Proceedings of the 1987 Winter Simulation Conference
A. Thesen, H. Grant, W. David Kelton (eds.)

SELF-INSURANCE BY SMALL SCALE COGENERATORS AGAINST THE RATCHET DEMAND EFFECT

Dr. L. Jackson Turvaville
Margaret Hong Chen
Tennessee Technological University
Cookeville, TN 38505

ABSTRACT

This paper develops a simulation model useful for investigating the dollar pool requirements of 20 companies who want to protect themselves from a series of large expenditures that will eventually occur. The time is uncertain. The contribution to a pool by the 20 companies is similar to an insurance arrangement. It permits a regular contribution instead of a catastrophic amount occasionally. The simulation provides dollar requirements of the pool. This paper does not extend these requirements to a determination of the monthly contributions that each pool participant should make.

1. INTRODUCTION

Simulation is used to investigate the operation of a group of small scale cogenerators who are insuring against the catastrophic nature of the ratchet demand clause. Some background information is in order.

Cogeneration is the sequential production of two types of energy - electrical and thermal (steam, hot water, etc) - obtained from burning one fuel such as oil, coal or gas. A cogeneration plant reduces total energy costs and can pay for itself in three to five years.

Being as cogeneration is an attractive investment for many businesses, it is gaining in popularity. According to Baltes, in 1983 the combined capacity in the U.S. is estimated at 9,100 megawatts. Based on U.S. Department of Commerce projections, a sum of 48,470 megawatts of cogeneration will be operating by the year 2000. Potential candidates include hotels, resorts, hospitals, laundries, food processors, prisons and manufacturing facilities.

Large and medium size cogenerators are permitted to sell energy to utilities. With a tie to the grid these cogenerators sell surplus electricity and receive electricity when needed in emergencies. The small scale cogenerators (15 kw to 150 kw systems) are not efficient so usually do not have surplus electricity. Thus a tie to the local utility would be for standby service - protection against an unexpected shut down.

Standby rates vary from utility to utility. A typical rate includes two parts - engery charges for kwh consumed and demand charges for the maximum kw established during any half-hour period (or an hour) in the billing month. While the billing demand is established in a very brief period out of maybe 720 hours in a typical month, the utility is required to have that capacity all the time. To be compensated for the investment at this capacity level, the utility might require that the demand charge (or a portion of it) be paid monthly for the following 11 months. This feature is called a ratchet demand clause and is frequently used.

As an example, assume a 100 kw demand is established during a few hour emergency. If the demand charge is $6.00 per kw, the cost for the month the downtime occurred would include a charge of $600 for the demand charge. The cogenerator would probably feel this is ok; it saved his operation for that period. But in the following 11 months when a bill for a portion of the $600 arrives, the cogenerator will not be too happy. An alternative to this would be installing a back-up system. For small-scale cogenerators this is not likely to be feasible.

A proposed unique additional alternative is for several small scale cogenerators to band together as "Self-Insurors". Monthly, each member would contribute into a pool. From the pool, payments would be made to compensate a member who has an emergency and is subjected to ratchet demand expenditures in future months. These expenditures are referred to as "penalties" in this paper although they really are legitimate reasonable charges imposed by electric utilites.

This study investigates by simulation the operation of a pool of 20 cogenerators. Each cogenerator is assumed to have different rates for demand charges. Failures are assumed to follow an exponential distribution. The mean time to failure varies among the cogenerators. Different lengths of demands are assumed during outages. This assists in determining the size of the demand. If the outage includes the peak portion of the 24 hour demand profile then the billing demand would reflect this peak.

Since monthly billing is standard, the time unit for this simulation study is taken to be months. It is felt the time period is short enough such that the probability of having more than one unexpected outage in a month is about zero.

Various runs were conducted with the model, some for several thousand trials. The results provide low and high values for monthly dollar requirements from the pool and a total annual dollar requirement. No attempt has been made yet to translate this information into the monthly contribution required from each member.

2. MODEL DEVELOPMENT

Model Design

The model is developed to simulate the operation of 20 cogenerators who have banded together to share the cost of the demand penalty imposed when a breakdown of a generator occurs. The model is developed to proceed through time, to record what happens and to provide a summary of the results.

Specifically the program begins with an inspection of each company each month. If no company has a failure in a given month, the program cycles to the next month, etc. When a failure does occur the model determines the length of the failure and then checks with the load profile of the company to decide the amount of the penalty. That penalty is included in the pool for the following 11 months.

The model serves several major purposes. Based on probability distributions and random numbers, failures of cogenerators and length of failures are determined. The model calculates the dollar amounts of penalties and does the bookkeeping related to the penalties for all 20 cogenerators on a month-by-month basis.

