quality data relevant to production.

The goal of IPC was to enable mold commissioning within one molding trial lasting one hour. All case studies to date have confirmed the feasibility of this objective. A typical case study comprised a comparison of a molder's existing molding conditions with the profiles recommended by the simulation (shown in Figure 7) and then fine tuned results using intelligent process control. The fan was molded from 20% glass filled polypropylene (Tonen Chemicals T001 PP C-520XKD on a Johns 400 tonne injection molding machine fitted with a Battenfeld (Bachmann) Unilog 4000 controller. To do this comparison, the system was used to control the injection molding machine according to the simulation's output profiles. Four parts were made with these conditions, to establish the quality of parts. Afterwards, the described process tuning method was used to adjust the profiles, so that a good part was produced. The initial profiles recommended the simulation produced a part that was approximately one millimeter short. No other defects were immediately apparent. The process tuning method produced a good part in seven shots, requiring approximately fifteen minutes from start-up. The normal procedure used to obtain suitable processing conditions for this application involved two tool trials each of four hours.

Characterization of Machine Capability

There is an industry-wide concession that part quality can vary when molded on different molding machines. However, most process engineers would be hard pressed to quantify the performance of their machines for direct comparison. This is most likely attributable to the difficulty of instrumenting, acquiring, and analyzing the process dynamics needed for decision support. Several companies currently perform these types of process audits throughout the plastics industry, for there is significant value to be gained from this knowledge. Typical results may include: repeatability of pressure, temperature, velocity; shot weight stability; etc. With this information, a molder can better match molding application requirements to a suitable machine. This can result in enhanced product quality, improved production yields, and lower production costs.

The described approach measures the machine capability on-line as part of the process characterization. This adds value in two ways. First, the system outputs the machine performance in quantitative units (such as "the standard deviation of ram velocity is 3.8 mm/sec."). This can be used for direct comparison to the performance of other machines and point out the need for improved control or maintenance. Second, the system directly verifies that the machine capability is suitable for the given application requirements. For instance, it can ascertain that the molding machine may not be sufficient for a given tight tolerance application.

Improved Product Quality

Another benefit of intelligent process control is the improvement of product quality and possible reduction in molding cost. In establishing a Process Window, the system provides verification that the molding process will most always produce acceptable moldings given natural variation of the process. By investigating the molded part quality within the window of the natural process variation, the described approach can improve all the molding parameters to ensure that defects do not occur. In the validation of this system, the authors witnessed a striking example of the value of this method. The application was an automotive instrument panel, shown in Figure 8, molded of a 20% talc-filled PP on a 350 ton hydraulic molding machine. The process was set-up correctly, with a switch-over from the filling to packing stage very close to the true end of fill of the cavity. This is generally perceived as a correct molding setting.

In establishing the Process Window, however, severe flash was encountered when natural variation of the process caused slightly larger injection strokes. While the nominal set-point provided excellent parts, roughly 10% of the parts would have flashed. Hence, the correct process set-up in this case was to switch from the filling to packing stage closer to 95% of end of fill! This scenario is shown in Figure 9. As such, the setting of each molding machine may differ slightly to accommodate each machine's unique production dynamics.

These types of quality improvements can only be determined with the robust process methods as presented in this paper. Without it, the molder does not know how far the process is from a critical quality boundary, which may only become evident later in production or end-use. Once the quality throughout the Process Window has been verified, it may be possible to reduce molding costs in production through temperature, pressure, or cycle time reductions.

Improved Process Yields

As previously mentioned, intelligent process control can result in improved product quality through process investigation and model development. Very few molders, however, have established such methods as Standard Operating Procedure (SOP). As such, the process engineer generally establishes a baseline process by which the attributes of the molded part seems acceptable.

This will generally result, however, in reduced production yields as validation results for the automotive instrument panel (Figure 8) will demonstrate.

This application has several functionally critical dimensions, one of which is identified in Figure 8 between the two primary mounting points. In this case, the specification was 351.7 ± 0.35 mm – typical of the industry standard of 0.2%. An experimental design, a Blocked Box Bhenkins Design of Experiments [41] was developed and tested. The design intent is to establish the dimensional properties and distributions across the feasible Process Window. At each point in the DOE, ten moldings were sampled and later measured in a controlled environment using a coordinate measurement machine.

