Performance Analysis of Service-Oriented Architectures with Multi-Factor Sensitivity Analysis

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***Abstract*—This paper presents a continuous investigation on performance analysis with sensitivity analysis. As an effort to develop a systematic approach to improve the performance of service-oriented software systems, the original work introduced a statistical approach of two-factor-based sensitivity analysis to software performance analysis. The goal of generating accurate performance feedback, however, was only partially achieved as performance analysis needs to consider more factors. This paper presents a generalization for the statistical method to handle multiple factors. In addition, it gives detailed discussions on sensitivity analysis with three factors, and provides experiment results to demonstrate the need and advantages of analyzing multiple factors at the same time.**

I. Introduction

The dramatically increased software complexity in the past decades has made productivity and time-to-market the major concerns of software industry. Traditional approaches of software development failed to cope with sophisticated applications of computer systems. In comparison, Component-Based Development (CBD) allows software systems to be developed from pre-produced parts, thus improving the productivity, quality, and maintainability of software products. CBD helps to increase productivity and reduce development efforts through larger-grained software reuse [13].

In addition, Service-Oriented Architectures (SOA) has gained a lot of attention in recent years [21]. As a new technology of dealing with the challenge of interoperability of systems in heterogeneous environments, SOA helps IT organizations to support alignment with business requirements that are changing at an increasing rate. A service-oriented architecture consists of a collection of services that communicate with each other, and the inter-service infrastructure becomes Web services-based when services communicate by means of the Internet. SOA promises the benefits of enhanced components reuse, improved reliability, and reduced development and deployment costs [12].

Software performance plays a key role in the success of software development, and now becomes even more important in the practice of component-based and Web service-based software systems [3]. As system architecture determines the quality of software, performance effects of architectural decisions can be evaluated at an early stage by constructing and analyzing quantitative performance models that capture both performance attributes of software components and their interactive characteristics as well. It is cost-effective to push performance analysis back to the early stage of architectural design.

The software industry has been actively working on the underlying technology for the design, implementation, and application of Web services and their interactions [1], [16], [8], [9], [7], [14]. Meanwhile, there is a growing body of research that studies performance analysis of software systems. Some researchers examine the role of software architecture in determining different quality characteristics in general [18], [2], while several others focused on performance characteristics in particular [20], [19]. In performance analysis, the robustness and reliability of analysis methods are a main issue [15], [6], [5].

There are typically three steps in performance evaluation of software architectures. The first step transforms the annotated UML model of a software architecture into a performance model, such as layered queuing network model (LQN). The second step then uses a performance analysis tool, such as the LQN solver, to conduct experiments on the performance model. Experiment results provide useful information for the predication of software performance, and are fed back in the last step for designers to refine software architecture.

Nevertheless, accurate results of performance analysis need to take sensitivity analysis into account, which should take place between the second and third steps before performance analysis results are used as feedback for architecture adjustments. For example, the introduction of security and cache behavior as individual factors to architecture reliability analysis helped to improve analysis results [17]. The investigation, however, was preliminary, and no attention was given to the interactions between factors that have great effects on system performance. Currently, little research has been done in sensitivity analysis for service-oriented software systems.

The authors of this paper reported last year an investigation on performance analysis with sensitivity analysis [22]. By applying the techniques of Design of Experiment (DOE), the previous work developed a statistical method to quantitatively analyze two-factor-based sensitivity of software performance. The method was able to analyze performance sensitivity in relation to both individual factors and their interactions. This paper further generalizes the presented method of sensitivity analysis to handle multiple factors. Experiment results provided at the end of this paper demonstrate that multi-factor-based sensitivity analysis produces more accurate results.

variation	df	mean square	F distribution
A	a-1	MS$_A$=SS$_A$/(a-1)	F$_0^A$=MS$_A$/MS$_E$
B	b-1)	MS$_B$=SS$_B$/(b-1)	F$_0^B$=MS$_B$/MS$_E$
A×B	(a-1)(b-1)	MS$_{AB}$=SS$_{AB}$/(a-1)(b-1)	F$_0^{AB}$=MS$_{AB}$/MS$_E$
Error	abc(n-1)	MS$_E$=SS$_E$/abc(n-1)	
Total	$abcn$-1	MS$_T$=SS$_T$/$abcn$-1	

TABLE I
TWO-FACTOR VARIANCE TABLE

II. SENSITIVITY ANALYSIS OF SOFTWARE PERFORMANCE

This section first studies the underlying mechanism of two-factor-based sensitivity analysis, and then extends the mechanism for multi-factor-based sensitivity analysis.