Figure 1 presents a general flow chart of the simulation model.

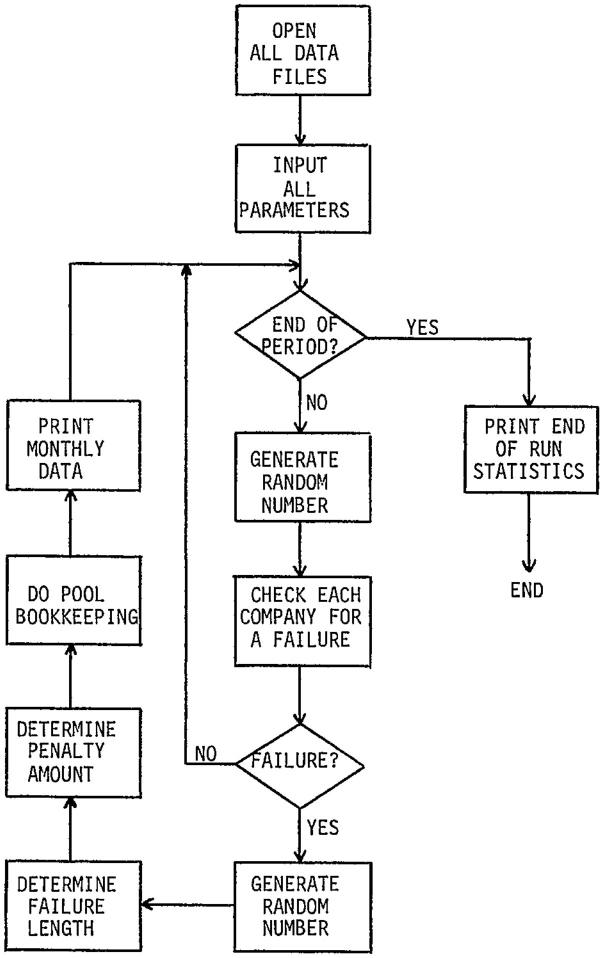

Figure 1. General Flow Chart of the Simulation Model.

<u>Input Data For This Model and an Example</u>

For the simulation model the Mean Time Between Failures (MTBF) for each of the units was arbitrarily selected within the following range:

$$6{,}000 \text{ Hours} \leq \text{MTBF} \leq 9{,}500 \text{ Hours}$$

Failures were assumed to follow an exponential distribution for this study; however, the model can easily accommodate other distributions.

For all operations the electric demand in kw varies over a 24 hour cycle. A typical demand profile for an enterprise might look like the one shown in Figure 2.

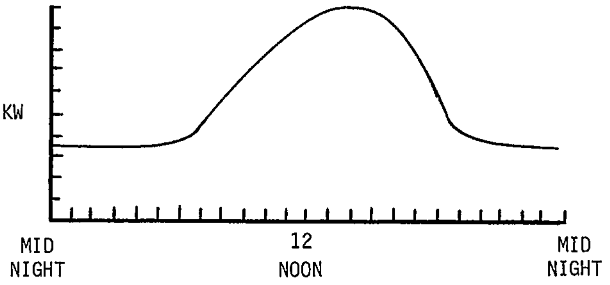

Figure 2. Typical Daily Demand Profile

From this profile it is apparent that if an unexpected outage occurs at 4:00 am, for example, and lasts only two hours, the demand established for that backup requirement from the local utility would be relatively small compared to the maximum demand that could be established. In Figure 2 the maximum demand would occur about 3:00 pm. If an outage occurs at 4:00 am and lasts for 11 hours or longer the maximum demand of the profile will be the billing demand the utility will use for that outage. For simplicity, the 24 hour demand profile is divided into three segments, eight hours each, and are called Phases. For each simulation trial in which an outage occurs, the phase in which the outage begins is determined. Then another random number is used to determine the length of the outage. This information is combined to determine the billing demand.

If an outage occurs in Phase I and the duration of the outage keeps it in Phase I, the backup demand established will be a given percent of the maximum possible. If the duration of the outage includes Phase II, then the back-up demand established will be a different percent of the maximum possible, and likewise for Phase III. Below are the ranges of percents that are assigned arbitrarily to each of the Phases for each of the 20 cogenerators:

Phase I	40% - 70%
Phase II	94% - 98%
Phase III	25% - 50%

The length of the outage is determined by an exponential distribution. For each cogenerator a mean value for length of time is in the following range:

$$1 \text{ Hour} \leq \text{Mean Time of Failure Length} \leq 24 \text{ Hours}$$

The value used for any particluar cogenerator is arbitrarily assigned before the simulation run.

