An Emergency Department Simulation and a Neural Network Metamodel

Lt. Col. Robert A. Kilmer
Department of Systems Engineering
United States Military Academy
ATTN: MADN-F
West Point, NY 10996
914-938-2700
914-938-5665 (fax)
fr3615@usma8.usma.edu

Alice E. Smith
Larry J. Shuman
Department of Industrial Engineering
University of Pittsburgh
1031 Benedum Hall
Pittsburgh, PA 15261
412-624-5045
412-624-9831 (fax)
aesmith@engrng.pitt.edu

Accepted April 1995 to the *Journal of the Society for Health Systems*, Special Issue on Simulation

An Emergency Department Simulation and a Neural Network Metamodel

Lt. Col. Robert A. Kilmer
Department of Systems Engineering
United States Military Academy
ATTN: MADN-F
West Point, NY 10996
914-938-2700
914-938-5665 (fax)
fr3615@usma8.usma.edu

Alice E. Smith
Larry J. Shuman
Department of Industrial Engineering
University of Pittsburgh
1031 Benedum Hall
Pittsburgh, PA 15261
412-624-5045
412-624-9831 (fax)
aesmith@engrng.pitt.edu

Abstract

This paper describes a discrete event stochastic simulation of a hospital emergency department, and the development of a metamodel of that simulation. The metamodeling technique used is artificial neural networks, which are trained using the output of the simulation. The performance of the neural network metamodel is compared to the simulation performance for estimating the mean and variance of patient time in the emergency department.

1. Introduction

Due to the stochastic nature, complex dynamics and interactions of inputs, activities and outputs of the hospital emergency department (ED), researchers and practitioners have turned to discrete event stochastic simulation as the methodology for examining the emergency department system. A simulation allows patient flow, layout, staffing, procedure and equipment alterations to be tested so that optimal control strategies for the ED can be developed. Motivation and generic structure for simulation of health care environments have been discussed by Bressan, Faccin and Romanin Jacur (1988) and Mahachek (1992). Published research on simulation in health care has addressed facilities planning (Dumas (1984)) and personnel scheduling (Ishimoto et al. (1990)). The critical care aspects of surgery have been the subject of simulations (Hunter, Asian and Wiget (1987), Lowery (1993)). Previous work in simulating the emergency department include Saunders, Makens and Leblanc (1989) and Weissberg (1977). These latter two simulations are constructed in a similar manner to the one described in this paper, but with less detail and flexibility.

There are drawbacks to the use of simulation, especially in environments where decisions are made frequently and under tight time constraints. To circumvent the long running times and multiple replications required for simulation analysis, metamodels can be developed and used. The objective of the metamodel is to accurately reproduce the simulation over wide ranges of interest, and to be computationally much more efficient than the simulation itself. A recent overview of simulation metamodeling can be found in Yu and Popplewell (1994).

Artificial neural networks, since they function as parallel universal approximators, have capabilities which make them good candidates for simulation metamodeling. This idea was pursued on very limited problems by Badiru and Sieger (1993), Hurrion (1992), Padgett and Roppel (1992), Pierreval (1992), and Pierreval and Huntsinger (1992), and was the subject of the authors' earlier work (Kilmer and Smith (1993), Kilmer, Smith and Shuman (1994)). In the last paper cited, it was shown that artificial neural networks trained with simulation output could effectively develop prediction intervals that were competitive in quality with those developed directly from the simulation model. The empirical basis of that work was a small inventory system from Law and Kelton (1991). This paper describes the neural network metamodeling technique applied to a large hospital ED simulation, discusses results, and makes comparison between the outputs of the neural metamodel and the simulation itself. The primary distinction between this work and earlier published work on metamodeling is the problem domain, health systems, and the size and complexity of the simulation which is to be metamodeled.

2. Overview of the ED Simulation

2.1. The Emergency Department Environment

The hospital studied is a 750-bed medical center located in Pittsburgh offering comprehensive medical and surgical services, with an ED which services over 4,200 patients per month. To consider possible changes to operating policies and procedures without disrupting vital care-providing services, a simulation model of the ED was commissioned by the hospital, and built by the Department of Industrial Engineering of the University of Pittsburgh in conjunction with Data Communications, Inc., a Pittsburgh firm developing decision support systems for health care providers. An important output variable of interest was mean patient time in the ED.

2.2. The Simulation Structure

In this project, the ED was modeled with the SIMAN simulation language running on a PC. The simulation is contained in two files, or frames. The model frame contains all the basic constructs that are used to describe or represent the actual ED system. Patient related services and locations in the ED are represented in the model frame in separate sections called stations. These stations include such areas as registration, triage, treatment rooms, X-ray, etc. Building the simulation model frame in this modular manner allows the simulation to be more easily verified and validated and, if necessary, to be modified or expanded. The experiment frame contains data distributions such as arrival times, service times, and patient flow patterns as well as the constructs for obtaining output data from the simulation. Since data related changes are made only to the experiment frame, the user can perform different simulation experiments without actually changing the structure of the system as represented in the model frame.

2.3. Simulation Constructs

The simulation consists of the following: the ED physical facilities and layout, servers (e.g. physicians, nurses and other support personnel), patients, and a procedure for representing patient arrivals, patient activities and treatments, server shift changes and server breaks. The simulation is considered to be terminating, with termination considered to take place at 7:30 AM each morning. In order to make development of simulation of the ED tractable, certain simplifying, but realistic, assumptions were necessary. These assumptions along with the simulation constructs are listed below.

Physical Layout of the ED

The physical facilities of the ED consist of 18 treatment rooms (two of which have two beds, while the rest have one bed), a waiting room, a registration desk, a triage room, an X-ray area, and separate stations for the unit secretary, nurses, nurses aides and physicians.

There are four possible entrances/exits to the ED. Two of these are represented as entrances only. Those patients whose mode of arrival is either helicopter or ambulance enter through the entrance which is closest to the helicopter dispatch office. All other ED patients i.e., walk-in patients, enter through the entrance which is next to the patient waiting room and leads into the registration desk area. All of the passageways to the ED are used as exits. Which exit that is used depends on the destination of the patient on departure from the ED.

Patients

Patients are represented as entities that flow through the simulation model. Although there are endless types of patients that visit the ED, it is possible to categorize the patients into three modes of arrival - life flight, ambulance/medic, and walk-in (includes auto, bus, etc.). Patient arrival distribution and parameters change every two hours over a 24 hour period, and consist of gamma and exponential distributions. The proportion of patient arrivals by each mode of arrival is distributed with a discrete probability mass function which is fixed for the 24 hour period.

