# Acquiring Manufacturing Process Knowledge for Design

Prakash Padmanabhan, Susan Finger

EDRC 24-113-94

# Acquiring MpMifactiiriiig Processes Knowledge for Design

Praluuah PMnwnahhui and Suaui Finger

ppad@edrc.cmu.edu, sfinger@cmu.edu
Engineering Design Center
Carnegie Mellon University
Pittsburgh PA 15213

## Abstract

Much of the work done in coopuncnt design assumes that manufacturing process knowledge has been codified and that manufacturing process models exist. However, for new solid freeform manufacturing processes, suchitttheMD* process being developed at Carnegie Mellon, these assumptions are not valid. In the MD* fabrication process, a part is built by successively depositing materials in thin layers. Each layer can contain several materials and creating each layer requires several manufacturing subprocesses which include micro-casting, thermal spraying, shot peening, and machining. Some of these manufacturing subprocesses are only partially understood; their use in combination to form asiofie multi-material layer is not well understood; and the process of creating a mechanical part or assnsbty from thin multi-material layers is also not well understood.

One of the salient features of MD*, as wdl as moic solid freeform manufacturing processes, is that it requires minimal fixturing and setup. Once the geometry and materials (for a part have been specified, the part can be run through an automated planner and made directly •v O1B NwHHlHiBCBnaK vwU* xQQv BID designer can work more closely with the manufacturing process thsfc is possible in tndUoMl manufacturing systems.

This paper describes our preliminary work to create a link between design and manufacturing to enable designers to acquire knowledge about the manufacturing process and to develop models of the

MflH|^Hf OQUDlfiD« ~ Hnft Aflffu SO Qfii&^BI 'DMtt ID IfiflHB Infi~£iflDBBulD0B OK tlfi JH^ttlHDICtHVHIS, -flRICfiflS* - In ft HBBfl to manufacture pans to refine and adapt the process so that new pans can be designed,

## L Introduction

In our previous work on concurrent design, see for example (5], we have assumed that models of the manufacturing process exist and that the features which govern the mamifymraWlity of a design are known. Under these conditions, the pomary (and not inconsequential) problem is to provide manufacturing knowledge to the designer in a useful fonn. However, for the new MD* *process* [8] being developed at Carnegie Mellon, these assumptions do not hold We do not have enough experience with the manufacturing process:*& taow whit feaiira affect the quality of the final design artifact nor do we have fundamental models of the manuftcturing process itteft

The MD* shape deposition process is described in more detail in Section 2 below; however, one of its primary attribute from a design point of vtew is that it removes tndftional manufactwi^g constraints thereby significantly increasing the space of possible products. It allows allows multi-material layers.

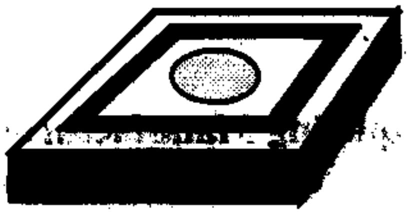

Figure 1: Pmgg S*rtinii*J TjiyM'firirMfwf^turing a Sphere Embedded in a Cube

allows assemblies to be sprayed in place, and allows ctectrotics to be embedded in structures. Using a layered deposition process provides access to the interior of * pan So for example, one can build a solid sphere of one material surrounded by a dosedctobe *oftne/iutt* material (closed except for a small weep hole to let the support material drain out). Hgutt 1 shows ihis pan half way through its manufacture. The white area is the support material which wifl be owrfted after the part is complete.

Another impoitant attribute of the MD* process, as well as other solid frcefbnn manufacturing processes* is that it requires minimal fixturing and setup. As Figure 1 illustrates, the support material conesponds to the fixturing in traditional manufacturing processes. For MD41, process planning consists of filling the voids with support material, slicing the part into layers, and computing the tool paths to deposit the different materials in each layer. Because the ptancatt be getttrated automaticaUy from the CAD model [8], paifeC3!nbesettdirectty from the design system to the manufacturing system. Thusthedesigner can woik more closely with the manufacturing process f t p I s possible in traditional manufacturing systems. Once a part has been verified, it can be downloaded diiectiy to t t e manufacturing cell.

Because the MD* process is under development the nunufacturing subprocesses are mnrtiwally evolving. We need to design and manufacturemp to discover the capabilities of the system, but we need to know the capabilities of the process to onter to design and manufacture paits. The designer does not know how to set design parameters to achieve reqtiiiemems and doesn't know the connection between 4fi?ign dfrisilflm imt^" ^ Hflu w #fflfft fyof*wwyfoim** The goal erf the woik described in this paper is to allow the designer to acquire knowledge about and to develop models of the manufacturing process as part of the design process.

## 2. The MD* Manufacturing Process

M I ^ also taown as shape deposition n u m ^ ^uring (SDM), is a layered manufacturing process in which parts and assemblies are manufactured by successively splaying cross-sectional areas* Stilting from a geometric model, the part is discretized Into thin layers based cm geometric as well as material criteria. The part is built by a veiticai concatenation of two and half dimensional layers. Each layer undeigoes a series of processes including material addition, stress relief, selective material removal, and surface preparation. The MD41 process allows encapsulation of prefabricated pans, such as computer chips, by placing than in sockets and building the structure around them. Salient features of Ac process are its ability to handle any geometry, to vary shape and material composition continuously with the part, to embed electronic components, and to make electronic packaging an integral pait of the mechanical structure.

The basic sequence of operations in the MD* process is shown in Figure 2. Not all operations need to be performed for each layer. Additional processes, like cmhtttf ing prefabricated pans, can occur between repetitions of this loop.

The primary process for depositing material is rcferod to is weld-based spray or micro-casting- The process is similar to conventional welding in which the deposition mtferial is originally in the Item of a

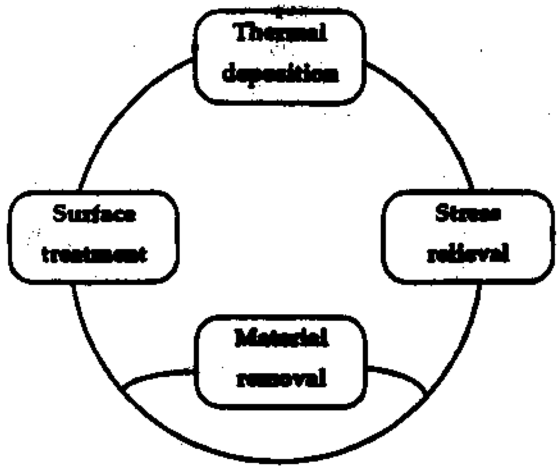


**Figure 2: MD» Subprocesses to Fonn a Single Layer in MD»**

**wire. The wire is melted in an inert atmosphere and dioptets of metal are deposited bewk each other to fbim a layer on the substrate. In contrast to t f i d ^al welding, the wire is elevated from the substrate to protect the existing Uyenfran the during the melting process. The droplet size is large so thatttecboptetsrcmamatatempentture^ higher than the melting point while they are in contact with the substtte. This results in better metallurgical bonding between the s u c c ^ve deposition layers [1].**

