Simultaneous Engineering of Quality Through Integrated Modeling

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Simultaneous engineering has become the means to ensure quality through incorporation of manufacturing. This proves difficult without quantitative support tools. We present here a modeling-based approach to simultaneously design a product and its production process. We demonstrate an approach of examining sensitivities of output to all inputs of a system, from product design specifications, process variables, and material specifications. We further develop mathematics of estimating the effects of in-line process control changes to improve quality. We demonstrate a method to choose noise sources to measure and process variables to control in-line based upon these measurements, and estimate the error reduction that such process control changes will provide. The tool allows simultaneous engineering of the product and process to improve quality.

1 Introduction

The primary motive behind simultaneous engineering, or the simultaneous development of a product and its manufacturing process, is to reduce development time, from concept to product being delivered off the manufacturing system. One major causal factor of improved time to market is the degree to which a team makes a product relatively easy to manufacture. Difficulty in manufacturing manifests naturally in degraded quality and performance of the product in the market. Here, we restrict to the Taguchi definition of quality, which operates in the embodiment design phase, and measures quality loss by deviations in manufacturing from design targets (Taguchi, 1986). Thus, we do not consider here upstream work in the conceptual design phases that seek target designs of high perceptual performance. In the embodiment design phase, simultaneous engineering teams have often focused upon quality in their deliberations. Yet the approaches used often have difficulty with products or processes that are complex and require more than group discussions to evaluate feasibility. In this paper we present a modeling based simultaneous engineering approach to product/process development that focuses upon quality, and show how it enables more robust product design. We demonstrate a method to choose noise sources to measure and process variables to control in-line based upon these measurements, and estimate the error reduction that such process control changes will provide. Further, we demonstrate how the modeling can lead to manufacturing process evolution to improve quality.

Simultaneous engineering is the approach used to ensure high quality in products with manufacturing engineers participating in the development process. The main limit to its effectiveness is that it is difficult for manufacturing engineers to be available, accurately determine, and clearly express whether a new product concept is feasible. Therefore we have proposed modeling as a means to support simultaneous engineering decision making (Ho and Otto, 1996). That is, an engineering team may apply manufacturing process models to the product concept, and so make determinations of formability. Taken one step further, one could argue that virtual processing simulation tools can act as a *virtual manufacturing advisor,* for a design engineer to use alone to determine manufacturability. Such is becoming the best-in-class development practices for the injection molding, casting, and sheet forming industries.

While using process simulation tools to virtually evaluate product concept manufacturability is conceivable and becoming used in practice for direct manufacturing forming constraint limits (tearing, incomplete mold fill, etc.), it is not clear the concept is feasible for *quality constraints,* or those limits on the product concept which arise by the defect rate becoming excessive. Due to a lack of modeling methods and uncertainty over model accuracy, such softer limits are more difficult to express, evaluate, and verify. Yet they are also the more typical problem: as any control factor is extended to extreme values, performance will first experience a spread in output variations before outright total failure on all units produced. In this paper we present a modeling based approach to simultaneous product/process development that includes quality constraints, and show how it enables more robust product design. Further, we demonstrate how the modeling leads to manufacturing process evolution to improve quality.

1.1 Systems Modeling of Variation. The study of manufacturing variations is typically posed as a problem of statistic analysis and random variables. Taguchi (1986) introduced the concept of off-line quality control, to make product design changes that make a product more robust. On-line quality control involves placing sensors in the manufacturing work-in-progress stream, and making adjustments to the equipment operating points in response to measured variation. Total Quality Management (Mizuno, 1988) approaches are used in industrial practice to ensure communication and agreement among the different groups in a development team. Statistical process control (Messina, 1987) is used to keep system outputs on track.

The basic metric in all of these thoughts is the variability of the product output, represented by variance,

$$\sigma^2(\mathbf{d}) = \int_N (f(\mathbf{d}, \mathbf{n}) - \bar{y})^2 pdf(\mathbf{n}) d\mathbf{n}, \qquad (1)$$

where $\mathbf{d}$ is a vector of design variables, $\mathbf{n}$ is a vector of noise variables, f is a mapping to a performance metric, $\bar{y}$ is the target value, and $pdf(\mathbf{n})$ is the probability density function representing the probabilities of noise variable values, and generally are also dependent on the design variable values. This is the basic definition of variation used in *robust design* (Taguchi, 1986), where $\mathbf{d}$ is chosen to minimize a monotonic transformation ($\log(\cdot)$) of Eq. (1).

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There has been much work to design products that are robust to manufacturing and other errors. Taguchi (1986) introduced the concept of robust design, and developed experimental procedures around the concept, which Phadke (1989) presents well. Peplinski et al. (1996) have developed design methods to explore regions of a design space which are robust. Clausing (1993) presents a total quality development approach to product design including robust design. Chen et al. (1996) uses a response surface model which minimizes variations due to both noise and design variables while introducing engineering constraints at the same time.

While such works considers downstream manufacturing errors as a simple vector space of possible errors and selects a design configuration which is most robust to this space, others have extended modeling of downstream manufacturing errors for more complex manufacturing systems. Otto and Antonsson (1993) introduced the concept of tuning adjustments, and presented design phase models of in-line process control variables that downstream manufacturing systems have to improve quality. Basically, on-line adjustment variables are introduced into the variance equation, and must be internally selected in response to the observed noise variations. The model becomes

$$\sigma^2(\mathbf{d}) = \int_N \min_{\mathbf{t}} (f(\mathbf{d}, \mathbf{n}, \mathbf{t}) - \bar{y})^2 pdf(\mathbf{n}) d\mathbf{n} \qquad (2)$$

where $\mathbf{t}$ is now an on-line process control variable, and optimized inside the noise integration for each value of noise observed. This modeling permits a true understanding of the expected variation, and permits product/process design trade-offs (Otto, 1994). Finch and Ward (1996) implement the concept into their interval mathematics for design. Kazmer et al. (1996) implement the concept in simulation for injection molded parts.

1.2 Simultaneous Engineering. Simultaneous engineering is a prerequisite concept needed to provide the foundation upon which technical process models support. Carter and Baker (1992) present managerial techniques to uncover what systems and support is required to successfully implement a concurrent engineering process into an organization. Clausing (1993) presents concepts needed to successfully operate in a concurrent engineering environment.

There remains much research into the tools, methods, and philosophy of simultaneous engineering, and extensions for particular domains. Carlson et al. (1996) develop a method to determine what systems and support is required to implement concurrent engineering in small companies.

What is missing in this set of work and the previous works on quality are tools that integrate the two concepts: methods to help with concurrent engineering deliberations and yet are quantitative on metrics of quality. For example, in Antonsson and Otto (1993) there is no discussion on how to make predictions of changes to the process quality control. That is, what is the effect of measuring and controlling different potential downstream adjustments? This is a question which product design, process design, and process operation engineers must simultaneously consider, and have reasonable predictions of impact of changes.

