Design of Reconfigurable Composite Microsystems Based on Hardware/Software Codesign Principles

Tianhao Zhang, Krishnendu Chakrabarty, and Richard B. Fair

***Abstract*—Composite microsystems that integrate mechanical and fluidic components with electronics are emerging as the next generation of system-on-a-chip. Custom microsystems are expensive, inflexible, and unsuitable for high-volume production. The authors address this problem by leveraging hardware/software codesign principles to design reconfigurable composite microsystems. They partition the system design parameters into nonreconfigurable and reconfigurable categories. In this way, operational flexibility is enhanced and the microsystems are designed for a wider range of application. In addition, the Taguchi robust design method is used to make the system robust, and response surface methodologies are used to explore the widest performance range for the system. A case study is presented for a microvalve, which serves as a representative microelectrofluidic device.**

***Index Terms*—Application flexibility, nonreconfigurable and reconfigurable design parameters, response surface, robustness, Taguchi method.**

I. Introduction

Composite microsystems that incorporate microelectromechanical and microelectrofluidic devices are emerging as the next generation of system-on-a-chip (SoC). Composite microsystems combine microstructures with solid-state electronics to integrate multiple coupled energy domains, e.g., electrical, mechanical, thermal, fluidic, and optical, on an SoC. The combination of microelectronics and microstructures enables the miniaturization and integration of new classes of systems that can be used for environmental sensing, control actuation, electromagnetics, biomedical analyses, agent detection, and precision fluid dispensing.

As the number of applications of integrated composite microsystems increases, there is a pressing need for optimization tools to reduce design time, maximize manufacturing yield, and provide high robustness. A number of design methodologies for microsystems has recently been proposed [1], [3], [8]. These methods lead to robust microsystems that meet performance goals and are relatively insensitive to design parameter variations. However, such systems are tailored toward "custom microsystems" whose performance is designed to be within a narrow range. This leads to expensive and inflexible systems that are not amenable to large-volume production [2].

We propose a reconfigurable composite microsystem design methodology that leverages hardware/software codesign principles to achieve functional unit reusability. The hardware/software codesign method provides design flexibility by allowing software to be compiled efficiently for a modular hardware platform [9]. We show that by partitioning the design parameters of microsystems into two categories—nonreconfigurable "hardware" and reconfigurable "software" design parameters (referred to as *NRDP*s and *RDP*s, respectively)—we can make the microsystem performance meet the flexibility requirement and be suitable for a wider range of applications. While the values of *NRDP*s are determined at fabrication time, the values of *RDP*s are configured (programmed) during operation. This design approach allows the system to conform to a wider range of performance specification. Such flexible microfluidic components and systems can be used to develop programmable lab-on-a-chip devices as well as electromechanical components that can be produced and sold in high volume. Table I illustrates the partitioning principle for a generic microelectrofluidic system.

The Taguchi experimental design method [11] provides an efficient method for performance variability reduction and is often used for offline parametric optimization control and high-performance design. The basic idea of this method is to identify the parameters or factors most influential in determining a performance metric and to compute an appropriate setting of the parameters. This is done using orthogonal arrays and design of experiments. We use the Taguchi method to ensure that the system performance lies within an acceptable range and the influence of parametric variations on the system performance is minimized. Statistical response surface analysis studies the system performance variability within a region. Thus, it characterizes the relationships between the basic electrical/mechanical parameters and system performance. This allows a designer to understand how fluctuations in design parameters shift the design point and the associated system behavior and then to explore the maximal system performance range.

The contributions of this paper include the following.

- On the analogy of the hardware/software codesign principles, we partition the set of design parameters into *NRDP*s and *RDP*s for application flexibility. This allows the system to be usable for a wider range of application.
- We use the Taguchi experiment design method to determine the values of *NRDP*s that make the system performance robust, that is, less sensitive to variation of *NRDP*s.
- We increase the application flexibility of composite microsystems using the response surface methodology.
- Given a range of values that *RDP*s can take, we design the system such that the range of system performance is maximized under the constraint that the performance is relatively insensitive to the variation of *NRDP*s.

The organization of the paper is as follows. The general problem statement and design approach are presented in Section II. We describe the Taguchi experiment design method [11], which is used to determine the value of *NRDP*s for the robust design. We also present the response surface methodology [5] to maximize the performance range for a given set of *RDP*s. Section III further describes the design procedure for achieving the application flexibility. Section IV presents a case study based on a microvalve, which serves as an example of electrostatic microfluidic devices. Conclusions are presented in Section V.

II. Design Approach

A. NRDPs and RDPs Partitioning

The overall microsystem cost and performance are affected by the partitioning of the design parameters into *NRDP*s and *RDP*s. The partitioning decision is dependent on the relationship between design parameters, system reliability, and cost. Some design parameters can be partitioned explicitly. For example, geometric design parameters, such as the length of the cantilever beam in the microvalve, must be configured before or during fabrication. These are the nonreconfigurable

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TABLE I
DESIGN PARAMETERS FOR A MICROFLUIDIC SYSTEM

Abstraction Level	Nonreconfigurable Design Parameters *(Hardware)*	Reconfigurable Design Parameters *(Software)*
System	Number of I/O Interface Ports	Plug in/out Strategy
	Number of Delivery Channel Buses	Process Scheduling
Component	Beam Dimension	Pressure
	Channel Diameter	Electrical Voltage
	Fabrication Materials	Operating Frequency