The subsequent analysis quantifies the process yield estimates. A typical process engineer, who 'correctly' sets the molding process to any uniformly-distributed point within the feasible window, would return a 98.25% yield. This is, in fact, very representative of many molding practices. By operating at the center of the molding window (far away from the quality boundaries in terms of natural process variation), however, the resulting production yield would be 99.94%. The reduction of 1.69% in defective parts will add tens of thousands of dollars directly to the profitability of the molding operation.

Reduced Production Costs

Intelligent process control has been shown to reduce production costs. One such case study involved taking an existing production tool and applying the on-line quality system to optimize part quality and reduce cycle time. The system comprised an Ube PZ III-350, a 350 ton injection molding machine equipped with the described on-line quality controller, a single cavity optical laser disc tool and Ube ABS VW 10 polymer. The existing process conditions were then compared with the initial simulation results, and then fine-tuned using the described approach.

The part (shown in Figure 10) was difficult to mold due to critical dimensional and aesthetic specifications. It was also difficult to fill with long thin ribs on the underside of the tray which also resulted in persistent sink marks. As the part is fundamentally a flat tray it has a strong tendency to warp and this was used as one of the quality metrics. Also, as the tool had been in production for over three years there was some wear around the gate which meant that there was a tendency to flash in that region.

The procedure was first to model the part and then perform a simulation to establish the initial processing conditions. The results were then fed to the process controller via a floppy disc. Using operator feedback on part quality, the initial simulation results were fine-tuned after which a procedure for cycle time minimization was implemented. The final part quality was superior to the existing production results. This was primarily due to the improved filling profile that minimized the frozen layer thickness thus allowing the polymer melt to fill all the thin ribs and the packing profile could then be more effective in compensating for the volumetric shrinkage. As the tool was no longer being used as a jig to hold the part flat as it cooled, the cooling time could be significantly reduced to the plastication time - the practical minimum. The process conditions for before and after intelligent process control are listed in Table 5.

The end result was a part with less visible sink marks, 30% less warpage, and a significant reduction in cycle time from 33.7 to 19.6 seconds (42%). If the improved quality levels do not directly command price premiums, then costs may be further removed from the part at the expense of quality to obtain similar profit increases. The machine rate, will increase due to the added capital investment of the on-line quality control system. However, this added expense is greatly off-set by the process improvements in quality, cycle-time, and increased unit price. The impact of the on-line quality control system on the economic value added in this case study are shown in Table 6. As a result of this implementation, the operating profits will increase $10,500 for one batch of 50,000 molded parts. This estimate, moreover, does not include additional savings relating to improved yield or machine commissioning times which were not estimated in this study.

CONCLUSIONS

The continued thrust of thermoplastics into advanced technical applications has resulted in end-user requirements which can exceed standard product development and manufacturing capabilities. The lack of process robustness is sometimes evidenced by long development cycles, excessive tooling costs, low process yields, and inferior product quality. Injection molding process simulation has provided major benefits to the product development cycle by facilitating evaluation of design candidates before tooling steel. At this time, however, the need for greater robustness in the molding process remains critical.

This paper has described a methodology for ensuring adequate process robustness and developing quality models on-line, using well-known experimental methods and rigorous mathematical techniques. As described, the approach is completely generic and caters well to each application's specific set of process dynamics and quality specifications. As described, the approach begins molding with a near 'optimal' set of process conditions predicted from simulation. Knowing that inaccuracies in the simulation method exist, the system then automatically adjusts the process to produce molded parts which meet the end-user specifications. Finally, the quality system continuously monitors the process, detecting and discarding defective parts due to random disturbances while adjusting the process for systematic errors.

It should be clear that the system has significant potential to achieve the levels of quality control and process robustness needed by industry. This paper has examined the impact of intelligent process control. Subsequent analysis has shown that such on-line quality control systems can generate added value through four mechanisms, by:

- improving product quality to command a price premium or remove cost from the product,
- improving the production yields of acceptable parts,
- reducing the cycle time without adversely affecting part quality, and
- reducing mold commissioning and set-up times.