1.3 Manufacturing Process Models. To support simultaneous engineering with analysis, first physics based models must be developed that represent the manufacturing process at a level of detail that is appropriate for the development phase. Often very simple models such as tables or graphed equations are adequate for design purposes, as argued by Subramaniam and Ulrich (1994). Ahmetoglu et al. (1994) have developed models of sheet forming, in the spirit of designing parts which are easy to form. Beiter and Ishii (1996) similarly have made models for the injection molding process. Kinematic equipment models (Donaldson, 1980; Slocum, 1992) prove useful for machining operations.

The manufacturing process of discussion here is for manufacturing *Low Temperature Cofired Ceramic* (LTCC) components for high operating temperature electronic packages (Jones, 1982; Hughes, 1967). Here electronic components, such as conductor wires, resistors, capacitors, and inductors, are screen printed onto thin ceramic sheets. These are then stacked and laminated one on top of each other, and fired in an oven to burn out carbon and other elements. The layers with inter-layer conductor connections form an electronic circuit assembly package to which silicon and other chips are placed upon and interconnected. Owczarek and Howland (1990) have modeled the screen printing process, producing a model of output thickness from operating and material variables. Beyne et al. (1987) have modeled the geometry of fired resistors, and developed a resistance model in terms of printed circuit topography. We make use of these models here.

This process is a good candidate for integrated analysis of quality, as it requires inputs from both design and manufacturing to produce a quality output. Historically, LTCC circuits have achieved high circuit performance yields only by providing surface layer components whose size (and therefore electrical circuit properties) can be trimmed after manufacture. This limits multiple layer circuit layout to require circuit access to the chip surface. It would be better if a method could be developed to produce circuits that work without this surface adjustment restriction.

We next review these underlying physical equations of the LTCC manufacturing system, including the screen printing, drying, and post-firing resistance models. In Section 3, we then develop our variance model to support the simultaneous engineering of quality. Finally, in Section 4, we use this to derive how the computational system can explore process control changes to improve quality, and predict which variables ought be measured and which ought be controlled.

2 Screen Printed Electronic Components

The manufacturing of an electronic circuit involves several serial operations. In the case of LTCC circuit manufacturing, a typical sequence of operations for the industry is shown in Fig. 1.

The screen printing process is widely used to place electronic components onto a substrate. This stage of an electronic circuit manufacturing strongly affects the performance of the end product. The physics involved with the screen printing of compo-

Nomenclature

y = output quality characteristic
d = design variable whose value can be chosen
n = noise variable whose value is random
pdf = probability density function of a random variable n
t = tuning variable that can be adjusted on-line
Δ_t = range of on-line adjustment available on t
μ = average of a distribution
σ = standard deviation of a distribution
σ_y = output standard deviation of y
σ_a = fraction of σ_y that is available to be possibly eliminated by an on-line tuning adjustment t
Δ_y = impact on y by Δ_t

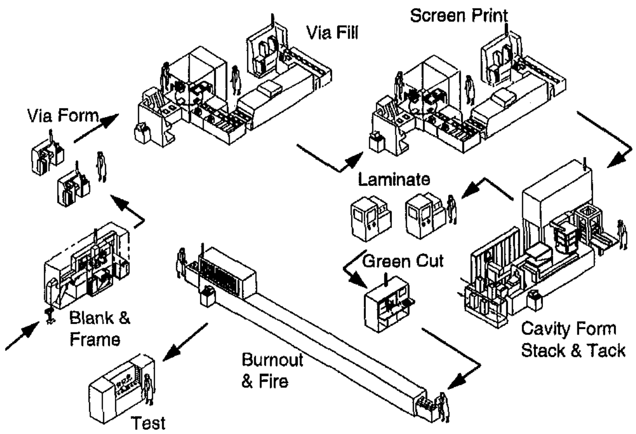

Fig. 1 Operation flow chart of an LTCC circuit

nents such as resistors and conductor lines require more complex models than the ones for simple solder screen printing. In solder screen printing, the geometry is the main performance measure. However, in the case of component screen printing, the physical performance of the component (e.g., resistance, conductivity) is the major output variable to be controlled. Thus, it is necessary to take into account the changes in the material and processing parameters in addition to the geometrical dimensions of the component to predict outcome.

The first step to model the behavior of a screen printed resistor is to calculate the dimensions of its wet geometry after the printing operation. Subsequently, a model of the drying process should be considered to relate the wet geometry to the dry geometry. Once the dry geometry is obtained, the resistance value of the resistor can be found by a physical relationship among the resistance, the dimensions and the material properties. In the remainder of the section, we now present the required underlying physical models of LTCC resistor fabrication. The result will be a mapping of component resistance as a function of design, material, process, and equipment variables.

2.1 The Screen Printing Model. In the wet geometry modeling, the thickness is the most sensitive dimension to the screen printing process. The other two dimensions of a resistor, the length and the width, can be assumed to be either normally distributed parameters or determined by other simple models. Thus, the following section will only focus on calculating the wet thickness.

As discussed by Owczarek and Howland (1990), the wet thickness of the resistor, t_w, is directly a function of the screen printing parameters. Figure 2 shows the screen printing dynamic geometry and the associated variables.

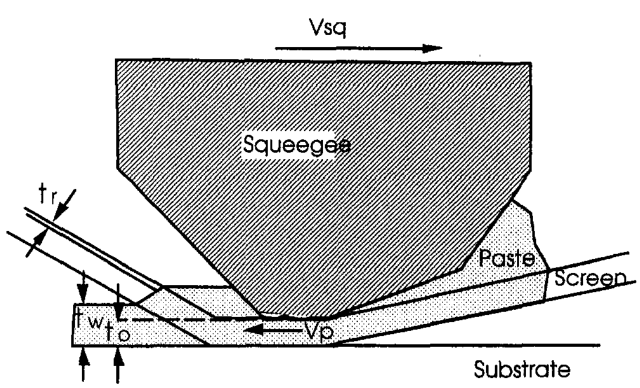

Fig. 2 The equivalent fluid dynamic behavior during screen printing

The thickness $t_w > t_o$ (where t_o is the equivalent passage thickness) because of the higher pressure formation ahead of the squeegee during paste flow under the squeegee. The mass continuity equation for the paste flow in a period of time, Δt per unit squeegee width requires

$$V_{sq}(\Delta t)(t_w - t_o + t_r) = V_p(\Delta t)t_o, \tag{3}$$

where V_{sq} is the squeegee transitional speed, V_p is the resistor paste flow speed, and t_r represents the thickness of the paste residue left on the screen.

(3) can be rewritten as

$$t_w = t_o\left(1 + \frac{V_p}{V_{sq}}\right) - t_r. \tag{4}$$

The equivalent passage thickness, t_o, can be calculated from subtracting the volume of the screen wires and the volume displaced by the squeegee from the volume of the screen filled with paste, and adding the equivalent open area thickness in case screen does not contact the substrate. Figure 3 shows the screen geometry and the other variables associated with the calculation of the equivalent passage thickness.

Based upon the volumetric balance, the following relationship can be written:

$$(t_o - t_e)L^2 = 2DL^2 - \frac{\Pi D^2 L}{\cos\gamma} - \Delta t_{sq}L^2, \tag{5}$$

where L is the resistor length, D is the screen wire diameter, M is the screen mesh count per inch, Δt_{sq} is the average squeegee penetration thickness into the screen, and t_e is the equivalent open area thickness.

