ESTIMATING THE EFFICIENCY OF COLLABORATIVE PROBLEM-SOLVING, WITH APPLICATIONS TO CHIP DESIGN

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Abstract:

We present a statistical framework to address questions that arise in general problems involving collaboration of several contributors. One instance of this problem occurs in the complex process of designing ultralarge-scale-integration semiconductor chips. In cases involving complex designs, the computer-aided design tools are unable to create designs that satisfy specified project criteria, and a number of questions arise about how to measure the effectiveness of systematic external intervention that is implemented with some supplemental algorithm. As an example, we apply the statistical framework to the problem of routing a functional unit of the IBM POWER4 microprocessor.

1. Introduction

Successful achievement of many complex tasks requires cooperation between a number of contributors, each of whom performs a given sub-task, possibly several times. The ability of a contributor to perform a sub-task well cannot be assessed based exclusively on results of this sub-task since each contributor operates independently and has a potential to impede the collaborative effort.

In this paper, we consider two types of contributors: (1) mandatory contributors, whose actions are required to achieve the goal and whose participation is thus mandated *a priori*; and (2) supplemental contributors, whose respective sub-tasks are performed only to improve the results of the mandatory contributors. We assume that criteria exist to enable a comparison of various designs, whether the goal is achieved or not. In such a formalism, a few questions to address include the following ones: (a) which contributors are essential to achieve the goal? (b) is addition of a given contributor likely to increase the design quality? (c) is the goal achievable? In this paper, we formulate criteria and present an approach to enable one to address questions such as these. For the sake of simplicity, we do not present a mathematical framework of this general problem. Instead, we consider in detail a specific problem related to chip design of ultra-large-scale-integrated (ULSI) circuits, such as systems-on-chips (SOCs).

In ULSI design, many steps in the design process are implemented with computer-aided design tools such as automated routers. In most cases, these tools are able to operate on the design data without external intervention and successfully complete a specified task to create a design that satisfies a set of objective criteria. In other cases, such as for complex designs, the tools are not able to complete the task successfully, and external intervention is helpful. This intervention can be implemented with a supplemental algorithm that is either fully automated or that relies on formally describable human expertise. In these cases, the collaborative effort involves a mandatory wire router and a supplemental algorithm that operate in turns, and progress is monitored after each *trial*. Here the term *trial* refers to a pair of *moves*; the first *move* is taken by the supplemental algorithm, and the second *move* is taken by the router. The sequence of trials is continued until either the goal is achieved or as long as one acts in accordance with one of several policies addressed later.

For the external intervention to work in a cooperative manner with the tool, the supplemental algorithm must identify those portions of the problem that pose difficulty for the tool and then attack those portions in the next *move*. The interactions of the external intervention and the tool are helpful to the extent that the tool is able to make additional progress, and the results tend to improve with each trial. Therefore, in the context of this example, we formulate a method for external intervention and introduce a statistical framework to provide quantitative information on the effectiveness of the intervention. Complete details are in Ref. ??.

2. Background

The ability to route ULSI designs is nontrivial since these designs contain large numbers of signals. An understanding of signal routing is also important to achieve optimal performance[1, 2, 3, 4, 5], power dissipation[6], and manufacturability[7, 8, 9, 10] of increasingly complex circuits. The standard objective criteria for a successfully routed chip design are that the connections for all signals are routed with zero violations and satify the project cycle time requirement. For some designs, the automated route tool is unable to route all signals without introducing violations in some signal routes. For other designs, the tool is able to create a wire layout with zero violations, yet there is a strong possibility that the layout can be improved further to enhance overall chip performance, yield, and reliability. For both types of designs, one can take advantage of external intervention that amounts to pre-routing part of the circuitry to make the subsequent work of the router easier. The pre-routed wires are implemented with a separate algorithm that inserts *custom interconnections* in the design layout.

3. Method for external intervention

In this section, we describe a method for external intervention in ULSI design and focus on the analysis of signal netlengths in a design layout; however, a similar analysis for vias or other physical properties can be obtained from the discussion.

3.1 Identify signals with excess route length

The first step is to identify signals with excess route length; these signals are potential targets for custom interconnections. In this step, the automated route tool routes the signals in a design, and the netlength L and Steiner length estimate L_S are measured for each signal. We introduce a measure of signal route complexity called the normalized excess Steiner length *NESL*,

$$NESL = \frac{L - L_S}{L_S}, \tag{1}$$

where *NESL* is a ratio that measures how closely the actual signal length L of approaches L_S. In the case that the automated router creates a long wire route for this signal, with L much greater than L_S, *NESL* is large. In this case, a large value of *NESL* indicates increased route complexity for this signal. In this framework, signal routes are ordered in decreasing value of *NESL*.

3.2 Identify congested regions

The next step is to identify congested regions in a design layout. In this step, two two-dimensional maps of the signal density and the via density are obtained from the routed design layout. We use the term *congested regions* to refer to those regions that exhibit high values of both signal density and via density compared with values in surrounding regions.

3.3 Identify signals to target for custom interconnections

The next step is to compare the locations of congested regions with locations of signals with large values of *NESL*. In this step, signals in congested regions are targeted for custom routes. In our experience, regions that are both congested and contain signals with large values of *NESL* are regions that contain signals that should be targeted for external intervention with custom interconnections.

