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The impact of predictive inaccuracies on execution scheduling

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Abstract

This paper investigates the underlying impact of predictive inaccuracies on execution scheduling, with particular reference to execution time predictions. This study is conducted from two perspectives: from that of job selection and from that of resource allocation, both of which are fundamental components in execution scheduling. A new performance metric, termed the degree of misperception, is introduced to express the probability that the predicted execution times of jobs display different ordering characteristics from their real execution times due to inaccurate prediction. Specific formulae are developed to calculate the degree of misperception in both job selection and resource allocation scenarios. The parameters which influence the degree of misperception are also extensively investigated. The results presented in this paper are of significant benefit to scheduling approaches that take into account predictive data; the results are also of importance to the application of these scheduling techniques to real-world high-performance systems.

Keywords: Performance prediction; Execution time; Scheduling; Job selection; Resource allocation; Performance evaluation

1. Introduction

Scheduling in a single processor environment consists, at its most basic level, of determining the sequence in which jobs should be executed. In a multi-processor or multi-computer environment, job scheduling also involves the process of resource allocation, that is, determining the resources to which a job should be sent for execution. The design of scheduling policies for parallel and distributed systems is the subject of a good deal of research [2,4,5,14,15]. These schemes are often based on the assumption that job execution times are known [5,9]. This information must therefore be obtained using some kind of predictive mechanism. A naïve approach might require the owner of the task to estimate the

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resource requirements; a more sophisticated technique would be to use performance prediction tools for this purpose. A number of increasingly accurate prediction tools have been developed that are able to predict the resource requirements (including execution time) of jobs using performance models [3,6–8] or historical data [1,13].

In spite of this, it is inevitable that the prediction data is unlikely to be entirely accurate, which may have a fundamental impact on job selection and resource allocation.

In the case of job selection, an inaccurate prediction may mean that the scheduler has an incorrect perception of the order in which the different jobs should execute. For example, it may be the case that the real execution time of job J_1 is greater than that of job J_2, but because of the inaccurate prediction the scheduler may view job J_1 as having a shorter execution time than job J_2. If the scheduling policy is based on job execution times (the shortest job serviced first, for example), then this misperception will impact on the order in which jobs are selected for execution. This will ultimately influence the scheduler and system performance.

When a scheduler receives a job in a parallel or distributed system, there may be a number of resources (processors or computers) available on which the job may be executed. If the resource allocation policy is also based on the expected execution time of the job on the different resources (select the computer that offers the shortest execution time, for example) then these inaccuracies might also cause the scheduler to make an erroneous choice. Again, this misperception will impact on the scheduling and system performance.

Misperception arises from the inaccurate prediction of, in this case, execution time and should be viewed as an inherent characteristic of any prediction-based scheduling scheme that operates in a complex, highly variable real-world system. This said, different scheduling policies would have different levels of sensitivity to the degree of misperception. Thus, the impact of inaccurate prediction on scheduling performance can be considered at two levels: firstly, at an underlying level, the degree of misperception originating from inaccurate prediction and secondly, at a higher level, the sensitivity of individual scheduling policies to this degree of misperception. This paper addresses the former, where the latter is the subject of future work.

Different prediction errors will lead to different degrees of misperception. This paper establishes the relationship between the predicted error and the degree of misperception in the context of job selection and resource allocation. This study provides an insight into the underlying impact of inaccurate prediction on job selection and resource allocation and in so doing significantly benefits the design and evaluation of scheduling policies that make use of predictive data.

The remainder of this paper is organized as follows. A formal analysis of the degree of misperception for job selection and resource allocation is presented in Section 2. The parameters that influence the degree of misperception are extensively evaluated using a selection of case studies; these case studies, together with supporting results, are presented in Section 3. The paper concludes in Section 4.

2. An analysis of the degree of misperception

2.1. Job selection

When performance prediction tools are used to estimate the execution times of jobs, the predicted execution time usually lies in an interval around the actual execution time (of the job) according to some probability distribution [7,8].

Suppose that the actual execution time of job J_i is x_i and that the predictive error, denoted by y_i, is a random variable in the range $[-ax_i, bx_i]$ following some probability density function, $g_i(y_i)$, where the possible value fields of a and b are [0, 100%] and $[0, \infty]$, respectively. It is assumed that the predictive errors of different jobs are independent random variables. The predicted execution time of job J_i, denoted by z_i, is computed using Eq. (1).

$$z_i = x_i + y_i \tag{1}$$

The predictive error (y_i) and the actual execution time (x_i) may follow any probability distribution, therefore, the relation between the predicted execution time (z_i) and the actual execution time is expressed linearly (in Eq. (1)). The aim therefore is to present general formula for the calculation of the degree of misperception, where the general form for the probability density functions of x_i and/or y_i can take on any specific expression from their respective application scenarios. The benefit of this approach is to broaden the general applicability of the research.