Equation (5) can be further simplified to

$$t_o = 2D - \frac{\Pi D^2}{L\cos\gamma} - \Delta t_{sq} + t_e. \tag{6}$$

Also

$$\cos\gamma = \frac{1}{\sqrt{1 + (DM)^2}}. \tag{7}$$

As a result, the equivalent passage thickness can be written as below:

$$t_o = D\left[2 - \frac{\Pi}{2}DM\sqrt{1 + (DM)^2}\right] - \Delta t_{sq} + t_e. \tag{8}$$

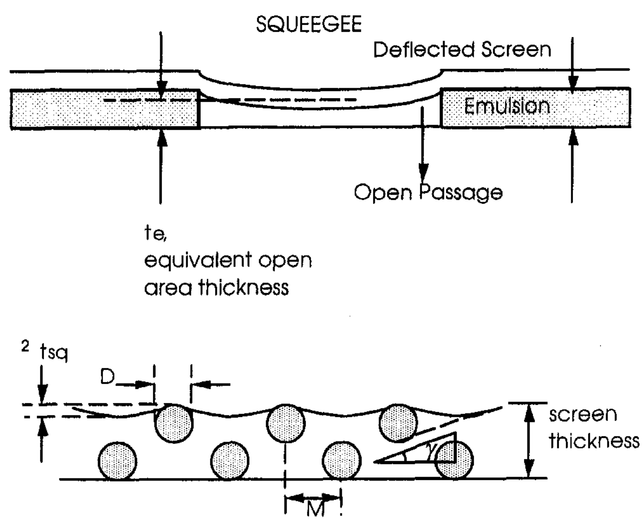

Fig. 3 Screen variables of resistor screen printing

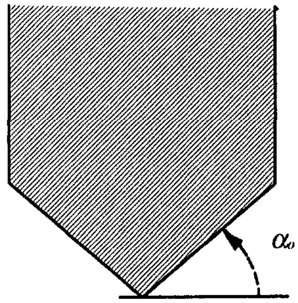

Fig. 4 Undeformed shape of the squeegee before printing

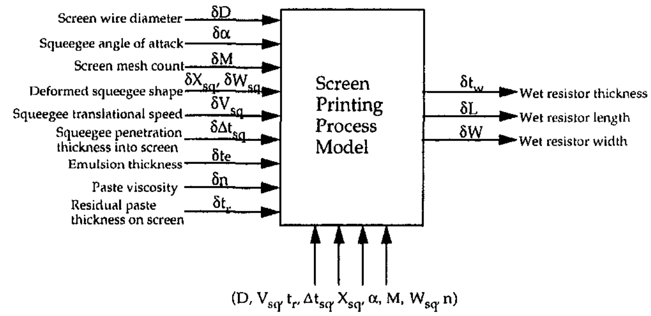

Fig. 6 Error map of screen printing process

Finally, the paste flow speed, V_p, can be approximated by the power law based upon the volumetric flow rate of the paste that is dependent on the flow area and pressure change at the tip of the squeegee. The flow area furthermore depends on screen mesh and wire size, on the deformation of the squeegee, on the magnitude of the force acting on the squeegee, and on the emulsion thickness and printed area width. Figures 4 and 5 describe the variables affecting the paste flow speed due to the deformation of the squeegee.

After several approximations and simplifications, the following equation can be derived to give the paste flow speed, V_p, in Eq. (4).

$$\frac{3}{2}\frac{\nu}{\epsilon}\left\{1-(1+\epsilon)^{-n}-\frac{2n}{n+1}\frac{V_p}{V_{sq}}[1-(1+\epsilon)^{-(1+n)}]\right\} = \left[\left(\frac{2n+1}{n+1}\right)\left(2\frac{V_p}{V_{sq}}\right)\right]^n \quad (9)$$

where

$$\epsilon = \frac{X_{sq}\tan(\alpha)}{t_o}, \quad (10)$$

$$\nu = \frac{X_{sq}}{W_{sq}}. \quad (11)$$

In this equality, n is the power law exponent determined by a Brookfield viscometer, X_{sq} is the distance from squeegee tip to location where squeegee angle of attack changes to its undistorted value, W_{sq} is the width of the flat portion of deformed squeegee, and α is the squeegee angle of attack.

A method to make use of these equations is to qualitatively consider them as black-box input-output models of the process error inputs to the work-in-process product output of each operation. These black box operation models can then be combined into a systems level view of the entire manufacturing process (Frey and Otto, 1996). The black box model of the screen printing process is shown in Fig. 6. The input errors are variations on the process input variables of Eqs. (4)–(11). It will be shown that the intermediate output variables of the screen printing process are consequently the error contributors to the final resistance of LTCC resistors.

We next repeat this modeling effort for the next operation in the LTCC circuit fabrication process, the drying operation.

2.2 The Resistor Drying Model.

Once the resistor is printed, a drying process is applied at 85°C–150°C for five to ten minutes in a continuous belt dryer. This step is necessary to transform the material properties of the resistor to desired levels. During the drying process, the resistor reaches its final shape. The dry thickness of the resistor is represented by t_{avg}. A mass balance of the drying process produces

$$t_{avg} = \frac{d_w \mu_{so}}{d_d} t_w, \quad (12)$$

where t_w is the wet thickness, d_d is the dry density, d_w is the wet density, and μ_{so} is the initial solids weight fraction of the resistor.

The drying stage of LTCC resistor printing is another major contributor of variability in resistance. There occur nonuniform changes in material properties of the resistor as well as a transformation to a final geometry. Depending on the material properties, environmental conditions such as the furnace temperature, and dimensional attributes, the final shape of the resistor varies significantly. A similar black box model of input-output relationship can be shown for the drying process as in Fig. 7. A number of the inputs into the drying model are in fact the outputs of the screen printing process model. Thus, the relationship between the submodels can be more explicitly realized.

2.3 The Geometry to Resistance Model.

After drying, the circuit is fired, and carbon constituents are burned away, leaving hard ceramic with metallic conductors and circuit ele-

