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MONTE CARLO SIMULATION: AN ALTERNATIVE TO SINGLE POINT DATA ENTRY FOR TECHNICAL MODELLING

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Abstract

Scenario planning is vital in many sugar industry projects, and the carrying out of a number of sensitivity analyses (or 'what if?' scenarios) can prove to be a tedious exercise. Monte Carlo simulation is a tool that can be used to make this task a lot simpler and faster.

The time-consuming task of varying the individual inputs in a technical or economic model using single point entry can be overcome with the use of random number generation (Monte Carlo simulation). The ability to define each variable input using probability frequency distributions makes it possible to run a model on Excel that can vary values around a predefined mean in a way that reflects the expected real-life behaviour of the variable in question. Most conventional computer models can be adapted to include a random number generator in this way. The model may be run numerous times and the multiple outputs obtained can be plotted on a probability frequency distribution diagram to demonstrate the likelihood of achieving a desired objective.

This paper illustrates the use of Monte Carlo simulation to predict the detailed mass and energy balance for an entire sugar factory. The total crush rate for the factory and the sucrose content of the cane supply were varied using bell-shaped normal distribution curves. Inputs using Monte Carlo simulation are not limited to two variables; however, they were limited in this paper for ease of illustration. The output obtained from the model was used to determine the availability of V4 vapour from the evaporator station for use in juice heating, and to quantify the amount of exhaust steam let-down that would be required to meet a shortage in V4 vapour supply. The paper highlights the advantages of random number generation when compared to single point data entry.

Keywords: sugar factory, modelling, simulation, Monte Carlo simulation

Introduction

The conventional approach to projects in the sugar industry, especially those that involve equipment sizing, requires some sort of modelling of the process. This usually includes the development of overall throughput strategy models, overall mass and energy balances and a comprehensive mass and colour balance for the raw boiling house. In addition, detailed design models are typically developed for individual unit operations or items of equipment (Schorn *et al.*, 2005).

Under normal circumstances, modelling is carried out in a deterministic way. In other words, all of the inputs to the model are assumed to have fixed, constant values, even though it is generally accepted that the behaviour of the factory is affected by day-to-day variations in such external factors as the quality of the cane received. The models used in the design process are usually developed for season-average conditions in the factory, or for the peak throughput periods of the year in terms of fibre, brix and non-pol. This results in a factory design that is optimal in terms of equipment sizing to accommodate these three major capacity parameters.

Under some circumstances, however, the behaviour of a sugar factory may be far more sensitive to changes in the input parameters than is usually encountered during the design process. This has, for example, been found to be the case when developing a design for a mill incorporating extremely high levels of energy efficiency. A particular example is discussed later. Under these conditions, it is essential to carry out a sensitivity analysis to determine how the selected process design behaves over a range of factory input conditions.

Sensitivity analyses can be carried out using deterministic modelling techniques, by selecting a variety of input scenarios and modelling each case individually (e.g. to determine how steam demand is affected by crush rate). Although a number of input variables may be changed at any one time, this does tend to make analysis and presentation of the results more difficult. This deterministic method has the disadvantage that it is time-consuming and labour-intensive. Because only a small subset of all the possible input variable combinations is usually tested in this way, it is possible that important system behaviour may be 'missed'. In addition, the results obtained by this technique do not provide any information regarding the frequency with which a given set of conditions might actually occur in practice.

Monte Carlo analysis provides an alternative to the deterministic modelling of sugar factory systems. In carrying out an analysis using this method, a decision is made as to which input parameters are to receive fixed constant values and which are to receive random values. The values of the randomised input parameters are chosen from a probability distribution that has been selected to accurately reflect their actual behaviour in practice. For example, some cane quality parameters may best be represented by appropriate bell-shaped normal distributions, with the mean and variance of each distribution determined from historical data.

When the fixed values or the statistical distributions of all of the input parameters have been selected, the simulation model can be run numerous times (perhaps up to 100 000 times or more). For each model run, the values of the statistical input variables are chosen randomly from the appropriate distributions and the output values of the model are recorded. The advantage of this method is that the full range of system behaviour can be investigated (with every possible combination of input variables being statistically feasible). Since the values of the input parameters in the model are selected using the probability distributions that they follow in the real-life factory situation, the range of outputs received will reflect the actual frequency with which these outputs will occur in practice. Given the large number of sample results (i.e. model runs) available, it is possible to carry out a variety of statistical analyses on the output range received. Analysis and presentation of the results is typically straightforward. Further background information on deterministic and stochastic (i.e. statistical) simulation techniques can be found in standard reference works on operations research (for example Winston, 1993).