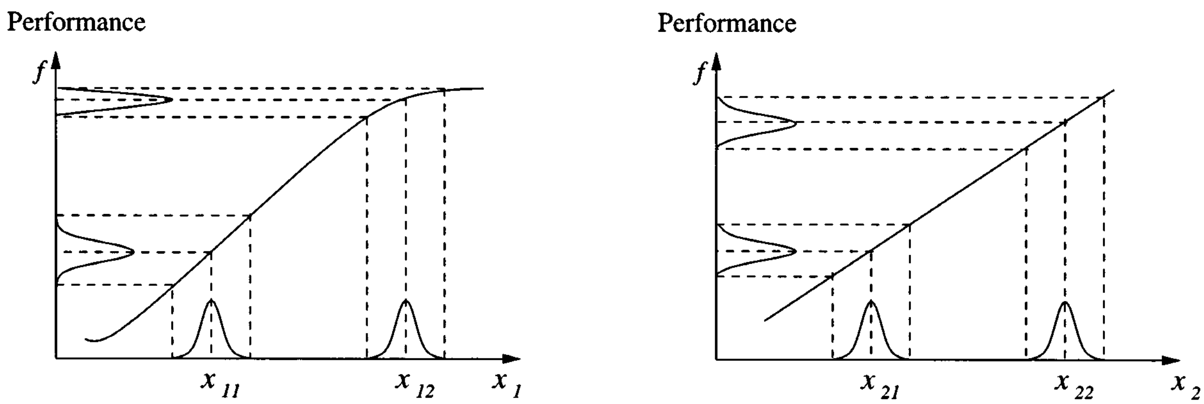

Fig. 1. Performance variability reduction.

prefabrication design parameters. Other design parameters can be categorized as either *NRDP*s or *RDP*s. The parameters that are configured before system execution are classified as *NRDP*s, while those parameters that can be configured during runtime are classified as *RDP*s. These postfabrication parameters can be configured before execution or during field operations. Some factors influencing this partitioning decision are as follows.

1) *Correlation*

Correlated parameters must be placed in the same category. These correlations and dependencies are generally determined by the designer. Alternatively, a database can be used to automatically extract these correlations. For example, there is significant correlation between the beam width and the perimeter of the moving electrode in accelerometers [12]. Therefore, these two parameters (beam width and perimeter of the electrode) must be placed in the same category.

2) *Ease of Control*

Some design parameters, e.g., fluid pressure and electrical voltage, are relatively easy to control during operation. Therefore, these can be placed in the *RDP* set to increase the application flexibility.

3) *Cost*

The cost of reconfiguration can also be a driving factor. For example, the channel length in a microvalve is expensive to alter after fabrication. Hence, it is preferably placed in the *NRDP* set to reduce cost.

The *NRDP* values are determined at manufacturing time, and this provides a nonreconfigurable "hardware" platform. *RDP*s constitute the "reprogrammable software" that run on this platform. In this way, composite microsystems provide design flexibility for product evolution and different application purposes.

B. Nonreconfigurable Platform Design Robustness

One of the system optimization objectives is to find *NRDP* values that make the system performance less sensitive to the fluctuation of the manufacturing process and the operating environment. The Taguchi experiment design method, which is widely used for offline parametric optimization control and high robust design [11], is used here to achieve this objective.

TABLE II
L_8 ORTHOGONAL ARRAY

No.	x_1	x_2	x_3	x_4	SNR
1	-1	-1	-1	-1	SNR_1
2	-1	-1	1	1	SNR_2
3	-1	1	-1	1	SNR_3
4	-1	1	1	-1	SNR_4
5	1	-1	-1	1	SNR_5
6	1	-1	1	-1	SNR_6
7	1	1	-1	-1	SNR_7
8	1	1	1	1	SNR_8

Fig. 1 illustrates the concept of performance variability (sensitivity) reduction. Consider two design parameters x_1 and x_2. The relationships between variability in design parameters x_1 and x_2, and the corresponding variability in system performance, are shown in Fig. 1. Due to the nonlinear relationship between the design parameter x_1 and system performance response f, the change of design point from x_{11} to x_{12} results in performance variability reduction. A similar change in design point from x_{21} to x_{22} yields no performance variability reduction due to the linear relationship between the design parameter x_2 and system performance response f.

The aim of performance variability reduction is to identify design parameters that have the most influence on performance variability and then set the values of these parameters to move the design point into the region where the performance sensitivity is minimized. At the same time, design parameters having the least influence on performance variability are used to perform functional tuning to ensure that overall system performance meets target specifications. For example, assume an initial design point of (x_{11}, x_{22}) in Fig. 1. After moving the design parameter x_1 from x_{11} to x_{12} to reduce performance variability,

