Artificial Intelligence for Constructing Accurate, Low-Cost Models and Simulations

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ABSTRACT

Modeling and Simulation is an important tool in the development of the highly effective weapons systems built by the United States and its allies. However, recent initiatives to reduce the cost of weapon systems through expanded use of modeling and simulation during the development process have not always lived up to expectations. Current practice in the construction of models and simulations primarily uses a manual implementation of equations to describe the entity being modeled. After verifying correct operation, these models are then validated by comparing them to data from real world tests to insure accuracy. These equation-based models require extensive time and money in order to construct high fidelity models that accurately represent the real world. Our research explores an alternate method of creating accurate models and simulations that can be done rapidly and at much lower cost. This approach uses hybrid artificial intelligence to create the models and simulations directly from validation data sets. Test results using this method of modeling militarily representative systems such as wing lift, radar, and Forward Looking Infrared (FLIR) demonstrated a reduction of over 90% in human labor required to create the models while simultaneously achieving approximately 70% better accuracy as compared to equation-based models prior to validation. Because this method builds the models from a data set, the method can be used to construct models of activities such as human decision-making that cannot be described using an equation-based approach. Additionally, the research demonstrated that models created using this method could be fully integrated with existing equation-based models. This research has the potential to dramatically improve the war-fighting capability of the United States and its allies by providing a fast, inexpensive method to model any entity for which data are available.

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Dr. David P. Brown is a Professor of Systems Engineering in the Technical and Engineering Department at Defense Acquisition University where he has been a faculty member for eight years. He retired from the U.S. Navy with over 22 years of operational and acquisition assignments. His operational experience includes over 2000 flight hours and 300+ carrier landings as a bombardier navigator in the A-6 Intruder. His acquisition experience includes Deputy Director of A-6 flight test at the Naval Air Test Center, AFX Lead Propulsion Engineer, Section Head for Tactical Engines at the Naval Air Systems Command and Propulsion Systems IPT Leader for the Joint Strike Fighter program. Dr. Brown is a 1978 graduate of the U.S. Naval Academy with a B.S. in Systems Engineering. He also has an M.S. in Aeronautical Engineering from the Naval Postgraduate School and a Ph.D. in Information Technology from George Mason University completing his dissertation in the area of modeling and simulation. He is also a graduate of the U.S. Naval Test Pilot School and Naval War College. He is a member of the International Council on Systems Engineering and is currently the leader of the Department of Defense Systems Engineering Community of Practice.

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command and control aircraft, where he achieved over 2000 flight hours, 300+ arrested landings and attained full Mission Commander designation. He also served as Assistant Navigator, USS Lexington and Battle Force Seventh Fleet Materiel Officer. His Navy acquisition tours were both in field and headquarters positions and include: E-2C Flight Test Project Officer, E-2C Avionics Project Officer, Chief Systems Engineer for both E-2C and Advanced Radar Development Team, and Deputy Program Manager for Foreign Military Sales for six active countries. His final tour was in executive leadership positions at NAVAIR Training Systems Division, Orlando, Florida, and he was the Lead Service Executive for I/ITSEC 2003. Mr. Mohler currently serves on the Board of Directors of Leadership Orlando and the National Center for Simulation. He is a member of the Project Managers Institute and a certified Project Management Professional (PMP).

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INTRODUCTION

Modeling and Simulation (M&S) is an important tool for performing trade studies in systems engineering. M&S provides designers with the ability to examine a large number of virtual designs before constructing a prototype or system. This provides a variety of benefits, including balancing requirements with available funding and schedule, determining risk areas, building efficient test plans and reducing test requirements. The aggressive use of modeling and simulation is one of the few tools that have demonstrated the simultaneous achievement of a better product brought to market in less time at a lower cost [DTSE&E, 1996].

Attaining these benefits currently requires an extensive up-front investment. In many cases, small programs do not have the resources to make this investment [DTSE&E, 1996]. Reducing the cost of modeling and simulation so that it becomes affordable for use in smaller programs and product developments would represent a substantial benefit to product and system development. Our research investigates reducing the high cost and length of time required to build models by introducing an alternative hybrid artificial intelligence method that creates models from data sets. These models are then compared in both time of construction and accuracy to the current equation-based modeling technique.

Benefits and Costs of Modeling and Simulation

As computer power continues to increase, model builders are able to build increasingly more complex and accurate virtual representations of real-world entities [Zittel, 1998]. These have provided impressive improvements in product quality, reductions in time to develop products and lower product costs. Table 1 provides a summary of some documented improvements from a study of the use of modeling and simulation in both the public and private sectors.