Within this framework, suppose two jobs J_1 and J_2 have the actual execution times x_1 and x_2, where $x_1 < x_2$. The predicted execution times of J_1 and J_2, that is z_1 and z_2, are therefore $x_1 + y_1$ and $x_2 + y_2$, respectively. Given that $x_1 < x_2$, a misperception occurs if $z_1 \geq z_2$. The degree of misperception for these two jobs, represented as MD (x_1, x_2), is defined by the probability that $z_1 \geq z_2$ while $x_1 < x_2$. This probability is denoted by $P_r(z_1 \geq z_2 | x_1 < x_2)$. Using Eq. (1), this probability can be further transformed:

$$P_{\mathrm{r}}(z_1 \geq z_2 | x_1 < x_2) = P_{\mathrm{r}}(x_1 + y_1 \geq x_2 + y_2 | x_1 < x_2) = P_{\mathrm{r}}(y_1 \geq y_2 + x_2 - x_1 | x_2 - x_1 > 0) \tag{2}$$

so that MD(x_1, x_2) is computed using

$$\mathrm{MD}(x_1, x_2) = P_{\mathrm{r}}(y_1 \geq y_2 + x_2 - x_1 | x_2 - x_1 > 0) \tag{3}$$

Eq. (3) demonstrates that the probability that a misperception occurs is the probability that given $x_2 - x_1 > 0$, the predictive error of J_1 (i.e., y_1) is greater than the predictive error of J_2 (i.e., y_2) plus the difference between x_2 and x_1. By constructing the coordinates of the predictive error y_1 and y_2, the inequality $y_1 \geq y_2 + x_2 - x_1$ means that y_1 and y_2 are given values from the area above the line $y_1 = y_2 + x_2 - x_1$.

Figs. 1a, 2a and 3a illustrate the relationship between the predicted execution times for J_1 and J_2; Figs. 1b, 2b and 3b show the corresponding value fields of the predictive error of J_1 and J_2 (y_1 and y_2) and the corresponding area in which $y_1 \geq y_2 + x_2 - x_1$.

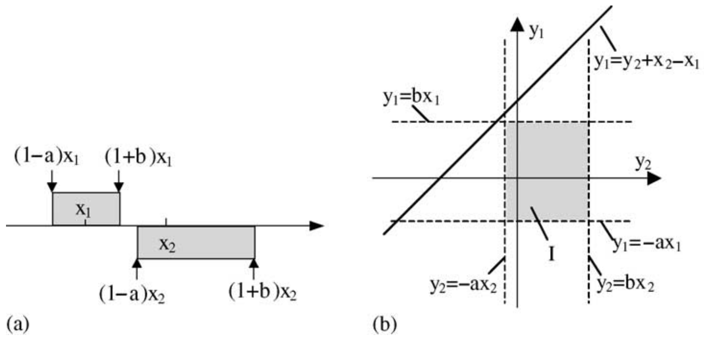

Fig. 1. (a) The predicted execution times of jobs J_1 and J_2 do not overlap and (b) the corresponding coordinate area from which the predictive errors y_1 and y_2 can be assigned values.

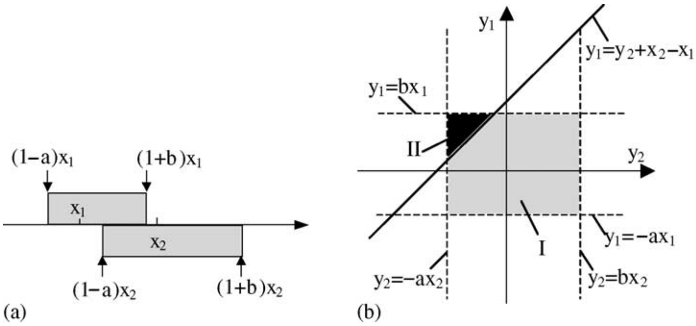

Fig. 2. (a) The predicted execution times of jobs J_1 and J_2 overlap, but the lower limit of the predicted execution time for J_2 does not cover x_1 and (b) the corresponding coordinate area of predicted errors of J_1 and J_2 (y_1 and y_2) in which the misperception occurs (the area is a triangle).

Fig. 1a illustrates the case when the ranges of predicted execution times of J_1 and J_2 do not overlap. In this case a misperception will not occur even if the predictions are not accurate. Fig. 1b shows the corresponding coordinate area of the predicted errors of J_1 and J_2 (area I), which is the area surrounded by the lines $y_1 = -ax_1$, $y_1 = bx_1$, $y_2 = -ax_2$ and $y_2 = bx_2$. As can be seen from the figure, all of area I is below the line $y_1 = y_2 + x_2 - x_1$. Hence, $P_r(y_1 \geq y_2 + x_2 - x_1 | x_2 - x_1 > 0)$ in Eq. (2) is equal to zero. This case is expressed more formally below:

$$\begin{aligned} &P_r(y_1 \geq y_2 + x_2 - x_1 | x_2 - x_1 > 0) = 0 \\ &\quad -ax_2 > -bx_1 + x_2 - x_1, \quad x_2 - x_1 > 0 \end{aligned} \tag{4}$$