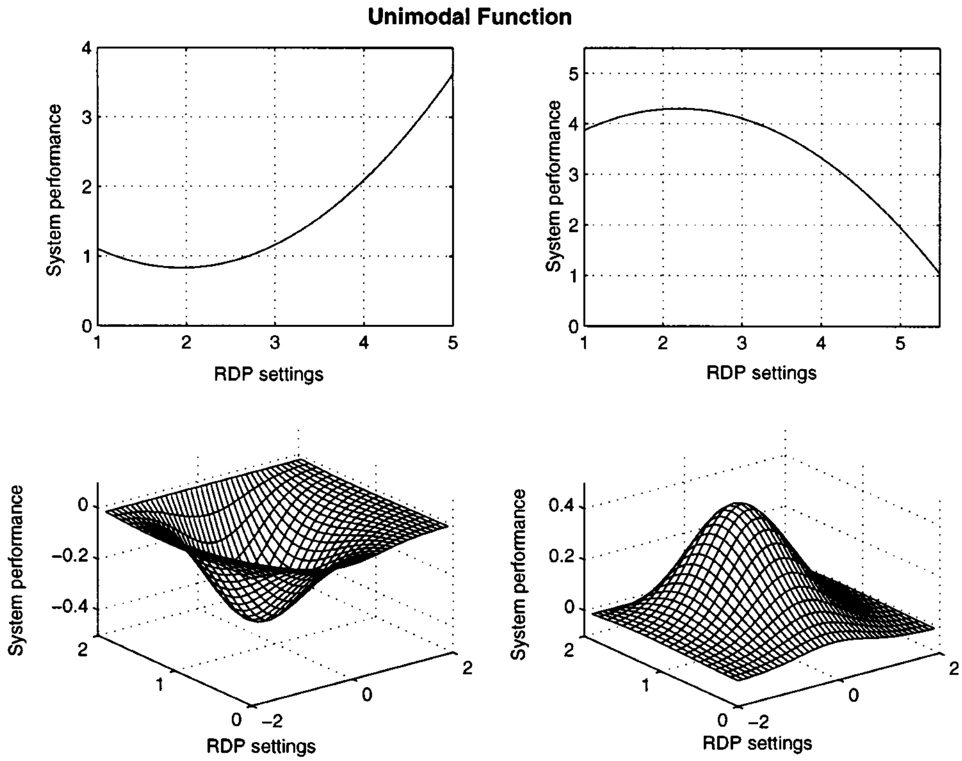

Fig. 2. Unimodal function for two and three dimensions.

the design parameter x_2 can be adjusted from value x_{22} to value x_{21} as a tuning factor to maintain the performance target. In this scenario, design parameter x_1 is used to reduce the variability at the expense of nominal system performance. Undesirable shifts in nominal system performance are, in turn, compensated via design parameter x_2.

Performance variability is computed based on a statistical metric, signal-to-noise ratio (SNR) [11]. Three common formulations of the signal-to-noise ratio (SNR) objective function are as follows.

- Maximize performance response

$$SNR = -10\log_{10}\left[\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right]. \quad (1)$$

- Minimize performance response

$$SNR = -10\log_{10}\left[\frac{1}{n}\sum_{i=1}^{n}y_i^2\right]. \quad (2)$$

- Target a particular performance specification while minimizing performance variance

$$SNR = -10\log_{10}\left[\frac{\sigma^2}{\mu^2}\right] \quad (3)$$

where

y_i performance response for the ith setting of the parameter combination;

n number of samples of the performance response corresponding to the number of design parameter combinations;

μ mean of overall performance response, $\mu = 1/n\sum_{i=1}^{n} y_i$;

σ^2 sample variance of performance response, $\sigma^2 = (1/n-1)\sum_{i=1}^{n}(y_i-\mu)^2$.

SNR transforms the performance response into the log domain and provides a standard representation of different design performance variability reduction objectives; the objective functions are generally constructed such that the larger the SNR, the better the performance. For instance, when the design objective is to maximize a performance metric, the larger the performance response, the larger its associated SNR (1). In a similar manner, when the design objective is to minimize a performance metric, the smaller the performance response, the larger its associated SNR (2). When SNR is applied to an on-target design, the smaller the performance variance to the target, the larger the associated SNR (3).

Design parameters are called factors and a particular parameter value is called a level. Combinations of parameters and values (factor levels) are delineated using orthogonal arrays [6]. Orthogonal arrays originate from design of experiments theory for studying a system involving a large number of parameters/variables with a small number of experiments. Parameters are listed horizontally, forming the columns and experiments or combinations of values of the parameters are listed vertically, forming the rows. An orthogonal array possesses the property that all columns are mutually orthogonal in that, for any pair of columns, all combinations of factor levels occur and they occur an equal number of times. Table II shows an orthogonal array L_8 with four columns and four design parameters on two factor levels. These factor levels are denoted by 1 and -1, respectively. Performance variability reduction computes the effect of each design parameter at several settings or levels on SNR and uses these results to determine the best combination of parameter settings for optimizing performance stability.

The effect of a design parameter at a particular setting (factor level), called the main effect, is defined as the deviation of the factor level; it is caused from the overall mean of the performance response, and is given by the following equation:

$$M_{x_1}^j = \frac{1}{n}\sum_{i=1}^{n} SNR_i \quad (4)$$

where

$M_{x_1}^j$ effect of design parameter x_1 at level j on SNR;

n number of experiments (simulations) involving the design parameter x_1 set to level j.

For example, the main effect of x_1 at level $j = -1$ on SNR is computed as the average of the SNRs corresponding to each performance response where x_1 is set to level $j = -1$. Since the main effect represents how close the performance response caused by a factor level is to the design objective, parameter settings having the largest main effect are desirable. In other words, levels that maximize the SNR result in the minimization of performance variability.

C. Degree of "Programmability" of Reconfigurable Design Parameters

The next design objective is to determine the degree of "programmability" of *RDP*s. Therefore, when *RDP*s run on the robust nonreconfigurable "hardware" platform, a composite microsystem can provide the design flexibility for product evolution and different application purpose. The following factors must be considered in this context.