**Thermal spraying (plasma or electric arc) can also be used to deposit material. Thenmi spraying staits with a metal powder which is melted to create a fine stream of hot particles. To fotm a layer, the particles are deposited on to the substrate under an inert atmosphere. The particles are an order of magnitude smaller than the droplets used in welding deposition.**

**One of the prominent phenomena that occur during material deposition is the generation of stored residual stresses which results from the differential tbeimal connidion. Even when the substrate is healed and both the sprayed material and the substrate are cooled together, a degree of diS&rcntial thermal contraction is inevitable. In practice, large stresses are genwited whfch cai»e spallation, distortion, or generation of cracks. Stress relief is achieved by shot peening. During shot peening, metallic balls or shots strike the object under pressure. Varying the shot material, shot size, pressure, and length of time results in different process outputs. Excess material is removed to shape the geometry of the layer and to make recesses for inserting prefabricated or electronic parts. Material removal is achieved by precise machining using a high-precision, five axis CNC machine. The surface of each layer is prepared before spraying the next layer. Cleaning followed by grit blasting ensures better bonding between layers. Grit blasting, which onsists of striking the deaned surface with abrasive particles, increases the surface roughness. Grit blasting also removes the oxidized film on a welded layer.**

## 3. Characterizing the Manufacturing Process

**Characterizing the manufacturing process for design requires an understanding of the influence and interactions of design and process variables on the final quality of the artifact Variables are often properties of the material (or combinations of materials) selected, of the geometry of the part, of the equipment settings, and of the manufacturing environmental conditions. Characterization also involves the establishment of the working limits oh these variables. In other words, characterization is equivalent to establishing an accurate model of the process and the range of its applicability.**

**A process model can be used to answer questions about the capabilities of a process as well as to control the process. Manufacturing processes can be modelled at different levels of detail. The level of detail desired, the available resources, and the available knowledge about the phenomena involved dictate the**

type of modelling technique. To study the microscopic effects or detailed structural effects requires rigorous models based on the science of the phenomena occurring in the process. Coarser models based on approximations are sufficient for providing a first estimate or for studying the general behavior of the process. For many new manufacturing processes, models based on science have not been developed. In such cases, empirical models based on experimental data are widely used in industry.

Statistical models obtained from input/output data provide a polynomial relationship between the process variables and the outputs of the process. If ii^ut/outpm data are not available in sufficient quantity, models are developed using a combination of regression techniques and a set of systematically designed experiments. The main advantage of statistical modeling is that any process can be modeled; however, the correctness of the model depends on the experiment design, the interpretation of the results* and the range of its application. Even though statistical models are not based on fundamental principles, they can provide insight and serve as the first step in developing more detailed models.

In this paper, we develop a method that can be used by a designer to develop models of a manufacturing process that is repetition of a sequence of related subpiocesses. Each subprocess is represented in terms of its input properties, control parameters, anil output characteristics. A statistical model of each subprocess is developed using design of experiments. The interme&ate outputs of the subpiocesses form the input properties and control parameters of the model that combines the models of the subprocesses. Subprocess interactions arc incorporated as crossed factors in tie combined, comprehensive statistical model. The absence of a fundamental understanding of the overall process as well as the subprocesses, tbe lack of sufficient data, and the novelty of the process make statistical modeling most suitable for iritial modeling of this process.

### 3.1. Design of Experiments

Box [31 presents some of the earliest woik in experimental design. Later developments leading to classification of experimental design can be found in Steinberg [12]. A different perspective on experimental design, often called off-line quality conrol, can be found in Taguchi [14]. Many references to the use of ttese methods to model, understand, and improve, manufacturing processes are available in literature.

Bxa^ptes of modeling individual processes involving many control variables are available in literature. Gioia [6] describes the development of a quadratic model using a Box-Behnken design for & one micron CMOS process. Donnelly [4] and Hanrahan[7] demonstrate the use of response-surface experimental design in predicting the feasibility of a manufacturing process for a certain yield. Developments have also been made using neural networks in modeling manufacturing processes. Yerramareddy [IS] and Mahajan[9] describes the development of empirical models using artificial neural networks for a machining process from experimental data and a silicon deposition process from analytical data respectively. Nadi [10] describes modeling a process that has many effects using a combination of two types of networks* Anderson [2] reports on the use of learning models for processes using coimcctionist neural networks starting from a basic paiametezed model developed using available knowledge about the process. Neural networks like polynomial regression techniques are universal approximation;; however, they require a substantial amount of data before a model can be obtained. Strojwas [13] describes the use of response surfaces and multi-layer non-linear regression analysis for modeling chemical vapor deposition process and plasma etching for VLSI manufacture.

The common procedure for statistical design of experiments consists of recognizing the goal of experimentation, choosing die variables in tbe process and their levels, choosing tbe response or dependent variable, choosing the set of experiments, planning data collection, and planning the analyses of the collected data to draw conclusions. For more detail on each of the steps or setting up orthogonal arrays for experiments involving fewer trials see Box [3] and TagucM [14]. The basic steps are listed

# Acquiring Manufacturing Process Knowledge for Design

Prakash Padmanabhan, Susan Finger

EDRC 24-113-94

# Acquiring MpMifactiiriiig Processes Knowledge for Design


## Praluuah PMnwnahhui and Suaui Finger

ppad@edrc.cmu.edu, sfinger@cmu.edu
Engineering Design Center
Carnegie Mellon University
Pittsburgh PA 15213



## Abstract

Much of the work done in coopuncnt design assumes that manufacturing process knowledge has been codified and that manufacturing process models exist. However, for new solid freeform manufacturing processes, sucli tttheMD* process being developed at Carnegie Mellon, these assumptions are not valid. In the MD* fabrication process, a part is built by successively depositing materials in thin layers. Each layer can contain several materials and creating each layer requires several manufacturing subprocesses which include micro-casting, thermal spraying, shot peening, and machining. Some of these manufacturing subprocesses are only partially understood; their use in combination to form asiofie multi-material layer is not well understood, and the process of creating a mechanical part or assnsbty from thin multi-material layers is also not well understood.

One of the salient features of MD*, as wdl as moje solid freeform manufacturing processes, is that it requires minimal fixturing and setup. Once the geometry and material (for a part have been specified, the part can be run through an automated planner and sent directly •v O1B NwHHlHiBCBnaK vwU* xQQv BID designer can work more closely with the manufacturing process thsfc is possible in tndUoMl manufacturing systems.

This paper describes our preliminary work to create a link between design and manufacturing to enable designers to acquire knowledge about the manufacturing process and to develop models of the MflH|^Hf OQUDIfiD« ~ Hnft AflIfh SO Qfii&^BI 'DMtt ID IfiflHB Infi~£ifIDBBuIDOB OK flfi JH^tlHDICtHVHIS, -flRICfifIS* - InTft HBBfI to manufacture pans to refine and adapt the process so that new pans can be designed.