A few patients are directly admitted to the hospital without treatment in the ED, and will be assigned to a treatment room in the ED only if the wait for a hospital bed is longer than 60 minutes. The time for a direct admit patient to receive a hospital bed is assumed to be distributed uniformly from 30 to 180 minutes.

For non-direct admit patients, an acuity level is assigned: emergent, urgent, or non-urgent. The probability of a patient having a particular acuity level is modeled as a fixed discrete probability mass function which depends on the patient's mode of arrival. An additional categorization of patients is on the type of care that will be provided to the patient - simultaneous care (service is provided only once by each server), sequential care (service is provided several times by each server), or observational care (nurses only check the patient occasionally). A final categorization is on the basis of patient disposition: left without treatment; treated and released; admitted - general medical/surgical unit; admitted - intensive care unit; patient died - morgue.

Servers

The facilities and staff are divided into two categories, those that provide service from a fixed station (e.g. secretaries) and those that travel throughout the ED (e.g. physicians and nurses). Based on these distinctions the stationary servers are modeled as resources and the mobile servers are modeled as transporters under the SIMAN conventions. This allows these servers to move freely throughout the ED as well as to transport patients from one location to another. There are three types of physicians - attending, third year residents, and first or second year residents. There are six types of nurses - nurses aide, charge nurse, triage nurse, emergent patient area nurse, urgent patient area nurse, and non-urgent patient area nurse. Service times of physicians and nurses are treated as exponential distributions with means dependent on the acuity level and care type (see below) of the patient. Service times of registration and admitting personnel are modeled as uniform distributions with ranges dependent on the arrival mode of the patient.

Server breaks are combined with lunches to give each worker the unofficial standard 45 minute lunch/dinner break rather than the officially prescribed 30 minute lunch break and two ten minute breaks.

Patient Flow

Direct admit patients (i.e. destination is an in-patient unit) of any mode of arrival or level of acuity have their own distinct flow through the ED: they go to registration and either depart the ED immediately and go to the admitting section of the hospital or are put in an ED treatment room, under observation by the staff, and then depart the ED and go to the admitting section where a bed is located.

All patients with destinations other than admitting use the following paths:

The flow of helicopter and ambulance patients, from entry to the ED until arrival at a treatment room, is: assigned a treatment room and a nurse; transported to a treatment room; registration clerk obtains registration information in the treatment room.

For walk-in patients, the flow from entry to the ED until arrival at the treatment room depends on the acuity of the patient. If the walk-in patient's acuity level is emergent, then after a short time in a triage station, the patient follows the path described above for helicopter and ambulance patients. If the walk-in patient's acuity level is not emergent then the patient goes to registration and then triage, waits (if necessary) for a treatment room, is assigned a treatment room and a nurse, and finally is transported to the treatment room. Once the patient arrives in a treatment room, the patient flow no longer depends on mode of arrival, but depends on acuity level, X-ray requirements and laboratory requirements.

Lab and X-ray requirements consist of three categories each - none, routine and extensive. A category of lab requirements and a category of X-ray requirements are assigned to each patient via discrete probability mass functions dependent on acuity level. Lab and X-ray service times are exponential distributions with means that depend on the patient's acuity level. The number and type of laboratory tests and X-rays influence whether the patient should be served simultaneously (care type = 1), sequentially (care type = 2), or just observed (care type = 3) by the ED staff.

Once a patient has been treated in the ED and the decision to admit is made, the patient will be admitted to either a general medical/surgical unit or to an intensive care unit. Waiting times for beds at these two types of units are distributed exponentially. A simplified depiction of the patient flow through the emergency department simulation is presented in Figure 1.

INSERT FIGURE 1 HERE.

2.4. Validation of the Simulation

Output data from the simulation was compared with observed data from the ED system. The quantity of patients and time in the system for different patient categories were extracted from the hospital databases for a two month period, and estimates were made of mean values.

These were compared to the estimates from the simulation model, where the simulation results were the averages of 10 replications of 61 days (two months) each. The comparisons are summarized in Table 1. These results show that the computer simulation is producing results which are consistent with what has actually occurred in the ED.

Table 1. Simulation Comparison with ED Records (in Replications of 61 Days Each).

Patient Type	Number in Data Base	Number in Simulation	Data Base Average System Time (min)	Simulation Average System Time (min)
Emergent	415	451	159	164
Urgent	4091	4166	176	172
Non Urgent	3963	3959	116	123
Total	8469	8576	147	149

3.0. Development of the Simulation Metamodel

3.1. Motivation for a Neural Network Based Metamodel

To alleviate the long running times necessary to explore and optimize a simulated scenario, a metamodel was developed. This is an especially important step for an environment such as the emergency department, where the stochastic nature causes queues to build up frequently and with little warning, and decisions need to be made quickly to relieve the resultant congestion. If a metamodel were available, it could then be used as a "real-time" decision aid to determine the best alternative to resolve the problem.

There are various approaches to metamodeling of simulations (see Barton (1992) for an excellent overview), but most are based on simplifying algorithmic or functional assumptions, such as polynomial regressions. Another disadvantage of traditional metamodeling techniques is that they are often limited to a subset of the simulation domain, and must be redeveloped or discarded when exploring other ranges. This would clearly be unworkable in a hospital emergency department where quick decisions of high quality must be made over the entire simulation domain (and possibly slightly beyond the simulation domain).

Neural networks offer universal function approximation capability based wholly on the data itself, i.e. they are purely empirical models which can theoretically mimic any relation to any degree of precision (Funahashi (1989), Hornik, Stinchcombe and White (1989)). In practicality, neural networks are limited in their approximation capability by finite and noisy data sets, and stochastic relationships. Limited research has been done on using neural networks as simulation metamodels; e.g. see the papers cited in Section 1. This research has been more of a conceptual nature, than a workable methodology. Earlier papers by the authors (Kilmer and Smith (1993) and Kilmer, Smith and Shuman (1994)) have addressed using neural network metamodels to perform the primary functions needed by discrete event stochastic simulation - estimation of mean output values, estimation of variance of output values, and development of prediction and confidence intervals for all ranges of the simulation domain. That work on a textbook simulation problem was encouraging, and prompted the work reported herein.

