October 14, 2005

Dear Ms. Moore and Mr. Sweetser:

Titan Corporation is pleased to provide the Return on Investment of IV&V Phase III Study Final Report, DID 06, approved for delivery under Task Order Number 31 Modification 3, Return on Investment for IV&V, for Contract Number GS-35F-4815G, BPA Order Number S-43619-Y, and Delivery Order 01. Enclosed is an electronic version of the Final Report for your review. This email and its attachment constitute the electronic delivery of Product GSFCY & NRC IVV-05-137.

Should you have any questions, please contact the undersigned.

Approved,

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Enclosures: Return on Investment of IV&V Phase III Study Final Report

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> NASA IV&V Facility Fairmont, WV 26554

DID Number: 06 INDEPENDENT VERIFICATION AND VALIDATION (IV&V) OF NASA PROGRAM SOFTWARE

Return on Investment of Independent Verification and Validation Study Phase III Final Report

October 14, 2005

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Abstract

This report documents results of the tasks associated with Phase III of the Independent Verification and Validation Return on Investment research. These tasks were to 1) develop initiating material for research to develop a full lifecycle prototype predictive ROI model, 2) produce prototype Bayesian belief network (BBN) sub-nets to model defect introduction and defect removal efficiency for IV&V and developers for the entire software lifecycle, 3) elicit PDFs for each node in the system of BBNs and 4) Calibrate the predictive model using existing case study data. The first task resulted in the development of a refined requirements phase BBN including updated pdf data. Tasks (2) and (3) were performed concurrently, resulting in complete lifecycle BBN diagrams and a software model. In Task (4) the prototype model was calibrated and produced predicted ROI results consistent with the case studies. The report concludes that the emphasis for the next phase of the ROI work should be collection of additional case studies and improved model calibration.

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1 Introduction

The independent verification and validation (IV&V) return on investment (ROI) study is developing the means to compute ROI for past projects and to predict ROI for new projects using available project data. The ROI study consists of a sequence of phases. Phase I entailed a set of preliminary direct ROI case studies. In Phase IIA, the team investigated the feasibility of computing indirect ROI and identified suitable project characteristics for indirect ROI and a candidate set of components of a predictive ROI model. Phase IIB produced a full lifecycle cost escalation model, proposed the Bayesian belief network (BBN) as a means to estimate defect density, and determined the sensitivity of the ROI model to variations in escalation rates and defect location rates. This report documents the results of Phase III which had four principal tasks:

- 1. Develop initiating material for research to develop a full lifecycle prototype predictive ROI model Sensitivity study
- 2. Produce prototype Bayesian belief network (BBN) sub-nets to model defect introduction and defect removal efficiency for IV&V and developers for the entire software lifecycle.
- 3. Elicit PDFs for each node in the system of BBNs
- 4. Calibrate the predictive model using existing case study data

2 Predictive Model Overview

The direct IV&V ROI model [DBO04] provides the means to compute ROI for completed IV&V projects. The model requires as inputs developer and IV&V costs (typically in equivalent person months (EPM)), software product size (measured in source lines of code (SLOC) or function points (FP)[FPUG00]), and measures of defect detection by the developer and IV&V for each type of issue (requirements, design, code, test, integration) and each development phase (typically in cost-to-fix EPM or issue size in FP). The direct ROI model is depicted graphically in Figure 1.

The complete set of inputs for the direct ROI model does not exist until the project is complete. Thus, the direct ROI model provides one measure of value added for complete projects, but does not (except reasoning by analogy) help in determining the potential value added of candidate IV&V projects. A predictive ROI model will permit assessment of ROI of candidate projects and therefore assist managers in resource allocation. A predictive model can also serve as the basis for a model-based effectiveness metric that will permit progressive monitoring of ongoing IV&V projects.

A predictive ROI model based on the direct ROI methodology must provide the means to determine early in the project all inputs to the direct ROI model. Estimates of developer and IV&V cost should be available early in the lifecycle as these estimates are normal project management requirements. Other inputs, specifically developer and IV&V defect discovery data, can't be known early in the project and must therefore be estimated using project characteristics that are known early in the lifecycle. The predictive ROI model uses the BBN technique [FKN01], [FKN01A] to estimate the inputs to the direct ROI model [DBO04] using information available early in the project lifecycle.

