

Setpoint Determination of Printing Systems Using Multiobjective Optimization

Sudhendu Rai

Ronald Rockwell

Xerox Corporation, Webster, New York

Abstract

This paper describes an automatic approach for developing models for the xerographic process based on experimental data. A nonlinear system model defining a vector mapping between the actuators and performance metrics is constructed using multivariate adaptive regression splines (MARS). Multiobjective optimization techniques based on an underlying adaptive simulated annealing approach are discussed which are then used for determining the Pareto-optimal setpoints of xerographic actuators that optimize image quality metrics.

The overall approach is applied to perform the automated setups of a high-end color machine, namely the DocuColor40. Experimental results show that high quality machine setups can be performed in an efficient and automated manner.

Introduction

A critical problem with copiers and printers that use the color xerographic process is the ability to nominally setup the machine to produce high quality prints. This step requires that the values of the various elements (such as current, voltages, laser illumination characteristics) that comprise the xerographic subsystem of machines be set to some nominal value.

In this paper, an approach to performing semi-automated setups will be developed and described. The application of MARS (Multivariate Adaptive Regression Splines [3],[4]) to modeling the color xerographic will be discussed. The application of multiobjective optimization techniques to the inverse problem of determining the best setpoints will be demonstrated. Results will be presented from experiments performed on the DocuColor-40 machine that demonstrate the efficacy of the approach.

Problem Definition

Setup of a machine involves several steps in which the different nominal operating setpoints of the machine are determined via a series of steps to produce desired color images on the final substrate. This includes setting up the machine so that the desired solid area and halftone patches are produced for all colors, the desired highlights are

obtained and the desired color balance is obtained. The machine setup is done for each of these image quality attributes and a set of parameters that control these attributes are "tuned" to obtain the desired response. In many of the present machines, the machine is setup for a set of image quality attributes sequentially. Thus for example, the machine may first be setup to get the right solid area response and halftone patches and once that has been accomplished to satisfaction, the machine is setup to obtain the desired highlights and other image quality attributes. While the control system of the machine automates much of this task, human assisted and manual adjustment must still be made to compensate for localized factors such as component wear, environmental conditions, and customer visual preferences

Suppose, that the image quality attributes under consideration in a particular step of the setup process are denoted by a vector $\mathbf{p} = [p_1, p_2, \dots, p_n]$ where $\mathbf{p} \in \mathbb{R}^n$. In other words one is interested in n image quality attributes. For example, in a particular step of the setup process, these could be the density of four 70% halftone patches namely, cyan, magenta, yellow and black. In that case, the vector describing the objectives of our optimization process would be a four dimensional vector.

Also suppose that the parameters used to setup the machine are denoted by $\mathbf{x} = [x_1, x_2, \dots, x_m]$ where $\mathbf{x} \in \mathbb{R}^m$. In other words, there are m parameters that have to be tuned to produce desired image quality attributes \mathbf{p} which depends on the parameters \mathbf{x} . Also suppose that each of these parameters x_i can take on a value between $x_{i,\min}$ and $x_{i,\max}$. The goal of the setup process can then be described as follows:

Find the appropriate values of each parameter x_i such that the image quality attributes attain the desired values \mathbf{p}_d .

Solution Procedure

The xerographic process is quasi-static and nonlinear i.e. the output response of the system as measured by image quality metrics is a nonlinear function of the system input variables (such as voltages, currents and beam-power of the laser) and drifts slowly enough in time so as to be assumed static at any given instant of time.

In this section, an experimental modeling technique called MARS [3],[4] will be introduced and applied to model the xerographic system.

Xerographic System Identification Using MARS

MARS [3],[4] is a method for flexible regression modeling of high dimensional data. It relies on fitting data to an expansion in product spline basis functions where the number of basis functions as well as parameters associated with each one (including product degree and knot locations) are automatically determined by the data. The model produced by this technique is continuous with continuous derivatives. The method has other attractive properties of rapid computability and also provides estimates on the degree of additive contributions and those associated with different multivariable interactions that enable understanding of the fundamental nature of the subsystem that generated the data.