3.4 Insert custom interconnections

The next step is to insert custom interconnections for targeted signals identified in III.C. In this step, the remaining signals are then routed with an automated route tool, and the routes are checked for electrical shorts and geometry violations. Procedures III.A to III.D are iterated until the wire layout contains no violations and satisifies the project cycle time requirement.

3.5 Quantify complexity of the interconnections

At this step in the process, a working design layout exists; in general, this design layout is non-unique. In this example, since we only consider netlengths of signal routes, the wire layouts that contain shorter signal routes are better layouts, where all other factors are assumed equivalent. It is possible therefore to assign a figure-of-merit to a design layout according to the following procedure.

First, the total interconnect length L_T and total interconnect Steiner length L_{ST} for all signals are obtained by taking the sum of the contributions for all signals. We introduce a measure of complexity of the design interconnections called the total excess Steiner length *TESL*,

$$TESL = L_T - L_{ST}, \tag{2}$$

where *TESL* is the length by which L_T exceeds L_{ST}.

We also introduce a second measure of interconnect complexity called the average normalized excess Steiner length $\langle NESL \rangle$,

$$\langle NESL \rangle = \frac{\sum_{i=1}^{N_{group}} NESL(i)}{N_{group}}, \tag{3}$$

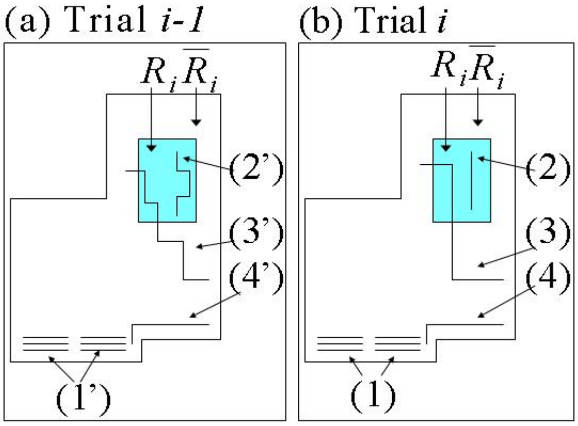

Figure 1: Region of influence in a design. The region of influence R_i is shaded blue. The remainder $\overline{R_i}$ is unshaded. (1') and (1) show custom interconnections inserted in both trials $(i-1)$ and i with total length $L_c^{(i-1)}$; (2') shows targeted routes in R_i; (2) shows custom routes in R_i; (3') shows routes that partially pass through R_i in trial $(i-1)$; (3) shows routes that partially pass through R_i in trial i with total length $L_o^{(i)}$; (4') and (4) show remaining routes that do not pass through R_i.

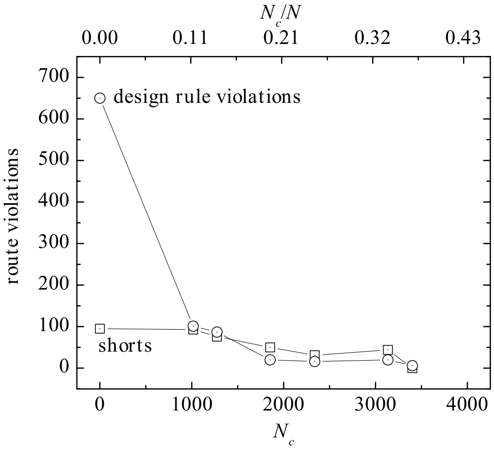

Figure 2: Number of route violations in the Instruction Fetch Unit (IFU). Design rule violations (circles) and electrical shorts (squares) are shown as a function of the number of custom interconnections N_c (lower abscissa) and fraction of custom interconnections N_c/N (upper abscissa).

where the average is taken over a group of signals N_{group}, and where $NESL(i)$ represents the $NESL$ of signal i. The group of signals can consist of the entire set of N signals in the design or a subset of signals $N_{group} \leq N$ in a congested region.

4. Statistical model of effectiveness

The quantities provided by the figures-of-merit in the previous sections are not absolute numbers and require a statistical treatment to assess their validity. In this section, we present the salient points of a statistical model of effectiveness of external intervention.

Let R_i denote the area, or region of influence, that physically encloses new custom interconnections for ΔN_c^i signals in trial i, as shown in Fig. 1. $\overline{R_i}$ denotes the complement of R_i and is design area that does not contain new custom interconnections. In this figure, R_i is shaded blue; $\overline{R_i}$ is unshaded. The variable N_c^i denotes the cumulative number of signals routed with custom routes in all trials, including trial i.

The total route length $L^{(i)}$ of all signal routes after completion of trial i is composed of four separate components: total length $\Delta L_c^{(i)}(R_i)$ of new custom interconnections contained in R_i in trial i; total length $L_c^{(i-1)}$ of all custom routes in previous trials 0 to $(i-1)$, where $L_c^{(i-1)} = \sum_{j=1}^{i-1} \Delta L_c^{(j)}(R_j)$; total length $L_o^{(i)}(R_i)$ of route segments routed by an automated router and at least part of the route passes through R_i; and total length $L_r^{(i)}(\overline{R_i})$ of route segments routed by an automated router and no part of the route passes through R_i. The total route length $L^{(i)}$ in trial i and $L^{(i-1)}$ in trial $(i-1)$ are described by the expressions,

$$L^{(i)} = L_c^{(i-1)} + \Delta L_c^{(i)}(R_i) + L_o^{(i)}(R_i) + L_r^{(i)}(\overline{R_i}), \quad (4)$$

$$L^{(i-1)} = L_c^{(i-1)} + \Delta L_t^{(i-1)}(R_i) + L_o^{(i-1)}(R_i) + L_r^{(i-1)}(\overline{R_i}), \quad (5)$$

respectively, where $\Delta L_t^{(i-1)}(R_i)$ is the total route length in trial $(i-1)$ of signals targeted for custom routes in trial i.