Table 1[1]. Measured Benefits of Modeling and Simulation

Who	What	Traditional Method	New Method with M&S
TRW	Radar Warning System Design	96 man-months	46 man-months
TARDEC	BFV Engineering and Analysis	4-6 man-months	0.5 man-months
TARDEC	Low Silhouette Tank Design	55 engineers – 3 years	14 engineers – 16 months
General Electric	Engine Fan Blade	4 weeks	A few hours
Lockheed Martin	Engineering Mock-ups	2100 hours	900 hours
Lockheed Martin	Changes per Final drawing	4	2
Lockheed Martin	Physical Mock-ups	$30M each	None
Lockheed Martin	Design Verification	Baseline	30% - 50% reduction from baseline
IBM	Computers	10,000 parts 4 years	4000 parts 2 years
Motorola	Cellular devices	Baseline	50% reduction in product cycle time
Sikorsky Aircraft	Helicopter External Working Drawings	38 draftsmen 6 months	1 engineer 1 month
NAVSEA	Ship Seakeeping Analysis	27 days	3.5 days
NAVSEA	Radar Cross Section Analysis	57 days	17 days
Comanche Helicopter Program	Source Selection	Prototype Fly-off $500M	Simulator/Surrogate Aircraft Fly-off $20M

As can be seen from these examples, most of the success stories found during this study involved large government programs and/or products developed by

[1] DTSE&E study (1996) “Study on the Effectiveness of Modeling and Simulation in the Weapon System Acquisition Process”, Final Report.

large corporations. Across complex Department of Defense (DoD) programs a conservative average cost benefit of operating costs for virtual/constructive training over live training has been at least 20:1. A simulated joint exercise led by NAVAIR Orlando at I/ITSEC 2003 again validated this ratio. The cost advantage would have been at least 30:1 if the cost of precision munitions and environmental costs were also included.[2]

Although the benefits of Modeling and Simulation are significant, these benefits come at a steep price. An aggressive M&S effort requires an extensive up front investment. For the virtual exercise at I/ITSEC 2003 costs ran between $300-400K for the two-day event, and had the advantage of millions of dollars of R&D supporting the products. Development of the Boeing 777, a recognized business success case in which M&S played a significant role, required an up front investment of roughly one hundred million dollars [Garcia, et. al., 1994]. The M&S core body of knowledge states under limitations that "M&S tools are not generally inexpensive and require an up-front investment cost" [Acquisition Functional Working Group, 1999]. This statement is backed up by results of a study looking at the cost of the M&S effort on Department of Defense programs summarized in table 2.

Table 2[3]. Department of Defense M&S Cost Data

Program	Approximate Total Program Cost	M&S Expenditures
LPD-17 (ship)	$10B	$38M
ATACMS/BAT (munition)	$5B	$25.2M
Javelin (missile)	$4B	$48M
AN/BSY-2 (sonar)	$3B	$58.3M

This same study found that program managers do not consider DoD-wide M&S investments as either cost or schedule effective [Hicks & Associates, Inc., 2001].

[2] Data provided courtesy of Northrop Grumman Corporation

[3] Hicks & Associates, Inc., (2001) "Modeling and Simulation Survey Briefing".

Why is M&S so Expensive?

Looking at the modeling of a simple system demonstrates the high cost and time associated with building equation-based models, even for systems that have well understood equations. One particular case evaluated the building of a model for simulating the performance of a spring-powered car [Brown, 1999]. The model was constructed for use by students taking a course in systems engineering at the Defense Systems Management College and was designed to demonstrate the value of modeling and simulation in cost-performance trades. The exercise involved conducting a series of trades to find a combination of variables that provided good performance for only two performance requirements at the lowest cost. The final equation of motion for this simple vehicle had 34 variables and 8 coefficients. Modeling and simulation of complex systems may require an extremely large number of variables and coefficients as well as the equations that relate them together. It is highly unlikely that a company making spring-powered cars could afford even a tiny fraction of the costs in table 2. The study compared a group of students who used the model with a control group that did not have access to the model. The use of M&S in the design phase resulted in better performance at lower cost for the same amount of time spent on the project [Brown, 1999]. The benefits of using M&S in the design phase of any project, regardless of size, are significant.

Once any model is built, it must be verified and validated before use [Acquisition Functional Working Group, 1999]. Verification tests that the model has been implemented correctly, while validation checks that the model or simulation accurately represents the real world system. To correctly validate a model, the actual system is tested over the range of values that the model or simulation is intended for use. The model predictions are checked against the test data. If the model does not agree within specified limits in any area with the test data, further tests are conducted to determine the cause of the difference. These causes are then mathematically incorporated into the model and the results checked again. This process continues until an acceptable agreement between the test data and the model is obtained. This explains the finding in the M&S Core Body of Knowledge which states that attempts to create high-fidelity models rapidly drive up the cost of a modeling effort [Acquisition Functional Working Group, 1999]. The key to wider use of M&S in product development is to significantly reduce the time and expense of current modeling methods.

Quantifying Predictive Accuracy

Another issue with current methods of modeling and simulation is quantifying the predictive accuracy. Models and simulations only approximate the real world. Most models provide a single predictive output for a single set of inputs. Instead of a single prediction, a better solution would be to provide the range of values over which the true answer would lie and identify which values are more likely than others.