The magnitude and ratio of these cost savings from intelligent process control will vary according to each application's specific product quality requirements and operating procedures. In these case studies, the net added-value of intelligent process control technology was approximately 10% of the molded part's material and machine costs. These type of improvements seem to be representative of large segments of the industry as confirmed with discussions of major manufacturers. However, the goals and expectations of implementing such an on-line quality control system must be considered within each molding operation prior to adoption of the technology. The described methods can become standard operating procedure for any molder. If implemented well, they will directly result in greater customer satisfaction as well as significant reduction in manufacturing costs.

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Table 1: Some Modeled Defects

Short Shot
Flash
Weld Line
Surface Defects
Dimensional Tolerances
Sink Marks
Warpage

Table 2: Quality Indicator Possibly Related to Part Quality

$P_{\max}$	Peak melt pressure
$\int P\,dx$	Injection energy
$S(eop)-S(sop)$	Stroke during packing
$\dot{x}_{\max}$	Maximum ram velocity
$\dot{x}(t_{gate})$	Ram velocity at gate
t_{cycle}	Cycle time
$\int\sqrt{e^2}\,dt$	RMS Controller error
t_{plast}	Plastication time

Table 3: Impact of Robust Mold Designs

Benefit	**Amount**
Reduced likelihood of molding trials	50%
Reduced mold development time	20%
Reduced material volume and cost	10%
Reduced cycle time	10%

Table 4: Manual and IPC Mold Commissioning Costs

Task Description	Manual	IPC
Initial Tuning	2 hours	1 hour
Design of Experiments	2	0
Process Investigation	2	0.5
Analysis	1	0
Iterations	5	3
Total Time	19	2.5
Cost Per Hour	50	10
Total Labor Cost	$850	$25

Table 5: Quantified Savings in Cycle Time (seconds)

	Existing Process Conditions	Process Conditions from IPC
Injection	2.7	2.6
Packing	5.0	3.0
Cooling	26.0	14.0
Total	33.7	19.6

Table 6: Impact of IPC for Laser Disk Tray

Parameter	Quantity
Increased Part Price Premium	\$0.05
Reduction in Machine Costs	\$0.16
Total Added Value per Part	\$0.21

