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VISUALIZE A PORT IN AFRICA

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ABSTRACT

Techniques to visualize quantitative discrete event simulation input and output data are presented. General concepts connected with graphical excellence are discussed in a simulation context. Brief examples of graphs and visualizations are presented from a classic model of African port operations.

1 INTRODUCTION

Visualization is a process of using multimedia to enhance human perception of system behavior. When employed with simulation, the purpose of visualization is to explore, explain, gain insight, and support decisions. Visualization can be described as a process which builds up perception in stages. It is highly dependent on the psychology and physiology of sight; however, the term is considered broadly here as any technique which enhances the mind's eye of perception ranging from ASCII text summaries to complex animation.

Computer simulation is a process of building and using models of systems which mimic the behavior of real or proposed systems such that that artificial behavior can be observed and quantified to support decisions. The simulation process has been described extensively. Excellent descriptions can be found in Banks, et al.(1996), Law and Kelton (1991), and Arthur and Nance (1996). Observation assisted by visualization and iteration is critical to each step of the process.

To simplify discussion, we may say simulation visualization generally involves three broad tasks in some form: input analysis, formulation, and output analysis. For example, in early stages, data is collected to support input analysis. The first question asked is what does the data *look* like. Are *observations* truly random? Is there structure which supports a probability distribution assumption? Is a simple univariate distribution assumption valid, or is some multivariate form appropriate? Can we *see* how well a statistical model fits the hypothesized distribution? The process of simulation is intertwined with multi-dimensional visualization and perception.

Visualization is also critical to formulation or model building. Here we are interested in visualizing system structure and behavior. Multiple versions of conceptual models are often required. Building model representations which tell a story which can be validated is critical. Edward Tufte (1997), in his recent book Visual Explanations, describes how we can effectively create visual reasoning which explains dynamic processes. Model building, verification (assuring the model works as intended) and validation (assuring the model matches reality for the purpose intended) are closely linked through visualization. Validation often involves communicating a conceptual visualization which can range from a sketch on the back of an envelope to a human computer interface (HCI) representation in a simulation language.

Output analysis tasks range from data analysis, to validation and decision support. Output data from one or multiple runs of a single model, or from multiple experimental design points for a single base model with variations, demands visual comparison. If a statistical relationship or response surface based on design points exists, visualization supports interpreting that surface. Output analysis can be ultimately framed as a series of pattern recognition tasks where iterative experimentation with a model and experimentation with the data yield insight. The modeler must efficiently "mine" and control data to be mined to uncover patterns. Efficiency is lost when misinterpretations of data cause errors in formulation, data interpretation or communication of results. Visual efficiency is achieved when a graphic based on data effectively represents all there is to know about a data set to support the decision at hand and no more.

In output analysis visualization provides a common ground of experience to convey complex data efficiently to a much wider audience which is often not versed in statistics. To coin a phrase from Clausewitz (1968), visualization is statistics by other means. Visualization advances have been made in many fields such as remote sensing, weather forecasting, aerodynamics, process management and computer capacity and performance analysis. It is clear that these advances can be applied generally in any simulation modeling exercise.

Edward Tufte (1983,1990,1997) has produced a series of texts both instructive and interesting for those pursuing the holy grail of efficient visualization. *Envisioning Information*, *The Visual Display of Quantitative Information* and his latest book, *Visual Explanations*, are worthy of lengthy consideration as they suggest a science of visualization. It is important to note that principles of good visualization must be experienced as well as discussed. Additional excellent guidance may be found in Chambers et. al. (1983), Cleveland and McGill (1988), Cleveland (1985), and Wildbur (1989). The human factors and human computer interface (HCI) literature also provides a wealth of insight into human information processing and perception which underlie good visualization. See, for example, Sanders and McCormack (1987).

Tufte (1983) provides the following set of concise visualization principles of excellence:

"Excellence in statistical graphics consists of complex ideas communicated with clarity, precision, and efficiency. Graphical displays should
- show the data
- induce the viewer to think about the substance rather than about methodology, graphic design, the technology of graphic production, or something else
- avoid distorting what the data has to say
- present many numbers in a small space
- make large data sets coherent
- encourage the eye to compare different pieces of data
- reveal the data at several levels of detail, from a broad overview to a fine structure
- serve a reasonably clear purpose: description, exploration, tabulation, or decoration
- be closely integrated with the statistical and verbal descriptions of a data set."