Figure 1: Direct ROI computation

2.1 Bayesian Belief Network Overview

A BBN consists of a hierarchy of nodes representing stochastic causal relationships. Figure 2 depicts a single node with two inputs. The node output is a random value with a probability density function (pdf) which depends on the values of input parameters A and B. The mapping of parameter values to pdfs could be done using historical data, if sufficient data existed. In the absence of a sufficient quantity of data, the mapping can be estimated using expert opinion. For the ROI BBN, the expert opinion approach was selected. For the ROI BBN, all nodes produce random variables in the range of 1 to 5, where 1 corresponds to the worst possible case and 5 corresponds to the best possible case.

Figure 2: BBN node

A complete BBN consists of a hierarchical set of nodes. Figure 3 shows a larger BBN fragment containing three nodes. Note that the inputs to node 3 are random variables and therefore node 3 must compute an expected probability density function. In practice, this is easily accomplished using the Monte Carlo method.

2.2 Function Point Ratios

For each development phase (requirements, design, code, test, integration), three BBN subnets were developed. The first subnet estimates product quality (with respect to defect density) on a scale of 1 to 5. The second subnet estimates developer defect detection efficiency on a scale of 1 to 5. The third subnet estimates IV&V defect detection efficiency on a scale of 1 to 5. In order to produce the inputs required by the direct ROI model, the BBN output must be converted into measures of defect size. Function points are a convenient measure early in the lifecycle because they can be estimated from system requirements and are independent of programming language. Therefore the subnet values (product quality, developer defect discovery efficiency , IV&V defect discovery efficiency) are used to estimate function point ratios (FPRs), which, scaled by the estimated product function points, provide suitable direct ROI model inputs. A high level flow diagram for the process (showing requirements phase defect function points only) is shown in Figure 4.

The overall process of developing the BBN model for one phase (requirements, design, code, test, integration) of the baseline IV&V process consists of the following steps:

- 1. Develop pictorially (based on elicitation from experts) the BBNs for defect introduction, defect detection by the developer, and defect detection by IV&V.
- 2. Elicit from the experts probability density functions for each causal dependency.
- 3. Implement the BBN in software using the Monte Carlo technique.
- 4. Calibrate the BBN output to case study data to predict discovered defect function points in-phase for the developer and IV&V

Figure 4: Predictive model defect function point computation

2.3 Defect Leakage Model

The direct ROI model requires as inputs discovered-defect function points for the developer and IV&V for each issue type and phase found. The BBNs were developed to compute in-phase discovered defects only. Although it would be possible to develop a BBN for each issue type for each development phase, that would require an additional fifteen subnets many of which would lack calibration data. Therefore, a leakage model was devised to estimate discovered defect function points out of phase (for example, requirements defect function points discovered in design, code, test, integration phases). Based on an extensive literature search, the Rayleigh leakage model [GJWE01], [KSH91] was selected. Calibration of the leakage model will be discussed later.

3 Complete Prototype BBN

The complete BBN framework consists of subnets for defect introduction and defect detection by the developer and IV&V for each development phase. As noted above, BBNs are used only for in-phase defect detection prediction. Defect discovery in subsequent phases is estimated using a calibrated Rayleigh leakage model. Table 1 lists the source of direct model inputs for each phase and issue type. Here, BBN indicates the source is the BBN and LM indicates the source is the calibrated Rayleigh leakage model applied to the BBN FPRs.

Issue type	Phase issue found							
	Requirements	Design	Code	Test	Int	Ops		
Requirements	BBN	LM	LM	LM	LM	LM		
Design		BBN	LM	LM	LM	LM		
Code			BBN	LM	LM	LM		
Test				BBN	LM	LM		
Integration					BBN	LM		

Table 1: Function point ratio source for ROI computation

3.1 BBN Subnets

Appendix A shows the complete set of BBNs. An example defect introduction subnet (requirements phase) is shown in Figure 5. The output of this subnet is requirements quality in the range of 1 to 5 where 1 is the worst possible quality and 5 is the best possible quality. An example defect detection BBN (IV&V, requirements phase) is shown in Figure 6. The output of the defect detection subnet is the ratio (FPR) of function points of defects discovered to total function points. The product of FPR and total function points is a suitable set of inputs for the direct ROI model.