It must be noted that neural networks and the other metamodeling techniques commonly used are deterministic. The stochastic aspect of the simulation is explicitly lost, however since only one replication using the metamodel is needed. Therefore, while possibly losing precision when moving from the simulation to a metamodel, the user also loses the rich stochastic framework of the simulation. Surrogates for the stochastic elements, such as expected value, moments and percentiles, must be used in deterministic metamodels. Thus the tradeoffs involve imprecision and simplification for increased speed.

3.2. Selection of Training Sets and Neural Network Architectures

The neural network metamodel was developed by creating two neural networks which work in parallel (see Figure 2). The first network predicts mean time in the ED for a given patient, and the second network predicts the variance of the mean time in the ED for that same patient. These parallel models work together to create prediction intervals over the simulation domain. The parallel neural networks can also work individually if the user desires. A subset of the controllable variables described in Section 2 was selected for inclusion in the neural network metamodel. The input variables were the means of the exponential random variables describing (a) intensive care unit bed waiting time, (b) general/surgical unit bed waiting time, (c) lab service time and (d) X-ray service time. Four continuous input neurons were used, one for each input variable. A designed training set of 81 observations was developed, while a designed testing set of 80 observations spanned the same variable ranges, but included different values (see Figure 3). Figure 3 shows each of the four variables relative to the other three variables. For example, row one, column two shows combinations of intensive care waiting time and general care waiting time for the training set (Figure 3a) and for the testing set (Figure 3b).

This test set was designed to validate the trained neural network on interpolation rather than extrapolation. While the simulation metamodel may be called upon to operate in an extrapolation mode, this might cause extremely misleading results (for more detail, see Kilmer, Smith and Shuman (1994)). Ten replications at each observation were used for all training points. One hundred replications at each observation were used for all testing points, so that the "correct" answer is known for each testing point.

INSERT FIGURES 2 AND 3 HERE

For the expected value neural network, there was one output variable of interest - expected time in the ED per patient. This was described by one continuous output neuron. In between there were two hidden layers with four neurons in each layer. For the variance neural network, the single output was also continuous and described the variance of the mean time estimate; i.e. the standard error of the mean. This was a more complex problem and necessitated an increased neural network size to two hidden layers with seven neurons in each. Both networks' values of the number of hidden neurons were identified by brief experimentation.

Two methods of training the neural network for the expected time in the ED were used. The first condensed the simulation replications into one expected value of time in the ED, and used that as the target output. For this method, there is one training pair for each combination of input values. This simplifies training and minimizes the training set, but removes some of the information that the replications contain. The second method used all replications individually, so that each combination of input values had training pairs equal to the number of replications. These methods are compared in detail in the authors' earlier papers (Kilmer and Smith 1993, Kilmer, Smith and Shuman 1994)). The neural network which predicts variance was trained with one training pair per combination of input values.

Networks were trained with a modified backpropagation algorithm using a smoothing factor, and the network which achieved the minimum mean absolute error over the entire training set was kept as the final trained network.

4.0. Results Comparing Direct Simulation and the Metamodel

The performance of the neural network metamodel was compared against direct simulation in three ways. The neural network's accuracy relative to the simulation for a given set of 10 replications was compared. The same comparison was made against 10 sets of 10 replications each of the simulation, representing the "true value" of the simulation output. Finally, prediction intervals were constructed from the neural network metamodel and from a given set of 10 simulation replications. These were compared by generating 100 replications of the simulation and placing them within each prediction interval.

4.1. Accuracy of the Metamodel Compared to Simulation

A first comparison of performance is to examine the accuracy of the neural network predictions over the test set for mean time in the ED and variance of that time. Examination of the training set is not meaningful since a neural network has so many free parameters, it can approximate any particular data set very accurately. The more important aspect of neural network performance is how well the model can generalize. That is, its accuracy on inputs different from the training set but still within the model domain. Figures 4 and 5 compare the test set predictions for expected value and variance of the neural network and direct simulation. In these figures, the open markered lines are the simulation output and the dark markered lines are the neural network output. Note that for the neural network, the test set predictions are an interpolation task, while for the direct simulation, the test set is input and replicated as any set of inputs would be. This means the simulation is essentially "perfect" on any set of inputs.

INSERT FIGURES 4 AND 5 HERE

As Figures 4 and 5 indicate, the neural network did extremely well on generalizing its training to the test set. The expected value of time in the system was an easier problem to learn, and therefore predictions are more accurate than for the variance. Variance predictions could probably be improved by training the variance neural network metamodel on sets of replications, i.e. use 10 sets of 10 replications each to develop 10 different variance values for each input vector. This of course would also increase the amount of work to develop the neural network metamodel since 100 instead of 10 replications would be required at each training and testing point.

A second comparison of the metamodel performance with direct simulation was done. Neural network predictions and two sets of 10 simulation replications (A and B) were compared to the 100 replications of the simulation at each of the test set points. The 100 replications were regarded as the "true value" of mean time and variance. Table 2 compares the mean absolute error (MAE) of the neural network and the two 10 replication simulation sets to the "true value" (the one generated by 100 replications) of the test set. From Table 2 it can be seen that even though the neural network metamodel is called upon to interpolate, performance is better than the two sets of direct simulation for both expected value and variance of time in the ED. Both the MAE over the test set and the single maximum error for the neural network metamodels are less than both simulation sets. The neural network trained on replications performed slightly better than the network trained on averages. This is consistent with the earlier observations of Kilmer, Smith and Shuman (1994).

Table 2. Error Comparisons of the Metamodel and Two Simulation Sets to the "True Value" of the Simulation.

Model	Data Used	MAE		Max Absolute Error	
		Mean	Variance	Mean	Variance
Direct Simulation	Set A - 10 Replications	4.33	14.16	13.03	69.90
Direct Simulation	Set B - 10 Replications	4.22	19.91	11.21	74.80
Direct Simulation	Average of Sets A&B	4.28	17.03	12.12	72.35
Neural Net	Individual Replications	1.81	8.6*	9.20	95.0*
Neural Net	Averages	2.13	8.6*	9.40	95.0*

* The neural network for variance estimation was the same for both the individual replications and averages neural networks for prediction of the mean.

4.2. Comparison of Prediction Intervals

One of the primary uses of simulation is comparing various alternatives with respect to particular measures of interest. One way the comparison can be made is with confidence and prediction intervals, where confidence intervals are associated with average values and prediction intervals are associated with individual observations. A comparison of the intervals generated through the neural network metamodel and by direct simulation is a fundamental test of the functionality of the metamodel approach. Prediction intervals for confidence factors of 80%, 90%, 95% and 99% were generated for the test set using the first set of 10 replications of the simulation (Set A in Table 2) and the two parallel neural metamodels (one for expected time and the other for variance). Table 3 shows the comparison of these intervals by the number of 100 separate simulation replications which fell within the interval, and on the low and high sides of the interval.