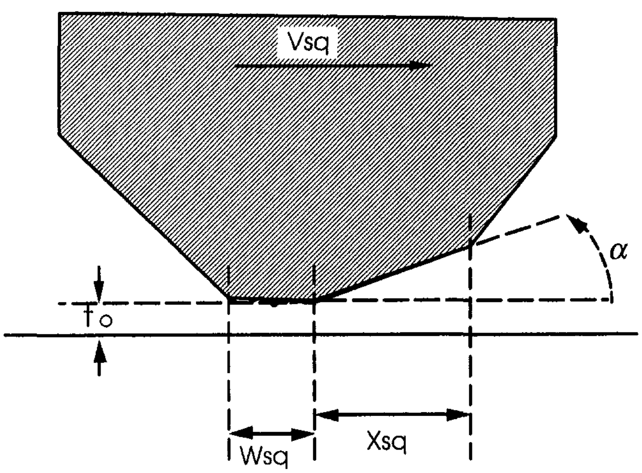

Fig. 5 The deformed geometry of the squeegee during printing

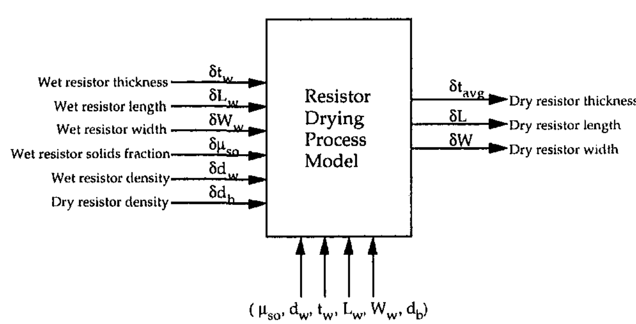

Fig. 7 Error map of resistor drying process

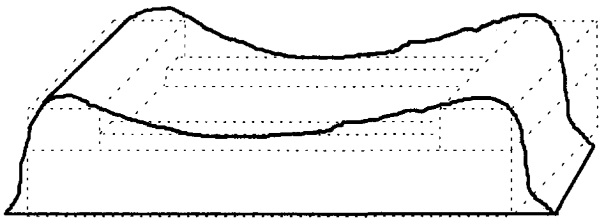

Fig. 8 Real and simplified geometry of a screen printed resistor

ments. Figure 8 shows the real and simplified geometry of a finished screen printed resistor.

Based upon the thick film resistor model developed by Beyne et al. (1987), a screen printed resistor can be considered in two regions. First region is the bulk region which consists of the middle section of the resistor. The geometry of the resistor in this region can be assumed to remain consistent along the length. The longitudinal ends of the resistor are defined as the termination regions that have different geometries and material properties than the bulk region due to the screen printing process characteristics and the settling of the ink during the drying process. The resistance of an LTCC resistor can be defined as a combination of these regions:

$$R = R_t + R_b + R_t, \tag{13}$$

where R_b is the resistance of the bulk area and R_t is the resistance at the termination area.

Figures 9 and 10 show the simplified geometry of a screen printed resistor.

The resistance of a block of material (as in Fig. 11) can be found by the following simple relationship

$$R = \rho \frac{L}{Wt}, \tag{14}$$

where ρ is the bulk resistivity of the material, L is the length of the block, W is the width of the block, and t is the thickness of the block.

Based upon the geometrical parameters defined in Fig. 10 and the above relationship for resistance, R_b and R_t can be furthermore defined as:

$$R_b = \frac{\rho_b}{t_b} \frac{(L - 2L_t)}{W - 2\left(1 - \frac{t_{be}}{t_b}\right)W_e}, \tag{15}$$

where ρ_b denotes the bulk resistivity, and

$$R_t = \frac{\rho_t}{t_t} \frac{L_t}{W - 2\left(1 - \frac{t_{te}}{t_t}\right)W_e}, \tag{16}$$

where ρ_t denotes the termination resistivity that is a result of interaction between the resistor material and the conductor material. This resistivity tends to be higher than the bulk resistivity

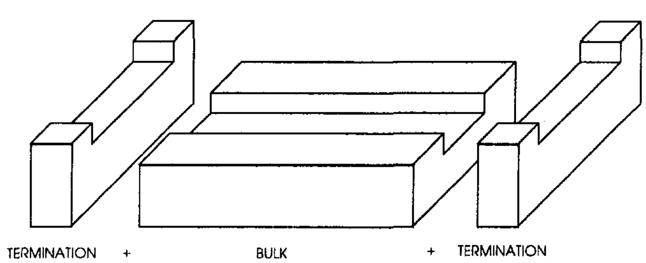

Fig. 9 Resistor geometry model

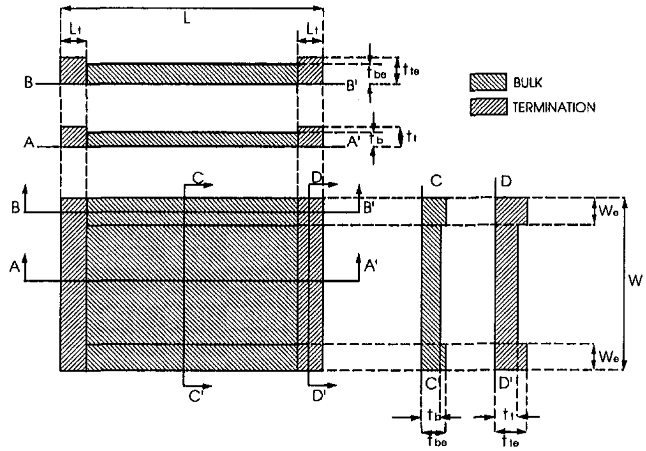

Fig. 10 Resistor model geometrical parameters

due to less conducting content or voids between resistor and conductor surfaces.

Combining Eqs. (15) and (16) with (13) we obtain

$$R = \frac{\rho_b}{t_b}\left\{\frac{1 - 2\beta\left(1 - \left(\frac{\rho_t/t_t}{\rho_b/t_b}\right)\right)(L_t/L)}{1 - 2(1 - (t_{be}/t_b))(W_e/W)}\right\}\left(\frac{L}{W}\right), \tag{17}$$

where

$$\beta = \frac{1 - 2(1 - (t_{te}/t_t))(W_e/W)}{1 - 2(1 - (t_{be}/t_b))(W_e/W)}. \tag{18}$$

As

$$2\frac{w_e}{w} < 1 = \text{limit of the model}$$

$$\left|1 - \frac{t_{te}}{t_t}\right| < 1 \text{ and } \left|1 - \frac{t_{be}}{t_b}\right| < 1$$

$$\frac{t_{be}}{t_b} \cong \frac{t_{te}}{t_t}$$

we can approximate $\beta \cong 1$. Therefore Eq. (17) is simplified to

$$R = \frac{\rho_b}{t_b}\left\{\frac{1 - 2\left(1 - \frac{\rho_t/t_t}{\rho_b/t_b}\right)\left(\frac{L_t}{L}\right)}{1 - 2\left(1 - \frac{t_{be}}{t_b}\right)\left(\frac{W_e}{W}\right)}\right\}\left\{\frac{L}{W}\right\}. \tag{19}$$

The form of Eq. (19) that fits with the production measurement data is

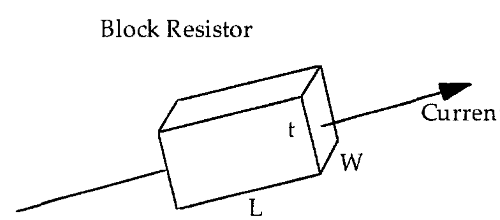

Fig. 11 Resistance of a block resistor

$$R = \frac{p_R}{t_b}\left(\frac{L - p_L}{W - 2\left(1 - \frac{t_{be}}{t_b}\right)W_e}\right) = p_R \frac{L - p_L}{t_{avg}W}, \quad (20)$$

where

$$t_{avg} = t_b + 2(t_{be} - t_b)\frac{W_e}{W}, \quad (21)$$

and p_R and p_L can be found statistically by fitting measured resistance values. p_L will be generally fixed to zero as it is very small compared to the resistor length, L, as determined by statistical fits of resistance, R.