Figure 1(a) shows examples of the four types of design routes in trial $(i-1)$: custom interconnections (1') inserted with length $L_c^{(i-1)}$, targeted routes (2') in R_i with length $\Delta L_t^{(i-1)}$, other routes that partially pass (3') through R_i with length $L_o^{(i-1)}$, and remaining routes (4') that do not pass through R_i with length $L_r^{(i-1)}(\overline{R_i})$. In Figure 1(b), the lengths of signals represented by those shown in (1)-(4) are described by the quantities $L_c^{(i-1)}$, $\Delta L_c^{(i)}(R_i)$,

$L_o^{(i)}(R_i)$, and $L_r^{(i)}(\overline{R_i})$, respectively. Note that custom interconnection lengths shown in (1) and (1') are equal to $L_c^{(i-1)}$.

In the following discussion, the simplified notation $\Delta L_c^{(i)}$, $\Delta L_t^{(i-1)}$, $L_o^{(i-1)}$, and $L_r^{(i-1)}$ is employed instead of $\Delta L_c^{(i)}(R_i)$, $\Delta L_t^{(i-1)}(R_i)$, $L_o^{(i-1)}(R_i)$, and $L_r^{(i-1)}(\overline{R_i})$, respectively, and the full notation is provided only where confusion is possible. For trial $(i-1)$, the variable $\tilde{L}^{(i-1)} = L^{(i-1)} - L_c^{(i-1)} = \Delta L_t^{(i-1)} + L_o^{(i-1)} + L_r^{(i-1)}$ represents the automated signal length that may be affected in trial i by the addition of custom interconnections with length $\Delta L_c^{(i)}$.

To evaluate the effectiveness of external intervention with custom interconnections, custom routes with length $\Delta L_c^{(i)}$ are first added to a design layout. The automated route program then completes the remaining routes. At this point, *variables that characterize the effectiveness of the external intervention in trial i are calculated.* The effectiveness $\epsilon_L^{(i)}$ of the external intervention on the total route length $L^{(i)}$ in trial i compared with the length in the preceeding trial is represented by the expression,

$$\epsilon_L^{(i)} = 1 - \frac{L^{(i)} - L_c^{(i-1)}}{\tilde{L}^{(i-1)}} = 1 - \frac{\Delta L_c^{(i)} + [L_o^{(i)} + L_r^{(i)}]}{[\Delta L_t^{(i-1)} + L_o^{(i-1)} + L_r^{(i-1)}]} \tag{6}$$

where the numerator in both fractions in Eqn. 6 represents the sum of $\Delta L_c^{(i)}$ and the total automated route length, and where the denominators in both fractions represent the total automated route length in trial $(i-1)$. For $\epsilon_L^{(i)}$ to be positive, the numerator in Eqn. 6 must be smaller than the denominator; in this case, the total automated wire length of the previous trial is replaced in the next trial with a lower combined wire length of custom routes and new automated routes.

The total effectiveness in Eqn. 6 can be represented as a weighted average of the following variables: effectiveness $\epsilon_{L_c}^{(i)}$ of the addition of custom interconnections in R_i, effectiveness $\epsilon_{L_o}^{(i)}$ of segments created by an automated router where at least part of the signal route passes through R_i, and effectiveness $\epsilon_{L_r}^{(i)}$ of remaining route segments that do not pass through R_i, that are given by the expressions,

$$\epsilon_{L_c}^{(i)} = 1 - \frac{\Delta L_c^{(i)}}{\Delta L_t^{(i-1)}}, \tag{7}$$

$$\epsilon_{L_o}^{(i)} = 1 - \frac{L_o^{(i)}}{L_o^{(i-1)}}, \tag{8}$$

and

$$\epsilon_{L_r}^{(i)} = 1 - \frac{L_r^{(i)}}{L_r^{(i-1)}}, \tag{9}$$

where each weight is the portion of the total length allocated to each type of route (custom, other, or rest), as described in [13].

We postulate that these three basic effectivenesses are random variables distributed according to the normal distribution with (unknown) means μ_{L_c}, μ_{L_o}, and μ_{L_r}, respectively. These means are basic parameters that characterize the inherent effect of external intervention; the means are assumed to be invariant from one trial to another. The (unknown) variances of the effectivenesses in Eqns. 7 - 9 are assumed to be inversely proportional to the *domains of impact* $\Delta L_t^{(i-1)}$, $L_o^{(i-1)}$, and $L_r^{(i-1)}$, respectively, with individual proportionality constants that are also assumed to be trial-invariant. In the following discussion, estimates of the mean effectivenesses and these proportionality constants are obtained from data in trials $1, 2, \ldots, n$. We assume that the correlation structure of the observed effectivenesses $(\epsilon_{L_c}^{(i)}, \epsilon_{L_o}^{(i)}, \epsilon_{L_r}^{(i)})$ is trial-invariant; this correlation structure is taken into account when performing statistical inference on these and derived parameters. We also assume that effectivenesses observed in different trials are mutually independent.