Tufte (1977) stresses the importance of viewing graphs as much in context as possible, allowing quantitative comparisons through labeling and scaling, facilitating the fundamental tasks of comparison. He prompts us to avoid "chart junk". This is perhaps one of the most important (of many) principles. Tufte (1997)describes a noted failure of particular graphic design: "The visual elements bounce and glow, as heavy lines activate the white space, producing visual noise." Visual noise saps processing capacity from the viewer and increases the inefficiency of a visualization.

Modelers should be constantly aware of the limitations of processing resources of the human brain-their own or a customer. A critical rule to follow is that of "smallest effective difference" in displaying chart objects. Tufte (1997) suggests we "make all visual distinctions as subtle as possible, but clear and effective." Visual noise can be created by distracting lines, shapes and colors. In analysis and results presentation, it should not be the analysts intention to make bold statements of graphic impact (e.g. heavy and light lines mixed, extensively highlighted text, stridently different colors, boxes of this and that, etc.). "Good form is clear but not a spectacle." Tufte (1997). For a modeler, since there is the potential to produce vast amounts of data from a simulation, it is important to have the ability to focus on key dimensions of display without clutter such that the analyst or customer becomes overwhelmed or confused.

Facilitating the ability to scan, compare and perceive repetition is a common thread in Tufte's work. Human learning thrives on repetition and emphasis. "Parallelism connects visual elements. Connections are built among images by position, orientation, overlay, synchronization and similarities in content. Parallelism grows from a common viewpoint that relates like to like." Tufte (1997). An extremely powerful technique applicable to many simulation analyses is the employment of "small multiples", producing visually distinct elements in a visualization. "Small multiples resemble the frames in a movie: a series of graphics showing the same combination of variables indexed by changes in another variable." Tufte, 1983. Small multiples and other related techniques allow the viewer to scan, and control the pace of interpretation. Efficient visualization thrives on clarity combined with pace of review and scan activity.

2 A VISUALIZATION EXAMPLE

A basic model of an African port described by Schriber, (1974) and implemented as an example in the AWESIM! simulation language in Pritsker et. al. (1997), can be used as a starting point to illustrate concepts and techniques. The model is based on a crude oil transshipment port with 3 berths and one tug servicing the port. An existing population of tankers uses the port. These tankers come in 3 sizes, and have a common interarrival rate but different loading times while they occupy a berth. The tug is a resource used to berth and deberth. Storms arrive randomly causing the tug operation to be shut down. A shipper is interested in adding to the load at the port by taking on a contract which will require an additional 5 tankers, all of the same type, which will cycle to and from the United Kingdom. The problem addressed by the model is how will this additional load impact the residence time in port. The AWESIM! language permits an icon based network model of this system, which may be seen in Pritsker. Techniques which could be used in input and output data analysis will be discussed.

2.1 Input Visualization - Plot the Data

The main input analysis task for the Africa port would be determining the probability density function for current ship interarrival times. Wandering over to the virtual shipping office (only mad dogs and modelers go out in the noonday sun!), the logs showing historical arrival times for the current population of tankers are examined and analyzed by computer. Considering manual analysis would be uncivilized! The laptop of today and the future can be outfitted with an impressive array of visualization support tools. We take the attitude that while on such a safari you can never use too much gun! Consider the likes of general statistical visualization packages such as Statistica™, Statgraphics™, SAS™ or SPSS™ supplemented by a general purpose spreadsheet package(s) like Microsoft Excel™, Lotus 1-2-3™, or Quattro Pro™ which have extensive graphic support. With the addition of macro programming, these tools become extremely powerful.

Scatter plots are extremely helpful in feeling out input data. One of the first tasks where observations occur sequentially is to simply plot the data against time to get a sense of variability and autocorrelation. Sorting and plotting largest to smallest to get a sense for regularity may also be valuable, as is plotting the percent of accumulated observations versus time. Where more than one variable is observed and associated to another, it may be beneficial to look for correlation, and the existence of relationship(s) between members of a group. For example, one might wonder if there is a relationship between arrival rates of pairs of one tanker type and another. It is important to note that spurious visual artifacts may mislead the analyst; however, carefully taking stock of potential relationships paves the way for statistical testing if warranted.