## L Introduction

In our previous work on concurrent design, see for example (5], we have assumed that models of the manufacturing process exist and that the features which govern the mamifymraWlity of a design are known. Under these conditions, the pomary (and not inconsequential) problem is to provide manufacturing knowledge to the designer in a useful fonn. However, for the new MD* *process* [8] being developed at Carnegie Mellon, these assumptions do not hold We do not have enough experience with the manufacturing process:*& taow whit feaiira affect the quality of the final design artifact nor do we have fundamental models of the manuftcturing process itteft

The MD* shape deposition process is described in more detail in Section 2 below; however, one of its primary attribute from a design point of vtew is that it removes tndftional manufactwi^g constraints thereby significantly increasing the space of possible products. It allows allows multi-material layers.

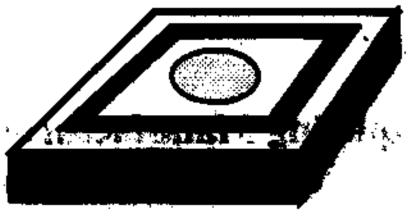

Figure 1: Pmgg S*rtinii*J TjiyM'firirMfwf^turing a Sphere Embedded in a Cube

allows assemblies to be sprayed in place, and allows ctectrotics to be embedded in structures. Using a layered deposition process provides access to the interior of * pan So for example, one can build a solid sphere of one material surrounded by a dosedctobe *oftne/iutt* material (closed except for a small weep hole to let the support material drain out). Hgutt 1 shows ihis pan half way through its manufacture. The white area is the support material which wifl be owrfted after the part is complete.

Another impoitant attribute of the MD* process, as well as other solid frcefbnn manufacturing processes* is that it requires minimal fixturing and setup. As Figure 1 illustrates, the support material conesponds to the fixturing in traditional manufacturing processes. For MD[41], process planning consists of filling the voids with support material, slicing the part into layers, and computing the tool paths to deposit the different materials in each layer. Because the ptancatt be getttrated automaticaUy from the CAD model [8], paifeC3!nbesettdirectty from the design system to the manufacturing system. Thusthedesigner can woik more closely with the manufacturing process f t p I s possible in traditional manufacturing systems. Once a part has been verified, it can be downloaded diiectiy to t t e manufacturing cell.

Because the MD* process is under development the nunufacturing subprocesses are mnrtiwally evolving. We need to design and manufacturemp to discover the capabilities of the system, but we need to know the capabilities of the process to onter to design and manufacture paits. The designer does not know how to set design parameters to achieve reqtiiiemems and doesn't know the connection between 4fi?ign dfrisilflm imt th ^ " ^ Hflu w #fflfft fyof*wwyfoim** The goal erf the woik described in this paper is to allow the designer to acquire knowledge about and to develop models of the manufacturing process as part of the design process.

## 2. The MD* Manufacturing Process

M I ^ also taown as shape deposition n u m ^ ^uring (SDM), is a layered manufacturing process in which parts and assemblies are manufactured by successively splaying cross-sectional areas* Stilting from a geometric model, the part is discretized Into thin layers based cm geometric as well as material criteria. The part is built by a veiticai concatenation of two and half dimensional layers. Each layer undeigoes a series of processes including material addition, stress relief, selective material removal, and surface preparation. The MD[41] process allows encapsulation of prefabricated pans, such as computer chips, by placing than in sockets and building the structure around them. Salient features of Ac process are its ability to handle any geometry, to vary shape and material composition continuously with the part, to embed electronic components, and to make electronic packaging an integral pait of the mechanical structure.

The basic sequence of operations in the MD* process is shown in Figure 2. Not all operations need to be performed for each layer. Additional processes, like cmhtttf ing prefabricated pans, can occur between repetitions of this loop.

The primary process for depositing material is rcferod to is weld-based spray or micro-casting- The process is similar to conventional welding in which the deposition mtferial is originally in the Item of a

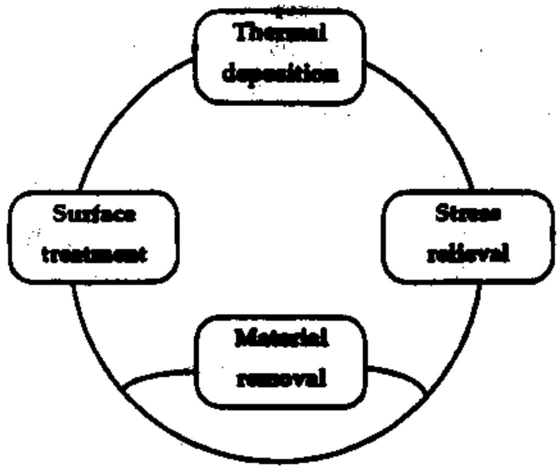


Figure 2: MD» Subprocesses to Fonn a Single Layer in MD»

wire. The wire is melted in an inert atmosphere and dioptets of metal are deposited bewk each other to fbim a layer on the substrate. In contrast to t f i d ^al welding, the wire is elevated from the substrate to protect the existing Uyenfran the during the melting process. The droplet size is large so thatttecboptetsrcmamatatempentture^ higher than the melting point while they are in contact with the substttte. This results in better metallurgical bonding between the s u c c ^ve deposition layers [1].

Thermal spraying (plasma or electric arc) can also be used to deposit material. Thenmi spraying staits with a metal powder which is melted to create a fine stream of hot particles. To fotm a layer, the particles are deposited on to the substrate under an inert atmosphere. The particles are an order of magnitude smaller than the droplets used in welding deposition.

One of the prominent phenomena that occur during material deposition is the generation of stored residual stresses which results from the differential tbeimal connidion. Even when the substrate is healed and both the sprayed material and the substrate are cooled together, a degree of diS&rcntial thermal contraction is inevitable. In practice, large stresses are genwited whfch cai»e spallation, distortion, or generation of cracks. Stress relief is achieved by shot peening. During shot peening, metallic balls or shots strike the object under pressure. Varying the shot material, shot size, pressure, and length of time results in different process outputs. Excess material is removed to shape the geometry of the layer and to make recesses for inserting prefabricated or electronic parts. Material removal is achieved by precise machining using a high-precision, five axis CNC machine. The surface of each layer is prepared before spraying the next layer. Cleaning followed by grit blasting ensures better bonding between layers. Grit blasting, which onsists of striking the deaned surface with abrasive particles, increases the surface roughness. Grit blasting also removes the oxidized film on a welded layer.

## 3. Characterizing the Manufacturing Process

Characterizing the manufacturing process for design requires an understanding of the influence and interactions of design and process variables on the final quality of the artifact Variables are often properties of the material (or combinations of materials) selected, of the geometry of the part, of the equipment settings, and of the manufacturing environmental conditions. Characterization also involves the establishment of the working limits oh these variables. In other words, characterization is equivalent to establishing an accurate model of the process and the range of its applicability.

