A METHOD FOR OPTIMAL DESIGN OF TIMBER HAULING SYSTEMS UNDER CONDITIONS OF UNCERTAINTY AND RISK

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ABSTRACT

This thesis describes a method for designing optimal timber hauling systems under conditions of uncertainty and risk. This method distinguishes between, and incorporates, natural uncertainty and parameter uncertainty. Natural uncertainty encompasses the variation of the trucking activity times (loading and unloading times, loaded and empty travelling times), and is handled by using probability distributions. Parameter uncertainty is the inability to accurately estimate the parameters of these probability distributions. In this study, parameter uncertainty is addressed from a Bayesian perspective by incorporating, together with some sample data, subjective estimates from experts. In addition, the decision on the optimum combination of trucks, loaders and unloaders is based on the decision maker's attitude toward risk. Design scenarios are analysed by formulating the sequence of hauling activities (i.e., loading, travelling loaded, unloading and travelling empty) as a queueing system, and the equipment combinations are then evaluated by simulation. The inputs to the simulation model include actions (representing the number of trucks, loaders and unloaders), probability distributions (of loading time, unloading time, travel loaded speed and travel empty speed), estimated parameters of these probability distributions, and constants (such as amount of wood to be hauled, hauling distances, etc). Using a cost equation, the simulation outputs are converted into cost and payoff tables. Employing utility functions, which quantify the decision maker's attitude to risk, the optimum combination of trucks, loaders and unloaders is determined based on expected payoff and expected utility criteria.

Using basic data supplied by Forest Engineering Research Institute of Canada (FERIC), a two-parameter gamma distribution is selected to represent the input variables in the simulation program. Calculations to estimate the parameters of the gamma distribution using Bayesian methodologies are contrasted with the classical statistical methods. Other possible applications to illustrate the applicability of Bayesian decision analysis in forestry are also presented.

The thesis concludes that Bayesian statistics and decision analysis which combines expert prior knowledge with available sample data provides a better methodology for designing timber hauling systems than that provided by classical decision analysis methodologies, especially where woodlands decisions are made with limited sample data.

Key words: Timber hauling, simulation, uncertainty, risk, Bayesian statistics.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Page

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Chapter 1

INTRODUCTION

1.1. BACKGROUND

Industrial consumption of wood and wood products in Eastern Canada has been continually increasing over the past years, and this trend is expected to continue into the future (Forestry Canada, 1993). At the same time, unit wood production costs have also been increasing. For example, according to Mooney (1993), unit wood production costs have increased from \$13 per m^3 in 1972 to a high of \$51 per m^3 in 1992.

Mooney estimates that hauling of primary wood products from forest to mill accounts for about 40 per cent of the total acquisition cost for the raw wood material (Mooney, 1993). Furthermore, the future trend will be to force transport costs even higher as haul distances in Eastern Canada continue to grow as harvesting operations moves further and further from the converting plants (Williams and Nader, 1993).

These present and future economic forces necessitate that forest hauling operations be conducted in the most efficient manner possible. As illustrated in Fig. 1, a typical hauling operation is a sequence of: loading, travel loaded, unloading and travel empty activities. Thus, it is essential that the equipment performing these activities be coordinated in such a fashion that all are being highly utilized. This in turn requires reducing truck waiting time, due to queueing at loading and unloading sites, and reducing the loader and unloader idle times, due to the absence of any trucks to service. These waiting and idle times are a function of the number and size of trucks in the hauling system, the number and productivity (i.e., the loading and unloading times) of loaders and unloaders in the system, and on the travel times between the loading and unloading sites. The cost to the hauling system for this non-utilized truck and loader time is then directly related to the waiting cost per unit time for the trucks and to the idle cost per unit time for the loaders/unloaders. Thus, the hauling operations manager or contractor must make effective decisions as to the proper numbers and types of equipment to select for a hauling system so as to minimize the total hauling costs.

Understanding the portion of each day spent in waiting and idle time for alternative hauling systems would enable woodlands managers to determine the most economical combinations of hauling equipment. This is not easy to do because of the intricacies involved in estimating the waiting and idle time. The environment in which trucking operations occur is highly variable and complex. In addition, random changes of topography, terrain and weather conditions complicate the estimating of hauling variables. Under these conditions of randomness, even an experienced woodlands manager cannot precisely know all outcomes of his decisions.

It is in the context of these operational decisions and challenges faced by the forest industry that researchers have conducted field studies and developed models to improve the efficiency and design of hauling operations.

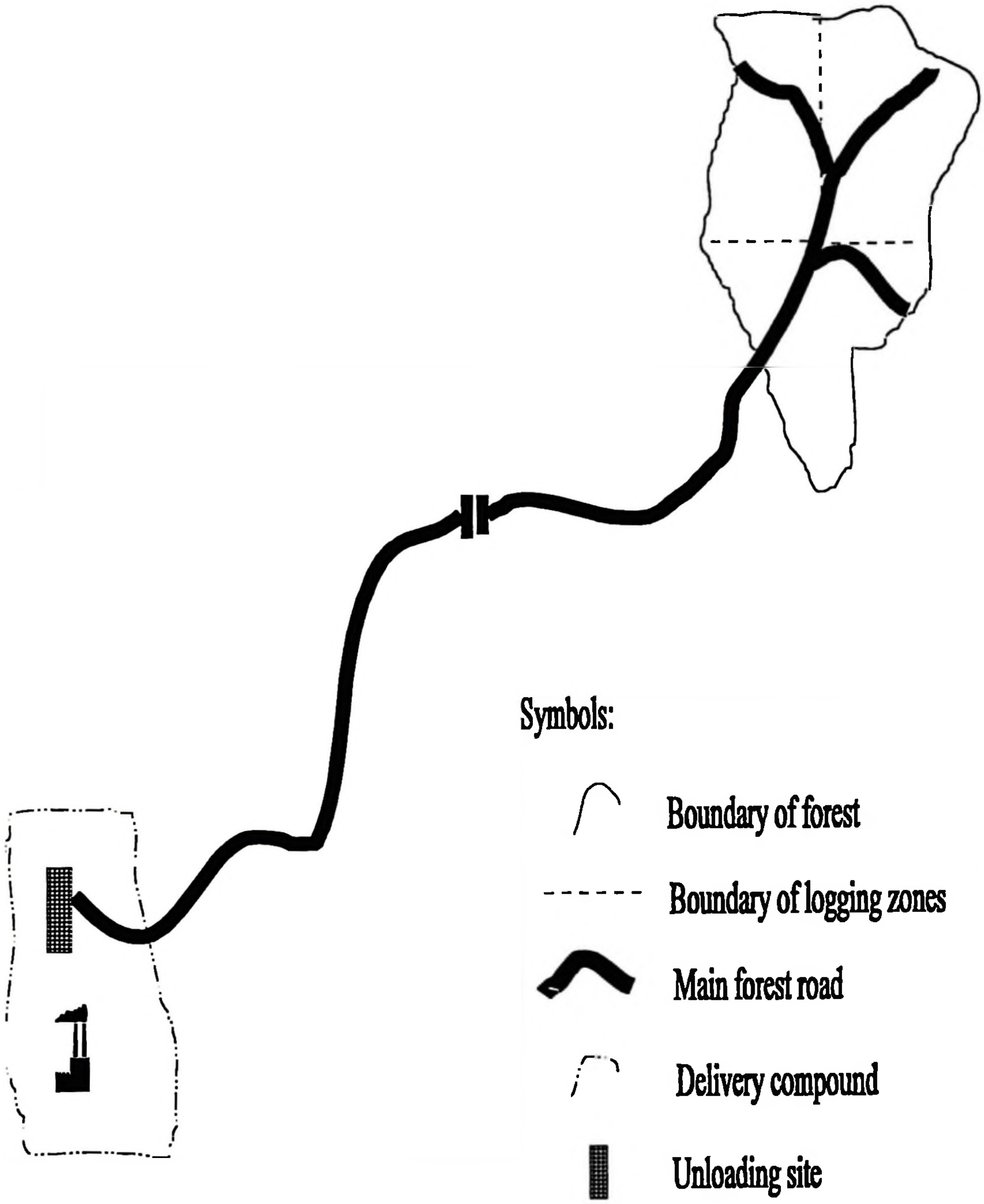

Fig. 1: A sketch of a typical timber hauling system in Eastern Canada.

1.2. HAULING OPERATIONS: CURRENT RESEARCH

Research into forest hauling systems can be divided into 2 broad approaches: deterministic and probabilistic. Determinism implies that the variables in forest transportation can be described or handled in a completely predictive manner. This approach discounts the random factors described previously and assumes that simple numerical values will adequately describe the hauling system variables. Many of the field studies in forest transportation report their findings from this deterministic perspective. Thus, for example, when equipment is being evaluated or tested, often the performance is only reported in terms of the mean - a deterministic fixed value. Examples of this kind of study include Lavoie (1979; 1980), Smith (1981) and Clark (1986a;1986b). An abbreviated list of recent computer models which take deterministic approach to forest transportation include those reported in Groves *et al.* (1987), Walker and Preiss (1988), Oakley and Marshall (1989), McNickle and Woollons (1990), Wightman (1990), Burger and Jamnick (1991), Weintraub *et al.* (1991), Feng and Douglas (1993), Jalinier and Nader (1993) and Jones (1994).

However, this deterministic treatment of loading time, unloading time or travel time cannot be expected to yield a reliable forecast in a nonuniform forest environment when the decisions involve the coordination, selection and scheduling of equipment within an efficient hauling system (Meng, 1975). The fact is that the forest environment is not deterministic; it is probabilistic. The variability in times for loading, travelling to mill, unloading and travelling to the forest is better characterized by using probability distributions.

To deal with the shortcomings of a deterministic approach in evaluating and predicting hauling system costs, other researchers have developed probability-based simulation models where the hauling system is modelled as a queueing system. In this approach, each activity in the operation (loading, travel loaded, etc) is characterized not by a fixed value, but by a probability distribution. This approach is illustrated in Fig. 2.

Ordinarily, a queueing system is characterized by a flow of customers arriving randomly at a facility which has one or more servers. If all the servers in the service facility are busy when a customer arrives at the queueing system, the customer must usually wait for service until a server is available. A hauling system can be considered as a queueing system where the trucks are the "customers" and the loaders and unloaders are the "servers".

Queueing systems can be studied by simulation. Inputs to the simulation model include the probability distributions of: loading times, unloading times, travel loaded speeds, travel empty speeds. For a given amount of wood to be hauled, certain hauling distances and numbers of pieces of equipment (i.e., the number of trucks, number of loaders and number of unloaders), the queueing system can be simulated to estimate the following:

- the average hauling cycle time
- the average waiting time of trucks to be loaded
- the average waiting time of trucks to be unloaded
- the average idle times for loaders
- the average idle times for unloaders.

These times can be converted to monetary values or any other measure of performance for decision-making purposes.

This kind of study of hauling systems provides a better understanding of the impact of various decisions inherent in timber hauling where queueing may be important, and would provide more specific answers to such questions as: (1) the waiting and idle times for a particular combination of equipment, and (2) how the various components of the system are capable of functioning together to reduce the hauling cost.

Early computerized simulation models in which the variation associated with times for loading, travelling and unloading was recognized and expressed by probability distributions originated in the 1970s.

One of the first studies is presented in the work by Routhier (1974). He developed a trucking simulator in which a normal distribution was used to characterize loading, unloading and trip durations, and an exponential distribution was used to represent breakdown durations. The field study for the validation of this trucking simulator is reported in Garner (1978).

Recent computer simulation studies include the model by McNickle and Woollons (1990) which analyzed a queueing system in a logging weighbridge installation. The arrival times were represented by an exponential distribution and the move-up and service times were represented by empirically observed distributions. Ada *et al.* (1987) also recommended the use of probability models to represent the duration of, and interval between, breakdowns of logging trucks.

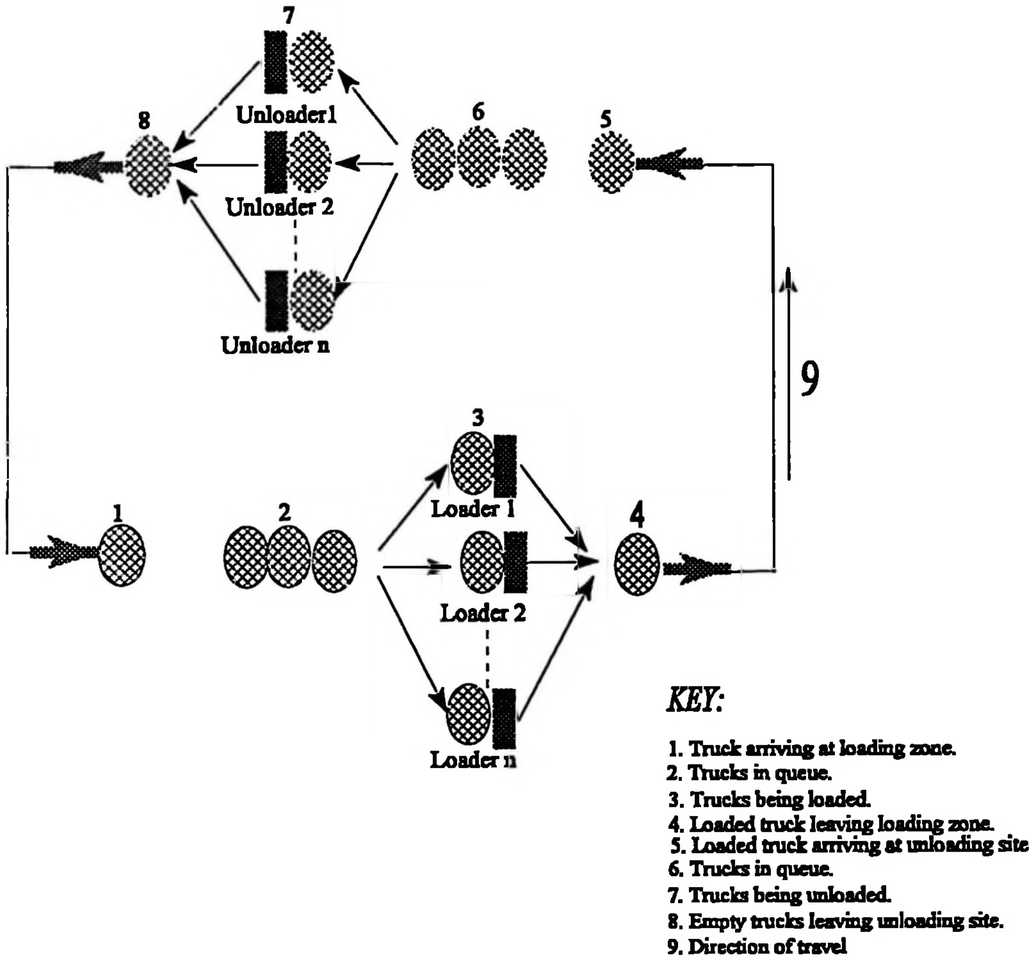

Fig. 2: A queueing model representing a timber hauling system from a loading zone to the mill.

Other important computerized forest harvesting simulation models in which times for loading, travelling and unloading were included in the models, and are represented by probability distributions, are also available in the forest engineering literature. The pioneering studies in this category include the models developed by Johnson *et al.* (1972), Johnson and Biller (1973), Biller and Johnson (1973), Martin (1973; 1975), O'Hearn *et al.* (1976) and Bradley and Winsauer (1978). These simulation models are also reported in Goulet *et al.* (1979, 1980a, 1980b), Stuart (1981) and Reinsinger *et al.* (1986). Most of these models used the normal distribution to quantify the random processes. For example, Martin (1973), in his Timber Harvesting and Transport Simulator (THATS), assumed normal distributions for felling, bunching, skidding, loading and hauling (though sometimes he assumed the lognormal distribution if skewness was detected in the time study data).

More recent work using the same modelling principle and approach is reported in Koger (1992). He developed a model called STALS-3 for analyzing skidding, loading and trucking interactions at a landing using queueing theory method. The application of the queueing method is based on the assumption that truck arrival times follow a Poisson distribution.

Other forms of probability distributions such as Weibull, gamma or lognormal (eg. see Law and Kelton, 1991), which have lower bounds and can describe data sets with some degree of positive skewness, and to a limited extent, may describe data sets with negative skewness, have not been considered.

1.3. CONTINUING PROBLEMS OF CURRENT RESEARCH IN HAULING SYSTEMS

Use of probabilistic simulation provides a more comprehensive approach in modelling truck hauling system performance than the deterministic approach, and thus should be an invaluable tool for managers seeking to design optimal hauling systems. However, this type of simulation has not been greatly used in the industry. Industrial models, whether spreadsheets or database systems, tend to use deterministic values in modelling hauling systems. This was recognized even in the 1970's by Garner (1978). Garner (1978) assumed that the reluctance by the industry in adopting the simulation model developed by Routhier in 1973 (even though it was available free of charge to member companies) was due to the fact that: (a) no study had verified the accuracy of the model by comparing the model results with actual field studies, and (b) small data sets in the logging industry are not appealing for use in simulation models which require large amounts of data.

An impediment to the use of probabilistic simulation models is that probability distributions to model the individual hauling activities (loading, unloading etc.) are usually only assumed. In most of the models described above, the normal distribution was assumed to reflect the actions of the model. However, the assumption of normality as the underlying distribution for loading, unloading and travel times is untenable because of two fundamental properties of the normal distribution. The first is the innate symmetry of the distribution. Experimental evidence (Ada *et al.* 1987) has indicated some degree of skewness in this measured data, so the symmetry of the normal distribution could be unrealistic. The second is that the normal distribution is unbounded at both tails, and since we know that times for loading, unloading or travel are bounded at least by zero on the lower tail, the use of the normal distribution to describe these activities is inaccurate.

Along with this, in practice, the actual parameters of the probability distribution function in question are also hardly ever known. In the classical statistical practice, these parameters are calculated from sample data (e.g., Giffin, 1971, pp. 139; Guttman *et al.* 1982, pp. 62-64 for average and standard deviation, pp. 163-164 for parameters of a distribution). An implicit assumption in using these models is that complete sample data is always available. Herein lies a great obstacle to the use of probabilistic simulation models: managers in practice have little or no access to enough equipment data to use as a sample to reliably determine the parameters of the probability functions. This is especially true if the equipment being considered is new and untried, but even with standard equipment, travel speed probability distribution parameters may be unavailable to managers operating in new cut blocks. For this reason, Garner (1978), acknowledged that simulation models require a large amount of data compared to that required by deterministic models.

Thus, managers must deal with 2 distinct types of uncertainty in probability-based simulation of hauling systems. The uncertainties may be identified as: (1) **natural or inherent uncertainty,** which is due to the inherent random characteristics of the phenomenon itself, and (2) **parameter uncertainty,** which is the result of using an insufficient amount of data to estimate the parameters associated with a probability distribution (Benjamin and Cornell, 1970).

No research in the simulation of forest hauling has dealt with the problem of parameter uncertainty. The probabilistic models to date have considered the inherent randomness associated with natural uncertainty only. However, when developing effective models for decision-making, the variability intristic in the random process, as well as the uncertainty due to limited knowledge of the parameters, both contribute to the variability of the outcome, and both must be taken into account.

Finally, the objective of the research to date has been only to develop the simulation models and produce solutions from the models. No research has incorporated decision-making analysis into the solution. This is due to the fact that current research would assume that the lowest cost output from the simulation would be the obvious "decision" of the manager. However, given that both natural and parameter uncertainty are relevant factors in simulation, the outputs derived from a simulation model have a degree of uncertainty associated with them. Therefore, decisions also need to reflect these conditions of uncertainty.

The forestry sector is very diverse with respect to the organizations that make it up. Large, multi-national companies whose hauling operations are integrated with pulp and paper production and sawtimber production dominate this sector. These companies have different sources of revenue and are large enough that they can survive temporary setbacks given that, over the long term, profitability is assured. In addition, they are managed by professional employees who have invested little or no personal wealth in the company. Linked to these larger organizations are the numerous contractors who supply a great deal of the primary wood products to many of these companies. Contractors vary greatly in terms of size, equipment used, education levels of employees, and financial strength. However, they have, to a greater degree than the managers of the large companies, invested their own wealth in the contract business. These contractors would thus be expected to be much more influenced by risk than the professional managers of the larger forest companies. Depending on their own current financial vulnerability, future business prospects, and personal attitudes to uncertainty, risk would be expected to play a more pronounced role in their decision-making.

Considering that in Eastern Canada, hauling operations are being increasingly carried out by contractors, attitudes to risk can no longer be ignored in the decision-making process. Hence, operations research in forest hauling needs to utilize a decision-making tool that accomodates risk in a rational manner. To date this has not been attempted in forest hauling research. In other words, current techniques either ignore risk completely or assume it is of no consequence.

Nevertheless, techniques have been described in the literature that can consider the uncertainties in parameter estimation and risks in decision-making. The introduction of parameter uncertainty and decision-making under risk would significantly improve and aid the process of designing optimal hauling systems. Such techniques include Bayesian statistics and decision analysis as explained in the next section.

1.4. BAYESIAN STATISTICAL METHODS AND DECISION ANALYSIS

The inability of the classical techniques described above to address the uncertainties and risk in decision-making lies with the assumption that the parameters are estimated by only one uniquely determinable value (Kyburg and Smokler, 1964; De Finetti, 1968). On the other hand, De Finetti's work has formed the basis of subjective, or "personalistic" approach to probability, whereby subjective probability is considered a quantification of uncertainty. This is the basis of the Bayesian statistical methods and decision analysis described next.

Bayesian statistical methods were pioneered by Bayes and Laplace two centuries ago. These methods, known under the names of Bayesian statistics, decision theory, and subjective probability are appropriate when the decision-making process is characterized by partial data set as is the case with data in the logging industry as explained previously. These methods allow the use of additional information about the unknown parameters of a probability distribution such as historical data or past experience and judgements to sharpen the parameter estimates where sample data or information is incomplete (Wonnacott and Wonnacott, 1969; Benjamin and Cornell, 1970). This prior information can be used to formulate subjective estimates regarding uncertain parameter values.

In addition, Bayesian methodology allows the combining of prior information with sample data to further improve the estimate of the parameters before making a decision. The prior information and sample data are combined through Bayes' theorem to generate or give the posterior information (Benjamin and Cornell, 1970, pp. 556; Guttman *et al.* 1982, pp. 191). In terms of probability, Bayes' Theorem can be expressed as:

Posterior Probability of Parameter, given the Sample	=	Sample Likelihood, given Parameter	×	Prior Probability of Parameter	÷	Marginal Sample Likelihood

The posterior distribution reflects the modification of the subjective knowledge about the values of the parameter expressed by the prior models in light of the observed sample data, and is the basis for subsequent decision-making.

Therefore, the Bayesian method provides the opportunity to incorporate any related information other than data (i.e., the engineering judgement and prior knowledge) that accurately reflects the true variation in the parameter to improve the quality of its estimate. In this way, it is possible to provide a basis for deciding if sampling is worthwhile in view of the benefit and cost of sampling. Funds and/or time are usually not available for obtaining a sample size necessary to achieve high degree of precision (if classical methods are to be used).

Also, in Bayesian statistics, decision-making under risk is handled in a systematic fashion. Through the utility theory, risk is quantified by means of a utility function which represents the decision maker's attitude toward risk. Then, the utility function, U(x), is combined with the posterior probability distributions of the parameters, P[parameter/sample] to give the expected utility of an action (a), EU(a) as follows (Benjamin and Cornell, 1970; deGroot, 1970):

$$EU(a) = \Sigma_{\text{all parameter}} U(x) P[\text{parameter/sample}]$$

Based on the expected utility, different actions can be ranked.

Bayesian methods have been used to address similar problems in other fields of engineering such as in reliability engineering (Martz and Waller, 1982), in irrigation and drainage systems (Musy and Duckstein, 1976; Tung, 1987) and in transportation (Dey and Fricker, 1994). However, in spite of the obvious potential and utility of the Bayesian statistical methods and decision analysis to similar problems in forest operations, such approaches have not yet been adopted in practice. Some aspects of forestry where the methods could clearly be useful are suggested and reported in Lussier (1961), Flora (1964), Dane (1965), Thompson (1968), Woodland (1970), and McCormack (1982).

The main reason Bayesian statistics and decision analysis have not been adopted in forestry research is that forest researchers tend to seek deterministic fixed values although the solution can only be produced in probabilistic values. As well, they are not fully familiar with the Bayesian statistical methods, especially the intimate connection with the utility theory under uncertainty and subjective probability as promoted by Ramsey (1926), DeFinetti (1968) and Savage (1977).

1.5. RESEARCH OBJECTIVES AND SCOPE

In view of the shortcomings in forest operations simulation research, and the potential offered by incorporating Bayesian statistics into the forest hauling context, the general objective of this research is to demonstrate: the methods of using probability distributions to represent the natural uncertainties, the pertinence of incorporating Bayesian methods in handling uncertainties involved in the estimation of parameters, and the suitability of applying the Bayesian decision-making approach for choosing an optimum hauling system under uncertainty and risk.

To accomplish this general objective, the following specific objectives are:

[1] To specify a suitable probability distribution so as to accurately represent natural variability in loading time, unloading time, travel loaded speed and travel empty speed as inputs for the simulation study of hauling systems.

[2] To apply Bayesian methods to improve estimates of the parameters.

[3] To explore effects of parameter uncertainty on optimal design decisions of hauling systems. This will examine whether optimal hauling systems based on Bayesian estimation methods differ from those determined based on classical estimation methods.

[4] To examine the influence of utility analysis on determining the optimal hauling system and on the ranking of the different hauling systems.

[5] To develop some continuous functions to approximate the solution of the queueing model as an alternative to long computer simulation runs.

It is assumed here that the simulation results are governed by parameters which are imprecisely estimated. Therefore, in estimating the parameters, the parameters will be assumed to be random variables with an a priori or prior probability distribution. The prior distributions are assumed to represent the totality of subjective or historical information available concerning the parameter (i.e., expresses the state of knowledge or ignorance about the unknown parameters) prior to the observation of the sample data. However, in order to make the best possible decision, it may be possible to revise or update the prior probabilities by combining them with sample data so that the final decision is based on more accurate probability estimates of the unknown parameters. This approach is distinct from the indirect and somewhat artificial classical approach of dealing with parameter uncertainty. This is a decided departure from the purely statistical view which does not admit subjective estimates as legitimate data when establishing a probability distribution.

Within this framework of uncertainty, a numerical assessment by the decision maker of his preferences among the possible outcomes of an action will be provided by means of utility functions. Then the decision criterion will be the expected utility which incorporates the utility function and the posterior distributions of the parameters. In this way it will be possible to incorporate the manager's attitude to uncertainty into decisions regarding the selection of a course of action.

It should further be noted that this dissertation research is not concerned with the study of the relationship between one factor and another factor. For example, it does not seek to study the factors related to travel time in hauling timber from point A to point B. It rather treats the hauling variables as random variables with probability distributions.

To the best of the author's knowledge, no one has yet proposed a decision-making model in the context of Bayesian statistical methods and decision analysis for dealing with this kind of problem in hauling systems design decisions.

Chapter 2

DESCRIPTION OF THE GENERAL METHOD FOR DESIGNING OPTIMAL HAULING SYSTEMS

In the previous chapter, two types of uncertainty and the problem of considering risk in the process of designing optimal hauling systems were discussed. This chapter, based on the Bayesian decision-making method, presents a general method for designing optimal hauling systems under conditions of uncertainty and risk. This method consists of the following stages:

First, a queueing model is formulated to represent the actual hauling operations.

Second, a computer simulation program is developed to derive solutions for the queueing model. The inputs to this model include: (a) the actions, representing the number of combinations of the trucks, loaders, and unloaders, (b) constants that describe a particular hauling situation such as the amount of wood to be hauled in different loading zones, number of hauling zones, hauling distance to each hauling zone, and so on, (c) the probability distributions of loading, unloading and travel speeds, and (d) values of the parameters of the probability distributions. A procedure to select appropriate input probability distributions is given and the parameters of the selected distributions are estimated using classical and Bayesian estimation procedures. The prime reason for using the Bayesian method is that it permits accounting for parameter uncertainty by including prior knowledge in a rational way.

Third, the solution from the queueing model which consists of average trucking, loading, unloading, waiting and idle times, overtime and number of trips required to complete the hauling operation is obtained by simulation.

Fourth, a formula for estimating the total cost using the simulation output or response functions is developed.

Fifth, a decision-making process (i.e., selecting an action that is the best) is proposed. For this purpose, a decision table of the resulting costs is constructed. The decision criteria are the total expected cost and total expected utility. The expected utility criterion is considered important in this research because it permits accounting for risk in a rational way.

Finally, an alternative method to long computer simulation runs for estimating the solution of the queueing model is proposed.

A graphical representation of the stages involved in this method is shown in Fig. 3.

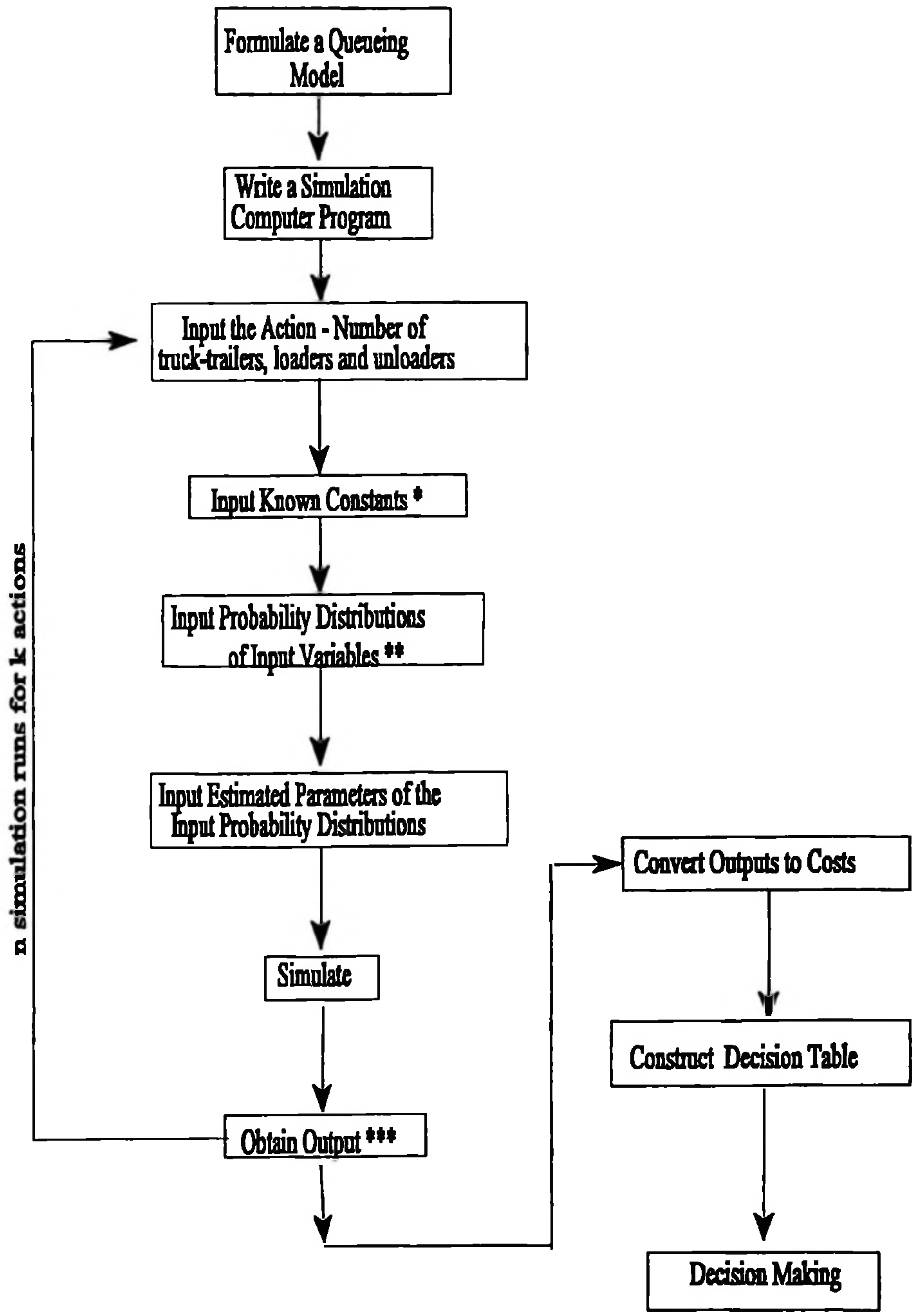

Fig. 3: A simplified diagram of stages involved in the method for designing optimal hauling systems. * includes amount of wood to be hauled, hauling distances and so on. ** are loading and unloading times and travel speeds. *** are trucking, loading, unloading, waiting, idle overtime times and number of trips.

2.1. FORMULATION AND ANALYSIS OF THE QUEUEING MODEL

As suggested in Chapter 1, the hauling activities, i.e., empty trucks travelling to loading zones to be loaded by an available loader (waiting to be loaded if necessary), travelling to delivery points to be unloaded by an unloader (waiting to be unloaded if necessary), and then returning to loading zones and joining the queue again, are to be represented by a queueing system as shown in Fig. 2. The other random factors that could occur in actual operations (such as machine breakdowns), are not included in the model. This was to keep the model simple and straightforward but fairly descriptive of hauling operations to allow the study of the types of uncertainty described earlier.

A computer simulation program written in GWBasic was developed in which simulation experiments could be performed on the queueing system. By varying the input data to the queueing model, it would be able to estimate and compare results.

The inputs to the simulation model are:

(a) the action, representing the number of trucks, loaders and unloaders

(b) constants that describe a particular hauling situation such as the amount of wood to be hauled from different loading zones, hauling distances, quantity of wood to be moved from each loading zone, costs per hour for a truck, loader and unloader, shift duration, overtime limit and overtime payment rate.