Table 3. Prediction Interval Results for Test Set.

Conf. Level	Neural Net - Replications			Neural Net - Mean			Simulation Intervals		
	Low	Interval	High	Low	Interval	High	Low	Interval	High
80	5.0	85.9	9.1	4.8	85.8	9.4	8.6	79.2	12.3
90	1.1	93.6	5.3	0.9	93.4	5.7	3.4	88.3	8.3
95	0.2	96.6	3.2	0.2	96.5	3.4	1.4	92.6	6.0
99	0.0	98.8	1.2	0.0	98.7	1.3	0.2	97.2	2.6

Table 3 shows that the neural network was very accurate in terms of the appropriate number of replications falling within the intervals, and the neural network trained on individual replications was slightly more precise than that trained on means. All the intervals in Table 3 do not reflect the symmetry expected in prediction intervals. That is, all intervals showed a marked differential in those observations on the high side of the interval versus those on the low side of the interval. An examination of the simulation output from those 100 replications show a positive skewness. This is not unexpected since time in the ED has a definite lower bound, but could extend out in time relatively unbounded in isolated instances. Although prediction intervals built using the predicted mean and variance cannot reflect asymmetries, predicting other statistics could. For example, percentiles could be predicted by a metamodel similarly trained to the variance network.

5.0. Discussion of Results

This paper has shown the real world application of an ED simulation and its neural network based metamodel. There are limitations of the metamodel. It is valid only for the specified parameter domains included in the training set. The number of replications for which the estimate of variance is valid is fixed at ten. The metamodel, as developed, cannot reflect the skewness of the distribution output. Similarly, the metamodel is completely deterministic so the stochastic variability of output of the simulation is lost, unless parallel models are used to also estimate the variance.

However, for most day to day decisions in the ED, the functionality required of the simulation is to estimate the mean value of the output variable(s), and to develop confidence intervals about that estimate. This information can also be used to perform response surface analysis and optimization. For these functions, the neural metamodel is an adequate surrogate for the simulation. The use of the metamodel does not require replications, and the software network runs in real time. For applications with space, weight or extreme time constraints, the neural metamodel could be translated into hardware form (VLSI).

The neural metamodel does not need to remain static. It can be updated through additional training as more simulation replications become available. The neural metamodel could also be updated through direct observation of the system, if that were possible. Both of these additional training methods could be applicable to the ED. More simulations may be run as computational resources and time allows, and the system may be observed directly through special studies or daily records. However, changes to the simulation (e.g., distribution parameters, addition or subtraction of variables) would invalidate the neural network metamodel, and a new metamodel reflecting the altered simulation would need to be developed.

Future research efforts in this area should include training with multiple sets of replications for variance estimates, and work on establishing the trade offs of using simulation computation time for replications versus new training points. Updating the neural metamodel with new simulation runs could also be investigated to develop a workable methodology. Another area mentioned in the previous section is using statistics besides mean and variance to account for asymmetries in the system. This is especially applicable in ED simulations of patient time in the system where one would expect a skewed distribution. The authors are pursuing efforts in all these areas.

References

Barton, R. R., 1992, "Metamodels for simulation input-output relations," *Proceedings of the 1992 Winter Simulation Conference*.

Badiru, A. B. and D. B. Sieger, 1993, "Neural network as a simulation metamodel in economic analysis of risky projects," Technical Report, Department of Industrial Engineering, University of Oklahoma.

Bressan, C., P. Facchin and G. Romanin Jacur, 1988, "A generalized model to simulate urgent hospital departments," *Proceedings of the IMACS Symposium on System Modelling and Simulation*, 421-425.

Dumas, M. B., 1984, "Simulation modeling for hospital bed planning," *Simulation*, vol. 43, no. 2, 69-78.

Fishwick, P. A., 1989, "Neural network models in simulation: a comparison with traditional modeling approaches," *Proceedings of the 1989 Winter Simulation Conference*, 702-710.

Funahashi, K., 1989, "On the approximate realization of continuous mappings by neural networks," *Neural Networks*, vol. 2, 183-192.

Hornik, K., M. Stinchcombe and H. White, 1989, "Multilayer feedforward networks are universal approximators," *Neural Networks,* vol. 2, 359-366.

Hunter, B., S. Asian and K. Wiget, 1987, "Computer simulation of surgical patient movement in a medical care facility," *Proceedings of the 11th Annual Symposium on Computer Applications in Medical Care*, 692-697.

Hurrion, R. D., 1992, "Using a neural network to enhance the decision making quality of a visual interactive simulation model," *Journal of the Operations Research Society*, vol. 43, 333-341.

Ishimoto, K, T. Ishimitsu, A. Koshiro and S. Hirose, 1990, "Computer simulation of optimum personnel assignment in hospital pharmacy using a work-sampling method," *Medical Informics*, vol. 15, 343-354.

Kilmer, R. A. and A. E. Smith, 1993, "Using artificial neural networks to approximate a discrete event stochastic simulation model," *Intelligent Engineering Systems Through Artificial*

Neural Networks, Volume 3, (C. H. Dagli, L. I. Burke, B. R. Fernandez, J. Ghosh, Editors), ASME Press, 631-636.

Kilmer, R. A., A. E. Smith and L. J. Shuman, 1994, "Using neural network metamodels to develop prediction intervals for discrete event simulation," *Intelligent Engineering Systems Through Artificial Neural Networks, Volume 4*, ASME Press, 1141-1146.

Law, A. and D. Kelton, 1991, *Simulation Modeling and Analysis*. McGraw-Hill, New York.

Lowery, J. C., 1993, "Multi-hospital validation of critical care simulation model," *Proceedings of the 1993 Winter Simulation Conference*, 1207-1215.

Mahachek, A. R., 1992, "An introduction to patient flow simulation for health-care managers," *Journal of the Society for Health Systems*, vol. 3, 73-81.

Padgett, M. L. and T. A. Roppel, 1992, "Neural networks and simulation: modeling for applications," *Simulation*, 295-305.

Pierreval, H., 1992, "Training a neural network by simulation for dispatching problems," *Proceedings of the Third Rensselaer International Conference on Computer Integrated Engineering*, 332-336.