Many current M&S software packages provide a sensitivity analysis feature. A sensitivity analysis varies the independent variables over their expected range of values in the anticipated operational environment to determine the sensitivities (or gradients) with respect to the dependent variables of interest [Arsham, 2002]. The model or simulation is run multiple times with the variable on which the analysis is being performed incremented by a fixed amount on each run. The analysis begins at either the highest or the lowest value of the sensitivity range and continues until the opposite end of the range is reached. A sensitivity analysis provides a more complete answer by specifying a range over which the answer may lie. However, this answer is incomplete in that it provides no information about where within the range the answer is most likely to fall. This analysis is sufficient in estimating model sensitivities only if the effects of the parameters on the model are independent and monotonic [Bankes, 1993]. No probability or confidence can be attached to the range of even the most sensitive variable. Furthermore, variables that show little sensitivity when varied independently may exhibit strong sensitivity when varied in combination with other variables. Thus, running a sensitivity analysis may not capture the true range of the solution space of the dependent variables.

The most complete method found was the modeling of all variables that exhibit variation as random variables [Bankes, 1993]. Each random variable is set to a distribution function that describes how the variable behaves. A Monte Carlo method is then employed which samples from each distribution over multiple computer runs to obtain a probability distribution of the dependent variables. This provides a complete probabilistic solution to the problem in that all correlations and synergistic effects are captured, the complete range of possible outputs is captured, and the likelihood of each answer within the range is specified. The accuracy of the output distribution is dependent only on the number of samples generated and is not dependent on the number of inputs. The Monte Carlo method also allows use of standard statistical techniques to estimate the precision of the output distribution. Although this method provides a more complete answer to predictive accuracy, its primary drawback is that it can take vast amounts of computer run time in order to generate the distribution if the model is large and complex.

TECHNICAL APPROACH

To reduce the cost of constructing models and simulations, the research approach focused on reducing the amount of human labor in the model building process. This was accomplished by using artificial intelligence agents to learn the relationships between variables directly from data sets creating computer-generated models. Although this approach is not new, the exact technical approach is unique in that a hybrid software package using both Bayesian and neural networks was created to conduct the research. This approach overcomes many limitations associated with curve fitting, which can not easily handle non-linear or discontinuous data sets.

Bayesian Networks

Bayesian networks are directed graphs for representing probabilistic dependencies among variables [Jensen, 1996]. Bayesian networks encode a complete and coherent probability distribution over many variables and can be used to evaluate both causal and evidential influences. A Bayesian network consists of a directed acyclic graph that represents dependencies among variables, together with local probability distributions defined for small clusters of directly related variables. Directed acyclic graphs consisting of nodes, which represent the variables, and arcs (or directed edges) that describe cause and effect relationships or statistical associations between the variables [Jensen, 1996]. Each variable has a finite set of mutually exclusive states. The graph may contain no directed cycles, or paths that lead from a node to itself and follow the direction of the arcs. Each node is conditionally independent of its non-descendents given its parents.

Probability information in a Bayesian network is specified via a local distribution for each node. The local distribution for a root node is simply an assignment of a probability to each state such that the probabilities sum to 1. A conditional probability table gives the local distribution for a child node. This table shows the probability of each possible state of the child conditional on each possible state of all of its parents. The joint distribution for all variables in the network is

given by the product of the local distributions for all the nodes:

$$P(X_1,...., X_n = \prod_{i=1}^{n} P(X_i \mid X_{pa(i)}) \qquad (1)$$

where $\underline{X}_{pa(i)}$ denotes the parents of variable X_i.

The conditional probability that variable E takes on value e given that H takes on value h is defined by the equation:

$$P(E = e \mid H = h) = P(E = e \, and \, H = h) \qquad (2)$$

A straightforward consequence of this definition is Bayes Rule, a powerful mathematical relationship by which probabilities can be modified to incorporate new evidence:

$$P(H \mid E) = P(H) * P(E \mid H) / P(E) \qquad (3)$$

The first term, P(H|E) is referred to as the "posterior probability" or the probability of H given evidence E. The term P(H) is the prior probability of H. The term P(E|H) is the "likelihood" and gives the probability of the evidence assuming hypothesis H is true. The last term is the probability of E that acts as a normalizing or scaling factor [Niedermayer, 1998].

To demonstrate a Bayesian network, an example for diagnosing problems with the air conditioning of any car using R-134a refrigerant is shown in figure 1.