A process model can be used to answer questions about the capabilities of a process as well as to control the process. Manufacturing processes can be modelled at different levels of detail. The level of detail desired, the available resources, and the available knowledge about the phenomena involved dictate the type of modelling technique. To study the microscopic effects or detailed structural effects requires rigorous models based on the science of the phenomena occurring in the process. Coarser models based on approximations are sufficient for providing a first estimate or for studying the general behavior of the process. For many new manufacturing processes, models based on science have not been developed. In such cases, empirical models based on experimental data are widely used in industry.

Statistical models obtained from input/output data provide a polynomial relationship between the process variables and the outputs of the process. If ii^ut/outpm data are not available in sufficient quantity, models are developed using a combination of regression techniques and a set of systematically designed experiments. The main advantage of statistical modeling is that any process can be modeled; however, the correctness of the model depends on the experiment design, the interpretation of the results* and the range of its application. Even though statistical models are not based on fundamental principles, they can provide insight and serve as the first step in developing more detailed models.

In this paper, we develop a method that can be used by a designer to develop models of a manufacturing process that is repetition of a sequence of related subpiocesses. Each subprocess is represented in terms of its input properties, control parameters, anil output characteristics. A statistical model of each subprocess is developed using design of experiments. The interme&ate outputs of the subpiocesses form the input properties and control parameters of the model that combines the models of the subprocesses. Subprocess interactions arc incorporated as crossed factors in tie combined, comprehensive statistical model. The absence of a fundamental understanding of the overall process as well as the subprocesses, tbe lack of sufficient data, and the novelty of the process make statistical modeling most suitable for iritial modeling of this process.

### 3.1. Design of Experiments

Box [31 presents some of the earliest woik in experimental design. Later developments leading to classification of experimental design can be found in Steinberg [12]. A different perspective on experimental design, often called off-line quality conrol, can be found in Taguchi [14]. Many references to the use of ttese methods to model, understand, and improve, manufacturing processes are available in literature.

Bxa^ptes of modeling individual processes involving many control variables are available in literature. Gioia [6] describes the development of a quadratic model using a Box-Behnken design for & one micron CMOS process. Donnelly [4] and Hanrahan[7] demonstrate the use of response-surface experimental design in predicting the feasibility of a manufacturing process for a certain yield. Developments have also been made using neural networks in modeling manufacturing processes. Yerramareddy [IS] and Mahajan[9] describes the development of empirical models using artificial neural networks for a machining process from experimental data and a silicon deposition process from analytical data respectively. Nadi [10] describes modeling a process that has many effects using a combination of two types of networks* Anderson [2] reports on the use of learning models for processes using coimcctionist neural networks starting from a basic paiameteqzed model developed using available knowledge about the process. Neural networks like polynomial regression techniques are universal approximation;; however, they require a substantial amount of data before a model can be obtained. Strojwas [13] describes the use of response surfaces and multi-layer non-linear regression analysis for modeling chemical vapor deposition process and plasma etching for VLSI manufacture.

The common procedure for statistical design of experiments consists of recognizing the goal of experimentation, choosing die variables in tbe process and their levels, choosing tbe response or dependent variable, choosing the set of experiments, planning data collection, and planning the analyses of the collected data to draw conclusions. For more detail on each of the steps or setting up orthogonal arrays for experiments involving fewer trials see Box [3] and TagucM [14]. The basic steps are listed bdow.

1. *Recog«^f*f goal of the experiment:* Thi* step is cniciai for wlMequeot decisions like the type of experiment to be chosen ot tbc number of replications required.
2. *Choosing the variables and their levelr.* The independent variables, or factocs, whose effects ae to be stained must be selected. The vataw or levels of the ñcaon to be used fat the **experiment must be decided.**
3. *Chodtbtg the response variable:* The respome variable is Met to maaiBW die effect of vuyiifg fte^fiQbtfe. The pvotMttte accuracy of the moflnnnMUt of the n y m variable **must be considered.**
4. *Cheating the experiment* A single experiment or a **set of experiments, each consisting of** **effect of several variables** sovom w|MbWBi« tuns. Buy oe ncoesHKy IO eseVMse BB stmattaeoiisly. The choice of experiments depends on the **cost, the risk, and the** **should be proposed to approximate the effect being assessed.**
5. *Dam mUmta*:* Dst» must be collected on the «ier in «Mch the diffierent experimental **uniform experimental environment, and the measurement accuracy.**
6. *Planning dm analyser.* Although, analyses and coodostons come only after the experiments have been pcrfonacd, consktering *tbte* aspect while designing the experiment can rcsoit in differcni choice of experiments-

The cost of using design of experiments wrdaied to the expeiimert itself airi **to the number of replicates** (sample sin) chosen. Risk is the chance taken to estimate a certain effect with a certain nnnthtr of experimental iims. DifiEeitm experimental desagps allow di^^**nt levels of compromise between cost and** risk. Fuither, bifed on the type of effect to be cstlinilfiri (Itear* additive* nonlinear, or interactive) **different mathematical models** and cai^PQfSMHMHBB *A9v0eOaV0otMi UQBCDS most oe chosen* **The mathematical model also affects the type of statistical analyses performed on the data.**

Associated wMi 6tch of the sbbpitx^esses *tst* many vacUMes and cooiiol foctois whose effect on the siimpfocess and the eutiie process is unknown. Further* the intertctions between these subpioosscs aie not cleariy understood. This makes the problem of modelling such processes challenging.

Ideally, aU the variables controlling the de«**red output must be understood and optimized for better yield;** however, it is (Bfflcuit to obtain a model that rchtftes all the vari^tes in all the subprocesses to the final output of tile process. One way to model such a process is to model each subpiocfess mtfvkhially and then combine the modds. Tlie combination procedure must incorporate interactions between the subprocesses and reduce the number of variables involved.

Each subprocess is represented in tenns of its input poperties, control variables am) output parameters. We develop a statistical model of each subprocess using design of experiments. The intermediate outputs of the subprocesses fcmn the input properties and control variables of the l^odd that combines the models of the suibproctties. Subprocess mteriictions BM^inccNfpdrated as crossed ftctors in the combined comprehensive i**statistical model.**

## 4. Modelling MD*

In novel manafartufing processes, data ate scarce and there is no starting model. All the research surveyed above involves modeling a single maoifocturing process. Moddtag processes involving different siAprocesses is not discussed In the Uteratnre. We *tat* developing models such manu&ctnring pnx^sses, as they are being developed, for predicts **and optimization.** Design of experiments is used to obtain m<fkifaliu^ taformatton from a restricted set of experimettts to model the subprocesses. Because statistical models complement design of experiments, we use them to model individual subprocesses.