Figure 5: Requirements quality BBN sub-net

Figure 6: IV&V requirements phase defect detection sub-net

3.2 Monte Carlo Implementation

The complete set of BBN sub-nets was implemented in MATLAB using a Monte Carlo technique. For the prototype software, each phase is implemented as a stand-alone MATLAB program. Inputs for subsequent phases from BBNs earlier in the lifecycle are manually entered in the prototype model. The number of Monte Carlo iterations is an input parameter; using 100,000 iterations was found to produce stable results. The structure of each BBN subnet model is as follows:

- Load BBN input data (elicited project characteristics, see section 5.1)
- Monte Carlo iteration loop
	- o For each node in succession
		- Interpolate in the node pdf tables to generate a pdf corresponding to the node inputs. Details of the pdf representation are presented in the next section.

- Using the MATLAB random number function and the pdf from the previous step, generate a node output
- o Store the iteration results
- Compute expected value and standard deviation for each node output
- Generate plots and print results

4 Node Probability Density Functions

4.1 PDF Representation

Each node in the ROI BBN produces a random variable between 1 and 5 with a pdf that depends on the node inputs. In order to avoid excessive complexity, each node has either two or three inputs. More complex relationships are represented by cascading the nodes. The node pdf functions are based on a set of elicited pdfs for each node. The pdfs are elicited from experts using a pdf editor graphical user interface (GUI). The pdf editor window for a typical node with two inputs is shown in Figure 7.

The pdfs are elicited for boundary cases and internal cases. Each pdf is approximated using a trapezoidal distribution by dragging the circles that correspond to the four points in the pdf. Thus, a pdf corresponding to a particular node input vector is approximated by the location of the four points that define the trapezoid. In order to implement the BBN in software, it is necessary to map the node inputs to the locations of the four points that characterize the node pdf. The location of each pdf point for a node with two inputs is a surface as shown in Figure 8, and the location of each pdf point for a three-input node is a hypersurface.

Figure 7: pdf editor GUI

A number of techniques for extending the elicited pdfs to node functions were evaluated. Most of the techniques used curve fitting to approximate the functions for each node point. None of the curve fitting techniques produced consistently satisfactory results. Therefore, the node pdfs are represented as lookup tables that are produced by interpolating and extrapolating in the elicited data to generate a grid of points that are compatible with the built-in MATLAB two- and three- dimensional interpolating

functions. The surface shown n Figure 8 was produced from the interpolating table for the second point of the node pdf function defined in Figure 7.

Figure 8: Interpolating surface

4.2 PDF Elicitation

Once the complete set of BBN subnets was defined, the pdf editor (Figure 7) was used to capture elicited pdfs for each node. The pdfs were validated using the plotting feature illustrated in Figure 8.

5 Model Calibration

After eliciting pdf functions, it was necessary to calibrate the predictive model to the case study data. The calibration was performed in four steps. First, BBN input data was collected from project managers for each of the four direct ROI case studies. FPRs were calculated for in-phase and leakage issues using the data collected for the direct ROI case studies. Next, FPR functions were developed for in-phase issues for each defect type (requirements, design, code, test, integration) for developer and IV&V issues. Last, the leakage model was calibrated to predict developer and IV&V defect detection in subsequent life cycle phases. Using the calibrated model, ROI was predicted for each of the four case studies and compared to case study results.

5.1 BBN Input Data Collection

The prototype predictive model was calibrated using the four direct ROI case studies previously reported [DBO03]. Inputs for each BBN sub-net for each of the four case studies were collected from IV&V project managers familiar with the case study projects. The inputs were collected using spreadsheets with embedded instructions. The spreadsheets included internal nodes to aid in validating the BBN topology and to ensure consistent data. Inconsistencies between internal nodes were discussed with the project managers and adjustments made to achieve consistent input. The spreadsheets were configured to automatically generate the MATLAB code. The score for each node is an estimated value in the range 1 - 10, a lower tolerance, and an upper tolerance. The range 1 – 10 was chosen because preliminary experiments indicated that eliciting inputs in the range $1 - 5$ provided insufficient discrimination among projects. The spreadsheet generates automatically the MATLAB code that interprets the inputs as triangular probability density functions as illustrated in Figure 9.

The MATLAB code then rescales the pdfs to the $1 - 5$ range used in the BBN. Appendix B contains the input descriptions contained in the spreadsheet files for each issue type.