A. Study of Two-Factor-Based Sensitivity Analysis

A typical service-oriented software architecture includes a set of components. Every component has several parameters as input variables, and the values of parameters can be either discrete or dividable into discrete segments. Factors are input variables to a software system whose changes in value effect the performance of the system. The objective of sensitivity analysis is to evaluate software systems in regard to their sensitivity to factor variations, and to determine the effects of factor variations on performance analysis in a quantitative manner.

Suppose A and B are two factors that take values at different levels whose indices are i and j respectively, where $1 \leq i \leq a$ and $1 \leq j \leq b$. Illustrated in Eq. 1 is a model for a two-factor factorial experiment with n observations per factor combination conducted in a completely randomized setting.

$$Y_{ijl} = \mu + A_i + B_j + AB_{ij} + \varepsilon_{ijl} \tag{1}$$

In the model, the population mean μ produces the average of all observations for $1 \leq l \leq n$. In particular, A_i is the effect of the ith level of factor A, B_j is the effect of the jth level of factor B, AB_{ij} is the joint effect caused by the interaction between A_i and B_j, and ε_{ijl} is a random error component. Correspondingly, sensitivity analysis needs to determine the individual and joint effects of factors A and B on system performance based upon observations from experiments.

Let $y_{i.}$ denote the total of all experiment observations under the ith level of factor A, $y_{.j}$ under the jth level of factor B, y_{ij} for the ijth combination of factors A and B, and $y_{..}$ the grand total of all the observations. The following set of equations defines population mean $\bar{y}_{..}$ and marginal means $\bar{y}_{i.}$, $\bar{y}_{.j}$, and $\bar{y}_{ij}$ for factor A, factor B, and their combination respectively.

$$y_{i.} = \sum_{j=1}^{b}\sum_{l=1}^{n} y_{ijl} \qquad \bar{y}_{i.} = \frac{y_{i.}}{bn} \tag{2}$$

$$y_{.j} = \sum_{i=1}^{a}\sum_{l=1}^{n} y_{ijl} \qquad \bar{y}_{.j} = \frac{y_{.j}}{an} \tag{3}$$

$$y_{ij} = \sum_{l=1}^{n} y_{ijl} \qquad \bar{y}_{ij} = \frac{y_{ij}}{n} \tag{4}$$

$$y_{..} = \sum_{i=1}^{a}\sum_{j=1}^{b}\sum_{l=1}^{n} y_{ijl} \qquad \bar{y}_{..} = \frac{y_{..}}{abn} \tag{5}$$

In the next equation defines the total sum of squares (SS_T).

$$\begin{aligned}
SS_T =& \sum_{i=1}^{a}\sum_{j=1}^{b}\sum_{l=1}^{n}(y_{ijl} - \bar{y}_{..})^2 \\
=& \sum_{i=1}^{a}\sum_{j=1}^{b}\sum_{l=1}^{n}[(\bar{y}_{i.} - \bar{y}_{..}) + (\bar{y}_{.j} - \bar{y}_{..}) \\
&+ (\bar{y}_{ij} - \bar{y}_{i.} - \bar{y}_{.j} + \bar{y}_{..}) + (y_{ijl} - \bar{y}_{ij})]^2 \\
=& \sum_{i=1}^{a}\sum_{j=1}^{b}\sum_{l=1}^{n}(\bar{y}_{i.} - \bar{y}_{..})^2 + \sum_{i=1}^{a}\sum_{j=1}^{b}\sum_{l=1}^{n}(\bar{y}_{.j} - \bar{y}_{..})^2 \\
&+ \sum_{i=1}^{a}\sum_{j=1}^{b}\sum_{l=1}^{n}(\bar{y}_{ij} - \bar{y}_{i.} - \bar{y}_{.j} + \bar{y}_{..})^2 \\
&+ \sum_{i=1}^{a}\sum_{j=1}^{b}\sum_{l=1}^{n}(y_{ijl} - \bar{y}_{ij})^2 \\
=& bn\sum_{i=1}^{a}(\bar{y}_{i.} - \bar{y}_{..})^2 + an\sum_{j=1}^{b}(\bar{y}_{.j} - \bar{y}_{..})^2 \\
&+ n\sum_{i=1}^{a}\sum_{j=1}^{b}(\bar{y}_{ij} - \bar{y}_{i.} - \bar{y}_{.j} + \bar{y}_{..})^2 \\
&+ \sum_{i=1}^{a}\sum_{j=1}^{b}\sum_{l=1}^{n}(y_{ijl} - \bar{y}_{ij})^2
\end{aligned}$$

By introducing a set of sum-of-square symbols SS_E, SS_A, SS_B, and SS_{AB} for random errors, factor A, factor B, and the interactive factor between A and B respectively, the above relationship results in a set of equations in Eq. 6–9.