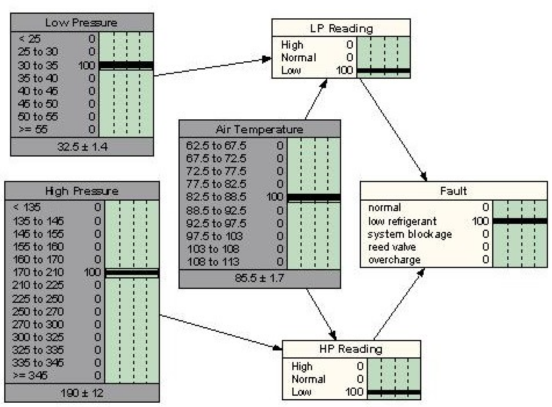

Figure 1. A/C Bayesian Network Model

In this example, diagnosing the system involves taking pressure readings from the high pressure output line from the compressor and the low pressure return line to the compressor. The readings are then evaluated as to whether they are high, normal, or low based on the outside air temperature. This information then determines the most likely status of the system. In figure 1, if the low side pressure is 32 psi, the high side pressure is 198 psi and the outside temperature is 84 degrees F, then the system is not operating normally and the most likely problem is that the refrigerant level is low.

The advantages of Bayesian networks include the capability to learn both the structure of the networks and the probabilistic relationships between the nodes from data sets. Through the use of Bayes Rule in calculating the distributions, networks respond nearly instantaneously to node state inputs. The output is a probability distribution that provides not only the range of values over which the answer may lie, but also the probability of each answer within the range. Bayesian networks can also provide these distributions with an incomplete set of input parameters. The principle disadvantage of these networks is that they cannot always provide predictions to inputs that were not in the learning data set.

Neural Networks

Neural networks are computational systems that mimic the computational abilities of biological systems by using large numbers of simple, interconnected artificial neurons [Maren et al., 1990] There are different types of neural network applications available for consideration. They fall into five basic categories: prediction, classification, data association, data conceptualization and data filtering. The primary use of a neural network in this research is for prediction. Types of predictive neural networks include the back-propagation, delta bar delta, extended delta bar delta, directed random search, higher order or functional link, and the self-organizing into back-propagation [Anderson and McNeil, 1992]. A feed-forward back-propagation networks (usually referred to as the back-propagation networks) was selected for use in this research. A neural network of this type contains an input layer, one or more hidden layers and an output layer. A typical back-propagation neural network is shown in figure 2. The input layer nodes feed the input values into the rest of the network. Connections between layers are bi-directional. Data values move from inputs through the hidden layers to the outputs during feed forward operation. During learning, error corrections are propagated back through the network starting from the output nodes and running upward through all hidden nodes from the bottom to the first hidden layer.

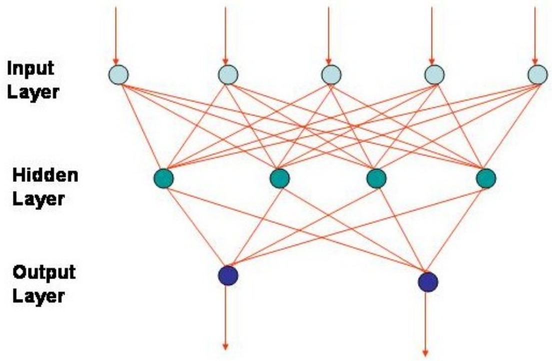

Figure 2. Example Neural Network

All hidden and output nodes in the network have the structure shown in figure 3.

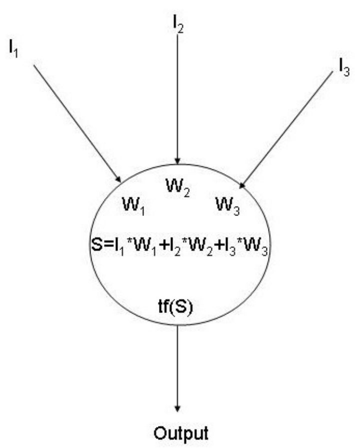

Figure 3. Neural Network Node

During feed forward operation, the node first calculates the sum of all inputs (I) times their weights (W). A transfer function is then applied to the sum. This function transforms the output into a number between zero and one (minus one and one in some software packages). There are several transfer functions that can be used. All functions have a ramp, bell or modified S-shaped curve that runs asymptotically along the X-axis approaching either the maximum or minimum value [Maren et al, 1990]. The type of transfer function is manually selected during network construction while the weights for each input connection is calculated during the learning process. All inputs must also be scaled to values between zero and one. Outputs, which are all values between zero and one, must be scaled in the reverse direction from a decimal value to the actual value.

The primary advantage of a neural network is that it is capable of adaptive learning of very complex problems [Maren et al., 1990]. These networks can predict additional values within the range of the training data set. Neural networks can also handle both non-linear and non-continuous functions. The disadvantages of neural networks include a single output predictive answer with no information of how probable or accurate that answer may be and the requirement for a complete set of inputs.

Hybrid Networks

Use of multiple types of artificial intelligence networks at the same time is currently an area of high interest to researchers. The Northrop Grumman Corporation (NGC) has used combinations of networks for data fusion and to handle uncertainty in highly complex data problems with high levels of uncertainty. Hybrid networks are emerging from NGC work with Applied Minds under a program called Futures Lab. This approach uses Bayesian networks, along with other types of artificial intelligence networks, to fuse evidence at the hypotheses while using neural networks to reconcile the network outputs.