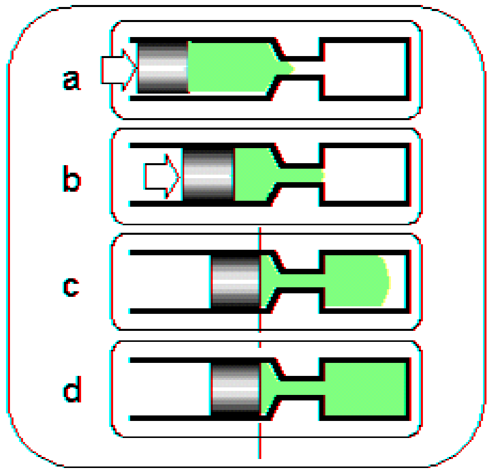


Figure 1: Machine Changeover

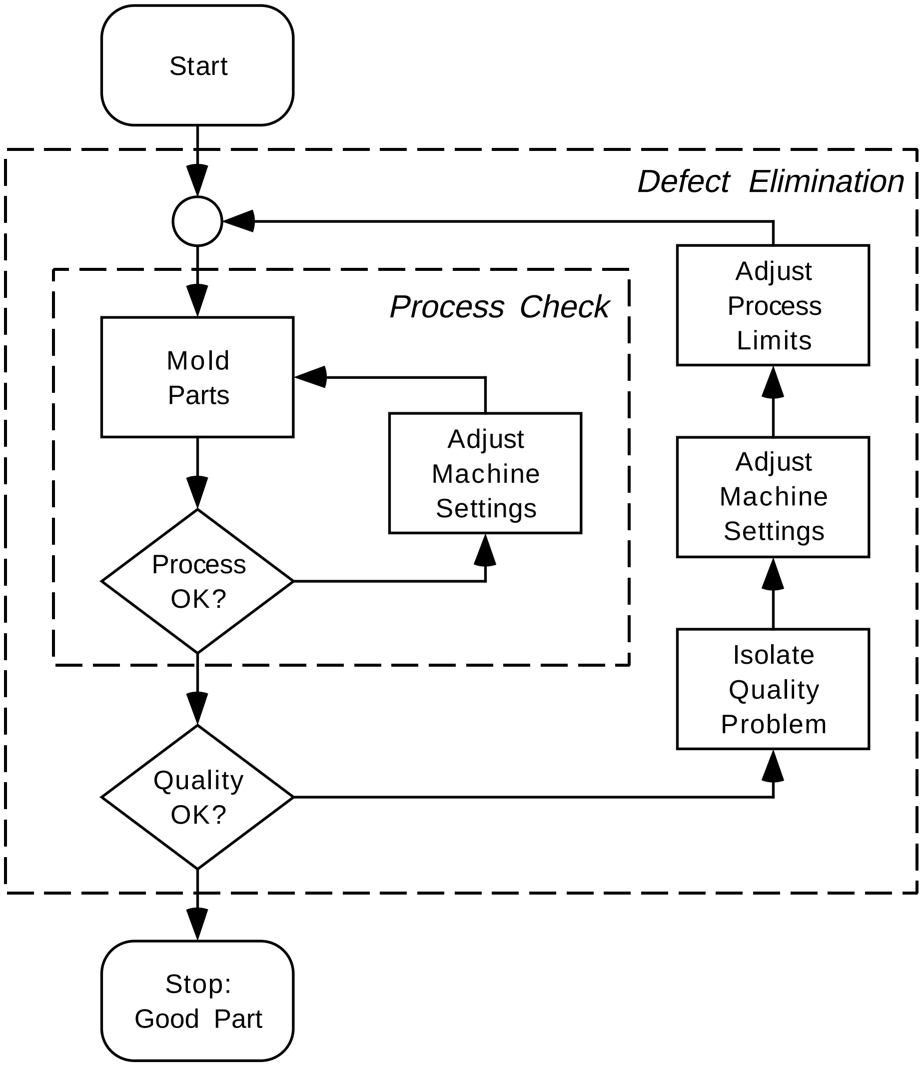


Figure 2: Process Tuning Architecture

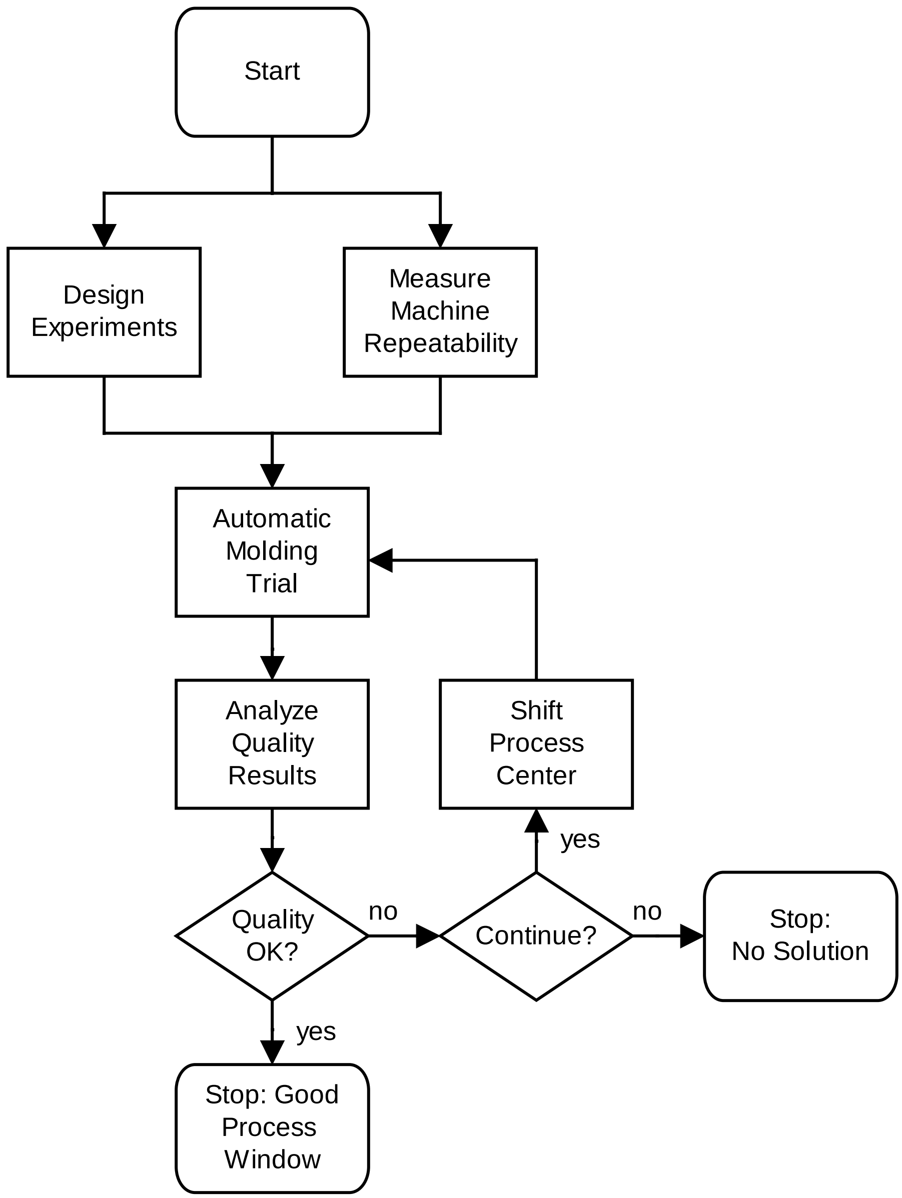