(c) probability distributions of the loading time, unloading time, and travel speed

(d) parameters of these probability distributions.

In the simulation model, the behaviour of the queueing system is simulated by moving the inputted data through the sequence of defined operating procedures. Trucks arrive at loading zones or unloading sites at random and are allocated to the nearest loader/unloader which is available or has a short queue. The duration of loading time, travel loaded speed, unloading time and travel empty speed are simulated using Monte Carlo sampling (White *et al.* 1975) from their respective probability distributions. These elements are then subsequently combined in their natural order and the model tracks any queueing that may take place at the loading and unloading sites. The flowchart of the simulation program as well as the computer listing are included in Appendix Ia and Ib. Thus, for each simulation run, a unique output result is obtained and this process is repeated for n successive days and k actions to be simulated.

The basic time unit for this model is a day, and therefore the simulation outputs derived are given on daily basis (estimated herein as the statistical average) based on n days of simulation.

In order for the different actions to be evaluated, a summary report of the simulation output is generated. The simulation output for each action represents the average values for n simulation days. The simulation output includes the following:

(i) Average trucking time (travel loaded and travel empty time).

(ii) Average waiting time of trucks at the loading sites.

(iii) Average waiting time of trucks at the unloading sites.

(vi) Average loading time.

(v) Average idle time for loaders.

(vi) Average unloading time.

(vii) Average idle time for unloaders.

(viii) Average overtime for trucks, loaders and unloaders.

(ix) Average number of truck trips.

The average number of truck trips is used for calculating the total number of working days required for hauling a given amount of wood (in units of truck-loads).

2.2. DESCRIPTION OF THE INPUT DATA

In the present study, the input data was divided into four categories. These categories include the actions, constants, probability distributions of loading times, unloading times, travel loaded speeds and travel empty speeds, and parameters of the input probability distributions. In the following sections, the input data are described and characterized.

2.2.1. Actions

A queueing system is identified by a certain number of loaders in different loading zones in the forest used to load wood into trucks, several trucks used to haul wood from the forest to delivery points, and a certain number of unloaders for unloading wood from the trucks at the delivery points. This input data is assumed to be under the control of the woodlands manager and therefore, the design decision problem is to select an "optimum combination" (D) of trucks, loaders and unloaders. Therefore, an action includes:

(i) Number of trucks in the system, N_t.

(ii) Number of loaders in the system, N_l.

(iii) Number of unloaders in the system, N_{ul}.

Therefore, **D** is an action vector (= a hauling system), whose components are N_t, N_l, and N_{ul}. Thus, $\mathbf{D} = (N_t \; N_l \; N_{ul})$.

2.2.2. Input Constants

The queueing system is also identified by input constants that are quantities which describe a particular hauling system and are necessary for the derivation of the queueing model. In the present study, it is assumed that these quantities could be estimated quite accurately (i.e., they are fixed) and do not change during the simulation. These input data can be changed only at the beginning of the simulation at the command of the analyst. The constants include:

(i) Costs per hour for a truck, loader and unloader.

(ii) Number of loading zones.

(iii) Distance from the unloading area to each loading zone (kms).

(iv) Quantity of wood to be moved from each loading zone (in unit of truck-loads).

(v) Shift duration (in hours).

(vi) Overtime limit (in hours).

(vii) Overtime payment rate.

A loading zone which corresponds to a logging area can have more than one landing. Therefore, several loaders can be assigned to one loading zone. However, the distances from the unloading site to landings within each loading zone are assumed to be the same. Furthermore, the loading zones are assumed to be sufficiently far apart that trucks cannot be transferred from one loading zone to another when the loaders are busy. Different sizes of trucks are considered by means of the number of truck-loads, that is, $6000m^3$ wood is equivalent to 100 truck-loads for a $60m^3$ capacity trailer. Loader or unloader sizes are incorporated by the average loading or unloading rates (in hours per truck-load). The quantity of wood in the forest is given in terms of full truck-loads. For example, 500 loads means 500 trips of fully loaded trucks of a particular size. The truck-loads can be converted to m^3 very easily. In addition, wood is not subdivided by wood form, source or species, but is simply regarded as units of truck-load.

2.2.3. Input Probability Distributions

Probability distributions are required to represent loading times, unloading times, travel loaded speeds, and travel empty speeds in the simulation. Two main reasons for using probability distributions to describe these times are to quantify the natural randomness, and to allow for queueing in the system.

(a) As a Result of the Natural Uncertainty

In loading, this variability is due to uncertain factors associated with natural distribution of landing quality (size and surface material), quantity and quality of pile, quality of logs, size of logs, weather conditions, and skill of loader operator. These factors are usually arbitrarily distributed and are beyond the control or prediction of the woodlands managers or engineers. This variation is reflected in measurements taken of loading time. For example, Conway (1976) estimated it to be anywhere from 20 to 60 minutes.

Unloading time is also affected by a number of factors which make its prediction uncertain. McMorland (1983) discusses most of these factors. Some of the most important ones may include the unloading place (i.e., whether it is directly to the deck, or conveyor, or the yard), size and quality of the yard (i.e. yard layout), travel distances within the yard, weather conditions and operator skill.

Travel speed or time is probably the most difficult hauling variable to predict due to its dependence on many factors in a vehicle-driver-road-environment system. Travel speed is fundamentally governed by the condition of the road, size of the load that may be hauled, and many other variables (Conway, 1976). However, the average travel time for a trip depends primarily on the distance travelled (Conway, 1976). Yet, the deviations of each trip from the average time is very common and is due to the other factors which cannot be determined exactly, i.e., road surfaces, road grades, alignment, and switchbacks, driving techniques (e.g., driving attitude, time required to shift gears), environmental factors (e.g., wind speed, temperature, rainfall and altitude) and load weight (e.g., overloaded and normally loaded).

Many researchers have been using the average value to represent these variables. This practice neglects the fact that the uncertain factors discussed above lead to random behaviour which cannot be described by an average value. For example Groves *et al.* (1987) has shown that the average value is not sufficiently accurate to predict travel times and he indicated travel time to have a positively skewed frequency distribution. This behaviour of travel time is a function of the randomness of these input factors.

The use of a probability distribution, rather than deterministic values, would give the investigator an immediate impression of the range of the data, its most frequently occurring values, and the degree to which it is scattered about its central or typical values. The probability distribution would also indicate whether the symmetry is neutral, or positively or negatively skewed.

(b) As a Result of the Nature of the Queueing Processes

Using probability distributions to model a hauling system will allow queues, or line-ups, to form at the loading and unloading sites. Using deterministic values to describe a transport system will generally not allow this. If, for example, the average time between truck arrivals is 30 minutes and the average loading rate is 30 minutes per load, then waiting time is zero, that is no queue would be modelled in such a situation, which is not necessarily true.

The process of determining the probability distributions to represent the variations in loading times, unloading times, travel loaded speeds and travel empty speeds, and the estimation of parameters of the probability distributions is described below.

2.2.4. Determination of Probability Distributions and Estimation of their Parameters

As stated by Dykstra (1978) and Law and Kelton (1991), the scientific quality of a computer simulation experiment is strongly influenced by the selection of the probability distributions to be used and by the determination of the specific parameters which particularize those distributions. This section, therefore, presents procedures for the selection of appropriate input probability distributions, and then suggests methods of estimating parameters of the selected probability distributions under conditions of uncertainty.

2.2.4.1. Determination of Probability Distributions

The procedure to determine appropriate probability distributions of the loading times, unloading times, travel loaded speeds and travel empty speeds requires having empirical data (which may be newly collected or historical) which can be used to fit theoretical distributions or to directly build empirical distributions. First, the summary statistics (such as mean, median, variance, skewness) are estimated from the data, and then the data is organized into histograms. These two tasks should at least give an indication of some possible families of distributions. Then the analysis proceeds as follows:

- *use of heuristic or graphical procedures.* This involves using visual appraisal of histograms, quantile summaries or box plots that depicts the empirical data and the fitted probability distributions (Law and Kelton, 1991, pp. 360-363).

- *use of statistical goodness-of-fit tests*. That is, to test the goodness-of-fit between the hypothesized distributions and the empirical data. The most commonly used tests are the chi-square statistic, Kolmogorov-Smirnov (K-S) statistic and Anderson -Darling (A-D) statistic. The details involved in the calculation of these statistics are available in many standard statistical textbooks (e.g. Benjamin and Cornell, 1970, pp. 440-475; Law and Kelton, 1991, pp. 382-393), and they will not be discussed here. These tests will establish the most appropriate theoretical distribution to represent a particular random variable.

Otherwise, if it happens that none of the hypothesized families of distributions fits the available data accurately, then use is made of the empirical data values themselves to define an empirical distribution. Law and Kelton (1991, pp. 350-352) provides ways of specifying empirical distributions.

2.2.4.2. Estimation of Parameters of the Probability Distributions

This section is concerned with the estimation of the parameters of the probability distributions. The parameters of the probability distributions for loading times, unloading times, travel loaded speeds and travel empty speeds are also inputs into the simulation model. There are two methods for estimating the parameters: the classical method and the Bayesian method.

(a) The Classical Estimation Method

The term "classical" is used here to mean the use of sample data alone to estimate the parameters. Under the classical estimation method, a parameter is considered to be a fixed constant and is estimated only from sample data. The classical methods of parameter estimation can be found in many textbooks. These methods are well-known and will not be discussed here.

(b) The Bayesian Estimation Method

In the forestry context, decisions are often made in situations (e.g., when new logging sites, machines or operators are being considered) in which sample data is either expensive or difficult to obtain. Under such circumstances, the classical estimation procedures may prove inappropriate for use in estimating the parameters of probability distributions.

The Bayesian method is shown in Fig. 4. The Bayesian method treats a parameter as a random variable with a probability distribution. To reduce the uncertainty involved in estimating parameters, the Bayesian method combines sample data with the prior information about the parameters to be estimated. The Bayesian philosophy is that the prior knowledge of "on-site" experts about the parameters to be estimated is useful in reducing the uncertainty by providing a better estimate for the parameters of the probability distributions. In other words, a woodlands manager or a forest engineer usually has some prior knowledge about the parameters of probability distributions of loading times, unloading times, etc. Mathematically, this can be described as follows:

If θ is taken to represent a parameter, then it is convenient to encode the manager's prior information about the parameter as a probability distribution, $g(\theta)$, which describes the alternative values of parameter θ. The $g(\theta)$ is commonly called the prior distribution and it depends upon a given expert's prior knowledge about θ.

Also, suppose that a woodlands manager or forest engineer is able to obtain some sample data about loading times, unloading times, etc. Furthermore assume that for each variable this sample of size n is $x_1, \ldots, x_n$ and is drawn from a probability distribution having θ as its unknown parameter. Then this sample data is used to define what is called a sample likelihood, $l(x_1, \ldots, x_n/\theta)$ which is the joint density or mass of the n random variables and is a function of θ. The likelihood, $l(x_1, \ldots, x_n/\theta)$ and the prior probability, $g(\theta)$ are then combined by using the Bayesian procedures to update the information about θ. The new information concerning θ, knowing the prior probability, $g(\theta)$ and the sample likelihood, $l(x_1, \ldots, x_n/\theta)$, is called the posterior distribution, $g(\theta/x_1, \ldots, x_n)$. Therefore, any inference to be made about the parameter has to be based on this distribution.

The posterior distribution is determined by Bayes formula as follows:

[1] $$g(\theta/x_1,\ldots,x_n) = \frac{l(x_1,\ldots,x_n/\theta)g(\theta)}{\sum_{all\ \theta} l(x_1,\ldots,x_n/\theta)g(\theta)}, \quad \textit{if } \theta \textit{ is discrete}$$

or

[2] $$g(\theta/x_1,\ldots,x_n) = \frac{l(x_1,\ldots,x_n/\theta)g(\theta)}{\int_\theta l(x_1,\ldots,x_n/\theta)g(\theta)d\theta}, \quad \textit{if } \theta \textit{ is continuous}$$

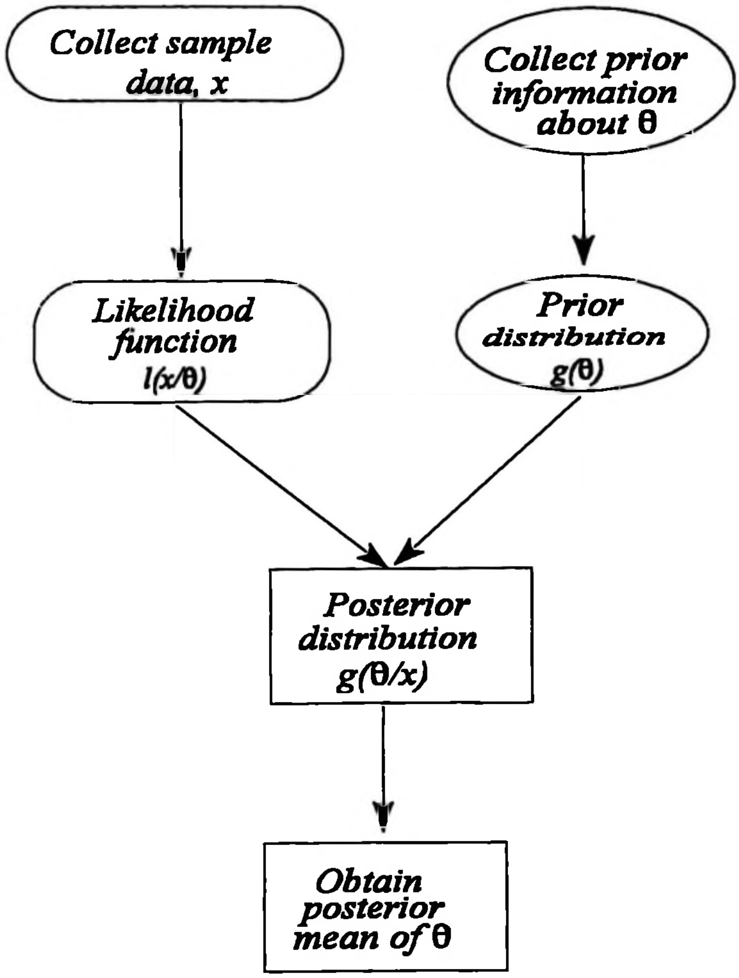

Fig. 4: Bayesian procedures for estimating parameters. $x = \{x_1, x_2, \ldots, x_n\}$

The posterior distribution summarizes all the information available about the parameter, combining the prior information through the prior distribution, and the sample information through the sample likelihood. If the mean value of parameter θ (also called the Bayes posterior mean) is desired, then it can be estimated relatively easily from the following relationships (Guttman *et al.* 1982; Martz and Waller, 1982):

[3] $$E(\theta/x_1,\ldots,x_n) = \sum_{all\ \theta} \theta_i\, g(\theta_i/x_1,\ldots,x_n), \quad \textit{if } \theta \textit{ is discrete}$$

or

[4] $$E(\theta/x_1,\ldots,x_n) = \int_\theta \theta\, g(t/x_1,\ldots,x_n)dt, \quad \textit{if } \theta \textit{ is continuous}$$

This Bayes posterior mean of the parameter then becomes an input to the queueing model.

The entire posterior probability distribution of the parameter is also an important input in decision-making to be discussed later in this chapter.

Specification of Inputs to the Bayesian Analysis

The available sample data concerning the random variable is converted into a sample likelihood whereas the prior information is expressed as a prior distribution on the parameter θ. It is these quantities that are actually used as inputs in the Bayes estimation of parameters.

(i) The Sample Likelihoods

The sample likelihood which is a function of the parameter θ, represents the entire evidence of the sample data. Normally, a statistical analysis of the observed sample data is carried out to determine the appropriate probability distribution. However, when sample data is not adequate for such analysis, a probability distribution may have to be assumed as an alternative. Then, a sample likelihood is defined from the assumed probability distribution. The method for defining a sample likelihood is available in many statistical textbooks such as Martz and Waller (1982, pp. 51) and Law and Kelton (1991, pp. 368) for a probability density function and Schlaifer (1959, pp. 338) for a probability mass function.

(ii) Prior Distributions

The prior distribution of the parameter θ reflects the prior information that is available for the specification of the parameter θ. This prior distribution may depend on several sources of prior information (Zellner, 1971, pp. 18-19), most notably the practical experience of a manager or forest engineer, and historical data.

When the parameter is considered to take discrete values, the specification of the prior distribution is straightforward. It involves a simple probability statement of the possible discrete values of the parameter that are thought to describe it. The only requirement is that probabilities must be nonnegative and must sum up to 1. If the prior information is based on historical data, then the prior probabilities should be close to the observed relative frequencies. When there is little or no historical data, the prior probabilities should be based on judgements. Techniques for quantification of judgement information are described in Winkler and Hays (1975, pp.483-485)

For the continuous case, the prior information involving the parameter is represented by a density function or a cumulative distribution function. The prior distribution can be characterized in many different ways. One way is to use the histogram approach in which the possible parameter values are divided into intervals, assigning subjective probability to each interval and then sketching a smooth density from a plot of a probability histogram (Berger, 1980, pp. 63). Another way is to specify a functional form of the density function and then subjectively determining its prior parameters. The prior parameters can be calculated from subjectively estimated moments (Spetzler *et al.* 1975; Hertz and Thomas, 1983, pp. 143; Keefer and Bodily, 1983) or from subjectively estimated percentiles to describe tail values, middle values and dispersion (Moder and Rodgers, 1968; Perry and Greig, 1975). For example, if the prior is assumed to have the gamma distribution (with shape parameter, α and scale parameter, β), with prior information on mean, $E(x)$ and variance, $Var(x)$, the specification of this prior distribution is completed since α and β can be calculated from the relationships, $E(x) = \alpha\beta$ and $Var(x) = \alpha\beta^2$. Other techniques for assessing continuous prior distributions can be found in the literature, e.g., Winkler and Hays (1975, pp.513-523) and Berger (1980, pp.63-74).

In general, several different prior probability distributions could be used to describe the unknown parameters. In the absence of any acceptable distribution from which to choose, Sprow (1967) has proposed certain practical requirements that a distribution should meet. These include that:

(a) the parameters to describe the distribution should be capable of unambiguous specification.

(b) the parameters should be easily understood by those who must specify them.

Other requirements can be found in many references such as DeGroot (1970), Martz and Waller (1982) and Press (1989).

2.3. THE CALCULATION OF COST

The cost of an action is calculated from the average operating time per day, hourly cost of a truck, loader and unloader (entered as constants in the simulation model), average number of trips per day, and numbers of trucks, loaders and unloaders in the system. The daily operating time for trucks includes the average times for: travel loaded, waiting at loading zones, loading, travel empty, waiting at unloading sites, unloading and overtime. Daily operating time for loaders and unloaders are: idle time for loaders and idle time for unloaders as well as loading, unloading and overtime times. The average number of trips per day is used to estimate the total number of working days.

It is the total cost which is used in decision-making. The waiting and idle times which indicate the relative amount of time lost in the system due to poor design of a hauling system at terminal points are reflected in the total cost. The total cost formula will be presented in the applications chapter. The decision-making criteria are discussed in the next section.

2.4. THE METHODS OF DECISION MAKING

The decision as to which action (hauling system) is the most desirable given the calculated system cost is another question to be addressed by the woodlands manager. Generally there are two basic approaches to decision-making that the woodlands manager can adopt (Markland, 1989). The two basic types of decision-making are:

(a) Classical decision-making.

(b) Bayesian decision-making.

In classical decision-making, the parameters of all probability distributions are known with certainty for each action. Thus, the expected cost of each action can be easily calculated, and the woodlands manager can determine an optimal action simply by selecting the action with the minimum expected total cost. This type of decision-making situation is very common and will not be discussed further.

In the Bayesian decision-making, parameter uncertainty and risk are considered. In this method, each parameter in the probability distribution can have more than one value and the probability distribution associated with each parameter can be estimated using the Bayesian parameter estimation method as explained in the previous sections. The method treats the problem of risk by using the concept of utility whereby the costs are replaced by utilities. Generally speaking, utility are numerical quantities assigned by an individual to certain outcomes to represent their current degree of desirability or displeasure to the individual (Winkler and Hays, 1975). Utility analysis involves the use of the utility theory to derive a utility function that logically represents the woodlands manager's subjective preference toward particular outcomes, i.e., his/her attitude towards risk.

The woodlands managers in large forest companies would most likely be more prone to make their decisions in the light of the highest expected monetary value, for they know that in the long run those decisions will result in maximum profits, and in the short term any setbacks can be absorbed by the company. The utility function of such a woodlands manager is linear and the expected monetary value would be a valid criterion for choosing among alternative actions. This manager is thus designated as risk-neutral in this thesis.

In the case of hauling contractors the situation may be quite the opposite. For a contractor who has had a recent string of financial setbacks and would be bankrupt if the contractor had another money-losing operation, the contractor would be more prone to take a less risky decision, even if the profit is less than that expected by the most probable outcome. Such a contractor is designated as risk-avoider in this thesis. Another contractor may be in a better financial position to take a risk, as the contractor has paid off the equipment loans and currently has a large cash reserve. This contractor would be more prone to take a riskier decision, in the hope of making a higher profit. Such a contractor is designated as risk-taker in this thesis. The utility function of a risk-avoider or risk-taker is not linear and as such the expected monetary value may not be a valid criterion for choosing among alternative actions. The valid criterion for choosing among alternative actions would be the expected utility.

This area of decision-making which appears to be applicable to this woodlands problem has not been previously employed. Consequently, the application of the

Bayesian decision-making is considered an important part of this thesis. The formulation of the expected value and expected utility criteria are explained in the next sections.

2.4.1. The Expected Value Criterion

The expected cost of an action can be determined either directly from the posterior means of the unknown parameters, or indirectly whereby the costs are estimated for possible values of the unknown parameter and then weighed by the posterior probability of the corresponding parameter set. Since the desire is to deliver timber from the forests to the utilization centres served by the system at minimum cost, the optimum hauling system selected should correspond to minimum total cost.

A convenient way to characterize such a decision problem is by means of a decision table (Table 1). The decision table approach is commonly referred to as "decision analysis" in many textbooks. Decision analysis is a well documented and accepted method for choosing and evaluating alternative actions when they are based on uncertain input parameters. The description of the theoretical basis and examples can be found in the literature (e.g. Hillier, 1963; Hespos and Strassmann, 1965; Howard, 1968; Raiffa, 1968; Schlaifer, 1969; Fishburn, 1970; Lifson, 1972; Brown *et al.* 1974; Winkler and Hays, 1975; Keeney and Raiffa, 1976; Kabus, 1981 and Hillier and Lieberman, 1990). This procedure simplifies the determination of optimal hauling system under conditions of uncertainty. The posterior probability or posterior mean of each parameter is estimated by use of the Bayesian estimation method. The posterior means of the parameters are inputs to the simulation model. The simulation output is used to calculate the costs of any system, which together with the posterior probability of the parameters are inputs for decision analysis.

Table 1: The decision table

		Set of Parameters								
	θ_1	θ_2	.	.	.	θ_j	.	.	.	θ_n
Probability	$p(\theta_1)$	$p(\theta_2)$	.	.	.	$p(\theta_j)$	.	.	.	$p(\theta_n)$
a_1	E_{11}	E_{12}	.	.	.	E_{1j}	.	.	.	E_{1n}
a_2	E_{21}	E_{22}	.	.	.	E_{2j}	.	.	.	E_{2n}
.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.
Actions .	.	.	.	.	.	.	.	.	.	.
a_i	E_{i1}	E_{i2}	.	.	.	E_{ij}	.	.	.	E_{in}
.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.
a_m	E_{m1}	E_{m2}	.	.	.	E_{mj}	.	.	.	E_{mn}

Note:

(1) θ_i ($i = 1, 2, \ldots, n$) represents a set of unknown parameters which consist of θ_l, θ_{ul}, θ_{tsl}, θ_{tsc}.

(2) $p(\theta_i)$ ($i = 1, 2, \ldots, n$) represents the joint probability of each parameter set in (1) above.

(3) a_j ($j = 1, 2, \ldots, m$) represents a particular combination of equipment.

(4) E_{ij} represent the conditional cost values that result from i^{th} set of parameter values when the combination of equipment is j.

However, the above approach does not take into account differing attitudes to risk for hauling contractors. Therefore, a method to account for woodlands manager's attitude toward risk is desirable. The utility analysis method is suggested to account for a manager's attitude toward risk, thereby the costs are replaced by utility values. Therefore, the prescribed decision criterion is maximization of expected utility. The expected utility criterion methodology is described in the next section.

2.4.2. The Expected Utility Criterion

The use of monetary values as the sole criterion for use in making decisions oversimplifies the decision-making process and clouds the issue of whether or not the objective has been met. The decisions may be different between a risk-avoider and risk-taker. Expected utility refers essentially to the satisfaction one would derive from probable monetary outcomes based on current financial position. Use is made of the utility theory to derive a utility function that logically represents the manager's subjective preference toward particular monetary outcomes, and then using the expected utility criterion to rank actions in a decision-making problem.

This method requires to present a decision maker with a series of choices among the outcomes requiring an assessment of preferences. Utility theory then determines the preference order, for the alternative, that the decision maker should have in order to be consistent with his decisions for the choices. The theory accomplishes this by using the decision maker's simpler responses to calibrate a mathematical model called a utility function. The utility function of the cost outcomes must be assessed. The standard interview techniques required in assessing the necessary information for developing a utility function from the appropriate decision makers are available in many references, e.g., Winkler and Hays (1975, pp. 566-573), Keeney and Raiffa (1976, pp. 188-200), Berger (1980, pp. 40-51) and de Neufville (1990, pp. 373-391). The steps involved in the assessment of utility function are the same for risk-avoider and risk-taker, and can be summarized as follows:

(i) Choose a range of values which encompass the lowest and highest possible outcomes from Table 1 above. For example, if the lowest and highest cost outcomes in Table 1 were \$10,352 and \$24,257 then the range of values chosen could be \$10,000 and \$25,000.

(ii) Since the utility function is a relative measure of the satisfaction derived from the possible outcomes, and these two values chosen are the lowest and highest possible outcomes, the utility values for these two outcomes are set to 0 and 1 respectively. Thus,

$$U(\$10{,}000) = 0$$

$$U(\$25{,}000) = 1$$

(iii) Determine the utility values for outcomes between \$10,000 and \$25,000 by asking the decision maker to select the probability (p) that would make him or her indifferent to: (a) a guaranteed outcome, x or (b) participating in a lottery such that:

$\$10{,}000 < x < \$25{,}000$ and $0 < p < 1$.

According to the second axiom of utility (see for example, Winkler and Hays, 1975, pp.568), the utility of x is given as

$U(x) = (p)(U(\$10,000)) + (1-p)(U(\$25,000))$

For example, suppose a sure outcome is \$20,000 and p-value selected is 0.5. At this point where the decision maker is indifferent to obtaining an outcome of \$20,000 for sure to that of obtaining an outcome of \$10,000 with probability of $p = 0.5$ and an outcome of \$25,000 with a probability of $(1-p) = 0.5$, the utility of \$20,000 is 0.5

(iv) Vary systematically the guaranteed outcomes, x, requesting him or her to reassign the probability (p) of success for a series of lotteries to establish enough utility values that can be plotted as points on a graph to fit a smooth curve (Winkler and Hays, 1975 and Ang and Tang, 1984). Alternatively, some simple mathematical function could be developed to approximate the assessed points (Winkler and Hays, 1975 and Ang and Tang, 1984). A mathematical form of utility functions such as quadratic utility function,

$$U(x) = ax^2 + bx + c$$

or exponential utility function,

$$U(x) = a + be^{-x}$$

could be developed for the assessed points.

In simple terms, the individual utility functions quantify how much one likes (dislikes) various levels of the cost values in Table 1. Therefore, the parameters of the utility function are directly related to the preferences for different levels of the cost. The utility function defined is then used to replace each cost value in Table 1 by utility values and with the posterior probability of the parameter values estimated with the Bayesian estimation method, the expected utility for each action can be defined according to Equations 5 or 6. This value of the expected utility which represents a single number for each alternative action is used as the basis for ranking the overall desirability of the actions.

$$[5] \quad E_{\xi}[U(Cost)] = \sum_{all\ \theta} U(Cost)g(\theta/x), \quad if\ \theta\ is\ discrete$$

or

$$[6] \quad E_{\xi}[U(Cost)] = \int_{\theta} U(Cost)g(\theta/x)d\theta, \quad if\ \theta\ is\ continuous$$

where U(Cost) represents the utility of cost, g(θ/x) is the posterior probability distribution of θ, and E_{ξ}[U(Cost)] is the expected value of U(Cost), which is the "risk" according to DeGroot (1970).

Therefore, the expected utility value incorporates risk. Thus, the complex interactions between the probable monetary values and qualitative judgement associated with these probable monetary values is integrated to provide a single number which allows the alternative actions to be ranked. An optimal hauling system is one which has the maximum expected utility.

The expected cost and expected utility decision-making criteria will demonstrated in Chapter 3.

2.5. DERIVATION OF THE AVERAGE TIME ELEMENTS OF ALTERNATIVE ACTIONS BY RESPONSE FUNCTIONS

The simulation procedure provided so far involves running the simulation model for n (days) x k (actions) runs to evaluate the actions. These simulation runs can be large especially if the number of actions to be evaluated is large and can take a long time even on a high speed computer. Because of this, a simple method in which the simulation model will only be run once is proposed.

This method involves running the simulation model once with all possible values of parameter θ in every specified probability distribution (together with other input data as described earlier at the beginning of this chapter) as inputs to the model to estimate the average waiting time at loading zones, waiting time at unloading sites, idle time for loaders, idle time for unloaders and number of trips. Then using the least squares method, response functions are developed for each of these time elements with the parameters of probability distributions used in the simulation model as independent variables. The general form of the response function is as shown in Equation 7.

The rest of the hauling cycle time elements (the average values of trucking speed, loading time and unloading time), can easily be estimated directly from their respective parameters using the relationships that exists between expected value [E(x)] and the parameters of a particular distribution.

[7] $AV = f(\theta_l, \theta_{ul}, \theta_{tsl}, \theta_{tsc})$

where,

AV represents the average value of either waiting time at loading zones, waiting time at unloading sites, idle time for loaders, idle time for unloaders or number of trips.

f represents the function that relates expected value to parameters.

$\theta_l, \theta_{ul}, \theta_{tsl}, \theta_{tse}$ represents the specific values of the parameter in the probability distributions of loading times, unloading times, travel loaded speeds and travel empty speeds respectively.

Therefore for a given action, it will be possible to estimate, relatively quickly, the average waiting time at loading zones, waiting time at unloading sites, idle time for loaders, idle time for unloaders and number of trips from the response functions without a need to re-run the simulation model.

The development and analysis of response functions will be presented in Chapter 4.

Chapter 3

APPLICATIONS OF THE METHOD AND DISCUSSION

This chapter provides specific applications of the general methods for designing optimal hauling systems under conditions of uncertainty and risk, using a simulated timber hauling system. The chapter will use the procedure as given below.

First, a typical timber hauling system decision problem is presented.

Second, based on the design methodology presented in Chapter 2, a description of input data required for the simulation of the hauling system is given.

Third, the simulation output is substituted into the cost formula to estimate the costs of alternative hauling systems. The cost will be estimated for different methods used for parameter estimation and the results obtained therein will be used for comparison.

Finally, in order to proceed with the decision-making analysis, the total expected cost and total expected utility calculation procedures are presented. The decision-making criteria will be the total expected cost and total expected utility. Therefore, an optimal hauling system to be selected is the one with the minimum total expected cost or highest total expected utility value.

3.1. PROBLEM DESCRIPTION

Typical woodlands operations include felling, limbing, bucking, skidding, loading, hauling and unloading functions. This study deals only with timber hauling systems which consists of, loading timber into trucks in a landing in the forest using loaders, hauling, and unloading timber from trucks at the delivery point by using unloaders. The equipment can be of different types and sizes. In this problem, 70 ton (gross-weight) trucks with 350-500 hp engines with trailers and 7-8 ton loaders or unloaders are considered. Furthermore, it is assumed that currently the company owns (or can hire) a total of 20 trucks, 5 loaders and 2 unloaders, each equipment of same type and size.

The selection of equipment for the timber hauling system can be influenced by several factors including the variations in the time required for loading, unloading and travelling, the amount of timber the company needs to haul in a given time period, etc. In this problem, it is assumed that the company has a contract to haul a total of 200 gross trucks-loads from landings in 3 loading zones in the forest to a mill some distance away as proposed below. The distance from the mill to each loading zone and the amount of wood to be hauled are assumed as follows:

Loading zone	Distance (km)	Amount of wood (units of truck-loads)
1	50	50
2	50	50
3	80	100

The following unit costs ($/hr) will be assumed for this example:

Truck . . . . $40 per hour.

Loader & Unloader . . . . . $50 per hour.

In addition, it is assumed that waiting times for the trucks to be loaded and unloaded will also cost $40 per hour and idle times for the loaders and unloaders will also cost $50 per hour. Finally, an 8-hour shift, and an overtime payment rate of 1.5, common in Eastern Canada, are assumed in this analysis.

The major decision problem involves selecting the numbers of each type of equipment to be used in order to achieve the minimum cost or the highest utility. A wide range of possible combinations of equipment exists. The total cost of any combination of equipment is a function of the average travelling time (travel loaded and travel empty), loading time, truck waiting time to be loaded, idle time of loaders, unloading time, truck waiting time to be unloaded, idle time of unloaders, overtime for trucks, loaders and unloaders, and number of trips. A more rationale approach (as opposed to the traditional approach) for estimating time elements (especially truck waiting time and loader/unloader idle time) is needed.