Literature review

As the name implies, 'Monte Carlo' simulation takes its name from the world famous gambling centre. However, the resemblance to gambling applies only to the use of and reliance on random numbers and chance when drawing conclusions.

Literature in the sugar industry relating to Monte Carlo simulation is limited, with Joyce and Hobson (2007) being a notable exception. Joyce (2007) presented a similar paper at the

Australian Coal Preparation Society symposium in 2007. These authors highlighted the need for alternatives to the standard deterministic modelling methods currently in use, as 'what if?' scenarios or sensitivity analyses can be tedious to carry out and the results are challenging to present to decision makers. They suggested that Monte Carlo simulation could be used to overcome the limitations of the conventional methods, while having the ability to use a variety of possible probability distributions to define each input variable. Their paper uses an example based on sugar industry engineering to demonstrate the value of utilising simulation techniques. It also addresses the advantages of utilising simulation and provides a methodology for the use of Monte Carlo simulation. This method, although new to the sugar industry, has been extensively used in the corporate world and is well documented in financial journals.

In particular, Joyce and Hobson (2007) related the use of Monte Carlo simulation as a tool for co-generation project analysis and capital budgeting. It was ground-breaking work, as the sugar industry is highly dependent on engineering models and is often not able to utilise more sophisticated techniques for project analysis due to the large amounts of variable inputs in these models. Particular aspects of sugar processing modelled as part of their study included the crushing of sugarcane, the production of electricity using bagasse and the various financial decisions that need to be made when analysing the feasibility of alternative sugarcane products. The work was specific to the sugar industry; however, it can be compared to work done in other industries, as discussed briefly here.

Nawrocki (2001) revisits modelling techniques used in financial literature, further exploring the advantages of simulation techniques as opposed to conventional techniques for financial feasibility studies and project analysis. He provides details of the developments in simulation analysis from the 1960s to 2000, highlighting its uses, appropriateness and effectiveness under various conditions. Of particular interest is that Nawrocki (2001) highlights the ideal criteria needed to utilise Monte Carlo simulation. He states that it should be used when it is impossible or too expensive to obtain data, the observed system is too complex, the analytical solution is difficult to obtain or when it is impossible or too costly to validate a mathematical experiment.

Sugar industry modelling fits these criteria well, as it is not always financially feasible to obtain data and the modelling of entire sugar mill systems can be fairly complex. It can be concluded that Joyce and Hobson (2007) used simulation analysis according to the criteria set out by Nawrocki (2001). They used simulation because it was too costly to use conventional techniques and the decision making was of a complex nature. Verbeeten (2006) lends further support to Nawrocki (2001) and Kleijnen (1995) and states clearly the criteria in which simulation analysis should be used. He argues in favour of probability distribution curves being used as inputs in technical models. In general, a survey of the literature supports the use of Monte Carlo simulation in complex modelling situations, such as those found in the sugar industry.

Factory design for high levels of energy efficiency

The continual increase in the cost of supplementary boiler fuel, combined with an emphasis on renewable energy and co-generation in the sugar industry, has led to a strong focus on increasing the energy efficiency of existing factories. Two of the primary ways in which energy efficiency may be improved are (i) to maximise the effective use of low-grade bleed vapour within the factory, and (ii) to minimise the quantity of vapour that is 'wasted' by being condensed in the final effect evaporator condenser. In order to make effective use of bleed vapour streams, their pressures should be maximised.

The two primary energy-saving principles mentioned above can not be followed to extremes, as a point can fairly easily be reached at which all of the 'unwanted' water content of the clear juice has been bled off as bleed vapour in the evaporator station. Under these conditions, any further demand for bleed vapour can not be met from the water content of the juice (without producing syrup at excessive brix levels) and will simply lead to a demand for more exhaust steam consumption in the evaporator station. This does not lead to any further improvement in energy efficiency.