1) *Microsystem Energy Requirement*
   The energy supply available for composite microsystems is limited due to miniaturization and integration. Hence, the energy requirement of *RDP*s must conform to this restriction. For example, the adjustable range of the electrical voltage must lie in the available voltage range.
2) *Physical Implementation*
   The limitation of physical implementation is also a key for "programmability" of *RDP*s. For example, the operating frequency of a micropump chamber may be limited by the feasibility of physical implementation.
3) *Fabrication Technology and Integration Level*
   With increasing complexity, the fabrication technology and integrated level also limit the operating range of *RDP*s.
4) *Operational Reliability*
   Higher degree of "programmability" of *RDP*s may lead to operational reliability problems, and it may be more difficult to maintain accurate control over a wider range.

Therefore, designers should consider the related constraints to determine a rational degree of "programmability" for the reconfigurable design parameters.

D. Determining the Performance Flexibility

Based on a certain setting of *NRDP*s and the determined programmability of *RDP*s, the composite microsystem performance flexibility can be obtained. The performance range is from the lowest performance to highest performance, and the response surface methodology can be used to identify this performance flexibility.

The response surface methodology can be used to directly represent the geometric relationships between the system performance and design parameters. This helps the designer to understand the causal relationships between how design parameters shift the design point and associated system behavior. Since the scope of variation of *RDP*s is usually limited, we assume that the relationship between *RDP*s and the system response can be represented as a unimodal function. This implies that on the system response surface, there is exactly one point possessing the minimum performance value and exactly one point possessing the maximum performance value, as shown in Fig. 2. Therefore, the local optimal design point is also the global optimal design point in this design space. While we make the unimodal function assumption here to illustrate our approach, we can handle a system with multimodal response surfaces through piecewise approximation techniques. In this case, as well as for the case where the system performance is not a continuous function of the *RDP* setting, we can use iterative search over subintervals in which the performance is a unimodal and continuous function. We can then compare the *RDP* setting and performance for each subinterval and choose an appropriate setting.

The minimum and maximum performance points can be formed via iterative search algorithms. When there is just one *RDP*, the relationship between system performance and the *RDP* can be represented with a curve in the X-Y plane, and a one-dimensional iterative search method, such as *Golden section* or *Fibonacci* search method, can be used to find the minimum and maximum performance points [7]. If the number of *RDP*s is greater than one, the response surface can be used to represent the relationship between system performance and *RDP*s. An iterative gradient search method, such as *Steepest ascent/descent* [5], can be used to find the optimal points.

III. Design Method

The goal of *NRDP*s/*RDP*s codesign is to obtain wider system performance within the feasible programmability range of *RDP*s and a robust setting of the nonreconfigurable "hardware" platform. Since this optimization problem involves multiple objectives, designers need to trade off each objective to get an appropriate design result. Therefore, the proposed optimization procedure includes six steps.

1) Depending on the partitioning criterion, the design parameters are grouped into *RDP* and *NRDP* sets.
2) Select a series of settings of *NRDP*s as a "hardware" platform.
3) Determine the degree of programmability of *RDP*s.
4) Using the response surface method and an iterative search algorithm, the minimum and maximum system performance values and related *RDP* values are found within the determined programmability of *RDP*s.
5) The system robustness (insensitivity to the variation of *NRDP*s) is represented using SNR and optimized using the Taguchi robust design methodology. Since the SNR value for a certain setting of *NRDP*s also depends on the setting of *RDP*s within their programmability range, the SNR for this setting of *NRDP*s may vary with the individual value of *RDP*s. However, with the unimodal assumption, it is reasonable to estimate the robustness for a certain setting of *NRDP*s using the average of SNRs which are calculated at the *RDP* nominal setting value, and the *RDP* values corresponding to the minimum and maximum performance values. The average of SNR value, $\overline{SNR^i}$, for the ith setting of the *NRDP*s is given by

$$\overline{SNR^i} = \frac{SNR^i_\alpha + \mathrm{SNR}^i_\beta + SNR^i_\gamma}{3}, \quad i = 1, 2, \ldots, n \tag{5}$$

   where
   - SNR^i_α — SNR value for the ith setting of the *NRDP*s with the *RDP* setting at the minimum performance value;
   - SNR^i_β — SNR value with the nominal setting of *RDP*s on the ith *NRDP* setting;
   - SNR^i_γ — SNR value with the *RDP* setting possessing the maximum performance value on the ith *NRDP* setting;
   - n — total number of the setting of *NRDP*s.
6) Calculate the main effect for each design parameter at a particular setting. Based on these main effect values, we can obtain the desired performance flexibility and robustness.

IV. Microvalve Modeling and Optimal Design Analysis

In this section, we present a case study for an electrostatic microfluidic device, the microvalve. A microvalve behavioral model is developed using the hardware description language, VHDL-AMS. The final optimized design result ensures robustness and a wider performance range for application flexibility.