Finally, as for the previous two submodels, it is desired to represent the input-output relationship among the variables in a similar black box diagram. In this model, the resistivity is an independent input to the model and can be determined by experimental techniques. The other three inputs are the outputs of the drying model. The final output is the desired resistance value, as shown in Fig. 12. The accuracy of the combined models into the entire system model, including the models if Figs. 6, 7 and 12, is shown in Fig. 13.

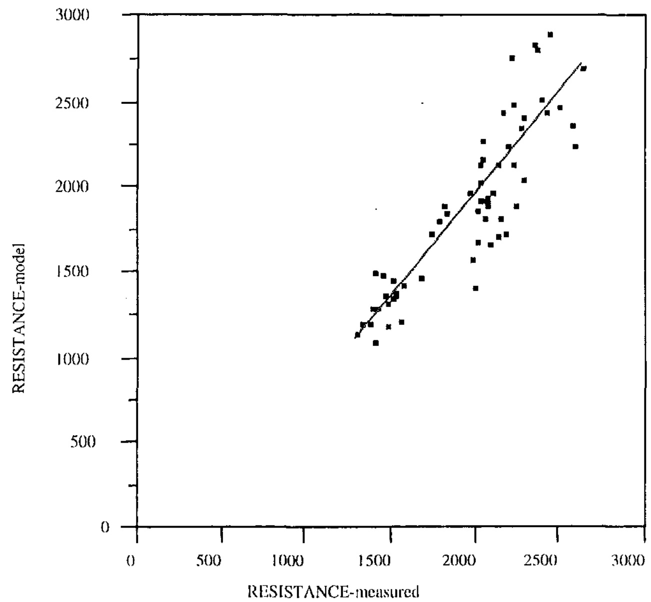

Fig. 13 System model accuracy

3 Simultaneous Engineering Quality Design Tool

To understand the quality of different product configurations at different process operating points, the three models of the manufacturing processes described in the previous section must be integrated into one combined model. This black box model takes all design, process, and material variables as well as statistical parameters as inputs. The model output is the desired nominal product performance, and its standard deviation as a measure of quality. Such a design tool was built for the LTCC resistor performance, as shown in Fig. 14.

The boxed cells represent the numerical values that can be modified by the user. These inputs include nominal values for each input variable as well as corresponding input standard error. Further, each nominal value is interval limited by a pre-agreed bound. This permits a design team to optimize and conduct what-if studies of the product-process as a system.

Beyond understanding the basic nominal performance, however, the errors in performance are also predicted. However, this requires more than a simple error propagation analysis, for a variety of reasons. First, the mapping among the variables is not simple, but requires simultaneous equation solving. Second, in-line process control can be an option, and needs exploration, as will be discussed later. In any case, in the last column, the cumulative contribution of each variable to the output variability is shown.

The error contribution of each variable to the final resistance error is calculated based upon the hierarchical relationships among the variables. First, the individual variability of each independent variable has to be determined by experiments or expert estimations. Then, using the principles of error propagation, the variability of dependent variables can be found. The error contribution of each independent variable to a dependent variable is represented by a percentage value. The contributions of lower level dependent variables to higher level dependent variables are also determined in a similar fashion. This process continues till we reach the final resistance error as the highest level dependent variable. Once all the intermediate error contributions are expressed in percentage terms, the error contribution of an independent variable is simply the sum of the products of all percentage values occur at every level of variable-specific error contributions.

In order to illustrate the calculation process, the error contribution calculation of the squeegee angle of attack, α, is shown

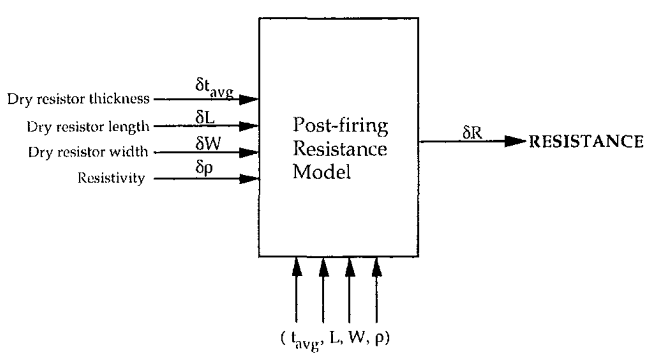

Fig. 12 Error map of post-firing resistance model

LTCC DESIGN TOOL	Value	Lower Limit	Upper Limit	Unit	Standard Error (σi)	Variance	Cumulative Contribution
Product Design Variables							
L, Resistor Length	320	20	320	mils	9.6	9.2E+01	11.1%
W, Resistor Width	40	10	50	mils	1.2	1.4E+00	11.1%
t_e, Emulsion height	0.8	0.7	1	mils	0.024	5.8E-04	12.9%
Equipment Design Variables							
D, Screen Wire Diameter	0.2	0.15	0.25	mils	0.006	3.6E-05	2.3%
M, Mesh Count	0.25	0.1	0.3	per mil	0.0075	5.6E-05	0.3%
Process Variables							
V_{sq} Squeegee Speed	10	5	100	mils/sec	0.3	9.0E-02	1.1%
t_r, Residual Ink Thickness	0.05	0	0.08	mils	0.0015	2.3E-06	0.0%
Δt_{sq} Squeege Penetration	0.1	0	0.16	mils	0.003	9.0E-06	0.2%
x_{sq} $X_{squeegee}$	10	0	20	mils	0.3	9.0E-02	12.1%
w_{sq} $W_{squeegee}$	5	0	10	mils	0.15	2.3E-02	0.2%
α, Squeegee Attack Angle	25	10	89	degrees	0.75	5.6E-01	15.4%
Material Variables							
d_{dry}, Dry Density of Ink	2.25	1.5	3	lb/in^3	0.0675	4.6E-03	11.1%
d_{wet} Wet Density of Ink	2.12	1.5	3	lb/in^3	0.0636	4.0E-03	11.1%
μ_{sq} Solids Weight Fraction	0.8	0	1	%/100	0.024	5.8E-04	11.1%
n, Power Law Exponent	0.6	0	1		0.018	3.2E-04	0.1%
Statistical Parameters							
INK TYPE	QT131						
Layer	avg	0	21	(use 1,6,11,16, or avg)			
X position on laminate	0	0	1	mils			
Y position on laminate	0	0	1	mils			
P_r, Resistivity	242			Ohm-mils	0	0.0E+00	0.0%
P_l, conductor fraction L	0.000			%/100	0	0.0E+00	0.0%
P_x, x position coefficient	-0.089						
P_y, y position coefficient	-0.092						
AVERAGE THICKNESS :	1.14	mils					100.00%
STANDARD ERROR :	0.09	mils					
RESISTANCE :	1698	Ohms					

Fig. 14 The LTCC design tool

in a hierarchical form in Fig. 15. For the system variables shown in Fig. 14, the error contribution of α to the resistance error is the product of the all intermediate contributions which is 10.4 percent.