$$SS_A = \frac{1}{bn}\sum_{i=1}^{a} y_{i.}^2 - \frac{y_{..}^2}{abn} \tag{6}$$

$$SS_B = \frac{1}{an}\sum_{j=1}^{b} y_{.j}^2 - \frac{y_{..}^2}{abn} \tag{7}$$

$$SS_{AB} = \frac{1}{n}\sum_{i=1}^{a}\sum_{j=1}^{b} y_{ij}^2 - \frac{y_{..}^2}{abn} - SS_A - SS_B \tag{8}$$

$$SS_T = \sum_{i=1}^{a}\sum_{j=1}^{b}\sum_{l=1}^{n} y_{ijl}^2 - \frac{y_{..}^2}{abn} \tag{9}$$

$$SS_E = SS_T - SS_A - SS_B - SS_{AB} \tag{10}$$

For each sum of squares, there is an associated degree of freedom (df) that represents the number of independent variable (Table I). Each sum of squares divided by its degrees of freedom produces a mean square (MS). Individual factor effects and their joint effects are finally decided by comparing their F distribution values F_0 with a cumulative F distribution

source of variation	degree of freedom	mean square	F distribution
A	a-1	$\mathrm{MS}_A = \mathrm{SS}_A/(a\text{-}1)$	$\mathrm{F}_0^A = \mathrm{MS}_A/\mathrm{MS}_E$
B	b-1	$\mathrm{MS}_B = \mathrm{SS}_B/(b\text{-}1)$	$\mathrm{F}_0^B = \mathrm{MS}_B/\mathrm{MS}_E$
C	c-1	$\mathrm{MS}_C = \mathrm{SS}_C/(c\text{-}1)$	$\mathrm{F}_0^C = \mathrm{MS}_C/\mathrm{MS}_E$
A×B Interaction	$(a$-1$)(b$-1$)$	$\mathrm{MS}_{AB} = \mathrm{SS}_{AB}/(a\text{-}1)(b\text{-}1)$	$\mathrm{F}_0^{AB} = \mathrm{MS}_{AB}/\mathrm{MS}_E$
A×C Interaction	$(a$-1$)(c$-1$)$	$\mathrm{MS}_{AC} = \mathrm{SS}_{AC}/(a\text{-}1)(c\text{-}1)$	$\mathrm{F}_0^{AC} = \mathrm{MS}_{AC}/\mathrm{MS}_E$
B×C Interaction	$(b$-1$)(c$-1$)$	$\mathrm{MS}_{BC} = \mathrm{SS}_{BC}/(b\text{-}1)(c\text{-}1)$	$\mathrm{F}_0^{BC} = \mathrm{MS}_{BC}/\mathrm{MS}_E$
A×B×C Interaction	$(a$-1$)(b$-1$)(c$-1$)$	$\mathrm{MS}_{ABC} = \mathrm{SS}_{ABC}/(a\text{-}1)(b\text{-}1)(c\text{-}1)$	$\mathrm{F}_0^{ABC} = \mathrm{MS}_{ABC}/\mathrm{MS}_E$
Error	$abc(n$-1$)$	$\mathrm{MS}_E = \mathrm{SS}_E/abc(n\text{-}1)$	
Total	$abcn$-1	$\mathrm{MS}_T = \mathrm{SS}_T/abcn\text{-}1$	

TABLE II
VARIANCE TABLE FOR THREE-FACTOR-BASED SENSITIVITY ANALYSIS

table value F_{α,df_1,df_2}, where α is a confidence level, df_1 is the degree of freedom associated with the numerator of the mean square, df_2 is the degree of freedom associated with the denominator the mean square [10]. The variation of a factor or the combined variation of two factors has significant effect on the performance of a software system only if its corresponding F distribution value F_0^A, F_0^B, or F_0^{AB} exceeds F_{α,df_1,df_2}.

B. Multi-Factor-Based Sensitivity Analaysis

Suppose there are m factors $A^{(w)}$, $1 \leq w \leq m$, each of which takes values at different levels indexed at i_v for $1 \leq i_w \leq a_w$. Illustrated in Eq. 11 is a general model of m-factor-based sensitivity analysis. Similar in format to Eq. 1, the analysis has to consider not only individual factor effects but also their joint effects in combinations from two up to all the m factors.