The pressure-driven check valves are very important to the behavior of the micropump since they determine the flow rate of the micropump. The major parts of the check valve are a cantilever beam and the valve

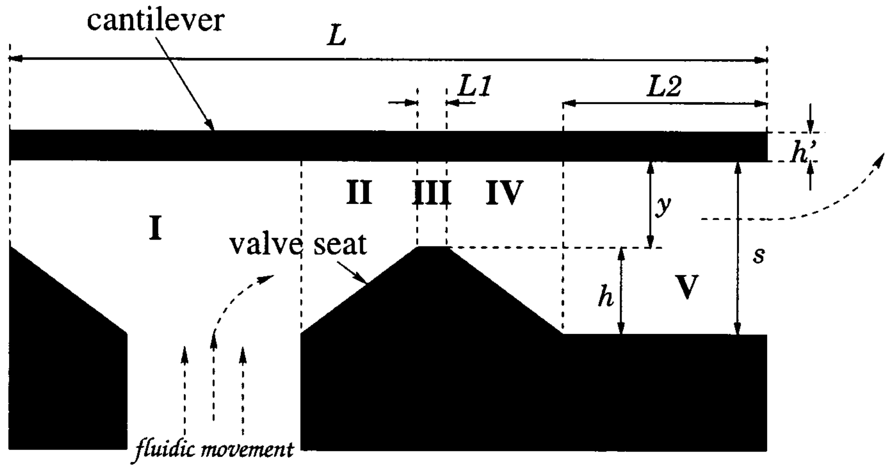

Fig. 3. Schematic view of the opening valve [14].

seat. Normally, the cantilever lies against the valve seat, thus closing the port to fluid flow. In operation, the fluid flow exerts pressure against the cantilever. The cantilever, acting like a spring, deflects and allows the fluid to flow through the valve. The schematic view of the opening valve is shown in Fig. 3 [14].

Our performance parameter here is the static flow rate. It is dependent on the structure parameters and the displacement of the valve, which is determined by the pressure difference

$$\begin{aligned}\Phi &= h(x_1, x_2, \ldots, x_n, y)\\ y &= f(p)\end{aligned}$$

where Φ is the static flow rate, $x_1, x_2, \ldots, x_n$ denote structural parameters, and y is the displacement of valve and p is the pressure difference.

In order to get the analytical behavior of the static fluid flow in the gap between the cantilever and the valve seat, the gap is divided into five pieces (Fig. 3). While studying the relationship between the pressure difference p and the displacement of cantilever beam at the individual regions, the overall analytical result of the flow rate, Φ, can be treated as a function of pressure difference p and the displacement y [14]

$$p = \sum_{i=I}^{V} \Delta p_i(\Phi, y) \quad (i = I, II, III, IV, V). \tag{6}$$

In addition, the behavior of the cantilever can be described by a second-order differential equation

$$m\ddot{y} + d\dot{y} + ky = pA \tag{7}$$

where m is effective mass of the cantilever, including the mass of the cantilever and that of the water surrounding the cantilever. The parameter d is the damping constant, determinated by the geometry of the cantilever, and k is the spring constant of the cantilever.

By substituting $y = f(p)$ in (7), we see that the static flow rate is fully determined by the actuated pressure difference and the structural parameters, $\Phi = h(x_1, x_2, \ldots, x_n, p)$. VHDL-AMS, as an analog hardware description language, is used to build this nonelectrical model [17], and an analog solver, Saber [16], is used to simulate the microvalve behavioral model

$$\Phi = \frac{\rho\alpha}{b^2 s^2}\left[-\frac{12\mu}{b}\left(\frac{l_1}{y^3} + \frac{l_1}{s^3}\right) + \sqrt{\frac{144\mu^2}{b^2}\left(\frac{l_1}{y^3} + \frac{l_2}{s^3}\right)^2 + \frac{2\rho}{b^2}\frac{\alpha p}{s^2}}\right] \tag{8}$$

TABLE III
*NRDP*s AND *RDP*s SETS

$NRDP$s	RDPs
L, b', h', h, l_1, b, l_2, E	P_a

TABLE IV
TOLERANCE FOR NONRECONFIGURABLE DESIGN PARAMETERS

$NRDP$s	L	b'	h'	h	l_1	b	l_2
Tolerance	$\pm 0.2\ \mu$m						

TABLE V
DESIGN LEVELS FOR *NRDP*S

$NRDP$s (μm)	L	b'	h'	h	l_1	b	l_2
(-1)	1280	800	12	40	4	320	80
Level (0)	1600	1000	15	50	5	400	100
(+1)	1920	1200	18	60	6	480	120

where i is the different pieces of the gap, which can be I, II, III, IV, V; α is a kinetic energy coefficient relevant to the fluidic velocity profile; h is the height of the valve seat, as shown in Fig. 3, $s = y + h$; b and l_1 are the width and the length of the valve seat, respectively; l_2 is the length of the cantilever over valve seat; L and b' are the length and the width of the cantilever, respectively; h' is the thickness of the cantilever; and E is Young's Modulus.

Depending on the physical principles of the microvalve and the partitioning criteria, the design parameters can be grouped into the *NRDP* and *RDP* sets. The geometric design parameters are grouped into the set of *NRDP*s, and the pressure difference P_a is placed in the *RDP* set. The partitioning is shown in Table III.

Our design objective is to minimize the variation of the overall flow rate Φ due to the fluctuation of design parameters. Here, we assume without loss of generality that the design parameter tolerances are $\pm 0.2\ \mu$m, as shown in Table IV.

To determine the *NRDP* setting for robust design, we use the three design levels for each *NRDP* as shown in Table V. Since the fabrication material is silicon, the Young Modulus E is taken to be 146.9 GPa. In addition, the *RDP* (pressure difference P_a) is assumed to be a sinusoidal pressure at a frequency of 100 Hz. The amplitude of P_a is limited in the range of 5,000 to 15 000 Pa, the nominal design setting value is set to 10 000 Pa.