This tool provides a design and manufacturing team the ability to adjust the nominal values of any variables to predict the performance and variance of the manufactured product. Thus, it also makes it possible for the designers to change the product design to minimize variability in the end product performance. Also, however, the cumulative error contribution predictions help the manufacturing teams to understand the major error contributors in the process. Once the design variables are determined, this tool can be used for an overall process optimization. After several iterations, one should be able to find a set of variable values which guarantees the target performance within an acceptable error range.

4 System Level Process Redesign

If the product configuration required cannot be reliably produced, manufacturing system changes are required. In-line process control or perhaps better processing technology must be introduced. The question is where in the process, and what? How should the system be redesigned to reduce variation? We now develop a simplified model that can be used in association with any black-box manufacturing system model to explore these questions, and demonstrate its efficacy with the LTCC product and process.

4.1 System Variation Models. Rather than minimizing the variability of each error source independently to achieve more robust performance, a system wide variation model as described in Section 3 can be used to reduce variational errors in a product at lower cost. However, this does not consider the factory floor process control actions that might be taken to reduce variation. The concept of using tuning variables for robust product design (Otto and Antonsson, 1993; Otto, 1994) has been introduced to minimize the error variation caused by noise. Tuning variables represent factory floor manufacturing adjustments after a design is selected (represented by design variables). They can be treated as feedback control variables that are set by the manufacturing team after the noise has occurred. The tuning variables practically offset the influences of noise variables to reduce total variation. Without considering the tuning variables, the variability of a product performance can be calculated by Eq. (1). With on-line process control, values of tuning variables can be selected to minimize variability after the design and noise variables are determined, as in Eq. (2).

While accurate, Eqs. (1) and (2) are computationally difficult. To a first order approximation, Equation (1) can be approximated by the error propagation formula,

$$\sigma_y^2 \approx \sum \left(\frac{\partial f}{\partial n_i}\right)^2 \sigma_{n_i}^2, \tag{24}$$

which proves more simple to evaluate for systems operating at points without excessive nonlinearity across perturbations, and with statistically independent inputs.

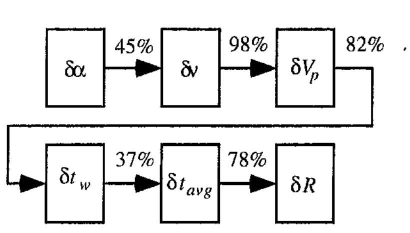

Fig. 15 The hierarchical error contribution computation for α

The linearized error propagation formula Eq. (24) is often used to understand the propagation of errors in manufactured products. Unfortunately, it is not valid in the presence of on-line process adjustments. The adjustments tune out the variation of some of the noise, and may introduce other (hopefully much smaller) errors. A similarly simplified version of Eq. (2) is needed to easily consider error propagation in manufacturing systems with adjustments. Yet until now there has been no linearized version of Eq. (2), the model with on-line process control.

To derive this linearized version of Eq. (2), one must consider the mechanics of on-line process control. Generally, to do an in-line adjustment, an operator must measure a pre-determined set of incoming variations on the work in progress. Based upon these in-line measurements, a value of the adjustment process variable is selected. Thus, there are two important aspects of the mechanics that are important for the earlier system and product design phase. Notably, the subset of noise variables to be measured and adjusted out must be selected. Second, at some point downstream a model or lookup table must be provided that instructs the operators what value of adjustment to use for each measurement of incoming noise.

To derive an error propagation formula incorporating process adjustment capability, consider categorizing the input noise variables $\mathbf{n}$ into those $\mathbf{n}_m$ that will be measured and used in a control law to determine values for the on-line adjustment, and those $\mathbf{n}_o$ that will not. The error propagation formula considering adjustments will then become

$$\sigma_y^2 \approx F(\sigma_{\mathbf{n}_m}, \Delta_t) + \sum_{n_o} \left(\frac{\partial f}{\partial n_i}\right)^2 \sigma_{n_i}^2, \tag{25}$$

where F is some function to be derived below. The point of Eq. (25) is to explicitly point out that in-line process adjustment and control can only reduce the output variation caused those input variations that are explicitly measured in-line. All other sources of variation are unaffected by the adjustment process and will continue to cause variation unabated.

To derive F, define σ_a as the standard deviation of the variation which is sought to be adjusted out

$$\sigma_a^2 = \sum_{n_m} \left(\frac{\partial f}{\partial n_i}\right)^2 \sigma_{n_i}^2, \tag{26}$$

and let Δ_y be the range on output that the adjustment process can accommodate

$$\Delta_y = \left|\frac{\partial f}{\partial t}\right| \Delta_t, \tag{27}$$

where Δ_t is the range of the in-line process adjustment. Equation (27) assumes approximate linearity of f with respect to t.

The error propagation formula [Equation (24)] applies to independent Gaussian distributed sources of variation. Consider the Gaussian distribution of Eq. (26) which represents the variation to be adjusted out, and also Eq. (27), the range of the in-line process adjustment, as all shown in Fig. 16. The density function of Eq. (26) is

$$pdf(y) = \frac{1}{\sigma_a\sqrt{2\pi}} e^{-y^2/2\sigma^2}. \tag{28}$$

The shaded area in Fig. 16 will be removed after the adjustment. The new distribution of variation after the adjustment is shown in Fig. 17, with a delta function at zero. Note the delta function at zero implies perfect ability to measure and adjust. If this is not the case, errors on these new terms can be added in the standard way [Eq. (1)]. The equation of the new density function becomes

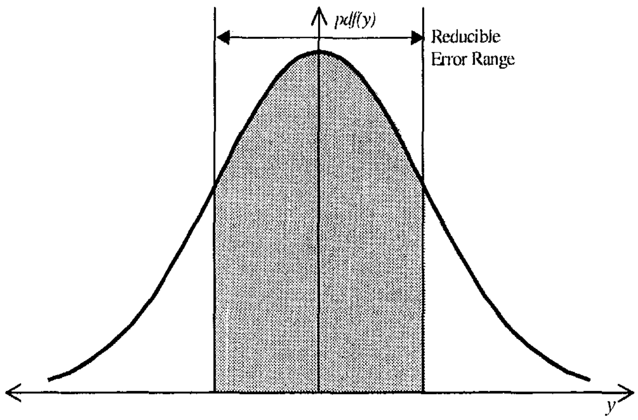

Fig. 16 Distribution of error to be adjusted out

$$pdf(y) = \begin{cases} \dfrac{1}{\sigma_a\sqrt{2\pi}} e^{-(y-\Delta_y)^2/2\sigma_a^2} & y < 0 \\ \dfrac{1}{\sigma_a\sqrt{2\pi}} e^{-(y+\Delta_y)^2/2\sigma_a^2} & y > 0 \end{cases}. \quad (29)$$

The standard deviation σ of this function must be determined. Applying Eq. (22) to Eq. (29),

$$\sigma^2 = \frac{1}{\sigma_a\sqrt{2\pi}} \int_{-\infty}^{0} y^2 e^{-(y-\Delta_y)^2/2\sigma_a^2} dy + \frac{1}{\sigma_a\sqrt{2\pi}} \int_{0}^{\infty} y^2 e^{-(y+\Delta_y)^2/2\sigma_a^2} dy. \quad (30)$$

Integrating, the result that we seek is

$$\sigma^2 = (\Delta_y^2 + \sigma_a^2)\left(1 - \text{erf}\left(\frac{\sqrt{2}\Delta_y}{2\sigma_a}\right)\right) - \sqrt{\frac{2}{\pi}}\,\sigma_a\Delta_y e^{-\Delta_y^2/2\sigma_a^2}. \quad (31)$$

This expression is exact for σ_a exact as the tuned standard deviation for normally distributed input data.