Multiobjective Optimization

Once a model of the xerographic system is obtained, the inverse problem of obtaining the optimal setpoints that will provide the desired image quality is solved using multiobjective optimization techniques [2].

Pareto-Optimality

Let us assume that the design variables of interest are represented by the vector:

$$\mathbf{x}=[x_1, x_2, \dots, x_n]^T \quad (4)$$

The performance criteria are represented by the vector:

$$\mathbf{f}(\mathbf{x})=[f_1(\mathbf{x}), f_2(\mathbf{x}), \dots, f_m(\mathbf{x})]^T \quad (5)$$

The equality constraints are given as:

$$\mathbf{g}(\mathbf{x})=[g_1(\mathbf{x}), g_2(\mathbf{x}), \dots, g_p(\mathbf{x})]^T = \mathbf{0} \quad (6)$$

and the inequality constraints are denoted by:

$$\mathbf{h}(\mathbf{x})=[h_1(\mathbf{x}), h_2(\mathbf{x}), \dots, h_q(\mathbf{x})]^T \leq \mathbf{0} \quad (7)$$

The design goal is to find a vector of design variables \mathbf{x}^* that simultaneously minimizes all the components of the objective function vector $\mathbf{f}(\mathbf{x})$ without violating the constraints specified by equations (5) and (6).

A vector \mathbf{x}^* is Pareto-optimal if and only if there is no other vector \mathbf{x} with the characteristics:

$$f_j(\mathbf{x}) \leq f_j(\mathbf{x}^*) \quad \text{for all } j \in \{1, \dots, m\}$$

and

$$f_j(\mathbf{x}) < f_j(\mathbf{x}^*) \quad \text{for at least one } j \in \{1, \dots, m\} \quad (8)$$

A Pareto-optimal solution (for the multi-objective minimization problem) is such that it is not possible to move feasibly from that solution to any other point in the design space without increasing at least one of the performance criterion. Figure 1 shows the Pareto-optimal solution curve.

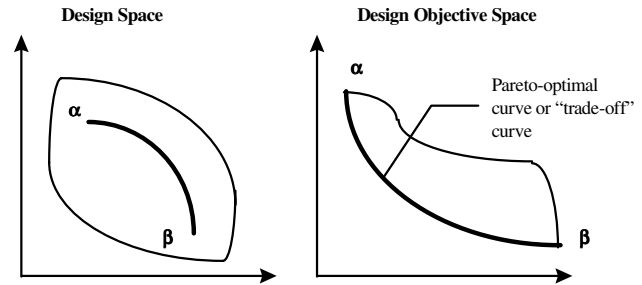


Figure 1. Mapping from the design variable space to the design objectives space showing the Pareto-optimal curve

Goal Programming Method of Obtaining Pareto-optimal solutions

The multi-objective problem of generating Pareto-optimal solutions [2] for the performance criteria vector $\mathbf{f}(\mathbf{x})$ is accomplished by formulating a scalar substitute problem,

$$\min p[\mathbf{f}(\mathbf{x})] \quad (9)$$

where the function p is called a preference function whose arguments are the components of the vector $\mathbf{f}(\mathbf{x})$. There are numerous methods of formulating the preference function such that minimizing the preference function yield a Pareto-optimal solution. In the following subsection, the goal programming method for obtaining Pareto-optimal solution will be described. The goal programming method uses vector norms or measures of distance in the space of objective functions to scalarize the vector minimization problem into a scalar minimization problem. The substitute problem is then written as:

$$p[\mathbf{f}(\mathbf{x})] = [\sum |f_j(\mathbf{x}) - y_j^n|^{1/n}]^{1/n} \quad 1 \leq n \leq \infty \quad (10)$$

Usually, the value of n is chosen to be 1 or 2.