Pierreval, H. and R. C. Huntsinger, 1992, "An investigation on neural network capabilities as simulation metamodels," *Proceedings of the 1992 Summer Computer Simulation Conference*, 413-417.

Saunders, C. E., P. K. Makens and L. J. Leblanc, 1989, "Modeling emergency department operations using advanced computer simulation systems," *Annals of Emergency Medicine*, vol. 18, 134-140.

Weissberg, R. W., 1977, "Using interactive graphics in simulating the hospital emergency department," in *Emergency Medical Systems Analysis* (T. R. Willemain and R. C. Larsen, Editors), Lexington Books, Lexington MA, 119-140.

Yu, B. and K. Popplewell, 1994, "Metamodels in manufacturing: a review," *International Journal of Production Research*, vol. 32, 787-796.

Figure 1. Patient Flow Through the Emergency Department Simulation.

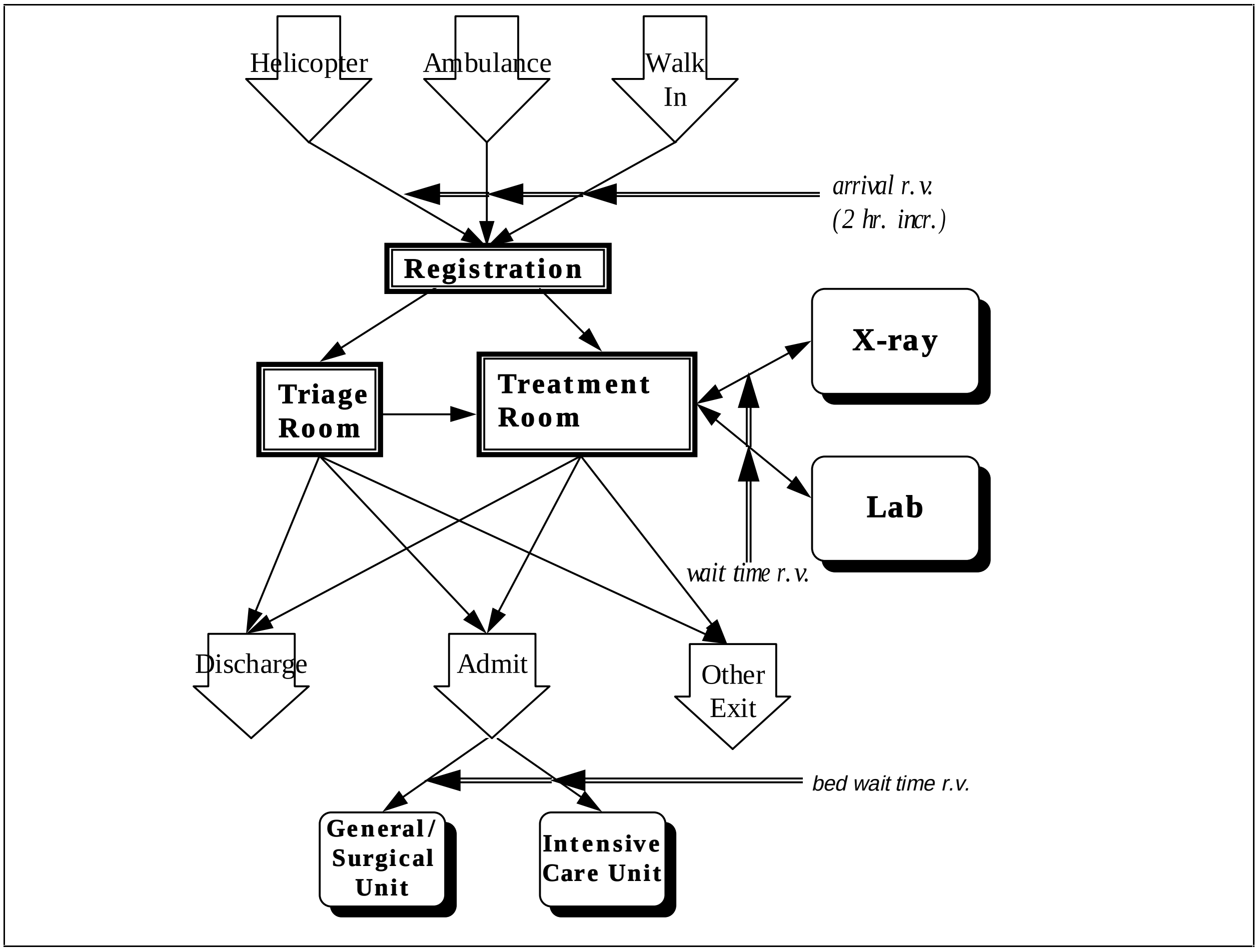


Figure 2. Architecture of Parallel Neural Metamodel.

