Estimating the Accuracy of the Return on Investment (ROI) Performance Evaluations

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Abstract

Return on Investment (ROI) is one of the most popular performance measurement and evaluation metrics. ROI analysis (when applied correctly) is a powerful tool in comparing solutions and making informed decisions on the acquisitions of information systems.

The ROI sensitivity to error is a natural thought, and common sense suggests that ROI evaluations cannot be absolutely accurate. However, literature review revealed that in most publications and analyst firms’ reports, this issue is just overlooked. On the one hand, the results of the ROI calculations are implied to be produced with a mathematical rigor, possibility of errors is not mentioned and amount of errors is not estimated. On the contrary, another approach claims ROI evaluations to be absolutely inaccurate because, in view of their authors, future benefits (especially, intangible) cannot be estimated within any reasonable boundaries.

The purpose of this study is to provide a systematic research of the accuracy of the ROI evaluations in the context of the information systems implementations.

The main contribution of the study is that this is the first systematic effort to evaluate ROI accuracy. Analytical expressions have been derived for estimating errors of the ROI evaluations. Results of the Monte Carlo simulation will help practitioners in making informed decisions based on explicitly stated factors influencing the ROI uncertainties.

The results of this research are intended for researchers in information systems, technology solutions and business management, and also for information specialists, project managers, program managers, technology directors, and information systems evaluators. Most results are applicable to ROI evaluations in a wider subject area.

Keywords: Return on Investment, ROI, evaluation, costs, benefits, accuracy, estimation error, error propagation, uncertainty, information system, performance measure, business value, effort estimation, cost estimation, software engineering.

This is the first version (V1.0) of the paper submitted to a peer-reviewed journal.
1.0 Introduction

Return on Investment (ROI) is one of the most popular performance measurement and evaluation metrics. ROI analysis (when applied correctly) is a powerful tool in making informed decisions on the acquisitions of information systems.

Public attention to the ROI has a clear dependency on the state of economy: rough times bring about tougher competition of projects for available dollars and spur interest of academics and practitioners to the evaluation methods, where ROI comes as a convenient tool. Renewed focus on ROI can be observed now.

Return on Investment (ROI) became a buzzword. It is everywhere. Google search brings back millions of hits, which mention ROI. Abbreviation “ROI” is arguably one of the most frequently used abbreviations. One of not many business abbreviations often used without spelling out.

1.1 Context

According to the Investopedia, ROI is a performance measure used to evaluate the efficiency of an investment or to compare the efficiency of a number of different investments. To calculate ROI, the benefit (return) of an investment is divided by the cost of the investment; the result is expressed as a percentage or a ratio [1].

The return on investment formula:

\[
ROI = \frac{\text{Gain from Investment} - \text{Cost of Investment}}{\text{Cost of Investment}}
\]

There are many other ROI definitions in the literature (e.g. [2, 3, 4]). Each definition focuses on certain ROI aspects. With all the diversity of the definitions, the primary notion is the same: ROI is a fraction, the numerator of which is “net gain” (return, profit, benefit) earned as a result of the project (activity, system operations), while the denominator is the “cost” (investment) spent to achieve the result.

In general, predicting future is notoriously prone to uncertainties and errors. Estimating future project costs and returns also is a challenging endeavor [8–11]. Due to a variety of reasons actual numbers usually differ from the ones estimated in advance. The errors in estimating costs and returns will propagate through the ROI formula and result in inaccuracies of the ROI evaluations.

Estimating the accuracy of the ROI evaluations should be considered an essential part of the ROI calculations because ROI is used to make critical business decisions. Neglecting to estimate ROI accuracy may lead to wrong decisions on acquisition of information systems.

The importance of the ROI accuracy can be demonstrated on a simple case.

Estimated costs $10M. Estimated returns $11M. Hence, estimated ROI will amount to a healthy 10%, and the system will be given a go ahead.

Now, let’s assume, that costs and returns in a sample case were estimated with +/-10% errors. If, further, costs were underestimated (actual costs equal $10M + 10% = $11M) and returns were overestimated (actual returns equal $11M – 10% = $9.9M. The actual
ROI will be ($9.9M - $11M)/ $11M = -10%. In other words, actual ROI will be negative, and the company, instead of making $1M, will lose $1M on this project.

The above example demonstrates that using the amount of the ROI evaluation without indicating the accuracy of this evaluation may lead to a completely wrong decision.

The ROI sensitivity to error is a natural thought, and common sense suggests that ROI evaluations cannot be perfectly precise. However, in most professional magazines’ publications and analyst firms’ reports, this issue is just ignored. The results of the ROI calculations are implied to be produced with a mathematical rigor, possibility of errors is not mentioned and amount of errors is not estimated.

In a relatively small set of publications, on the contrary, the ROI is claimed to be an absolutely imprecise method (because, in view of their authors, intangible benefits cannot be assessed with any reasonable accuracy). This trend completely denies ROI method the right to existence. Conclusions are based on the qualitative considerations (and often on believes), no method is used to estimate ROI accuracy and amount of errors also is not estimated.

1.2 Purpose of the Paper

The purpose of this study is to estimate the accuracy of the ROI evaluations. The study provides estimates of the ROI accuracy in the context of the information systems implementations. Although the focus of the research is on the information systems, significant part of it can be applied to other types of systems and other fields of ROI evaluations.

1.3 Research Questions

The research is intended to answer the following questions:
- What factors influence the accuracy of the ROI calculations/evaluations?
- What are the accuracies of estimating project costs of the information systems implementations?
- What are the accuracies of estimating project benefits of the information systems implementations?
- How inaccuracies of determining project costs and benefits propagate through the ROI calculations and affect ROI accuracy?
- What levels of the quantitative error estimates of the ROI evaluations can be expected for typical scenarios of the information system implementations?

1.4 Theory and Methodology

Several methodologies have been used to achieve the research objectives:

1. Systematic literature review method was used to gather and analyze information related to the accuracy of estimating project costs and returns, distribution functions of errors.
2. Measurements theory and error analysis, specifically, propagation of uncertainties methods were used to derive analytical expressions for ROI errors.
3. Monte Carlo simulation methodology was used to design and deliver a quantitative experiment to model costs and returns estimating errors and calculate ROI accuracies.

4. Spreadsheet simulation (Microsoft Excel spreadsheets enhanced with Visual Basic for Applications) was used to implement Monte Carlo simulations.

1.5 Research Scope and Limitations

This research has the following scope limitations and assumptions.

1. Definition from the Investopedia treats ROI as a measure / metric / ratio / number [1]. In some cases, return on investment is understood as a “method” or “approach” – “ROI analysis” [4, 5]. This research is focused on the ROI as an individual measure.