3.2. THE SOLUTION

This is a typical design problem that can be handled by applying the design methodology described in Chapter 2. The simulation program developed for this methodology requires the hauling system to be specified through input data. The input data are of three types: the actions, the constants, and the various probability distributions for loading times, unloading times, travel loaded speeds and travel empty speeds and their specific parameter values. These input data can be described as follows:

3.2.1. Actions

The first input to the simulation model involves the set of alternative actions. The actions represents the number of trucks, loaders and unloaders in a timber hauling system. For the given problem, assume the following total number of each equipment can be specified:

- The total number of trucks can be: 5, 10 and 20.
- The total number of loaders can be: 3, 4 and 5.
- The total number of unloaders can be: 1 and 2.

Therefore, an action, $\mathbf{D}_1$= 5, 3, 1 represents 5 trucks, 3 loaders and 1 unloader. Similarly, another action, $\mathbf{D}_2$ = 5, 3, 2 represents 5 trucks, 3 loaders and 2 unloaders, and so on. This means that for this decision problem, there are a total of 18 alternative actions under consideration.

3.2.2. Input Constants

The next input to the simulation model are the constants. According to timber hauling problem described above, these constants include:

- Total number of loading zones = 3.
- Gross truck-loads in loading zone 1 = 50.
- Gross truck-loads in loading zone 2 = 50.
- Gross truck-loads in loading zone 3 = 100.
- Distance to loading zone 1 = 50 km.
- Distance to loading zone 2 = 50 km.
- Distance to loading zone 3 = 80 km.
- Cost of a truck per hour = $ 40.
- Cost of a loader per hour = $ 50.
- Cost of an unloader per hour = $ 50.
- Duration of a shift = 8 hours.
- Overtime limit = 0 hours.
- Overtime payment rate = 1.5

3.2.3. Probability Distributions and their Parameter Values

The next input to the simulation model involves the assessment of the probability distributions for loading times, unloading times, travel loaded speeds and travel empty speeds and their specific parameter values. Once the probability distributions are assessed, their parameters have to be estimated.

The assessment of the probability distributions and the estimation of their parameter values are given in the following sections.

Assessment of Probability Distributions

The raw data concerning the loading times, unloading times, travel loaded speeds and travel empty speeds for the given equipment operating in Eastern Canada were unpublished data supplied by the Forest Engineering Research Institute of Canada (FERIC) to this author for the purpose of this study. These data were assumed appropriate for use in determining suitable probability distributions that represents these random variables.

The first step in this assessment involved summarizing the available raw FERIC data into relative frequency tables and histograms. The resulting relative frequency of the FERIC data for loading times, unloading times, travel loaded speeds and travel empty speeds are tabulated respectively in Tables 2, 3, 4 and 5.

The predominant characteristics of each data set is the shift away from the origin and the apparent positive skewness. This can be seen from the relative frequency histogram for each data set in Fig. 5 for loading times, Fig. 6 for unloading times, Fig.

7 for travel loaded speeds and Fig. 8 for travel empty speeds.

Table 2: Loading time/truck-load for a 4 m^3 capacity loader.

Class Interval (hours/load)	Number of observations	Relative frequency
0.10 - 0.200	1	0.003
0.20 - 0.30	14	0.040
0.30 - 0.40	72	0.205
0.40 - 0.50	104	0.295
0.50 - 0.60	83	0.236
0.60 - 0.70	32	0.091
0.70 - 0.80	23	0.065
0.80 - 0.90	13	0.037
0.90 - 1.00	2	0.006
1.00 - 1.10	3	0.009
1.10 - 1.20	3	0.009
1.20 - 1.30	2	0.006

Mean = 0.47 hours/load.
Standard Deviation = 0.167 hours/load.
Number of observations = 352.

Table 3: Unloading time/truck-load for a 4 m^3/load capacity unloader.

Class Interval (hours/load)	Number of observations	Relative frequency
0.10 - 0.20	1	0.004
0.20 - 0.30	96	0.409
0.30 - 0.40	106	0.451
0.40 - 0.50	21	0.089
0.50 - 0.60	8	0.034
0.60 - 0.70	2	0.009
0.70 - 0.80	1	0.004

Mean = 0.285 hours/load.
Standard Deviation = 0.084 hours/load.
Number of observations = 235.

Table 4: Travel speeds of a loaded truck (70 ton).

Class Interval (km/hour)	Number of observations	Relative frequency
35 - 45	2	0.005
45 - 55	85	0.228
55 - 65	151	0.405
65 - 75	69	0.185
75 - 85	35	0.094
85 - 95	20	0.054
95 - 105	9	0.024
105 - 115	2	0.005

Mean = 65.69 km/hour.
Standard Deviation = 9.80 km/hour.
Number of observations = 373

Table 5: Travel speeds of an empty truck (70 ton).

Class Interval (km/hour)	Number of observations	Relative frequency
45 - 55	3	0.009
55 - 65	20	0.062
65 - 75	94	0.292
75 - 85	100	0.311
85 - 95	52	0.161
95 - 105	41	0.127
105 - 115	11	0.034
115 - 125	1	0.003

Mean = 78.46 km/hour.
Standard Deviation = 12.10 km/hour.
Number of observations = 322.

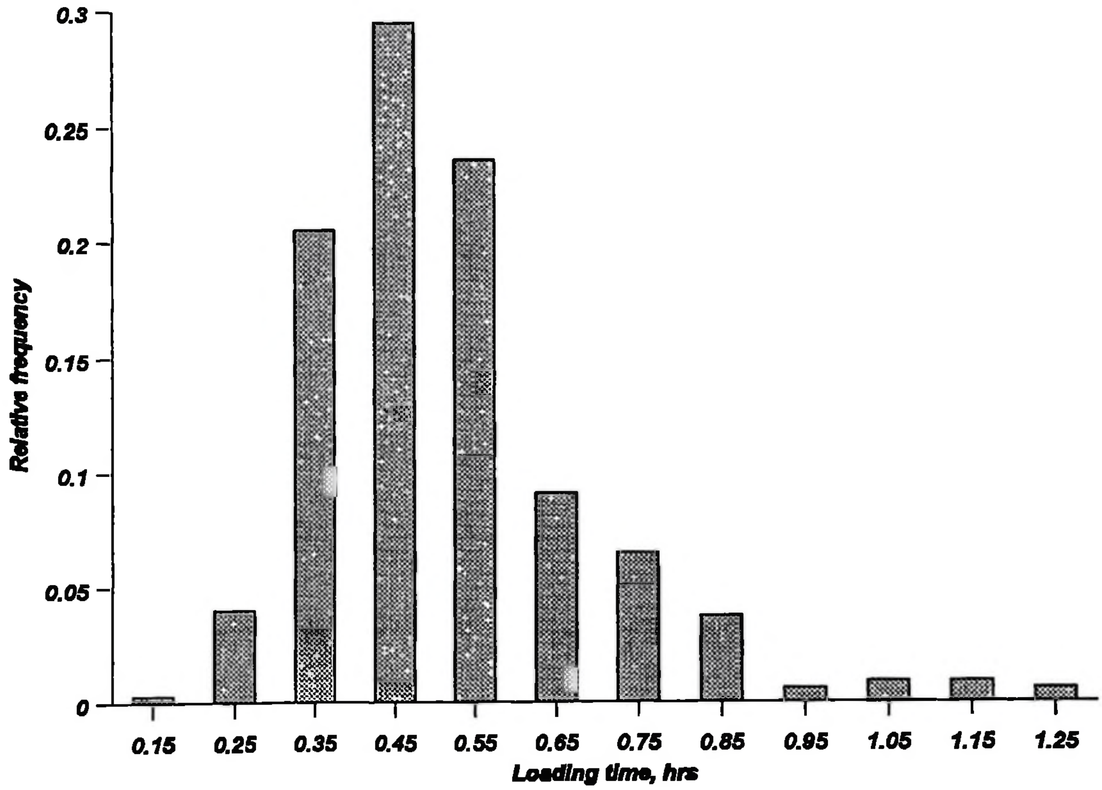

Fig. 5: Relative frequency histogram for loading times data.

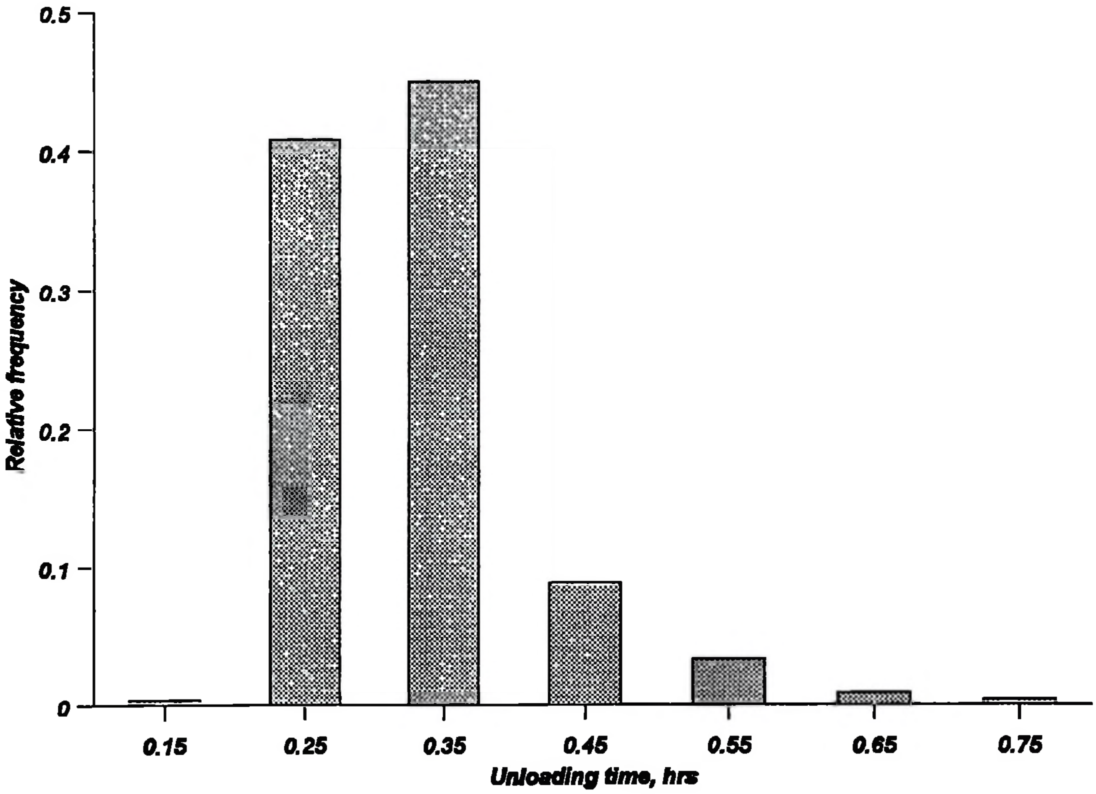

Fig. 6: Relative frequency histogram for unloading times data.

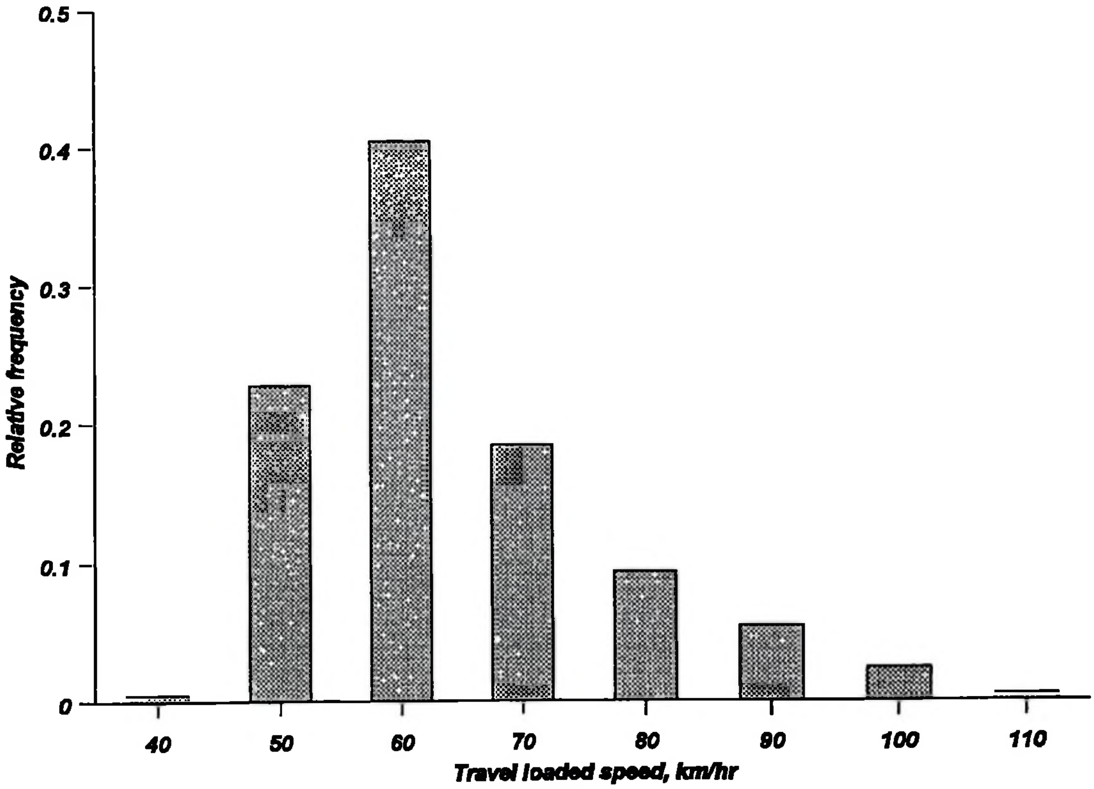

Fig. 7: Relative frequency histogram for travel loaded speeds data.

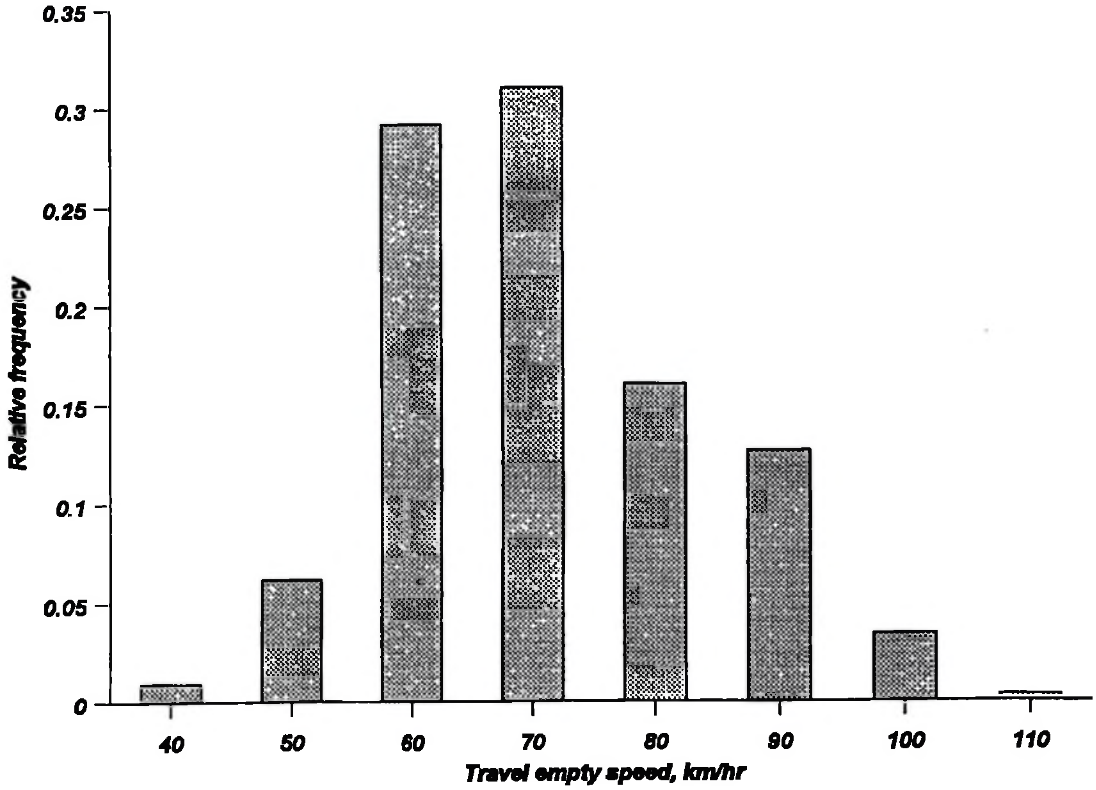

Fig. 8: Relative frequency histogram for travel empty speeds data.

The second step involved carrying out statistical analysis on each set of data supplied by FERIC to determine a probability distribution which was suitable for the observed data representing each hauling variable.

The UniFit2 distribution-fitting package (Law and Vincent, 1993), which goes through steps similar to those recommended in Chapter 2 for determining an appropriate distribution was used for this purpose.

The results of this analysis indicated that the gamma distribution provided the best fit for each set of data. This is not surprising because the gamma density function is limited to positive values and is skewed to the right similar to the observed data. Hence, the gamma distribution was adopted for this study as generator of loading times, unloading times and travel speeds in the simulation program. The density of the gamma distribution is commonly known as follows:

$$[8] \qquad f(x) = \begin{cases} \dfrac{x^{\alpha-1}}{\beta^{\alpha}\Gamma(\alpha)} \exp\left(-\dfrac{x}{\beta}\right), & \textit{for } x \geq 0 \\ 0 & \textit{elsewhere} \end{cases}$$

where α and β are its shape and scale parameters respectively.

The last step involved finding out an appropriate algorithm for generating random loading time, unloading time and travel speed variates from the gamma distribution. The algorithm given in Law and Kelton (1991, pp. 489) is used. It was verified that the travel empty speed was approximately 1.2 times that of the travel loaded speed. So, only the travel loaded speed, to be referred simply as travel speed will be considered. To use this algorithm, the unknown parameters of the gamma distribution had to be estimated. That is, though the gamma distribution was assumed to be stable between similar hauling systems, its parameters should be updated to local conditions since no hauling situations are identical. This study offers a useful way to handle this problem.

Estimation of Parameters of the Gamma Distribution

Parameter estimation to some extent depends on the situation of sample data at the time of decision-making. In general, the larger the sample upon which the parameters are estimated, the more confidence one can have that the estimated parameters are close to the true ones. However, in the design of a timber hauling system presented, two possible situations may present themselves:

Situation 1:

The manager can only obtain a small sample because of lack of funds or time. Sometimes it may be possible to borrow some data from identical operations elsewhere. However, since no two hauling situations are identical, a method that may help to convert the parameters to suit to local conditions may be required. For any of these situations, the Bayesian method of parameter estimation proposed should prove very useful.

Situation 2:

The manager can obtain enough sample data either by sampling his equipment in the field or using sample data from other locations that may not be different from his own operations. Usually, for this situation, the classical parameter estimation method is used.

This section deals with the parameter estimation based on the Bayesian methods only. The parameter estimation based on the classical methods will be demonstrated later in other sections of this chapter for comparison.

Specific Applications of Bayesian Method

In Chapter 2, θ was used to represent the unknown parameter of a probability distribution of the random variable X. It was also shown that if the desired goal is to obtain means of the parameter θ for use in simulation and response functions analysis of the hauling systems, then according to the Bayesian approach for parameter estimation, the mean of θ is to be based on its posterior distribution. This posterior distribution, $g(\theta/x_1, ..., x_n)$ can be obtained from the likelihood and prior distribution for the random variable using the Bayes rule (Equations 1 or 2).

The following calculations in which the goal was to obtain the posterior distribution and the mean of either parameter β or α of the gamma distribution, follows exactly the same procedure provided in Chapter 2 when the parameter of interest was θ (now replaced by either parameter α or β of gamma distribution).

For simplicity, the analysis of the sample likelihood will be demonstrated for only one parameter of the gamma distribution. The technique is, of course, not restricted to one parameter, nor it is applicable to the gamma distribution only. However, adding a parameter would greatly add to the computational work.

The likelihood

From FERIC data, the gamma distribution with parameters α and β was verified as suitable for modelling loading times, unloading times and travel speeds. Furthermore, it is assumed that a decision is to be made when the variance of X, Var(x) is known and fixed, namely, $\alpha\beta^2 = \mathrm{Var}(x) = C$ (constant) and $\alpha = C/\beta^2$. Then, the simulation output can be thought to depend on only the unknown value of the scale parameter β. Therefore, β is a random variable and it replaces θ according the procedure presented in Chapter 2.

Suppose the random variable X represents the loading time (unloading time or travel speed) and $x_1, x_2, x_3, ..., x_n$ is a completely random sample of n observations taken from the gamma distribution described above in Equation 8, then the sample likelihood under the assumption that $\alpha\beta^2 = C$ for discrete approximation of the posterior distribution of parameter β can be analysed as presented below.

Discrete Approximation of Sample Likelihood

Discretization is straightforward and has the added advantage of avoiding mathematical complexities that add little to the understanding of the Bayesian approach.

The development of the sample likelihood which follows is taken from Schlaifer (1959):

(a) Find a standardized gamma distribution through the following stages. First, the value of parameter β is set to 1 giving the following formula for the gamma distribution:

$$g(x) = \frac{x^{\alpha-1}e^{-x}}{\Gamma(\alpha)}$$

where x represents the sample mean. Second, a standardized random variable, t is defined from the sample mean $\bar{x}$ as

$$t = \frac{\bar{x}}{\beta} .$$

Then substituting t for x gives the following standardized gamma distribution

[9] $$g(t) = \frac{t^{\alpha-1}e^{-t}}{\Gamma(\alpha)}$$

(b) Determine the width of the bar in the t histogram. First, a width of the bar in the x histogram (i.e., the space between two adjacent possible values of x) called δt is specified. Then this value is used to determine the width of the bar in the t histogram as $\delta t/\beta$.

(c) Determine the height of the bar in the t histogram. This value is approximately equal to the height of the standardized gamma distribution with $\alpha = C/\beta^2$ at the point

$t = \bar{x} / \beta$.

(d) Calculate the area of the bar (i.e., the likelihood) in either histogram. It can approximately be shown to be

[10] $\quad (l_1,\ldots,l_n/\beta) = g(t).\delta t/\beta$

Prior Distributions

Other available information about parameter β has to be expressed as a prior distribution of the parameter β. It is believed that several external sources of prior information can be gathered from an experienced manager, experienced machine operators or from historical data for which a prior distribution for parameter β can be formed.

The different ways of forming a discrete prior probability distribution from some prior information will be demonstrated in Section 3.3.

Calculation of Posterior Distribution

Using the sample likelihood defined in Equation 10, the posterior distribution of β can be calculated from the prior distribution of β, $g(\beta)$ using the general Bayes formula (Equation 1 or 2) as follows:

Given that the prior distribution of β in Equation 10 above is described by some potential values of β for which their probabilities can subjectively be assigned by an experienced manager, (i.e., the parameter can be described by a mere probability statement of the possible discrete values that β can take, then the posterior distribution can be determined relatively easily by setting a table (Table 6) and applying the Bayes formula in tabular form.

Calculation of Posterior Mean

Given a posterior distribution of β, the desired mean value of the parameter can be calculated from the following equation,

$$[11] \qquad E(\beta/x_1,\ldots,x_n) = \sum_{\beta} \beta_i \; g(\beta_i/x_1,\ldots,x_n)$$

Table 6: Tabular form of calculation of posterior distribution from a discrete prior distribution and likelihood function.

β	Prior $g(\beta)$	Likelihood $l(t/\beta)$	Joint $g(t,\beta)$	Posterior $g(\beta/t)$
β_1	$g(\beta_1)$	$t^{\alpha-1} e^{-t} \delta t/\beta_1\Gamma(\alpha)$	$g(\beta_1).t^{\alpha-1} e^{-t} \delta t/\beta_1\Gamma(\alpha)$	$g(\beta_1).t^{\alpha-1} e^{-t} \delta t/\beta_1\Gamma(\alpha)/M$
β_2	$g(\beta_2)$	$t^{\alpha-1} e^{-t} \delta t/\beta_2\Gamma(\alpha)$	$g(\beta_2).t^{\alpha-1} e^{-t} \delta t/\beta_1\Gamma(\alpha)$	$g(\beta_2).t^{\alpha-1} e^{-t} \delta t/\beta_1\Gamma(\alpha)/M$
-	-	-	-	-
-	-	-	-	-
-	-	-	-	-
β_i	$g(\beta_i)$	$t^{\alpha-1} e^{-t} \delta t/\beta_i\Gamma(\alpha)$	$g(\beta_i).t^{\alpha-1} e^{-t} \delta t/\beta_i\Gamma(\alpha)$	$g(\beta_i).t^{\alpha-1} e^{-t} \delta t/\beta_i\Gamma(\alpha)/M$
SUM	1.00	-	M	1.0000

where $t = \frac{\bar{x}}{\beta}$

and δt = the space between two adjacent possible values of the random variable t.

3.3. SIMULATION ANALYSIS AND OUTPUT

Several simulations in which different estimates of parameters β and α of the gamma distribution determined by using the different methods together with other input data as described in Sections 3.2.1 and 3.2.2 were used as inputs to the simulation model. The outputs were derived by running the model for a simulated 30 days for each of the 18 actions. This length of the simulation run produced an acceptable level of accuracy. The validation of the simulation model was done by the use of chi-square goodness-of-fit tests between the simulation results and reproduction of the gamma distributions, and also by comparing with the simulated outputs with manual calculations. The validation tests indicated a high degree of accuracy of the simulation results.

The primary objective of these simulation studies was to examine the effect on total cost of the method used to estimate the parameters of the gamma distribution representing loading and unloading times and travel speed. Therefore, two groups of simulations were run. The first group used parameters estimated by the Bayesian approach and the second group used parameters estimated from large and small samples using the classical approach.

The simulation output which represents the average values based on 30 simulation runs of each action provides the information required for the calculation of the cost of each action according to Equation 12.

$$[12] \quad TC = WD\{[(TC_t)(tt_t) + (TC_w)(tt_w) + (TC_t)(OP_r-1)(ot_t)]n_t + [(LC)(tt_l) + (LC_i)(it_l)$$

$$+(LC)(OP_r-1)(ot_l)]n_l + [(ULC)(tt_{ul}) + (ULC_i)(it_{ul}) + (ULC)(P_r-1)(ot_{ul})]n_{ul}\}$$

where

TC	=	the total cost of an action ($)
WD	=	total number of working days (days)
TC_t	=	cost of travelling for a truck ($/hour)
tt_t	=	travelling time for a truck (hours/day)
TC_w	=	cost of waiting for a truck ($/hour)
tt_w	=	waiting time for a truck (hours/day)
OP_r	=	overtime payment rate
ot_t	=	overtime for a truck (hours/day)
n_t	=	total number of trucks
LC	=	cost of loading for a loader ($/hour)
tt_l	=	loading time for a loader (hours/day)
LC_i	=	cost of idle loader ($/hour)
it_l	=	idle time for a loader (hours/day)
ot_l	=	overtime for a loader (hours/day)
n_l	=	total number of loaders
ULC	=	cost of unloading for an unloader ($/hour)
tt_{ul}	=	unloading time for an unloader (hours/day)
ULC_i	=	cost of idle unloader ($/hour)
it_{ul}	=	idle time for an unloader (hours/day)
ot_{ul}	=	overtime for an unloader (hours/day)
n_{ul}	=	total number of unloaders.

3.3.1. Results of Simulation

The results reported in the following sections are based on the "all-loading zones" policy where trucks are assigned to all loading zones. Also, the simulations are based on a policy where a truck costs $40 per hour regardless of how long it waits at the loading and unloading sites.

3.3.1.1. Simulation Output with Bayesian Approach

When sample data is small, the Bayesian methodology treats parameters of a probability distribution as random variables and each parameter is represented by a posterior distribution that combines sample data with prior information about the parameter.

In this analysis, a small sample data drawn randomly from FERIC time study data reported earlier was used. The measurements randomly sampled were:

Loading time (hours/truck-load):

$x_1 = 0.5, x_2 = 0.28, x_3 = 0.66, x_4 = 0.48, x_5 = 0.80$

Unloading time (hours/truck-load):

$x_1 = 0.50, x_2 = 0.42, x_3 = 0.32, x_4 = 0.37, x_5 = 0.18$

Travel speed (km/hour):

$x_1 = 89, x_2 = 69.5, x_3 = 81, x_4 = 62, x_5 = 91$

The relevant summary statistics were:

Loading time:

No. of observations, n = 5

Sum = 2.72

Mean = 0.54

Variance = 0.031

Unloading time:

No. of observations, n = 5

Sum = 1.79

Mean = 0.36

Variance = 0.012

Travel speed:

No. of observations, n = 5

Sum = 392.5

Mean = 78.5

Variance = 125.2

Case 1: Simulation Output and Total Cost based on Posterior Means with a Discrete Prior Distribution

The main assumption in this analysis is that the prior information and probability statement about the expected value and variance estimates of the loading time, unloading time and travel speed obtained from experienced managers or machine operators is in discrete form. Then this prior information and probability statements about these variables can be converted into a prior information and probability statement of parameter β under the assumption of fixed variance, and later be combined with the small sample to calculate the posterior distribution of β.

The first step in determining the possible values of β and α involves giving the possible values of the expected values, E(x), variance (C), Var(x) and probability statement about E(x) values. These estimates are determined by using the procedure described below.

First, the probable estimates of the expected values and their relative likelihoods, or probabilities, and variances are obtained from local "experts". For example, assume through interviews with an experienced woodlands manager or truck driver it is possible to gather the following estimates of the expected values and variances:

For loading time, the most likely value of the mean loading time is 0.45 hours/load but it may be as large as 0.55 or as small as 0.35 and the variance is 0.01. The relative likelihoods or probabilities assigned to these mean values are as follows:

Expected value (hours/load)	Prior probability
0.35	0.3
0.45	0.6
0.55	0.1
Sum	1.0

Similarly for unloading time, the most likely value of the mean loading time is 0.30 hours/load but it may be as large as 0.40 or as small as 0.20 and the variance is 0.01. The relative likelihoods or probabilities assigned to these means are as follows:

Expected value (hours/load)	Prior probability
0.20	0.3
0.30	0.5
0.40	0.2
Sum	1.0

Similarly for travel speed, the most likely value of the mean loading time is 70 km/hour but it may be as large as 80 or as small as 60 and the variance is 100. The relative likelihoods or probabilities assigned to these means are as follows:

Expected value (km/hour)	Prior probability
60	0.4
70	0.5
80	0.1
Sum	1.0

The second step involves using Equations 13 and 14 to determine the estimates for β and α.

[13] $E(x) = \alpha\beta$

[14] $Var(x) = C = \alpha\beta^2$

The resulting estimates of β and α for fixed values of variance are then as given below:

For loading time,

E(x)	β	α
0.35	0.029	12
0.45	0.022	20
0.55	0.018	30

For unloading time,

E(x)	β	α
0.20	0.050	4
0.30	0.033	9
0.40	0.025	16

Similarly for travel speed,

E(x)	β	α
60	1.667	36
70	1.429	49
80	1.250	64

The next step is to estimate the posterior mean of parameter β as a Bayesian point estimate. This proceeds as follows:

Computation of likelihoods

The computation of likelihoods involves estimating the standardized random variable t by dividing the sample mean by β, estimating the height of the standardized gamma distribution g(t) at t using Equation 10 and estimating the width of every bar in the underlying histogram given by $\delta t/\beta$. Taking loading time as an example for β = 0.029, sample mean = 0.54, and α = 12 , the likelihood for β = 0.029 is calculated as follows:

- t = 0.54/0.029 is 18.62

- the height, g(t) from Equation 10 is 0.0191

- the width, $\delta t/\beta$ is $\delta t/0.029$

Therefore, the area of the bar (i.e., the likelihood) = $(0.0191)(\delta t/0.029) = 0.6586\delta t$

The following likelihoods for all possible β were computed in the manner described above.

β	t	Height g(t)	Width $\delta t/\beta$	Area $l(t/\beta)$
0.029	18.62	0.0191	$\delta t/0.029$	$0.6586\delta t$
0.022	24.55	0.0461	$\delta t/0.022$	$2.09555\delta t$
0.018	30.00	0.0726	$\delta t/0.018$	$4.03333\delta t$

Determination of prior distribution of β

The prior probability information about the expected values were converted into prior probability statements for the three possible β values estimated above for loading time:

Given that

$$\alpha_i \beta_i^2 = Var(x) = C = 0.01 \ (i = 1, 2, 3) \text{ or } \alpha_i = 0.01/\beta_i^2 \ (i = 1, 2, 3) \quad (*)$$

and since

$$P[E(x_1) = 0.35] = 0.3, P[E(x_2) = 0.45] = 0.6 \text{ and } P[E(x_3) = 0.55] = 0.1$$

then

$$P[\alpha_1\beta_1 = 0.35] = 0.3, P[\alpha_2\beta_2 = 0.45] = 0.6 \text{ and } P[\alpha_3\beta_3 = 0.55] = 0.1$$

Using (*) above, the probability statement became,

$$P(\beta_1 = 0.029) = 0.3$$

$$P(\beta_2 = 0.022) = 0.6$$

$$P(\beta_3 = 0.018) = 0.1$$

The same procedure was used to determine the prior probability of β for unloading time and travel speed, resulting in the following prior probability statements:

For unloading time:

$P(\beta_1 = 0.050) = 0.3$

$P(\beta_2 = 0.033) = 0.5$

$P(\beta_3 = 0.025) = 0.2$

Similarly for travel speed:

$P(\beta_1 = 1.667) = 0.4$

$P(\beta_2 = 1.429) = 0.5$

$P(\beta_3 = 1.250) = 0.1$

Computation of the Posterior Distribution

The likelihoods and prior distribution of β determined above were inputs to the computation of the posterior distribution of β according the Bayes theorem as given in Table 6. By applying the methodology in Table 6, posterior distribution of β were calculated as follows:

β	Prior g(β)	Likelihood l(t/β)	Joint g(t,β)	Posterior g(β/t)
0.029	0.3	0.65868t	0.19768t	0.1064
0.022	0.6	2.09558t	1.25738t	0.6766
0.018	0.1	4.03338t	0.40338t	0.2170
Sum:	1.0		1.85828t	1.0000

Calculation of Bayes posterior mean

The Bayes posterior mean of β was calculated by using Equation 13 as follows:

$$E(\beta/x_1, \ldots, x_n) = (0.029)(0.1064) + (0.022)(0.6766) + (0.018)(0.2170)$$

$$= 0.022$$

And the corresponding α was estimated as follows:

$$\alpha = Var(x)/[E(\beta/x_1, \ldots, x_n)]^2$$

$$= 0.01/(0.022)^2$$

$$= 20$$

The posterior distributions and means of β for unloading time and travel speed and their corresponding α's were calculated in the same manner. The resulting Bayes posterior means of β and α estimated were:

- for unloading time, $\beta = 0.032$ and $\alpha = 9.77$
- for travel speed, $\beta = 1.428$ and $\alpha = 49$

The simulation output

When β and α values estimated above and other input data as described in Sections 3.2.1 and 3.2.2 were inputted into the simulation model, the resulting simulation output was as summarized in Table 7 (all times except the total working days are in hours).