To justify these assumptions, we note that external intervention in a given trial consists of a sequence of sub-tasks of roughly the same type and magnitude; accordingly, the domains of impact consist of sub-domains of an appropriate unit size. The observed trial effectiveness is then an average of sub-domain effectivenesses, and under some relatively weak assumptions about the inter-dependence of variables related to sub-domains, normality of the trial effectivenesses is justified by the Central Limit Theory. The assumption that the mean effectivenesses and the correlation structure remain invariant from trial to trial is justified by sub-tasks and related sub-domains being similar from trial to trial; the proportionality constants represent variance of effectiveness observed for a sub-domain of unit size. These assumptions may be over-simplified and should be viewed as a first step toward understanding the properties of the collaborative effort that enable practical decision-making in an environment with a low amount of available data. With a better understanding of interactions between the router and supplemental algorithm, one may also wish to explore more elaborate models. There is also a possibility that this work can lead to further simplification; for example, one can conclude that

μ_{L_r} can be assumed to be equal to zero, or some correlations can be assumed to be equal to zero, or both. In practice, adequacy of the assumed models should be monitored with standard goodness-of-fit tests[14] to detect deviations from the model and to learn about their nature.

To describe the overall progress of external intervention in the design process, we introduce another figure-of-merit called the cumulative netlength effectiveness defined by $\epsilon_L^{(i)(0)} = 1 - L^{(i)}/L^{(0)}$; this cumulative effectiveness is computed for trials $i = 1, 2, \ldots, n$, where $L^{(0)}$ is the initial total netlength. The additional superscript (0) in $\epsilon_L^{(i)(0)}$ indicates that the cumulative effectiveness is measured with respect to the initial wire layout. The distribution of the cumulative effectiveness depends entirely on the basic parameters introduced above.

4.1 Estimation of model parameters

The wire layout in each trial contains a different number of custom interconnections. From n independent trials, one can obtain unbiased estimates $\hat{\mu}_{L_c}$, $\hat{\mu}_{L_o}$, and $\hat{\mu}_{L_r}$, of the mean effectivenesses by calculating a weighted average of the appropriate effectiveness of individual trials. The standard errors and correlation structure of these estimators can be obtained from the data with standard statistical methods, as described in [**?**]. Furthermore, one can obtain standard errors for derived quantities, such as total effectiveness or projected effectiveness of future trials, as illustrated in the next section.

In practice, it is important to establish as soon as possible that the observed effects are not due to chance (that is, that the underlying effectivenesses are not zero or are even of the opposite sign). Evidence against the hypothesis of zero effect of external intervention can be measured with so-called *p-values*; these quantities are denoted as *p-value*(μ_{L_c}), *p-value*(μ_{L_o}), and *p-value*(μ_{L_r}) for custom routes, other routes, and the rest of the routes, respectively. For example, under the assumption that $\mu_{L_c} = 0$, *p-value*(μ_{L_c}) is the probability that the estimated effectiveness will exceed the value of $\hat{\mu}_{L_c}$ actually observed in n trials[15].

Confidence bounds for the effectivenesses of external intervention with custom interconnections can also be constructed from the trial data. We postulate *a priori* that the effect of the use of custom interconnections is greater than zero; therefore, only the lower confidence bound is computed. In the following discussion, the 95% Lower Confidence Bound (LCB) for μ_{L_c} is denoted by $LCB_{0.95,\mu_{L_c}}$; the two-sided 95% confidence intervals for μ_{L_o} and μ_{L_r} are given by pairs of bounds $[LCB_{0.975,\mu_{L_o}}, UCB_{0.975,\mu_{L_o}}]$ and $[LCB_{0.975,\mu_{L_r}}, UCB_{0.975,\mu_{L_r}}]$.

4.2 Statistical method to forecast further external intervention

In standard chip design practice, work on wire layout stops as soon as the signal connections in a wire layout contain no violations and satisfy the project cycle time requirement. Since the completion of this work typically occurs before the deadline to transfer the layout to manufacturing, an opportunity exists to improve the layout characteristics further. In this case, the question to address is: to what extent is an additional *trial* likely to improve the design quality? One can decide to proceed with an additional trial if the cumulative effectivenesses of physical characteristics of interest are likely to improve; note that the proposed trial can improve some characteristics and degrade others. Tools to forecast the effects of additional external intervention can be most useful in this context. We have developed a statistical-based framework for physical design to forecast the potential effect of custom interconnect design on physical properties of routes. This framework provides designers with quantitative metrics of their efforts and with the ability to direct and plan additional efforts.

In this framework, we represent the estimated total effect for netlengths with the variable $\hat{\mu}_L^{(n+1)}$. The underlying mean effectiveness, $\mu_L^{(n+1)}$, is a function of the basic parameters; its estimate can be obtained in terms of $(\hat{\mu}_{L_c}, \hat{\mu}_{L_o}, \hat{\mu}_{L_r})$ from all previous trials $1, 2 \ldots n$. Furthermore, one can forecast the total netlength $L^{(n+1)}$ in the next trial $(n+1)$ with the expression,

$$L^{(n+1)} = L_c^{(n)} + \Delta L_t^{(n)}(R_{(n+1)})(1-\hat{\mu}_{L_c}) + L_o^{(n)}(R_{(n+1)})(1-\hat{\mu}_{L_o}) + L \tag{10}$$

where $R_{(n+1)}$ is the region of influence projected to contain additional custom interconnections $\Delta N_c^{(n+1)}$[**?**].