2. ROI analysis can be performed with different purposes. As it was mentioned, ROI can provide rational for the future investments and acquisition decisions (e.g. project prioritization/ justification and facilitating informed choices about which projects to pursue). Evaluating future investments and making decisions on the information systems acquisitions are the processes based on the predicted data. By definition predicted data is likely to have certain level of variance from the amounts that will be really experienced later.

3. To avoid unnecessary complications and focus on the ROI accuracy, it has been assumed that:
   - Projects are relatively short-time efforts and value of money is not explicitly considered;
   - Such effects as “negative benefits” [46] or decrease of productivity immediately after implementation of a new information system are not considered.

4. Software effort/costs and benefits estimation methods are out of the research scope. It is assumed that appropriate methods were used to estimate costs and benefits, and the results are available to the ROI estimators.

1.6 Target Audience

The results of this research are intended for researchers in information systems, technology solutions and business management, and also for information specialists, project managers, program managers, technology directors, and information systems evaluators. Most results are applicable to ROI evaluations in a wider subject area.

1.7 Significance and Contribution of the Research

The importance of the problem is due to a wide use of the ROI evaluations in making investment decisions.

The main contribution of the study is that this is the first systematic effort to evaluate ROI accuracy. Analytical expressions have been derived for estimating errors of the ROI evaluations. Results of the Monte Carlo simulation will help practitioners in making informed decisions based on explicitly stated factors influencing the ROI uncertainties. Also, the paper contributes to more accurate ROI evaluations by drawing evaluators’ attention to the ways of minimizing evaluation errors.
2.0 Literature Review

2.1 ROI Accuracy Estimation

A literature review has been conducted in support of this research. The review didn’t reveal any papers specifically investigating methods of estimating ROI accuracy or case studies on this topic.

Two articles deal with the ROI accuracy [6, 7]. The value of these articles is in demonstrating the approach, and illustrating the level of the ROI accuracy for a typical CRM project. Accuracy assessment of the ROI calculations was performed on a specific example. Though not claiming any generic value, it was shown that even relatively low-level errors of estimating costs and returns (+/- 10%) may lead to significant ROI inaccuracies. That led to a conclusion that to make ROI number meaningful, it should be provided with an assessment of its accuracy.

Further literature review was focused on the accuracy of the components used to calculate ROI: costs and financial returns/benefits.

2.2 Cost Accuracy Estimation

A cluster of publications was retrieved that deal with the accuracy of forecasting costs in various industries and project settings, e.g. [8-11].

A subsection of this cluster deals with the software development effort estimation and its accuracy. A variety of estimation techniques are being used, which could be divided into several categories: estimation by analogy, parametric models, expert estimation, artificial intelligence methods [15, 27, 28, 41, 60]. Mostly often used techniques, to name a few, are: COCOMO II (Constructive Cost Model II) [17, 18], Function Point Analysis [19, 20], Use Case Points Method [14, 21], a variety of artificial intelligence (machine learning) methods that are based on neural networks, fuzzy logic, regression trees, rule induction, Bayesian belief networks, evolutionary computation, grey relational models, etc. [16, 22, 23, 37, 38].

Several authors compared the cost estimate at different stages of a product lifecycle (especially, at early stages) and the actual costs when the project was completed. The deviation/error of the estimates was documented.

A variety of estimation accuracy measures are being used [16, 27, 28, 29, 31, 33, 34]: e.g. Balanced Relative Error (BRE), Balanced Relative Error Bias (BREbias), Magnitude of Error Relative to the estimate (MER), Magnitude of Relative Error (MRE), Magnitude Relative Error Bias (MREbias), Mean Absolute Error (MAE), Mean Absolute Relative Error (MARE), Mean Balanced Relative Error (MBRE), Mean Inverted Balanced Relative Error (MIBRE), Mean Magnitude of Relative Error (MMRE), Mean Variation from Estimate (MVFE), Median Magnitude of Relative Error (MdMRE), Percentage of predictions falling within x% of the actual values (PRED(x%)), Relative Root Mean Squared Error (RRMSE), Root Mean Squared Error (RMSE), Variance Absolute Relative Error (VARE), Weighted Mean of Quartiles of relative errors (WMQ). These measures are used separately or in combinations.
Although criticized [33, 34], the Mean Magnitude of Relative Error (MMRE) remains the most commonly used measure. In order to present results of different papers in a more comparable form, this measure is used in the literature review (where possible).

In [14], the authors assess the accuracy of the software effort estimation performed with two methods: use-case point method (UCP) and UCP method enhanced with human-computer interaction techniques (iUCP). Seven real world projects were estimated. The authors conclude that Mean Magnitude of Relative Error for iUCP was 34.3% and 69.6% for UCP.

In [28], the authors propose to improve UCP method by employing a novel log-linear regression model and multilayer perceptron (MLP): feed-back neural network. The purpose of this work is to tackle limitations of the original UCP method, namely the assumption of the linear relationship between the software size and effort, and exclusion of the team productivity from the estimating effort. Seventy projects were evaluated. The accuracy of the effort estimation for the log-linear regression model, MLP and standard UCP were respectively: 39.2%, 40% and 46.7% (MMRE). For a subset of the data which included only small projects (under 3,000 person-hours), MLP outperformed other models.

In [31, 32], the authors explore the accuracy of the budget, effort and schedule estimates based on a set of 171 projects undertaken by a large Dutch multinational company during a three-year period. The MMRE for the budget and effort predictions are 26% and 103% respectively. The study shows that there were no relation between accuracy of budget, schedule and effort. Also, the study found that there was no improvement in the organization’s accuracy estimation over time.

In [35], the authors proposed a fuzzy model to enhance COCOMO II. They conclude that their model is more accurate than COCOMO: MMRE 37% over 41% respectively.

In [38], the authors proposed a model based on grey relational analysis to address outlier detection, feature subset selection and effort prediction, and compared this model with stepwise regression model. The resulted accuracy on the Desharnais data set – part of the PROMISE Software Engineering Repository [12] was 41.4% for grey model versus 46.5% for stepwise regression model (MMRE).

In many papers, including some of those mentioned above, authors analyse and compare two to three estimating methods. Usually, a new or improved method proposed by the authors is compared to one of the most commonly used (e.g. UCP, COCOMO). In [26], the authors offer a broader scope. They investigate accuracy of the COCOMOII, SEER-SEM, SLIM by QSM, and TruePlanning by PRICE Systems in the same context. All methods are compared using a variety of performance measures for both project effort and duration based on a set of 56 projects. The authors conclude that the COCOMOII model is inferior to the other three in estimating effort (MMRE 74% vs 34-41%), and that the results for all four methods cannot be statistically differentiated with respect to duration (MMRE 81-99%).