The total cost

The simulation output in Table 7 provided all values required for the calculation of the total cost of each action. Substituting the relevant values in Equation 12, the resulting total costs for each action were as presented in Table 8. Table 8 is a form of a decision table showing the total costs predicted against the action taken and the given parameters.

Table 7: Simulation output with Bayes posterior means of parameters based on discrete prior distribution equal to $\alpha = 20$ and $\beta = 0.022$ for loading time, $\alpha = 9.77$ and $\beta = 0.032$ for unloading time, and $\alpha = 49$ and $\beta = 1.428$ for travel speed.

ACTIONS	Trucking time (hrs)				Loading (hrs)			Unloading (hrs)			Total working days[3]
	Total working	Wait[1]	Wait[2]	Over-time	Total working	Over-time	Idle	Total working	Over-time	Idle	
5,3,1	6.64	0.25	0.32	0.00	5.32	0.00	3.77	7.72	0.00	4.38	17.65
5,3,2	6.36	0.26	0.04	0.00	5.09	0.00	3.56	7.56	0.00	5.95	17.91
5,4,1	6.64	0.04	0.49	0.00	5.35	0.00	4.19	7.73	0.00	4.47	17.50
5,4,2	6.34	0.05	0.05	0.00	5.10	0.00	3.91	7.52	0.00	5.90	17.65
5,5,1	6.50	0.00	0.53	0.00	5.19	0.00	4.28	7.40	0.00	4.19	17.91
5,5,2	6.28	0.00	0.09	0.00	4.95	0.00	4.02	7.54	0.00	5.91	17.20
10,3,1	6.82	0.44	0.97	0.00	6.07	0.00	3.33	8.35	0.35	2.59	9.76
10,3,2	6.68	0.47	0.11	0.00	6.04	0.00	2.93	8.14	0.14	4.89	9.02
10,4,1	7.12	0.25	1.17	0.00	6.18	0.00	4.02	8.64	0.64	2.47	9.51
10,4,2	6.53	0.30	0.22	0.00	5.56	0.00	3.26	7.99	0.00	4.83	9.26
10,5,1	7.11	0.23	1.16	0.00	6.03	0.00	4.29	8.68	0.68	2.59	9.38
10,5,2	6.54	0.26	0.26	0.00	5.45	0.00	3.62	7.94	0.00	4.66	9.27
20,3,1	8.51	1.17	3.12	0.51	6.29	0.00	1.97	11.52	3.52	2.28	5.92
20,3,2	6.99	1.32	0.31	0.00	6.71	0.00	1.33	8.67	0.67	2.85	4.90
20,4,1	8.40	0.77	3.39	0.40	6.12	0.00	2.90	11.40	3.40	2.20	5.93
20,4,2	7.10	0.86	0.56	0.00	6.55	0.00	2.21	8.87	0.87	2.76	4.61
20,5,1	8.32	0.66	3.49	0.32	5.89	0.00	3.32	11.30	3.30	2.22	5.87
20,5,2	7.15	0.75	0.64	0.00	6.32	0.00	2.83	8.92	0.92	2.74	4.59

[1] waiting time of trucks at loading zones.
[2] waiting time of trucks at unloading sites.
[3] total working days required for hauling 200 truck loads.

Table 8: Total cost of alternative actions with posterior mean of parameters based on discrete prior distribution equal to: $\alpha = 20$ and $\beta = 0.022$ for loading time, $\alpha = 9.77$ and $\beta = 0.032$ for unloading time, and $\alpha = 49$ and $\beta = 1.428$ for travel speed.

ACTIONS	Total cost ('000\$)[1]
5, 3, 1	43.80
5, 3, 2	50.16
5, 4, 1	48.30
5, 4, 2	52.28
5, 5, 1	52.38
5, 5, 2	55.37
10, 3, 1	41.20
10, 3, 2	39.81
10, 4, 1	43.94
10, 4, 2	41.44
10, 5, 1	46.18
10, 5, 2	43.58
20, 3, 1	53.70
20, 3, 2	37.59
20, 4, 1	54.23
20, 4, 2*	37.42
20, 5, 1	55.82
20, 5, 2	38.38

[1] total cost incurred for hauling 200 truck-loads.
* action with minimum total cost.

Case 2: Simulation Output and Total Cost based on Posterior Means with a Discrete Uniform Prior Distribution

In this situation, it is assumed that the prior knowledge of the expected values is provided in terms of an interval $E(x_a)$ and $E(x_b)$. Then this prior knowledge of the lower and upper mean estimates of loading time, unloading time and travel speed is converted to prior distribution of β. The assumption is made here that β is distributed according to uniform distribution.

Suppose an experienced manager had provided the expected lower and upper values to be 0.2 and 0.6 hours/truck-load for loading time, 0.1 and 0.5 hours/truck-load for unloading time and 55 and 85 km/hour for travel speed. Each of the continuous uniform prior distributions given, can be approximated by a discrete uniform distributions as follows:

For loading time: $P[E(x_a) = 0.20] = 1/3$, $P[E(x_m) = 0.40] = 1/3$ and $P[E(x_b) = 0.60] = 1/3$

For unloading time: $P[E(x_a) = 0.10] = 1/3$, $P[E(x_a) = 0.30] = 1/3$ and $P[E(x_b) = 0.50] = 1/3$

For travel speed: $P[E(x_a) = 55] = 1/3$, $P[E(x_a) = 70] = 1/3$ and $P[E(x_b) = 85] = 1/3$

This subjective information about the possible expected values of loading time, unloading time and travel speed is then converted into prior estimates of β and α following exactly the same procedure provided when the prior distribution of β is discrete. These estimates become:

Loading time		Unloading time		Travel speed	
β	α	β	α	β	α
0.050	4	0.130	1	1.818	30
0.025	16	0.033	9	1.429	49
0.017	35	0.020	25	1.176	72

The development of the prior probability statement about β using information given above was carried out by exactly the same procedure provided for Case 1 above and is given as follows:

For loading time,

$$P(\beta_1 = 0.050) = 1/3$$

$$P(\beta_2 = 0.025) = 1/3$$

$$P(\beta_3 = 0.017) = 1/3$$

For unloading time,

$$P(\beta_1 = 0.130) = 1/3$$

$$P(\beta_2 = 0.033) = 1/3$$

$$P(\beta_3 = 0.020) = 1/3$$

For travel speed,

$$P(\beta_1 = 1.818) = 1/3$$

$$P(\beta_2 = 1.429) = 1/3$$

$$P(\beta_3 = 1.176) = 1/3$$

Note that the variances for the calculation of α and β assumed known and fixed were 0.01 for loading and unloading times and 100 for travel speed.

The information given above was used in the estimation of the sample likelihoods and posterior distribution of β according to Table 6. For example, for loading time these estimates were determined as follows:

Computation of the Likelihoods

β	t	α	Height g(t)	Width $\delta t/\beta$	Area $g(t).\delta t/\beta$
0.050	10.80	4	0.0043	$\delta t/0.050$	$0.08600\delta t$
0.025	21.60	16	0.0331	$\delta t/0.025$	$1.32400\delta t$
0.017	31.76	35	0.0632	$\delta t/0.017$	$3.71777\delta t$

where, $t = \frac{\bar{x}}{\beta}$ and $g(t) = \frac{t^{\alpha-1}e^{-t}}{\Gamma(\alpha)}$

Computation of the Posterior Distribution

β	Prior $g(\beta)$	Likelihood $l(t/\beta)$	Joint $g(t,\beta)$	Posterior $g(\beta/t)$
0.050	1/3	$0.08600\delta t$	$0.02877\delta t$	0.0168
0.025	1/3	$1.32400\delta t$	$0.44133\delta t$	0.2582
0.017	1/3	$3.71777\delta t$	$1.23922\delta t$	0.7250
Sum:	1.0		$1.70922\delta t$	1.0000

Then the posterior mean of β was calculated as follows:

$$E(\beta/x_1, \ldots, x_n) = (0.050)(0.0168) + (0.025)(0.2582) + (0.017)(0.7250)$$

$$= 0.020$$

The corresponding α calculated from the relationship, $\alpha = C/\beta^2$ was 25.

The posterior means of β and their corresponding α's for the case of unloading time and travel speed were calculated in like manner. This calculation resulted in the following estimates:

- for unloading time, $\beta = 0.035$ and $\alpha = 8$
- for travel speed, $\beta = 1.308$ and $\alpha = 58$.

The simulation output

When posterior means of β calculated above and other input data as described in Sections 3.2.1 and 3.2.2 were inputted into the simulation model, the resulting simulation output was as summarized in Table 9.

The total cost

Using the simulation output from Table 9, Equation 12 was evaluated for each action. The resulting total costs calculated for this method of parameter estimation are shown in Table 10.

Table 9: Simulation output with Bayes posterior means of parameters based on discrete uniform prior distribution equal to $\alpha = 25$ and $\beta = 0.020$ for loading time, $\alpha = 8$ and $\beta = 0.035$ for unloading time, and $\alpha = 58$ and $\beta = 1.308$ for travel speed.

ACTIONS	Trucking time (hrs)				Loading (hrs)			Unloading (hrs)			Total working days[3]
	Total working	Wait[1]	Wait[2]	Over-time	Total working	Over-time	Idle	Total working	Over-time	Idle	
5,3,1	6.58	0.31	0.24	0.00	5.59	0.00	3.75	7.93	0.00	4.90	16.63
5,3,2	6.61	0.30	0.02	0.00	5.79	0.00	3.90	8.07	0.07	6.49	16.53
5,4,1	6.43	0.06	0.38	0.00	5.30	0.00	3.94	7.66	0.00	4.69	16.85
5,4,2	6.35	0.07	0.05	0.00	5.34	0.00	3.91	8.12	0.12	6.52	16.35
5,5,1	5.40	0.00	0.46	0.00	5.16	0.00	4.10	7.53	0.00	4.55	16.95
5,5,2	6.38	0.00	0.10	0.00	5.12	0.00	3.99	8.09	0.09	6.51	16.17
10,3,1	6.89	0.53	0.80	0.00	6.27	0.00	2.91	8.34	0.34	2.65	9.42
10,3,2	6.75	0.61	0.07	0.00	6.40	0.00	2.75	8.35	0.35	5.23	8.66
10,4,1	7.05	0.32	0.97	0.00	6.18	0.00	3.59	8.51	0.51	2.61	9.09
10,4,2	6.42	0.37	0.11	0.00	5.68	0.00	2.99	8.09	0.09	5.10	8.84
10,5,1	6.92	0.29	0.98	0.00	5.89	0.00	3.81	8.33	0.33	2.59	9.26
10,5,2	6.48	0.32	0.17	0.00	5.60	0.00	3.43	8.20	0.20	5.13	8.75
20,3,1	8.26	1.50	2.48	0.26	6.51	0.00	1.31	10.97	2.97	2.20	5.86
20,3,2	7.14	1.81	0.12	0.00	7.21	0.00	0.87	8.85	0.85	3.63	4.87
20,4,1	8.04	0.96	2.90	0.04	6.13	0.00	2.28	10.64	2.64	2.17	5.95
20,4,2	7.01	1.11	0.31	0.00	6.63	0.00	1.55	8.80	0.80	3.05	4.57
20,5,1	8.07	0.81	3.05	0.07	6.12	0.00	3.07	10.72	2.72	2.16	5.94
20,5,2	6.98	0.96	0.42	0.00	6.27	0.00	2.22	8.76	0.76	3.02	4.57

[1] waiting time of trucks at loading zones.
[2] waiting time of trucks at unloading sites.
[3] total working days required for hauling 200 truck loads.

Table 10: Total cost of alternative actions with posterior means of parameters based on discrete uniform prior distribution equal to: α= 25 and β= 0.020 for loading time,= 8 and β= 0.035 for unloading time, α= 58 and β= 1.308 for travel speed.

ACTIONS	Total cost ('000$)[1]
5, 3, 1	42.41
5, 3, 2	49.60
5, 4, 1	45.98
5, 4, 2	51.61
5, 5, 1	46.55
5, 5, 2	54.48
10, 3, 1	38.83
10, 3, 2	39.07
10, 4, 1	40.86
10, 4, 2	39.92
10, 5, 1	43.20
10, 5, 2	42.17
20, 3, 1	48.70
20, 3, 2	37.64
20, 4, 1	49.24
20, 4, 2*	36.20
20, 5, 1	51.19
20, 5, 2	36.83

[1] total cost incurred for hauling 200 truck-loads.

* action with minimum total cost.

Case 3: Simulation Output and Total Cost based on Posterior Means with Normal Prior Distribution

In this case, the prior distribution of the parameter is to be determined from available historical data. The assumption made here is that $\bar{x}$, the mean of a random sample of size n is normally distributed. This prior information can then be converted to prior information about β by exactly the same method that was used when the prior distribution of β was discrete (i.e., refer to Case 1 above).

Three samples of 20 observations each obtained from FERIC data described earlier for loading time, unloading time and travel speed represented the historical data for this analysis. The mean and standard deviation of each of these samples were 0.45 and 0.173 (in hours) for loading time, 0.30 and 0.1 (in hours) for unloading time and 70 and 10.68 (in km/hour) for travel speed. It was assumed that n = 20 was large enough for the sample mean, $\bar{x}$, to have approximately a normal distribution. Using this historical data, the normal prior distributions of $\bar{x}$ were then determined by discrete approximation where the possible values of $\bar{x}$ were grouped into class intervals and assigning all the probability in a class interval to the $\bar{x}$ at its mid-point as shown below.

For loading time,

Interval (hours/load)	Mid Point, $\bar{x}$	Variance	Probability
0.39 - 0.43	0.41	0.03	0.1515
0.43 - 0.47	0.45	0.03	0.6970
0.47 - 0.51	0.49	0.03	0.1515

Similarly for unloading time,

Interval (hours/load)	Mid Point, $\bar{x}$	Variance	Probability
0.225 - 0.275	0.25	0.01	0.1271
0.275 - 0.325	0.30	0.01	0.7458
0.325 - 0.375	0.35	0.01	0.1271

Similarly for travel speed,

Interval (km/hour)	Mid Point, $\bar{x}$	Variance	Probability
62.5 - 67.5	65	114	0.1469
67.5 - 72.5	70	114	0.7062
72.5 - 77.5	75	114	0.1469

With $\bar{x}$ (= E(x)) and Var(x), the parameter of gamma distribution, β and α were estimated from Equations 13 and 14 as follows.

For loading time,

E(x)	β	α
0.41	0.073	5.62
0.45	0.067	6.72
0.49	0.061	8.03

Similarly for unloading time,

E(x)	β	α
0.25	0.040	6.25
0.30	0.033	9.09
0.35	0.029	12.07

Similarly for travel speed,

E(x)	β	α
65	1.754	37.06
70	1.629	42.97
75	1.520	49.34

The prior probability of β was then determined as provided before for Case 1 above and is given as follows:

For loading time,

$$P(\beta_1 = 0.073) = 0.1515$$

$$P(\beta_2 = 0.067) = 0.6970$$

$$P(\beta_3 = 0.061) = 0.1515$$

Similarly for unloading time,

$$P(\beta_1 = 0.040) = 0.1271$$

$$P(\beta_2 = 0.033) = 0.7458$$

$$P(\beta_3 = 0.029) = 0.1271$$

Similarly for travel speed,

$$P(\beta_1 = 1.754) = 0.1469$$

$$P(\beta_2 = 1.629) = 0.7062$$

$$P(\beta_3 = 1.520) = 0.1469$$

The information given above was used in the estimation of the sample likelihoods and posterior distribution of β according to Table 6. For example, for loading time these estimates were determined as follows:

Computation of the Likelihoods

β	t	α	Height g(t)	Width δt/β	Area g(t).δt/β
0.073	7.40	5.62	0.0997	δt/0.073	1.36558δt
0.067	8.06	6.72	0.1126	δt/0.067	1.68066δt
0.061	8.85	8.03	0.1216	δt/0.061	1.99934δt

where, $t = \dfrac{\bar{x}}{\beta}$ and $g(t) = \dfrac{t^{\alpha-1}e^{-t}}{\Gamma(\alpha)}$

Computation of the Posterior Distribution

β	Prior $g(\beta)$	Likelihood $l(t/\beta)$	Joint $g(t,\beta)$	Posterior $g(\beta/t)$
0.073	0.1515	$1.36588\delta t$	$0.20698\delta t$	0.0931
0.067	0.6970	$1.68068\delta t$	$1.71408\delta t$	0.7711
0.061	0.1515	$1.99348\delta t$	$0.30208\delta t$	0.1358
Sum:	1.0000		$2.22298\delta t$	1.0000

Then the posterior mean of β was calculated as follows:

$$E(\beta/x_1, \ldots, x_n) = (0.073)(0.0931) + (0.067)(0.7711) + (0.061)(0.1358)$$

$$= 0.067$$

The corresponding α calculated from the relationship, $\alpha = C/\beta^2$ was 6.68.

The posterior means of β and their corresponding α's for the case of unloading time and travel speed were calculated in like manner. This calculation resulted in the following estimates:

- for unloading time, $\beta = 0.033$ and $\alpha = 9.18$
- for travel speed, $\beta = 1.618$ and $\alpha = 43.55$.

The simulation output

Inputting the posterior means of β and other input data as described in Sections 3.2.1 and 3.2.2 into the simulation model, the summary simulation output is presented in Table 11.

The total cost

With simulation output from Table 11, Equation 12 was evaluated for each action with results shown in Table 12.

Table 11: Simulation output with Bayes posterior means of parameters based on normal prior distribution equal to $\alpha = 20$ and $\beta = 0.022$ for loading time, $\alpha = 9.77$ and $\beta = 0.032$ for unloading time, and $\alpha = 49$ and $\beta = 1.428$ for travel speed.

ACTIONS	Trucking time (hrs)				Loading (hrs)			Unloading (hrs)			Total working days[3]
	Total working	Wait[1]	Wait[2]	Over-time	Total working	Over-time	Idle	Total working	Over-time	Idle	
5,3,1	6.62	0.26	0.30	0.00	5.35	0.00	3.76	7.86	0.00	4.71	17.24
5,3,2	6.59	0.30	0.02	0.00	5.45	0.00	3.78	7.82	0.00	6.27	17.50
5,4,1	6.44	0.04	0.39	0.00	5.14	0.00	3.95	7.53	0.00	4.51	17.50
5,4,2	6.32	0.04	0.05	0.00	5.13	0.00	3.93	7.75	0.00	6.16	17.05
5,5,1	6.37	0.00	0.39	0.00	5.14	0.00	4.24	7.51	0.00	4.41	17.39
5,5,2	6.24	0.00	0.07	0.00	4.90	0.00	3.97	7.74	0.00	6.17	17.09
10,3,1	6.87	0.47	0.85	0.00	6.14	0.00	3.25	8.40	0.40	2.79	9.85
10,3,2	6.71	0.54	0.13	0.00	6.00	0.00	2.88	8.00	0.00	4.87	9.10
10,4,1	6.99	0.28	0.97	0.00	6.00	0.00	3.80	8.47	0.47	2.56	9.48
10,4,2	6.49	0.30	0.18	0.00	5.60	0.00	3.29	8.04	0.04	4.99	9.09
10,5,1	7.04	0.23	1.04	0.00	5.99	0.00	4.19	8.53	0.53	2.55	9.47
10,5,2	6.53	0.25	0.19	0.00	5.42	0.00	3.52	8.13	0.13	5.04	8.98
20,3,1	8.45	1.21	2.90	0.45	6.46	0.00	1.91	11.25	3.25	2.24	6.05
20,3,2	7.09	1.43	0.23	0.00	6.96	0.00	1.30	8.92	0.92	3.39	4.91
20,4,1	8.37	0.79	3.24	0.37	6.18	0.00	2.80	11.20	3.20	2.22	6.07
20,4,2	7.08	0.90	0.52	0.00	6.59	0.00	2.19	8.84	0.84	2.90	4.71
20,5,1	8.09	0.69	3.18	0.09	6.04	0.00	3.41	10.96	2.96	2.19	6.21
20,5,2	7.11	0.82	0.51	0.00	6.35	0.00	2.71	9.03	1.03	3.14	4.64

[1] waiting time of trucks at loading zones.
[2] waiting time of trucks at unloading sites.
[3] total working days required for hauling 200 truck loads.

Table 12: Total cost of alternative actions with posterior means of parameters based on normal prior distribution equal to: α= 6.68 and β= 0.067 for loading time, α= 9 and β= 0.033 for unloading time, and α= 43.55 and β= 1.618 for travel speed.

ACTIONS	Total cost ('000$)[1]
5, 3, 1	43.44
5, 3, 2	51.05
5, 4, 1	47.11
5, 4, 2	52.26
5, 5, 1	51.03
5, 5, 2	55.50
10, 3, 1	40.38
10, 3, 2	39.91
10, 4, 1	42.00
10, 4, 2	41.11
10, 5, 1	44.99
10, 5, 2	42.99
20, 3, 1	51.73
20, 3, 2	37.58
20, 4, 1	52.96
20, 4, 2*	37.24
20, 5, 1	53.66
20, 5, 2	38.19

[1] total cost incurred for hauling 200 truck-loads.

* action with minimum total cost.

3.3.1.2. Simulation Output with Classical Approach

(a) Based on Large Sample

In this application, it was assumed here that large data samples for estimating the parameters could be obtained from various sources. One possibility is to gather data from direct observations. In most cases this is not feasible. Another possibility is to use data collected elsewhere for similar situations from reliable sources such as the Forest Engineering Research Institute of Canada (FERIC). This possibility is feasible provided that a fairly elaborate assessment of the equipment and forest conditions existed during the time of data collection is done to ensure that they are reasonably representative of local hauling system and conditions.

Suppose that detailed time study data supplied by FERIC is considered reasonably suitable to represent the current situation. The summary statistics of this sample data are given in Table 13.

The parameters of the gamma distribution (α and β) were estimated using the method of *Maximum Likelihood Estimators* (MLE's) (Law and Kelton, 1991). The values of α and β estimated from this sample data are shown in Table 14.

Table 13: Summary statistics of sample data from FERIC studies.

Operation	Statistics		
	Sample size (n)	Mean	Variance
Loading	352	0.45 (hours)	0.0279 (hours)^2
Unloading	470	0.29 (hours)	0.0071 (hours)^2
Travel speed	373	65.69 (km/hr)	96.0037 (km/hr)^2

Table 14: Estimated values of α and β for the sample data from FERIC studies

	Estimated parameter	
Operation	α	β
Loading	7.258	0.062
Unloading	12.083	0.024
Travel speed	44.990	1.460

The simulation output

When the parameter values in Table 14 and other input data as described in Sections 3.2.1 and 3.2.2 were inputted into the simulation model, the summary results of the simulation associated with each action-parameter pair were as presented in Table 15.

The total cost

The total costs evaluated by substituting relevant values from simulation output (Table 15) in Equation 12 are presented in Table 16 below.

Table 15: Simulation output with parameters estimated by using the classical approach based on large sample equal to $\alpha = 7.258$ and $\beta = 0.062$ for loading time, $\alpha = 12$ and $\beta = 0.024$ for unloading time, and $\alpha = 45$ and $\beta = 1.40$ for travel speed.

ACTIONS	Trucking time (hrs)				Loading (hrs)			Unloading (hrs)			Total working days[3]
	Total working	Wait[1]	Wait[2]	Over-time	Total working	Over-time	Idle	Total working	Over-time	Idle	
5,3,1	6.57	0.24	0.25	0.00	5.14	0.00	3.62	7.50	0.00	4.57	18.07
5,3,2	6.46	0.22	0.02	0.00	5.08	0.00	3.57	7.33	0.00	5.81	18.57
5,4,1	6.50	0.04	0.35	0.00	5.14	0.00	4.02	7.38	0.00	4.47	17.86
5,4,2	6.22	0.03	0.06	0.00	4.89	0.00	3.76	7.14	0.00	5.71	18.07
5,5,1	6.56	0.00	0.39	0.00	5.16	0.00	4.25	7.37	0.00	4.38	17.91
5,5,2	6.21	0.00	0.06	0.00	4.87	0.00	3.99	6.98	0.00	5.52	17.97
10,3,1	6.89	0.45	0.73	0.00	6.16	0.00	3.29	8.46	0.46	3.14	10.17
10,3,2	6.81	0.55	0.11	0.00	6.03	0.00	2.94	8.12	0.12	5.15	9.40
10,4,1	7.08	0.27	0.89	0.00	6.12	0.00	3.93	8.56	0.56	2.97	9.68
10,4,2	6.60	0.30	0.15	0.00	5.58	0.00	3.28	7.81	0.00	4.92	9.33
10,5,1	7.09	0.21	0.91	0.00	6.05	0.00	4.30	8.61	0.61	2.91	9.60
10,5,2	6.55	0.26	0.16	0.00	5.43	0.00	3.63	7.84	0.00	4.90	9.35
20,3,1	8.20	1.19	2.55	0.20	6.35	0.00	1.90	10.96	2.96	2.36	6.17
20,3,2	6.98	1.37	0.19	0.00	6.78	0.00	1.45	8.81	0.81	3.63	5.17
20,4,1	8.00	0.80	2.77	0.00	6.09	0.00	2.75	10.76	2.76	2.34	6.19
20,4,2	7.15	0.92	0.36	0.00	6.66	0.00	2.29	8.95	0.95	3.30	4.77
20,5,1	7.99	0.67	2.96	0.00	5.97	0.00	3.38	10.77	2.77	2.33	6.27
20,5,2	7.13	0.77	0.41	0.00	6.44	0.00	2.92	8.96	0.96	3.29	4.70

[1] waiting time of trucks at loading zones.
[2] waiting time of trucks at unloading sites.
[3] total working days required for hauling 200 truck loads.

Table 16: Total cost of alternative actions with parameters estimated using the classical approach based on large sample data equal to: α= 7.258 and β= 0.062 for loading time, α= 12 and β= 0.024 for unloading time, and α= 45 and β= 1.46 for travel speed.

ACTIONS	Total cost ('000\$)[1]
5, 3, 1	44.44
5, 3, 2	51.75
5, 4, 1	48.16
5, 4, 2	53.04
5, 5, 1	53.19
5, 5, 2	56.74
10, 3, 1	41.84
10, 3, 2	41.81
10, 4, 1	43.52
10, 4, 2	42.34
10, 5, 1	46.03
10, 5, 2	44.50
20, 3, 1	50.66
20, 3, 2	38.91
20, 4, 1	50.88
20, 4, 2*	38.13
20, 5, 1	53.24
20, 5, 2	38.24

[1] total cost incurred for hauling 200 truck-loads.
* action with minimum total cost.

(b) Based on Small Sample

Most often small samples are used to estimate the parameters regardless of what effect they might have on the simulation output. As a comparison with large sample and Bayesian methods, the small sample data sets whose statistics were given in Section 3.3.1.1, were used to estimate parameters of gamma distribution using the classical approach just as it was done for large sample case above.

The estimated α and β for the small sample are given in Table 17.

Table 17: Estimated values of α and β for the small sample.

	Estimated parameter	
Operation	α	β
Loading	10	0.056
Unloading	11	0.033
Travel speed	49	1.600

The simulation output

Inputting the values of α and β in Table 17 together with other input data described in Sections 3.2.1 and 3.2.2 into the simulation model, the simulation output resulting is as given in Table 18.

The total cost

Equation 12 was used to calculate the total cost of alternative actions shown in Table 19 below using information contained in Table 18.

Table 18: Simulation output with parameters estimated by using the classical approach based on small sample equal to $\alpha = 10$ and $\beta = 0.056$ for loading time, $\alpha = 11$ and $\beta = 0.033$ for unloading time, and $\alpha = 49$ and $\beta = 1.60$ for travel speed.

ACTIONS	Trucking time (hrs)				Loading (hrs)			Unloading (hrs)			Total working days[3]
	Total working	Wait[1]	Wait[2]	Over-time	Total working	Over-time	Idle	Total working	Over-time	Idle	
5,3,1	6.71	0.34	0.35	0.00	5.47	0.00	3.50	7.85	0.00	3.91	17.09
5,3,2	6.39	0.36	0.04	0.00	5.29	0.00	3.31	7.48	0.00	5.60	17.65
5,4,1	6.56	0.06	0.58	0.00	5.26	0.00	3.80	7.60	0.00	3.82	17.54
5,4,2	6.23	0.07	0.10	0.00	5.06	0.00	3.58	7.28	0.00	5.33	17.29
5,5,1	6.44	0.00	0.60	0.00	5.21	0.00	4.06	7.39	0.00	3.64	17.70
5,5,2	6.16	0.00	0.11	0.00	5.02	0.00	3.83	7.42	0.00	5.54	16.95
10,3,1	7.18	0.59	1.38	0.00	6.14	0.00	2.73	8.82	0.82	2.22	10.29
10,3,2	6.74	0.69	0.15	0.00	6.18	0.00	2.28	8.11	0.11	4.37	9.13
10,4,1	7.25	0.37	1.59	0.00	6.13	0.00	3.52	8.90	0.90	2.15	10.15
10,4,2	6.67	0.44	0.25	0.00	5.85	0.00	2.89	8.08	0.08	4.23	9.14
10,5,1	7.33	0.31	1.65	0.00	6.09	0.00	3.87	8.99	0.99	2.15	10.05
10,5,2	6.56	0.36	0.27	0.00	5.53	0.00	3.20	7.96	0.00	4.13	9.14
20,3,1	8.97	1.68	3.27	0.97	6.48	0.00	1.17	12.46	4.46	2.15	6.33
20,3,2	7.30	2.01	0.34	0.00	7.26	0.00	0.80	9.26	1.26	2.92	5.27
20,4,1	8.78	1.11	3.71	0.78	5.97	0.00	2.05	12.23	4.23	2.11	6.45
20,4,2	7.10	1.22	0.84	0.00	6.52	0.00	1.51	8.96	0.96	2.48	5.22
20,5,1	8.79	0.92	3.91	0.79	5.88	0.00	2.75	12.27	4.27	2.09	6.42
20,5,2	7.32	1.11	0.94	0.00	6.50	0.00	2.28	9.15	1.15	2.43	5.01

[1] waiting time of trucks at loading zones.
[2] waiting time of trucks at unloading sites.
[3] total working days required for hauling 200 truck loads.

Table 19: Total cost of alternative actions with parameters estimated using the classical approach based on small sample data equal to: $\alpha = 10$ and $\beta = 0.056$ for loading time, $\alpha = 11$ and $\beta = 0.033$ for unloading time, and $\alpha = 49$ and $\beta = 1.60$ for travel speed.

ACTIONS	Total cost ('000$)[1]
5, 3, 1	43.68
5, 3, 2	49.77
5, 4, 1	48.14
5, 4, 2	51.62
5, 5, 1	52.39
5, 5, 2	54.73
10, 3, 1	43.79
10, 3, 2*	40.54
10, 4, 1	46.63
10, 4, 2	42.52
10, 5, 1	49.54
10, 5, 2	43.92
20, 3, 1	58.67
20, 3, 2	41.75
20, 4, 1	59.66
20, 4, 2	41.40
20, 5, 1	61.20
20, 5, 2	42.34

[1] total cost incurred for hauling 200 truck-loads.
* action with minimum total cost.

3.3.2. Optimal actions with deterministic values in simulation

To further compare the optimal actions resulting from the probabilistic-based simulation model discussed so far, a trial was made to see what would happen if only average values of loading time, unloading time and travel speeds were used in the simulation instead of generating their values from the gamma distribution. The average values were calculated from the same large and small samples used in the proceeding analyses. The simulation output (Appendix II) and cost calculations (Appendix III) were done in the same manner as before, therefore they are not detailed here. The resulting optimal actions are presented in Table 20.

3.3.3. Summary of optimal actions

In summary, the optimal actions obtained for the different methods adopted for parameters estimation and for the non-probability based simulation are summarized in Table 20. For this hauling situation considered, the optimal actions are different for the Bayesian methods, the classical methods utilizing small samples, and the deterministic simulation. Note that the optimal action is similar for Bayesian methods and classical methods utilizing large samples.

Table 20. Summary results of the optimal actions.

Method		Optimal Action
Bayesian	With discrete prior	20, 4, 2
	With uniform prior	20, 4, 2
	With normal prior	20, 4, 2
Classical	With large sample	20, 4, 2
	With small sample	10, 3, 2
Deterministic simulation	Large sample averages	20, 3, 2
	Small sample averages	10, 3, 2

3.3.4. Discussion of Parameter Estimation, Simulation and Total Cost Results

3.3.4.1. The estimated mean values of the parameter β

The Bayesian approach of parameter estimation was compared with the classical approach. The statistic of interest was the mean value of β. The Bayesian approach required the estimation of the Bayes posterior mean of β. Three distinct ways of posterior mean determination were pursued. These were the Bayes posterior mean utilizing a discrete prior distribution, the Bayes posterior mean utilizing a discrete uniform prior distribution, and Bayes posterior mean utilizing a normal prior distribution. The classical means were those based on a large sample and on a small sample.