$$\begin{aligned} Y_{i_1 i_2 \cdots i_m l} = \mu &+ A^{(1)}_{i_1} + A^{(2)}_{i_2} + \cdots + A^{(m)}_{i_m} \\ &+A^{(1)}A^{(2)}_{i_1 i_2} + A^{(1)}A^{(3)}_{i_1 i_3} + \cdots + A^{(1)}A^{(m)}_{i_1 i_m} \\ &+A^{(2)}A^{(3)}_{i_2 i_3} + A^{(2)}A^{(4)}_{i_2 i_4} + \cdots + A^{(2)}A^{(m)}_{i_2 i_m} \\ &+\cdots+ \\ &+A^{(m-1)}A^{(m)}_{i_{m-1} i_m} \\ &+A^{(1)}A^{(2)}A^{(3)}_{i_1 i_2 i_3} + \cdots + A^{(1)}A^{(2)}A^{(m)}_{i_1 i_2 i_m} \\ &+A^{(2)}A^{(3)}A^{(4)}_{i_2 i_3 i_4} + \cdots + A^{(2)}A^{(3)}A^{(m)}_{i_2 i_3 i_m} \\ &+\cdots+ \\ &+A^{(m-2)}A^{(m-1)}A^{(m)}_{i_{m-2} i_{m-1} i_m} \\ &+\cdots+ \\ &+A^{(1)}A^{(2)}\cdots A^{(m)}_{i_1 i_2 \cdots i_m} + \varepsilon_{i_1 i_2 \cdots i_m l} \end{aligned} \tag{11}$$

For simplicity, the following discussion concentrates on the case when m=3, but the generalization from two to three applies to multiple factors. When three factors are under consideration at the same time, the general model takes the form of Eq. 12, based upon which a variance table can be constructed in Table II by following the procedure. It takes seven steps to determine individual factor effects and their joint effects on system performance.

$$\begin{aligned} Y_{ijlk} =& \mu + A_i + B_j + C_k + AB_{ij} + BC_{jk} + AC_{ik} \\ &+ ABC_{ijk} + \varepsilon_{ijkl} \end{aligned} \tag{12}$$

1) Perform n times of experiment with A, B, and C set to different values, which leads to $a\times b\times c\times n$ experiments in total. In the experiments, each observed response y_{ijkl} is an output of a performance metrics during performance analysis when A, B, and C take values at different levels indexed respectively at i for $1 \leq i \leq a$, j for $1 \leq j \leq b$, and k for $1 \leq k \leq c$.
2) Calculate the mean of performance responses by keeping one factor constant while varying the levels of all the other factors within their value ranges. This step results in three group means $\bar{y}_{i..}$, $\bar{y}_{.j.}$, and $\bar{y}_{..k}$.

$$y_{i..} = \sum_{j=1}^{b}\sum_{k=1}^{c}\sum_{l=1}^{n} y_{ijkl} \qquad \bar{y}_{i..} = \frac{y_{i..}}{bcn} \tag{13}$$

$$y_{.j.} = \sum_{i=1}^{a}\sum_{k=1}^{c}\sum_{l=1}^{n} y_{ijkl} \qquad \bar{y}_{.j.} = \frac{y_{.j.}}{acn} \tag{14}$$

$$y_{..k} = \sum_{i=1}^{a}\sum_{j=1}^{b}\sum_{l=1}^{n} y_{ijkl} \qquad \bar{y}_{..k} = \frac{y_{..k}}{abn} \tag{15}$$

3) Calculate the means of joint performance responses $\bar{y}_{ij.}$, $\bar{y}_{.jk}$, $\bar{y}_{i.k}$, and $\bar{y}_{ijk}$ between factors A, B, and C.

$$y_{ij.} = \sum_{k=1}^{c}\sum_{l=1}^{n} y_{ijkl} \qquad \bar{y}_{ij.} = \frac{y_{ij.}}{cn} \tag{16}$$

$$y_{i.k} = \sum_{j=1}^{b}\sum_{l=1}^{n} y_{ijkl} \qquad \bar{y}_{i.k} = \frac{y_{i.k}}{bn} \tag{17}$$

$$y_{.jk} = \sum_{i=1}^{a}\sum_{l=1}^{n} y_{ijkl} \qquad \bar{y}_{.jk} = \frac{y_{.jk}}{an} \tag{18}$$

$$y_{ijk} = \sum_{l=1}^{n} y_{ijkl} \qquad \bar{y}_{ijk} = \frac{y_{ijk}}{n} \tag{19}$$

4) Calculate overall mean $\bar{y}_{...}$ of performance responses.

$$y_{...} = \sum_{i=1}^{a}\sum_{j=1}^{b}\sum_{k=1}^{c}\sum_{l=1}^{n} y_{ijkl} \qquad \bar{y}_{...} = \frac{y_{...}}{abcn} \tag{20}$$

5) Calculate the sums of squares with Eq. 21–29.