Fig. 2a illustrates the case when the predicted execution times of J_1 and J_2 overlap and the lower limit of the predicted execution time of J_2 is greater than x_1. The corresponding coordinate area of y_1 and y_2 is shown in Fig. 2b (area I); part of this area is above the line $y_1 = y_2 + x_2 - x_1$ (area II), which is itself surrounded by the three lines $y_1 = bx_1$, $y_2 = -ax_2$ and $y_1 = y_2 + x_2 - x_1$. When y_1 and y_2 are assigned values from area II, y_1 and y_2 satisfy $y_1 \geq y_2 + x_2 - x_1$ and a misperception will occur; a misperception will not occur if y_1 and y_2 are assigned values from any other area in I, although prediction errors will still exist. The probability in Eq. (2) is equal to the double integral of the probability density functions of predicted

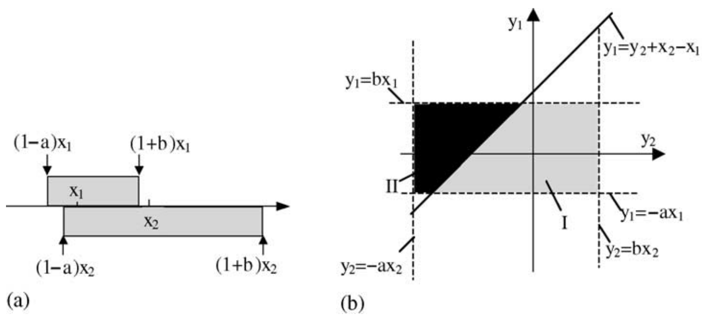

Fig. 3. (a) The predicted execution times of jobs J_1 and J_2 overlap and the lower limit of the predicted execution time for J_2 covers x_1 and (b) the corresponding coordinate area of predicted errors of J_1 and J_2 (y_1 and y_2) in which the misperception occurs (the area is a trapezoid).

errors (i.e., $g_1(y_1)$ and $g_2(y_2)$) in area II and is calculated using Eq. (5).

$$P_{\rm r}(y_1 \geq y_2 + x_2 - x_1 | x_2 - x_1 > 0) = \int_{-ax_2+x_2-x_1}^{bx_1} \int_{-ax_2}^{y_1-(x_2-x_1)} g_1(y_1)g_2(y_2)\mathrm{d}y_2\mathrm{d}y_1$$
$$-ax_1 - (x_2 - x_1) < -ax_2 \leq bx_1 - x_2 - x_1), \quad x_2 - x_1 > 0 \tag{5}$$

Fig. 3a illustrates a second case when the predicted execution times of J_1 and J_2 overlap. It differs from Fig. 2a in that the value field of J_2's predicted execution time covers x_1. The corresponding coordinate area in which y_1 and y_2 satisfy $y_1 \geq y_2 + x_2 - x_1$ is a trapezoid and is highlighted in area II (in Fig. 3b). The formula for calculating the probability in Eq. (2) differs from Eq. (5), that is

$$P_{\rm r}(y_1 \geq y_2 + x_2 - x_1 | x_2 - x_1 > 0) = \int_{-ax_1}^{bx_1} \int_{-ax_2}^{y_1-(x_2-x_1)} g_1(y_1)g_2(y_2)\mathrm{d}y_2\mathrm{d}y_1$$
$$-ax_2 \leq ax_1 - (x_2 - x_1), \quad x_2 - x_1 > 0 \tag{6}$$

Eqs. (4)–(6) account for all possible relations between the predicted execution times of jobs J_1 and J_2.

If the probability density function of a job's actual execution time in a job stream is $f(x)$ and the value field of the real execution time x is $[xl, xu]$, then the degree of misperception of this job stream, denoted by $\overline{\mathrm{MD}}$, is defined by the average of the degree of misperception for any two jobs in the job stream. $\overline{\mathrm{MD}}$ is computed using Eq. (7), where $\mathrm{MD}(x_1, x_2)$ is derived from Eqs. (4)–(6).

$$\overline{\mathrm{MD}} = \int_{xl}^{xu} \int_{x_1}^{xu} f(x_1) f(x_2) \mathrm{MD}(x_1, x_2)\mathrm{d}x_2\mathrm{d}x_1 \tag{7}$$

There are several independent parameters in Eqs. (4)–(7), including a, b, xu, xl, $f(x)$, and $g_i(x_i)$. It is highly beneficial to study how these parameters influence the value $\overline{\mathrm{MD}}$; this is the subject of the investigation presented in Section 3.

2.2. Resource allocation

In dedicated environments, the execution time of a single unit of work can be represented as a predicted point value [10–12]. However, in non-dedicated environments, the existence of background workloads on the resources causes a variation in unit execution times [3,10–12]. Hence, it can be assumed that the actual execution time of one unit of work locates across a range around the predicted point value following a certain probability [10,12,16].