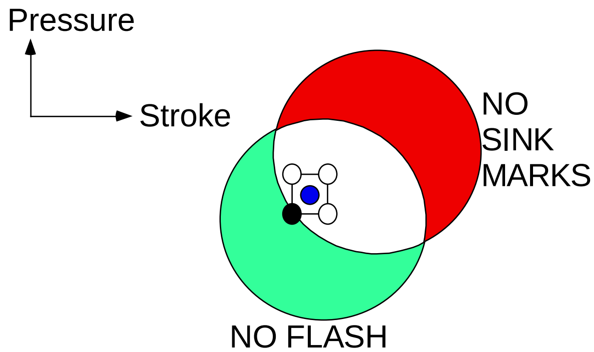


Figure 3: Process Characterization Architecture



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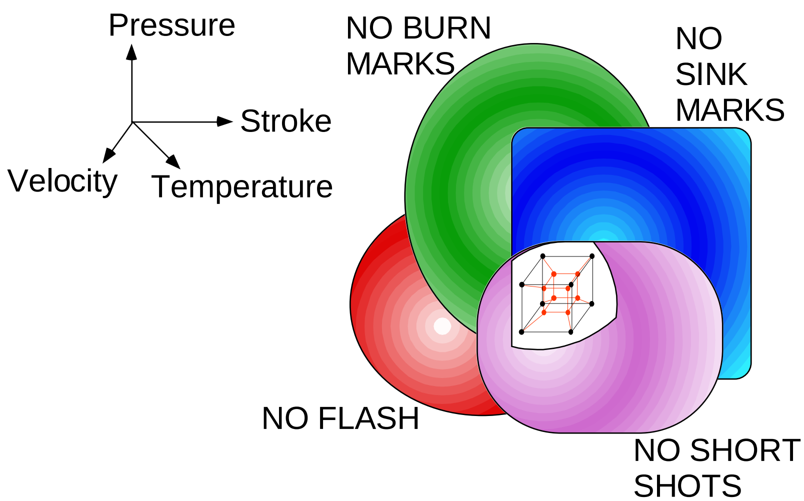