With this framework, one can forecast whether the proposed trial $(n+1)$ should be attempted and whether this trial has a reasonable chance to improve physical properties of the design routes. In particular, the projected value of the total netlength $L^{(n+1)}$ is compared with the value $L^{(n)}$ of trial n to ascertain whether intervention in trial $(n+1)$ with proposed custom interconnections will further reduce the total cumulative length of the design interconnections.

In practice, a decision to proceed with an additional trial will not be made from predictions of netlength alone; the forecasted effect on other physical characteristics, such as the total number of vias, can be obtained with the same approach. The projected effect on these characteristics also needs to be considered and might point to an opposite conclusion. In this case, a decision to proceed must consider all projected changes in relevant physical characteristics of the layout. An example of this situation is discussed in the next section of this paper. In the following discussion, the *p-value* for netlengths in the projected trial $(n+1)$ is represented by the variable $p\text{-}value(\mu_L^{(n+1)})$. The 95% Lower Confidence Bound (LCB) for $\mu_L^{(n+1)}$ is represented by $LCB_{0.95,\mu_L^{(n+1)}}$.

5. Application to POWER4 Instruction Fetch Unit

We now apply the statistical framework described in the preceeding sections to the problem of routing a functional unit of the IBM POWER4 microprocessor[16, 17, 18, 19].

5.1 External intervention

An automated route tool[20] is not able to route three congested regions of the POWER4 Instruction Fetch Unit (IFU) without introducing violations in some of the signal routes. We refer to the congested regions as 1, 2, and 3 in the following discussion. Figure 2 shows that the largest number of violations (electrical shorts and design rule violations) occurs for $N_c = 0$ where the automated route tool operates without external intervention. To assist the route tool, custom interconnections are added for signals with large *NESL* in the congested regions according to the procedure described in Section III.

Figure 3 shows the total length L_T and total Steiner length L_{TS} for IFU interconnections as a function of the number of custom interconnections N_c (lower abscissa) and the fraction of custom interconnections N_c/N (upper abscissa). This figure shows that L_T is reduced for signals targeted for custom interconnections as N_c is increased. For $N_c/N = 0.37$, the total interconnect length is reduced by approximately 25mm (0.5%). Figure 4 shows *TESL* as a function of N_c and N_c/N. For $N_c/N = 0.37$, the figure shows that *TESL* is reduced by 13%.

Figure 5 shows $\langle NESL \rangle$ for signals targeted for custom interconnections in three congested regions as a function of N_c (lower abscissa) and N_c/N (upper abscissa). The solid dots in the figure indicate external intervention. Figure 5 shows that the external intervention is immediately effective in Region 3, where custom routes are introduced in trial 3 as shown by the red circular dot. In Region 2, the first external intervention occurs in trial 2, and the second external intervention occurs in trial 5, as shown

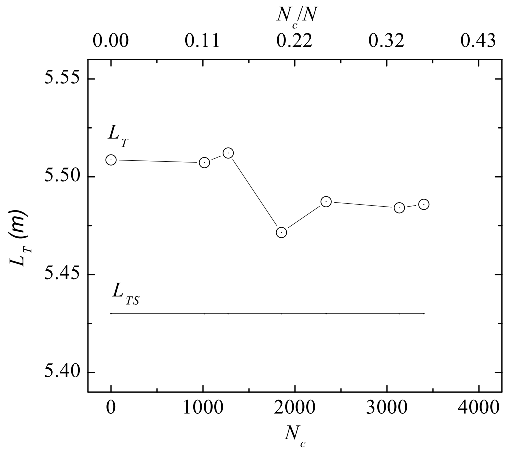

Figure 3: Total interconnect length L_T (*meters*) of all N IFU signals as a function of N_c (lower abscissa) and fraction of custom interconnections N_c/N (upper abscissa). $L_{TS} = 5.43$ *meters* is the Steiner limit.

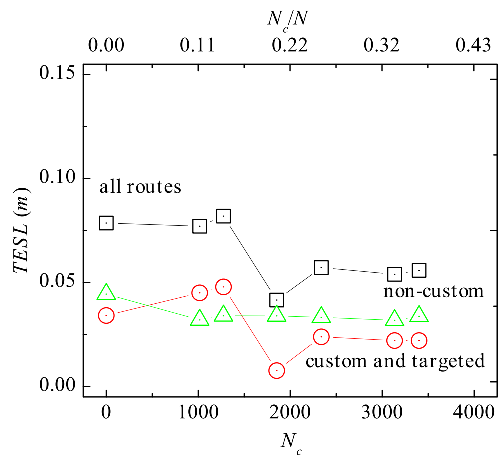

Figure 4: *TESL* (*meters*) for all N signals, signals targeted for custom interconnections, and signals with non-custom interconnections as a function of the number of custom interconnections N_c (lower abscissa) and fraction of custom interconnections N_c/N (upper abscissa).

by the green hexagonal dots; the latter is more effective. As a result, $\langle NESL \rangle$ is reduced from 0.02 to 0.01 in Region 2 and from 0.055 to 0.02 in Region 3. In Region 1, the effect of the external intervention is not immediately visible, and $\langle NESL \rangle$ remains approximately constant at 0.02 as N_c increases because the overall length of the custom interconnections is approximately equal to the overall netlength of the automated routes in this region.