The density of the probability of occurrence of values of a random variable over a range can be represented by a probability density function if the variable is continuous, or a probability mass function if discrete (piling up probability only at specific points). A host of mathematical models have been employed to represent the probability distributions for various types of data under the assumption that these mathematical models are valid patterns which can effectively characterize real world data. One of the first pattern matching tasks a simulation modeler faces is which model to choose. Sometimes it is necessary to form a more general empirical model of the data which does not conform to an existing standard pattern; thus one choice in the selection from standard patterns is no choice.

One of the most powerful techniques for visualizing this pattern is the humble histogram. This is composed by partitioning the range of observed values into sub ranges or bins for continuous data (or exact points for discrete data) and plotting the frequency of observations or the fraction of observations falling in each bin. While a variety of rules exist for choosing the number of bins, it is recommended to try a range of bin sizes with the goal of building a smooth distribution analog, Law and Kelton (1991). By convention, this data is typically represented as a bar or column chart. When contiguous end points of the sub-ranges are made the edges of the bars, the eye perceives a pattern which can be compared to the patterns of potential mathematical models such as normal, exponential, lognormal, poisson, or other density functions. Excellent presentations of various basic univariate patterns can be found in statistical texts. See, for example, Law and Kelton (1991).

A histogram from the shipping office data for all current arrivals is presented in Figure 1. It can be seen that the fit clearly does not look as if distributed exponentially as shown with the overlay. It is important to note that larger sample sizes facilitate both the visual strength of the pattern and the ability to detect multi-modal patterns and irregularities in a proposed model. Experimenting with the bin size with a visualization tool is recommended

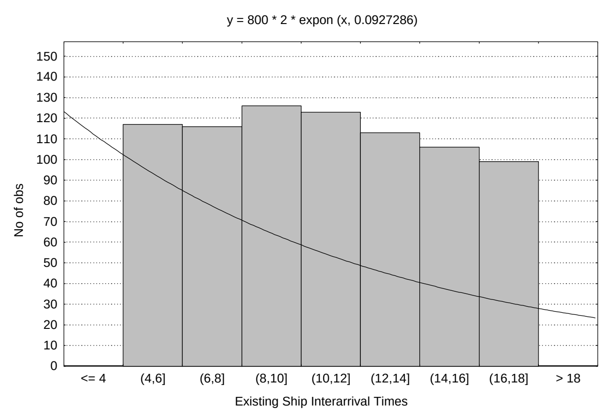


Figure 1: Histogram of Existing Ship Population Interarrival Time Distribution.

A visual goodness of fit test can be performed by constructing a so called P-P or Q-Q plot for candidate distributions for the observed data. These plots are based on the existence of an empirical cumulative distribution function for the data where the data are sorted and indexed from i=1 to n from smallest to largest, $F^*_n(X_{(i)}) = (i-0.5)/n$. The P-P plot is formed by plotting a hypothesized, or "model" cumulative distribution value $F^{\sim}_n(X_{(i)})$ vs $F^*_n(X_{(i)})$. Alternatively, the Q-Q plot is formed by plotting sorted observed values versa values from the hypothesized distribution at observed quantiles where the quantiles are defined as $q_i = (i-0.5)/n$, i.e. $x(i)$ (the observed data) vs. a value a from the hypothesized distribution at that quantile, the values $\tilde{x}(i) = F^{-1}_n(q_{(i)})$. Excellent descriptions of these techniques are found in Law and Kelton (1991). A poor pattern match is indicated by a nonlinear relation evident in a P-P plot as shown in Figure 2 where an exponential distribution is tested. Residual plots or mean square error calculations can be compared based on calculating simple linear regressions for alternative plots.