5.2 FPR Calibration

The FPR calibration mapped the three BBN outputs (quality Q_{ϕ} , developer defect discovery efficiency $D_{\phi\phi d}$ and IV&V defect removal efficiency $D_{\phi\phi i}$, where ϕ represents the development phase and issue type). The mapping functions consist of lookup tables for each phase for developer and IV&V that map quality and efficiency to FPR. The main steps in the calibration for each issue type were as follows:

- Run the BBN model for each case study using the elicited BBN inputs
- Convert the case study defect data (actual data) to FPR
- Plot the actual FPR as a function of quality and defect discovery efficiency to identify candidate approximating functions
- Fit approximating functions to the BBN output and case study FPR
- Generate FPR lookup tables suitable for MATLAB cubic spline interpolation and implementation in the MATLAB BBN models

• Re-run the BBN using the calibrated FPR functions and compare computed FPR with actual FPR.

5.2.1 Developer-Discovered FPR Calibration

For developer-discovered issues, plotting actual FPR vs requirements quality and developer defect removal efficiency, it was observed that FPR varies directly with the distance from the origin in the (Q_R, D_{rrd}) plane. Therefore, an approximating function of the form

$$
FPR_{\scriptscriptstyle RRd} = c_{\scriptscriptstyle RRd} \sqrt{Q_{\scriptscriptstyle R}^2 + D_{\scriptscriptstyle RRd}^2}
$$

was used. The calibrated curve is shown in Figure 10. Here the circles are the case study data points and the solid trace is the approximating function. The corresponding interpolating surface is shown in Figure 11.

Figure 10: Requirements phase FPR_{DDd} calibration

Figure 11: FPR_{RRd} interpolating surface

5.2.2 IV&V-Discovered FPR Calibration

For IV&V-discovered issues, a more complex relationship was postulated and observed to fit well to the four case studies. The defect detection opportunity was postulated to be a function of Q_{ϕ} such that there is an optimal point that depends on issue type. For Q_{ϕ} values lower than the optimal point, the defect discovery opportunity is reduced because defect discovery is inherently more difficult. For Q_{ϕ} values greater than the optimal point, defect discovery opportunity is reduced because there should be fewer defects to discover. It was also observed that the effectiveness of IV&V defect discovery exhibits an inverse exponential relationship with IV&V efficiency score. The best fit for IV&V effectiveness was a function of the form

$$
Eff_{IV\&V} = a e^{-bD_{\phi\phi i}} \cos(c D_{\phi\phi i})
$$

where *a*, *b*, *c* are coefficients determined using a nonlinear least squares technique. Due to the difficulty in fitting functions to the opportunity data, interpolating tables were produced graphically and used to generate interpolating surfaces for FPR. An example IV&V FPR interpolating surface is shown in Figure 12.

Figure 12: FPR_{RRi} interpolating surface

5.2.3 FPR Calibration Results

The results of the in-phase issue detection FPR calibration are shown in Tables 2 - 6. For requirements defects, the case study data was consistent with the Q_{ϕ} and D_{rrx} results for all projects. Consequently, the predicted FPRs agree within one standard deviation with the actual FPRs. For subsequent life cycle phases, there are outliers that resulted from project anomalies. For example, project B produced no design documentation although many characteristics of the developer's process were judged by the IV&V project manager to be relatively good. Project C was terminated before any code, test, or integration issues were reported, suppressing IV&V defect FPR even though a relatively good IV&V process was underway when the development project was terminated. For all of the case study projects, it is evident that in-phase issue reporting for the later lifecycle phases tended to be lower than earlier lifecycle phases. Of course, due to the relatively small cost escalation factors for the later lifecycle phases, this factor will have a relatively small impact on ROI.

Table 2: Requirements phase FPR calibration

Table 3: Design phase FPR calibration

Table 4: Code phase FPR calibration

Table 5: Test phase FPR calibration

Table 6: Integration phase FPR calibration

Case	Developer FPR			IV&V FPR			
	Actual	Predicted	Std Dev	Actual	Predicted	Std Dev	
A	0	0.019	0.005	$\boldsymbol{0}$	0.0004	0.0002	
B	0	0.018	0.005	$\boldsymbol{0}$	0.0002	0.0001	
\mathcal{C}	0.037	0.007	0.004	$\boldsymbol{0}$	0.0003	0.0002	
D	0.002	0.011	0.005	0.003	0.0005	0.0002	

5.2.4 Leakage Model Calibration

The leakage model was calibrated using only two of the four case studies. The other two case studies reported no defect leakage to subsequent life cycle phases. The lack of leakage data for the two projects resulted from project anomalies rather than the lack of defect leakage. One project did not track post-phase issues and for the other project, the case study was based on a database snapshot that didn't include the leakage data for IV&V and for which case study developer leakage data was estimated by IV&V project managers due to the lack of actual developer data.