In [39], the authors compare several models: estimation by analogy enhanced with fuzzy grey relational analysis, case-based reasoning, multiple linear regression and artificial
neural networks. The resulted accuracy on the Desharnais data set was 30.6%, 38.2%, 39.9%, 61.2%, respectively (MMRE).

The study [29] has even broader scope – it includes most available historical data sets, performance measures and estimating methods. However, the results are presented in the form of ranking estimating methods without providing actual accuracy values.

The literature review revealed several important notions shared by many researchers:

- Cost prediction for software development projects is prone to errors.
- Estimates are mostly overoptimistic and underestimating is a problem for the software industry [30, 35]. 60-80% of the projects experience effort or schedule average overruns of 30-40% [42].
- A known cone of uncertainty illustrates that the variation of costs for the initial project phase could have as much as a +/-400% error [35]. The authors of the [43] referring to an earlier publication indicate that cost estimates at the conceptual stage are in the range of -30% to +50%, which reduces to between -5% and +15% when the detailed design phase is entered.
- Factors, contributing to the estimation errors, include: estimation process complexity, volatile and unclear requirements, redefinition of requirements under pressure from senior management and clients, lack of experienced resources for estimation, misuse of estimates, technical complexity, requirements redefinition, business domain instability, selection of a proper estimation technique, managerial issues [15, 32, 44].

Most authors admit limitations of the accuracy estimating studies [23, 26]:

- Incomplete project data affecting the accuracy of estimations.
- Limited number of projects with data on actual costs making results less reliable.

These limitations pose risks on the validity of the estimation results.

Table I illustrates estimating errors collected from 15 studies. For better visualization, Fig. 1 shows cost/effort error estimates. Two outliers: 9% and 1,218% were not included. The graph demonstrates that 75% of the sample error estimates fall within the error range of 20% to 60%.

| No. | Estimation Method/Model | Estimated Project Parameter | Error Measure | Error/Accuracy | Reference |
|-----|-------------------------|-----------------------------|---------------|----------------|-----------|
| 1   | UCP                     | Cost                        | MMRE          | 34.3%          | [14]      |
| 2   | iUCP                    | Cost                        | MMRE          | 69.6%          | [14]      |
| 3   | UCP                     | Cost                        | MMRE for 95% of the projects | 9%          | [13]      |
| 4   | N/A                     | Duration                    | MMRE          | 22%            | [15]      |
| No. | Estimation Method/Model                        | Estimated Project Parameter | Error Measure | Error/Ac curacy | Reference |
|-----|-----------------------------------------------|----------------------------|---------------|-----------------|-----------|
| 5   | N/A                                           | Effort                     | MMRE          | 24%             | [15]      |
| 6   | Intermediate COCOMO                           | Effort                     | MMRE          | 18.6%           | [16]      |
| 7   | Radial Basis Neural Network                   | Effort                     | MMRE          | 17.3%           | [16]      |
| 8   | Generalized Regression Neural Network         | Effort                     | MMRE          | 34.6%           | [16]      |
| 9   | COCOMO                                        | Effort                     | MMRE          | 52%             | [22]      |
| 10  | Levenberg-Marquardt Based Neural Network      | Effort                     | MMRE          | 123%            | [22]      |
| 11  | Back Propagation Based Neural Network         | Effort                     | MMRE          | 1,218%          | [22]      |
| 12  | Bayesian Regularization Based Neural Network  | Effort                     | MMRE          | 48%             | [22]      |
| 13  | SEER-SEM                                      | Effort                     | MMRE          | 57%             | [23]      |
| 14  | SEER-SEM Enhanced with Nuero-Fuzzy Model      | Effort                     | MMRE          | 39%             | [23]      |
| 15  | COCOMO Enhanced with Computing Intelligence Techniques | Effort                     | MMRE          | 23%             | [24]      |
| 16  | COCOMO                                        | Effort                     | MMRE          | 26%             | [24]      |
| 17  | Fuzzy Neural Network                          | Effort                     | MMRE          | 22%             | [25]      |
| 18  | COCOMOII                                      | Effort                     | MMRE          | 74%             | [26]      |
| 19  | COCOMOII                                      | Duration                   | MMRE          | 91%             | [26]      |
| 20  | SEER-SEM                                      | Effort                     | MMRE          | 36%             | [26]      |
| 21  | SEER-SEM                                      | Duration                   | MMRE          | 81%             | [26]      |
| 22  | SLIM by QSM                                   | Effort                     | MMRE          | 41%             | [26]      |
| 23  | SLIM by QSM                                   | Duration                   | MMRE          | 84%             | [26]      |
| 24  | TruePlanning by Price Systems                 | Effort                     | MMRE          | 34%             | [26]      |
| 25  | TruePlanning by Price Systems                 | Duration                   | MMRE          | 99%             | [26]      |
| 26  | UCP with log-linear regression model          | Effort                     | MMRE          | 39.2%           | [28]      |
| 27  | UCP with Multilayer Perceptron (MLP)          | Effort                     | MMRE          | 40%             | [28]      |
| 28  | UCP                                           | Effort                     | MMRE          | 46.7%           | [28]      |
| 29  | N/A                                           | Cost                       | MMRE          | 26%             | [31]      |
| 30  | N/A                                           | Effort                     | MMRE          | 103%            | [31]      |
| 31  | COCOMO II                                     | Effort                     | MMRE          | 41%             | [35]      |
| 32  | COCOMO II enhanced with Fuzzy Model           | Effort                     | MMRE          | 37%             | [35]      |
| 33  | Grey Relational Model                         | Effort                     | MMRE          | 41.4%           | [38]      |
| 34  | Stepwise Regression Model                     | Effort                     | MMRE          | 46.5%           | [38]      |
| 35  | Estimation by Analogy enhanced with fuzzy grey relational analysis | Effort                     | MMRE          | 30.6%           | [39]      |
| No. | Estimation Method/Model                     | Estimated Project Parameter | Error Measure | Error/Accuracy | Reference |
|-----|-------------------------------------------|----------------------------|---------------|---------------|-----------|
| 36  | Case-Based Reasoning                       | Effort                     | MMRE          | 38.2%         | [39]      |
| 37  | Multiple Linear Regression                 | Effort                     | MMRE          | 39.9%         | [39]      |
| 38  | Artificial Neural Networks                 | Effort                     | MMRE          | 61.2%         | [39]      |
| 39  | Intermediate COCOMO                        | Effort                     | MMRE          | 64%           | [40]      |
| 40  | COCOMO II                                  | Effort                     | MMRE          | 45%           | [40]      |
| 41  | MOPSO Model                                | Effort                     | MMRE          | 58%           | [40]      |
| 42  | Support Vector Regression (SVR) Model      | Effort                     | MMRE          | 46%           | [40]      |
| 43  | Software Engineering Laboratory (SEL) Model| Effort                     | MMRE          | 81%           | [40]      |
| 44  | Walton-Felix Model                         | Effort                     | MMRE          | 52%           | [40]      |
| 45  | Bailey-Basil Model                         | Effort                     | MMRE          | 84%           | [40]      |
| 46  | Halsted Model                              | Effort                     | MMRE          | 43%           | [40]      |
| 47  | Doty Model                                 | Effort                     | MMRE          | 49%           | [40]      |