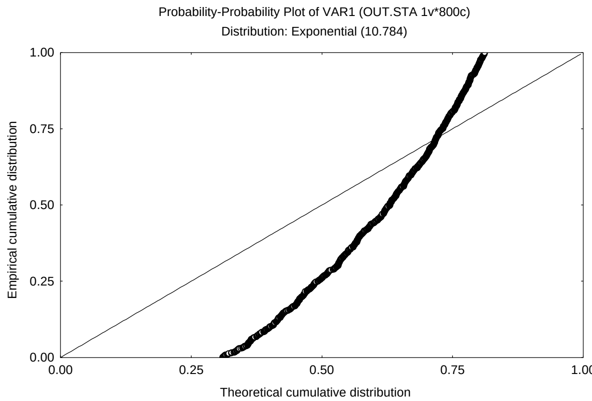


Figure 2: P-P Plot for the (Uniform) Interarrival Time Distribution of Existing Ships Based on a Erroneous Hypothesized Exponential Distribution.

Various other tools are available to build input distributions which do not depend on classic parametric models. This category of tools one might call empirical distribution builders. Such tools also allow the user to visually interact in the input model building process. This type of support can be found in Riskview Pro™. See also Wagner and Wilson (1996).

When data is sorted by time of occurrence, it is possible to consider the sequence of observations as a realization of a time series. Under the assumption that the process underlying the data is weakly stationary, i.e. a stochastic dependence relying only on relative position in the sequence, it is possible to see temporal structure using the sample autocorrelation function (SACF) where the autocorrelation function (ACF) is defined as $\rho_k = \gamma_k / \gamma_0$ where γ_k and γ_0 are the autocovariances at lag k and zero respectively where k ranges from 0 to n, the sample size. An approximate two standard deviation confidence interval for the sample ACF at lag k is plus or minus $2n^{1/2}$. See Abraham and Ledolter (1983). The SACF is commonly represented graphically with bars. It is particularly helpful in discerning periodic or seasonal fluctuations in an input or output process. The SACF is now widely available in a variety of statistical software, or can be computed and plotted directly in a spreadsheet. The SACF for the sequence of interdeparture times for the existing ship population is shown in Figure 3. In this example using Statistica ™ software, it is seen that there apparently is autocorrelation in the interarrival series which cannot be explained by random variation (all autocorrelations fall outside confidence intervals defined by white noise variation).

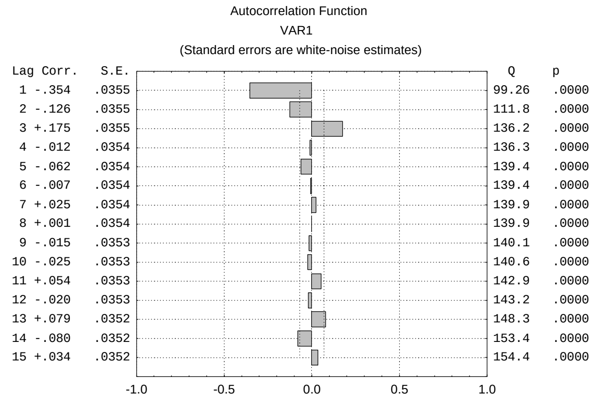


Figure 3: An example SACF graph indicating statistically significant autocorrelation patterns in the arrival series suggesting a simple Uniform probability density function model would not be appropriate..

2.2 Output Data Visualization

Visualization of simulation model output data is used to represent model results in a way that is understandable to analyst and customer. Each has separate needs. The analyst requires speed and strong exploration support. The customer requires clear, understandable, interpretive graphics. These needs may not always overlap well. An analyst, well versed in model design and behavior, can dispense with niceties of display in the output exploration phase for personal use, but cannot do so when communicating results. In the communications phase, all the attributes of excellence previously addressed must be evident. The focus here is on techniques for the visual exploration of output data. Techniques discussed under input data are relevant here. Histograms and scatter plots are the essentials of output analysis. Scatter plots can be used to display clustering and linear relations in two, three, or more dimensions. Variations on simple scatter plots are widely available for the display of multivariate data. Suggestions include engineering plots (multiple 2 dimensional plots organized in columns and rows by variable), and 3 dimensional representations which can include dynamic interaction in various software packages. See Chambers et al. (1983) and Cleveland and McGill (1988) for excellent examples and principles. The SACF can be used to highlight autocorrelation and subjectively validate model results. See Sargent (1996). The SACF can also be represented in higher dimensions through cross correlations at time lags similar to the SACF. This is particularly true when spatial attributes can be mapped to output variables and the concepts of small multiples are employed. P-P and Q-Q plots can help in characterizing output, and the principles behind their use can be used to compare different model or run output. Output visualizations serve to characterize risk - variability and stability as well as periodic ("seasonal") temporal behavior. With increased speed of input/output, computation, and increased storage capacity, possibilities for visualizing stored output data have expanded greatly.