Work by Singh *et al.* (1997) showed that energy efficiency could be optimised for the Malelane factory by making use of a triple effect evaporator station, with the bleed vapours from all three effects being used in the factory. All, or almost all, of the water content contained in the clear juice stream can be effectively utilised as bleed vapour under these conditions, with very little vapour 'wasted' by condensation in a condenser. This conclusion has subsequently been verified in work carried out by Tongaat-Hulett Sugar to design factories capable of operating at very high levels of energy efficiency.

As an example of Monte Carlo simulation in the sugar industry, it was decided to make use of a recent design for a factory operating with a process exhaust steam consumption of slightly over 38% on cane. In order to achieve this level of energy efficiency, a quadruple effect evaporator station was selected. However, instead of running the final effect vessels at a pressure of between 15 and 20 kPa(a), it was decided to operate them at an elevated pressure of 35 kPa(a). This raises the pressure profile of the evaporator station and allows for more effective use of the low-grade bleed vapour streams within the factory. The final effect syrup brix targeted in the evaporator station design was around 64%. The juice leaving the fourth effect vessels would then be flash-cooled to a pressure of 15 kPa(a) in a separate flash cooler, in the process carrying out the final evaporation of the syrup to above 65% brix and also producing a low-temperature syrup for the pan floor. The design of the evaporator station thus effectively contains five effects. However, only four of these make use of steam to carry out evaporation, while the fifth effect carries out a simple flash-evaporation process.

The elevated pressure of the V4 bleed vapour stream from the proposed evaporator station allows it to be effectively used for process heating purposes. Under season-average crushing conditions, the quantity of V4 bleed vapour produced by the fourth effect evaporators is almost exactly balanced against the demand of this vapour stream for juice heating. The production of vapour from the clear juice stream in the evaporator station is also exactly balanced by the demand for bleed vapours in the factory and there is no need to condense any 'excess' V4 vapour in a condenser or to let down any exhaust steam into the V4 vapour range to make up for an excess of demand over supply. This yields maximum energy efficiency for the factory. However, it is obviously unlikely that any mill will operate continuously at season-average conditions over the entire crushing season. More detailed modelling work is needed to investigate the behaviour and efficiency of this evaporator station design under varying crushing conditions and to investigate the control system to be used to balance the supply and demand of bleed vapour from the station (which is of major concern and importance in a design of this nature).

The production of and demand for bleed vapour from an evaporator station is a complicated function with many variables. It is extremely difficult to predict without making use of a detailed mass and energy balance for a factory. Although deterministic modelling can be used to investigate the sensitivity of the proposed factory design to changes in the factory inputs, this situation is an ideal candidate for the use of Monte Carlo analysis.

Implementing the Monte Carlo simulation

The Monte Carlo method involves statistically varying a range of inputs in a mathematical model, while obtaining outputs as probability distribution curves. Although the inputs are varied in a randomised way, the Monte Carlo simulation makes it possible to constrain inputs to follow defined probability distributions. These distributions are used to represent the actual sample distribution of particular model inputs. A typical probability distribution for an input might be the normal distribution (or bell curve). Visual Basic script can be used to simplify the implementing of Monte Carlo simulation (see Appendix A).

A distinct advantage of Monte Carlo simulation is that it can remove some of the bias of actual data. When, for example, there is an outlier in a set of actual data, and the curve is not uniform or smooth, results from the model can be compromised. However, if a probability distribution is fitted to this data and this probability distribution is then used in the model, the possibility of outliers affecting the results is eliminated and the Monte Carlo simulation can be used to generate a much smoother set of results. There is also the advantage that simulation can use thousands of inputs as opposed to only a few sets of sampled data or selected scenarios. The more random numbers that are generated, the smoother the output curves will become. This is demonstrated in Figures 1 and 2, where Figure 1 shows the results of selecting 100 random input values from a particular distribution, and Figure 2 shows similar results using 1 000 random inputs. The values shown are taken from a normal distribution for the tons of cane crushed per hour by a mill, with a mean value of 385 t/h and a variance of 36 t^2/h^2.