Using averages of the available leakage data, the Rayleigh model was calibrated for IV&V and developer-discovered defects by fitting the cumulative issues to the Rayleigh function. The results of developer calibration are shown in Figure 13 and the results of IV&V calibration are shown in Figure 14. In both cases, the cumulative FPR is normalized to the in-phase data so that the computed issues in each subsequent phase is the product of the leakage factor and in-phase FPR. In the figures, the small circles represent the case study data and the solid lines represent the leakage model.

The Rayleigh leakage model has been shown to be effective for large numbers of projects. However, it was observed that leakage exhibits rather large variances. With only

two case studies upon which to calibrate leakage, it was not possible to compute the standard deviations of the estimates. Therefore, for the prototype model, it was assumed that the leakage standard deviation is proportional to the standard deviation for in-phase issues of each issue type. That is, the standard deviation of predicted FPR for a particular issue type for subsequent phases is assumed to be the product of the in-phase standard deviation and the ratio of predicted leakage FPR and in-phase FPR.

Figure 13: Leakage model calibration for developer-discovered defects

Figure 14: Leakage model calibration for IV&V-discovered defects

5.3 ROI Computation

Using the calibrated prototype predictive model, ROI was computed for each of the four case studies. ROI computations were made using the subnet results illustrated in Figure 4. The direct ROI model [DBO04], [DBO03], implemented in MATLAB, used the FPR results of Tables $2 - 6$ and the leakage model of Figure $13 - 14$ to estimate developer defect discovery probabilities for each Monte Carlo iteration and then to compute expected without-IV&V BRAK. Next, the COCOMO [BAB00] coefficient was calibrated to the with-IV&V results and then used to compute without-IV&V results. Using the with- and BBN-predicted without-IV&V development costs and the actual IV&V cost, ROI was computed. The results of the ROI computation are listed in Table 7.

For two cases (B & C) , predicted ROI is somewhat larger than actual ROI. In both cases, this was due to the fact that BBN predicted in-phase issues when the case study data contained no in-phase issues. To more accurately portray the actual case study situation in those cases, the elicited IV&V data for phases in which there were no IV&V issues due to lack of data availability, all IV&V inputs for those phases were set to 1.0 with zero tolerance and the BBN was then re-run. Using the corrected IV&V input data, predicted ROI for both cases is closer to actual ROI.

Table 7: Predicted ROI results

Among the four case studies, Case D had the most complete data for both IV&V and the developer. There were reported issues for both IV&V and the developer for all lifecycle phases and the project was completed successfully. Therefore, it is not a coincidence that the best agreement between actual and predicted direct ROI was exhibited by Case D.

The actual ROI computation for Case B was the least certain. Developer issue distribution among phases was not available when the case study was performed, so a conservative leakage model (developer issues distributed equally among the phases) was assumed. Due to the lack of design documentation, the developer found no design defects and IV&V found design defects only in the code phase via source code analysis. Furthermore, IV&V was not complete when the case study was performed, so no IV&V issues found in the test or integration phase were included in the original case study. It is reasonable to expect that full-lifecycle IV&V and elimination of the conservative (from the IV&V ROI perspective) assumptions would increase Case B ROI significantly.

6 Summary

The prototype predictive ROI model was developed as planned and node probability density functions (pdfs) were developed using the pdf editor. The predictive model for each BBN subnet was implemented in MATLAB. The model was calibrated using case study data to compute function point ratios (FPRs) for developer and IV&V-discovered in-phase issues. A Rayleigh defect leakage model was calibrated to the developer and IV&V case study data to predict out-of-phase FPRs. ROI was computed using a

 \overline{a}

[∗] IV&V inputs for phases for which there was no IV&V activity set to 1.0 (minimum value)

MATLAB Monte Carlo implementation of the direct ROI algorithm and BBN-predicted ROI was computed for each of the four case studies.