It is believed there are three levels of output visualization, each requiring greater time, effort and cost for the modeler. Basic off the shelf exploratory visual exploratory data analysis (VEDA) techniques, either in the simulation graphical user interface (GUI) itself, or in the supporting software, represent the first level. The second level is represented by modest custom design and programming using visualization tools. This level, in most cases, would be used more for communication. The idea is that levels one and two are within reach of sophisticated computer literate analysts. The third level includes custom designed data visualizations which are generally characterized by moderately high effort, art and cost. The third level includes techniques such as custom 3D and virtual reality displays as well as simulation animation. This level is used almost exclusively for communication in the areas of decision support, validation and training. In the third level, the value of the visualization is justifiable in its own right. Animation techniques arguably cross levels two and three, but generally require a specific decision on incurring additional cost of production; therefore, are placed in the third level.

In output data visualization, one of the most important goals should be to show comparisons and relative risks in a simple display, as well as show attributes of stabilization and variability over time. Box plots attributed to Tukey (1977), represent an excellent technique for representing multivariate simulation output data. These plots have evolved into many forms. Generally, the box plot depicts the upper and lower quartiles as the top and bottom of a rectangle, and the median is shown as a horizontal line through the rectangle (when the boxes are aligned vertically). Lines extend above and below the box to terminate in "adjacent values" defined as the largest observation greater than or equal to 1.5 times the interquartile range, Q(.75)-Q(.25), and the smallest value less than or equal to 1.5 times the interquartile range. See Chambers et al (1983). Values outside the adjacent values are plotted separately. Multiple box plots can be shown on one plot to compare the distributions of different variables, or the same variable in different time or other dimensional blocks called "strip" box plots. See Chambers et al. (1983). Ideas for maximizing the information value of reduced box plots through minimizing chart ink have been presented by Tufte (1983). Box plots are readily available in statistical packages. It is interesting that the same general result can be achieved by adapting so called "high-low-close" (HLC) and "high-low-open-close" (HLOC) charts found in a spreadsheet package. For example, "high" and "low" can be set at simple maximum and minimum and "open" and "close" can be set to Q(.25) and Q(.75). For example, the times in port for each of the three current tanker types and the additional tanker type are shown as a before and after plot using the Statistica™ software in Figure 4. Times in port without the additional ships ("NO") are depicted on the left while times for four ship types ("YES") are shown on the right. As in this example, box plots are very good at comparing different experimental design points. In this case we can readily visualize increased magnitude and variability of port time by making a quick scan facilitated by the graph. Additionally, strip box plots can be employed to show the distribution across runs or within one long simulation run of a particular simulation to indicate when steady state is achieved. See Welch (1983).

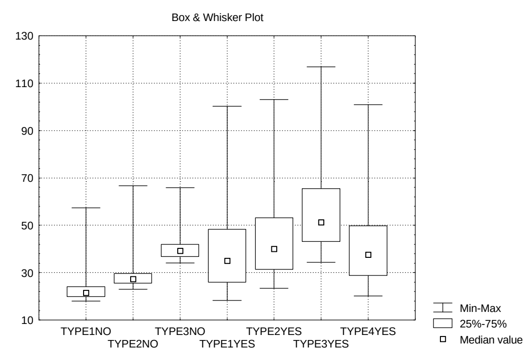
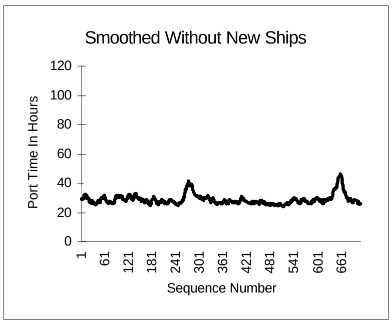


Figure 4: Comparative Box Plots For Ship Time In Port For Runs With and Without New Ships in the System.