An exhaustive search to find optimal *NRDP* setting for robust design is very difficult. The complexity of exhaustive search is $O(3^n)$, where

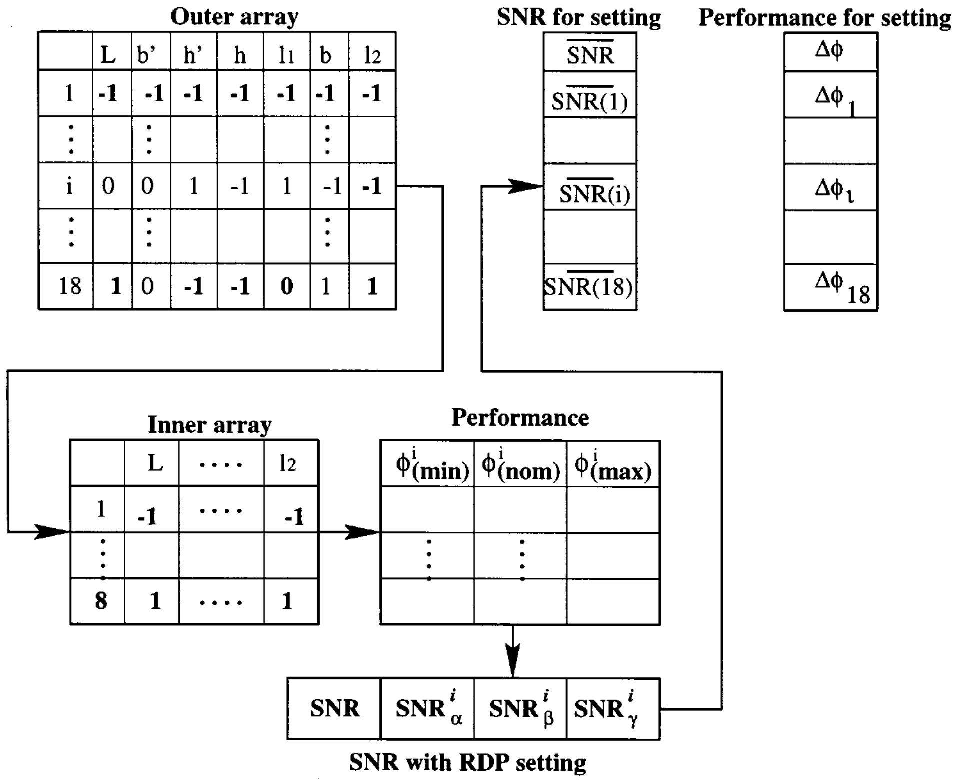

Fig. 4. Experiment design.

n is the number of *NRDP*s. However, most practical systems are dominated by some of the design parameters, and most higher order interactions are negligible. Therefore, a $1/3^p$ fraction of the original orthogonal array is used for experimental designs with reduced $O(3^{(n-p)})$ complexity, where p is related to the order of interactions. We use the inner orthogonal array L_8 with two levels (-1, 1) for *NRDP* tolerance and the outer orthogonal array L_{18} (Addelman–Kempthorne construction [6]) with three levels (-1, 0, 1) for *NRDP*s setting to directly evaluate the contribution of individual parameters to overall design robustness [5].

Therefore, by using the one-dimensional iterative *Fibonacci search* method, the setting points of P_a, $P_a(\min)$, and $P_a(\max)$, with the minimum flow rate and the maximum flow rate, respectively, can be obtained for each *NRDP* setting. In addition, by calculating the average SNR value at the P_a nominal setting $P_a(\text{nom})$, $P_a(\min)$ and $P_a(\max)$, the average robustness of a setting of nonreconfigurable "hardware" platform is obtained. The design procedure is illustrated in Fig. 4 and is explained as follows.

1) *Design the Outer Array*

Based on the orthogonal array L_{18}, and the three design levels for each *NRDP* shown in Table V, the outer array is obtained as in the Fig. 4, each row represents a setting of *NRDP*s. For instance, in the first row, the L value, -1, means that the length of the cantilever is 1280 μm in this setting.

2) *Design the Inner Array*

Depending on the *NRDP* tolerance shown in Table IV and the L_8 orthogonal array structure [6], we can obtain the inner array for each row of the outer array, meaning each setting of *NRDP*s. For example, if the inner array shown in Fig. 4 is developed depending on the ith setting of the outer array, the value of L at the first row in the inner array, -1, implying that the value of L is 1599.8 μm.

TABLE VI
AVERAGE SNR RATIO FOR THE DESIGN PARAMETERS

Parameter	Average SNR^* by level		
	lower (-1)	normal (0)	high (+1)
L	66.67	65.90	64.95
b'	65.42	65.67	66.43
h'	64.26	66.36	66.90
h	65.86	65.87	65.79
l_1	65.85	65.85	65.82
b	64.47	65.97	67.08
l_2	65.86	65.84	65.83

TABLE VII
FLOW-RATE RANGE $\Delta\Phi$ [μl/ min] FOR THE DESIGN PARAMETERS

Parameter	$\Delta\Phi = \Phi_{max} - \Phi_{min}$ by level		
	lower (-1)	normal (0)	high (+1)
L	218.26	272.64	326.58
b'	218.54	272.53	326.42
h'	272.50	272.80	272.18
h	272.42	272.49	272.57
l_1	272.47	272.50	272.51
b	217.83	272.47	327.18
l_2	272.33	272.49	272.66

3) *Search the Design Performance*

Within the degree of "programming" of the *RDP* (pressure difference P_a), we can obtain three performance values for ith *NRDP* setting by the iterative searching method: minimum flow rate ($\Phi^i_{\min}$), normal flow rate (Φ^i_{nom}), and the maximum flow rate ($\Phi^i_{\max}$).