$$SS_A = \frac{1}{bcn}\sum_{i=1}^{a} y_{i..}^2 - \frac{y_{...}^2}{abcn} \tag{21}$$

$$SS_B = \frac{1}{acn}\sum_{j=1}^{b} y_{.j.}^2 - \frac{y_{...}^2}{abcn} \tag{22}$$

$$SS_C = \frac{1}{abn}\sum_{k=1}^{b} y_{..k}^2 - \frac{y_{...}^2}{abcn} \tag{23}$$

$$\begin{aligned} SS_{AB} &= \frac{1}{cn}\sum_{i=1}^{a}\sum_{j=1}^{b} y_{ij.}^2 - \frac{y_{...}^2}{abcn} \\ &\quad -SS_A - SS_B \end{aligned} \tag{24}$$

$$\begin{aligned} SS_{AC} &= \frac{1}{bn}\sum_{i=1}^{a}\sum_{k=1}^{c} y_{i.k}^2 - \frac{y_{...}^2}{abcn} \\ &\quad -SS_A - SS_C \end{aligned} \tag{25}$$

$$\begin{aligned} SS_{BC} &= \frac{1}{an}\sum_{j=1}^{b}\sum_{k=1}^{b} y_{.jk}^2 - \frac{y_{...}^2}{abcn} \\ &\quad -SS_B - SS_C \end{aligned} \tag{26}$$

$$\begin{aligned} SS_{ABC} &= \frac{1}{n}\sum_{i=1}^{a}\sum_{j=1}^{b}\sum_{k=1}^{b} y_{ijk}^2 - \frac{y_{...}^2}{abcn} \\ &\quad -SS_A - SS_B - SS_C - SS_{AB} \\ &\quad -SS_{AC} - SS_{BC} \end{aligned} \tag{27}$$

$$SS_T = \sum_{i=1}^{a}\sum_{j=1}^{b}\sum_{k=1}^{c}\sum_{l=1}^{n} y_{ijkl}^2 - \frac{y_{...}^2}{abcn} \tag{28}$$

$$\begin{aligned} SS_E &= SS_T - SS_A - SS_B - SS_C - SS_{AB} \\ &\quad -SS_{BC} - SS_{AC} - SS_{ABC} \end{aligned} \tag{29}$$

6) Fill in Table II for the factors and their interactions with the calculated sums of squares and F distribution values.
7) Compare each F distribution value with the cumulative F distribution table value F_{α,df_1,df_2}. An individual factor or a joint group of several factors has significant effect on the performance of a software system only if its corresponding F distribution value exceeds F_{α,df_1,df_2}.

III. Feedback Generation

Sensitivity analysis takes place before performance analysis results are used as feedback for software designers to refine the architecture design of a software system. In the past, sensitivity analysis has been relying upon human experts to decide the quality of an architecture design by interpreting visually the graphical display of analysis results. Quantitative analysis as presented in the previous section, on the other hand, determines the quality of a design by examining numerically experiment results. It not only results in more accurate analysis but also allows for process automation.

Quantitative sensitivity analysis helps to decide the effects of factors. In addition, its results also provide direct guidance for factor configuration. The group means of one factor contains the information of its tendency on effecting system performance when other factor take different values. A group mean is optimal if the differences of means before it are significant and the differences of means after it are insignificant. This task can be accomplished with the Student-Newman-Keuls(SNK) test in another procedure of seven steps [11].

1) Calculate $a\times b\times c$ means by taking the average of n experiment results obtained with factors A, B, and C set to different levels indexed respectively at i for $1 \leq i \leq a$, j for $1 \leq j \leq b$, and k for $1 \leq k \leq c$.
2) Arrange all the means in an increasing order from low to high.
3) Take the mean square for the error (MS_E) from the variance table (Table II), together with its degrees of freedom (df_E).
4) Obtain the standard error of the means by using the following equation:

$$S_s = \sqrt{\frac{MS_E}{n}} \tag{30}$$

5) Enter a table of significant ranges at the desired confidence level α.
6) Multiply the ranges by S_s to obtain a group of $a\times b\times c$-1 least significant ranges (LSR).
7) Check the differences between means with their corresponding LSR. Groups of means with insignificant differences of means lead to optimal performance.

IV. Experiments and Discussions

CDSS (Clinical Decision Support System) is a clinical system that assists medical decisions by processing multi-domain medical data from neonatal, prenatal, and obstetrical areas [4]. It is a service-oriented system, and performance analysis plays a key role for the adjustment of relationships between services. In particular, the sensitivity of performance metrics to variations in the duplicates of services has a deep impact on the performance after the basic infrastructure is built. Among all performance metrics, the average response time is dominating. As a result, the following subsection studies the sensitivity of response time to duplicates of services.