The following example will illustrate the procedure followed by the model to determine the billing demand given that a failure has occurred. Assume the maximum demand is 25 kw. Phase I begins at 3:00 am. The mean time between failures is 8.550 hours. The mean length of the failure is 20 hours. The demands as a function of the maximum profile demand for the Phases are 50% (I), 95% (II) and 30% (III). The model uses a random number to generate the time of the outage. In this example, the outage occurs at time 1700 (5:00 pm). Another random number determines that the failure lasts 6 hours. Thus the system is back on line at 2300 (11:00 pm). The determination of the billing demand requires looking at the Phase(s) in which the outage occurs. Figure 3 below illustrates this analysis.

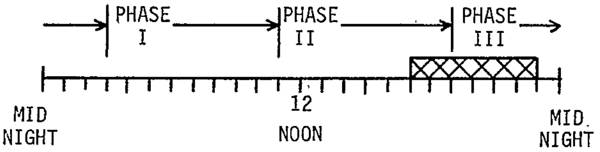

Figure 3. Profile Line Diagram with Phase and Outage Locations for Example Problem

Based on the assumed data the billing demand is determined by considering the Phase(s) in which the outage occurs and the maximum demand of the profile. In this example Phase II includes two hours of the outage. Thus 95% of the peak demand will be the billing demand or .95 (25 kw) = 23.75 kw. Notice that most of the outage is in Phase III which uses 30% of the peak as the billing demand. It must be remembered though, that the maximum demand for a short interval (usually a 1/2 hour or 1 hour interval) is what establishes the billing demand. The maximum would occur in Phase II, not Phase III.

Model Verification and Validation

The model appears to be accurately representing the real world system being studied. A hand simulation trace was conducted on a two month period randomly selected from the thousands of months that have been run. The results were exactly as the model generated. This confirmed that the model is doing its bookkeeping accurately.

The model assumes the time between failures is exponentially distributed for each cogenerator. For each of the 20 cogenerators used in this study, a different MTBF was used. It is assumed that the model is valid if the average of the time between failures generated in the simulation run has a probability of 95% or less of occurring based on the assigned MTBF. For example, company 1 was assigned a MTBF of 7000 hours. The simulation results for 12 runs of 20 years each yielded the largest average time between failures to be 10,950 hours. Using the exponential distribution with a mean of 7000:

$$P(x \leq 20{,}970) = 0.95$$

Thus if x were 10,950 hours it is not unexpected. Similar results were found for all 20 cogenerators. There was no significant difference between the simulation results and the expected results.

The length of failures is also a random occurrence with an exponential distribution. The results for one 20 year run were investigated to see if there appeared to be any significant differences between the expected length and the experimental results. Looking at company 2, for example, the expected length was assigned as five hours. The 20 year simulation result for one run yielded an average length of 5.4 hours. Using the same analysis as in the preceeding paragraph there appears no reason to suspect the results would be unexpected. All evidence indicates the model is performing as expected.

3. RESULTS

The model was developed to provide useful data on a month-by-month basis. The following information is displayed monthly during the simulation run:

1. the company(s) that failed during that month,
2. the day of the month the failure(s) occurred,
3. the hour of the day the failure(s) occurred,
4. the length in hours of the failure(s), and
5. the total pool penalty for that month.

At the end of a simulation run cumulative statistics are also displayed. Those include:

1. histogram data of the pool penalties,
2. a list of each company with the total number of failures that occurred during the run,
3. the cumulative sum of all of the monthly penalties the company sustained during the entire run,
4. the total monthly pool penalties for the entire run, and
5. the total failures in the run.

Many runs were made using the model. Fifty year runs were tried, but there did not seem to be any difference in the behavior of the pool for the 50th year than for earlier years. Twenty year runs were used to collect data. Different runs were conducted using different random seeds for varying results.

The basic objective of the simulation model is to provide information that would assist in establishing a pool that would pay the demand penalty of the pool members when they occur. The pool would be funded by monthly contributions from each of the cogenerators making up the pool. Given this objective the output that seems most useful is the month by month pool penalties and a distribution of the monthly pool penalties. Figure 4 below provides a plot of the monthly maximum and minimum pool penalty per year for a typical 20 year simulation run. The minimum monthly value ranged from a low of $7,335 (other than for year 1 which will always be zero) to a high of $10,609. The maximum monthly value ranged from a low of $9,376 to a high of $15,086.

It was expected that the values plotted in Figure 4 would have stabilized in 20 years. A longer run of 50 years was conducted with no replications to see if the monthly information would settle down - it did not.