The results reported in the proceeding section showed that the classical approach with small sample resulted in higher values of β than the Bayesian approach or classical approach with large sample. The result for the classical approach with small sample might be due to the effect of small samples in estimating the parameters, which do not eliminate parameter uncertainty. The consequence of this is reflected in the loading and unloading rates and travel speeds estimated. That is, the overestimation of parameters results in slower loading and unloading rates, and higher travel speeds. The specific effects of the estimated parameters on the simulation output for alternative actions are discussed in the next sections.

3.3.4.2. Effect of Parameter Estimation on the Simulation Output and Total Cost

The parameters estimated by Bayesian and classical approaches were applied to evaluate the total cost of 18 different actions using simulation. In the simulation runs, 30 operating days were run for each type of parameter value (with all other input data as described at the beginning of Chapter 3 held constant) for each action. Statistical analysis of the simulation output was carried out for each action. The results of these simulations appear in Tables 7, 9 and 11 for the Bayesian method, and in Tables 15 and 18 for the classical method. Also, the total cost of alternative actions calculated from these simulation outputs using Equation 12 are provided in Tables 8, 10 and 12 for the Bayesian method, and in Tables 16 and 19 for the classical method.

The range of the statistics calculated for the total cost over the considered design actions are summarized in Table 21.

Table 21: Range of statistics for total cost for both Bayesian and classical estimation methods.

Statistics	Total cost ('000$)				
	Bayesian approach			Classical approach	
	With discrete prior	With uniform prior	With normal prior	Large sample	Small sample
Minimum	37.42	36.20	37.24	38.13	40.54
Maximum	55.82	54.48	55.50	56.74	61.20

Generally the results indicate a considerable spread in total costs as affected by parametric uncertainty, especially in the case of the classical approach with a small sample. Also, the classical approach with a small sample resulted in higher cost values than the other approaches. This is more pronounced for actions with large numbers of trucks than those with small numbers of trucks. This may be due to the tendency of the classical approach with small samples to overestimate the parameters values; resulting in slower loading and unloading rates and higher travel speeds. The consequence of this is reflected in the costs evaluated for alternative actions. For an action with low numbers of trucks, the combined effect of high speeds and low loading and unloading rates did not affect the total costs very much. However, for an action with large numbers of trucks, congestion at loading and unloading sites and high overtime resulted as shown in Tables 7, 9, 11, 15 and 18. This led to high total costs.

The high degree of variability of the simulation output and cost values, especially for the classical method with a small sample, support the contention about the need to address risk in decision-making.

On comparing the effect of different parameter values on cost outputs, the cost values seemed to be very sensitive to the value of parameter used. The Bayes posterior mean results were always closer to the classical approach with large samples than the classical approach with small samples. In addition, the action with lowest total cost as shown in Tables 8, 10 and 12 for the Bayesian method, and in Table 16 for the classical method with large sample was quite different from the classical approach with small sample (Table 19). Also, the results in Table 27 in which the entire posterior distribution is considered, show similar trends. Furthermore, the actions with lowest total cost were the same for the Bayesian methods and the classical approach with a large sample.

In addition, these results have shown that there was not significant difference in the optimal hauling system between the different Bayesian approaches used. Therefore, the results of this study provide support for observations made by DeGroot (1970) that the effectiveness of a Bayesian decision is relatively insensitive to small changes in the prior probability distribution of the parameter.

Consistent with the expectations outlined in previous chapters, it can be concluded that the simulation output and estimated cost values are very sensitive to the value of β used. Thus, there has been a significant reduction in parameter uncertainty as a result of using Bayesian procedures for parameter estimation. This suggests that parameter estimation procedures that rely on small sample data alone are not sufficient to impart a significant reduction in the uncertainty of the model parameters.

The methodologies used also allow for evaluation of the effect of changes on number of trucks, loaders or unloaders on the total cost using the estimated parameters. Regardless of the type of parameter used, the impact of an action (i.e., number of trucks, loaders and unloaders) on total cost can be estimated. For example, the total cost figures presented in Tables 8, 10 and 12 for the Bayesian method, and in Tables 16 and 19 for the classical methods are shown to decrease as the number of trucks change from 5 to 10 and increase as the number change from 10 to 20 regardless of the number of loaders in the system. Also, in the same tables it is shown that actions with low number of loaders are only superior when the number of trucks is low. For large numbers of trucks (for example 20), this trend is reversed. This might be due to formation of long waiting lines. However, 10 trucks is a minimum for systems with fewer numbers of loaders.

This finding indicates the impact on total cost of different combinations of hauling equipment. It illustrates how the determination of the optimum combination of hauling equipment may not be straightforward. However, the information derived through this method can provide guidelines and simplify the process of determining the optimal combination of equipment for a hauling situation of similar nature as the one considered in this application.

3.3.4.3. Effect of the use of deterministic average values in the simulation

The optimal action based on deterministic averages was different from that of the Bayesian and classical methods (with large sample only) as described in earlier sections. Furthermore, the optimal actions were different for deterministic averages estimated from the large sample as well as the small sample. These results indicate the danger of using deterministic average values especially when the values are derived from small data sets. Further simulation studies to compare the probabilistic approach and the deterministic approach are provided in Chapter 6.

3.4. DECISION MAKING

This section considers the methods for choosing the optimum action under conditions of uncertainty and risk. As explained in Chapter 2, in larger forestry companies, where temporary setbacks can be absorbed by the company, woodlands managers should be expected to make decisions with maximum profits over the longer term in mind. Therefore the decision maker would be expected to be risk-neutral and the practical decision criteria would normally be the expected monetary outcome. However, for hauling contractors, the decision-making process would be expected to be more influenced by their attitudes toward risk. Some could be expected to be risk-averse, if they are not in a position to absorb financial setbacks, while others could be expected to "take a chance", knowing that they could survive losses. For either risk-avoiders or risk-takers, the practical decision criteria would be the expected utility value. The expected monetary value and expected utility crteria are presented in the next subsections.

3.4.1. Based on Total Expected Monetary Value

Use of the mean of distribution of the parameter

The total expected cost can be determined by using the mean of the posterior distribution of β in the simulation, as it was done in the proceeding sections of this chapter. The optimal actions under this method of decision analysis are reported in Table 20.

Use of the entire probability of the parameter

The method of decision analysis employing the mean of the distribution of the parameter just explained is non-standard. The standard method of decision analysis involves the use of the entire posterior probability of parameter β. In this method, the cost corresponding to each action and each possible value of parameter β is determined using the simulation program and the costs for different action-parameter pairs are presented in the form of a decision table. Then, the dollar values are weighted by the posterior probability values of β and the sum of the weighted dollar values is the total expected payoff for each action. This method of decision analysis for this particular decision problem is demonstrated in the following sub-sections.

3.4.1.1. Determination of the Possible Values of Parameter β

The first step in this method of decision analysis involves establishing the possible values of the parameter β under investigation. The values of β used in the computation of the posterior mean of β, when the prior distribution of β is discrete (from Section 3.3.1 under Case 1) as shown below were used in this analysis.

Loading time		Unloading time		Travel speed	
β	α	β	α	β	α
0.029	12	0.050	4	1.667	36
0.022	20	0.033	9	1.429	49
0.018	30	0.025	16	1.250	64

3.4.1.2. Construction of the Decision Table

In this step of decision analysis, the β and α values calculated above were inputted with other input data (as described in Sections 3.2.1 and 3.2.2) to the simulation program to estimate the cost. The resulting costs for alternative actions are presented in Table 22. Note that Table 22 includes only admissible actions (i.e., actions that are not dominated by any other action). The elimination of inadmissible actions reduces the "dimension" of the decision-making problem by enabling the decision maker to confine attention to the admissible actions (Winkler and Hays, 1975, pp. 557-558). Next, the costs in Table 22 were converted into payoffs according to the total budget allocated for this particular hauling operation. For this illustration, the budget for hauling 200 truck-loads was assumed to be \$50,000. Based on this budget, the payoffs presented in Table 23 were established.

Table 23 also includes the probability distribution of each of the β values specified in Section 3.4.1.1 above. These probabilities are necessary for the computation of the total expected payoff for each action. According to Bayesian decision-making, this probability distribution is the **posterior distribution.** The following posterior distributions of the β values as calculated in Section 3.3.1 were adopted.

For loading time,

$g(\beta/t)[\beta_{ul} = 0.029] = 0.1064$

$g(\beta/t)[\beta_{ul} = 0.022] = 0.6766$

$g(\beta/t)[\beta_{ul} = 0.018] = 0.2170$

For unloading time,

$g(\beta/t)[\beta_{ul} = 0.050] = 0.1191$

$g(\beta/t)[\beta_{ul} = 0.033] = 0.7078$

$g(\beta/t)[\beta_{ul} = 0.025] = 0.1731$

For travel speed,

$g(\beta/t)[\beta_{ts} = 1.667] = 0.1023$

$g(\beta/t)[\beta_{ts} = 1.429] = 0.7116$

$g(\beta/t)[\beta_{ts} = 1.250] = 0.1861$

By assuming independence of β_l, β_{ul}, β_{ts}, then the probability of each β_l-β_{ul}-β_{ts} pair in Table 23, is simply the product of their individual posterior probabilities. For example, for the posterior probability of $\beta_{ts} = 1.667$, $\beta_l = 0.029$ and $\beta_{ul} = 0.050$ equal to 0.1023, 0.1064 and 0.1191 respectively, then the joint probability equals (0.1023)(0.1064)(0.1191) = 0.0013 as shown in column 4 of Table 23. This implies that the probability that the average travel speed is 60 km/hour, the loading time per load is 0.35 hours and the unloading time per load is 0.20 hours, is 0.0013. It is these probabilities that were used in the calculation of the total expected payoff and total expected utility of each action.

3.4.1.3. Computation of the Total Expected Payoffs

The joint probability of each β_r-β_{ul}-β_u pair is included in the payoff table as shown in Table 23. Then these probabilities were used in the calculation of the total expected payoff of each action shown in the last row of Table 23. To illustrate the calculations, the total expected payoff, EP of Action (5,3,1) in Table 23 was calculated as follow:

$$
\begin{aligned}
\text{EP(Action-5,3,1)} &= [(0.0013)(\$8{,}490) + (0.0077)(\$4{,}140) + (0.0019)(\$1{,}280) \\
&\quad + \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots + (0.0048)(\$8{,}890) + \\
&\quad (0.0286)(\$7{,}560) + (0.0070)(2{,}410)] \\
&= \$6{,}470
\end{aligned}
$$

The results of similar calculations for the other actions are shown in the last row, Table 23. The action (with 20 trucks, 4 loaders and 2 unloaders) is shown to provide the highest total expected payoff, with an expected payoff of $12,640. Note that this result is similar to that in Table 8 obtained by the "first" method (employing the mean of the posterior distribution of β) of decision analysis.

Table 22: Costs (in '000$) for alternative actions

Parameter values				Actions												
			#trucks	5	10	10	10	10	10	10	20	20	20	20	20	20
			#ldrs	3	3	3	4	4	5	5	3	3	4	4	5	5
			#unldrs	1	1	2	1	2	1	2	1	2	1	2	1	2
β_{ts}	β_l	β_{ul}														
1.667	0.029	0.050		41.51	37.59	39.11	39.70	40.77	41.34	43.18	38.82	40.95	35.73	42.19	37.08	42.22
1.667	0.029	0.033		45.86	41.64	42.64	43.80	45.46	45.88	53.80	38.45	49.14	39.21	54.58	40.27	55.70
1.667	0.029	0.025		48.72	44.19	49.48	46.62	52.36	48.75	65.32	43.68	55.20	45.15	66.95	46.53	68.36
1.667	0.022	0.050		44.95	42.00	40.01	43.44	42.80	45.62	44.73	38.88	42.64	37.79	42.15	38.69	44.01
1.667	0.022	0.033		47.49	43.49	44.06	45.45	47.19	47.69	49.68	40.30	53.41	40.42	54.74	41.62	56.52
1.667	0.022	0.025		49.86	46.08	49.97	48.49	52.64	51.25	57.62	45.01	65.85	47.48	66.57	45.92	68.91
1.667	0.018	0.050		43.41	41.49	45.24	43.83	41.85	40.51	43.85	43.45	46.13	44.02	44.52	40.56	41.19
1.667	0.018	0.033		49.27	45.90	45.75	48.28	47.44	51.53	49.66	44.17	53.68	42.51	57.29	43.15	54.96
1.667	0.018	0.025		49.25	57.30	54.49	52.84	52.38	51.21	49.97	48.55	66.28	47.07	69.36	46.73	68.08
1.429	0.029	0.050		40.89	35.32	37.44	37.05	38.02	39.45	40.96	38.22	32.76	39.13	32.13	42.41	33.12
1.429	0.029	0.033		42.42	38.93	38.06	41.33	40.24	45.06	41.78	50.71	35.24	53.23	35.77	55.10	37.02
1.429	0.029	0.025		40.28	32.81	35.92	34.22	36.70	36.72	39.21	29.74	30.90	29.70	30.91	30.73	31.50
1.429	0.022	0.050		42.12	36.53	39.35	38.12	40.20	40.69	41.81	40.47	35.22	40.85	34.20	42.30	35.70
1.429	0.022	0.033		43.09	40.25	40.25	42.79	41.28	45.03	43.41	51.73	37.20	53.16	36.82	54.89	38.83

Table 22. (Continued)

Parameter values				Actions												
			#trucks	5	10	10	10	10	10	10	20	20	20	20	20	20
			#ldrs	3	3	3	4	4	5	5	3	3	4	4	5	5
			#unldr	1	1	2	1	2	1	2	1	2	1	2	1	2
β_{ls}	β_l	β_{ul}														
1.429	0.022	0.025		45.18	48.14	41.19	50.26	42.98	54.29	46.09	64.40	42.77	65.75	43.79	68.34	45.14
1.429	0.018	0.050		43.41	38.24	40.60	39.42	41.75	42.07	42.89	40.50	38.10	41.40	37.00	42.75	40.50
1.429	0.018	0.033		45.00	41.69	41.37	43.95	42.61	46.80	44.60	53.49	41.11	54.57	38.83	55.21	39.72
1.429	0.018	0.025		46.38	48.89	43.16	51.23	45.09	56.30	46.81	65.76	43.90	66.72	45.26	68.37	46.35
1.250	0.029	0.050		37.16	32.37	33.11	34.11	34.60	36.49	36.51	38.26	30.04	39.89	29.71	40.76	30.60
1.250	0.029	0.033		39.43	36.69	35.26	39.09	36.58	42.51	39.61	51.07	33.32	52.88	34.08	54.49	34.99
1.250	0.029	0.025		40.75	46.18	42.68	49.03	42.14	51.74	44.43	63.94	42.68	65.16	43.51	66.69	43.77
1.250	0.022	0.050		38.84	33.94	35.27	35.75	36.31	38.34	38.54	38.49	33.51	40.06	31.67	41.35	32.60
1.250	0.022	0.033		40.74	37.82	36.52	40.53	38.49	43.32	41.00	51.61	35.12	52.65	34.97	54.32	35.98
1.250	0.022	0.025		42.74	46.87	38.79	50.00	40.84	52.21	42.85	64.32	42.19	65.23	43.17	67.17	43.73
1.250	0.018	0.050		41.11	35.01	37.25	35.01	38.66	39.99	40.76	42.00	36.61	40.55	35.01	40.31	35.97
1.250	0.018	0.033		42.44	39.41	38.71	41.53	40.40	44.21	42.26	52.28	39.88	52.89	36.95	54.69	37.67
1.250	0.018	0.025		47.59	47.74	43.32	50.10	45.41	52.56	47.64	64.60	42.97	66.35	39.87	67.59	44.46

Table 23: Payoffs and total expected payoff (in '000$) for alternative actions

Parameter values				Actions												
			#trucks	5	10	10	10	10	10	10	20	20	20	20*	20	20
			#ldrs	3	3	3	4	4	5	5	3	3	4	4	5	5
			#unldrs	1	1	2	1	2	1	2	1	2	1	2	1	2
β_{ts}	β_l	β_{ul}	Probability													
1.667	0.029	0.050	0.0013	8.49	12.41	10.89	10.30	9.23	8.66	6.82	11.18	9.05	14.27	7.81	12.92	7.78
1.667	0.029	0.033	0.0077	4.14	8.36	7.36	6.20	4.54	4.12	-3.80	11.55	0.86	10.79	-4.58	9.73	-5.70
1.667	0.029	0.025	0.0019	1.28	5.81	0.52	3.38	-2.36	1.25	-15.32	6.32	-5.20	4.85	-16.95	3.47	-18.36
1.667	0.022	0.050	0.0082	5.05	8.00	9.99	6.56	7.20	4.38	5.27	11.12	7.36	12.21	7.85	11.31	5.99
1.667	0.022	0.033	0.0490	2.51	6.51	5.94	4.55	2.81	2.31	0.32	9.70	-3.41	9.58	-4.74	8.38	-6.52
1.667	0.022	0.025	0.0120	0.14	3.92	0.03	1.51	-2.64	-1.25	-7.62	4.99	-15.85	2.52	-16.57	4.08	-18.91
1.667	0.018	0.050	0.0026	6.59	8.51	4.76	6.17	8.15	9.49	6.15	6.55	3.87	5.98	5.48	9.44	8.81
1.667	0.018	0.033	0.0157	0.73	4.10	4.25	1.72	2.56	-1.53	0.34	5.83	-3.68	7.49	-7.29	6.85	-4.96
1.667	0.018	0.025	0.0038	0.75	-7.30	-4.49	-2.84	-2.38	-1.21	0.03	1.45	-16.28	2.93	-19.36	3.27	-18.08
1.429	0.029	0.050	0.0090	9.11	14.68	12.56	12.95	11.98	10.55	9.04	11.78	17.24	10.87	17.87	7.59	16.88
1.429	0.029	0.033	0.0536	7.58	11.07	11.94	8.67	9.76	4.94	8.22	-0.71	14.76	-3.23	14.23	-5.10	12.98
1.429	0.029	0.025	0.0131	9.72	17.19	14.08	15.78	13.30	13.28	10.79	20.26	19.10	20.30	19.09	19.27	18.50
1.429	0.022	0.050	0.0573	7.88	13.47	10.65	11.88	9.80	9.31	8.19	9.53	14.78	9.15	15.80	7.70	14.30
1.429	0.022	0.033	0.3408	6.91	9.75	9.75	7.21	8.72	4.97	6.59	-1.73	12.80	-3.16	13.18	-4.89	11.17

Table 23. (Continued)

				Actions												
Parameter values			#trucks	5	10	10	10	10	10	10	20	20	20	20	20	20
			#ldrs	3	3	3	4	4	5	5	3	3	4	4	5	5
			#unldrs	1	1	2	1	2	1	2	1	2	1	2	1	2
β_{ts}	β_{l}	β_{ul}	Probability													
1.429	0.022	0.025	0.0833	4.82	1.86	8.71	-0.26	7.02	-4.29	3.91	-14.40	7.23	-15.75	6.21	-18.34	4.86
1.429	0.018	0.050	0.0184	6.59	11.76	9.40	10.58	8.25	7.93	7.11	9.50	11.90	8.60	13.00	7.25	9.50
1.429	0.018	0.033	0.1093	5.00	8.31	8.63	6.05	7.39	3.20	5.40	-3.49	8.89	-4.57	11.17	-5.21	10.28
1.429	0.018	0.025	0.0267	3.62	1.11	6.84	-1.23	4.91	-6.30	3.19	-15.76	6.10	-16.72	4.74	-18.37	3.65
1.250	0.029	0.050	0.0024	12.84	17.63	16.89	15.89	15.40	13.51	13.49	11.74	19.96	10.11	20.29	9.24	19.40
1.250	0.029	0.033	0.0140	10.57	13.31	14.74	10.91	13.42	7.49	10.39	-1.07	16.68	-2.88	15.92	-4.49	15.01
1.250	0.029	0.025	0.0034	9.25	3.82	7.32	0.97	7.86	-1.74	5.57	-13.94	7.32	-15.16	6.49	-16.69	6.23
1.250	0.022	0.050	0.0150	11.16	16.06	14.76	14.25	13.69	11.66	11.46	11.51	16.49	9.94	18.33	8.65	17.40
1.250	0.022	0.033	0.0891	9.25	12.18	13.48	9.47	11.51	6.68	9.00	-1.61	14.88	-2.65	15.03	-4.32	14.02
1.250	0.022	0.025	0.0218	7.26	3.13	11.21	0.00	9.16	-2.21	7.15	-14.32	7.81	-15.23	6.83	-17.17	6.27
1.250	0.018	0.050	0.0048	8.89	14.99	12.75	14.99	11.34	10.01	9.24	8.00	13.39	9.45	14.99	9.69	14.03
1.250	0.018	0.033	0.0286	7.56	10.59	11.29	8.47	9.60	5.79	7.74	-2.28	10.12	-2.89	13.05	-4.69	12.33
1.250	0.018	0.025	0.0070	2.41	2.26	6.68	-0.10	4.59	-2.56	2.36	-14.60	7.03	-16.35	10.13	-17.59	5.54
Total expected payoff				6.47	8.96	9.77	6.69	8.32	3.96	6.06	-3.13	12.40	-4.00	12.64	-5.77	11.21

• action with highest total expected payoff

3.4.2. Based on the Total Expected Utility

This is the decision criterion which incorporates attitudes to risk. In order to be able to calculate the expected utility, their respective utility functions must be assessed. The assessed utility function is then used to convert the payoff values in Table 23 to utility values. And finally, the utility values are weighted by the posterior probability values of parameter values (specified in Section 3.4.1.2 above) using Equation 5 and the resulting sum is the total expected utility. The action corresponding to the highest total expected utility is the optimum hauling system. Therefore, the utility function must first be assessed. In the next section, the method of establishing the utility functions and the use of utility functions to convert the payoff table (Table 23) to utility table are demonstrated.

3.4.2.1. Assessment of Utility Function

The calculations of the total expected payoffs assumed that the decision maker is risk neutral and his utility function is approximately linear. However, under conditions of risk, the utility function may not be linear but quite nonlinear and also is different between a risk-taker and a risk-avoider. The assessment of the utility function can be done using the same method as was explained in general terms in Chapter 2 and is explained here by an example. This method proceeded as follows:

Step 1: The best (\$20,290) and worst (-\$19,360) possible outcomes from Table 23 were identified. Then, two outcome values which encompass these two upper and lower values were selected. In this example, the numbers chosen were \$25,000 and -\$25,000. Then the lowest possible outcome (-\$25,000), which is the least favourable, is assigned a utility value of 0 and the highest possible outcome (\$25,000), which is most favourable is assigned a utility value of 1. Or mathematically,

$$U(-\$25{,}000) = 0 \text{ and}$$

$$U(\$25{,}000) = 1$$

Thus two points on the utility function have been determined.

Step 2: A third point somewhere between points 0 and 1 was determined. To determine the utility preferences of the decision-maker, questions are asked to relate the probability value he/she attaches to profits or losses associated with various probable outcomes. First, any payoff value is selected, say \$20,000, and its utility value, U(\$20,000), is determined by considering the following choice of alternatives:

Alternative I: Receive \$20,000 for certain.

Alternative II: Receive \$25,000 with a probability p or receive -\$25,000 with a probability (1-p)

The probability p where the decision-maker is indifferent to either alternative I or II is the utility of $20,000. For example, assume that a decision maker is indifferent to either alternative at p = 0.8. At p = 0.8, where the expected value (EV) of alternative II is (0.8)($25,000) + (0.2)(-$25,000) = $15,000, the decision-maker shows himself to be a risk-taker since the expected value of the uncertain alternative is less than that of the certain alternative. Thus, a third point on the utility function has been determined.

Step 3: By repeating step 2 through a selected range of certain outcomes and probabilities p, several more points were obtained.

Utility values for a typical risk-taker and a typical risk-avoider are presented in Table 24, the utility curves for both types of decision-makers are presented in Fig. 9, and equations approximating these curves are given in Equations 15 and 16. Tables 25 and 26 represent utility values calculated from Table 23 using Equations 15 and 16 for risk-avoider and risk-taker respectively.

Table 24: Payoff Values and their Associated Utility Indices.

Point	Payoff Values ('000$) (certainty equivalent)	Utility Index	
		Risk-Avoider	Risk-Taker
1	25	1.00	1.00
2	20	-	0.75
3	10	0.90	0.45
4	-10	0.50	0.05
5	-15	0.35	-
6	-25	0.00	0.00

Utility Function for a Risk-Avoider:

[15] $\text{Utility} = -0.00038(\text{Payoff})^2 + 0.0200167(\text{Payoff}) + 0.7373399, \quad r^2 = 0.999$

Utility Function for a Risk-Taker:

[16] $\text{Utility} = 0.000476(\text{Payoff})^2 + 0.019289(\text{Payoff}) + 0.201622, \quad r^2 = 0.997$

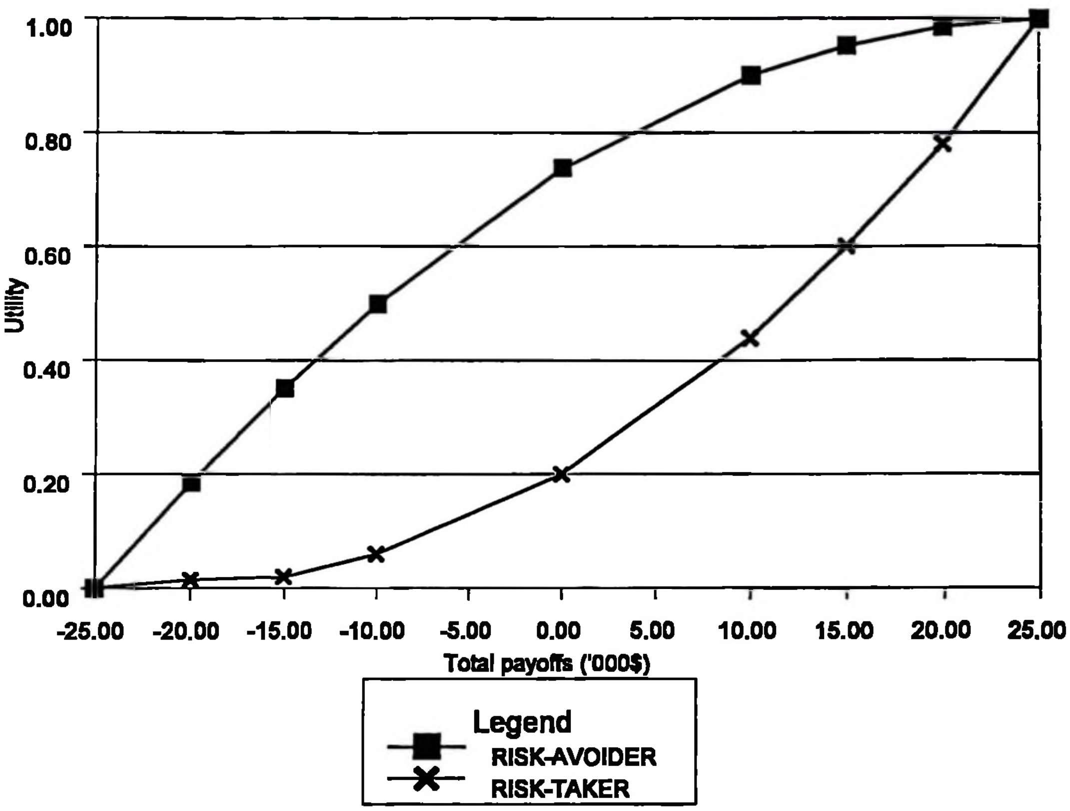

Fig. 9: Two possible utility functions for risk-avoider and risk-taker. The relative utility is plotted against the total payoffs of an action.

3.4.2.2. Computation of the Total Expected Utility

All inputs for the calculation of the total expected utility of each action are now available. The computation of the total expected utility was achieved by weighing each utility value in Tables 25 and 26 by its corresponding probability of the β_l-β_{ul}-β_u pair. Then the resulting sum was the total expected utility for that action. The resulting total expected utility for each hauling system are shown in the last row of Table 25 for the risk-avoider curve developed in the last section and in Table 26 for the risk-taker curve developed in the last section. To illustrate the calculations, the total expected utility of the first action (5 trucks, 3 loaders and 1 unloader) of Table 25 is:

$$\begin{aligned} EU(\text{Action-5,3,1}) = {} & [(0.0013)(0.880) + (0.0077)(0.814) + (0.0019)(0.762) + \\ & (0.0082)(0.829) + \ldots + (0.0286)(0.867) + (0.0070)(0.783)] \\ = {} & 0.849 \end{aligned}$$

The results of similar calculations for other actions are shown in the last rows of Tables 25 and 26. With the particular utility functions assessed, the risk-averse manager should pick the action corresponding to 10 trucks, 3 loaders and 2 unloaders, whereas the risk-taking manager should pick the action corresponding to 20 trucks, 4 loaders and 2 unloaders. These action are shown to provide the highest total expected utility of 0.894 and 0.482 for the risk-avoider and risk-taker respectively. Also the ranking of the hauling systems is completely different (see Table 27 for the first five best actions).