Suppose a distributed system consisting of n heterogeneous computers $c_1, c_2, \ldots, c_n$, where computer c_i is weighted w_i $(1 \leq i \leq n)$, which represents the time it takes to perform one unit of computation. Now suppose for any i, j $(1 \leq i, j \leq n)$, $w_i < w_j$ if $i < j$. A job with size s is therefore predicted to have the execution time sw_i on computer c_i. The predicted execution time of a job is denoted by z_{c_i}, that is

$$z_{c_i} = sw_i \tag{8}$$

However, in shared environments this might not be the case because of the existence of background workload. The actual execution time of a job on c_i is therefore denoted by x_{c_i}.

For a job with size s, its predicted error on computer c_i, denoted by y_{c_i}, is computed using

$$y_{c_i} = z_{c_i} - x_{c_i} \tag{9}$$

Suppose y_{c_i} falls in the range $[-sw_i \times a, sw_i \times \mathrm{b}]$ following the probability density function $g_{c_i}(y_{c_i})$. Hence, x_{c_i} locates in the range $[sw_i \times (1-a), sw_i \times (1+b)]$.

For two computers c_i and c_j, suppose that $w_i < w_j$. The predicted execution time of a job with size s on c_i and c_j therefore satisfies $sw_i < sw_j$. However, the range of the job's actual execution time on computer c_i is $[sw_i \times (1-a), sw_i \times (1+b)]$ and may overlap with that on computer c_j, which is $[sw_j \times (1-a), sw_j \times (1+b)]$.

Consequently, the actual execution time on computer c_i may be greater than that on c_j. In this case, the inaccurate predictions cause a misperception in the order of the actual execution times on these two computers. Depending on the individual scheduling algorithm, this misperception may lead to the wrong resource being selected for the job. Similarly, the degree of misperception for a job with size s on two computers c_i and c_j, denoted by $\mathrm{MD_c}(c_i, c_j)$, is defined by the probability that $x_{c_i} \geq x_{c_j}$ while $z_{c_i} < z_{c_j}$. This probability is denoted using $P_\mathrm{r}(x_{c_i} \geq x_{c_j} | z_{c_i} < z_{c_j})$, which can be further transformed using Eq. (10), and Eqs. (8) and (9).

$$\begin{aligned} P_\mathrm{r}(x_{c_i} \geq x_{c_j} | z_{c_i} < z_{c_j}) &= P_\mathrm{r}(z_{c_i} - y_{c_i} \geq z_{c_j} - y_{c_j} | z_{c_i} < z_{c_j}) \\ &= P_\mathrm{r}(y_{c_j} \geq y_{c_i} + sw_j - sw_i | w_j - w_i > 0) \end{aligned} \tag{10}$$

That is, $\mathrm{MD_c}(c_i, c_j)$ is computed using

$$\mathrm{MD_c}(c_i, c_j) = P_\mathrm{r}(y_{c_j} \geq y_{c_i} + sw_j - sw_i | w_j - w_i > 0) \tag{11}$$

Applying a similar method to that used to compute $\mathrm{MD}(x_1, x_2)$, the equation for computing $\mathrm{MD_c}(c_i, c_j)$ is

$$\mathrm{MD_c}(c_i, c_j) = \begin{cases} 0 \quad bsw_j \leq -asw_i + s(w_j - w_i) \\ \int_{-asw_i}^{bsw_j - s(w_j - w_i)} \int_{yc_i + s(w_j - w_i)}^{bsw_j} g_{c_i}(y_{c_i}) g_{c_j}(y_{c_j}) \mathrm{d}y_{c_j} \mathrm{d}y_{c_i} \\ \quad -asw_i + s(w_j - w_i) < bsw_j < bsw_i + s(w_j - w_i) \\ \int_{-asw_i}^{bsw_i} \int_{yc_i + s(w_j - w_i)}^{bsw_j} g_{c_i}(y_{c_i}) g_{c_j}(y_{c_j}) \mathrm{d}y_{c_j} \mathrm{d}y_{c_i} \\ \quad bsw_j \geq bsw_i + s(w_j - w_i) \end{cases} \tag{12}$$

The degree of misperception for a job with size s for n heterogeneous computers $c_1, c_2, \ldots, c_n$, denoted by $\overline{\mathrm{MD}}_\mathrm{c}$, is defined using the average of the degree of misperception for the job on any two computers, which can be computed using

$$\overline{\mathrm{MD}}_\mathrm{c} = \frac{1}{C_n^2} \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \mathrm{MD_c}(c_i, c_j) \tag{13}$$

3. An evaluation of the degree of misperception

In Section 2 the general formula for calculating the degree of misperception for job selection and resource allocation were presented.