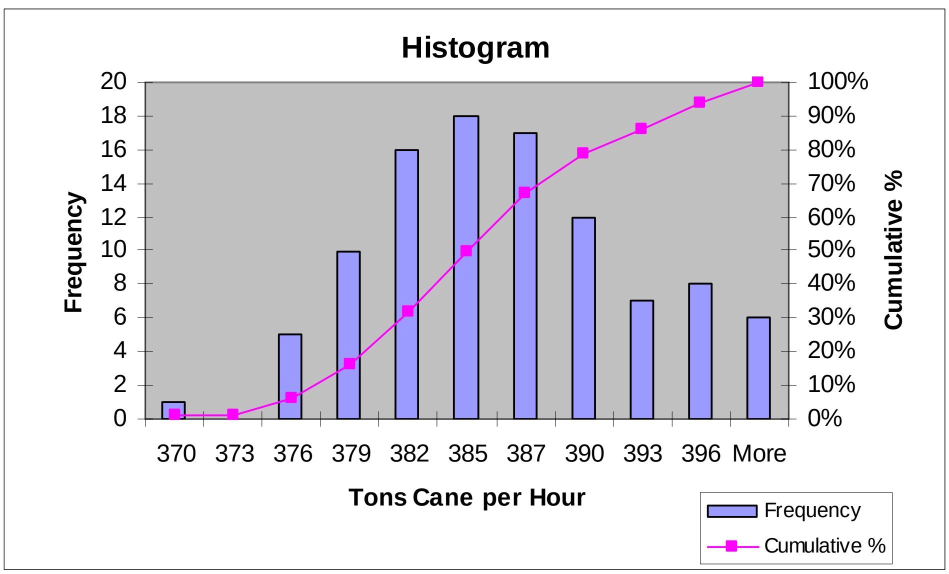

Figure 1. Tons cane per hour as a simulation input, using 100 samples from a normal distribution.

Results of the Monte Carlo simulation process

For the purpose of demonstrating the use of Monte Carlo simulation, the energy-efficient factory design discussed above was chosen. The dynamics of the factory energy balance (Rein and Hoekstra, 1994) were investigated using single point deterministic methods. It became apparent that the V4 demand for juice heating would exceed the available supply during certain periods of factory operation. During other periods, an excess supply of V4 would become available.

Periods of operation during which the availability of V4 bleed vapour exceeds the demand for juice heating are readily dealt with. The installation of a condenser to consume the excess V4 vapour and control the pressure at a fixed value of 35 kPa(a) is fairly simple. During periods when the V4 vapour demand is greater than can be supplied by the fourth effect evaporator, it would be necessary to let down exhaust steam into this vapour range to maintain the target pressure of 35 kPa(a). There will thus be a certain percentage of time when it will be necessary to let down exhaust in order to compensate for the higher V4 vapour demand. The objective of the current study was to quantify this period of time and the average amount of exhaust steam let-down likely to be required. Single point deterministic modelling would make it almost impossible to determine the percentage of time during which demand would outstrip supply, and it was thus necessary to use simulation to quantify the likely effect of this on energy efficiency.

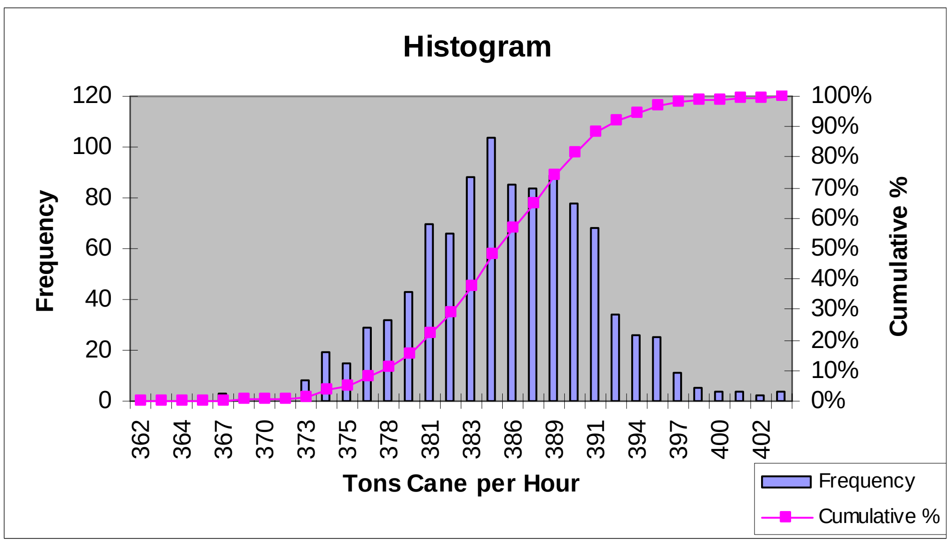

Figure 2. Tons cane per hour as a simulation input, using 1 000 samples from a normal distribution.