A. Case Study

Three factors are chosen for this case study. They are factor A for processCDSS service time (ms), factor B for multiplicity factor of SOAP1 execute time, and factor C for the number of EPRT thread. Each factor has variations at three fixed levels, and two experiments are conducted with factors A, B, and C set to values at different levels indexed respectively at i for $1 \leq i \leq 3$, j for $1 \leq j \leq 3$, and k for $1 \leq k \leq 3$. Table III(a) shows the observations obtained when running the experiments. Response time is in seconds.

By apply the steps of multi-factor-based sensitivity analysis (Section II-B), a variance table is constructed in Table III(b). At a confidence level of 1%, factors A and C have significant impact on system response time due to the fact that both F_0^A at 38.554 and F_0^C at 24.336 exceed the cumulative F distribution table value $F_{0.01,2,27}$, which is 5.49. In addition, factors A

A	B	C		
		2	4	6
300	0.5	5.54	5.43	4.96
		5.567	5.51	5.613
	1	5.954	5.6	5.55
		6.15	5.59	5.779
	2	6.334	6.01	6.03
		6.589	5.79	5.65
500	0.5	5.809	5.849	5.84
		5.939	5.266	5.25
	1	7.103	5.86	5.31
		7.098	5.965	6.001
	2	7.13	6.03	5.105
		7.144	5.65	6.158
1000	0.5	9.359	6.26	6.38
		9.4	6.499	6.53
	1	9.887	6.83	7.62
		9.879	6.33	5.088
	2	10.92	6.12	6.489
		10.83	8.875	8.076

(a) Data Collection

variation	SS	df	MS	F_0
A	46.79609	2	23.398	38.554*
B	5.394474	2	2.697	4.444
C	29.53809	2	14.769	24.336*
A×B	1.530214	4	0.383	0.630
A×C	18.56695	4	4.642	7.648*
B×C	1.068571	4	0.267	0.440
A×B×C	0.346414	8	0.043	0.071
Error	16.38596	27	0.607	
Total	119.6267	53		

(b) Variance Table of Sensitivity Analysis

TABLE III
A CASE STUDY OF CDSS

and C have significant joint impact on system response time as F_0^{AC} at 7.648 exceed 5.49. All the others do not have significant impacts. However, if the confidence level changes to 5%, factor B also shows significant impact as F_0^B at 4.444 exceeds $F_{0.05,2,27}$, which is 3.35.

B. Comparison with Two-Factor-Base Analysis

Multi-factor-based sensitivity analysis considers more factors at the same time than two-factor-based sensitivity analysis. Its results are more complete and accurate, especially when there are significant joint effects due to interactions between factors. As a comparison study, suppose only two factors A and C are considered at the same time. Three groups of experiments are conducted with factor B being set at 0.5, 1, and 2 separately. Provided in Tables IV–VI are the observations of experiments and the corresponding variance tables for the special cases.

According to Table IV(b), factors A and C have significant individual and joint effects. However, if either Table V(b) or Table VI(b) is used, factors A and C have only significant individual effect but no joint effects as the F distribution value F_0^{AC} in both tables are less than $F_{0.05,4,9}$=4.415. This study shows that two-factor-based sensitivity analysis may reach to conflicting conclusions. Depending on the value of the third factor, wrong decisions could be reached by sensitivity analysis with only two factors.

A	C		
	2	4	6
300	5.54	5.43	4.96
	5.567	5.51	5.61
500	5.809	5.849	5.84
	5.939	5.266	5.25
1000	9.359	6.26	6.38
	9.4	6.499	6.53

(a) Data Collection for B=0.5

variation	SS	df	MS	F_0	$F_{0.05,df,df_e}$
A	13.941	2	6.970	102.864	3.199
C	5.326	2	2.663	39.301	3.199
A×C	6.592	4	1.648	24.324	4.415
Error	0.609	9	0.067		
Total	26.470	17			

(b) Variance Table for B=0.5

TABLE IV
TWO-FACT-BASED SENSITIVITY ANALYSIS FOR B=0.5

A	C		
	2	4	6
300	5.954	5.6	5.55
	6.15	5.59	5.779
500	7.103	5.86	5.31
	7.098	5.96	6.001
1000	9.887	6.83	7.62
	9.879	6.33	5.088

(a) Data Collection for B=1

variation	SS	df	MS	F_0	$F_{0.05,df,df_e}$
A	10.969	2	5.485	13.63	3.199
C	11.867	2	5.933	14.75	3.199
A×C	6.362	4	1.59	3.95	4.415
Error	3.62	9	0.402		
Total	32.819	17			