Research Software Implementation

To conduct the research, a software package capable of creating Bayesian network models from data sets was required. A search of existing applications found no software package suitable for creating engineering models from data sets containing mixtures of discrete and continuous variables. The primary deficiency was the absence in currently available packages of methods for intelligent, simultaneous discretization of multiple continuous variables. This led to the development of the derivative method of discretization that is implemented in the research software package described below. The software package, BN Builder, integrates new code to implement the discretization of continuous variables with four commercial software packages providing the rest of the functionality. The software architecture and data flow are presented in figure 4. The input to the software is an Microsoft® Excel data set. A neural network is manually created using QNET 2000. The weights are learned from the input data set. Bayesian network structure learning is performed by BN PowerConstructor, one of the modules in the BN PowerSoft collection by Jie Cheng of the University of Alberta, Canada.

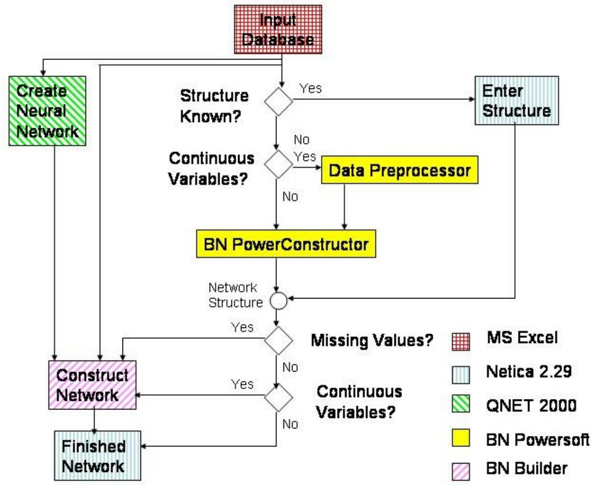

Figure 4. Research Software Architecture

The neural network generates additional data for the learning data set based on user input. The BN builder software creates a Bayesian network using the augmented data set. Nodes with continuous data values are discretized using the derivative method. Additional uncertainty from the neural network predictions is captured during learning by comparing neural network predictions with the training data and adding the additional variance into the node probability distribution. The output of the research software is a Bayesian network that is capable of making probabilistic predictions to incomplete input data and that can make predictions to inputs not contained within the learning data set.

METHODOLOGY

The methodology used to conduct the research consisted of comparing models and simulations constructed using a conventional, manual equation-based implementation with computer-generated models and simulations created using the software described above. Equation-based models were constructed using mathematical equations from published textbooks. The same individual constructed all but one model with construction time recorded to the nearest minute. A complete description of all models, tests and results can be viewed at https://acc.dau.mil/aicrms. The models used in the research are listed in table 3. Models were evaluated at the first step of the validation process. The computer-generated models were constructed by dividing the validation test data into a learning set and a test set of data points. The test set always contained input conditions not contained within the learning set.

Table 3. Research Model Matrix

Model	Name
1	Amplifier
2	LRC electrical circuit
3	Elevator control
4	Radar
5	Forward Looking Infrared (FLIR)
6	Commuter
7	Wing Lift

The computer-generated model was constructed from the learning data set, and then used to predict the outputs of the test data set. The predictions were compared to the test data for accuracy using the percent difference between the prediction and measurement as the accuracy metric. The equation-based models were used to predict the same outputs of the test data set.

Hypothesis #1 – Time of Construction

Null hypothesis H_O^1: There is no difference in construction time between computer-generated models and equation-based models.

Alternate hypothesis H_A^1: There is a difference in construction time between computer-generated models and equation-based models.

Hypothesis #2 – Model Accuracy

Null hypothesis H_O^2: There is no difference in predictive accuracy between computer-generated models and equation-based models.

Alternate hypothesis H_A^2: There is a difference in predictive accuracy between computer-generated models and equation-based models.

RESULTS

An equation-based model and a computer-generated model were constructed for each system listed in table 3. The wing model was not included in the time comparison as it was constructed by an outside source with no record of construction time. A comparison of construction times is included in figure 5. As can be seen in figure 5, the computer-generated models were constructed in less time than the manually constructed equation models in all cases except the amplifier. This was due to a unique case where the modeling software package came with a pre-built amplifier element.