Combining this with the variation that is not measured in-line and cannot be adjusted out, the error propagation formula with adjustment is

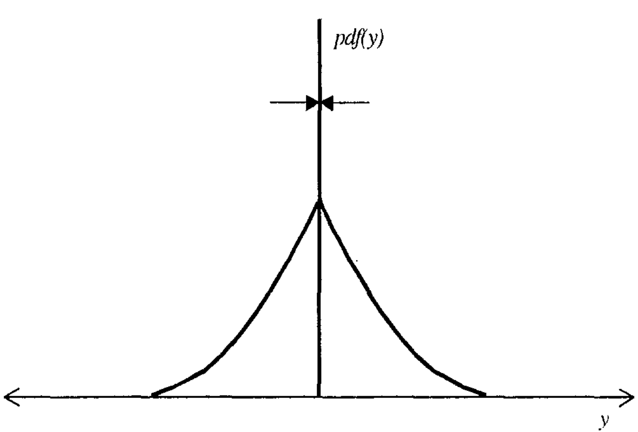

Fig. 17 Distribution of error after adjustment

$$\sigma_y^2 = (\Delta_y^2 + \sigma_a^2)\left(1 - \text{erf}\left(\frac{\sqrt{2}\Delta_y}{2\sigma_a}\right)\right) - \sqrt{\frac{2}{\pi}}\,\sigma_a\Delta_y e^{-\Delta_y^2/2\sigma_a^2} + \sum_{\substack{\text{unadjusted}\\ \text{noise factors}}} \left(\frac{\partial f}{\partial n_i}\right)^2 \sigma_{n_i}^2, \quad (32)$$

which is a restatement of Eq. (25).

Equation (32), while exact, can be difficult to compute quickly. An alternative is to expand Eq. (31) into a series, and keep only the initial lower order terms. Dividing Eq. (31) by σ_a^2 produces

$$s^2 = (r^2 + 1)\left(1 - \text{erf}\left(\frac{\sqrt{2}r}{2}\right)\right) - \sqrt{\frac{2}{\pi}}\, re^{-r^2/2}, \quad (33)$$

where $s = \sigma/\sigma_a$ and $r = \Delta_y/\sigma_a$. Expanding erf $(\cdot)$ and exp$(\cdot)$ into series and combining, one can derive a series expansion for Eq. (33) about $r = 0$ as

$$s^2 = 1 + r^2 + \sqrt{\frac{2}{\pi}} \sum_{i=0}^{\infty} \frac{\left(\frac{-1}{2}\right)^{i+1}}{i!(2i+1)} (2 + 2i + r^2) r^{2i+1}. \quad (34)$$

The graph of the actual function and the first five expansions of Eq. (34) is shown in Fig. 18. One would like to have Δ_y be capable of adjusting out all effects of σ_a, and so the required range of approximation is out to about $r = 3$. Examining Fig. 18, it is clear that a rather large expansion of s^2 is then needed.

For more rapid relative comparisons among different adjustment options, however, the second order approximation of Eq. (31) might be useful, which then becomes

$$\sigma^2 = \Delta_y^2 + \sigma_a^2 - 2\sqrt{\frac{2}{\pi}}\,\sigma_a\Delta_y. \quad (35)$$

4.2 Application to the LTCC Production System. In the LTCC manufacturing case, the error on a performance metric of an LTCC resistor (e.g. resistance, thickness, etc.) can be related to noise variable errors as shown in Fig. 19. The linearized form of the variability equation [Eq. (24)] can be used to predict the standard error of resistance, as shown in the *LTCC Design Tool* in Fig. 14, and discussed in the previous section. The amount of variation predicted, however, proved excessive for many desired electric circuit product configurations, as in-

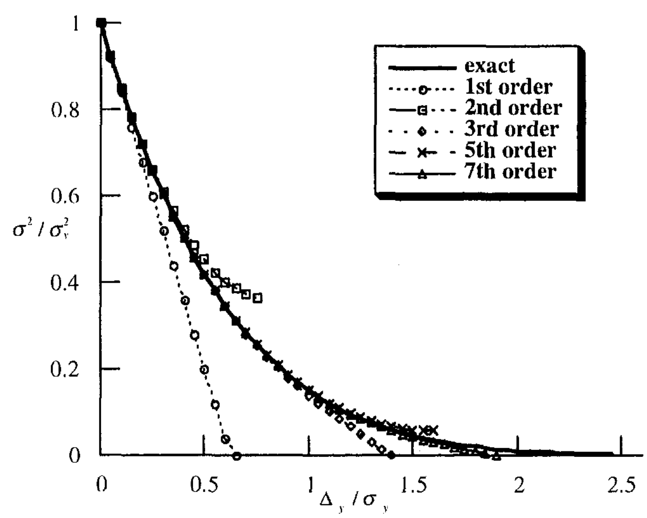

Fig. 18 Reduced variance as a function of adjustment range, with different approximations

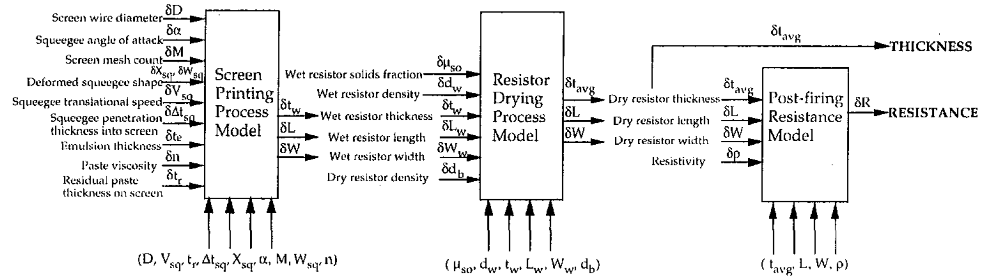

Fig. 19 Box model of the LTCC errors without the tuning adjustments

deed actual production bore out. This posed a new problem on how to improve the current processing capability. Either new process technology or process control was needed, though it was not clear what or where.

Given that, the notion of variability reduction using tuning adjustments was applied to the LTCC error model. As candidate errors whose effects might be adjusted out, four noise variables that prove easy to measure were chosen: emulsion thickness t_e, initial solids weight fraction of the resistor paste μ_{so}, wet paste density d_w, and the power law exponent n that depends on paste viscosity. These are easily measured before each screen printing job, and so offer good candidates to base the setting of an adjustment control. Next, different adjustment variables were considered, including the squeegee translational speed, V_{sq}, and the squeegee angle of attack α. These variables can be adjusted relatively easily by the operators with no change in the equipment. In summary, the proposed concept is that either V_{sq} or α might be adjusted by the screen printing operator based upon a lookup table (yet to be developed) of measurements of t_e, μ_{so}, d_w, and n.