There exists no formal benchmark with which to test system performance with respect to metrics such as the degree of misperception. Further, the exploration in Section 2 presents general formula where the probability density functions of the actual execution time (x_i) and the predictive error (y_i) can take on any specific expression from their respective application scenarios. Hence, we present a series of

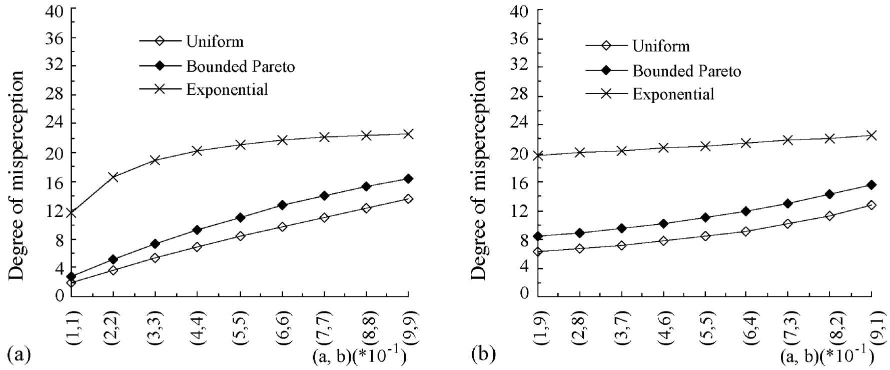

Fig. 4. Impact of the parameters a and b on $\overline{\mathrm{MD}}$: (a) the impact of the range size of predicted errors and (b) the impact of the range location of predicted errors.

case studies in which x_i and y_i are assigned specific probability distributions (with variable parameters) that represent realistic workload models according to different application scenarios (an approach also adopted in [10,15,16]). In this section a series of case studies are conducted, for which specific probability distributions are determined, that explore how the parameters in these formulae impact on the value assigned to the degree of misperception.

3.1. Job selection

The parameters a and b represent the range of predicted errors in Eqs. (4)–(6). Fig. 4a and b show the impact of the parameters a and b on the value $\overline{\mathrm{MD}}$. It is difficult to evaluate the impact of these parameters if the probability density function of predicted errors takes a general form. In the following parameter evaluation therefore, the predicted error for the execution time of x is assumed to follow a uniform distribution in $[-ax, bx]$, whose probability density function $g_x(y_x)$ is expressed as

$$g_x(y_x) = \frac{1}{(b+a)x}$$

Three types of job stream are investigated. The actual execution times in these job streams follow a uniform, Bounded Pareto and Exponential distribution, respectively. Their probability density functions $f(x)$ are shown in Table 1. The job execution times in the job stream following the exponential distribution have no upper limit. Only those execution time values in [10,14.6] need be considered, as according to the probability density function 99% of the execution times locate in this range. This simplification does not impact on the accuracy of the results.

Table 1
The range of job execution times in the three job streams

	Uniform	Bounded Pareto	Exponential
$f(x)$	$\dfrac{1}{xu - xl}$	$\dfrac{\alpha \times xl^{\alpha}}{1-(xl/xu)^{\alpha}} x^{-\alpha-1} (\alpha = 1)$	$\dfrac{1}{\beta} \mathrm{e}^{-(x-xl)/\beta} (\beta = 1)$
$[xl, xu]$	[10, 100]	[10, 40]	[10, 14.6]

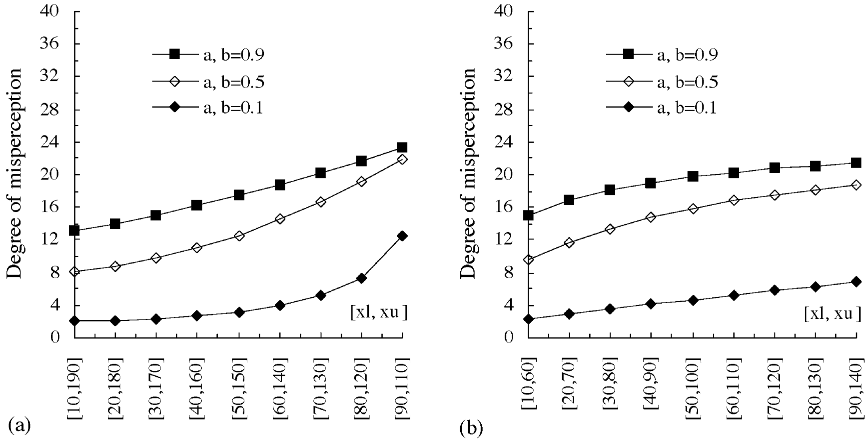

Fig. 5. The impact of actual execution times on the degree of misperception: (a) the impact of the range size of actual execution times and (b) the impact of the range location of actual execution times.

In Fig. 4a, *a* and *b* increase from 10% to 90% (in increments of 10%). This results in the range of predicted error for the actual execution time of *x* increasing from $[-0.1x, 0.1x]$ to $[-0.9x, 0.9x]$, while the average predicted error remains unchanged (at 0).

As can be observed in Fig. 4a, under all three probability distributions the degree of misperception increases as *a* and *b* increase. The reason for this is because as *a* and *b* increase, the predicted execution times of jobs have a higher probability of overlapping, leading to an overall increase in $\overline{\mathrm{MD}}$. This result suggests that when the average predicted error is the same, the range of predicted errors is critical to the value of $\overline{\mathrm{MD}}$.