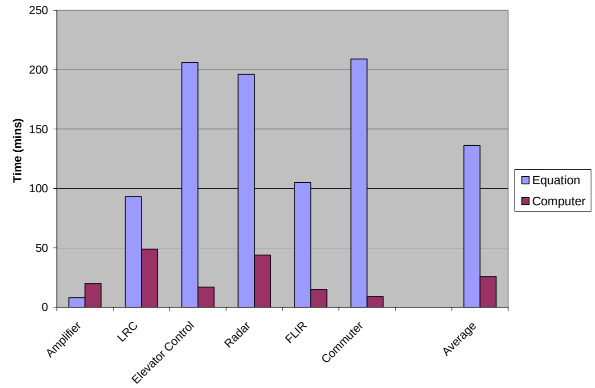

Figure 5. Model Construction Time

Hypothesis H[1] was tested with the data of figure 5 resulting in a rejection of the null hypothesis. The computer-generated models took less time to construct in five of six cases and overall took an average of one fifth the time to construct as compared to equation-based models. The difference is so great in these five cases that it supports a conclusion that construction time for computer-generated models is less than equation-based models at 95% confidence.

The cost of modeling and simulation is driven mostly by the human labor involved in the process. Although computer equipment and software require upfront investments, the cost of computer run time, once purchased, is negligible. The average times to perform specific tasks while constructing the models are presented in figures 6 and 7.

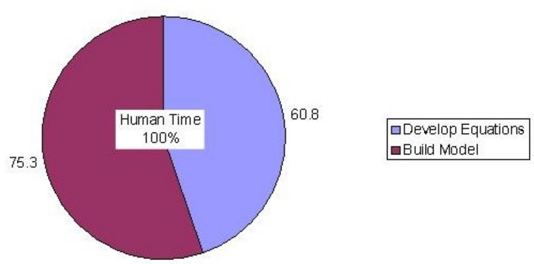

Figure 6: Equation-based Model Task Times

As can be seen in figures 6 and 7, not only has the average time of construction been reduced from 136 to 26 minutes, but the task loading requiring human work has been reduced from 100% in the equation-based models to 47% for the computer-generated Bayesian network models resulting in a total reduction in human labor of over 90%.

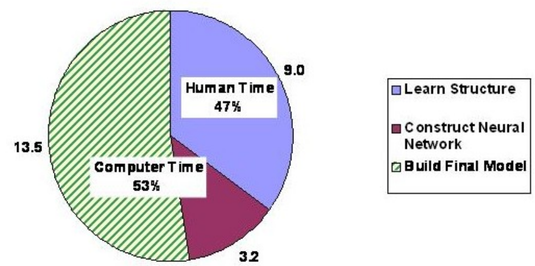

Figure 7: Computer-generated Model Task Times

Reviewing the breakdown of model task times, as model complexity increases, total construction time increases. However, the human tasks associated with model construction remains nearly constant. Learning the network structure and constructing the neural network both require human input, but are computer-aided tasks. The increase in construction time is almost completely attributable to increased computer run time of the BN Builder program. This leads to a conclusion that models created using computer generated Bayesian networks would be much less expensive to build than equation-based models. Not only is time of construction significantly less, but the human labor involved is also reduced. Because there is no longer a strong relationship between complexity and human labor required, costs to construct computer-generated Bayesian networks are not sensitive to problem complexity.

Hypothesis H[2] was tested using thirteen cases generated from six of the models. The elevator control model was not included as it had a discrete output. The control system sent the elevator to the correct floor in all cases for both types of models. A summary of model errors is presented in figure 8.

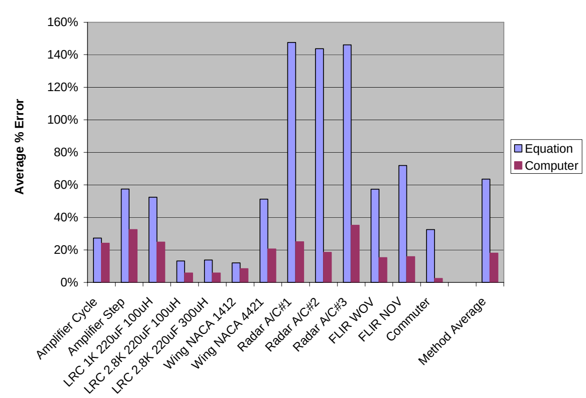

Figure 8. Model Error Comparison

Hypothesis H^2 is tested with the data of figure 8 resulting in a rejection of the null hypothesis. The error associated with computer constructed Bayesian network models is lower in all twelve cases and averaged over 70% less as compared with the equation-based models. The magnitude of the difference in error is great enough to establish a statistical difference between these two methods at 95% confidence.

Two models that demonstrate the unique capabilities of computer-generated models are the wing aerodynamics and Forward Looking Infrared (FLIR) models. The aerodynamics of an airfoil such as a wing are described by the Navier-Stokes equations. Unfortunately, even with the vast power of today's computers, for problems of interest the full Navier-Stokes equations are still too expensive to solve. Instead, the equations must be solved through approximations using numerical methods referred to as Computational Fluid Dynamics (CFD). One such method is a panel code model developed at the Naval Postgraduate School which assumes that the airflow is inviscid, incompressible and irrotational. As can be seen in figure 8 for a thin wing such as the NACA 1412 airfoil, these assumptions are valid and the results are accurate. However, for a thicker wing such as the NACA 4421, a loss of lift (C_L) occurs at higher angles of attack (AOA) due to a breakdown of at least one assumption as can be seen in figure 9. The computer-generated models, by comparison, are able to learn from the data set that there is a loss of lift at higher angles of attack for thicker wings and are therefore able to make a much more accurate prediction of C_L.