For the purposes of this demonstration, only two inputs to the energy balance model were varied: (i) tons of cane crushed per hour by the factory, and (ii) sucrose content of cane. The cane crush rate was varied using a normal distribution with a mean value of 385 t/h and a variance of 36 t^2/h^2, while the sucrose % cane value was varied using a normal distribution of mean value 12% and variance $0.64\%^2$. The other operating variables (such as imbibition % fibre) were kept at constant values. A summary diagram of the process is shown in Figure 3.

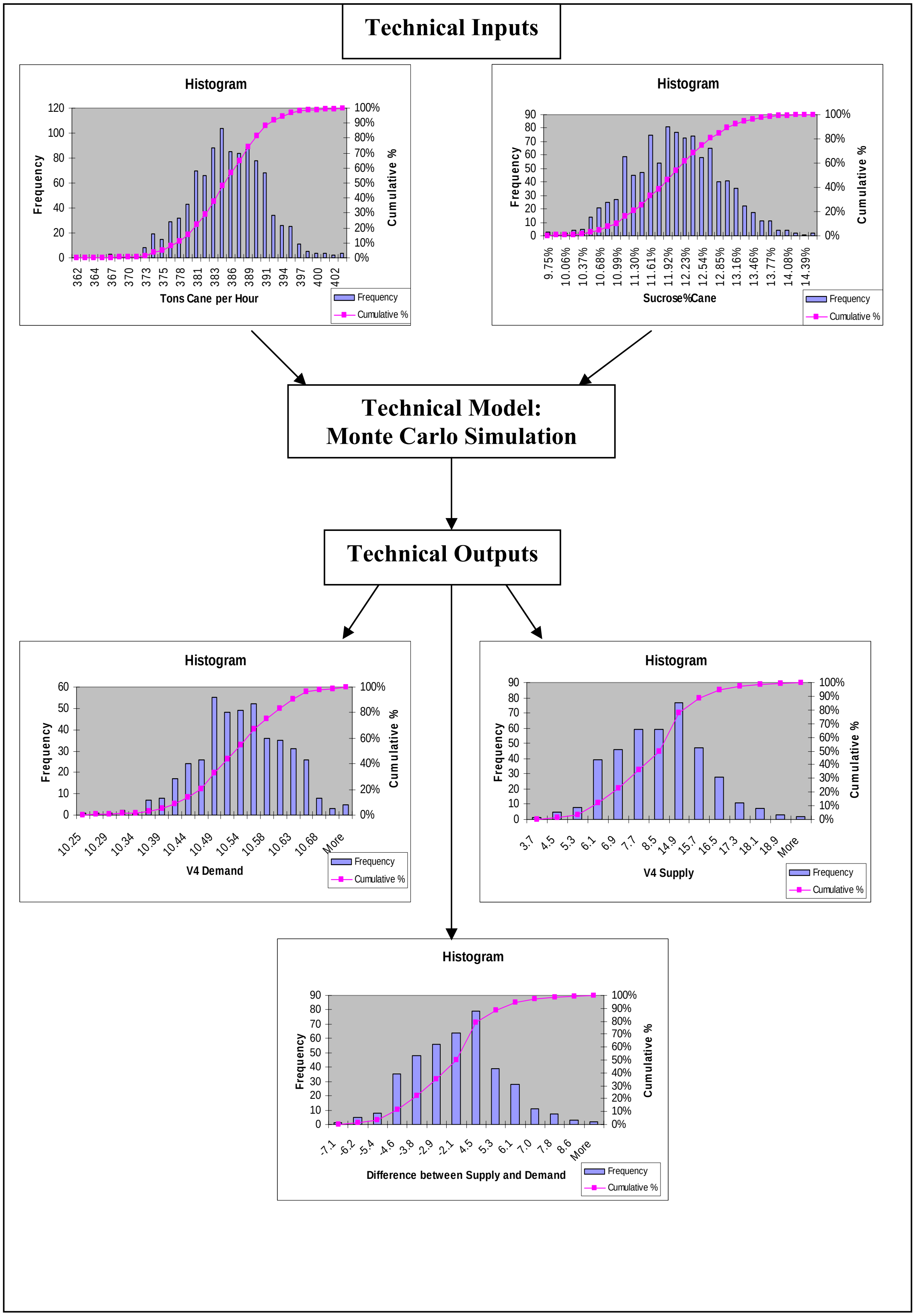

Figure 3. The Monte Carlo simulation process.