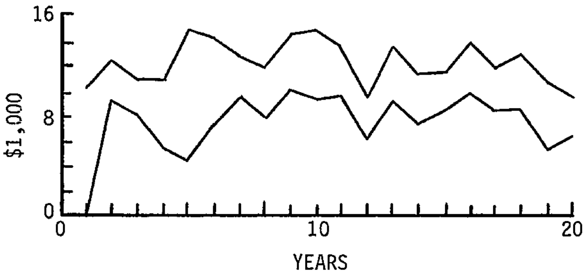

Figure 4. Maximum and Minimum Monthly Pool Penalty Per Year for a Typical 20 Year Simulation Run.

Since the monthly pool penalty continues to fluctuate, it would be of interest to see a distribution of all the monthly pool penalties. This information is displayed in Figure 5. The histogram represents 20 years runs replicated 12 times or a total of 2880 monthly pool penalties. Note the distribution approximates a normal distribution with a mean of $9,890.

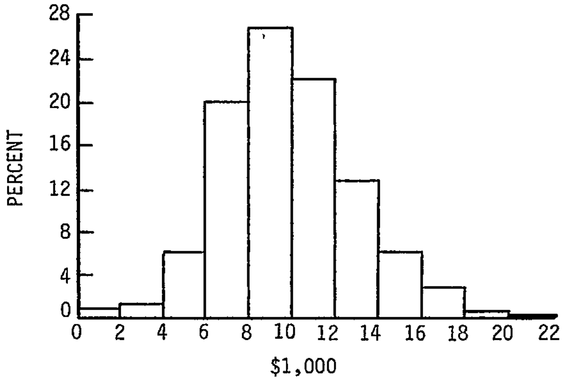

Figure 5. Histogram of Monthly Pool Penalty Amount for 20 Cogenerators, 10 Year Runs, 12 Replications.

The typical run used to provide data for Figure 4 is also used to determine the pool penalties expressed as annual dollars. The first 12 months are totaled to yield the annual pool penalty for year 1, etc. This information is plotted in Figure 6. It also does not stabilize into a constant but continues to fluctuate.

4. CONCLUSIONS

The simulation model provides very realistic data. The data is exactly what a group of cogenerators could expect if they were to band together to spread out the penalty of ratchet demand rates. It does appear simulation is an appropriate analysis technique because of the complexity of combining a number of conditional probability situations. Simulation allows the use of many different probability distributions for determining the time to failure and the length of the failure. This approach allows the model to be very "real-worldish".

The pooling concept for minimizing or spreading out the risk for the penalty of the ratchet clause should encourage more small-scale cogenerators to be placed in service. The cogeneration concept does provide a more effective utilization of fuel resources. Perhaps the simulation concept introduced here will cause some feasibility studies to be accepted that otherwise would not. This would result in more small-scale cogeneration systems to be on-line, which in turn might even save a very valuable natural resource - energy.

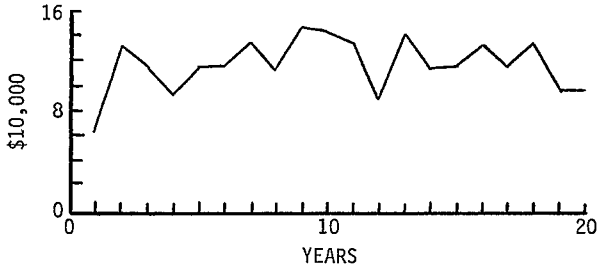

Figure 6. Total Annual Pool Penalty for a Typical 20 Year Simulation Run (same data as in Figure 4).

ACKNOWLEDGMENTS

The authors were supported by the Center of Electric Power -- Modeling, Simulation, and Control, a Center of Excellence at Tennessee Technological University, Summer 1987.

REFERENCES

Baltes, R.T., (1987). Could Cogeneration be in Your Future?. Energy Management IE News XXII, No. 1, 1-3.

AUTHORS' BIOGRAPHIES

L. JACKSON TURVAVILLE is a Professor of Industrial Engineering in the Department of Industrial Engineering at Tennessee Technological University. He received a B.I.E. and M.S. in Industrial Engineering from the University of Florida in 1956 and 1958 respectively and the Ph.D in Industrial Engineering from the Georgia Institute of Technology in 1967. His working experience has been in industry with Tampa Electric Co., Martin Company of Orlando, Eastern Airlines and in teaching with the University of Florida and Tennessee Tech. His current research interests include the application of simulaiton to energy management related problems.

L. Jackson Turvaville
Box 5011, TTU
Cookeville, TN 38505, U.S.A
(615) 372-3260

MARGARET HONG CHEN is an M.S. student in the Department of Industrial Engineering at Tennessee Technological University. She received a B.S. in Management Engineering from Shanghai Jiao Tong University in 1984. Her current research interests include the application of the PC to solving economic analysis problems using simulation.

Margaret Hong Chen
Box 6927, TTU
Cookeville, TN 38505, U.S.A.
(615) 372-5982