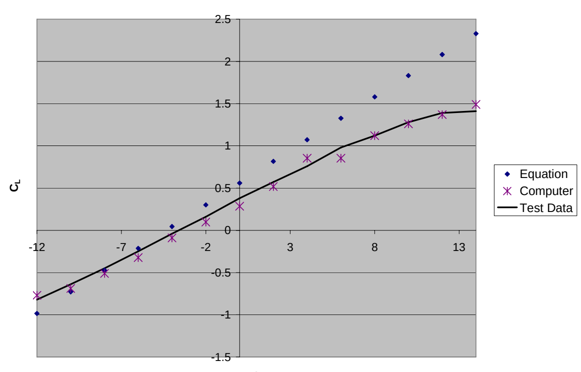

Figure 9: Wing Model Comparison

The second example of special interest is the FLIR models. The test data for the FLIR in its Wide Field of View (WFOV) setting for the detection range versus temperature differential between a fixed size test target and the background is shown in figure 10.

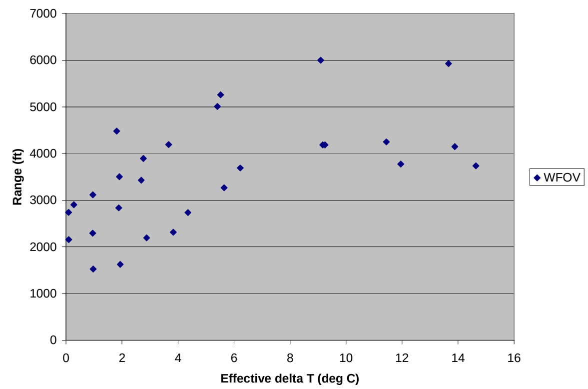

Figure 10: WFOV FLIR Test Data

The data were measured by multiple students at the Naval Test Pilot School using both white and black hot polarity settings on a commercial FLIR. The data set contains scatter due to random measurement errors from multiple students collecting the data. This data provided a challenging learning problem for the computer-generated models due to the scatter. In theory, there should be no difference between the white and black hot settings. However, when the computer-generated model was created, a relationship was found between the polarity setting and the range. This resulted in separate predictions for the two settings in the computer-generated model as shown in figure 11. As can be seen in figure 11, the system demonstrated less detection range capability in the white hot setting. This was captured by the computer-generated model resulting in polarity setting as an input and far greater accuracy when compared with the test data than the equation-based model prediction.

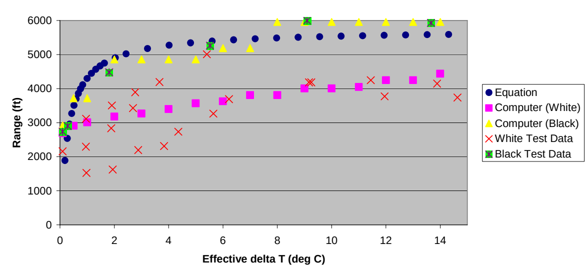

Figure 11: WFOV FLIR Model Comparison

There is no mathematical explanation for this test result, but the fact that it exists is clearly shown in figure 11. Because of this unusual result, electro optic experts from the Naval Air Test Center were asked to review the data. They verified that there was in fact a difference between the polarity settings of this particular system, attributing the difference to either a display unit that provides a better display of dark on a

light background or the possibility that the human eye can detect black on white better than white on black backgrounds.

Discussion

The equation-based models presented in this paper demonstrate that real world systems rarely perform in accordance with theoretical physics-based equations. Equations are only approximations of the complexities of the real world. During validation, corrections must be made to the model equations in order to get the predictions to match the real world data within the desired accuracy. This may include additional testing to determine the source of the difference between the equations and the real world data. By continuing to add corrections, the equation-based models can be made as accurate as the computer-generated models. However, this would require even greater human labor further increasing the time advantage and cost savings of the computer-generated models over the equation-based models.

By comparison, the computer-generated models are capable of learning the relationships between the variables including the many non-linearities and other factors that are not captured using an equation-based approach. Additionally, the time required to create a model using this technique is relatively insensitive to model complexity. Only the computer run time while the model is being constructed increases significantly with complexity, adding little to the cost of model construction.

The authors do not claim that computer-generated models are the best choice in every case. Each modeling method has certain advantages depending on specific circumstances of what is being modeled. Based on test results, the following circumstances favor the use of an equation-based approach:

- Validated equation-based models already exist
- Modeling function blocks already exist
- There is a scarcity of available data on what is being modeled
- The element being modeled does not require many function points

The following circumstances favor a computer-generated Bayesian network approach

- Database of observed or test data already exists
- Problem is not well understood and/or equations do not exist
- Problem is complex
- There may be unknown non-linearities
- Hidden variable relationships may exist
- Problem is a control application or decision problem

The conditions most favorable to computer-generated models are those with the greatest potential to reduce the time of construction and expense of modeling and simulation.