Abbreviations used in the table:

- MMRE - Mean Magnitude of Relative Error
- MMERE - Mean Magnitude of Error Relative to the Estimate

**Fig. 1.** Sample graph of cost/effort error estimates

### 2.3 Estimating Accuracy of the Financial Returns/Benefits

Estimation of the financial returns received much less attention in the academic literature than estimation of the costs. The main reasons for that are the difficulties in identifying, quantifying and monetizing benefits (e.g. [50, 52, 55, 56, 57, 58]).
There are certain explanations for that:

- Actual costs are recorded through the project life and finalized at the end of the project. Benefits are only starting to emerge and accrue when the implementation is completed [52]. Usually, there are no processes and information systems to record value of benefits. After the project has been closed, there is just nobody to collect and explore the data.
- A commonly documented type of benefit is worker productivity gain and related time and, consequently, financial savings. Obviously, these savings can be realized only if certain percent of the workforce is terminated after the system implementation [48, 52]. However, there is no body of evidence to substantiate this being a regular practice. Hence, there is lack of data to support initial project benefit estimates or to measure variances.
- If regarding costs we can state that there is lack of historical data. Then we should admit that there is almost no benefits data. Companies consider benefits data even more confidential than cost information.
- The direct impact of the information system implementation project is difficult to establish [57].
- Measuring benefits, which may be tangible, quasi-tangible and/or intangible, is another challenge [52].
- Lack of research and commonly accepted benefits estimating methods [58]. “Effective methods for modelling software benefits tend to be highly domain-specific” [59].

Another challenge is the evolution of the information systems and their respective benefits over time. This process is illustrated on Fig. 2 [53, 54, 57]. The chart demonstrates that modern information systems tend to deliver benefits (in full accordance with the purposes they were created for) that are largely intangible and hardly can be estimated in financial terms, e.g. enhanced collaboration, more pertinent search results, etc. [52, 55, 56, 58].

Given this trend, the developments with the ROI use could be predicted:

- Researchers will develop methods of quantification and monetization of the tangible and intangible benefits and ROI will be presented as an integrated measure.
- ROI will be phased out as a performance measure for information systems.

Identification of benefits should be closely aligned with the systems’ goals/objectives. The desire to find hard-dollar benefits (inherent to older generations of the information systems) may divert researchers’ attention from assessing the actual benefits of the systems.

For example, measuring benefits of the enterprise content management (ECM) system only by the volume of computer memory – and hence actual dollars saved as a result of reduced document duplication) may seem to be simple and attractive, but questionable, because it doesn’t reflect the benefits the system was designed for. Another example.
Fig. 2. Evolution of the Information Systems and their Benefits
Often benefits of the web conferencing systems (WCS) are limited to the savings on travel for meeting participants that these systems offer plus even more popular and appealing “green effects” (reducing carbon emissions due to eliminating travel). At least reduced travel can be easily estimated in the employees’ time savings and expressed in dollars. However, the actual benefit – value added – visual collaboration (on content and personal) will not be accounted for.

In [51], the authors are investigating return on IT security investment. In this case the benefits are viewed as cost savings gained because of decreased probability of a security incident due to the implementation of security measures. The authors state that such benefits are very hard to predict accurately.

In [47], the authors evaluate ROI for a hospital electronic medical record (EMR) system. Financial benefits are estimated based on the expected cost savings due to reduction of length of stay, transcription time and laboratory time. The reduction of these three parameters is considered to be a result of the efficiency gained with EMR implementation. Calculation of the benefits is based on a number of assumptions. For example, reduction of length of stay is expected to be 10.5% based on research published by other authors. The number was selected as a conservative estimate from a range of similar published assessments with a high level going up to 30%. In its turn, reduction in length of stay will save impatient meals and clinical staff time. Clinical staff (nurses and doctors) is assumed to spend 60% in managing inpatients. Assessments of the time saved then converted into financial benefits. The assumptions, adopted in this case, bring in significant uncertainties. All of them are heavily dependent on multiple specific parameters of the hospital location, bed-size, processes used, configuration of the EMR system, etc. There are neither established methods nor historical databases to verify the accuracy of the calculated benefits.

In [55], the author proposes a framework to analyze benefits and costs of the enterprise information systems. The purpose is to enhance the expert judgement, which is perceived to be subjective, by a fuzzy logic model. The framework has a theoretical nature and examples of its actual use with quantitative assessments are not provided.

In [58], the authors propose a profitability estimation method for software projects dubbed SW-WiBe. This framework is based on the expert assessments of quantifiable and non-quantifiable benefits enhanced with Delphi process.

In [45], the authors analyze the benefits of advertising and state that determination of statistically sound evidence of the returns to advertising is very difficult, even when researching large campaigns with millions of observations.

There are some studies that attempted creation of high-level frameworks to capture systems benefits: e.g. capture IT capability from a hospital IT portfolio perspective [49], or examine the overall relationship between IT utilization and financial performance in hospitals [50].

The literature review didn’t reveal any studies neither on the methodology of estimating accuracy of predicted benefits nor on actual numbers based on the case studies.

As the literature review reveals, methods used to estimate benefits are similar to those used to estimate costs: analogy [47], expert judgement [57, 58], expert judgement enhanced with fuzzy models [55], etc. That led us to the assumption that we can expect the same quantitative levels of benefits estimation accuracy as we experience for cost estimation accuracy. This assumption will be used in the sections below devoted to the quantitative estimation of the ROI accuracy.
### 3.0 Analytical Estimation of the ROI Accuracy

The ROI is defined as:

\[
R_{est} = \frac{B_{est} - C_{est}}{C_{est}}
\]  

(1)

where \( C_{est} \) is an estimate of the cost to implement a project (predicted cost);
\( B_{est} \) is an estimate of the benefit (financial return) from the project implementation (predicted benefit);
\( R_{est} \) is the value of the ROI calculated based on the estimated costs and benefits (predicted ROI).

Equation (1) represents a complex non-linear function a sample of which is shown in Fig 3.