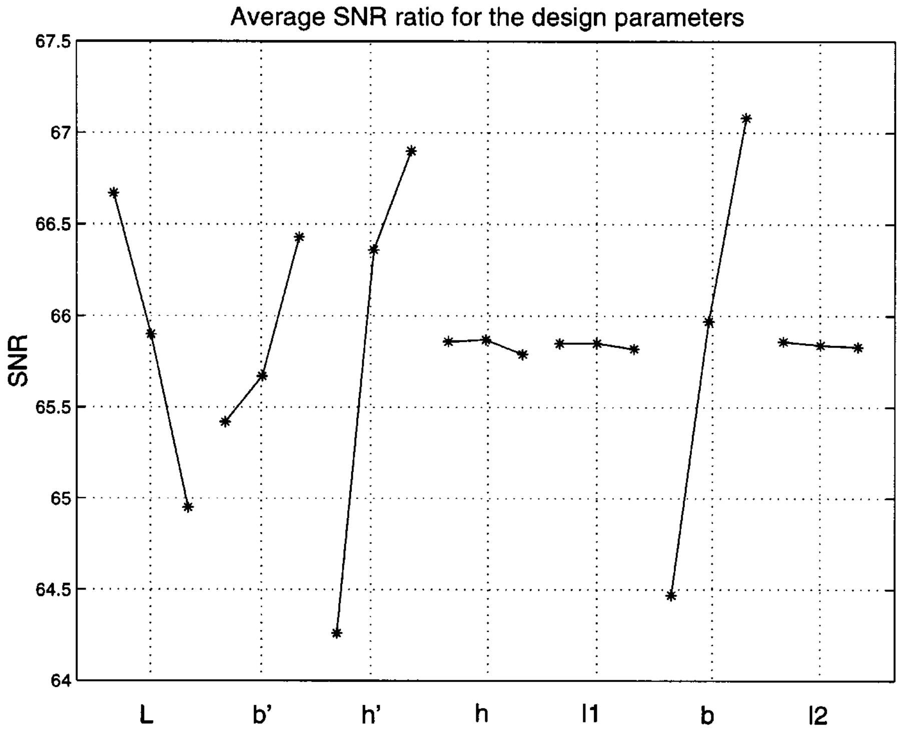

Fig. 5. Plot of design parameter effect on SNR.

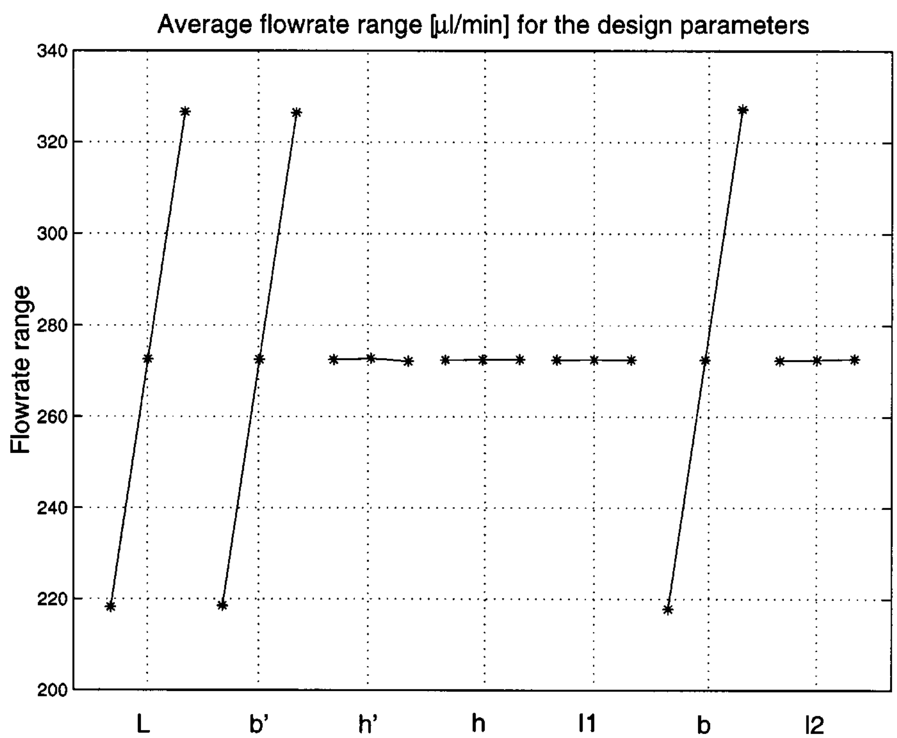

Fig. 6. Plot of design parameter effect on flowrate range.

4) *Calculate the Robustness for Each Setting of Design Parameters*

Based on the SNR objective functions, the related system robustness for three design performances can be calculated as SNR^i_α, SNR^i_β, and SNR^i_γ, respectively. The overall robustness of a setting of design performance $(\overline{SNR^i})$ is the average of each SNRs, as given in (5).