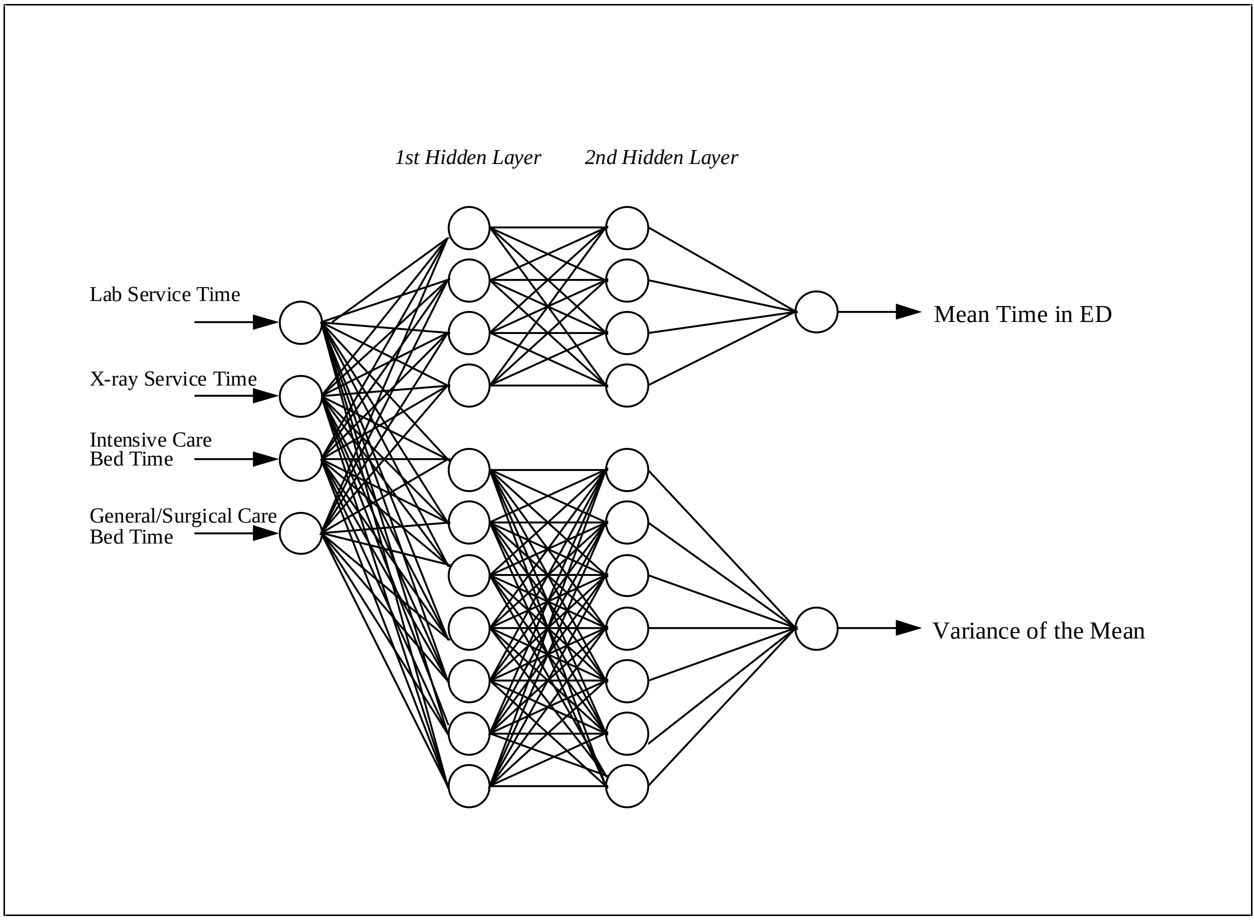


Figure 3. Training and Testing Sets (all axes in minutes).

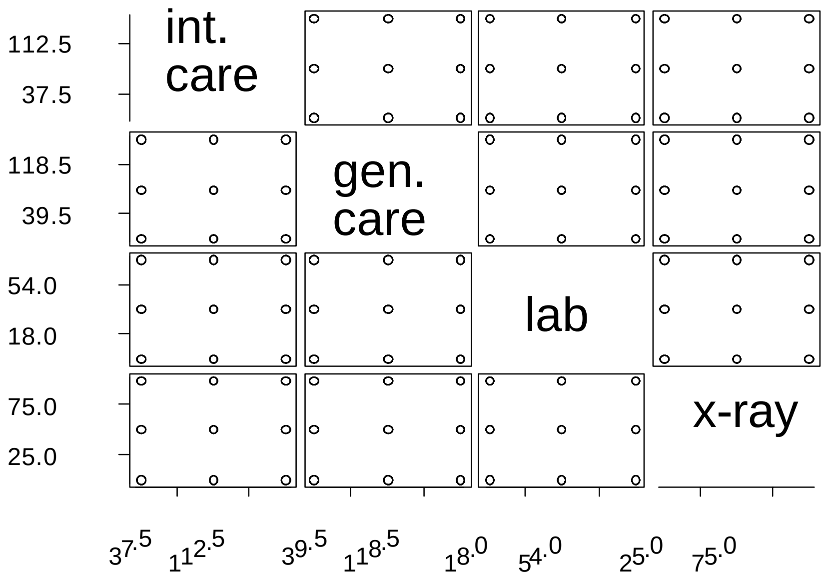


Figure 3a. Training Set Values for Emergency Department Simulation.

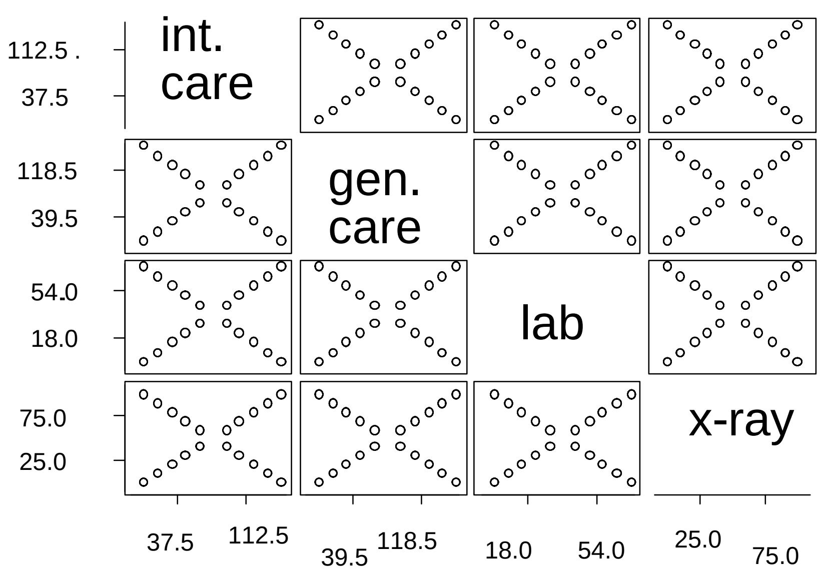
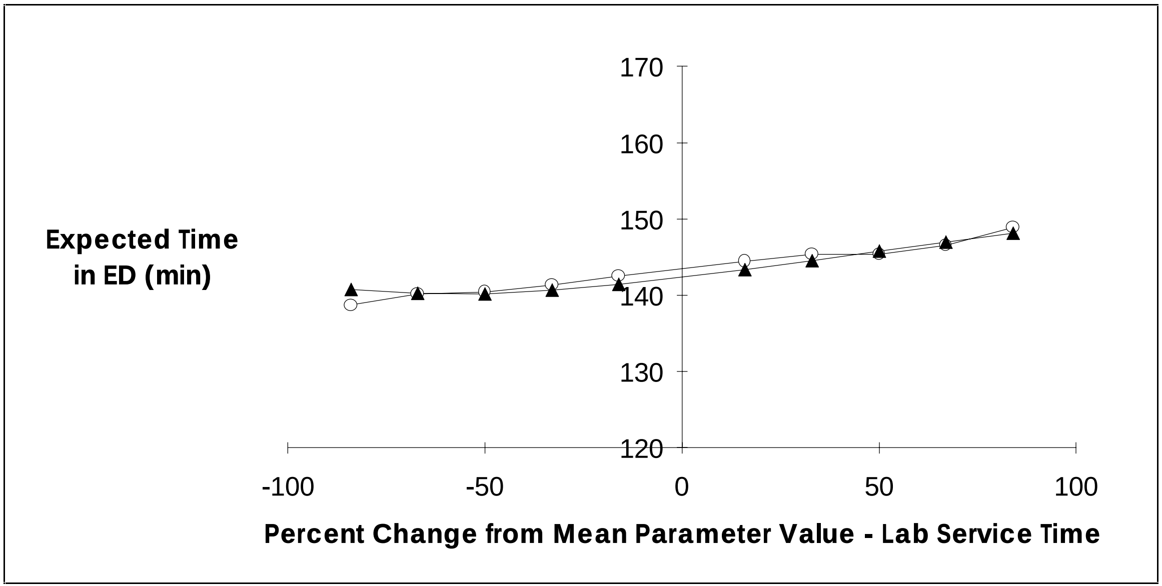