![Graph for (x-y)y^100](image)

**Fig 3. Sample Graph of the ROI Function. Source: Google.ca [67]**

Due to the uncertainties of the estimation process, actual costs \( (C_{act}) \) and actual benefits \( (B_{act}) \), realized after the project is completed, will be different from the estimated ones. Because of multiple impacting uncertainties the absolute estimating errors could be considered random and expressed as follows:

\[
\delta C = C_{act} - C_{est}
\]

\[
\delta B = B_{act} - B_{est}
\]
Hence, the actual ROI will also be different from the estimated one. The error of estimating ROI can be written as:

\[ \delta R = R_{act} - R_{est} \]

The problem is to define an analytical expression for the ROI estimation error as a function of the uncertainties measuring costs and benefits:

\[ \delta R = f[\delta C, \delta B, R(C, B)] \]

or for the relative ROI error:

\[ \frac{\delta R}{R} = F\left(\frac{\delta C}{C}, \frac{\delta B}{B}, R(C, B)\right) \]

Similar problems are well-known in the physical sciences and engineering, and studied in the measurements theory and error analysis [61, 62]. In measurements, involving taking readings from two or more physical devices/meters, there is a need to assess the error of the experimental result when the readings are combined in an equation, e.g. three sides of a block are measured with a tape measure and then the volume of the block is calculated by multiplying these readings and the volume of the block is determined. Uncertainties that occurred in measuring the sides will propagate through the equation/formulae and affect the uncertainty of the calculated result. Usually, this area of studies is called error propagation or propagation of uncertainties and it is based on the mathematics of stochastic processes and, specifically, on algebra of stochastic variables. Measurement theory developed certain methods of calculating output errors depending on the type of the equations/formulae used: whether the measured parameters are added, deducted, multiplied, etc. This research follows the considerations accepted in the measurements theory. However, it should be noted that some assumptions and subsequent mathematical approximations common for the measurement field (e.g. the absolute error of the measurement is much smaller than the value of the measured quantity) may not be valid for all ROI evaluation scenarios. So, error analysis mathematics should be applied with caution.

**Maximum probable error – worst-case scenario.** Let’s determine the maximum probable error for ROI. In the equation (1), a variable \(B_{est}\) is used more than once. That may lead to an effect of errors cancelling themselves (i.e. compensating errors) [61, p. 74]. We can re-arrange equation (1) to avoid using a variable more than once

\[ R_{est} = \frac{B_{est}}{C_{est}} - 1 \] (2)

According to [61, p. 66], any problem for propagation error can be subdivided into sequence of steps, each of them based on the elementary mathematical operation. The second term in equation (2) doesn’t include error component and could be neglected in the further error analysis. The first term is a quotient of two variables and error propagation for such a function is well-known [61, 62]. The maximum value of the ROI in equation (2) will occur when the numerator will be maximum and denominator will be minimum:
Minimum value can be expressed as

\[ R_{est} - \delta R = \frac{B_{est} - \delta B}{C_{est} + \delta C} \]  \hspace{1cm} (4)

Following [63, 64], we can rewrite equation (3)

\[ B_{est} + \delta B = (R_{est} + \delta R)(C_{est} - \delta C) = R_{est}C_{est} - R_{est}\delta C + C_{est}\delta R - \delta R\delta C \]

Assuming the errors are small, the last term \((\delta R\delta C)\) can be neglected, and absolute ROI error can be written as

\[ \delta R \approx (B_{est} + \delta B - R_{est}C_{est} + R_{est}\delta C)/C_{est} \]  \hspace{1cm} (5)

Taking into account that \(R_{est} = B_{est}/C_{est}\) and substituting into equation (5), the expression for the maximum probable absolute error will be:

\[ \delta R \approx \frac{C_{est}\delta B + B_{est}\delta C}{C_{est}^2} \]  \hspace{1cm} (6)

or, multiplying both numerator and denominator by \(B_{est}\), and rearranging

\[ \delta R \approx \frac{B_{est}}{C_{est}} \left( \frac{\delta B}{B_{est}} + \frac{\delta C}{C_{est}} \right) \]  \hspace{1cm} (7)

As it is observed in [61, 62, 64], error for a quotient is better expressed in terms of the relative error. Dividing both parts of equation (7) by \(R_{est}\), we get the following formula

\[ \frac{\delta R}{|R_{est}|} \approx \frac{\delta B}{B_{est}} + \frac{\delta C}{C_{est}} \]  \hspace{1cm} (8)

We arrived at a formula that is commonly used in the error propagation assessments for quotients [61, 62, 64].

Another approach to calculate maximum probable error is as follows. Equation (2) may be rewritten to show maximum and minimum levels of the ROI

Maximum

\[ R_{est} + \delta R = \frac{B_{est} + \delta B}{C_{est} - \delta C} - 1 \]  \hspace{1cm} (9)
Following a method used in [61, p. 51; 65], equation (10) can be rewritten as

\[
R_{est} + \delta R = \frac{B_{est}}{C_{est}} \left( 1 + \frac{\delta B / B_{est}}{1 - \delta C / C_{est}} \right) - 1
\]  

(11)

Using a binomial theorem, a component of (11) can be simplified (approximated by a Taylor series)

\[
\frac{1}{1 - \delta C / C_{est}} \approx 1 + \delta C / C_{est} + (\delta C / C_{est})^2 + \cdots
\]

Using only the first two terms of the approximation, equation (11) can be rewritten as

\[
R_{est} + \delta R \approx \frac{B_{est}}{C_{est}} \left( 1 + \frac{\delta B / B_{est}}{1 + \frac{\delta C / C_{est}}{B_{est}}} \right) - 1
\]  

(12)

Rearranging equation (14), the error can be expressed as

\[
\delta R \approx \frac{B_{est}}{C_{est}} \left( 1 + \frac{\delta B}{B_{est}} + \frac{\delta C}{C_{est}} + \frac{\delta B}{B_{est}} \frac{\delta C}{C_{est}} \right) - 1 - R_{est}
\]

Assuming again that the relative errors are small, so the last term in the brackets can be neglected and substituting \( R_{est} = \left( \frac{B_{est}}{C_{est}} \right) - 1 \)

\[
\delta R \approx \frac{B_{est}}{C_{est}} \left( 1 + \frac{\delta B}{B_{est}} + \frac{\delta C}{C_{est}} \right) - 1 - \frac{B_{est}}{C_{est}} + 1 =
\]

\[
\frac{B_{est}}{C_{est}} \left( \frac{\delta B}{B_{est}} + \frac{\delta C}{C_{est}} \right)
\]  

(13)

Similar results can be gained if we use a generalized formula for a maximum probable error which for our case could be expressed through the total differential of a function [61, p. 75; 63]

\[
dR = \left( \frac{\partial R}{\partial B} \right) dB + \left( \frac{\partial R}{\partial C} \right) dC
\]

Assuming \( dR = \delta R \), and likewise for the other differentials, and that the variables \( C \) and \( B \) are independent, the result for errors

\[
\delta R \approx \left| \frac{\partial R}{\partial B} \right| \delta B + \left| \frac{\partial R}{\partial C} \right| \delta C
\]  

(14)
Formula (14) neglects higher order derivatives of the function which is considered a good approximation when the errors are small.