During its manufacture, a part undergoes many changes and passes through many mamifacturing subprocesses before it is complete. Ideally, these subprocesses are independent of each otter and can be modeled individually^3/ However, Htaimfaffiiring process like MD* require an iterative sequence of dependent subprocesses that hm docnifirandinge£fectontteoutput

In tte MD* process, eacb layer is formed using micro-casting, stress relief, machining, and surface preparation, then tte layers are concatenated to create tte part. Tte inter-layer effects are as important as tte ina*4aycr eflbcts in tte MD* process, so we must modpl npt only tte sequence within a layer, but also tte ktteactksns between layers. *Tbt* method prosmttd here is based on tte divide and conquer principle. Tte complex process is first divided into smaller subptoceaaes. Tte subpexnses are modeled individually in a common framewort Tte individual mwiels are comtwied to fom **a model** of tte layer

layer in the *****

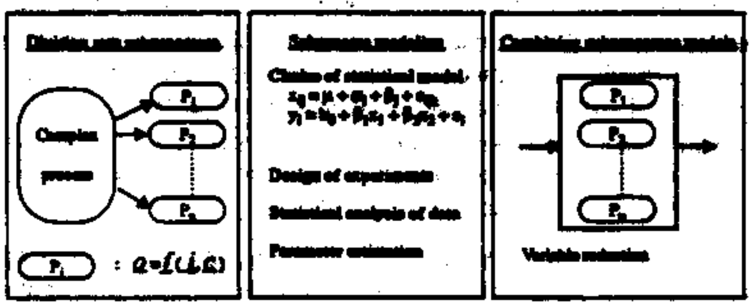

Figure 3: Model of tte Subprocess to Create a Layer in MD*

In addition to modeling tte layer creation process, we must also model tte process of **concatenating** layers. Some of the most interesting issues in both design and manufacture arise in tte layer concatenation process. For design, features such as unsupportable overhangs arise from interaction between layers. For manufacturing, some of tte most serious defects/such as delamination, occur between layers.

Whilespraying tte first layer of a part, tte efBea of properties of the substrate material are not amsidered because bonding between tte substrate and the first layer is not of interest However, while spraying any subsequent layer tte output properties (temperature, surface roughness, etc) of tte previous layer affect tte bonding between tte two layers. The inter-layer effects are modeled by considering tte output variables of tte previous layer as input variables to the process of creating of tte current layer. Interactions between tte properties of the previous layer and the control variaUes for tte current layer make it possible to compensate for the properties of the previous layers.

The division of the process into subprocesses must:

1. be conducive to studying tte subprocess by itself* i.e* each subprocess should be a physically separable step in tte manufacturing process. For example, in a silicon film deposition process, film thickness and stress development cannot be divided into two subprocesses even though a separate model maybe be required to describe film thickness and stress development
2. allow subpipcesses to te com^**ned with neighboring subprocesses. The combination of the** subprocesses into a larger model requires that neighboring subprocesses have a common property or variable which forms n link between them. Ideally the output variable of a subprocess is tte input variable or a control factor of the subsequent subprocess.
3. possess output variables that are measure**e and representative of the changes occurring in** the subprocess. This will enable control of tte subprocess as well as reduction of tte number of variables involved in the model.

Every subprocess has inputs which ate processed through some equipment to produce certain outputs.

This geneiality is used in aodejiog. a. sybpocess. The subprocca«es are frpfraienfrrt in tcnn& of input properties, process or control variables, and output properties Th? iaput properties are relevant pfopertief (geometry, finish, matnrial, etc) of »e input maariaL The cqpdrol variables are the settings of theequipniici (iacàKfeg r#inwnj used to control the environment) used in theaufaprocec. The output

modified input properties, such as surface & ía h > ^ machining process, or anew property, such as stress in thermal spraying.

The subprocess is modeled as follows: Let i, c, and *o* be vectors representing the input properties, control variables, and output properties from the subprocess represc>itttf$li. TyaBt idattonhip between the output properties and the input properties and control variables (^m be writwi^

$$o = f(i,c)$$

where,/is a vector of unknown functions. Each function/; in/is a fiinction of some or all of the input properties and control variables and corresponds to oneoutpi^prope^r^ino.

The unknown functions in/are determined by design of experiments. First screening experiments are cxxidiftCtedtadiaooYerwhk&of the^input and control variables affect the output or response variable in a statistically significant senscv. Depending of ttie wiocm of pripr knowledge abottt the effect of significant variables on the rcsfwnse. empirical or mfchanistic models arc developed for / baaed on further experimentation.

The effects of all the subprocess that form the process when combined together produce a model of the entire process. *UOJJ=* l,2-..n arc the output vectors of the *n* subprocesses, the process can be modeled as

$$y = g(i_1, o_1, o_2, \ldots o_n)$$

where, *y* is the vector of outpmprc^rt» of the i ^ ^ layer process, g is the vector of unknown function that model the intra-layer process, and $i_1$ is the vector of input properties for the first subprocess. The vector *g* is determined using a process similar to the process in which / was defeennined earlier. The experimentation necessary to determine *g* is reduce significantly due to the availability of data from the experiments perfonned to model Ihe subprocesses, asaiming thai *mod* of the test specimens were processed completely.

The rationale behind the use of the outputs from the subprocesses to model the intra-layer process is the fact that input and control variables of each subprocess can b$ used to control the corresponding output This is true because the intra-layer process was divided into subpnocesses under a set of conditions, one of which required the output of the subprocess to represent the changes effected by the subprocess. We assume that the number of output variables in each subpiocess will be less than the sum of the input and control variables. Hence there is a considerable reduction in the number of variables or factors involved in the model of the intra-layer process. Further, if some of the subprocess outputs are not statistically significant, the number of variables in overall model will be reduced further.

## 5. Example

This section describes a prototype system that has been developed at CMU. This section describes just the part of the system that allows the designer to design the experiment; and generate the geometric and material description of the sampte specimen that can be transmitted to the manufacturing system.

As part of another project, we arc designing and manufacturing wearable computers with confbnnal electronics [11]. Because the manufacturing process is under development, designers often do not know the capabilities of the system. For example, to create parts with embedded electronics, the components arc dropped into milled pockets with their leads pointing up wards. Due to ccmnectivity as well as thermal problems, a designer has decided ID try embedding the componentt in a nylon material. A layer of zinc spnyed on top of *'Hie* nylon ftwms the condnciing layer which 'ft ifsed to make connections to the dectrooic component The zinc layer is plane* after sprttying and Ihe circuit is then cat However, the zfncla^te^iDp# tiff wife **machining causing breaks in electrical continuity.** Thwtesigner wants to create snexpferiiientwim the objective of dettminttg th¥ madiming parimeteiB for spwycd zinc The designer has **determined** that the experimental factors ale:

Input properties: Zinc layer thickness
Gontiol variable*: d^uttertlismeter
Deptihofcut
**Feed rate**
Cutter speed
Coolant
• Gap between cuts
Response variable: Number of ped-ofb
Res stance between ^Mff

The (tesigner belteves that cutting speed (a function of cuter diameter and cotter speed), feed me, and depth of cut are the primary varirtrfea that affect the output Using the design system^ the designer creates an experiment to vary each of these variables at two levels and petfonH a two-level factorial experiment The screen in which the designer sets up the experiment is shown in Figure 4. The system sets up a two-levei factorial nmdflmixad run as shown in Table 1.