Output data for both line and scatter plots can often be manipulated to better represent output process dynamics in a way that is more visually appealing than simply showing the value of state variables at points where the state changes. For example, we might view Q(t), the number in a queue at time t, only at points where the state changes. This results in a line graph with numerous vertical and horizontal segments which can be visually tiring and distracting. An alternative might be to capture smoothed data when the model is running by using a moving average or a standard forecasting technique such as exponential smoothing. Such smoothing may be extremely helpful in visualizing complex dynamics and variability. For example, we might use a smoothed value such as $\mathbf{S_{i+1}=\alpha x_{i+1} + (1\text{-}\alpha)S_i}$ to represent a smoothed series within the simulation where the subscript represents a sequence number for an event change point.

This series can be sampled at discrete equally spaced times. This is a simple technique which allows computationally efficient smoothing of observations on many variables. While such processing creates a lagged approximation of the true process, it is intuitively appealing and understandable. The α value is typically set to a small value between 0.0 and 1.0, normally between .1 and .3. Larger values of α cause the smoothed series to "track" more the latest data more tightly. Smoothing methods allow the eye to scan and interpret large scale dynamics more readily. Such series can be averaged or smoothed across realizations produced by multiple runs. An unsmoothed vs. smoothed example for the time in port all waiting ships is shown in Figure 5.



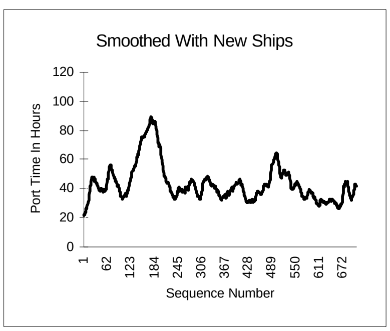


Figure 5: Overlays of Exponentially Smoothed Time in Africa Port for Existing Ships (Top) and Existing Ships With New Ships Added (Bottom).

This example also depicts the design points before and after the additional ships are added. It is easy to sense the variability in these runs. In a way, smoothed data plots perform a lot of the visual summarization for the brain, decreasing workload, and making communication easier. It is believed that smoothing represents a corollary to the "smallest effective difference" principle espoused by Tufte, (1997). There is a caution here that the modeler must be aware that the techniques may hide important artifacts; therefore it is advisable to see the data both ways.

Visual exploratory data analysis (VEDA) of simulation output data analysis is often aided by awareness of human workload reduction techniques. There are many methodologies for displaying multivariate data, such as Chernhoff faces, stem and leaf plots, engineering plots, etc. See Chambers et al. (1983). In general, multivariate display of data is a difficult problem. When the modeler is familiar with a VEDA technique, it may prove valuable for analysis where there is great familiarity with the data and there is expected behavior to look for in the output. On the other hand, often the techniques do not work well in communication to others not familiar with data and technique. Use of any high dimensional display (3 or higher) takes particular care in educating the customer. Users are well advised to avoid too much "gee whiz!" factor inherent in these displays. For repetitive use, where the customer or decision maker accepts a specific technique, particularly where the technique is offered with data to the customer for manipulation, it is more valuable. Unfortunately many displays seem to overload the brain. The more structure, or clutter which must be interpreted in such a display (icons, text, multiple white space activating lines etc.), the harder it is to build a true intuitive visualization. In essence, the viewer's mind must work through the visual grammar of the display as well as the data itself.

One useful technique is to build up multiple images from time varying data from simulations. Here, familiarity with the organization and scaling of the data, and an inherent understanding of the overall format is critical to derive value. Alternatively, data represented or mapped to a grid can be displayed in multiple surface or contour plots. Although surface plots often are pleasing to look at, they are often difficult to interpret, particularly for subtle variations, and should be avoided for complex process display. In some instances, surface plot usability can be improved by smoothing techniques and combining them with other displays..