Substituting equation (2) into (14) and taking partial derivatives of the ROI function with respect of B and C

\[ \delta R \approx \left| \frac{\partial}{\partial B} \left( \frac{B_{est}}{C_{est}} - 1 \right) \right| \delta B + \left| \frac{\partial}{\partial C} \left( \frac{B_{est}}{C_{est}} - 1 \right) \right| \delta C = \]

\[ \left| \left( \frac{1}{C_{est}} \delta B \right) \right| + \left| B_{est} \frac{\partial}{\partial C} \left( \frac{1}{C_{est}} \right) \delta C \right| = \]

\[ \left| \frac{1}{C_{est}} \delta B \right| + \left| B_{est} \left( - \frac{1}{C_{est}^2} \delta C \right) \right| = \]

\[ \frac{C_{est} \delta B + B_{est} \delta C}{C_{est}^2} = \]

\[ \frac{B_{est} \left( \delta B \right)}{C_{est} \left( \frac{B_{est}}{B_{est} + C_{est}} \right)} \]

(15)

We can observe that equations (7), (13, (15) provide the same result. ROI maximum probable error approximately equals benefits-costs ratio multiplied by the sum of benefits and costs relative errors.

**Probable error.** Maximum probable error, presented in a previous subsection, dealt with a worst-case scenario: the errors assume largest possible values and in a most “unpleasant” way, i.e. benefits are overestimated and costs are underestimated, or vice versa. Although important and conceivable, this scenario will not occur often. In a more likely scenario, when errors are random and independent, errors of estimating benefits and costs will have different signs and may be partially compensating each other. This scenario also needs to be assessed.

A generalized formula for a probable error for a two-variable function R has been derived in [61, pp. 75, 141; 62]:

\[ \delta R \approx \sqrt{\left( \frac{\partial R}{\partial B} \delta B \right)^2 + \left( \frac{\partial R}{\partial C} \delta C \right)^2} \]

(16)

Substituting equation (2) into (16) and taking partial derivatives of the ROI function with respect of B and C, equation (16) can be transformed

\[ \delta R \approx \sqrt{\left( \frac{\partial R}{\partial B} \delta B \right)^2 + \left( \frac{\partial R}{\partial C} \delta C \right)^2} = \]

(17)
\[
\sqrt{\left[ \frac{\partial}{\partial B} \left( \frac{B_{\text{est}}}{C_{\text{est}}} - 1 \right) \delta B \right]^2 + \left[ \frac{\partial}{\partial C} \left( \frac{B_{\text{est}}}{C_{\text{est}}} - 1 \right) \delta C \right]^2} = \\
\sqrt{\left( \frac{1}{C_{\text{est}}} \delta B \right)^2 + \left[ B_{\text{est}} \left( \frac{1}{C_{\text{est}}} \right) \delta C \right]^2} = \\
\sqrt{\left( \frac{1}{C_{\text{est}}} \delta B \right)^2 + \left[ B_{\text{est}} \left( -\frac{1}{C_{\text{est}}}^2 \right) \delta C \right]^2} = \\
\sqrt{\frac{C_{\text{est}}^2 \delta B^2 + B_{\text{est}}^2 \delta C^2}{C_{\text{est}}^4} \cdot \frac{B_{\text{est}}^2}{B_{\text{est}}^2}} = \\
\frac{B_{\text{est}}}{C_{\text{est}}} \sqrt{\left( \frac{\delta B}{B_{\text{est}}} \right)^2 + \left( \frac{\delta C}{C_{\text{est}}} \right)^2}
\]

ROI probable error approximately equals benefits-costs ratio multiplied by the square root of the sum of squared benefits and costs relative errors.

**Breakdown of benefits and costs.** So far in this section to simplify the layout of the mathematical formulae, it was assumed that the value of the benefits (financial returns) is given by a single number \( B_{\text{est}} \). For example, the project has a single type of benefits: cost savings due to downsizing, e.g. salaries and wages of the full time employees saved due to the system implementation. In general, there could be a variety of the benefits types: e.g. increased revenues due to increased sales, or sales margins; revenue enhancement, e.g. additional revenues were gained due to better targeted marketed and advertising; revenue protection, e.g. imminent fine was avoided (due to demonstrated compliance with regulatory requirements). The same refers to the costs. Common types of the costs include:

- Cost of software development or customization/configuration.
- Cost of IT infrastructure, e.g. Software/licenses - initial and annual maintenance;
- Hardware - if IS run in-house (e.g. purchasing and installation of new servers); Hosting - if information system provided as Software as a Service by a third party.
- Cost of labour, e.g. direct operating expenses (DOE). Salaries and wages plus benefits for full time equivalent positions; Consultant services of installation, configuration, software customization, integration that requires skills not available within the I&IT Department.
- Cost of training, e.g. IT personnel training by a third party; Program area end-user training by a third party.
So for a generic project, benefits $B_{est}$ and costs $C_{est}$ will be represented by summations of individual benefits and costs

$$B_{est} = \sum_i B_i \quad \quad C_{est} = \sum_j C_j$$

where $B_i$-i-th component of the financial return; and $C_j$-j-th component of the system cost.

Most likely, each of these benefits and costs types will be estimated separately using different tools/methods, and have their own (specific) estimation error values, i.e. $\delta B_i$ and $\delta C_j$. As it is derived in [61, 62], uncertainty propagation for the operation of summation can be estimated using the following formulae:

$$\delta B \approx \sum_i \delta B_i \quad \quad \delta C \approx \sum_j \delta C_j \quad \quad (18)$$

$$\delta B \approx \sqrt{\sum_i (\delta B_i)^2} \quad \quad \delta C \approx \sqrt{\sum_j (\delta C_j)^2} \quad \quad (19)$$

General procedure for estimating ROI errors will be to calculate overall errors of benefits and costs using equations (18) or (19) and then substitute the results in equations (15) or (17).

### 4.0 Estimating ROI Accuracy with Monte Carlo Simulation

Monte Carlo simulation offers itself as a flexible technique for estimating ROI accuracy. It provides much more comprehensive insights into dependences of the costs and benefits uncertainties and ROI errors. The simulation was implemented on Excel spreadsheets using Visual Basic for Applications (VBA). The Monte Carlo simulation process flowchart used in the study is shown in Figure 4.