During external intervention, the total interconnect length can increase, as indicated in Fig. 3 at trial 2. In addition, the observed effectiveness for some characteristics can be negative, as shown for netlengths in Fig. 6 at trial 2. These observations can occur as a result of statistical fluctuations; recall that the goal of the process is to achieve a wire layout with zero violations as opposed to minimal netlength. Reduction in total interconnect length or number of vias or both is a useful by-product of the external intervention and can predict the degree of success toward achieving the goal, but is not a goal itself. Even if the goal is achieved, and if a decision is made to continue the collaboration, the new focus is on other design properties, such as yield and performance. A reduction in total netlength or number of vias or both is primarily of interest because this reduction is associated with better design properties.

As discussed in the next section, the main benefit of the collaborative effort for this particular design layout is a reduction in the number of vias as opposed to reduction in the netlength. In essence, the message is that the collaborative effort enables one to reduce significantly the number of vias without paying a penalty in terms of increased netlength.

5.2 Statistical model

Custom interconnections are added in the IFU in six trials (n=6). Complete details are in [?]. Associated with each trial is a different number of custom interconnections N_c and different region of influence R_i. Tables 1 and 2 show that the estimated effect of custom interconnections is distinctly positive with 6.7% effectiveness and 95% LCB of +2.2%. The effect is statistically significant as the associated *p-value*$(\mu_{L_c}) = 0.051\%$. For the other routes that pass through R_i, the effectiveness is -2.4% with *p-value*$(\mu_{L_o}) = 0.039 < 0.05$; this result indicates evidence that routes in R_i are negatively affected by the custom route activity. The magnitude of this impact can be characterized by the confidence interval for μ_{L_o} of $[-4.5\%, -0.18\%]$. Although netlengths of other signals are increased, the longer routes of these signals do not negatively affect other design requirements, such as signal timing requirements. For the rest of the routes that do not pass through R_i, the estimated effect is $\tilde{\mu}_{L_r} = -0.074\%$ with standard error 0.091% (In this discussion, $\tilde{\mu}$ is used instead of $\hat{\mu}$ to designate values of estimators that are actually measured from our data). There is no evidence of negative impact caused by the custom routing activity since the *p-value*$(\mu_{L_r}) = 0.46 > 0.05$. The 95% confidence interval for μ_{L_r} is $[-0.31\%, 0.16\%]$.

Tables I and II indicate that external intervention with custom interconnections has a strong positive effect on the number of vias in R_i. For example, the number of vias is reduced by 65.4% in signal routes targeted for custom interconnections; this effect is statistically significant as the associated *p-value*$(\mu_{v_c}) = 0.000013\%$; the 95% LCB is 56.5% >> 0. For other routes and the rest of the routes, there is no evidence of negative impact caused by the custom routing activity. For the other routes, the estimated effect is $\tilde{\mu}_{v_o} = -4.1\%$ with standard error 2.2%, resulting in *p-value*$(\mu_{v_o}) = 0.12 > 0.05$; the 95% confidence interval for μ_{v_o} is $[-9.7\%, 1.5\%]$. For the rest of the routes, the estimated effect is $\tilde{\mu}_{v_r} = 0.09\%$ with standard error 0.43%, resulting in *p-value*$(\mu_{v_r}) = 0.85 > 0.05$; the 95% confidence interval for μ_{v_r} is $[-1.0\%, 1.2\%]$.

Figures 6(a) and 6(b) show the cumulative effectivenesses for netlengths $\epsilon_L^{(i)(0)}$ and vias $\epsilon_v^{(i)(0)}$, respectively, for trials $i = 1, 2, \ldots, 6$ as well as for projected trial 7. The figure shows that the cumulative effectivenesses for netlengths and vias tend to increase with each additional trial $i = 1, 2, \ldots, 6$ and reach 0.41% and 19.3%, respectively, at trial $i = 6$. For projected trial $i = n + 1 = 7$, Fig. 6 shows that the value for cumulative effectiveness is approximately constant for vias and is reduced for netlengths. The forecasted reduction for netlengths is predicted primarily because of the negative value of $\hat{\mu}_{L_o}$ and large value of the domain of impact $L_o^{(6)}$. In this situation, since there is a conflict between the projected results for netlengths and vias, the question that arises at trial 6 is whether to proceed with trial 7? In order to answer this question, we can decide to act in accordance with one of several policies. For example, one policy is to proceed only if we see strong evidence for improvement in the projected trial; another possible policy is to proceed unless there is evidence that the result would be worse. In both cases, the decisions whether to proceed are primarily based on the *p-values* of the projected effectivenesses.