Table 25: Utilities for payoffs in Table 23 and total expected utilities for alternative actions for risk-avoider

Parameter values				Actions												
			#trucks	5	10	10*	10	10	10	10	20	20	20	20	20	20
			#ldrs	3	3	3	4	4	5	5	3	3	4	4	5	5
			#unldrs	1	1	2	1	2	1	2	1	2	1	2	1	2
β_{ls}	β_l	β_{ul}	Probability													
1.667	0.029	0.050	0.0013	0.880	0.927	0.910	0.903	0.889	0.882	0.856	0.914	0.887	0.946	0.870	0.932	0.970
1.667	0.029	0.033	0.0077	0.814	0.878	0.864	0.847	0.820	0.813	0.656	0.918	0.754	0.909	0.638	0.896	0.611
1.667	0.029	0.025	0.0019	0.762	0.841	0.747	0.801	0.688	0.762	0.341	0.849	0.623	0.825	0.289	0.802	0.242
1.667	0.022	0.050	0.0082	0.829	9.873	0.899	0.852	0.862	0.818	0.832	0.913	0.864	0.925	0.871	0.915	0.843
1.667	0.022	0.033	0.0490	0.785	0.852	0.843	0.821	0.791	0.782	0.744	0.896	0.665	0.894	0.634	0.878	0.591
1.667	0.022	0.025	0.0120	0.740	0.810	0.738	0.767	0.682	0.712	0.563	0.828	0.325	0.785	0.301	0.813	0.223
1.667	0.018	0.050	0.0026	0.853	0.880	0.824	0.846	0.875	0.893	0.846	0.852	0.809	0.843	0.836	0.892	0.884
1.667	0.018	0.033	0.0157	0.752	0.813	0.816	0.771	0.786	0.706	0.744	0.841	0.659	0.866	0.571	0.857	0.629
1.667	0.018	0.025	0.0038	0.752	0.571	0.640	0.677	0.688	0.712	0.738	0.766	0.311	0.793	0.207	0.799	0.251
1.429	0.029	0.050	0.0090	0.888	0.949	0.929	0.933	0.923	0.906	0.887	0.920	0.969	0.910	0.974	0.867	0.967
1.429	0.029	0.033	0.0536	0.867	0.912	0.922	0.882	0.897	0.827	0.876	0.723	0.950	0.669	0.945	0.625	0.933
1.429	0.029	0.025	0.0131	0.896	0.969	0.943	0.958	0.936	0.936	0.909	0.987	0.981	0.987	0.981	0.982	0.978
1.429	0.022	0.050	0.0573	0.871	0.938	0.907	0.922	0.897	0.891	0.876	0.894	0.950	0.889	0.959	0.869	0.946
1.429	0.022	0.033	0.3408	0.858	0.896	0.896	0.862	0.883	0.827	0.853	0.702	0.931	0.670	0.935	0.630	0.914

Table 25. (Continued)

Parameter values				Actions												
			#trucks	5	10	10*	10	10	10	10	20	20	20	20	20	20
			#ldrs	3	3	3	4	4	5	5	3	3	4	4	5	5
			#unldrs	1	1	2	1	2	1	2	1	2	1	2	1	2
β_{ls}	β_{l}	β_{ul}	Probability													
1.429	0.022	0.025	0.0833	0.825	0.773	0.883	0.732	0.859	0.645	0.810	0.370	0.862	0.328	0.847	0.242	0.826
1.429	0.018	0.050	0.0184	0.853	0.920	0.892	0.907	0.877	0.872	0.860	0.893	0.922	0.881	0.933	0.862	0.893
1.429	0.018	0.033	0.1093	0.828	0.877	0.882	0.844	0.864	0.797	0.834	0.663	0.885	0.638	0.913	0.623	0.903
1.429	0.018	0.025	0.0267	0.805	0.759	0.856	0.712	0.826	0.596	0.797	0.327	0.845	0.296	0.824	0.241	0.805
1.250	0.029	0.050	0.0024	0.932	0.972	0.967	0.959	0.955	0.938	0.938	0.920	0.985	0.901	0.987	0.890	0.983
1.250	0.029	0.033	0.0140	0.906	0.936	0.950	0.910	0.938	0.866	0.904	0.715	0.965	0.677	0.960	0.640	0.952
1.250	0.029	0.025	0.0034	0.890	0.808	0.863	0.756	0.871	0.701	0.837	0.384	0.863	0.346	0.851	0.297	0.847
1.250	0.022	0.050	0.0150	0.913	0.961	0.950	0.945	0.940	0.919	0.917	0.917	0.964	0.899	0.977	0.882	0.971
1.250	0.022	0.033	0.0891	0.890	0.925	0.938	0.893	0.917	0.854	0.887	0.704	0.951	0.682	0.952	0.644	0.943
1.250	0.022	0.025	0.0218	0.863	0.796	0.914	0.737	0.889	0.691	0.861	0.373	0.870	0.344	0.856	0.282	0.848
1.250	0.018	0.050	0.0048	0.885	0.952	0.931	0.952	0.915	0.899	0.890	0.873	0.937	0.892	0.952	0.896	0.943
1.250	0.018	0.033	0.0286	0.867	0.907	0.915	0.880	0.894	0.840	0.870	0.690	0.901	0.676	0.934	0.635	0.926
1.250	0.018	0.025	0.0070	0.783	0.781	0.854	0.735	0.821	0.684	0.782	0.364	0.859	0.308	0.901	0.268	0.837
Total expected Utility				0.849	0.881	0.894	0.849	0.874	0.804	0.841	0.693	0.891	0.667	0.890	0.631	0.873

* action with highest total expected utility

Table 26: Utilities for payoffs in Table 23 and total expected utilities for alternative actions for risk-taker

Parameter values				Actions												
			#trucks	5	10	10	10	10	10	10	20	20	20	20*	20	20
			#ldrs	3	3	3	4	4	5	5	3	3	4	4	5	5
			#unldrs	1	1	2	1	2	1	2	1	2	1	2	1	2
β_{ls}	β_{l}	β_{ul}	Probability													
1.667	0.029	0.050	0.0013	0.399	0.514	0.468	0.451	0.420	0.404	0.355	0.477	0.415	0.574	0.381	0.530	0.381
1.667	0.029	0.033	0.0077	0.289	0.396	0.369	0.339	0.299	0.289	0.135	0.488	0.219	0.465	0.123	0.434	0.107
1.667	0.029	0.025	0.0019	0.227	0.330	0.212	0.272	0.159	0.226	0.018	0.342	0.114	0.306	0.011	0.274	0.009
1.667	0.022	0.050	0.0082	0.311	0.386	0.442	0.348	0.365	0.295	0.316	0.475	0.369	0.508	0.382	0.481	0.334
1.667	0.022	0.033	0.0490	0.253	0.347	0.333	0.299	0.259	0.249	0.208	0.433	0.141	0.430	0.121	0.397	0.096
1.667	0.022	0.025	0.0120	0.204	0.284	0.202	0.232	0.154	0.178	0.082	0.309	0.015	0.253	0.013	0.288	0.007
1.667	0.018	0.050	0.0026	0.349	0.400	0.304	0.339	0.390	0.427	0.338	0.348	0.283	0.334	0.322	0.426	0.408
1.667	0.018	0.033	0.0157	0.216	0.289	0.292	0.236	0.254	0.173	0.208	0.330	0.137	0.373	0.086	0.356	0.118
1.667	0.018	0.025	0.0038	0.216	0.086	0.125	0.151	0.158	0.179	0.202	0.231	0.014	0.262	0.007	0.270	0.008
1.429	0.029	0.050	0.0090	0.417	0.587	0.519	0.531	0.501	0.458	0.415	0.495	0.676	0.467	0.698	0.365	0.663
1.429	0.029	0.033	0.0536	0.375	0.473	0.500	0.405	0.435	0.309	0.392	0.188	0.590	0.144	0.572	0.116	0.532
1.429	0.029	0.025	0.0131	0.434	0.674	0.568	0.624	0.542	0.542	0.465	0.788	0.744	0.789	0.743	0.750	0.721
1.429	0.022	0.050	0.0573	0.383	0.548	0.461	0.498	0.436	0.422	0.392	0.429	0.591	0.418	0.625	0.378	0.575
1.429	0.022	0.033	0.3408	0.358	0.435	0.435	0.365	0.406	0.309	0.349	0.170	0.526	0.145	0.539	0.119	0.476

Table 26. (Continued)

Parameter values				Actions												
			#trucks	5	10	10	10	10	10	10	20	20	20	20*	20	20
			#ldrs	3	3	3	4	4	5	5	3	3	4	4	5	5
			#unldrs	1	1	2	1	2	1	2	1	2	1	2	1	2
β_{ts}	β_{l}	β_{ul}	Probability													
1.429	0.022	0.025	0.0833	0.306	0.239	0.406	0.197	0.360	0.128	0.284	0.023	0.366	0.016	0.340	0.008	0.307
1.429	0.018	0.050	0.0184	0.349	0.494	0.425	0.459	0.393	0.384	0.363	0.428	0.499	0.403	0.533	0.366	0.428
1.429	0.018	0.033	0.1093	0.310	0.395	0.403	0.336	0.370	0.268	0.320	0.140	0.411	0.123	0.476	0.114	0.450
1.429	0.018	0.025	0.0267	0.278	0.224	0.356	0.179	0.308	0.099	0.268	0.016	0.337	0.012	0.304	0.008	0.278
1.250	0.029	0.050	0.0024	0.528	0.690	0.663	0.628	0.612	0.549	0.548	0.494	0.776	0.445	0.789	0.420	0.755
1.250	0.029	0.033	0.0140	0.459	0.543	0.589	0.469	0.546	0.373	0.453	0.182	0.656	0.150	0.629	0.125	0.598
1.250	0.029	0.025	0.0034	0.421	0.282	0.368	0.221	0.383	0.170	0.234	0.025	0.368	0.019	0.347	0.012	0.340
1.250	0.022	0.050	0.0150	0.476	0.634	0.589	0.573	0.555	0.491	0.485	0.487	0.649	0.440	0.715	0.404	0.681
1.250	0.022	0.033	0.0891	0.421	0.507	0.548	0.427	0.487	0.352	0.414	0.172	0.594	0.154	0.599	0.127	0.566
1.250	0.022	0.025	0.0218	0.367	0.267	0.478	0.202	0.418	0.161	0.364	0.023	0.381	0.018	0.356	0.011	0.341
1.250	0.018	0.050	0.0048	0.411	0.598	0.525	0.598	0.482	0.442	0.420	0.383	0.545	0.426	0.598	0.433	0.566
1.250	0.018	0.033	0.0286	0.375	0.459	0.480	0.399	0.431	0.329	0.379	0.160	0.446	0.150	0.534	0.122	0.512
1.250	0.018	0.025	0.0070	0.251	0.248	0.352	0.200	0.300	0.155	0.250	0.021	0.361	0.013	0.446	0.010	0.323
Total Expected Utility				0.348	0.420	0.439	0.359	0.399	0.293	0.341	0.208	0.471	0.190	0.482	0.167	0.440

* action with the highest expected utility

Table 27: Ranking of actions based on total expected payoffs and total expected utility criteria.

Rank	Based on Total Expected Payoffs	Based on Total Expected Utility	
		Risk-Avoider	Risk-Taker
1	20, 4, 2	10, 3, 2	20, 4, 2
2	20, 3, 2	20, 3, 2	20, 3, 2
3	10, 3, 2	20, 4, 2	20, 5, 2
4	20, 5, 2	10, 3, 1	10, 3, 2
5	10, 3, 1	10, 4, 2	10, 3, 1

3.4.3. Discussion of the Results of Decision Analysis

The results of the computation of the total expected cost and total expected utility are presented in Table 23 for total expected payoffs and in Tables 25 and 26 for total expected utility. As expected, the optimal hauling system selected when risk is taken into consideration is quite different from that which would be made if only monetary values are considered. The optimal hauling system under the expected cost criterion method of decision analysis is 20 trucks, 4 loaders and 2 unloader whereas with the expected utility, the optimal hauling system is 10 trucks, 3 loaders and 2 unloader for the risk-averse manager or 20 trucks, 4 loaders and 2 unloaders for the risk-accepting manager. Also the ordering of the potential actions (see, for example, Table 27 for the first five best actions) is completely different when based on expected monetary value against that based on expected utility for a risk-avoider. However, the ordering of the first two potential actions was not different between the expected payoff criterion and the expected utility criterion for the risk-accepting manager. This result suggests that such a woodlands manager should obviously investigate the potential actions further and assess the value or utility of any other influencing factors.

In general , these results suggest that utility analysis is important in determining the optimal combination of hauling equipment. When some of the inputs in determining optimal hauling systems are uncertain, the resulting outputs are always risky. Neglecting uncertainty and risk would sometimes lead to decisions that seem intuitively unreasonable. As demonstrated in this application, the optimal hauling system selected when risk analysis is taken into account is quite different than that which would be made if only monetary values are considered.

Chapter 4

RESPONSE FUNCTIONS - DEVELOPMENT, ANALYSIS AND OUTPUT

The purpose of this chapter is to develop response functions to provide an alternative to the simulation procedure. The method used to develop the response functions and step-by-step sample calculations for obtaining the time elements for cost evaluation based on the response functions methodology are presented. The idea behind the response function methodology is to develop continuous functions for estimating average waiting and idle times as well as average number of trips in which parameters (β) of the gamma distributions for loading time, unloading time and travel speed are the independent variables. The other time elements, i.e., average loading time, average unloading time and average travel speed (both loaded and empty) can be calculated from the estimated parameters of the gamma distribution (α, β) from Equation 13. Thus, the process of determining total time spent in the system per day is reduced to only solving response functions for waiting and idle times, and number of trips. The simulation procedure is used only once at the beginning just to provide data for development of the response functions. Then in subsequent designs of hauling systems, it will only be required to evaluate the response functions.

4.1. DEVELOPMENT OF RESPONSE FUNCTIONS

The development of response equations proceeded as follows:

By using the simulation model, all possible (from the lowest to the highest possible) values of the scale parameter (β) of the gamma distribution (for loading time, unloading time and travel speed) that could occur are simulated to determine the average waiting time at loading zones, waiting time at unloading sites, idle time for loaders, idle time for unloaders and total number of trips. In this case, for loading time, six levels of β simulated were: 0.01, 0.03, 0.05, 0.07, 0.09 and 0.11. For unloading rate, six levels of β simulated were: 0.01, 0.03, 0.05, 0.07, 0.09 and 0.11. Finally, for the travel speed, also six levels β simulated were: 0.6, 1.0, 1.4, 1.8 and 2.2. The ranges of β for each random variable was selected based upon the desire to test the different actions over a wide range of values of β. Note that the values of α equaled 20 for loading time, 9.77 for unloading time and 49 for travel speed and were kept constant throughout the simulation.

Using the simulation model, different values for average waiting time at loading zones (WaitTL), average waiting time at unloading zones (WaitTUNL), average idle time for loaders (IdleTL), average idle time for unloaders (IdleTUNL) and average number of trips (No. of trips) for each action over the values of β were derived. Appendix IV shows such simulation outputs for development of response functions for action 1. Ordinary least square method was then applied to each set of data for all actions as presented in Appendix IV to construct response functions, with β values for loading time, unloading time and travel speed as the independent variables. The form of the response function was chosen based on F ratios, error sum of squares, and R^2 values. An example of these functions for action 1 are represented by Equations 17, 18, 19, 20 and 21 below. Response functions for other actions obtained in the same manner and their regression coefficients are given in Appendix V.

Response Functions for Action 1 (5 trucks, 3 loaders and 1 unloader):

$$[17]\ WaitTL = -0.128 + 10.61\,\beta_l + 23.46\,\beta_l^2 - 73.89\,\beta_l^3 - 4.57\,\beta_{ul} + 52.67\,\beta_{ul}^2 - 191.48\,\beta_{ul}^3$$

$$+ 0.127\,\beta_{tr} + 0.032\,\beta_{tr}^2 - 0.013\,\beta_{tr}^3 \qquad r^2 = 0.997$$

$$[18]\ WaitTUNL = 0.85 - 19.351\,\beta_l + 47.42\,\beta_l^2 + 358.8\,\beta_l^3 + 2.63\,\beta_{ul} + 15.63\,\beta_{ul}^2 + 474.54\,\beta_{ul}^3$$

$$- 0.56\,\beta_{tr} + 0.39\,\beta_{tr}^2 - 0.065\,\beta_{tr}^3 \qquad r^2 = 0.999$$

$$[19]\ IdleTL = 7.75 - 30.55\,\beta_l - 359.47\,\beta_l^2 + 2870.37\,\beta_l^3 + 29.94\,\beta_{ul} - 651.93\,\beta_{ul}^2 + 2731.48\,\beta_{ul}^3$$

$$- 11.06\,\beta_{tr} + 9.25\,\beta_{tr}^2 - 2.28\,\beta_{tr}^3 \qquad r^2 = 0.979$$

$$[20]\ IdleTUNL = 11.16 + 72.87\,\beta_l - 1015\,\beta_l^2 + 6890.66\,\beta_l^3 - 87.9\,\beta_{ul} + 583.90\,\beta_{ul}^2 - 1784.29\,\beta_{ul}^3$$

$$- 9.71\,\beta_{tr} + 5.93\,\beta_{tr}^2 - 1.35\,\beta_{tr}^3 \qquad r^2 = 0.978$$

$$[21]\ No.Trips = 11.63 - 61.83\beta_l - 28.93\beta_l^2 + 1111.11\beta_l^3 + 33.12\beta_{ul} - 1150.94\beta_{ul}^2 + 6041.67\beta_{ul}^3$$

$$- 7.60\beta_{ts} + 8.22\beta_{ts}^2 - 2.01\beta_{ts}^3 \qquad r^2 = 0.989$$

where β_l = parameter (β) of gamma distributed loading time.

β_{ul} = parameter (β) of gamma distributed unloading time.

β_{ts} = parameter (β) of gamma distributed travel speed.

The time elements used in calculation of the total cost according to Equation 12 are given below.

- *Average trucking time* (= travel loaded time + travel empty time). This is estimated based on the hauling distance, d (km) and the estimated parameters (α_{ts}, β_{ts}) of gamma distributed travel speed, as follows:

Average trucking time/trip = $d/[\alpha_{ts}\beta_{ts}] + d/[1.2(\alpha_{ts}\beta_{ts})] + 0.33$

Note: travel empty speed was 1.2 times that for travel loaded and 0.33 hours is time spent for weighing.

- *Average waiting time for trucks at loading zones.* This is estimated from the response equation (Equation 17).

- *Average waiting time for trucks at unloading sites.* This is estimated from the response function (Equation 18).

- *Average loading time.* This is estimated based on estimated parameters (α_l, β_l)

of gamma distributed loading time as follows:

Average loading time/truck load = $\alpha_l\beta_l$.

- *Average idle time for loaders.* This is estimated from response function (Equation 19).

- *Average unloading time.* This is estimated based on estimated parameters (α_{ul}, β_{ul}) of gamma distributed unloading time as follows:

Average unloading time/truck load = $\alpha_{ul}\beta_{ul}$

- *Average idle time for unloaders.* This is estimated from response function (Equation 20).

Another input required for estimation of the total cost according to Equation 12 is the average number of trips per day. This is also estimated from response equation (Equation 21). With the amount of wood to be hauled known (in terms of truck-loads), total number of working days are estimated. This completed all the information required for the calculation of the time elements without a need for simulation. The total cost is then determined relatively easily and quickly by just substituting the posterior mean of β for loading time, unloading time and travel speed into the equations developed above.

4.2. A STEP-BY-STEP SAMPLE CALCULATION FOR ACTION 1

The Bayes posterior means of β based on discrete prior distribution are used for this calculation. Therefore,

$\alpha_l = 20$, $\beta_l = 0.022$, $\alpha_{ul} = 9.77$, $\beta_{ul} = 0.032$, $\alpha_{ts} = 49$ and $\beta_{ts} = 1.428$. For a hauling distance, d of 50 km and 80 km, the average trucking time per trip is given by:

$$\text{Average trucking time/trip} = \{[d_1/[\alpha_{ts}\beta_{ts}] + d_1/[1.2(\alpha_{ts}\beta_{ts})] + 0.33]$$

$$+ [d_2/[\alpha_{ts}\beta_{ts}] + d_2/[1.2(\alpha_{ts}\beta_{ts})] + 0.33]\}/2$$

$$= \{[50/[49 \times 1.428] + 50/[1.2(49 \times 1.428)] + 0.33] + [80/[49 \times 1.428]$$

$$+ 80/[1.2(49 \times 1. 428)]+ 0.33]\}/2$$

$$= 4.07/2$$

$$= 2.04 \text{ hours.}$$

For the calculation of number of trips per day, the 6 values are substituted in Equation 21 above to give,

No. of trips/truck/day = 10.40/5 = 2.08

With this number of trips per day, the average trucking time per day becomes,

Average trucking time/day = (2.04)(2.08)

= 4.24 hours.

By substituting the values of gamma parameters given in Equations 17 and 18 for waiting time for trucks at loading zones and unloading site respectively, the average values are found to be:

Average waiting time at loading zones/day = 0.23 hours.

and average waiting time at unloading site/day = 0.62 hours.

The average loading time/truck load = $(\alpha_l)(\beta_l)$

= (20)(0.022)

= 0.44 hours.

Therefore, average loading time/day becomes

= (0.44 hours/trip)(3.47 trips)

= 1.53 hours.

The average unloading time/truck load = $(\alpha_{ul})(\beta_{ul})$

= (9.77)(0.032)

= 0.31 hours

Then, the average unloading time/day becomes

= (0.31 hours/trip)(10.40 trips)

= 3.22 hours.

Similarly substituting the values of gamma parameters in Equations 19 and 20 for idle times for loaders and unloaders respectively, the average values are found to be:

Average idle time for loaders/day = 4.37 hours.

and Average idle time for unloaders/day = 4.37 hours.

Substituting these estimated average values in Equation 12, the resulting total cost for the operation to take about 17 working days is \$ 43817.50.

4.3. DISCUSSION OF RESULTS OF THE RESPONSE FUNCTIONS ANALYSIS

The response functions developed performed very well in estimating the average waiting times, idle times and number of trips of alternative actions. These average values as well as total cost resulting from this approach were approximately similar with those resulting from simulation analysis (Table 28). From these results it can be suggested that the response functions approach to estimating the average waiting times, idle times and number of trips of alternative actions is effective and can be a better alternative to the rather time-consuming simulation approach.

It is also worth noting that the response functions analysis provides a better understanding with regard to how much of each parameter used (which reflects the capacity of machine used) contributes to waiting or idle times. This provides an immediate understanding of which machines types and combinations (other things being equal) that should be eliminated for further considerations.

Table 28: Output values for action 1 resulting from response functions approach versus those resulting from simulation approach.

Approach	Hours per day							No. of trips	Total working days	Total cost ('000$)
	Trucking time	Waiting time[1]	Waiting time[2]	Loading time	Idle time[3]	Unloading time	Idle time[4]			
Response functions	5.54	0.22	0.39	1.69	3.73	3.57	4.27	11.53	17.25	43.36
Simulation	5.53	0.22	0.33	1.55	3.73	3.24	4.40	11.53	17.65	43.13

[1] waiting time of trucks at loading zones.
[2] waiting time of trucks at unloading sites.
[3] idle time for loaders.
[4] idle time for unloaders.

Chapter 5

OTHER POSSIBLE APPLICATIONS

This chapter is concerned with other possible applications of the Bayesian method that could be investigated in the designing process of an optimal hauling system. Three such possible applications of the method include determining:

(a) the best action based on a policy of allocating trucks to different loading zones.

(b) the best action based on different cost levels charged to the waiting and idle times.

(c) the best action when new equipment is being considered.

It should be noted that these illustrative studies are by no means exhaustive, but are just a few examples of the many potential applications of Bayesian methodology in the designing of optimal hauling systems.

5.1. SIMULATION OUTPUT AND TOTAL COST BASED ON ONE-LOADING ZONE POLICY OF ALLOCATION OF TRUCKS TO LOADING ZONES

In previous simulations for all methods of parameter estimation, the "all-loading zone" policy was applied. For this policy, all available trucks are assigned to all loading zones according to amount of timber in each loading zone. The policy of concern in this section involved assigning all available trucks to a loading zone, and not sending them to the next loading zone until all the wood is hauled. This policy is referred to as "one-loading zone" policy. These policies may have significant effect on the simulation output and therefore on the total cost of the action.

Therefore, the objective of this study was to compare the predictions from two policies for which trucks can be assigned to different loading zones. The comparisons were made using the Bayesian posterior means parameters (based on discrete prior distribution) only.

Using parameter values of gamma distribution estimated using this method of parameter estimation and other input data as described in Sections 3.2.1 and 3.2.2 at the beginning of Chapter 3, the simulation model was run to provide information for computing the total cost according to Equation 12. The simulation output is provided in Appendix VI. The resulting total cost for alternative actions computed are presented in Table 29.

5.1.1. Discussion of the Simulation and Total Cost Results

Tables 8 and 29 represent results of the total cost for alternative actions for "all-loading zones" policy and "one-loading zone" policy respectively (other input data as described in Sections 3.2.1 and 3.2.2 held constant). The results indicate that the optimal action to be different between the two policies. The optimal action for "all-loading zones" policy is 20 trucks, 4 loaders and 2 unloaders; whereas for the "one-loading zone" policy the optimal action is 10 trucks, 3 loaders and 2 unloaders. Also, the results indicate that for both policies, the total costs increased with increasing number of trucks in the system. Furthermore, the results show lower total costs for the "one-loading zone" policy than for the "all-loading zones" policy over all actions considered. For the "one-loading zone" policy, waiting time and idle time are shortened, allowing for trucks to make a few more trips, therefore shortening the total number of working days. This type of information can provide guidelines with respect to the design of harvesting operations, for example, whether to place all harvesting machines in one place or to place them in different parts of the forests. Placing machines in one place might have an added advantage in that it would be easier to coordinate the various phases of harvesting operations as opposed to scattering the equipment over different regions of the timber reserves.

To determine the effect on total costs between policy 1 and policy 2, percentage difference is calculated. The percentage difference is calculated as follows:

Let $E(Cost_1)$ be the total cost of each action resulting from adopting policy 1. Similarly, $E(Cost_2)$ is the total cost of each action resulting from adopting policy

2. Then the percentage difference is calculated from the following formula:

$$\%Diff. = \frac{ABS\left[E(Cost_1) - E(Cost_2)\right]}{E(Cost_2)} \times 100$$

The resulting percentage differences are summarized in Table 30. The percentage difference values do not appear to follow any particular pattern. However, the percentage difference values associated with actions with high numbers of trucks (i.e., 20) are significantly lower than the ones associated with actions with small numbers of trucks (i.e., 5 or 10). This indicates the difference between the two policies to be more important for actions with small numbers of trucks than the ones with large numbers of trucks.

Table 29: Total cost of alternative actions based on "one-loading zone" policy with posterior means of parameters based on discrete prior distribution equal to: α= 20 and β= 0.022 for loading time, α= 9.77 and β= 0.032 for unloading time, and α= 49 and β= 1.428 for travel speed.

ACTIONS	Total cost ('000\$)[1]
5, 3, 1	39.47
5, 3, 2	41.62
5, 4, 1	43.28
5, 4, 2	45.32
5, 5, 1	47.79
5, 5, 2	48.59
10, 3, 1	39.05
10, 3, 2*	34.53
10, 4, 1	41.96
10, 4, 2	36.27
10, 5, 1	45.25
10, 5, 2	38.49
20, 3, 1	50.83
20, 3, 2	35.10
20, 4, 1	52.49
20, 4, 2	35.52
20, 5, 1	54.55
20, 5, 2	36.82

[1] total cost incurred for hauling 200 truck-loads.

* action with minimum total cost.

Table 30: Percentage difference in total costs associated with "all-loading zones" and "one-loading zone" policies.

ACTIONS	% Difference in Total Cost by the two policies Bayesian approach based on discrete prior
5, 3, 1	10.97
5, 3, 2	20.54
5, 4, 1	11.60
5, 4, 2	15.36
5, 5, 1	9.62
5, 5, 2	13.96
10, 3, 1	5.51
10, 3, 2	15.31
10, 4, 1	4.50
10, 4, 2	14.24
10, 5, 1	2.05
10, 5, 2	13.22
20, 3, 1	5.66
20, 3, 2	7.10
20, 4, 1	3.33
20, 4, 2	5.36
20, 5, 1	2.33
20, 5, 2	4.24

5.2. SIMULATION OUTPUT AND TOTAL COST BASED ON A POLICY FOR COSTING WAITING OR IDLE TIMES OF TRUCKS

Sometimes the costs of machine waiting or idle time may be charged at a lower rate compared to that of productive time. In this demonstration, five levels of waiting time cost and six levels of idle time cost including the ones used in all previous simulations are examined for only Bayesian posterior means of parameters based on discrete prior distribution and "all-loading zones" policy of assigning trucks to loading zones. The five levels of waiting time costs considered are: $40 per hour, $30 per hour, $20 per hour, $10 per hour and $0 per hour, and the six levels of idle time costs considered are: $50 per hour, $40 per hour, $30 per hour, $20 per hour, $10 per hour and $0 per hour.

In this analysis, only the cost of waiting time (TC_i), cost of idle time for loaders (TC_j) and cost of idle time for unloaders (ULC_j) in total cost equation (Equation 12) are changed. Therefore, based on the simulation output in Table 7, the resulting total costs for the different levels of waiting time cost and idle time cost calculated are as presented in Table 31 and Table 32 respectively.

Table 31: Total cost for different levels of waiting time cost for "all-loading zone" policy with posterior means of parameters based on discrete prior distribution equal to: α= 20 and β= 0.022 for loading time, α= 9.77 and β= 0.032 for unloading time,0 and α= 49 and β= 1.428 for travel speed.

ACTIONS	Total cost ('000$)[1]				
	Waiting cost ($ per hour)				
	40	30	20	10	0
5, 3, 1	43.80	43.30	42.81	42.31	41.81
5, 3, 2	50.16	49.89	49.62	49.35	49.08
5, 4, 1	48.30	47.84	47.38	46.92	46.46
5, 4, 2	52.28	52.19	52.11	52.02	51.93
5, 5, 1	52.38	51.92	51.45	50.98	50.51
5, 5, 2	55.37	55.29	55.22	55.14	55.06
10, 3, 1	41.20	39.77	38.34	36.92	35.49
10, 3, 2	39.81	39.29	38.76	38.23	37.71
10, 4, 1	43.94	42.56	41.18	39.81	38.43
10, 4, 2	41.44	40.96	40.49	40.01	39.52
10, 5, 1	46.18	44.84	43.50	42.17	40.83
10, 5, 2	43.58	43.11	42.63	42.16	41.68
20, 3, 1	53.70	48.36	43.01	37.67	32.32
20, 3, 2	37.59	35.95*	34.32*	32.69*	31.05*
20, 4, 1	54.23	49.08	43.93	38.78	33.63
20, 4, 2	37.42*	36.08	34.74	33.40	32.06
20, 5, 1	55.82	50.62	45.42	40.21	35.01
20, 5, 2	38.38	37.08	35.79	34.49	33.20

[1] total cost incurred for hauling 200 truck-loads.

* minimum total cost.

Table 32: Total cost for different levels of idle time cost for "all-loading zone" policy with posterior means of parameters based on discrete prior distribution equal to: α= 20 and β= 0.022 for loading time, α= 9.77 and β= 0.032 for unloading time, and α= 49 and β= 1.428 for travel speed.

ACTIONS	Total cost ('000$)[1]					
	Idle cost ($ per hour)					
	50	40	30	20	10	0
5, 3, 1	43.80	41.07	38.34	35.59	32.86*	30.12
5, 3, 2	50.16	46.10	42.05	37.99	33.93	29.87
5, 4, 1	48.30	44.62	40.93	37.25	33.57	29.89
5, 4, 2	52.28	47.56	42.84	38.12	33.40	28.68
5, 5, 1	52.38	47.87	43.35	38.83	34.31	29.80
5, 5, 2	55.37	49.93	44.49	39.04	33.60	28.16*
10, 3, 1	41.20	39.93	38.65	37.38	36.10	34.83
10, 3, 2	39.81	38.13	36.45	34.77*	33.09	31.41
10, 4, 1	43.94	42.14	40.34	38.54	36.74	34.94
10, 4, 2	41.44	39.36	37.28	35.20	33.12	31.04
10, 5, 1	46.18	43.87	41.55	39.24	36.93	34.62
10, 5, 2	43.58	41.08	38.58	36.07	33.57	31.06
20, 3, 1	53.70	53.19	52.68	52.17	51.66	51.15
20, 3, 2	37.59	37.10	36.62	36.13	35.65	35.16
20, 4, 1	54.24	53.38	52.53	51.67	50.82	49.96
20, 4, 2	37.42*	36.74*	36.07*	35.39	34.71	34.03
20, 5, 1	55.82	54.64	53.46	52.28	51.10	49.92
20, 5, 2	38.38	37.46	36.55	35.64	34.72	33.81

[1] total cost incurred for hauling 200 truck-loads.

* minimum total cost.

5.2.1. Discussion of the Simulation and Total Cost Results

The results appear in Tables 31 and 32. The effect on total cost for a given number of combination of equipment over the range of waiting time cost can be observed in Fig. 10. The actions arbitrarily selected for the comparison are (20, 4, 2), the optimum action when the cost of waiting time is \$40 per hour and (20, 4, 1). Results in Table 31 and in Fig. 10 illustrate a decrease in total cost when waiting time cost decreases. This decrease is more pronounced in hauling systems with 1 unloader (e.g., action - 20, 4, 1) which are characterized by long waiting times. Also, according to Table 31, the optimum solution seems to be affected by changes in waiting time. For example, the optimum action is 20 trucks, 4 loaders and 2 unloaders for waiting time cost at \$40 per hour. But, the optimum action is 20 trucks, 3 loaders and 2 unloaders for waiting time cost at \$0 per hour, \$10 per hour, \$20 per hour and \$30 per hour. Similarly, the total costs tend to decrease as idle time cost decreases, and the decrease is more pronounced in hauling systems with low number of trucks (e.g., 5 trucks) which are characterized by long idle times. Also, the optimum action seems to be affected by changes in idle times as shown in Table 32.

These results may not be surprising because of a wide range in waiting times for different actions especially for those with only 1 unloader in the system (see Table 7). In this example, the optimum action (20 trucks, 4 loaders and 2 unloaders) when the charge for waiting time is high (i.e., \$40 per hour) corresponds to a waiting time of 1.42 hours per day, but the optimum action changed to 20 trucks, 3 loaders and 2 unloaders when there is no charge for waiting time corresponds to waiting time of 1.63 hours per day.

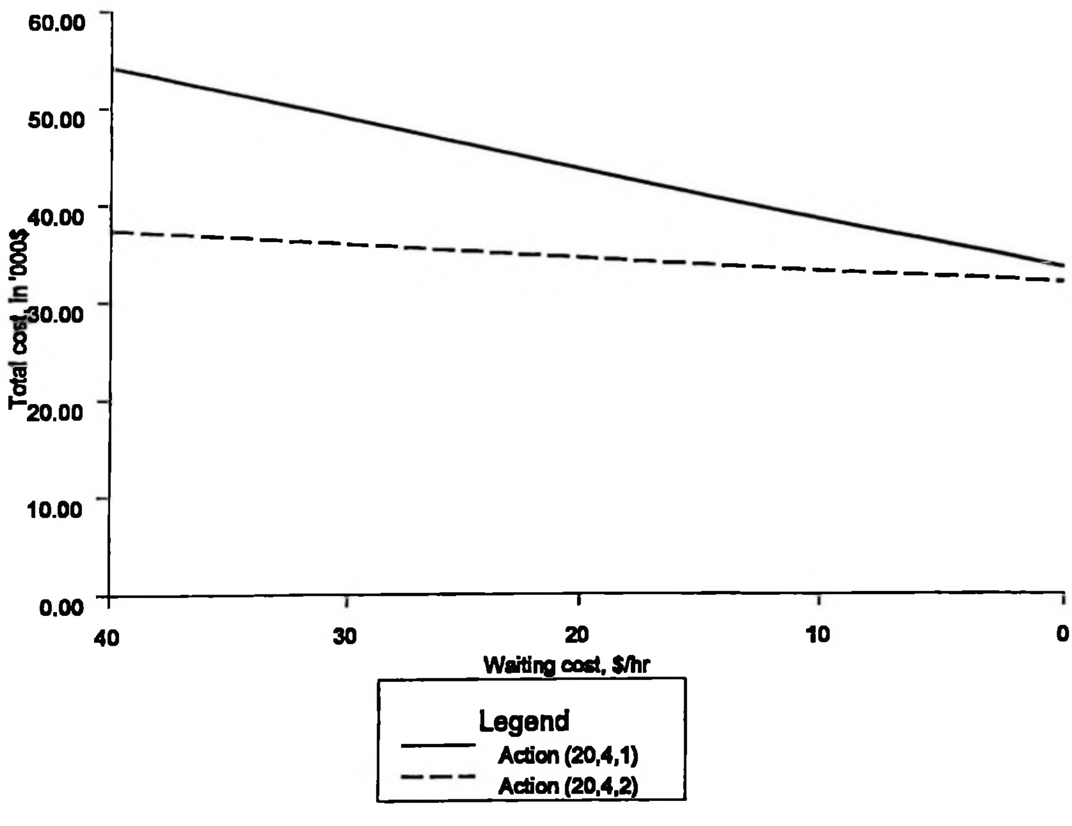

Fig. 10: Comparison of total costs as related to various waiting time costs based on Bayes posterior means (with discrete prior).

5.3. SIMULATION OUTPUT AND TOTAL COST WITH A DIFFERENT UNLOADING MACHINE

In the previous simulations employing Bayesian posterior means with discrete priors for unloading time, parameters α and β of 9.77 and 0.032 respectively were used, meaning that the average unloading rate was about 0.31 hours per load. The simulation output and the total costs resulting from the simulation are as reported in Tables 7 and 8 respectively. The optimal action was determined to be 20 trucks, 4 loaders and 2 unloaders. In this application, a slower unloading machine is used but the loaders and trucks are kept the same. An unloading rate of about 0.36 hours per load (i.e., where parameters α and β are estimated to be 9.77 and 0.037 respectively) is examined.