The outputs obtained from the model are demonstrated in Figures 4, 5 and 6. These represent the V4 demand for juice heating, the supply of V4 available from the evaporator station and the difference between these quantities. It is apparent from Figure 6 that there are occasions when the difference between supply and demand is negative, implying that demand exceeds supply. Statistical analysis of the data in Figure 6 was carried out to determine the percentage of time during which the supply of vapour was sufficient to meet demand. This equated to approximately 42%, indicating that exhaust let-down would have to be used 58% of the time to make up for the deficit in V4 supply. The average quantity of exhaust steam make-up required was found to be 1.9 t/h[†], with a peak demand of up to 7.1 t/h being expected under certain operating conditions.

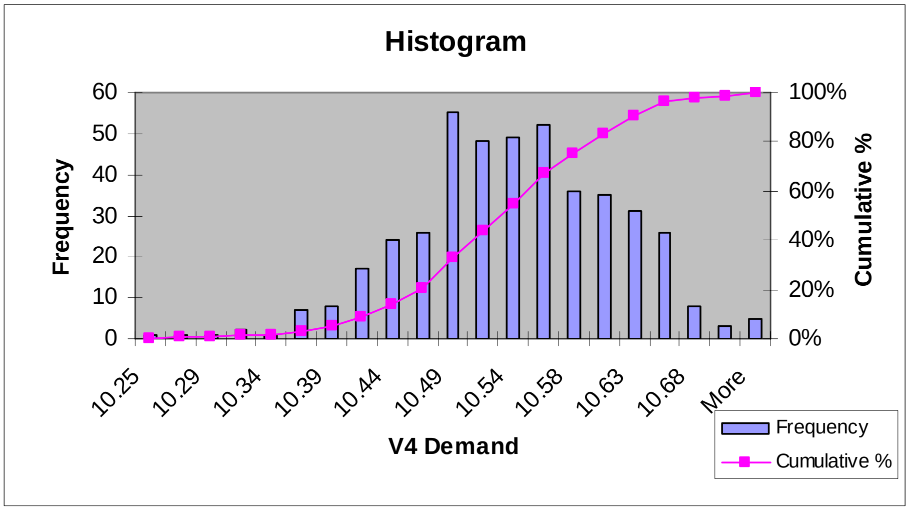

Figure 4. V4 vapour demand for juice heating.

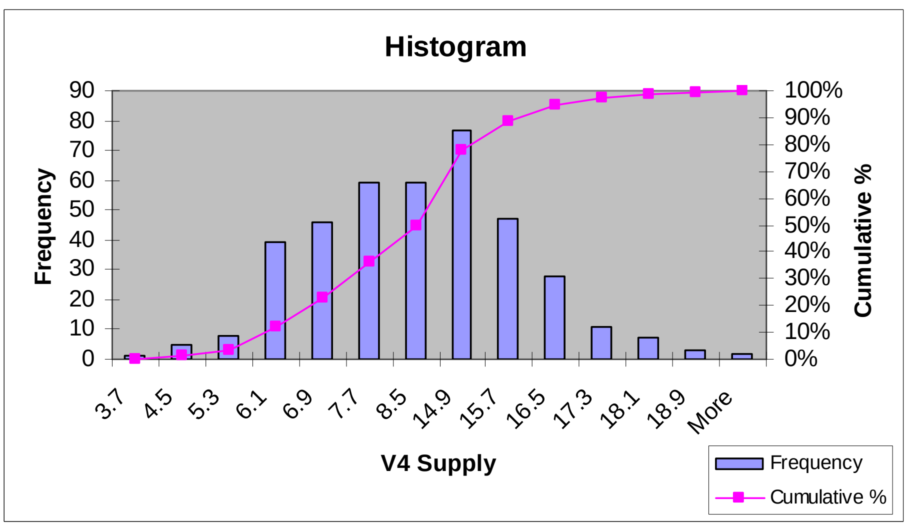

Figure 5. V4 vapour supply from the evaporator station.