Table 3 summarizes the projected results for proposed trial $i = 7$; the table shows a negative projected mean effectiveness for netlengths and a positive projected mean effectiveness for vias. The table

Table 1: Effectiveness of external intervention for trials $i = 1, 2, \ldots, 6$ in the Instruction Fetch Unit. For netlengths L (upper half of the table): $\epsilon_{L_c}^{(i)}$, $\epsilon_{L_o}^{(i)}$, $\epsilon_{L_r}^{(i)}$, $\epsilon_{L}^{(i)}$ (%) with the corresponding values for $\Delta L_t^{(i-1)}$, $L_o^{(i-1)}$, $L_r^{(i-1)}$, $L^{(i-1)}$ (*meters*). For vias V (bottom half of the table): $\epsilon_{v_c}^{(i)}$, $\epsilon_{v_o}^{(i)}$, $\epsilon_{v_r}^{(i)}$, $\epsilon_{v}^{(i)}$ (%) with the corresponding values for $\Delta v_t^{(i-1)}$, $v_o^{(i-1)}$, $v_r^{(i-1)}$, $v^{(i-1)}$.

L	custom interconnect		other routes		rest of routes		all routes	
i	$\epsilon_{L_c}^{(i)}$	$\Delta L_t^{(i-1)}$	$\epsilon_{L_o}^{(i)}$	$L_o^{(i-1)}$	$\epsilon_{L_r}^{(i)}$	$L_r^{(i-1)}$	$\epsilon_{L}^{(i)}$	$L^{(i-1)}$
1	9.2	1.05	−4.5	1.78	−0.57	2.68	0.027	5.51
2	7.0	0.163	−1.3	1.14	−0.064	4.20	−0.11	5.51
3	7.7	0.52	−0.19	0.100	0.013	3.78	0.92	5.51
4	−13.0	0.13	−1.2	0.24	0.099	3.53	−0.40	5.47
5	5.3	0.061	0.0043	0.50	−0.0012	3.20	0.086	5.49
6	−4.3	0.23	−1.4	0.83	−0.026	2.64	0.051	5.48
V	custom interconnect		other routes		rest of routes		all routes	
i	$\epsilon_{v_c}^{(i)}$	$\Delta v_t^{(i-1)}$	$\epsilon_{v_o}^{(i)}$	$v_o^{(i-1)}$	$\epsilon_{v_r}^{(i)}$	$v_r^{(i-1)}$	$\epsilon_{v}^{(i-1)}$	$v^{(i-1)}$
1	69	7630	−1.7	26210	−2.1	32515	6.2	66355
2	59	2016	−7.3	16109	0.44	41730	0.34	62255
3	65	8327	−0.52	1162	0.80	49339	9.8	62052
4	25	1119	0.66	2290	0.088	46702	0.67	56279
5	78	2682	2.7	5048	−0.41	41206	4.2	55946
6	73	976	−16	5181	1.1	40129	0.71	53892

also shows that there is strong evidence for negative impact on netlengths. In fact, the probability to measure $\tilde{\mu}_L^{(7)} \leq -1.0$ under the assumption that there is no negative impact is smaller than $1-$ *p-value*$(\mu_L^{(7)}) = 1 - 0.996 = 0.004$. Therefore, if we act in accordance with the second policy, we do not proceed with trial 7. This conclusion is also reached under the first policy; in fact, for the observed data, one does not even need *p-values* to establish that there is no evidence for strong improvement in the projected trial. Therefore, we decided not to add the projected custom routes to the design layout, and declare the design layout complete at trial $n = 6$. Complete details are in [?].

6. Discussion

The approach presented in this paper is an initial attempt to formalize interactions in a collaborative effort geared to achieving a certain goal. It is quite likely that some of the assumptions made in developing this approach will need modification for more complex forms of interaction; such modifications can either be developed empirically or with detailed knowledge about the nature of the interaction. With statistical methods for monitoring model adequacy and simulation analysis, one should be able to arrive at models that are useful for a problem of interest and examine the effects of possible model mis-specification or violation of the basic assumptions.

The problem of wire route configurations that we choose to illustrate the proposed methodology appears to be one for which potential long-term benefits can be substantial. Because of increasing design complexity, it is generally difficult for routing programs to achieve a routable design layout within specified constraints such as geometry, real estate or critical area, as well as multiple objectives imposed by current engineering requirements. Furthermore, if a router fails to produce an acceptable design layout, it is typically impossible to determine whether this failure occurs because of shortcomings of its own algorithm or because no routable design layouts exist.

7. Conclusions

To illustrate a collaborative system in which several contributors strive to achieve a goal, we consider a specific example of interaction between an automated route program and a supplemental prerouting algorithm. The statistical framework that we introduce to assist computer-aided design tools in typical design processes should be applicable for other problems involving collaborative efforts. The relevant class of problems consists of those problems

Table 2: Estimated effectiveness of external intervention in the Instruction Fetch Unit. The *mean effectiveness*, *standard error*, *p-value*, *lower confidence bound LCB*, and *upper confidence bound UCB* are shown for custom interconnections, the other routes, and the rest of the routes in %. The confidence intervals have 95% coverage; for μ_{L_c} and μ_{v_c}, only the lower 95% bound is given.