Using these parameter values of gamma distribution for unloading time and α = 20 and β = 0.022 for loading time and α = 49 and β = 1.428 for travel speed as used before and other input data as described in Sections 3.2.1 and 3.2.2 at the beginning of Chapter 3, the simulation model was run to provide information for computing the total cost according to Equation 12. The simulation output is provided in Appendix VII. The resulting total cost for alternative actions computed are presented in Table 33.

Table 33: Total cost of alternative actions based on a different unloading machine with posterior means of parameters based on discrete prior distribution equal to: α= 20 and β= 0.022 for loading time, α= 9.77 and β= 0.037 for unloading time, and α= 49 and β= 1.428 for travel speed.

ACTIONS	Total cost ('000$)[1]
5, 3, 1	44.44
5, 3, 2	49.42
5, 4, 1	49.26
5, 4, 2	51.85
5, 5, 1	53.76
5, 5, 2	54.96
10, 3, 1	44.48
10, 3, 2	41.02
10, 4, 1	47.68
10, 4, 2	42.52
10, 5, 1	50.84
10, 5, 2	44.51
20, 3, 1	59.57
20, 3, 2*	40.07
20, 4, 1	61.70
20, 4, 2	41.27
20, 5, 1	62.60
20, 5, 2	41.77

[1] total cost incurred for hauling 200 truck-loads.

* action with minimum total cost.

5.3.1. Discussion of Simulation and Total Cost Results

The results reported in Appendix VII and in Table 33 show different simulation output and total costs from those reported in Tables 7 and 8. See, for example, the difference in waiting time at the unloading site between the two configurations. The long waiting times resulting from using a slower unloading machine for this application are quite evident. In addition, the resulting optimal action is 20 trucks, 3 loaders and 2 unloaders as opposed to 20 trucks, 4 loaders and 2 unloaders determined in previous application. Again this shows the usefulness of this method in analyzing different operational settings for purposes of designing optimal hauling systems.

Chapter 6

PROBABILISTIC APPROACH VERSUS DETERMINISTIC APPROACH: FURTHER SIMULATION STUDY

6.1. INTRODUCTION

The simulation method used in this thesis was based on the use of probability distributions to represent the trucking activities as opposed to using deterministic average values. Table 20 shows the optimal actions for the probabiliy-based methods and the deterministic methods. It can be noted from Table 20 that the optimal deterministically derived actions are not very different from the probability based actions. It could perhaps be argued that since using deterministic averages do not result in very different cost outcomes (especially if small samples are used as shown in Table 19 and Appendix III), determinism's greater simplicity would justify using it in designing hauling systems. In fact, throughout much of forestry, deterministic averages are used for this very reason. Typical data used in forestry are average tree size (m^3/stem), average radial diameter growth (cm/year), average volume growth (m^3/ha/year), average productivity (m^3/pmh or ha/pmh), average unit wood cost ($\$/m^3$), average stand age (years), and so on. Though taking this approach is often appropriate in forestry, it is not appropriate in the design of hauling systems. In the examples given above the values are essentially independent from one another. Average volume growth (m^3/ha/year), for example, is not specified in the context of an inter-dependent system where another component must be coordinated with it. In harvesting systems this component interdependence exists, but is assumed to be satisfied, so that, for example, a delimber with a capacity of 30 m^3/pmh is assumed to have sufficient wood available at roadside. By having a sufficient buffer of wood between each machine in the system, waiting due to wood shortages is minimized. However, a hauling system is a queueing system where several pieces of equipment must be coordinated and must function together. In this context independent average values are meaningless. If a loader has an average productive capacity of 25 m^3/pmh, yet has no trucks available to load, that production figure is meaningless.

Depending on the specific parameters of the hauling system in question, the difference in outcome between taking a deterministic approach or taking a probabilistic approach will vary. In the example given in Table 20, the difference was not very great. There is no *a priori* way to determine if the difference in outcome will be substantial or not. If a continued reliance is made on a deterministic approach in designing hauling systems, sooner or later the decisions made will deviate substantially from the decision that would have been made had a probabilistic approach been adopted. To illustrate this, a comparison (in addition to the one provided already in Section 3.3.2 of Chapter 3) between using determinism or using probability is provided to demonstrate the substantial deviations that can be encountered between the two basic approaches.

6.2. DESCRIPTION OF THE SIMULATED SYSTEM AND INPUT DATA

This analysis was conducted on a hauling system, in which, to maintain simplicity, there was only one action (5 trucks, 1 loader and 1 unloader), one loading zone with 300 truckloads of wood, 50 km away from the mill. The detailed description of the simulation and the rest of the input data are the same as that provided at the beginning of Chapter 3. The output for a Bayesian probability-based simulation with parameters α and β the same as that in Section 3.3 - Case 1, and the classical probability-based simulation with parameters α and β the same as those given in Table 17 are contrasted with a deterministic simulation in which the average values were calculated from a small sample (those given in Section 3.3.1.1 in Chapter 3). The total cost was calculated as in the proceeding chapters using Equation 12.

6.3. RESULTS AND DISCUSSION

The results of this analysis are presented in Table 34. As seen from Table 34, there is a large difference in the output and cost between the two probability-based approaches and the deterministic one. In this case, the deterministic approach overestimated the cost of the hauling operation by about 20%. As can be seen, determinism has the potential to greatly miscalculate waiting and idle times in a queueing system. The possible error that could result from selecting an 'optimum' system based on these deterministic results could be serious.

Table 34: Simulation Output and Cost for action (5,1,1) based on the probabilistic simulation approach versus those that are based on simulation with deterministic values approach.

Approach	Hours per day									
	Trucking time	Wait time[1]	Wait time[2]	Loading time	Idle time[3]	Unload time	Idle time[4]	No. of trips	Total working days[5]	Total cost[6] ('000$)
Probabilistic simulation										
- Bayes approach	6.77	1.14	0.10	6.55	0.79	7.66	3.57	14.27	21.00	43.43
- Small sample	6.75	1.19	0.11	6.65	0.94	7.72	4.11	13.63	22.00	45.58
Non-probabilistic simulation										
- Small sample	6.93	1.97	0.00	7.01	0.53	7.72	3.69	12.00	25.00	53.42

[1] waiting time of trucks at loading zones.
[2] waiting time of trucks at unloading sites.
[3] idle time for loaders.
[4] idle time for unloaders.
[5] total number of days required for hauling 300 truck loads.
[6] total cost incurred for hauling 300 truck loads.

Chapter 7

CONCLUSION

7.1. SUMMARY AND CONCLUDING REMARKS

The current study on the application of the Bayesian methods for the optimal design of hauling systems under conditions of uncertainty and risk has been detailed in the previous chapters and will now be summarized.

The problems encountered in the process of designing optimal hauling systems were identified by qualitatively analyzing all the factors affecting system performance in a timber hauling situation, and by surveying available literature on studies related to design decisions of hauling systems. The major shortcomings of the current approaches are the inability to incorporate both natural and parameter uncertainties in the model inputs, and the inability to incorporate risk in decision-making. The objective was therefore to develop and demonstrate a methodology that incorporates natural and parameter uncertainties and risk using the Bayesian decision-making approach into a decision model framework for selecting the "best" hauling system. "Best" means the optimum combination of trucks, loaders and unloaders to achieve minimum cost for a certain amount of wood to be hauled. The "minimum cost" is expressed in both monetary values and utility values.

A general method was presented in Chapter 2 and its application in Chapters 3, 4 and 5. The method can be summarized as follows. First, an application was made in which hauling operations were represented by a queueing model. The inputs to the model were categorized into actions, input constants, probability distributions of loading time, unloading time, travel loaded and travel empty speeds, and parameters of the probability distributions. The actions under the control of the hauling manager consisted of the number of trucks, loaders and unloaders to select for the hauling operation. The parameters of the probability distributions, were estimated by using both the Bayesian and classical methods of parameter estimation. The constants, under the control of the forest manager (i.e., assumed that they, could be estimated relatively accurately), were: costs per hour (for truck, loader and unloader), number of loading zones, distance to each loading zone (km), quantity of wood to be moved from each zone (in unit of truck-loads), shift duration (hours), overtime limit (hours) and overtime payment rate.

Second, the simulation output was converted to cost of the operation using a total cost formula. Then in order to proceed with the decision-making process, the cost values were presented in decision table form and later converted to utility values by use of the postulated utility function. The decision criteria for determining which hauling system was optimal were the total expected cost and total expected utility.

Finally, response functions were developed as alternatives to long computer simulation runs. The response functions estimate the average waiting and idle times, and the number of trips for each action in which the values of parameters of the input probability distributions for loading times, unloading times and travel speeds are the independent variables. The response functions proved to be very accurate and effective.

Some of the important findings and conclusions that can drawn from this thesis are:

(1) ***Determination of Input Probability Distributions***:

By using time study data supplied by the Forest Engineering Research Institute of Canada (FERIC) for loading, travel loaded, unloading and travel loaded times, the gamma distribution was found to fit well all the data sets. The normal distribution, most often used to generate random loading, unloading and travel times (such as Routhier, 1974) or exponential distribution used in queueing models for loading or unloading (such as McNickle and Woollons, 1990; Koger, 1992) were shown to be inappropriate for these variables.

(2) ***The Estimation of Parameters of the Input Probability Distributions:***

(i) Concerns that parameter uncertainty might affect the design of optimal hauling systems was confirmed by both theoretical and empirical analyses. When applied to the particular hauling situation presented in this study, the Bayesian approach resulted in a quite different optimal hauling system from that of the classical approach with small sample statistics alone. The classical approach always overestimated the parameter values, resulting in different total expected cost values. Comparing the Bayesian estimation method and the classical case with large sample, it was shown that they both led to the same optimum solution. This demonstrated that when sample data is small, Bayesian estimation methods are better in reducing parameter uncertainty than the classical estimation methods which rely on sample data alone.

(ii) There was no significant difference in optimal hauling systems for the Bayesian approach between the different prior distributions used. Further examination on the effect of other possible prior distributions on Bayesian analysis is required before a definitive conclusion can be drawn.

(3) *Utility Analysis*:

The decision maker's attitude toward risk was pursued through utility analysis. A risk-averse and a risk-preference utility function was used to define manager's preference scale for different outcomes. Utility analysis showed that decisions made when risk is taken into consideration are quite different from those that would result based on expected payoff.

(4) Comparison of simulation output and costs between a probabilistic approach and a deterministic approach

A simulation study conducted showed that simulation output and cost were different between the two approaches, indicating a danger in basing hauling system decisions on deterministic values.

7.2. RECOMMENDATIONS FOR FUTURE WORK

The aim of this thesis has been to incorporate the knowledge of a field of statistics that has not yet been introduced into forestry operations and to demonstrate theoretically the possibilities that this statistical approach can yield for forestry operations research. This thesis has demonstrated that Bayesian statistics and decision analysis can be successfully incorporated in a forest operation context and can lead to improved decisions over that of the classical approaches. Due to time constraints, typical subjective prior probabilities for parameter estimates were assumed, rather than determined from actual field interviews. Likewise, typical risk-averse and risk-accepting utility curves were also assumed. Continuing from where this study ends, further research should obtain actual subjective prior probabilities for parameter estimates from local "experts". Other posssible research advances, refinements and other areas of application are summarized below.

The determination of total cost of alternative hauling systems should be expanded to include the effects of other real-life phenomena such as the duration and interval of machine breakdowns and breaks, machine maintenance programs, "shift-level" decisions (i.e., staggering start times of truck shifts so that the queueing is minimized, number of shifts), co-ordinated harvesting and hauling activities, and development of new machine prototypes. In all these cases, "expert" estimates of expected values and variances can be obtained from similar already-existing policies and machines to allow new alternative hauling systems to be evaluated.

This study has not considered the different investment levels that would be required to support the different combinations of equipment required. Further study should consider the effect of investment required on the decision alternatives.

Furthermore, a thorough investigation involving more sophisticated applications utilizing alternative assumptions for posterior analysis for cases where both scale and shape parameters of gamma distribution are unknown should be done. This is important to determine under what circumstances the parameter uncertainty should be recognized explicitly.

The fact that more and more hauling is done by hauling contractors in Eastern Canada implies that the Bayesian decision-making with expected utility would have more potential than the decision-making based solely on expected cost. Because of this, a further examination of Bayesian decision-making with expected utility from extensive field studies on a broader scale is worth examination. Results from research in this direction should provide more definitive answers to questions on the extent of risk-averseness and risk-proneness of different contractors and also should uncover useful interview techniques that will allow researchers to draw out the utility curves from managers (whether contractors or corporate managers) in the industry. This would verify whether attitudes to risk vary among contractors and professional managers as has been argued in this thesis.

It is also possible that the benefits of the Bayesian statistics and decision-making as demonstrated for determining the optimal hauling systems be extended to other forest operations activities, such as harvesting. This is because: (i) all logging activities are generally probabilistic in nature due to operating conditions in the natural environment

(ii) all logging activities are also characterized by little or no sample data, which leads to parameter uncertainties (iii) the logging industry is characterized by "local experts" who can readily estimate local conditions (iv) the logging industry is wide-ranging in terms of organizations involved: from very large multi-national corporations to small family owned operations. The sector is also very cyclical with 'boom' and 'bust' periods. Thus there will be distinctly differing attitudes to uncertainty and risk throughout the industry and through the cycles. Bayesian decision-making will accomodate this complexity.

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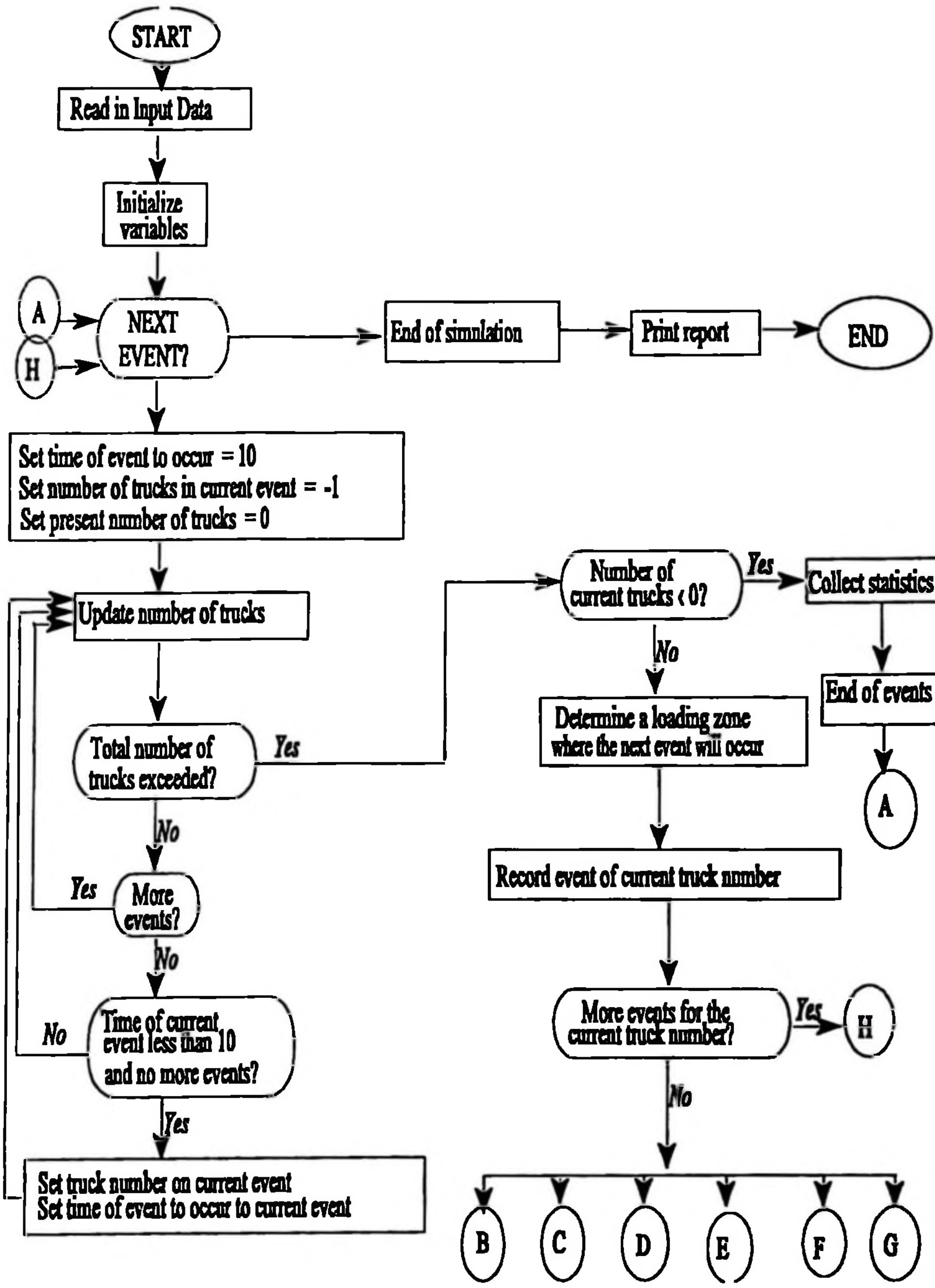
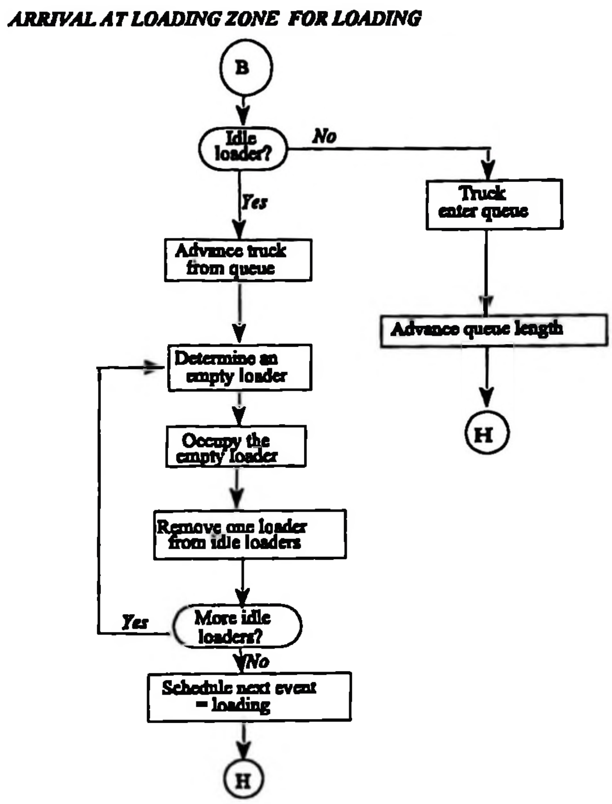
APPENDICES

APPENDIX Ia

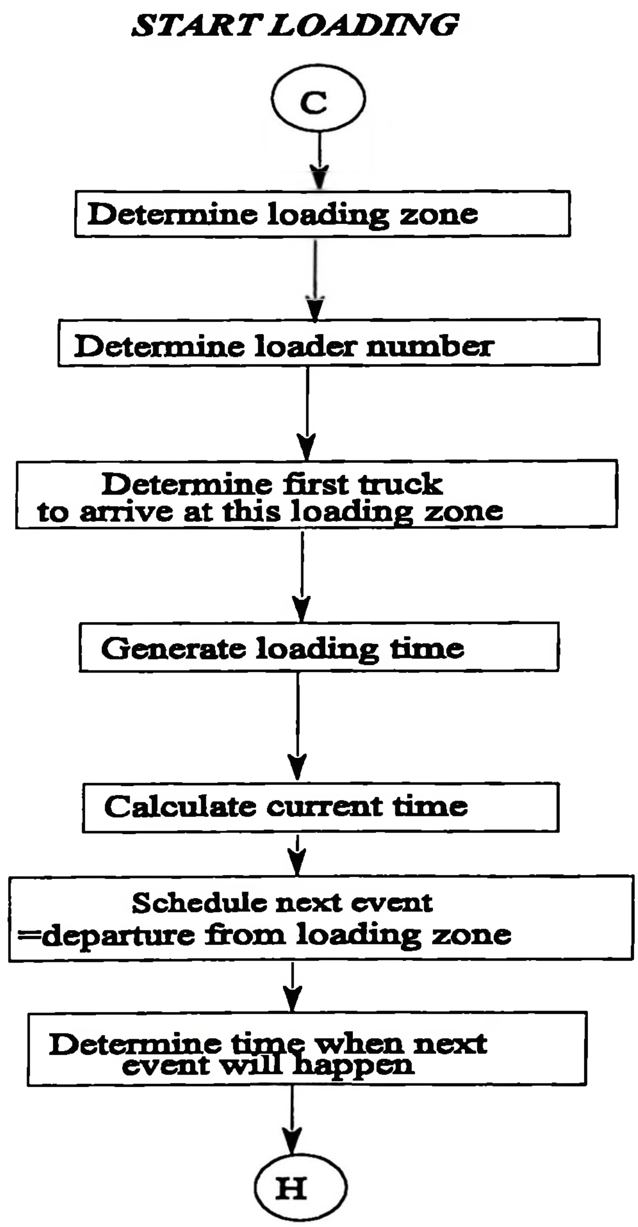
A FLOWCHART OF THE SIMULATION PROGRAM IN GENERAL TERMS



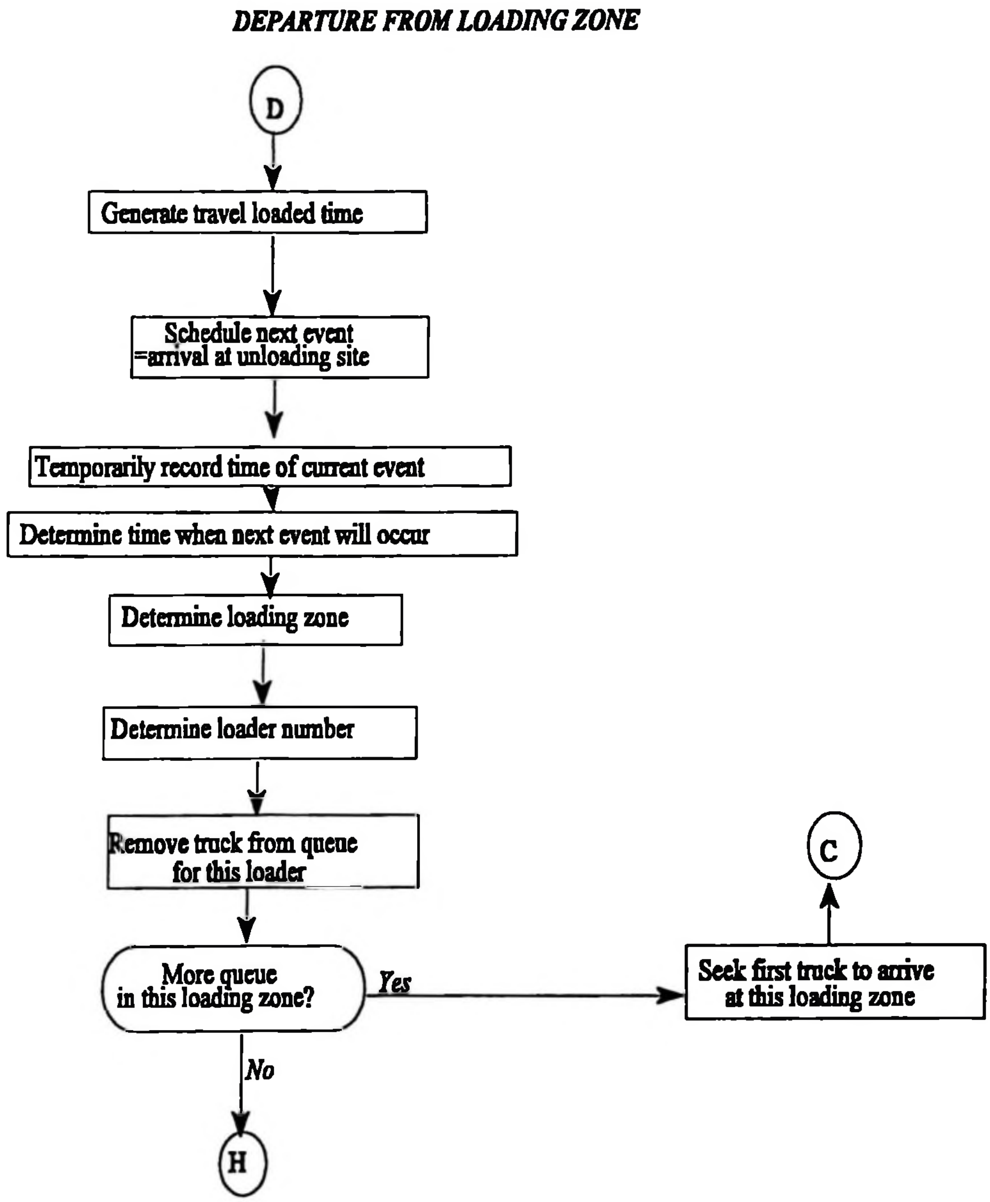
Appendix Ia. (Continued)



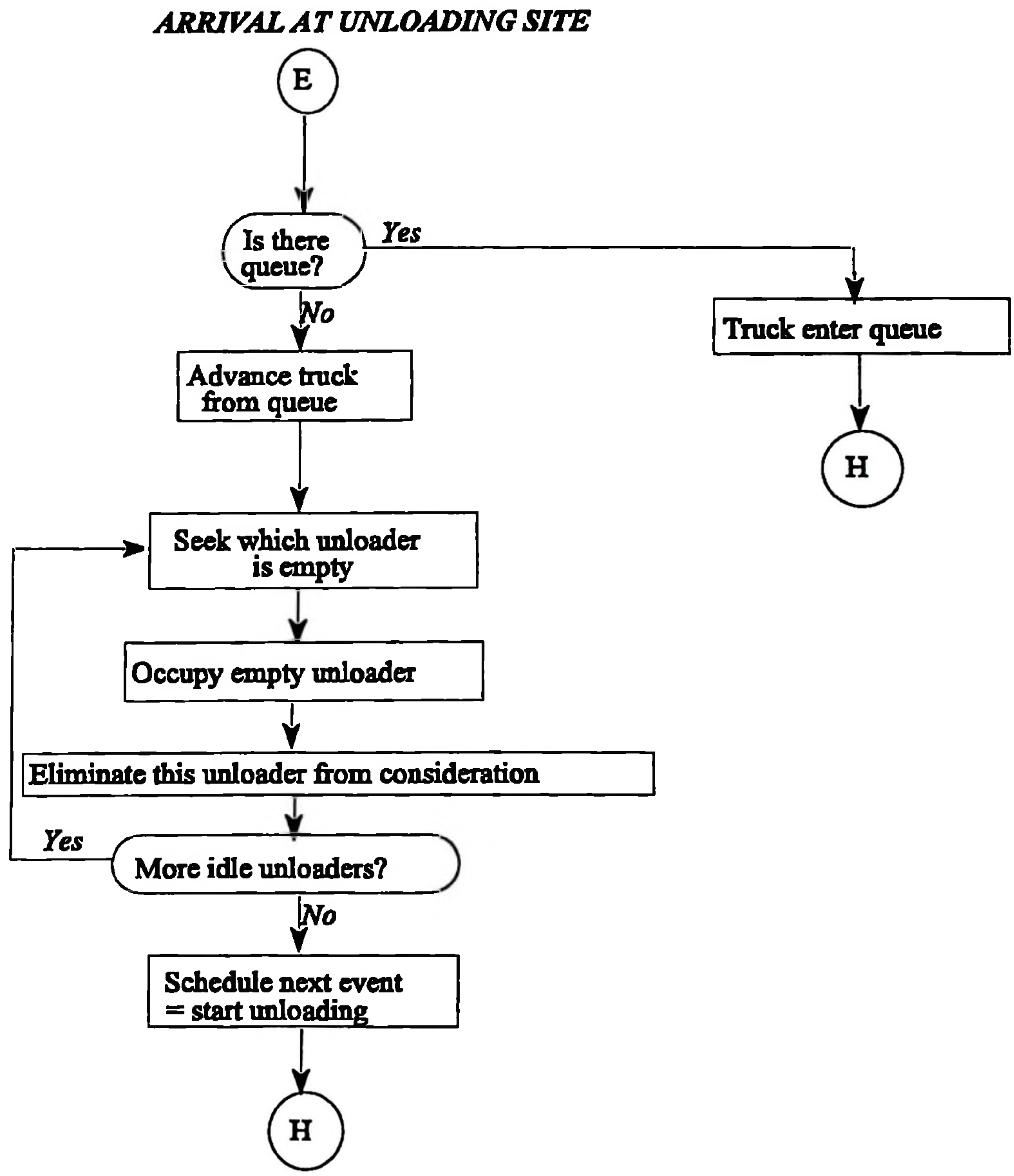
Appendix Ia. (Continued)



Appendix Ia. (Continued)

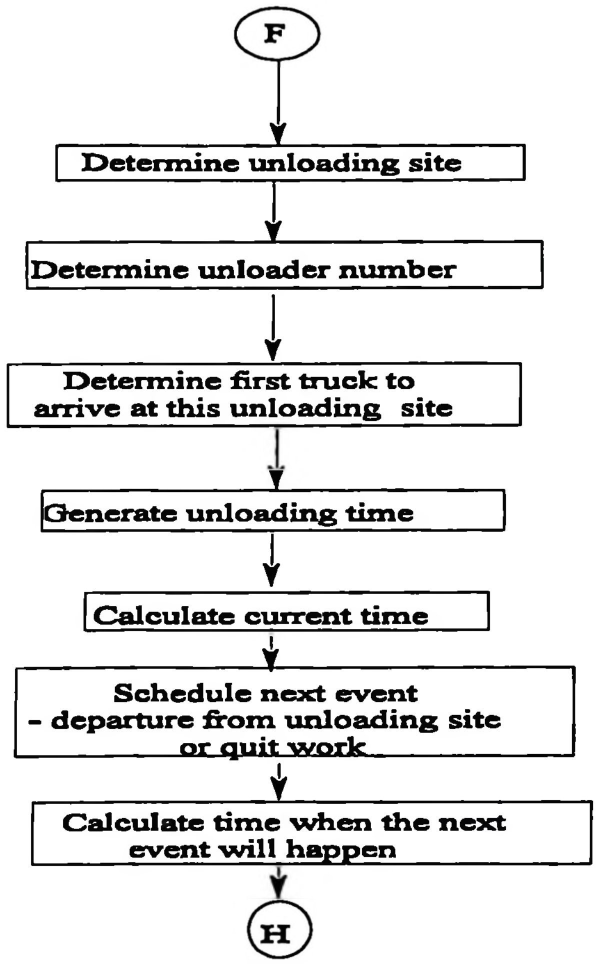


Appendix Ia. (Continued)

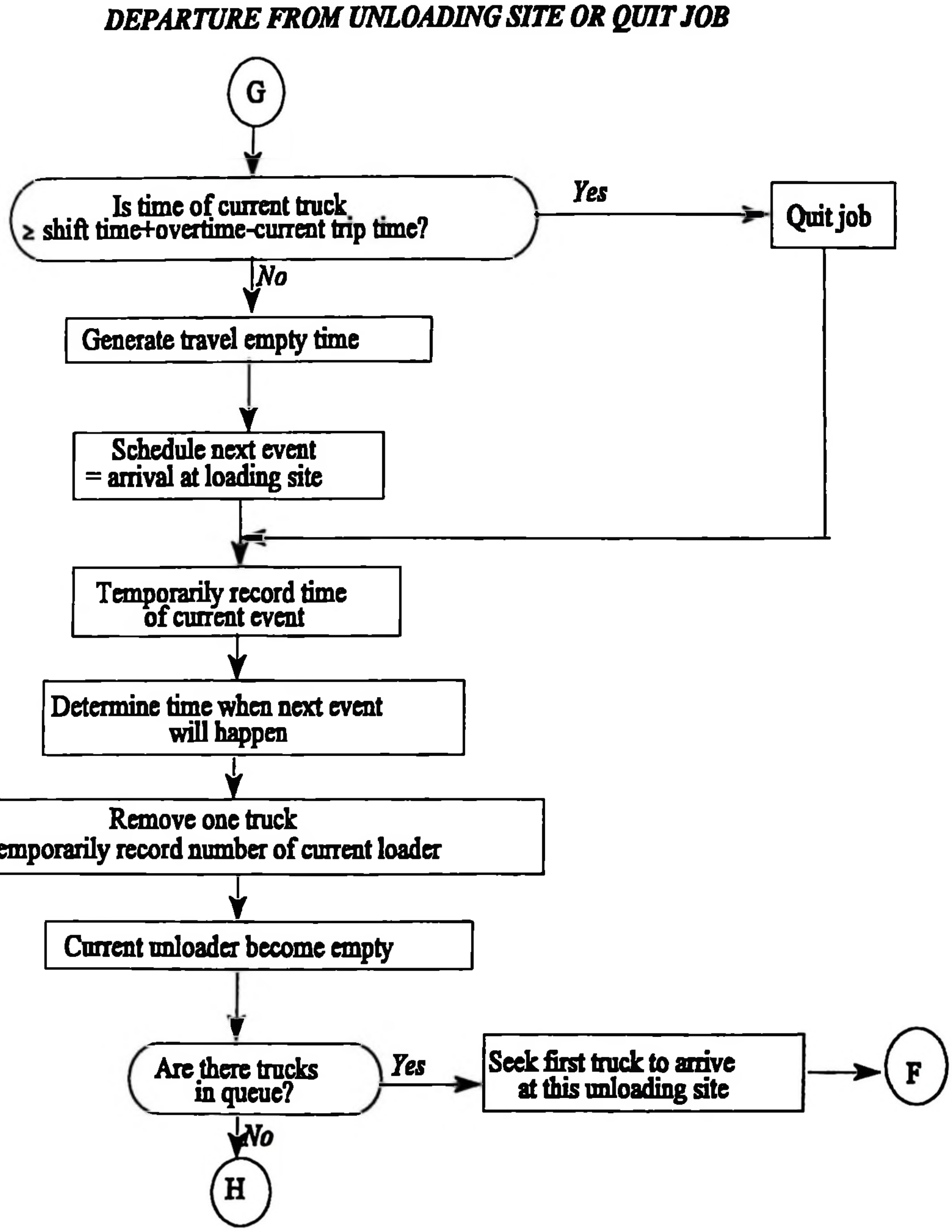


Appendix Ia. (Continued)

START UNLOADING



Appendix Ia. (Continued).