Model Integration

Equation-based models and computer-generated Bayesian network models are not mutually exclusive methods of modeling and simulation. When modeling complex systems, the problem is usually broken down into smaller, simpler subsystems that are constructed, tested and then integrated into the final complex model or simulation. This approach lends itself to creation of integrated models where each component to be modeled is individually evaluated to determine which modeling method would be best under the particular circumstances. For the research, one integrated simulation was the detection of a target aircraft by the radar model. In this example, the equation-based radar model previously described was corrected for the validation data resulting in a good match between predictions and real world tests. An aircraft target model was created using the equations of motion to control target movement within the simulation. The radar cross section of the target was modeled as a computer-generated Bayesian network from unclassified radar cross section measurements of a World War II aircraft. Construction of a physics-based equation model for aircraft radar cross section would probably be impossible on a desktop computer.

The radar was stationary for this simulation. The target flies a closing track from right to left across the front of the radar. The target tracking simulation results are shown in figure 12. As can be seen in the target track, the simulation provides an extremely realistic target engagement. As the target aircraft moves toward the radar, both the range and aspect of the aircraft change. This causes scintillation, where the target fades in and out between different radar scans. Those with radar operating experience will recognize this real world phenomenon on the track of figure 12. In addition to this example, several other integrated equation/computer-generated models were constructed and tested. These models offered extremely improved flexibility to the model builder based on the attributes of the particular sub element being created.

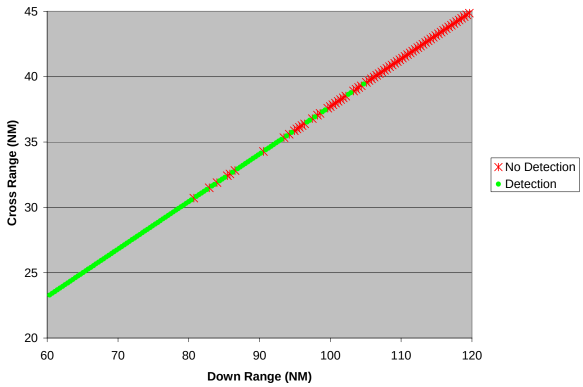

Figure 12. Radar Target Tracking Simulation

Of particular note were models constructed using the computer-generated Bayesian network models to make human decisions or otherwise perform control functions within the simulations. These integrated simulations were shown to be more effective than those using a rule-based approach to decision-making or control.

SIGNIFICANT CONTRIBUTION

The primary contribution produced by this research is the demonstration that highly complex model elements can be created directly from data sets in a small fraction of the time required to build the same model using a manual, equation-based method. Since modeling costs are primarily driven by human labor, this research demonstrates that significant cost reductions are possible. Not only were models created in far less time, but in every case the computer-generated models were more accurate than the equation-based models prior to corrections for model validation. The computer-generated models also quantify the accuracy of the prediction where as the equation-based models must be run many times to obtain the same distributions. We also demonstrated that computer-generated models can be integrated with equation-based models providing never before seen flexibility in model element creation along with reuse of existing model assets. Additionally, the research can improve training simulations through construction of computer-generated models of the actions of an adversary. By integrating the model into a training simulation, human trainees would be exposed to training scenarios that respond to their actions much more like the adversary would respond. Not only would these models respond much more like humans than rule-based models, but could be rapidly and inexpensively updated as new information becomes available.

CONCLUSIONS

Modeling and Simulation is an important tool in the development of the highly effective weapons systems built by the United States and its allies. It has been demonstrated that the benefits of M&S are applicable to programs of any size. However, M&S generally requires a significant upfront investment; one that smaller programs cannot afford to make. This research has demonstrated that it is possible to significantly reduce M&S costs making this tool affordable for small programs and more cost effective for large ones. Based on labor costs, the reduction demonstrated in this research is approximately 90% while simultaneously achieving a 70% increase in predictive accuracy. The authors acknowledge that computer-generated Bayesian network models are not the optimal choice for every situation. We demonstrate that integrated models can be constructed using both equation-based and computer generated models. Together, these integrated models and simulations provide tremendous flexibility to the model developer.

Work continues to further improve this process. The method of discretization has currently been updated to handle any data set. Future plans include automation of the neural network build process and integration of the structural learning program into the main software application. These improvements are designed to further reduce human labor to only a few minutes, irregardless of the size or complexity of the model. Additionally, we are continuing to explore potential applications of creating more complex integrated models mixing model types. The ability to mix predictive artificial intelligence decision making into physical simulations could have exciting applications in the areas of training and operations research.

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