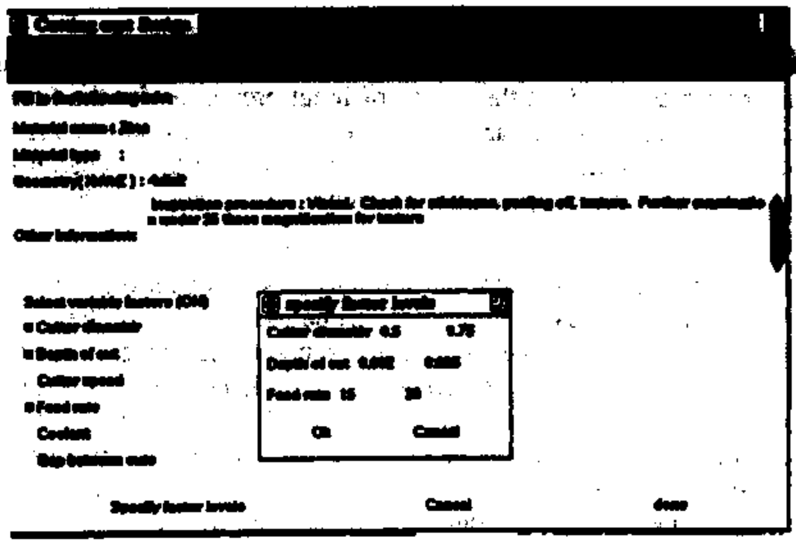


Figure 4: Screen to Design an Experiment for a Machining Process

The initial model is a linear model that assumes that the output variables are a linear function of the a)ntrol variables. Depending on the outcome of the experiment **the linear model may need to be refined** or a more cwnpikated model substituted

$$y_1 = \Sigma a_i v_i + \varepsilon$$
$$y_2 = \Sigma b_i v_i + \varepsilon$$

where

a| and bj arc the unknown parameters (co-efficients) to be determined
v, site tte Viriibtes (feed, £peed, depth) ill the experimental irms
$y_x$ and $y_2$ aie flie outputs ofllie process (peel oflfc, resistance)
£ is the error

| Run Number | Dimeter (in) | Depth of cut (in) | Feed me (in/tec) |
|---|---|---|---|
| 1 | 0.5 | aoo2 | u |
| 2 | 0.75 | 0.002 | 15 |
| 3 | 0.75 | 0.005 | 30 |
| 4 | 0.75 | 0.005 | 15 |
| 5 | 0.5 | 0.005 | 30 |
| 6 | 0.5 | 0.005 | 15 |
| 7 | 0.75 | OJ002 | 30 |
| 8 | 0.5 | ojaaz | 30 |

Table 1: Rxpcrimcntai Design for Marhining Zinc Layer

After the mn table is generated, the system will attomatically genenrte the geometric model for a sample specimen with the appropriate process control variables to nm the experiment on the manufacturtag system.

## 6. Conetasieii

We have presented a preliminary version of a system that allows designm to acquire data about a process by designing and naming experiments on the jnanufacturiiig system. We have presented models of rfiMM>iMiaBrai» MMMMSK^MBX mwnnjMutiii n i mSflV UBzlDVB n w H w y i r gunwgofTPJMHiK

Currently, because of the lack of data on the MD* processes, we are focussing on designing experiments to characterize the manufacturing subpiocesses. As the models of the process improve, we will also begin to synthesize the knowledge so that design advisors can be built

## 7. References


1. Amon, G, Prinz, E B., Schmaltz, K., "Numerical Modelling of Thexmal Spray Systems," Technical Report EDRC 24-106-93, Engineering Design Research Center, Carnegie Mellon University, 1993.

2. Anderson, C W., Franklin, J. A., Sutfton, R. S, "learning a N b n l i ^ Model of a Manufacturing Process using Multilayer Connectionist Networks," *Proceedings of the 5th IEEE International Symposium on Intelligent Control,* IEEE, Philadelphia, PA, 5-7 September 1990.

3. Box, G. E. P., Hunter, W. G. and Hunter, J. S., *Statistics for Experimenters,* John Wiley & Sons, New Yoik, 1978.

4. Donnelly, A. T., "Response-surface Experimental Design," *IEEE Potentials.* February 1992, pp. 19-21.

5. Finger, S., Fox, M. S., Prinz, F. B., and Rinderie, J. R., "Concurrent Design," *Applied Artificial*

*Intelligence,* Vol. 6,1992. pp. 257-283.

6. Gioia, S.. Miller, G. and Daughtoo. W., "Application of Statistical Experimental Design to the Development of a One Micron CMOS Process," *Proceedings of the IEEE 1989 National Aerospace and Electronics Conference,* IEEE, Dayton, OH, May 1989.

7. Hanrahan, J. J. and Baltus, T. A., "Efficient Engineering through Computer-Aided Design of Experimentt," *IEEE Transactions on Industry Applications,* Vol. 28, No. 2,1992. pp. 293-296.

8. Hartman, K.. Krishnan, iU Merz. R.. NepkriUk, G., Prim F. B.. Scautiz,L^Teik, M. and Weiss. L. E., "Robot-Assisted Shape Deposition Manufacturing," *Proceedings ofthe 1994 IEEE International Conference on Robotics and Automation,* IEEE, San Diego, May 1994.

9. Mahajan, R. L., Wang, X, A., Xie. H. andLee, Y. C "Neural Network and Fuzzy Models for Real Time Control of a CVD Epitaxial Reactor;" *SP1E Science of Artificial Networks,* Vol. 1710,1992, pp. 598-607.

10. Nadi, F., Agogino, A. M. and Hodges, D. A., "Use of Influence Diagrams and Neural Networks in Modelling Semiconductor Manufacturing Processes," *IEEE Transactions on Semiconductor Manufacturing,* Vol. 4, No. 1,1991, pp. 52-58.

11. Sieworek, D. S., Smailagic, A., Lee, J.Y.C and Tabatabai, AJLA., "An Interdisciplinary Concurrent Design Methodology as Applied to the Navigator Wearable Computer System," EDRC Technical Report xxxx, Carnegie Mellon, May 1993.

12. Steinberg M. S. and Hunter, G. H.. "Experimental Design: Review and Comment," *Technometrics,* VoL 26, No. 2,1984. pp. 71-96.

13. Strojwas. A. J.. "Design for Manufacturability and Yield," *Microelectronics Journal,* Vol. 21, No. 2,1990, pp. 53-66.

14. Taguchi, G., *System ofExperimental Design, vol. 1 and vol. 2,* UNIPUB-Kraus International Publications, White Plains, 1987.