An image display, built using the IDL™ language, for 100 runs of Africa Port output is shown in Figure 6 and a comparable shaded surface plot for the same data is shown in Figure 7. For the image representation, time is represented on the horizontal axis and run number for 100 runs is displayed on the vertical axis. From left to right, the first image shows 80 hour observations on a smoothed observation of ship time in port where new tankers are inserted into the system at the 8640 hour point. The image represents a gray scale picture composed of pixels representing time in port on a scale of 0 (black) to 200 (white) hours. Note the dramatic occurrence of high times (whiter grays) in system which occur for long periods after the new ships are inserted. In this sort of display it is not the absolute numerical value of the smoothed observations, but the patterns which can be seen by scanning the images. This relatively simple technique can form the basis for exploring and comparing the output data space in search of intuition concerning behavior. Relationships between runs and types of data can be seen fairly well with practice, particularly when the interactive display of actual values is readily available. This type of technique has shown promise in depicting the stabilization point(s) for large steady state models as this example depicts. Additionally, mapping colors to data values can be used to highlight specific ranges. Almost any data can be displayed as such an image. Data may be composed of histogram data, SACFs, response surfaces etc. Additionally, coupling this presentation and various other plots or spatial maps can greatly enhance perception of the model behavior and data space which is facilitated by scanning small multiples. The ability to slice, fly through and otherwise interact with the model data is greatly enhanced. Such image generation might be classified as a level three technique by some analysts; however, simple contour plots often are readily available, and can be manipulated to achieve similar visual impact.

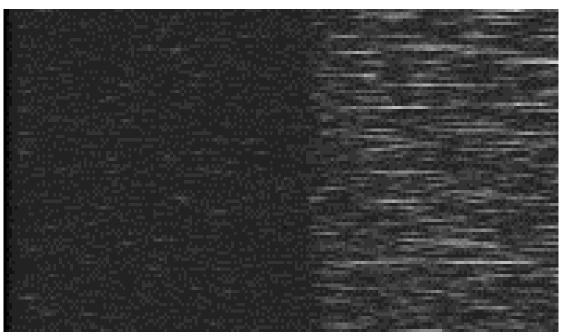


Figure 6: Image built from exponentially smoothed observations of all ship times in port. The image shows model results without new ships for 100 runs arranged top to bottom for 200 consecutive 80 hour observations arranged in horizontal sequence from left to right. Dramatic increase in striated brightness indicates insertion of new ships at 8640 hour point. Indistinct edge shows stabilization after insertion of new ships.

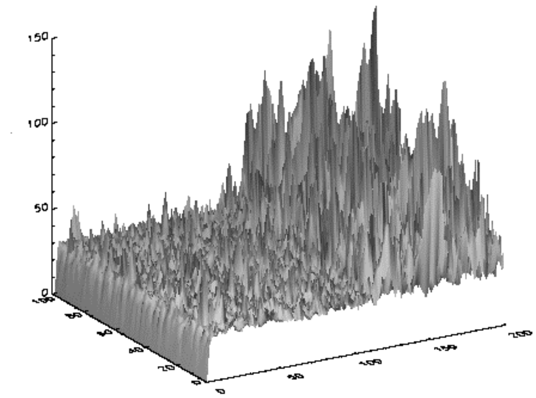


Figure 7: Shaded surface plot of data shown in Figure 6. X axis is sample number, Y axis is run number and Z axis is smoothed time in port.

Other level three techniques include enhanced graphic designs, virtual reality displays, and animation. While this capability is within the reach of many modelers, it may not be cost effective to pursue. Virtual reality displays are displays of output data where the viewer can interact with 3D constructs based on data value. These techniques have analysis value; however, the usability of the methods is very similar to any high dimensional display mentioned previously. They can be difficult to interpret, and often require both a strong computer and display system, not to mention a strong stomach. This area is very rapidly evolving and is perhaps the brightest star on the horizon. The greatest drawback to their widespread use today is cost and usability.

One cannot leave a discussion of visualization without mentioning animation. Principles for effective animation have been proposed by Swider et al. (1994). These principles are very much aligned with overall graphics principles. Admonitions are to manage both the animation and the users training and approach to the tasks at hand for which the animation is designed and to "avoid overloading the user with too much visual information." Additionally, the interaction of color, contrast, movement, scale, time passage and complexity are often hurdles to effective use.

3 SUMMARY AND CONCLUSION

Effective visualization in building and analyzing simulation models can be viewed at a level of importance which increasingly matches the importance of a sound knowledge of statistics and probability in modeling simulation input and output. This brief tutorial represents a small introduction to the general topic. Of note is that many of the sources represented in the biography are both entertaining and informative. There is an inherent pleasure in viewing "excellent" graphics. It is hoped that the reader comes away with a sense that numerous options exist to be explored, and that a few principles of excellence will improve the caliber of future efforts.