Application to Color Setup of Docucolor-40

An example of the approach to performing setups in color machines will be demonstrated for the setup step DC919 for the Docucolor 40 machine. The goal of this setup is to obtain zero across the page variation in print quality. The four input parameters available for setting up for minimal inboard/outboard variation are laser beam-power of four laser raster output scanners that write the image on the photoreceptor. Each of these four "knobs" can take on a value between 0-255. These parameters $\mathbf{x}=[x_1, x_2, x_3, x_4]$ were chosen to vary between 0-200. A L9 orthogonal array [1] was used to design the experiments and the difference between the color of two patches on a standard test pattern (one on the inboard side and one on the outboard side of the page) was chosen as the desired responses. The goal of this setup process is to obtain the setup values for \mathbf{x} so that the L,a,b (a metric for measuring the color value of patches) values of the two patches are the same.

The machine was run at the setpoints given by the L9 orthogonal array where the three levels chosen for each "knob" was 0,100 and 200 and the inboard/outboard L,a,b

values were measured. For this experiment this was done by first scanning the image as tiff file using a scanner and then processing the image to obtain the L,a,b values. (Other methods for measuring the L,a,b values such as using a spectrophotometer can also be used).

A nonlinear MARS model was obtained that captured the dependence of each of the six output measured responses (L,a,b for the inboard and L,a,b for the outboard). Let us assume that the relationships are denoted as $L1(\mathbf{x}), L2(\mathbf{x}), a1(\mathbf{x}), a2(\mathbf{x}), b1(\mathbf{x})$ and $b2(\mathbf{x})$. The objective of this step of the DC40 setup is to obtain a setup point that minimizes the difference between L1 and L2, a1 and a2, and b1 and b2.

The results of the experiment are shown below in Table 1.

Table 1 : Experimental Data

	Input Variables				Inboard Measure			Outboard Measure		
	Bk	Y	M	C	L	a	b	L	a	b
1	0	0	0	0	63.10	3.70	9.29	75.30	1.51	11.79
2	0	100	100	100	72.47	3.00	8.84	77.42	2.03	11.14
3	0	200	200	200	80.95	3.08	6.89	80.13	1.67	11.81
4	100	0	100	200	76.92	4.53	23.78	79.04	1.60	16.70
5	100	100	200	0	72.47	-9.98	2.91	77.89	-2.29	9.55
6	100	200	0	100	69.00	13.09	-2.38	75.80	4.35	8.02
7	200	0	200	100	76.75	-8.39	22.03	77.73	-2.42	16.11
8	200	100	0	200	72.44	13.76	12.99	77.21	5.25	13.56
9	200	200	100	0	69.10	-2.17	-8.57	76.52	0.14	5.48

Thus a goal programming approach [2] using adaptive simulated annealing method [5],[6] was used to simultaneously minimize the difference for each of the three objectives using adaptive simulated annealing algorithm. (This algorithm has the capability to search for global minima within the space of the design variables without getting "stuck" at a local minima). The results of the optimization and the corresponding results of running the machine at the setpoint to obtain a verification print are shown below.

Table 2: Comparison between analytical predictions and experimental observations.

Pareto-Optimal Setpoints			
Bk	Y	M	C
115	118	161	197

	Inboard Measure			Outboard Measure			
	L	a	b	L	a	b	ΔE
Predicted	79.58	3.11	15.88	79.16	2.24	14.03	2.08
Measured	79.3	1.7	13.7	79.3	1.8	13.7	0.1

The results of setting up the machine at the Pareto-optimal setpoint is shown in Table 2. Through this example,

we show that it is possible to setup the machine to less than 2.0 ΔE inboard variation.

Conclusions

This approach is generic and can be extended to simultaneously setup a machine for any number of image quality attributes. If the particular printing process has slowly varying parameters (quasi-static), this algorithm (MARS or linear model with an optimizer to obtain the appropriate setpoints) also provides a method for controlling the quasi-static process. The models can also be linearized about the setpoints determined above for use in linear controller design.

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Biography

Sudhendu Rai received his B.Tech degree from IIT (India) in 1988, MS degree from Caltech in 1989 and a Phd. degree from MIT in 1993 all in Mechanical Engineering. Since 1995 he has worked in the Wilson Center for Research & Technology at Xerox Corporation in Webster, N.Y. His work has been in the area of multiobjective optimization of xerographic processes, design of distributed control systems for paper handling and document factory workflow optimization and control. He is a member of ASME and Sigma Xi.