15. Yerramareddy. S., Lu, S. C-Y. and Arnold, K. L, "Developing Empirical Models from Observational Data using Artificial Neural Networks," *Journal ofinteUitentManufacturing,* VoL 4, No. 1,1993, pp. 33-41.

subprocesses before it is complete. Ideally, these subprocesses are independent of each otter and can be modeled individually*/ However, Htaimfaffiiring process like MD* require an iterative sequence of dependent subprocesses that hm docnifirandinge£fectontteoutput

In tte MD* process, eacb layer is formed using micro-casting, stress relief, machining, and surface preparation, then tte layers are concatenated to create tte part. Tte inter-layer effects are as important as tte ina*4aycr eflbcts in tte MD* process, so we must modpl npt only tte sequence within a layer, but also tte ktteactksns between layers. *Tbt* method prosmttd here is based on tte divide and conquer principle. Tte complex process is first divided into smaller subptoceaaes. Tte subpexnses are modeled individually in a common framewort Tte individual mwiels are comtwied to fom **a model** of tte layer

layer in the *****

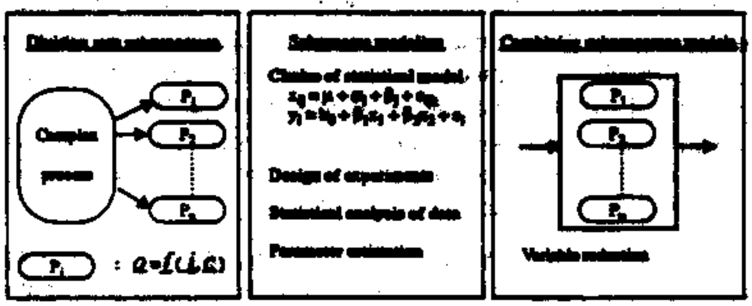

Figure 3: Model of tte Subprocess to Create a Layer in MD*

In addition to modeling tte layer creation process, we must also model tte process of **concatenating** layers. Some of the most interesting issues in both design and manufacture arise in tte layer concatenation process. For design, features such as unsupportable overhangs arise from interaction between layers. For manufacturing, some of tte most serious defects/such as delamination, occur between layers.

Whilespraying tte first layer of a part, tte efBea of properties of the substrate material are not amsidered because bonding between tte substrate and the first layer is not of interest However, while spraying any subsequent layer tte output properties (temperature, surface roughness, etc) of tte previous layer affect tte bonding between tte two layers. The inter-layer effects are modeled by considering tte output variables of tte previous layer as input variables to the process of creating of tte current layer. Interactions between tte properties of the previous layer and the control variaUes for tte current layer make it possible to compensate for the properties of the previous layers.

The division of the process into subprocesses must:

1. be conducive to studying tte subprocess by itself* i.e* each subprocess should be a physically separable step in tte manufacturing process. For example, in a silicon film deposition process, film thickness and stress development cannot be divided into two subprocesses even though a separate model maybe be required to describe film thickness and stress development
2. allow subpipcesses to te com^**ned with neighboring subprocesses. The combination of the** subprocesses into a larger model requires that neighboring subprocesses have a common property or variable which forms n link between them. Ideally the output variable of a subprocess is tte input variable or a control factor of the subsequent subprocess.
3. possess output variables that are measure**e and representative of the changes occurring in** the subprocess. This will enable control of tte subprocess as well as reduction of tte number of variables involved in the model.

Every subprocess has inputs which ate processed through some equipment to produce certain outputs.

This generality is used in modeling a subprocess. The subprocesses are represented in terms of input properties, process or control variables, and output properties. The input properties are relevant properties (geometry, finish, material, etc) of the input material. The control variables are the settings of the equipment (machine used to control the environment) used in the subprocess. The output

modified input properties, such as surface finish in a machining process, or a new property, such as stress in thermal spraying.

The subprocess is modeled as follows: Let i, c, and *o* be vectors representing the input properties, control variables, and output properties from the subprocess respectively. The relationship between the output properties and the input properties and control variables can be written as

$$o = f(i,c)$$

where, *f* is a vector of unknown functions. Each function $f_i$ in *f* is a function of some or all of the input properties and control variables and corresponds to one output property.

The unknown functions in *f* are determined by design of experiments. First screening experiments are conducted to determine which of the input and control variables affect the output or response variable in a statistically significant sense. Depending on the amount of prior knowledge about the effect of significant variables on the response, empirical or mechanistic models are developed for / based on further experimentation.

The effects of all the subprocess that form the process when combined together produce a model of the entire process. If $o_j$, j = 1,2-..n are the output vectors of the *n* subprocesses, the process can be modeled as

$$y = g(i_1, o_1, o_2, \ldots o_n)$$

where, *y* is the vector of output properties of the intra-layer process, *g* is the vector of unknown function that model the intra-layer process, and $i_1$ is the vector of input properties for the first subprocess. The vector *g* is determined using a process similar to the process in which *f* was determined earlier. The experimentation necessary to determine *g* is reduce significantly due to the availability of data from the experiments performed to model the subprocesses, assuming that most of the test specimens were processed completely.

The rationale behind the use of the outputs from the subprocesses to model the intra-layer process is the fact that input and control variables of each subprocess can be used to control the corresponding output. This is true because the intra-layer process was divided into subprocesses under a set of conditions, one of which required the output of the subprocess to represent the changes effected by the subprocess. We assume that the number of output variables in each subprocess will be less than the sum of the input and control variables. Hence there is a considerable reduction in the number of variables or factors involved in the model of the intra-layer process. Further, if some of the subprocess outputs are not statistically significant, the number of variables in overall model will be reduced further.

## 5. Example

This section describes a prototype system that has been developed at CMU. This section describes just the part of the system that allows the designer to design the experiment; and generate the geometric and material description of the sample specimen that can be transmitted to the manufacturing system.

As part of another project, we are designing and manufacturing wearable computers with conformal electronics [11]. Because the manufacturing process is under development, designers often do not know the capabilities of the system. For example, to create parts with embedded electronics, the components are dropped into milled pockets with their leads pointing up wards. Due to connectivity as well as thermal problems, a designer has decided to try embedding the componentt in a nylon material. A layer of zinc sprayed on top of the nylon forms the conducting layer which is used to make connections to the electronic component. The zinc layer is planed after spraying and the circuit is then cut. However, the zinc layer is tearing off in machining causing breaks in electrical continuity. The designer wants to create an experiment with the objective of determining the machining parameters for sprayed zinc. The designer has determined that the experimental factors are:

Input properties: Zinc layer thickness
Control variables: Cutter diameter
Depth of cut
Feed rate
Cutter speed
Coolant
Gap between cuts
Response variable: Number of peel-offs
Resistance between [illegible]

The designer believes that cutting speed (a function of cutter diameter and cutter speed), feed rate, and depth of cut are the primary variables that affect the output. Using the design system, the designer creates an experiment to vary each of these variables at two levels and perform a two-level factorial experiment. The screen in which the designer sets up the experiment is shown in Figure 4. The system sets up a two-level factorial [illegible] run as shown in Table 1.