(b) Variance Table for B=1

TABLE V
TWO-FACT-BASED SENSITIVITY ANALYSIS FOR B=1

A	C		
	2	4	6
300	6.334	6.01	6.03
	6.589	5.79	5.65
500	7.13	6.03	5.105
	7.144	5.65	6.158
1000	10.92	6.12	6.489
	10.83	8.875	8.076

(a) Data Collection for B=2

variation	SS	df	MS	F_0	$F_{0.05,df,df_e}$
A	23.416	2	11.708	18.124	3.199
C	13.414	2	6.706	10.382	3.199
A×C	5.957	4	1.489	2.305	4.415
Error	5.814	9	0.645		
Total	48.602	17			

(b) Variance Table for B=2

TABLE VI
TWO-FACT-BASED SENSITIVITY ANALYSIS FOR B=2

C. Configuration Feedback

As factors A and C have significant joint effects on system response time, the procedure of feedback generation (Section III) is applied to determined configurations of A and C that lead to better performance. Given in the first row of Table VII is the ordered means of the 27 pairs of experiment observations (Table III(a)). Meanwhile, MS_E and df_E can be obtained directly from Table III as 0.607 and 27 respectively. The following equation then produces the standard error of means S_s.

$$S_s = \sqrt{0.607/2} = 0.551$$

Afterwards, the significant ranges at a confidence level of 5% and the least significant ranges (LSR) are calculated, and then filled into the second and third rows of Table VII. By following the last step of SNK test (Section III), the remaining rows of Table VII finally list all the differences between the 27 means, in which the emphasized numbers indicate significant differences between means. For example, the last row of the last column has a value of 5.59, which is the difference between the $27th$ mean (10.88) and first mean (5.29). The value 5.59 is larger than the value (3.24) of the $27th$ LSR. The difference is therefore considered significant.

This quantitative analysis classifies the $27th$ means into two groups. One group consists of the means causing significant mean differences, i.e., the $25th$, $26th$, and $27th$ means; and the other group consists of all the other means. Due to the fact that the $25th$, $26th$, and $27th$ means come from three combinations of factors A, B, and C with i, j, and k set to (3, 1, 1), (3, 2, 1), and (3, 3, 1). A conclusion can then be reached: no mater what is the value of factor B, an increase of factor C from 1 to 2 is going to create the worst response time when factor A is set at 1000(ms). However, this situation improves when factor C takes a value of 3. All other combinations demonstrate no significant difference.

D. Visual Interpretation

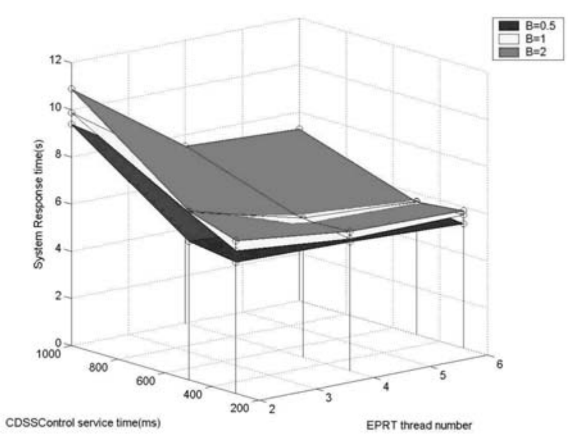

Fig. 1. Simulation Results

Fig. 1 exhibits variations of response time in relation to factors A, B and C. This figure demonstrates that the response time is sensitive to both processCDSS services processing time