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REFERENCES

Abraham, B. and J Ledolter, 1983. *Statistical Methods for Forecasting*. New York: John Wiley and Sons.

Banks, J., J. S. Carson II, B. L. Nelson, 1996. *Discrete Event System Simulation*. Upper Saddle River, New Jersey: Prentice Hall, Inc.

Chambers, J. M., Cleveland W. S., Kleiner, B., Tukey, P. A. 1983. *Graphical Methods for Data Analysis*. Belmont, California: Wadsworth, Inc.

Cleveland, W. S. 1985. *The Elements of Graphing Data*. Murray Hill, New Jersey: Wadsworth, Inc.

Cleveland, W. S. and McGill, M. E. 1988. *Dynamic Graphs for Statistics*. Belmont, California: Wadsworth, Inc.

Gross, N. 1996. Zap! Splat! Smarts! *Business Week*, December 23, 1996, 64-71.

Law, A. M. and W. D. Kelton 1991. *Simulation Modeling and Analysis, 2nd ed*. New York: McGraw-Hill.

Lewis, P. A. W. and Orav, E. J. 1989. *Simulation Methodology for Statisticians, Operations Analysts, and Engineers*, Vol. I. Belmont, California: Wadsworth & Brooks/Cole.

Arthur, D. A. and Nance, R. E. 1996. Independent Verification and Validation: A Missing Link in Simulation Methodology? In *Proceedings of the 1996 Winter Simulation Conference*, ed. J. Charnes, D. Morris, D. Brunner, J. Swain, 230-235. Piscataway New Jersey: Institute of Electrical and Electronics Engineers.

Pritsker, A. A. B, J. J. O'Reilly and D. K. LaVal 1997. *Simulation With Visual SLAM and AweSim*. West Lafayette, Indiana: Systems Publishing Corporation.

Sanders, M. S., and McCormick, E. J. 1987. *Human Factors in Engineering and Design*. London: McGraw-Hill Inc.

Sargent, R. G. 1996. Some Subjective Validation Methods Using Graphical Displays of Data. In *Proceedings of the 1996 Winter Simulation Conference*, ed. J. Charnes, D. Morris, D. Brunner, J. Swain, 345-351. Piscataway New Jersey: Institute of Electrical and Electronics Engineers.

Swider, C. L., Bauer, K. W. Jr., and Schuppe, T. F. 1994. The Effective Use of Animation in Simulation Model Validation. In *Proceedings of the 1994 Winter Simulation Conference*, ed. J. D. Tew, S. Manivannan, D. A. Sadowski, and A. F. Seila, 633-640. Piscataway, New Jersey: Institute of Electrical and Electronic Engineers.

Schriber, T. J. 1974. *Simulation Using GPSS*. New York: John Wiley & Sons.

Tufte, E. R. 1997. *Visual Explanations, Images and Quantities, Evidence and Narrative*. Cheshire, Connecticut: Graphics Press.

Tufte, E. R. 1990. *Envisioning Information*. Cheshire, Connecticut: Graphics Press.

Tufte, E. R. 1983. *The Visual Display of Quantitative Information*. Cheshire, Connecticut: Graphics Press.

Tukey, J. W. 1977. *Exploratory Data Analysis*, Reading Massachusetts: Addison-Wesley Publishing Co.

Von Clausewitz, C., 1968. *On War*. ed. A. Rapoport. Middlesex, England: Penguin Books.

Wagner M. A. F. and J. R. Wilson, 1996. Recent Developments in Input Modeling With Bezier Distributions. In *Proceedings of the 1996 Winter Simulation Conference*, ed. J. Charnes, D. Morris, D. Brunner, J. Swain, 1448-1452. Piscataway New Jersey: Institute of Electrical and Electronics Engineers.

.Welch, P. D. The Statistical Analysis of Simulation Results in *The Computer Performance Modeling Handbook*. ed. S. S. Lavenburg, 268-328. New York: Academic Press.

Widbur, P. 1989. *Information Graphics*. New York: Van Nostrand Reinhold.

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