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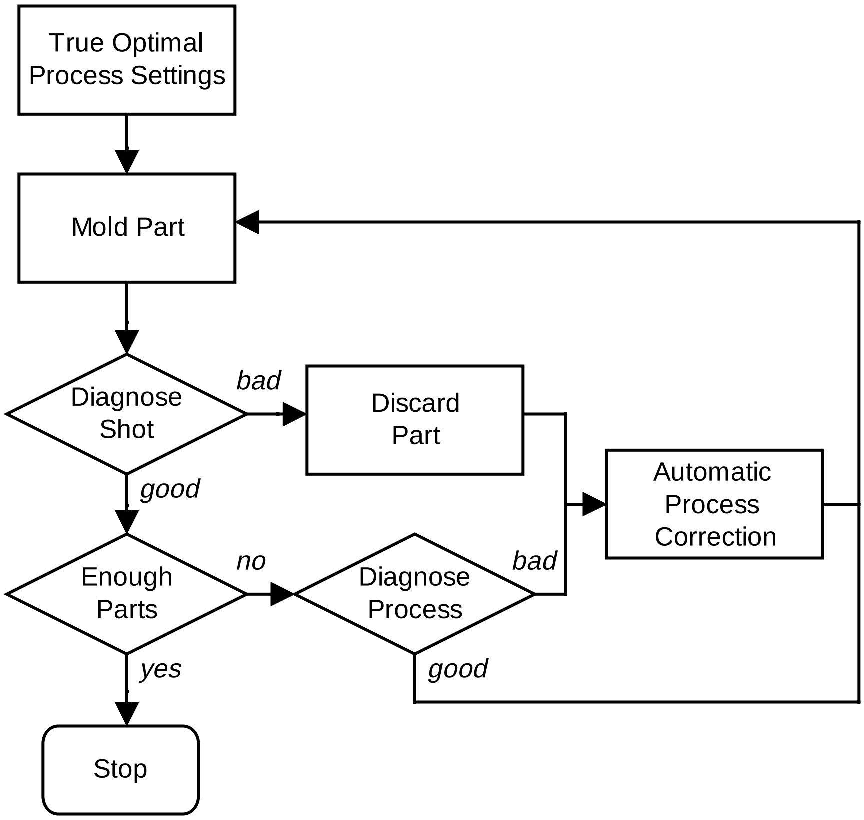