TABLE VII
AN EXAMPLE OF FEEDBACK GENERATION

1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**
5.29	5.47	5.55	5.55	5.56	5.60	5.63	5.66	5.66	5.84	5.84	5.87	5.90	5.91	6.05	6.35	6.38	6.46	6.46	6.58	7.10	7.14	7.28	7.50	9.38	9.88	10.88
range	2.90	3.51	3.87	4.13	4.33	4.50	4.64	4.75	4.86	4.96	5.04	5.12	5.19	5.26	5.32	5.38	5.43	5.48	5.53	5.58	5.63	5.69	5.74	5.79	5.84	5.89
LSR	1.60	1.93	2.13	2.28	2.39	2.48	2.55	2.62	2.68	2.73	2.78	2.82	2.86	2.90	2.93	2.96	2.99	3.02	3.05	3.07	3.10	3.13	3.16	3.19	3.22	3.24
	0.18	0.08	0.01	0.00	0.04	0.04	0.02	0.01	0.18	0.00	0.03	0.03	0.01	0.14	0.30	0.03	0.08	0.01	0.12	0.52	0.04	0.15	0.22	1.88	0.50	0.99
		0.26	0.08	0.01	0.04	0.07	0.06	0.03	0.18	0.18	0.03	0.06	0.04	0.15	0.44	0.33	0.10	0.08	0.13	0.64	0.56	0.18	0.36	*2.10*	2.39	1.50
			0.27	0.09	0.05	0.08	0.10	0.07	0.21	0.18	0.21	0.06	0.07	0.18	0.45	0.47	0.40	0.11	0.20	0.65	0.68	0.70	0.40	*2.24*	*2.60*	*3.38*
				0.27	0.13	0.09	0.10	0.11	0.25	0.21	0.22	0.24	0.07	0.21	0.48	0.48	0.54	0.41	0.23	0.72	0.68	0.82	0.92	2.28	2.75	3.59
					0.31	0.16	0.11	0.11	0.28	0.25	0.24	0.24	0.25	0.21	0.51	0.51	0.56	0.55	0.53	0.75	0.76	0.83	1.04	*2.80*	*2.78*	*3.74*
						0.35	0.19	0.12	0.29	0.28	0.28	0.27	0.26	0.39	0.51	0.54	0.58	0.56	0.67	1.05	0.78	0.90	1.04	2.92	*3.30*	3.77
							0.37	0.19	0.30	0.29	0.32	0.31	0.28	0.40	0.69	0.54	0.62	0.59	0.68	1.19	1.09	0.93	1.12	2.93	*3.42*	*4.30*
								0.38	0.37	0.30	0.32	0.34	0.32	0.42	0.70	0.72	0.62	0.62	0.71	1.20	1.22	1.23	1.14	*3.00*	*3.43*	*4.41*
									0.55	0.37	0.33	0.35	0.36	0.46	0.72	0.72	0.79	0.62	0.74	1.23	1.24	1.37	1.45	3.03	*3.50*	4.42
										0.55	0.40	0.36	0.36	0.49	0.76	0.75	0.80	0.80	0.74	1.26	1.26	1.38	1.59	3.33	*3.53*	*4.50*
											0.59	0.43	0.37	0.50	0.80	0.78	0.82	0.81	0.92	1.26	1.30	1.41	1.60	3.47	*3.83*	4.52
												0.61	0.44	0.51	0.80	0.82	0.86	0.83	0.92	1.44	1.30	1.44	1.62	*3.48*	*3.97*	*4.82*
													0.63	0.58	0.81	0.83	0.90	0.87	0.95	1.45	1.47	1.44	1.66	*3.51*	*3.98*	*4.96*
														0.77	0.88	0.83	0.90	0.90	0.99	1.47	1.48	1.62	1.66	3.54	*4.01*	*4.98*
															1.07	0.91	0.91	0.91	1.02	1.51	1.51	1.63	1.83	*3.54*	*4.04*	*5.00*
																1.09	0.99	0.92	1.03	1.54	1.54	1.65	1.84	3.72	*4.04*	*5.04*
																	1.17	0.99	1.04	1.55	1.58	1.69	1.87	*3.72*	*4.22*	*5.04*
																		1.18	1.11	1.56	1.58	1.73	1.90	*3.75*	*4.23*	*5.21*
																			1.29	1.63	1.59	1.73	1.94	*3.79*	*4.25*	5.22
																				1.81	1.67	1.74	1.94	3.82	*4.29*	*5.24*
																					1.85	1.81	1.95	3.83	*4.33*	*5.28*
																						2.00	2.03	*3.84*	*4.33*	5.32
																							2.21	*3.91*	*4.34*	5.32
																								4.09	*4.41*	5.33
																									4.60	*5.41*
																										5.59

(factor A) and the number of EPR database thread (factor C). When processCDSS service time increase to 1000ms and EPRT thread number decrease to 2, the response time increase greatly, no mater if multiplicity factor of SOAP1 execute time is set to 0.5, 1, or 2. The conclusion of visual analysis is consistent with the conclusion of the quantitative analysis. However, visual analysis relies on human interpretation, which may result in difficulties when the volume of data is huge.

V. Conclusion

This paper develops a method of multi-factor-based sensitivity analysis for performance analysis of service-oriented software systems. By apply statistical techniques, it is able to quantitively analyze the effects on system performance from not only individual services but also the interactions between them. This method also produces helpful feedback of service configuration for optimal performance. Experiments demonstrate that sensitivity analysis with multiple factors produces accurate results. In addition, quantitative analysis is particularly valuable for automated processing. Further research is under active investigation to improve the proposed method by considering uncontrollable factors, and to apply in practice.

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