Based upon this proposed process control, Fig. 20 shows the modified systems model for LTCC error behavior. The errors on the adjustable variables are measured to determine the required change in the tuning adjustment variable.

The application of the tuning adjustment concept to the LTCC Design Tool is shown in Fig. 21. The effect of using the squeegee translational speed V_{sq} as a tuning variable can be observed from the values of total resistance standard error with and without the adjustment. While the standard error was 155 Ohms without the control mechanism, after the addition of the tuning variable, the standard error could be reduced to 90 Ohms. This represents a 41.9 percent reduction in standard error, all without any replacement of equipment, only changes in process operation.

In the second approach, the squeegee angle of attack, α was explored as a tuning variable. Figure 20 shows how this can be represented in an error box model. Here the error contribution of the adjustable noise factors can be reduced by 47.7 percent. This proves larger, and also easier for an operator to control. Therefore this variable offers the most improvement with least effort.

The final LTCC design concept shown so far has turned out to be a powerful tool for not only choosing the best design alternative but also optimizing the manufacturing process such that the selected design concept could be feasibly produced. In the studied example, we were able to quantify the difference between two possible variables that were considered for feedback control purposes. LTCC Design Tool clearly showed the implications of using any of the two variables based upon two criteria; total variation reduction and required measurable range on control variables. Doing so, we were able to discover α to be the better option as a control variable.

5 Conclusions

We have developed here a means to explore design and manufactured quality as a systems level concurrent engineering support tool. We also explore using different available process variables as on-line process control variables to reduce the variation caused by noise variables which must then be measured.

We here consider processes that can be modeled reasonably accurately. In particular, if a model suggests a change will improve quality, then in physical production the change in fact does improve quality. A more demanding requirement in a model is to accurately predict effects of relative changes. That is, for example, stating that changing the first input variable has 1.5 times the reduction in quality as changing a second input variable. Relative changes, while desirable in a model, are not absolutely necessary to effective use of analytic models in simultaneous engineering. Just knowing what variables really can do, in conjunction with working knowledge of the system, can lead to effective engineering by the simultaneous engineering teams.

It is interesting to speculate on the applicability of the approach to systems which have complexity due to inability to model physics at the start. This is always the difficulty encoun-

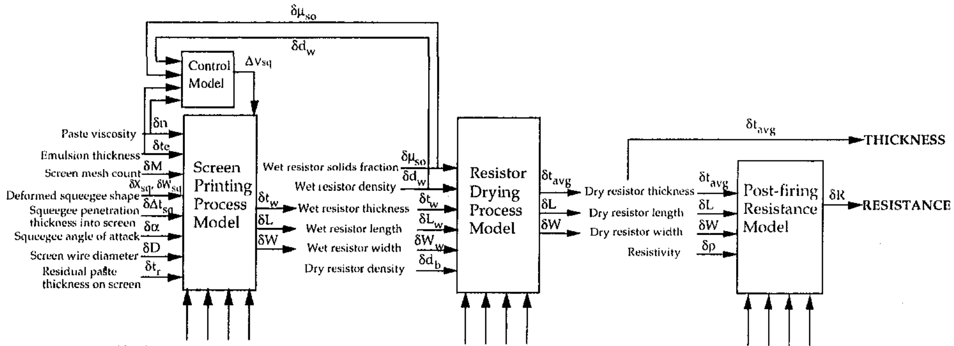

Fig. 20 Box model of the LTCC errors with tuning adjustments

LTCC DESIGN TOOL	Value	Lower Limit	Upper Limit	Unit	Standard Error (σi)	Variance	Cumulative Contribution	On/Off	Δ	Si^2*σi^2
Product Design Variables										
L, Resistor Length	320	20	320	mils	9.6	9.2E+01	11.1%		0	2594.81
W, Resistor Width	40	10	50	mils	1.2	1.4E+00	11.1%		0	2594.81
te, Emulsion height	0.8	0.7	1	mils	0.024	5.8E-04	12.9%		0	3028.33
Equipment Design Variables										
D, Screen Wire Diameter	0.2	0.15	0.25	mils	0.006	3.6E-05	2.3%		0	537.419
M, Mesh Count	0.25	0.1	0.3	per mil	0.0075	5.6E-05	0.3%		0	74.7213
Process Variables										
Vsq, Squeegee Speed	10	5	100	mils/sec	0.3	9.0E-02	1.1%	on	0	259.5
tr, Residual Ink Thickness	0.05	0	0.08	mils	0.0015	2.3E-06	0.0%		0	2.8352
Δtsq, Squeege Penetration	0.1	0	0.16	mils	0.003	9.0E-06	0.2%		0	47.3177
xsq Xsqueegee	10	0	20	mils	0.3	9.0E-02	12.1%		0	2848.36
Wsq Wsqueegee	5	0	10	mils	0.15	2.3E-02	0.2%		0	54.6536
α, Squeegee Attack Angle	25	10	89	degrees	0.75	5.6E-01	15.4%	on	3	3625.5
Material Variables										
ddry, Dry Density of Ink	2.25	1.5	3	lb/in^3	0.0675	4.6E-03	11.1%		0	2594.81
dwet, Wet Density of Ink	2.12	1.5	3	lb/in^3	0.0636	4.0E-03	11.1%		0	2594.81
μso, Solids Weight Fraction	0.8	0	1	%/100	0.024	5.8E-04	11.1%		0	2594.81
n, Power Law Exponent	0.6	0	1		0.018	3.2E-04	0.1%		0	18.6215
Statistical Parameters										
INK TYPE	QT131									
Layer	avg	0	21	(use 1,6,11,16, or avg)						
X position on laminate	0	0	1	mils						
Y position on laminate	0	0	1	mils						
Pr, Resistivity	242			Ohm-mils	0	0.0E+00	0.0%			
Pl, conductor fraction L	0.000			%/100	0	0.0E+00	0.0%			
Px, x position coefficient	-0.089									
Py, y position coefficient	-0.092									
							100.00%			

AVERAGE THICKNESS : 1.14 mils
STANDARD ERROR : 0.09 mils
RESISTANCE : 1698 Ohms
STANDARD ERROR : 153 Ohms — 27% Error Resistor (3 sigma) — Cumulative Standard Error
REDUCED ERROR : 112 Ohms — 20% — Controlled Standard Error

Fig. 21 The LTCC design tool with squeegee speed used as a tuning parameter

tered with analytic models, they are predictive, but only within some representative domain of interest over the physical system. If additional dynamics enter which causes the models used to no longer hold, additional modeling must be done. Two approaches to this problem seem worth exploring, to find means to incrementally augment models with added dynamics as it is encountered (Ho and Otto, 1996) and to explore sensitivity in variables, to be sure of the dynamics of the important variables, sub-systems, and interfaces.

The approach presented, nonetheless, should work with any manufacturing system that has been physically modeled. Systems level input-output black-box representations provide a useful means to represent the system components, for visualizing possible measurement and control schemes. Combining the individual models into a quantitative system model as here for total product/process optimization also makes discussions among the various factions become based upon real analysis, not presumed behavior.

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