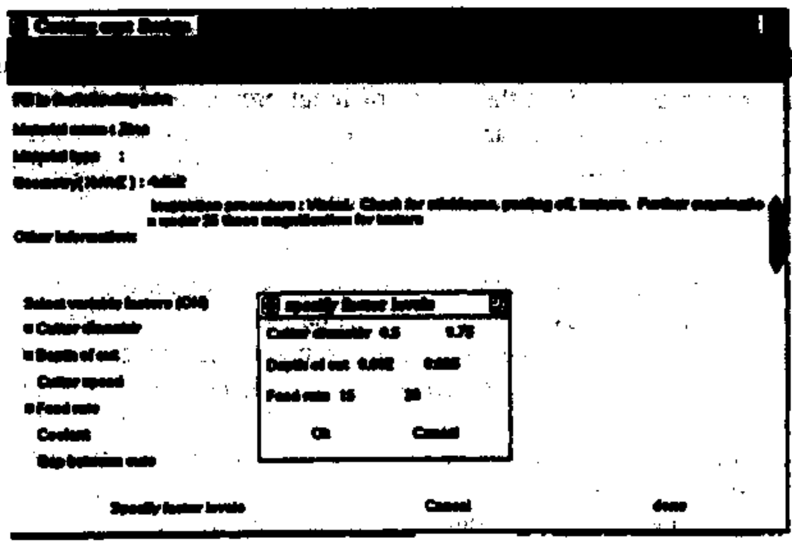

Figure 4: Screen to Design an Experiment for a Machining Process

The initial model is a linear model that assumes that the output variables are a linear function of the control variables. Depending on the outcome of the experiment the linear model may need to be refined or a more complicated model substituted.

$$y_1 = \Sigma a_i v_i + \varepsilon$$
$$y_2 = \Sigma b_i v_i + \varepsilon$$

where

a| and bj arc the unknown parameters (co-efficients) to be determined
v» site tte Viriibtes (feed, £peed, depth) ill the experimental iruns
$y_x$ and $y_2$ aie flie outputs ofllie process (peel offc, resistance)
£ is the error

| Run Number | Dimeter (in) | Depth of cut (in) | Feed me (in/tec) |
|---|---|---|---|
| 1 | 0.5 | aoo2 | u |
| 2 | 0.75 | 0.002 | 15 |
| 3 | 0.75 | 0.005 | 30 |
| 4 | 0.75 | 0.005 | 15 |
| 5 | 0.5 | 0.005 | 30 |
| 6 | 0.5 | 0.005 | 15 |
| 7 | 0.75 | OJ002 | 30 |
| 8 | 0.5 | ojaaz | 30 |

Table 1: Rxpcrimcntai Design for Marhining Zinc Layer

After the mn table is generated, the system will attomatically genenrte the geometric model for a sample specimen with the appropriate process control variables to nm the experiment on the manufacturtag system.

## 6. Conetasieii

We have presented a preliminary version of a system that allows designm to acquire data about a process by designing and naming experiments on the jnanufacturiiig system. We have presented models of rfiMM>iMiaBrai» MMMMSK^MBX mwnnjMutiii n i mSflV UBzlDVB n w H w y i r gunwgofTPJMHiK

Currently, because of the lack of data on the MD* processes, we are focussing on designing experiments to characterize the manufacturing subpiocesses. As the models of the process improve, we will also begin to synthesize the knowledge so that design advisors can be built

## 7. References


1. Amon, G, Prinz, E B., Schmaltz, K., "Numerical Modelling of Thexmal Spray Systems," Technical Report EDRC 24-106-93, Engineering Design Research Center, Carnegie Mellon University, 1993.

2. Anderson, C W., Franklin, J. A., Sutfton, R. S, "learning a N b n l i ^ Model of a Manufacturing Process using Multilayer Connectionist Networks," *Proceedings of the 5th IEEE International Symposium on Intelligent Control,* IEEE, Philadelphia, PA, 5-7 September 1990.

3. Box, G. E. P., Hunter, W. G. and Hunter, J. S., *Statistics for Experimenters,* John Wiley & Sons, New Yoik, 1978.

4. Donnelly, A. T., "Response-surface Experimental Design," *IEEE Potentials.* February 1992, pp. 19-21.

5. Finger, S., Fox, M. S., Prinz, F. B., and Rinderie, J. R., "Concurrent Design," *Applied Artificial*

*Intelligence,* Vol. 6,1992. pp. 257-283.

6. Gioia, S.. Miller, G. and Daughtoo. W., "Application of Statistical Experimental Design to the Development of a One Micron CMOS Process," *Proceedings of the IEEE 1989 National Aerospace and Electronics Conference,* IEEE, Dayton, OH, May 1989.

7. Hanrahan, J. J. and Baltus, T. A., "Efficient Engineering through Computer-Aided Design of Experimentt," *IEEE Transactions on Industry Applications,* Vol. 28, No. 2,1992. pp. 293-296.

8. Hartman, K.. Krishnan, iU Merz. R.. NepknUk, G., Prim F. B.. Scautz,L^Teik, M. and Weiss. L. E., "Robot-Assisted Shape Deposition Manufacturing," *Proceedings of the 1994 IEEE International Conference on Robotics and Automation,* IEEE, San Diego, May 1994.

9. Mahajan, R. L., Wang, X, A., Xie. H. and Lee, Y. C "Neural Network and Fuzzy Models for Real Time Control of a CVD Epitaxial Reactor;" *SP1E Science of Artificial Networks,* Vol. 1710,1992, pp. 598-607.

10. Nadi, F., Agogino, A. M. and Hodges, D. A., "Use of Influence Diagrams and Neural Networks in Modelling Semiconductor Manufacturing Processes," *IEEE Transactions on Semiconductor Manufacturing,* Vol. 4, No. 1,1991, pp. 52-58.

11. Sieworek, D. S., Smailagic, A., Lee, J.Y.C and Tabatabai, AJLA., "An Interdisciplinary Concurrent Design Methodology as Applied to the Navigator Wearable Computer System," EDRC Technical Report xxxx, Carnegie Mellon, May 1993.

12. Steinberg M. S. and Hunter, G. H.. "Experimental Design: Review and Comment," *Technometrics,* VoL 26, No. 2,1984. pp. 71-96.

13. Strojwas. A. J.. "Design for Manufacturability and Yield," *Microelectronics Journal,* Vol. 21, No. 2,1990, pp. 53-66.

14. Taguchi, G., *System of Experimental Design, vol. 1 and vol. 2,* UNIPUB-Kraus International Publications, White Plains, 1987.

15. Yerramareddy. S., Lu, S. C-Y. and Arnold, K. L, "Developing Empirical Models from Observational Data using Artificial Neural Networks," *Journal of inteUitent Manufacturing,* VoL 4, No. 1,1993, pp. 33-41.