The in-phase FPR computations for requirements and design phases for both developer and IV&V issues are in excellent agreement with actual data except for two easily understood anomalies in the case study data. Agreement between predicted and actual values decreases progressively as the lifecycle proceeds to code, test, and integration phases. This decline in precision of the predictive model for later lifecycle phases is attributed to decreasing availability of case study data for the later lifecycle phases. The decline in precision is ameliorated by the decreasing importance, in the direct ROI sense, of the later lifecycle phases.

The fidelity of post-phase (leakage) defect FPR is lower than in-phase fidelity due to the apparently higher variability of leakage behavior and limited amount of calibration data. As was shown in the Phase IIB sensitivity study [DBO04A], ROI is highly dependent on leakage rates because estimation of post-phase developer defect detection drives the probability distribution across lifecycle phases and therefore the expected value of cost-to-fix escalation. For example, the sensitivity study showed that for a hypothetical project with an IV&V ROI of 8.5, significantly reducing developer defect detection efficiency (or increasing leakage rate) can increase IV&V ROI to 25.3. Therefore, the variation in ROI exhibited by the predictive model is well within the envelope to be expected from the sensitivity study results.

7 Conclusions and Recommendations

The predictive IV&V ROI model produces credible ROI estimates for the four case studies. The initial calibration predicts potential full-lifecycle ROI more accurately than truncated-lifecycle ROI. Therefore, it appears that the predictive model is particularly well-suited to prediction of achievable ROI for a specified set of project circumstances. Thus, the prototype predictive model appears to be particularly well-suited to use in a model-based effectiveness measurement framework.

The prototype predictive model also suggests that although per-issue ROI is higher for early lifecycle activities, overall ROI is better for full-lifecycle IV&V. The prototype model provides the means to further explore this phenomenon via additional cases using hypothetical IV&V projects.

Proposed future work includes additional case studies and development of a production ROI model. The results of the prototype model calibration suggest that initial emphasis should be placed on expanding the calibration database via additional case studies. The additional case studies will provide more insight into IV&V ROI, will improve the model calibration database, and will serve as the basis for automating ROI data collection for inprogress projects. Additional experience working with the prototype model in the process of doing the additional case studies will facilitate improved production model requirements.

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Appendix A – BBN Diagrams

This appendix contains the complete set of BBN diagrams for each phase.

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User Involvement UserInvolve **Budget margin Staff Level** Novelty of ReqDevStfLvl **ReqDevBudget** Problem or User Systems Schedule Expertise(*) Approach Process pressure Novel UserExper **Effectiveness Actions** Turnover ReqDevSched ReqDevProcEff ReqDevTrnOvr Quality of User Development Quality Resource Input Staff Experience Availability Organization ReqQualUserInput External constraint Level ReqDevQualOrg ReqDevResAvail pressure ReqDevExpr ReqExtCstr Domain Expertise Requirements ReqDevDomain Stability Process Definition, ReqStab Product Standards, **Quality Criteria** Process System $(CMM?)$ Adherence documentation DevCMM ReqProcAdhere quality SysDocQual **Staff Ability** Process Rigor Development Problem Problem Space (who) Complexity (what) (how Tools RegDevStaff ReqProcRigor ReqCplx ReqProbSpc ReqDevTool Requirements Quality RegQual

Requirements Defect Introduction

Developer Requirements Defect Removal Efficiency

Design Defect Introduction

Developer Design Defect Removal Efficiency

8 Oct 05

Code Defect Introduction

Developer Code Defect Removal Efficiency

Test Defect Introduction

Developer Test Defect Removal Efficiency

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Integration Defect Introduction

Simulation Validity **Test Case Automation** SimVal **IIdAuto** Analytical **Tools IIdANL** Process **Review Quality IIdTools Effectiveness Actions IIdReviewQual** IntDevProcEff Techniques **External constraint** Employed
IldTech pressure Defect Removal IntExtCstr **Staff Ability** Effort/Focus IntDevStaff **IIdFocus** D_{IId} **Integration Test** Quality IntQual (68) $\mathsf{FPR}_{\mathsf{Ild}}$ *DID Number: 06* 35 *CM Number: GSFC & NRC IVV-05-137*

Developer Integration Defect Removal Efficiency

IV&V Integration Defect Removal Efficiency

Appendix B – BBN Input Definitions

B.1 Requirements Issue Subnet

B.2 Design Issue Subnet

B.3 Code Issue Subnet

B.4 Test Issue Subnet

B.5 Integration Issue Subnet