Netlengths	*mean(%)*	*std. error(%)*	*p-value*	$LCB(\%)$	$UCB(\%)$
custom	$\tilde{\mu}_{L_c} = 6.7$	$\hat{\sigma}(\hat{\mu}_{L_c}) = 2.3$	0.015	2.2	–
other	$\tilde{\mu}_{L_o} = -2.4$	$\hat{\sigma}(\hat{\mu}_{L_o}) = 0.85$	0.039	−4.5	−0.18
rest	$\tilde{\mu}_{L_r} = -0.074$	$\hat{\sigma}(\hat{\mu}_{L_r}) = 0.091$	0.46	−0.31	0.16
Vias	*mean(%)*	*std. error(%)*	*p-value*	$LCB(\%)$	$UCB(\%)$
custom	$\tilde{\mu}_{v_c} = 65.4$	$\hat{\sigma}(\hat{\mu}_{v_c}) = 4.4$	0.000013	56.5	–
other	$\tilde{\mu}_{v_o} = -4.1$	$\hat{\sigma}(\hat{\mu}_{v_o}) = 2.2$	0.12	−9.7	1.5
rest	$\tilde{\mu}_{v_r} = 0.085$	$\hat{\sigma}(\hat{\mu}_{v_r}) = 0.43$	0.85	−1.0	1.2

Table 3: Projected effectiveness of external intervention in the Instruction Fetch Unit. The projected effectiveness, *standard error*, *p-values*, and 95% *lower confidence bounds* (*LCBs*) are shown for netlengths and vias for the proposed trial $i = n + 1 = 7$.

All nets	*mean(%)*	*standard error(%)*	*p-value*	$LCB(\%)$
Netlengths	$\hat{\mu}_L^{(7)} = -1.0$	$\hat{\sigma}(\hat{\mu}_L^{(7)}) = 0.24$	*p-value*$(\mu_L^{(7)}) = 0.996$	−1.5
Vias	$\hat{\mu}_v^{(7)} = 0.10$	$\hat{\sigma}(\hat{\mu}_v^{(7)}) = 0.75$	*p-value*$(\mu_v^{(7)}) = 0.45$	−1.4

in which contributors seek to achieve a goal by proceeding one step at a time without interfering with each other.

In high technology industries, collaborative solutions to complex problems involve the participation of highly skilled personnel and sophisticated computer programs. This work is a preliminary attempt to establish a mathematical framework for formalizing the interaction of these entities and for optimizing these interactions.

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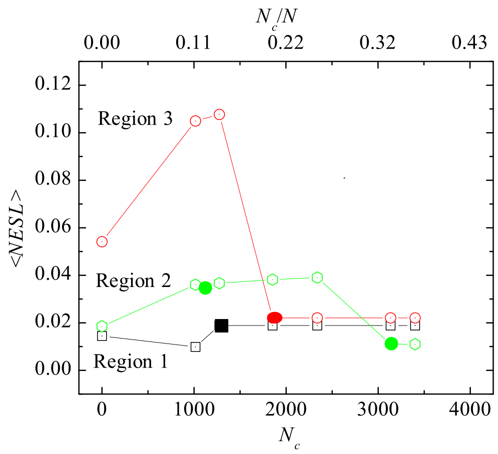

Figure 5: Average normalized excess Steiner length $\langle NESL \rangle$ for IFU signals that are targeted for custom routes as a function of N_c (lower abscissa) and fraction of custom interconnections N_c/N (upper abscissa) in three congested regions. For Region 1, the solid black square dot indicates external intervention in trial 2. For Region 2, the solid green hexagonal dots indicate external intervention in trials 1 and 5. For Region 3, the solid red circular dot indicates external intervention at trial 3.

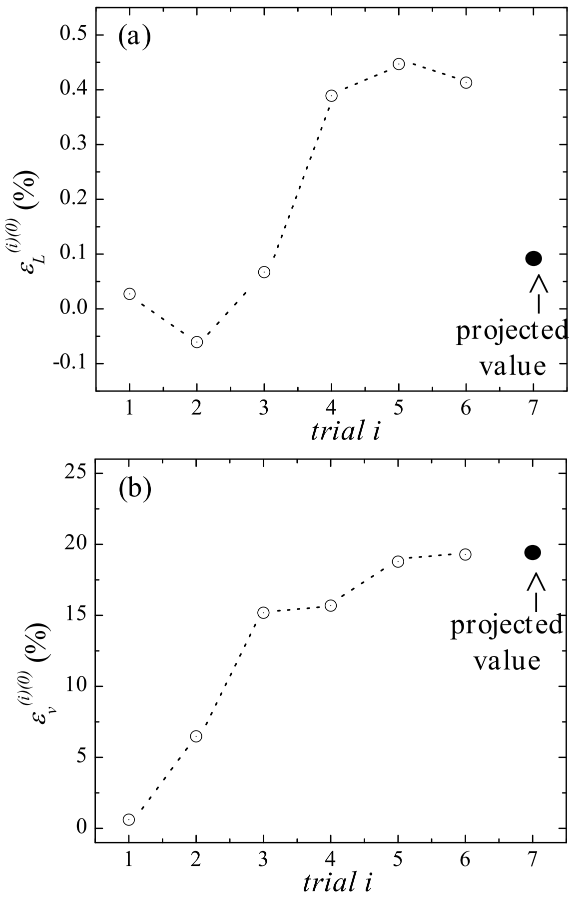

Figure 6: Measured cumulative effectivenesses for netlengths (a) $\epsilon_L^{(i)(0)}$ and for vias (b) $\epsilon_v^{(i)(0)}$ in the IFU for each trial $i = 1, 2, \ldots, 6$. The solid dots show the projected values of cumulative effectiveness in trial $i = 7$ for netlengths (a) and vias (b).

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