Figure 3b. Testing Set Values for Emergency Department Simulation.

Figure 4. Mean ED Time Results of Neural Network Trained on Replications and Simulation for Test Set (neural network on dark markered lines on all graphs).



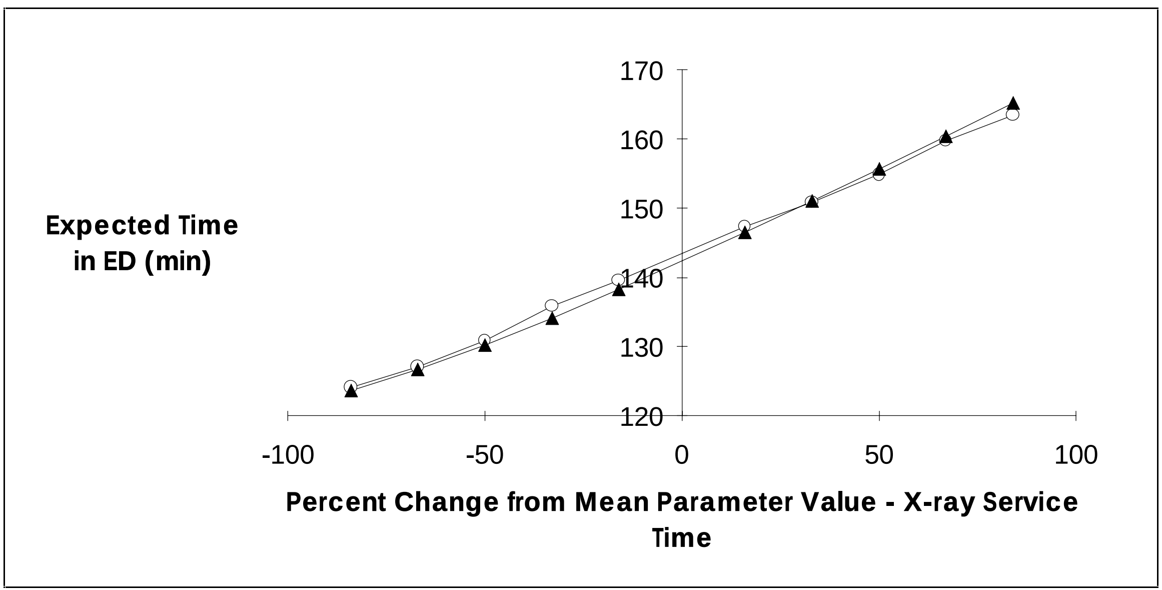
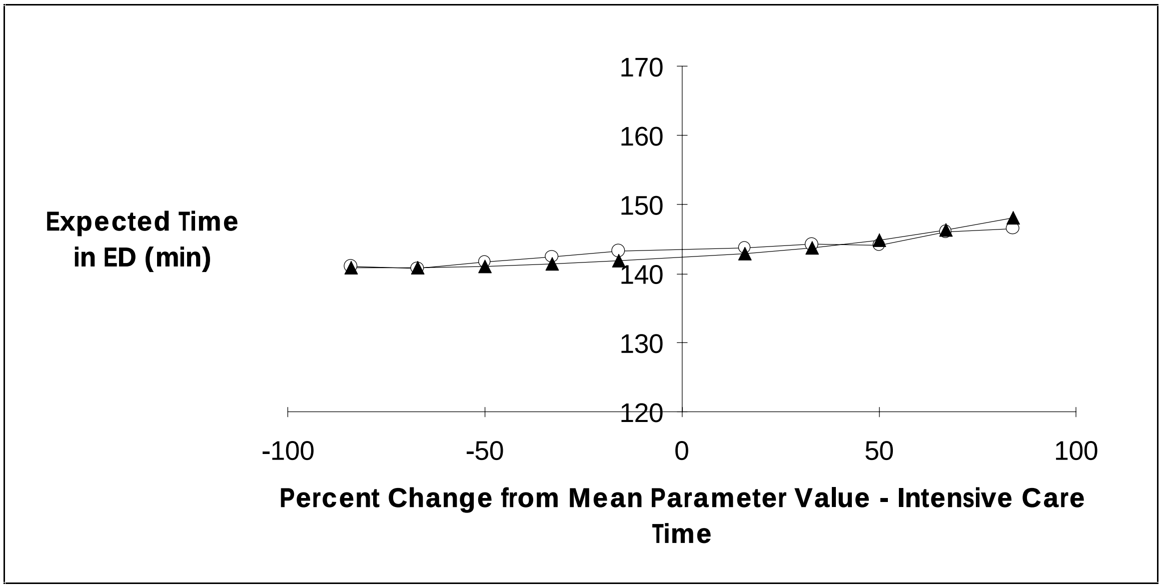


Figure 4 Continued. Mean ED Time Results of Neural Network Trained on Replications and Simulation for Test Set.