Figure 6: Production Quality Control Architecture

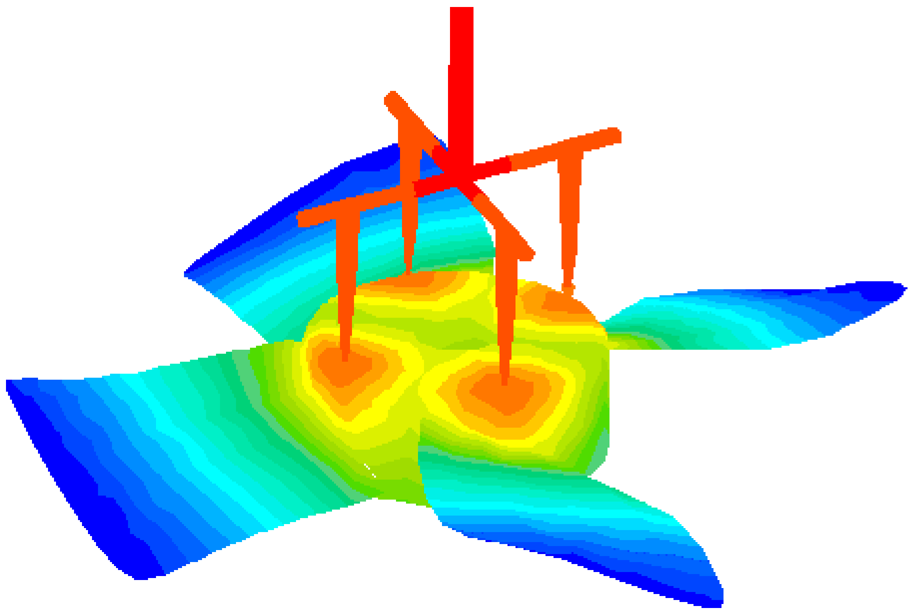

Figure 7: CAE of Automotive Fan

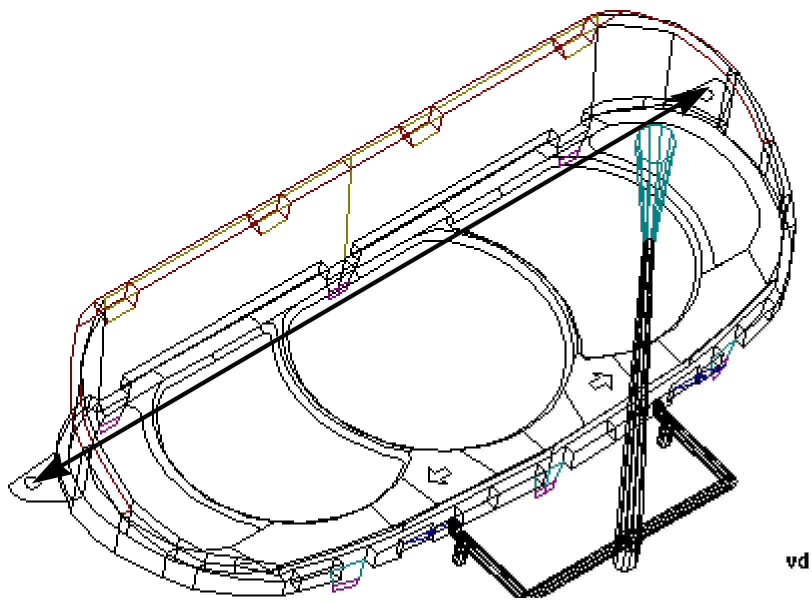

Figure 8: Model of Automotive Instrument Panel

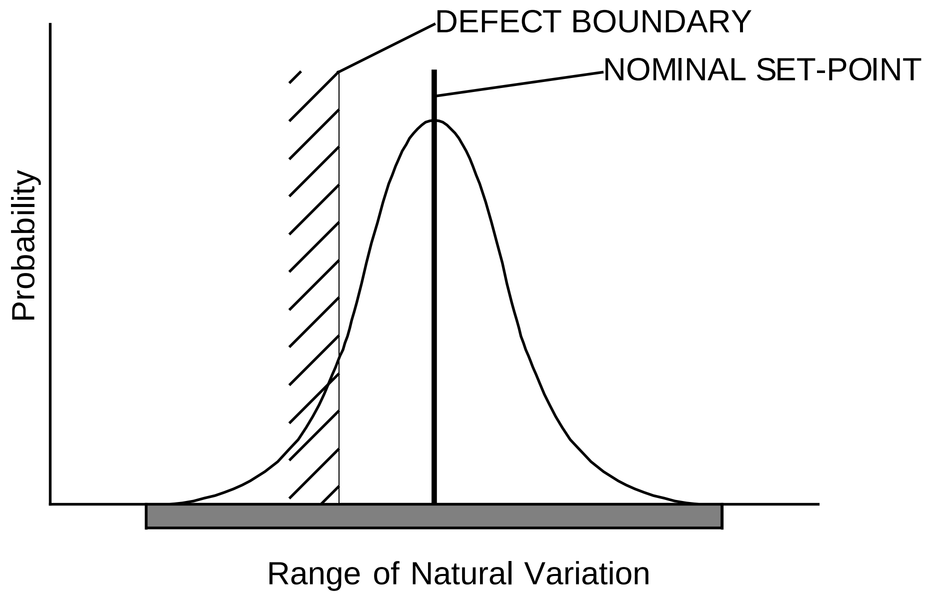

Figure 9: Distribution of Defects

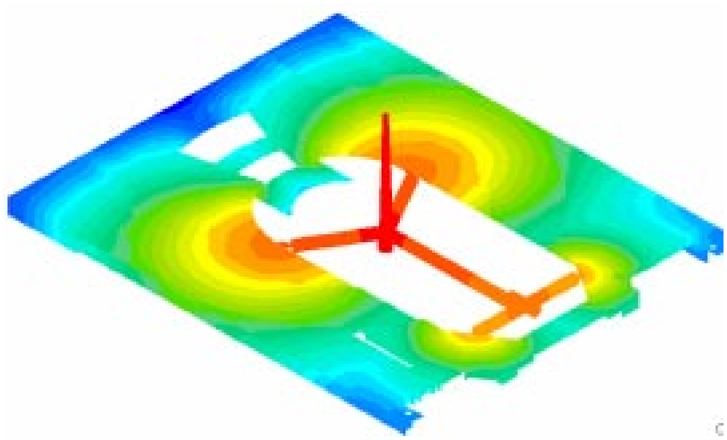

Figure 10: CAE of Laser Disk Tray

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