5) *Calculate the Main Effect*

As shown in the Table VI, the main effect for design levels of each design parameter is the average of the SNR with the same setting for the whole design solutions. For example, the main effect for the length of the cantilever L at lower level (-1), $M_L^{-1} = 66.67$, is the average of SNR for the design solutions where L is set to -1.

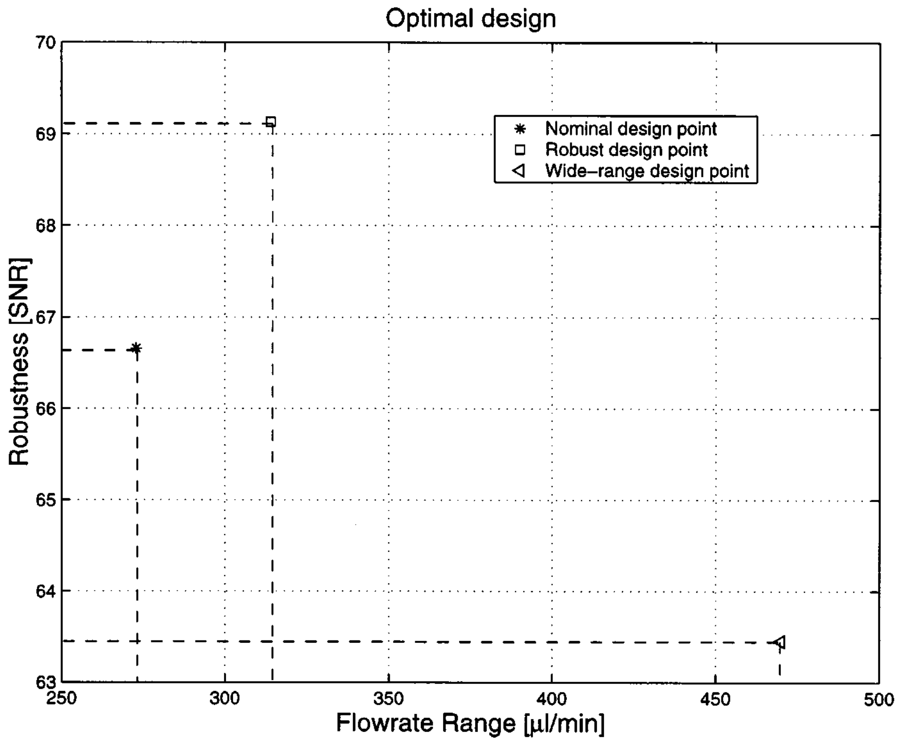

Fig. 7. Plot of optimal design points.

TABLE VIII
DESIGN INFORMATION

Optimal Design	L	b'	h'	h	l_1	b	l_2	Range ($\Delta\Phi$)	$(\overline{SNR})$
Nominal Design	1600	1000	15	50	5	400	100	272.86	66.66
Most Robust	1280	1200	18	50	5	480	80	314.00	69.13
Widest Range	1920	1200	15	60	6	480	120	469.86	63.45

6) *Calculate the Flow-Rate for Design Levels*

The application flexibility of the system, the range of the flowrate, for each design parameter setting can also be calculated, as shown in Table VII. The $\Delta\Phi$ is the difference between the maximum flowrate and the minimum flowrate within the *Performance* table in Fig. 4. For example, regardless of other design parameter settings, with L set at the lower level (1280 μm), the system flow-rate range $\Delta\Phi$ is 218.26 $\mu\mathrm{l}/\min$

Additionally, the following important observations can be made concerning the optimal system design.

1) Figs. 5 and 6 illustrate that the microvalve robustness and the flow-rate range for different *NRDP* setting within the range of *RDP*s, respectively. The setting of *NRDP*s is depending on the design objectives (robustness versus performance range); there does not exist a unique design point that satisfies conflicting design requirements.
2) In studying robust design, we note that the length of the cantilever (L), the width of the cantilever (b'), the thickness of the cantilever (h'), and the width of the valve seat (b) have a significant effect on SNR. Except for h', they also have a significant effect on the average flow-rate range. The setting with $L_{(-1)}$, $b'_{(+1)}$, $h'_{(+1)}$, $h_{(0)}$, $l_{1\ (0)}$, $b_{(+1)}$, $l_{2\ (-1)}$ is clearly the most robust. The robustness of this setting of the design parameters, $\overline{SNR}$, is the average of the main effects for each design parameter.
3) In attempting design for wider flow-rate range design, we note that the length of the cantilever (L), the width of the cantilever (b'), and the width of the valve seat (b) have a significant effect on the average flow-rate range. The setting with $L_{(+1)}$, $b'_{(+1)}$, $h'_{(-1)}$, $h_{(+1)}$, $l_{1\ (-1)}$, $b_{(+1)}$, $l_{2\ (+1)}$ possesses the widest flow-rate range.

Fig. 7 and Table VIII present the optimal design results: optimal design for the widest flow-rate range and the optimal design for robustness. In addition, Figs. 5 and 6 also directly provide very useful information for related performance improvement. For example, increasing the value of L, b', and b increases the range of flow rate, while decreasing the value of L and increasing the value of b improves the microvalve robustness. Based on these performance analyzes, other feasible design solutions can also be obtained.

V. CONCLUSION

We have leveraged hardware/software codesign principles for the design of reconfigurable composite microsystems. Operational flexibility and system robustness are enhanced by partitioning the design parameters into nonrecofigurable and reconfigurable parameters and through the use of the Taguchi experiment design method. A case study for a microvalve demonstrates the flexibility of this approach.

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