[†]The mean value of 1.9 t/h reflects an average taken over the entire operating period of the factory and includes periods during which a surplus of V4 vapour was available from the evaporator station (the let-down requirement is obviously zero under these circumstances).

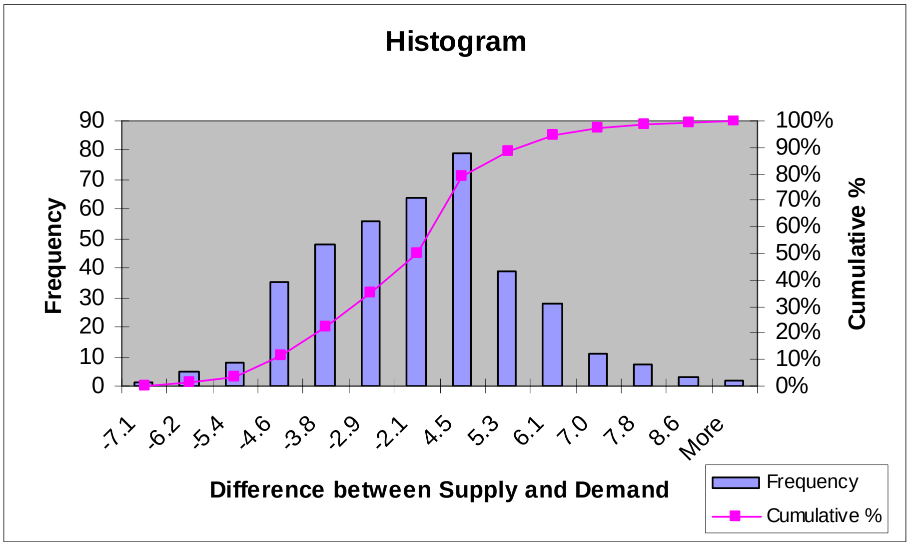

Figure 6. Difference between V4 vapour supply and demand.

The use of Monte Carlo simulation has made it possible to quantify the percentage of the time that exhaust steam make-up to the V4 range will be required. The average quantity of exhaust steam consumption for this purpose has also been determined and can be allowed for in the season-average steam balance design. From a project planning and feasibility perspective, the results obtained here are considered acceptable, as the use of V4 will lead to substantial savings in energy costs and an improvement in the plant's energy efficiency (even allowing for the minor requirement for exhaust steam let-down). From an operational perspective, the need for exhaust let-down has been investigated and the design of an appropriate control system for the evaporator and heating station can be developed.

Conclusions

In the example discussed here, it is evident that it would have been time-consuming and tedious to use single point entry (deterministic) methods to determine the availability of V4 vapour and to quantify the demand for V4 make-up with exhaust steam. Using Monte Carlo simulation, the entire energy balance model for the proposed factory was run on a stand-alone computer over a period of four hours, and generated outputs that have provided a reasonable indication of how the plant will perform in practice. The proposed factory project can now be justified economically, taking into account the need to supply exhaust steam let-down into the V4 vapour range under certain operating conditions.

Monte Carlo simulation techniques can be relatively easily incorporated into process or technical models. All that is required is that the model inputs are changed from being deterministic in nature to being stochastic (based on appropriate probability distribution functions). A random number generator and predefined user probability distributions can then be used as inputs to run the model.

A combination of Excel spreadsheet modelling and Visual Basic can be used to run thousands of iterations within a few hours, depending on the size of the technical or economic model. This can lead to more accurate modelling of projects and realistic expectations of plant performance. Distinct operating scenarios for a particular factory can be identified and the frequency at which these operating scenarios occur can be quantified using Monte Carlo analysis.

It must be stressed, however, that the model is only as good as the inputs, and, as with any laboratory data, where the inputs are flawed, errors in the output will be magnified and could lead to poor decision making.

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APPENDIX A

Monte Carlo Simulation: Visual Basic Script