As a first step of setting a new case, a project cost value (used as an actual cost) was randomly selected from one of the three project ranges: small (100K-500K), medium (501K-900K) or large (901K-1,300K). Using the cost value, benefit amount was calculated at a certain benefit-cost ratio. Actual ROI was calculated using a standard formula:

$$R_{act} = \frac{B_{act} - C_{act}}{C_{act}}$$

Estimated ROI will differ from the actual value due to the uncertainties in estimating benefits and costs. These uncertainties were generated through a range of relative errors of benefits and costs $\delta B / B_{act}, \delta C / C_{act}$.
Upper and lower levels of the estimated benefits were calculated as follows:

\[ B_{estU} = B_{act} + B_{act}(\delta B/B_{act}) \]
\[ B_{estL} = B_{act} - B_{act}(\delta B/B_{act}) \]

Then, estimated value of benefits \( \beta_i \) was generated as a random number within the lower and upper bounds \( \beta_i \in [B_{estL}, B_{estU}] \). Microsoft Excel VBA RND function was used to generate random numbers uniformly distributed within the specified interval.

Estimates of costs \( \zeta_i \) were generated using the same approach \( \zeta_i \in [C_{estL}, C_{estU}] \).
Estimated ROI values were calculated as

\[ R_{esti} = \frac{\beta_i - \zeta_i}{\zeta_i} \]

Finally, ROI error \( \delta R \) (mean absolute error), after \( N \) Monte Carlo iterations, was calculated as

\[ \delta R = \frac{1}{N} \sum_{i}^{N} |R_{act} - R_{esti}| \]

Several cases were run to determine the required number of iterations. Appendix 2 presents the charts showing the behaviour of the ROI error with different iterations numbers. The results demonstrate that the amount of the ROI error converges to the first or second decimal of a percent when the number of iterations reaches 15,000 to 20,000. As the runtime was not an issue (under 10 sec for a single point) due to a relatively simple model, the number of iterations was set to 30,000.

Results of the simulation are shown on the Figures 5-7. Fig. 5 shows dependences of the ROI error \( \delta R \) with the increase of the relative errors of benefits and costs estimates \( \delta B / B_{act} \), \( \delta C / C_{act} \) for the errors in the range from 0 to 45%. Fig. 6 shows similar data for the larger errors: 40% to 95%. Fig 7 shows ROI errors for the projects of different sizes (large vs small).

Fig. 5. ROI error for the low lower-level benefits and costs relative errors
Fig. 6. ROI error for the low higher-level benefits and costs relative errors

Fig. 7. ROI errors for the projects of different sizes (large vs small)
5.0 Discussion

Analytical expressions for the ROI errors derived in Section 3.0 are based on certain assumptions and simplifications. The prime one is that benefits and costs estimating errors are small and Taylor series expansion can be used. The validity of the resulting formulae needs to be checked to verify applicability of the approximations.

Equation (13) for the ROI maximum probable error was derived using the first two items in the Taylor series expansion:

\[
\frac{1}{1 - \delta C / C_{est}} \approx 1 + \delta C / C_{est} \tag{20}
\]

Fig 8 demonstrates the graphs for the left (exact) and right (approximated) parts of the equation (20) for a range of the cost relative errors $\delta C / C_{est}$.

Fig. 8. Taylor series expansion

The graph shows that variance between the exact and approximated solutions increases rapidly when value of the relative error exceeds 15-20%. This data suggests that approximated expressions for the ROI errors are best used for relative errors under 15-20%. It should be noted that the approximated line goes below the exact line. As a result approximated errors may underestimate real ROI errors.

Analytical expressions (with better ROI accuracy) for the cases with larger errors of costs and benefits are difficult to derive. There are studies in this area, e.g. [66], but the complexity of the solutions preclude them from being recommended for practitioners.

Let’s perform direct ROI calculations using standard formula (not equations derived for the ROI errors) for a simple case. Information system is being implemented with estimated benefits.
$B_{est} = $120,000 and costs $C_{est} = $100,000. Using equation (1), the value of the ROI for this case $R_{est} = 0.2$ or 20\%. Now, assuming there are uncertainties in benefits and costs estimations, let’s calculate maximum and minimum values of the ROI using equations (9) and (10) for different values of errors. The results of these calculations are presented in Fig 9. Note that ROI is a two-variable function and generally requires 3-dimensional representation. In order for better 2-dimensional visualization, each point of the graph was calculated for equal values of errors $\delta B / B = \delta C / C$ (horizontal axis). The graph also shows maximum and minimum absolute ROI errors (variations from the calculated ROI which equals to 20\%). Actual ROI value will be within the upper (maximum) and lower (minimum) boundaries shown on the graph. It should be noted that the “funnel” of ROI errors is not symmetrical regarding the expected value of 20\% with zero errors. Overestimating ROI is more likely than underestimating. Also, with no surprise, it should be noted that even with modest levels of the benefits and costs estimation errors ROI errors tend to be rather high (e.g. for $\delta B / B = \delta C / C = +/- 10\%$, absolute ROI errors could be up to +27\% ÷ -22\%).

![Fig. 9: Maximum and minimum ROI levels and ROI errors for a sample case](image)

Fig 10 shows ROI errors calculated according to different formulae using the same sample case: D-RIO – direct calculation using (9) and (10); MP-ROI – maximum probable ROI using (15) and summing in quadrature using (17). Data for this graph is presented in the Appendix 1.

Results of the simulation presented in the Section 4 show how the ROI absolute mean error is changing with the relative errors of benefits and costs. The behaviour of the graphs is different for the lower and higher levels of the relative errors. For better visual perception they are demonstrated separately. The graph for the lower error levels (see Fig. 5) shows almost linear relationship between the ROI absolute error and relative errors of benefits and costs (especially when relative errors are under 30\%). The graph for the higher error levels (over 40\%) shows
Fig 10. Sample case comparison of errors calculated with different methods
exponential growth (see Fig. 6). As it might be expected, simulation has shown no difference for the ROI error behaviour for the projects of different sizes. Fig. 7 shows identical ROI errors for the small and large projects (for the same relative errors of benefits and costs).

**Assumptions / Limitations**

It should be noted that analytically derived formulas are approximations based on the Tailor series expansion. They should be applied with caution, especially when the relative errors of benefits and costs are over 15-20%.

Simulation results include the assumption that the relative errors of benefits and costs are equal (to ensure better visual presentation). Also, the distribution of the relative errors of benefits and costs was set to be uniform.

To round off the Discussion section, it is important to note that as any project is a unique endeavour (by definition), the same characteristic applies to the value of ROI errors in each project. It means that there are no any standard or expected ROI error amounts. Everything depends on how accurate were the financial assessments of the project benefits and costs. Project manager or analyst has to make ROI error estimations in specific conditions of the project. The results of this study provide a foundation for such estimations.