It can also be observed that under the same *a* and *b*, the degree of misperception is highest under an exponential distribution; this decreases under a Bound Pareto distribution and is recorded at its lowest level under a uniform distribution. The rational behind this is that the size of the range of actual execution times is smallest when the execution times follow an exponential distribution and is largest when following a uniform distribution. This result implies that the actual execution times will also influence the degree of misperception. This is demonstrated in the case study presented in Fig. 5.

Fig. 4b shows that the range of predicted error for the actual execution time of *x* remains unchanged (at *x*), while the location of the range shifts towards the left from $[-0.1x, 0.9x]$ to $[-0.9x, 0.1x]$. The result of this is that the degree of misperception increases as the range location shifts leftwards (see Fig. 4b). The supposition for this is as follows. Consider Figs. 2a and 3a; when (a, b) is (0.1, 0.9), the range of predicted errors for x_1 and x_2 are $[-0.1x_1, 0.9x_1]$ and $[-0.1x_2, 0.9x_2]$, respectively. The size of the range where the predicted execution times for x_1 and x_2 overlap is therefore

$$0.9x_1 + 0.1x_2 - (x_2 - x_1)$$

However, when (a, b) is (0.9, 0.1), the range of predicted errors are $[-0.9x_1, 0.1x_1]$ and $[-0.9x_2, 0.1x_2]$, respectively, and the size of the overlapping ranges is therefore

$$0.9x_2 + 0.1x_1 - (x_2 - x_1)$$

Since x_2 is greater than x_1, hence

$$0.9x_1 + 0.1x_2 - (x_2 - x_1) < 0.9x_2 + 0.1x_1 - (x_2 - x_1)$$

we find that in general the size of the overlapping ranges is greater when (a, b) is (0.9, 0.1) than when (a, b) is (0.1, 0.9). This therefore leads to the increased degree of misperception. This result has an important implication in that compared with an overestimation of execution time, the same level of underestimation may result in a higher degree of misperception.

Fig. 5a and b shows the impact of actual execution times on the degree of misperception. The results show the data for the actual execution times following a uniform distribution; the results for the Bounded Pareto distribution display a similar pattern. This study does not consider execution times with an exponential distribution as their range size ($xu - xl$) is fixed when 99% of the execution times are considered.

Fig. 5a shows the impact of the size of the range of actual execution times (i.e., $xu - xl$). In this same figure, the average of the actual execution times remains the same (at 100) while the range size of execution times decreases from 180 to 20 (with decrements of 20). This experiment is conducted with different values for a and b and it can be observed (in Fig. 5a) that for the same values of a and b, the degree of misperception increases as the range size decreases. It is clear that as the range size of the actual execution times decrease, the value of $x_2 - x_1$ (in Figs. 2a or 3a) also decreases (on average) under the same a and b. As a result of this, the overlapping area of the two predicted execution times increases, which leads to an overall increase in $\overline{\mathrm{MD}}$. This result suggests that when the average execution times are the same, a greater variance in execution time is of benefit, as this will reduce the degree of misperception.

Fig. 5b demonstrates the impact of the location of the range of actual execution times. In Fig. 5b the range size of execution times remains constant (at 50) while the range shifts from [10, 60] to [90, 140]. As can be seen in Fig. 5b, the degree of misperception increases in all cases as the range location shifts from [10, 60] to [90, 140]. The reason for this is that as the range location shifts, the mean execution time increases. Under the same a and b, the larger the actual execution time, the greater the range of its predicted error. Consequently, corresponding predicted execution times have a higher probability of overlapping with each other, which then incurs a higher degree of misperception. This result shows that when other parameters remain constant, the job stream with the greater average execution time tends to cause the highest degree of misperception.

3.2. Resource allocation

In Eqs. (12) and (13), the parameters that determine $\overline{\mathrm{MD}}_c$ include the error range parameters a and b, the computer weight w_i and the probability density function of predicted errors $g_{c_i}(y_{c_i})$. In the following case study, the values of these parameters are as in Table 2 unless otherwise stated.

In the following figures, the predicted error for the execution time of x is also assumed to follow a uniform distribution in $[-asw_i, bsw_i]$, whose probability density function $g_{c_i}(y_{c_i})$ is expressed as follows:

Table 2
Default values for the experimental parameters

w_1	$w_i - w_{i-1}$ $(2 \le i \le n)$	n	s
10	5	6	50

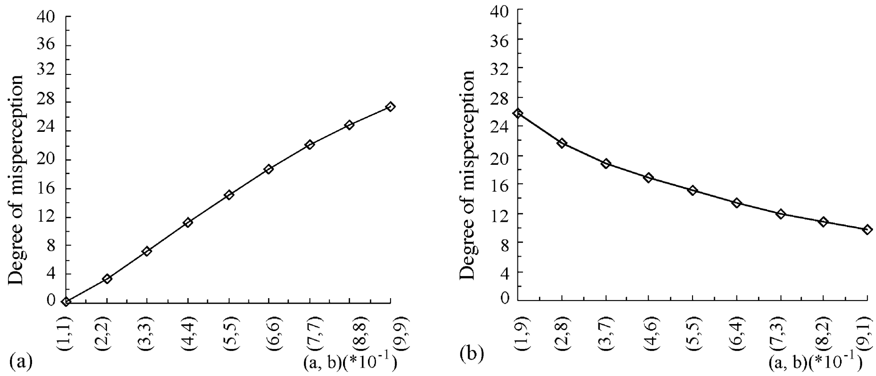

Fig. 6. Impact of the parameters a and b on $\overline{\mathrm{MD}}_\mathrm{c}$: (a) the impact of the range size of predicted errors and (b) the impact of the range location of predicted errors.

$$g_{c_i}(y_{c_i}) = \frac{1}{(b+a)sw_i}$$

The parameters a and b indicate the range of predicted error. Fig. 6a shows the impact of the range size on $\overline{\mathrm{MD}}_\mathrm{c}$. The result has a similar pattern to that seen in Fig. 4a, which suggests that the range size of predicted errors is also critical to the value of $\overline{\mathrm{MD}}_\mathrm{c}$. In a similar trend that that seen in Fig. 4b, Fig. 6b demonstrates the impact of the range location on $\overline{\mathrm{MD}}_\mathrm{c}$. In the study of resource allocation, $[sw_i(1-a), sw_i(1+b)]$ represents the range of actual execution times. Hence, the process where (a, b) shifts from (1, 9) to (9, 1) means that the predicted execution time sw_i changes gradually from an underestimate to an overestimate. Fig. 6b demonstrates that $\overline{\mathrm{MD}}_\mathrm{c}$ decreases as (a, b) shifts from (1, 9) to (9, 1). These results coincide with those seen in Fig. 4b, in that compared with an overestimate in execution time, the same level of underestimation may incur a higher degree of misperception.

Fig. 7a shows the impact of computer weight (or heterogeneity) on $\overline{\mathrm{MD}}_\mathrm{c}$. In Fig. 7a the weight difference between computer c_i and c_{i-1} is fixed (at 5). As w_1 increases (which represents a resource c_1 becoming

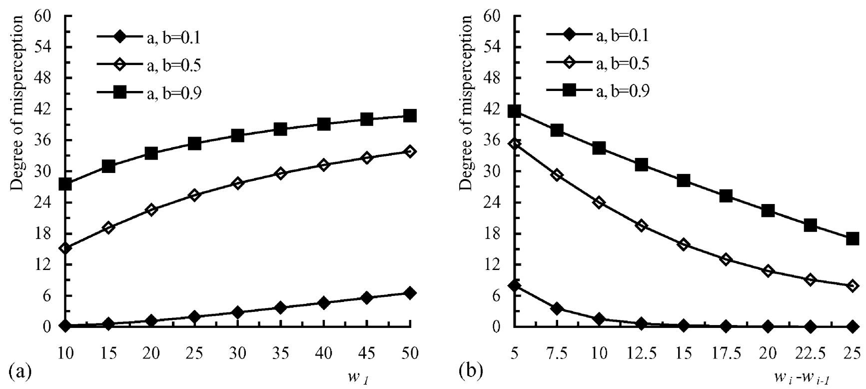

Fig. 7. The impact of computer weight (heterogeneity) on $\overline{\mathrm{MD}}_\mathrm{c}$: (a) the impact of the size of computer weights and (b) the impact of the weight difference between computers.

slower), the weights of the remaining computers increase. It can be observed in Fig. 7a that under all values of a and b, $\overline{\mathrm{MD}}_{\mathrm{c}}$ increases as w_1 increases. This is because as w_i increases, the range of the actual execution time ($[sw_i(1-a), sw_i(1+b)]$) also increases. This in turn increases the probability that the range of actual execution times on different computers overlap, which results in an increased $\overline{\mathrm{MD}}_{\mathrm{c}}$. This observation suggests that the use of slower computers will tend to generate higher degrees of misperception than the use of faster computers.

Fig. 7b demonstrates the impact of computer heterogeneity. In Fig. 7b, the difference between w_i and w_{i-1} ($2 \le i \le n$) increases while the mean computer weight remains constant (at 70). It can be observed from this figure that $\overline{\mathrm{MD}}_{\mathrm{c}}$ decreases as $w_i - w_{i-1}$ increases. The supporting hypothesis is that as $w_i - w_{i-1}$ increases, the difference between the predicted execution times on two computers c_i and c_j (i.e., $sw_j - sw_i$) also increases, which in turn reduces the probability that the ranges of their actual execution times overlap. This result implies that using resource pools with higher heterogeneity will result in a lower degree of misperception.