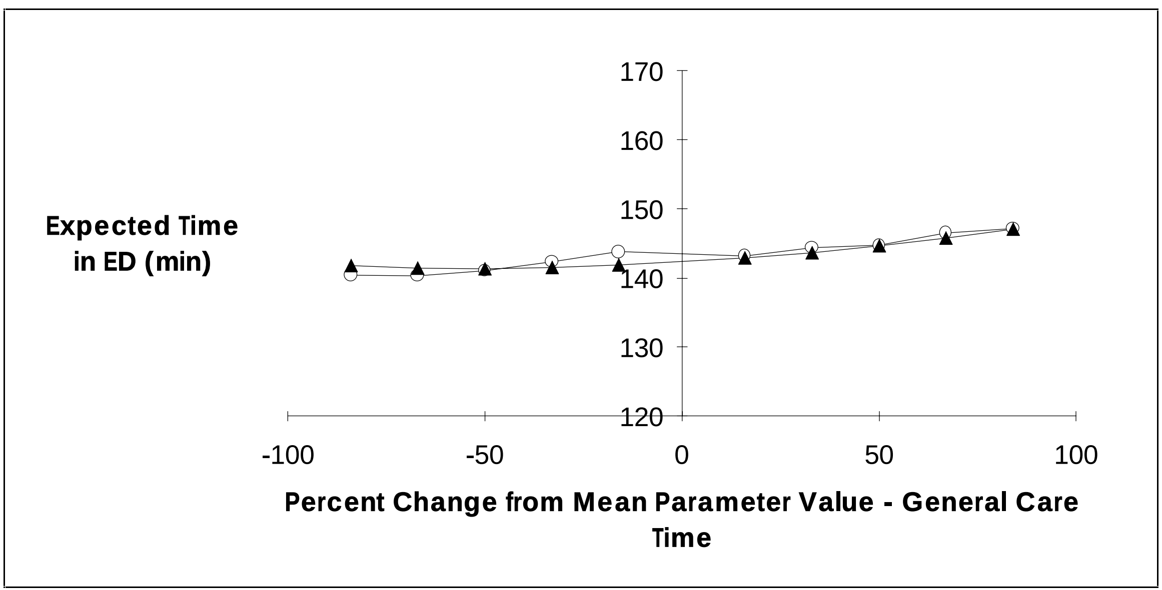
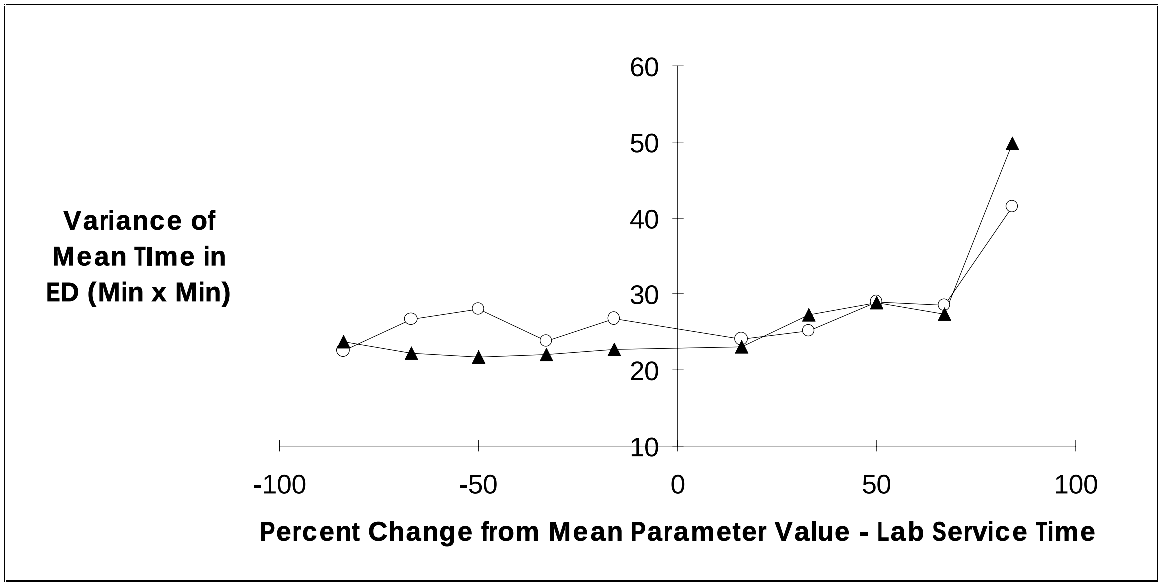


Figure 5. Variance Results of Neural Network Trained on Replications and Simulation for Test Set (neural network on dark markered line on all graphs).



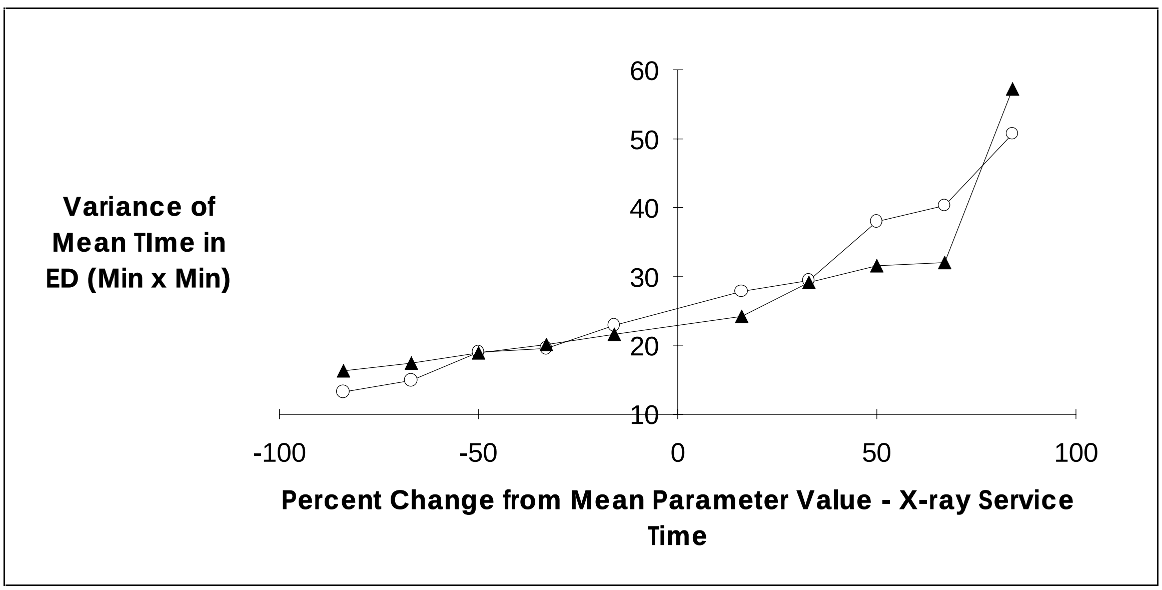


Figure 5 Continued. Variance Results of Neural Network Trained on Replications and Simulation for Test Set.