When assessing the ROI uncertainty, it is also noteworthy to take into account the ultimate financial implications not the intermediate parameters. For example, a company is developing a new software solution. The workload has been estimated with uncertainty of +/-50%. It seems at this point that expected ROI error will also be very large. And it is true, if the project would be developed in-house and workload will be directly translated into costs with the similar errors. However, if the software development would be outsourced through a fixed-price contract – the financial/cost uncertainty for the company will be close to zero, and so will be ROI error.

### 6.0 Concluding Remarks

Estimating accuracy of the ROI evaluations should become a part of the ROI assessments’ best practices in order to avoid erroneous investment decisions. This study provided a systematic research (both analytical and using simulation) of the accuracy of the ROI evaluations in the context of the information systems implementations and laid foundation for further theoretical and practical works in this area.

**Future research** may be focused on developing a framework of assessing and presenting benefits accuracy in a more standardized way. Also, research can be conducted into mathematical aspects of estimating ROI accuracy in the cases when estimating errors of benefits and costs are large, and have various probability distribution functions.
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# APPENDIX 1

| | Direct Calculation | Maximum Probable | Quadrature |
|---|---|---|---|
| | D-ROI<sub>max</sub> | D-ROI<sub>min</sub> | MP-ROI<sub>max</sub> | MP-ROI<sub>min</sub> | Q-ROI<sub>max</sub> | Q-ROI<sub>min</sub> |
| | | | | | | |
| | | | | | | |
| 0 | 20.0% | 20.0% | 20.0% | 20.0% | 20.0% | 20.0% |
| 2 | 24.9% | 15.3% | 24.8% | 15.2% | 23.4% | 16.6% |
| 4 | 30.0% | 10.8% | 29.6% | 10.4% | 26.8% | 13.2% |
| 6 | 35.3% | 6.4% | 34.4% | 5.6% | 30.2% | 9.8% |
| 8 | 40.9% | 2.2% | 39.2% | 0.8% | 33.6% | 6.4% |
| 10 | 46.7% | -1.8% | 44.0% | -4.0% | 37.0% | 3.0% |
| 12 | 52.7% | -5.7% | 48.8% | -8.8% | 40.4% | -0.4% |
| 14 | 59.1% | -9.5% | 53.6% | -13.6% | 43.8% | -3.8% |
| 16 | 65.7% | -13.1% | 58.4% | -18.4% | 47.2% | -7.2% |
| 18 | 72.7% | -16.6% | 63.2% | -23.2% | 50.5% | -10.5% |
| 20 | 80.0% | -20.0% | 68.0% | -28.0% | 53.9% | -13.9% |
| 22 | 87.7% | -23.3% | 72.8% | -32.8% | 57.3% | -17.3% |
| 24 | 95.8% | -26.5% | 77.6% | -37.6% | 60.7% | -20.7% |
| 26 | 104.3% | -29.5% | 82.4% | -42.4% | 64.1% | -24.1% |
| 28 | 113.3% | -32.5% | 87.2% | -47.2% | 67.5% | -27.5% |
| 30 | 122.9% | -35.4% | 92.0% | -52.0% | 70.9% | -30.9% |
| 32 | 132.9% | -38.2% | 96.8% | -56.8% | 74.3% | -34.3% |
| 34 | 143.6% | -40.9% | 101.6% | -61.6% | 77.7% | -37.7% |
| 36 | 155.0% | -43.5% | 106.4% | -66.4% | 81.1% | -41.1% |
| 38 | 167.1% | -46.1% | 111.2% | -71.2% | 84.5% | -44.5% |
| 40 | 180.0% | -48.6% | 116.0% | -76.0% | 87.9% | -47.9% |
| 42 | 193.8% | -51.0% | 120.8% | -80.8% | 91.3% | -51.3% |
| 44 | 208.6% | -53.3% | 125.6% | -85.6% | 94.7% | -54.7% |
| 46 | 224.4% | -55.6% | 130.4% | -90.4% | 98.1% | -58.1% |
| 48 | 241.5% | -57.8% | 135.2% | -95.2% | 101.5% | -61.5% |
| 50 | 260.0% | -60.0% | 140.0% | -100.0% | 104.9% | -64.9% |
### APPENDIX 2

#### Bact/Cact=1.1

**dB=dC=5**  
Cost Range 100K to 500k

| N     | Ave   | Min    | Max    |
|-------|-------|--------|--------|
| 10    | 5.4058% | -7.4844% | 10.0421% |
| 20    | 3.5967% | -7.9257% | 7.5358%   |
| 50    | 3.0697% | -10.2313% | 8.9274%   |
| 75    | 3.4111% | -7.9361% | 8.3195%   |
| 100   | 4.0876% | -9.4908% | 9.2203%   |
| 200   | 3.9203% | -11.0379% | 10.2695% |
| 400   | 3.5300% | -10.8864% | 9.6588%   |
| 700   | 3.7058% | -10.8948% | 9.9604%   |
| 1000  | 3.6453% | -10.7220% | 10.2798% |
| 1500  | 3.7162% | -11.5020% | 10.0824% |
| 2000  | 3.6010% | -10.8795% | 9.9286%   |
| 5000  | 3.6503% | -11.5323% | 10.2414% |
| 10000 | 3.7007% | -11.1216% | 10.2939% |
| 15000 | 3.6628% | -11.3609% | 10.3456% |
| 20000 | 3.6673% | -11.4138% | 10.4110% |
| 25000 | 3.6684% | -11.4760% | 10.3522% |
| 30000 | 3.6745% | -11.4294% | 10.4023% |
| N    | Ave    | Min    | Max    |
|------|--------|--------|--------|
| 10   | 21.9767% | -35.3774% | 27.0580% |
| 20   | 14.1337% | -32.8124% | 27.2233% |
| 50   | 20.3691% | -61.5395% | 40.2094% |
| 75   | 17.4400% | -56.6937% | 28.4314% |
| 100  | 18.1585% | -58.5428% | 37.9934% |
| 200  | 18.6154% | -59.7676% | 39.0890% |
| 400  | 17.1086% | -59.9600% | 41.8181% |
| 700  | 17.8145% | -62.2705% | 41.8480% |
| 1500 | 17.5647% | -62.2291% | 41.7842% |
| 2000 | 17.7702% | -63.7504% | 42.4491% |
| 5000 | 17.8485% | -62.7745% | 42.8578% |
| 10000| 17.6013% | -63.9564% | 42.6477% |
| 15000| 17.6425% | -64.7943% | 43.2480% |
| 20000| 17.6075% | -64.2323% | 43.1229% |
| 25000| 17.5840% | -64.4520% | 43.1093% |
| 30000| 17.5646% | -64.4063% | 43.0740% |

Bact/Cact=1.3
dB=dC=20%
Cost Range 100K to 500k