4. Conclusions

This paper documents the underlying impact of inaccurate prediction on job selection and resource allocation. A new performance metric, termed the degree of misperception, is introduced in order to facilitate this exposition. General formulae have been developed to calculate the degree of misperception for a variety of job streams and for distributed resource pools of varying levels of heterogeneity. The parameters that influence the degree of misperception are also investigated. This study underpins the design and evaluation of different scheduling mechanisms for parallel and distributed systems that take prediction into account. It is likely that different scheduling policies will have different levels of sensitivity to this degree of misperception. Further work is planned to investigate how individual scheduling policies and specific performance measures are affected by this new performance metric.

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References

[1] D.A. Bacigalupo, S.A. Jarvis, L. He, G.R. Nudd, An investigation into the application of different performance prediction techniques to e-commerce applications, in: Proceedings of the 18th IEEE International Parallel and Distributed Processing Symposium 2004 (IPDPS'04) on International Workshop on Performance Modelling, Evaluation and Optimization of Parallel and Distributed Systems, Sante Fe, New Mexico, USA, April 26–30, 2004.

[2] J. Cao, D.P. Spooner, S.A. Jarvis, S. Saini, G.R. Nudd, Grid load balancing using intelligent agents, Future Generation Comput. Syst. (2004) (special issue on Intelligent Grid Environments: Principles and Applications).
[3] L. Gong, X.H. Sun, E.F. Watson, Performance modelling and prediction of nondedicated networking computing, IEEE Trans. Comput. (2002) 1041–1055.
[4] L. He, S.A. Jarvis, D.P. Spooner, G.R. Nudd, Dynamic, capability-driven scheduling of DAG-based real-time jobs in heterogeneous clusters, Int. J. High Perform. Comput. Network. (2004).
[5] L. He, S.A. Jarvis, D.P. Spooner, G.R. Nudd, Performance-based dynamic scheduling of hybrid real-time applications on a cluster of heterogeneous workstations, in: Proceedings of the International Conference on Parallel and Distributed Computing (Euro-Par 2003), August 26–29, 2003, #####, Klagenfurt, Austria, 2003.
[6] S.A. Jarvis, D.P. Spooner, H.N. Lim Choi Keung, J. Cao, S. Saini, G.R. Nudd, Performance prediction and its use in parallel and distributed computing systems, in: Proceedings of the 17th IEEE International Parallel and Distributed Processing Symposium 2003 (IPDPS'03) on International Workshop on Performance Modelling, Evaluation and Optimization of Parallel and Distributed Systems, April 22–26, Nice, France, 2003.
[7] G.R. Nudd, D.J. Kerbyson, E. Papaefstathiou, S.C. Perry, J.S. Harper, D.V. Wilcox, PACE-a toolset for the performance prediction of parallel and distributed systems, Int. J. High Perform. Comput. Appl. 14 (3) (2000) 228–251 (special issue on Performance Modelling).
[8] E. Papaefstathiou, D.J. Kerbyson, G.R. Nudd, D.V. Wilcox, J.S. Harper, S.C. Perry, A Common Workload Interface for the Performance Prediction of High Performance Systems, in: Proceedings of the IEEE International Symposium On Computer Architecture, Workshop on Performance Analysis in Design (PAID'98) Barcelona, 1998.
[9] X. Qin, H. Jiang, Dynamic, reliability-driven scheduling of parallel real-time jobs in heterogeneous systems, in: Proceedings of the 30th International Conference on Parallel Processing, Valencia, Spain, September 3–7, 2001.
[10] J.M. Schopf, F. Berman, Performance prediction in production environments, in: Proceedings of the 12th International Parallel Processing Symposium on Parallel and Distributed Processing (IPPS/SPDP'98), Orlando, FL, 1998.
[11] J.M. Schopf, F. Berman, Using Stochastic Information to Predict Application Behavior on Contended Resources, Int. J. Found. Comput. Sci. 12 (3) (2001) 341–364 (special issue on Parallel Distributed Computing).
[12] J.M. Schopf, F. Berman, Stochastic Scheduling, SuperComputing'99, November 13–19, Portland, OR, USA.
[13] W. Smith, I. Foster, V. Taylor, Predicting application run times using historical information, in: Proceedings of the Fourth Workshop on Job Scheduling Strategies for Parallel Processing, #####, 1998.
[14] D.P. Spooner, S.A. Jarvis, J. Cao, S. Saini, G.R. Nudd, Local grid scheduling techniques using performance prediction, IEE Proc. Comp. Digit. Technol. 150 (2) (2003) 87–96.
[15] X.Y. Tang, S.T. Chanson, Optimizing static job scheduling in a network of heterogeneous computers, in: Proceedings of the 29th International Conference on Parallel Processing (ICPP 2000), August 21–24, Toronto, Canada, 2000.
[16] L. Yang, J.M. Schopf, I. Foster, Conservative Scheduling: Using Predicted Variance to Improve Scheduling Decisions in Dynamic Environments, SuperComputing 2003. November 15–21, Phoenix, AZ, USA.

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