APPENDIX Ib

COMPUTER PROGRAM

```
@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@
@                                            @
@                                            @
@ THIS COMPUTER SIMULATION PROGRAM WRITTEN IN GWBASIC @
@   IS USED TO SIMULATE AND ANALYSE A QUEUEING SYSTEM  @
@ FOR TIMBER HAULING OPERATIONS - LOADING, HAULING AND @
@   UNLOADING, AND IT ACCOUNTS FOR ANY QUEUEING THAT   @
@     MAY TAKE PLACE AT LOADING AND UNLOADING POINTS   @
@                                            @
@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@
```

```
10 DIM EVENT(400,3),LDLEN(5),START(5,50),DIST(5),LMD(10,1),TRUCK(5),
     LOADER(5)
20 DIM ILOADER(5,50),EVESEQ(800,3),TTL(5),TTE(5),ATT(5),ATT2(5),
     TRIPTIME(5), GROSS(5),D$(12)
30 DIMDAYTRUCK(50,4),DAYLOAD(20,3),DAYUNLOAD(20,3),
     JOBTRUCK(100,4),JOBLOAD(100,3),JOBUNLOAD(100,3)
35 DIM VT(25),LT(25),UT(25):REM number of simulations for truck speed, loading
     time,unloading time
40 DIM AT(25),AL(25),AU(25),RR(5),WWE(3)
-----------------------------------------------------------------------------

75 REM: MAIN PROGRAM
110 Rem: Initial values
400 TITLE$=" job  trucks loaders unloaders truck-V   load-T   unload-T
     daytrips wait-ld wait-unld  loadidle unloadidl   trkwkT  trkovT
     loadwkT loadovT  unldwkT  unldovT cost*1000:   costtrk   costload
     costunld"
450 GOSUB 2000
460 GOSUB 2500
470 GOSUB 2700
480 GOSUB 3500
-----------------------------------------------------------------------------

500 Rem: Main Menu
510 CLS
511 IF T1$<>"" THEN PRINT "duration of running:";T1$+"-"+T2$
512 PRINT "":PRINT    "----- main menu -----":PRINT""
520 PRINT "     0. exit"
530 PRINT "     1. input constants"
540 PRINT "     2. input parameters of distributions"
550 PRINT "     3. input actions"
```

```
560 PRINT "     4. name result files"
570 PRINT "     5. run simulation"
580 PRINT "     6. print result files or parameters"
585 PRINT "     7. make and print outcome tables"
590 INPUT "please select number of your choice";CH$:IF CH$="" THEN GOTO
      590 ELSE CH=ASC(CH$)-48
600 IF CH>7 OR CH<0 THEN GOTO 590
610 CH=INT(CH):T1$=""
620 IF CH=0 THEN GOTO 800
630 IF CH=1 THEN GOSUB 2140:GOTO 450
650 IF CH=2 THEN GOSUB 2600:GOTO 450
660 IF CH=3 THEN GOSUB 2840:GOTO 450
680 IF CH=4 THEN GOSUB 3560:GOTO 450
690 IF CH<>5 THEN GOTO 720
710 GOSUB 1000:CLEAR:GOTO 400
720 IF CH=6 THEN GOSUB 25000:GOTO 510
730 IF CH=7 THEN GOSUB 35000:GOTO 510
800 END
```

```
1000 REM: JOB REPEAT SUBROUTINE
1002 INPUT "how many days to be simulated";TOTALDAYS:JOBCOUNT=0
1003 IF TOTALDAYS<=0 THEN GOTO 1360
1004 INPUT "random seed=";SEED:RANDOMIZE (SEED)
1005 OPEN "o",#2,NAMESUM$:PRINT #2," summary file name=";NAMESUM$;
      " days of simulation=";TOTALDAYS:PRINT #2,TITLE$
1006 IF EVEREP$="Y" THEN OPEN "o",#3,NAMEEVE$
1007 IF DAYREP$="Y" THEN OPEN "o",#4,NAMEDAY$
1008 IF JOBREP$="Y" THEN OPEN "o",#5,NAMEJOB$
1009 GOSUB 2700
1010 FOR IA1=1 TO ATRUCK
1020 FOR IA2=1 TO ALOAD
1030 FOR IA3=1 TO AUNLD
1040 FOR IS1=1 TO STRUCK
1050 FOR IS2=1 TO SLOAD
1060 FOR IS3=1 TO SUNLD
1065 JOBCOUNT=JOBCOUNT+1
1070 FOR I=0 TO TOTALDAYS:FOR J=0 TO 4:JOBTRUCK(I,J)=0: NEXT J:
```

```
      FOR J=0 TO 3:JOBLOAD(I,J)=0:JOBUNLOAD(I,J)=0:NEXT J:NEXT I
1095 VE=1.2*53*VT(IS1):VL=53*VT(IS1)
1100 LMD(1,0)=22*LT(IS2):LMD(0,0)=10*UT(IS3)
1110 UNLOADER=AU(IA3):NTRUCK=AT(IA1):NLOADER=AL(IA2)
1140 GOSUB 22000:REM assignment of trucks and loaders to each loading zone
1150 IF EVEREP$="Y" THEN PRINT #3,"* * * job(";JOBCOUNT;"):trucks=";
      NTRUCK;" loaders=";NLOADER;" unloaders=";UNLOADER;" truck
      speed=";VL;" loading time=";LMD(1,0);"unloading time="; LMD(0,0);"* **"
1152 IF DAYREP$="Y" THEN PRINT #4,"* * * job(";JOBCOUNT;"):trucks=";
      NTRUCK;" loaders=";NLOADER;" unloaders=";UNLOADER;" truck
      speed=" ;VL;"loading time="LMD(1,0);"unloading time="; LMD(0,0);"* * *"
1160 PRINT "* * * job(";JOBCOUNT;"):trucks=";NTRUCK;"loaders=";
      LOADER;" unloaders=";UNLOADER;" truck speed=";VL;" loading
      rate=";LMD(1,0);" unloading rate=";LMD(0,0);"* * *"
1200 GOSUB 1500
1300 NEXT IS3
1310 NEXT IS2
1320 NEXT IS1
1330 NEXT IA3
1340 NEXT IA2
1350 NEXT IA1
1355 T2$=TIME$: RETURN
-----------------------------------------------------------------------------------
1500 REM: DAY REPEAT SUBROUTINE
1510 DAYS=0:ALLEVENT=0
1520 DAYS=DAYS+1:'GOSUB 22150
1530 IF DAYS>TOTALDAYS THEN GOTO 1770
1540 MTRUCK=0:U=0:K=0
1545 OADER(0)=UNLOADER:FOR I=0 TO ZONE:FOR J=0 TO LOADER(I):
      ILOADER(I,J)=0:NEXT J:NEXT I
1550 FOR I=1 TO ZONE:FOR J=1 TO TRUCK(I): MTRUCK=MTRUCK+1:
      EVENT(MTRUCK,1)=0: rem EVENT(MTRUCK,1)=START(I,J) start from
      unloading zone
1555 NEXT J:NEXT I
1560 MLOADER=0:FOR I=1 TO ZONE:LDLEN(I)=-LOADER(I):MLOADER=
      MLOADER+LOADER(I):NEXT I:LDLEN(0)=-UNLOADER
1565 IF MTRUCK<>NTRUCK OR MLOADER<>NLOADER THEN STOP
1570 FOR I=1 TO NTRUCK:EVENT(I,0)=6:rem start from unloading zone
1575 EVENT(I,2)=0:NEXT I
1580 REM: To get triptime()
1590 FOR I=1 TO ZONE
```

```
1600 ATT(I)=DIST(I)/VL:ATT2(I)=DIST(I)/VE
1614 TRIPTIME(I)=ATT(I)+ATT2(I)+LMD(1,0)+LMD(0,0)+0.333:Rem Gamma
1620 NEXT I
1640 REM: To seek current event
1650 TCUR=9.999999E+37:IITRUCK=-1
1660 FOR I=1 TO NTRUCK:IF EVENT(I,0)<0 THEN GOTO 1680
1670 IF EVENT(I,1)<TCUR AND EVENT(I,2)<10000 THEN IITRUCK= I:
     TCUR=EVENT(I,1)
1680 NEXT I:IF IITRUCK<0 THEN GOTO 1740
1690 WIITRUCK=IITRUCK:GOSUB 7000:IZONE=WIZONE
1700 CASE=EVENT(IITRUCK,0):GOSUB 33240
1710 IF EVENT(IITRUCK,0)<0 THEN GOTO 1650
1720 ON EVENT(IITRUCK,0) GOSUB 11000,12000,13000,14000,15000,16000
1730 GOTO 1650
1740 MAXI=U:GOSUB 34000:ALLEVENT=ALLEVENT+MAXI
1750 GOSUB 4000:REM daily statistics
1760 GOTO 1510
1770 '
1780 GOSUB 6000:REM set up summary table
1790 RETURN
-------------------------------------------------------------------------------
2000 REM: SUBROUTINE TO INPUT CONSTANTS
2020 OPEN "i",#1,"fixpara.hau"
2030 INPUT #1,ZONE
2040 FOR I=1 TO ZONE
2050 INPUT #1,DIST(I)
2060 NEXT I
2070 FOR I=1 TO ZONE
2080 INPUT #1,GROSS(I)
2090 NEXT I
2100 INPUT #1,SHIFT,OVERTIME
2110 INPUT #1,CTR,CLD,CUNLD,COVER
2120 GROSSTASK=0:FOR I=1 TO ZONE:GROSSTASK=GROSSTASK
     +GROSS(I):NEXT I
2130 CLOSE #1:RETURN
-------------------------------------------------------------------------------
2140 REM: SUBROUTINE TO UPDATE INPUT CONSTANTS
2150 PRINT "# of loading zones=";ZONE;:INPUT W$:IF W$<>"" THEN
```

```
ZONE=VAL(W$)
2160 FOR I=1 TO ZONE
2170 PRINT "distance to loading zone";I;"=";DIST(I);: INPUT W$:IF W$<>""
     THEN DIST(I)=VAL(W$)
2180 NEXT I
2190 FOR I=1 TO ZONE
2200 PRINT "gross loads in loading zone";I;"=";GROSS(I);:INPUT W$:IF
     W$<>"" THEN GROSS(I)=VAL(W$)
2210 NEXT I
2220 PRINT "duration of a shift=";SHIFT;:INPUT W$:IF W$<>""THEN
     SHIFT=VAL(W$)
2230 PRINT "overtime limit=";OVERTIME;:INPUT W$:IF W$<>"" THEN
     OVERTIME=VAL(W$)
2235 PRINT "overtime fee rate=";COVER;:INPUT "";W$: IF W$<>"" THEN
     COVER=VAL(W$)
2240 PRINT "cost of truck per hour=";CTR;:INPUT W$: IF W$<>"" THEN
     CTR=VAL(W$)
2250 PRINT "cost of loader per hour=";CLD;:INPUT W$: IF W$<>"" THEN
     CLD=VAL(W$)
2260 PRINT "cost of unloader per hour=";CUNLD;:INPUT W$:IF W$<>""
     THEN CUNLD=VAL(W$)
2265 PRINT "overtime payment rate=";COVER;:INPUT W$: IF W$<>"" THEN
     COVER=VAL(W$)
2280 REM: To save input constants
2290 OPEN "o",#1,"fixpara.hau"
2300 PRINT #1,ZONE
2310 FOR I=1 TO ZONE:PRINT #1,DIST(I);:NEXT I:IF ZONE>0 THEN PRINT
     #1,""
2320 FOR I=1 TO ZONE:PRINT #1,GROSS(I);:NEXT I:IF ZONE>0 THEN
     PRINT #1,""
2330 PRINT #1,SHIFT,OVERTIME
2340 PRINT #1,CTR,CLD,CUNLD,COVER
2350 CLOSE #1:RETURN
------------------------------------------------------------------------------------------
2500 REM: SUBROUTINE TO INPUT PARAMETERS OF DISTRIBUTIONS
2510 OPEN "i",#1,"states.hau":STRUCK=0:SLOAD=0:SUNLD=0:W=1
2520 LINE INPUT #1,VT$
2530 LINE INPUT #1,LT$
2540 LINE INPUT #1,UT$
2560 W=INSTR(W,VT$,","):IF W>0 THEN STRUCK=STRUCK+1:
     VT(STRUCK)=VAL(MID$(VT$,W+1)):W=W+1:GOTO 2560 ELSE W=1
2570 W=INSTR(W,LT$,","):IF W>0 THEN SLOAD=SLOAD+1:LT(SLOAD)=
```

```
        VAL(MID$(LT$,W+1)):W=W+1:GOTO 2570 ELSE W=1
2580 W=INSTR(W,UT$,","):IF W>0 THEN SUNLD =SUNLD+1: UT(SUNLD)
        = VAL(MID$(UT$,W+1)):W=W+1:GOTO 2580 ELSE W=1
2590 CLOSE #1:RETURN
-------------------------------------------------------------------------------------------
2600 REM: SUBROUTINE TO UPDATE PARAMETERS OF DISTRIBUTIONS
2610 PRINT "parameters for travel speed distribution=";MID$(VT$,2);"?"; :LINE
        INPUT W$:IF W$<>"" THEN VT$=","+W$
2620 PRINT "parameters for loading time distribution=";MID$(LT$,2);"?"; :LINE
        INPUT W$:IF W$<>"" THEN LT$=","+W$
2630 PRINT "parameters for unloading time distribution=";MID$(UT$,2); "?";:
        LINE INPUT W$:IF W$<>"" THEN UT$=","+W$
2640 OPEN "o",#1,"states.hau"
2650 PRINT #1,VT$:PRINT #1,LT$:PRINT #1,UT$
2660 CLOSE #1
2670 RETURN
-------------------------------------------------------------------------------------------
2700 REM: SUBROUTINE TO INPUT ACTIONS
2710 OPEN "i",#1,"actions.hau":AUNLD=0:W=1
2720 INPUT #1,QZONE
2730 ATRUCK=0:ALOAD=0
2740 LINE INPUT #1,AT$
2750 LINE INPUT #1,AL$
2760 LINE INPUT #1,AU$
2770 'IF QZONE<>ZONE THEN CLOSE #1:GOSUB 2840
2790 W=INSTR(W,AT$,","): IF W>0 THEN ATRUCK=ATRUCK+1 :
        AT(ATRUCK) =VAL(MID$(AT$,W+1)):W=W+1:GOTO 2790 ELSE W=1
2800 W=INSTR(W,AL$,","):IF W>0 THEN ALOAD=ALOAD+1: AL(ALOAD)=
        VAL(MID$(AL$,W+1)):W=W+1:GOTO 2800 ELSE W=1
2820 W=INSTR(W,AU$,","):IF W>0 THEN AUNLD=AUNLD+1: AU(AUNLD)
        =VAL(MID$(AU$,W+1)): W = W+1: GOTO 2820 ELSE  W=1
2830 CLOSE #1:RETURN
-------------------------------------------------------------------------------------------
2840 REM: SUBROUTINE TO UPDATE PARAMETERS OF DISTRIBUTIONS
2860 PRINT "# of trucks=";MID$(AT$,2);"?";:LINE INPUT W$:IF W$<>""
        THEN AT$=","+W$
2870 PRINT "# of loaders=";MID$(AL$,2);"?";:LINE INPUT W$:IF W$<>""
        THEN AL$=","+W$
2890 PRINT " # of unloaders=";MID$(AU$,2);"?";:LINE INPUT W$:IF
        W$<>"" THEN AU$=","+W$
2900 OPEN "o",#1,"actions.hau"
```

```
2905 PRINT #1,ZONE
2910 PRINT #1,AT$
2920 PRINT #1,AL$:PRINT #1,AU$
2930 CLOSE #1
2940 RETURN
-----------------------------------------------------------------------------------
3500 REM: SUBROUTINE TO SAVE FILE NAMES
3510 OPEN "i",#1,"reports.hau"
3520 INPUT #1,EVEREP$,NAMEEVE$
3530 INPUT #1,DAYREP$,NAMEDAY$
3540 INPUT #1,JOBREP$,NAMEJOB$
3545 INPUT #1,NAMESUM$
3550 CLOSE #1:RETURN
-----------------------------------------------------------------------------------
3560 REM: SUBROUTINE TO UPDATE THE STATUS OF SAVED FILES
3565 PRINT " file name of all job summary(the outcome)=";NAMESUM$;:
       INPUT "";W$:IF W$<>"" THEN NAMESUM$=W$ ELSE IF
       NAMESUM$ ="" THEN NAMESUM$="summary"
3570 PRINT "the event reports to be saved(y/n):";EVEREP$;:INPUT"";W$: IF
       W$<>"" THEN W$=LEFT$(W$,1)
3580 IF W$="y" OR W$="Y" THEN EVEREP$="Y" ELSE IF W$<>""THEN
       EVEREP$="N"
3590 IF EVEREP$<>"Y" THEN GOTO 3610
3600 PRINT " file name of event reports=";NAMEEVE$;:INPUT"";W$:IF
       W$<>"" THEN NAMEEVE$=W$ ELSE IF NAMEEVE$=""THEN
       NAMEEVE$="events"
3610 PRINT "the daily reports to be saved(y/n):";DAYREP$;:INPUT"";W$:  IF
       W$<>"" THEN W$=LEFT$(W$,1)
3620 IF W$="y" OR W$="Y" THEN DAYREP$="Y" ELSE IF W$<>""THEN
       DAYREP$="N"
3630 IF DAYREP$<>"Y" THEN GOTO 3650
3640 PRINT " file name of daily reports=";NAMEDAY$;:INPUT"";W$:IF
       W$<>"" THEN NAMEDAY$=W$ ELSE IF NAMEDAY$=""THEN
       NAMEDAY$="days"
3650 PRINT "the job reports to be saved(y/n):";JOBREP$;:INPUT "";W$:IF
       W$<>"" THEN W$=LEFT$(W$,1)
3660 IF W$="y" OR W$="Y" THEN JOBREP$="Y" ELSE IF W$<>""THEN
       JOBREP$="N"
3670 IF JOBREP$<>"Y" THEN GOTO 3690
3680 PRINT " file name of job reports=";NAMEJOB$;:INPUT"";W$:IF W$<>""
       THEN NAMEJOB$=W$ ELSE IF NAMEJOB$=""THEN
NAMEJOB$="jobs"
```

```
3690 OPEN "o",#1,"reports.hau"
3700 PRINT #1,EVEREP$:PRINT #1,NAMEEVE$
3710 PRINT #1,DAYREP$:PRINT #1,NAMEDAY$
3720 PRINT #1,JOBREP$:PRINT #1,NAMEJOB$
3725 PRINT #1,NAMESUM$
3730 CLOSE #1:RETURN
```

```
4000 REM: SUBROUTINE TO RECORD DAILY STATISTICS
4005 REM: daytruck(j,0)=trips of truck j,daytruck(j,1) = worktime of truck j,
       daytruck(j,2)=waitingtime of truck j at load site, daytruck(j,3)=waitingtime
       of truck j        at unload site
4010 REM:dayload(j,0)=# of load of loader j, dayload(j,1)=worktime,
       dayload(j,2)=operation time, j-general number
4030 '
4050 FOR J=0 TO NTRUCK:FOR I=0 TO 4:DAYTRUCK(J,I)=0:NEXT I:NEXT
       J
4060 FOR WU=1 TO MAXI
4070 DAYTRUCK(EVESEQ(WU,0),0)=DAYTRUCK(EVESEQ(WU,0),0)+1
4080 IF EVESEQ(WU,2)=6 THEN DAYTRUCK(EVESEQ(WU,0),1) =
       EVESEQ(WU,1)
4090 IF EVESEQ(WU,2)=2 THEN DAYTRUCK(EVESEQ(WU,0),2)=
       DAYTRUCK(EVESEQ(WU,0),2)+(EVESEQ(WU,1)-EVESEQ(WU-1,1))
4100 IF EVESEQ(WU,2)=5 THEN DAYTRUCK(EVESEQ(WU,0),3)=
       DAYTRUCK(EVESEQ(WU,0),3)+(EVESEQ(WU,1)-EVESEQ(WU-1,1))
4150 NEXT WU
4155 REM: Recording daily statistics starting from loading zone
4156 w=0:FOR I=1 TO ZONE:FOR J=1 TO TRUCK(I):W=W+1:
       DAYTRUCK(W,1)= DAYTRUCK(W,1)-START(I,J):NEXT J:NEXT I
4160 FOR I=1 TO NTRUCK:DAYTRUCK(I,4)=DAYTRUCK(I,1)-SHIFT
4170 IF DAYTRUCK(I,4)<0 THEN DAYTRUCK(I,4)=0
4180 NEXT I
4200 FOR J=1 TO NTRUCK
4210 DAYTRUCK(J,0)=INT(DAYTRUCK(J,0)/6):DAYTRUCK(0,0)=
       DAYTRUCK(0,0)+DAYTRUCK(J,0)
4220 FOR I=1 TO 4:DAYTRUCK(0,I)=DAYTRUCK(0,I)+ DAYTRUCK(J,I):
       NEXT I
4230 NEXT J
4400 REM: Statistics for loading and unloading
4410 FOR I=0 TO NLOADER:FOR J=0 TO 3:DAYLOAD(I,J)=0:NEXT J:NEXT I
4420 FOR I=0 TO UNLOADER:FOR J=0 TO 3:DAYUNLOAD(I,J)=0:NEXT J:
       NEXT I
4430 'LOADER(0)=UNLOADER:FOR I=0 TO ZONE:FOR J=0 TO LOADER(I):
```

```
LOADER(I,J)=0:NEXT J:NEXT I
4460 FOR WU=1 TO MAXI
4470 IF EVESEQ(WU,3)=0 THEN GOTO 4530
4480 IF EVESEQ(WU,3)<100 THEN DAYUNLOAD(EVESEQ(WU,3),0)=
     DAYUNLOAD (EVESEQ(WU,3),0)+1 :DAYUNLOAD(EVESEQ(WU,3),2)
     =DAYUNLOAD (EVESEQ(WU,3),2)+EVESEQ(WU+1,1)-
     EVESEQ(WU,1) ELSE GOTO 4520
4490 IF DAYUNLOAD(EVESEQ(WU,3),1)<EVESEQ(WU+1,1) THEN
     DAYUNLOAD(EVESEQ(WU,3),1)=EVESEQ(WU+1,1)
4500 GOTO 4530
4520 IF EVESEQ(WU,3)>100 THEN WILOADER=EVESEQ(WU,3):
     GOSUB 7060: DAYLOAD(WIILOADER,0)=DAYLOAD(WIILOADER,0)+
     1: DAYLOAD(WIILOADER,2)=DAYLOAD(WIILOADER,2)+
     EVESEQ(WU+1,1)-EVESEQ(WU,1)
4525 IF DAYLOAD(WIILOADER,1)<EVESEQ(WU+1,1) THEN
     DAYLOAD(WIILOADER,1)=EVESEQ(WU+1,1)
4530 NEXT WU
4535 GOSUB 7200
4540 FOR I=1 TO NLOADER:DAYLOAD(I,3)=DAYLOAD(I,1)-SHIFT
4550 IF DAYLOAD(I,3)<0 THEN DAYLOAD(I,3)=0
4560 NEXT I
4570 FOR I=1 TO UNLOADER:DAYUNLOAD(I,3) = DAYUNLOAD(I,1) -
     SHIFT
4580 IF DAYUNLOAD(I,3)<0 THEN DAYUNLOAD(I,3)=0
4590 NEXT I
4592 FOR I=1 TO NLOADER:FOR J=0 TO 3:DAYLOAD(0,J)=DAYLOAD(0,J)
     + DAYLOAD(I,J):NEXT J:NEXT I
4594 FOR I=1 TO UNLOADER:FOR J=0 TO 3:DAYUNLOAD(0,J)=
     DAYUNLOAD(0,J)+DAYUNLOAD(I,J):NEXT J:NEXT I
4600 REM: Daily report
4605 IF DAYREP$<>"Y" THEN GOTO 5000
4610 PRINT #4,"    daily statistics of truck   day=";DAYS
4615 PRINT #4," # trips  workT  waitT at load  waitT at unload  overT"
4630 FOR J=0 TO NTRUCK
4640 IF J=0 THEN PRINT #4,"  sum"; ELSE PRINT #4, USING "#####";J;
4650 PRINT #4,USING "########";DAYTRUCK(J,0);
4660 FOR I=1 TO 4:PRINT #4,USING "##########.###";DAYTRUCK(J,I); :
     NEXT I:PRINT #4,""
4670 NEXT J
4680 PRINT #4,"---------------------------------------------------------"
4710 PRINT #4," daily statistics of loaders   "
4715 PRINT #4,"load#   trucks    workT    operationT       overT"
```

```
4730 FOR I=0 TO NLOADER
4740 IF I=0 THEN PRINT #4,"  sum"; ELSE PRINT #4,USING "#####";I;
4750 PRINT #4,USING "#########";DAYLOAD(I,0);
4760 FOR J=1 TO 3:PRINT #4,USING "##########.###";DAYLOAD(I,J);:NEXT
       J:PRINT #4,""
4770 NEXT I
4780 PRINT #4,"------------------------------------------------------------"
4810 PRINT #4,"  daily  statistics of unloaders "
4815 PRINT #4,"   #    trucks    workT   operationT      overT"
4830 FOR I=0 TO UNLOADER
4840 IF I=0 THEN PRINT #4,"  sum"; ELSE PRINT #4, USING "#####";I;
4850 PRINT #4,USING "#########";DAYUNLOAD(I,0);
4860 FOR J=1 TO 3:PRINT #4,USING "##########.###";DAYUNLOAD(I,J);:
       NEXT J:PRINT #4,""
4870 NEXT I
4880 PRINT #4,"========================================"
5000 REM: Job statistics
5010 '
5020 FOR I=0 TO 4:JOBTRUCK(DAYS,I)=JOBTRUCK(DAYS,I)+
       DAYTRUCK(0,I) : NEXT I
5030 FOR I=0 TO 3:JOBLOAD(DAYS,I)=JOBLOAD(DAYS,I) +
       DAYLOAD(0,I):JOBUNLOAD(DAYS,I)=JOBUNLOAD(DAYS,I) +
       DAYUNLOAD(0,I) : NEXT I
5090 RETURN
```

```
6000 REM: SUBROUTINE TO SET UP SUMMARY TABLES
6010 ' Job report
6020 FOR I=1 TO TOTALDAYS:FOR J=0 TO 4:JOBTRUCK(0,J)=
       JOBTRUCK(0,J)+ JOBTRUCK(I,J):NEXT J:NEXT I
6030 FOR I=1 TO TOTALDAYS:FOR J=0 TO 3:JOBLOAD(0,J)=
       JOBLOAD(0,J) + JOBLOAD(I,J):JOBUNLOAD(0,J)=JOBUNLOAD(0,J)+
       JOBUNLOAD(I,J):NEXT J: NEXT I
6040 IF JOBREP$<>"Y" THEN GOTO 6100
6050 GOSUB 9600
6100 REM: To make decision table
6110 'to record one job for specific lmd()
6140 DAYWAITLD=JOBTRUCK(0,2)/TOTALDAYS/NTRUCK:
       DAYWAITUNLD=JOBTRUCK(0,3)/TOTALDAYS/NTRUCK
6150 DAYIDLELD=(JOBLOAD(0,1)-JOBLOAD(0,2))/TOTALDAYS/NLOADER
       DAYIDLEUNLD=(JOBUNLOAD(0,1) - JOBUNLOAD(0,2))/
       TOTALDAYS/ UNLOADER
6160 DAYTRIPS=JOBTRUCK(0,0)/TOTALDAYS
```

```
6170 DAYTRKWK=JOBTRUCK(0,1)/TOTALDAYS/NTRUCK:DAYTRKOV=
     JOBTRUCK(0,4)/TOTALDAYS/NTRUCK
6180 DAYLDWK=JOBLOAD(0,1)/TOTALDAYS/NLOADER: DAYLDOV=
     JOBLOAD(0,3)/TOTALDAYS/NLOADER
6190 DAYUNLDWK=JOBUNLOAD(0,1)/TOTALDAYS/UNLOADER:
     DAYUNLDOV= JOBUNLOAD(0,3)/TOTALDAYS/UNLOADER
6200 WKDAYS=GROSSTASK/DAYTRIPS
6220 COST1=(CTR*DAYTRKWK+CTR*(COVER-1)*DAYTRKOV)*
     WKDAYS*NTRUCK
6230 COST2=(CLD*DAYLDWK+CLD*(COVER-1)*DAYLDOV)*WKDAYS*
     NLOADER
6240 COST3=(CUNLD*DAYUNLDWK+CUNLD*(COVER-1)*DAYUNLDOV)
     * WKDAYS * UNLOADER
6250 COST=CTR0*NTRUCK+CLD0*NLOADER+CUNLD0*UNLOADER+
     COST1+COST2+COST3
6260 'to save states, actions, cost
6300 PRINT NTRUCK;NLOADER;UNLOADER;VT(IS1);LMD(1,0);LMD(0,0);
     DAYTRIPS; DAYWAITUNLD;DAYWAITLD;DAYIDLELD;
     DAYIDLEUNLD; DAYTRKWK;DAYTRKOV; DAYLDWK;DAYLDOV;
     DAYUNLDWK;DAYUNLDOV;COST/1000;COST1/1000;COST2/ 1000;
     COST3/1000
6305 PRINT #2,USING "####";JOBCOUNT;
6310 PRINT #2,USING"#######.##"; NTRUCK;NLOADER; UNLOADER;
     VT(IS1); LMD(1,0):LMD(0,0);DAYTRIPS;DAYWAITLD;
     DAYWAITUNLD; DAYIDLELD;DAYIDLEUNLD:DAYTRKWK;
     DAYTRKOV; DAYLDWK;DAYLDOV;DAYUNLDWK; DAYUNLDOV;
     COST/1000;COST1/1000;COST2/1000;COST3/1000
6350 RETURN
6359 RETURN
```

```
7000 REM: SUBROUTINE TO GET LOADING ZONE NUMBER
7005 ' ,input wiitruck ,output wizone,witruck
7010 WS=0:FOR W=1 TO ZONE
7020 WS=WS+TRUCK(W)
7030 IF WS>=WIITRUCK THEN WIZONE=W:WITRUCK=
     WIITRUCK-(WS-TRUCK(W)): GOTO 7050
7040 NEXT W
7050 RETURN
```

```
7060 REM: SUBROUTINE TO DETERMINE LOADER SEQUENCE
7065 ' input wiloader=100*izone+j,output wiiloader
7070 WZ=INT(WILOADER/100):WII=WILOADER MOD 100
7080 WIILOADER=0
7090 FOR W=1 TO WZ-1:WIILOADER=WIILOADER+LOADER(W):NEXT W
```

```
7100 WIILOADER=WIILOADER+WII
7110 RETURN
---------------------------------------------------------------------------
7200 REM: SUBROUTINE TO DETERMINE LOADER/UNLOADER WORKTIME
7210 W=0:P=0:FOR I=1 TO ZONE:Q=0
7220 FOR J=1 TO LOADER(I):W=W+1
7230 IF DAYLOAD(W,1)>Q THEN Q=DAYLOAD(W,1)
7240 NEXT J
7245 'IF Q<SHIFT THEN Q=SHIFT
7250 FOR J=P+1 TO P+LOADER(I):DAYLOAD(J,1)=Q:NEXT J
7260 P=P+LOADER(I)
7270 NEXT I
7300 Q=0:FOR J=1 TO UNLOADER
7310 IF DAYUNLOAD(J,1)>Q THEN Q=DAYUNLOAD(J,1)
7320 NEXT J
7325 'IF Q<SHIFT THEN Q=SHIFT
7330 FOR J=1 TO UNLOADER:DAYUNLOAD(J,1)=Q:NEXT J
7350 RETURN
9000 RETURN
---------------------------------------------------------------------------
9600 REM: SUBROUTINE TO MAKE JOB REPORT
9610 PRINT #5,"* * * job(";JOBCOUNT;"): trucks=";NTRUCK;"loaders=";
     NLOADER;" unloaders=";UNLOADER;" truck speed=";VT(IS1);"loading
     rate=";LMD(1,0);" unloading rate=";LMD(0,0);"* * *"
9612 FOR I=1 TO ZONE:PRINT #5,"trucks to zone(";I;")=";TRUCK(I);" loaders
     in zone(";I;")=";LOADER(I):NEXT I
9615 PRINT #5,"  job statistics of truck  "
9620 PRINT #5,"day trips orkT waitT at load waitT at unload overT"
9630 FOR I=0 TO TOTALDAYS
9640 IF I=0 THEN PRINT #5,"  sum"; ELSE PRINT #5,USING "#####";I;
9650 PRINT #5,USING "#########";JOBTRUCK(I,0);
9660 FOR J=1 TO 4:PRINT #5,USING "##########.###";JOBTRUCK(I,J);:
     NEXT J: PRINT #5,""
9670 NEXT I
9680 PRINT #5,"-----------------------------------------------------"
9710 PRINT #5,"  job statistics of loaders  "
9715 PRINT #5," day  trucks   workT  operationT   overT"
9730 FOR I=0 TO TOTALDAYS
```

```
9740 IF I=0 THEN PRINT #5," sum"; ELSE PRINT #5,USING "#####";I;
9750 PRINT #5,USING "#########";JOBLOAD(I,0);
9760 FOR J=1 TO 3:PRINT #5,USING "##########.###"; JOBLOAD(I,J);:
     NEXT J: PRINT #5,""
9770 NEXT I
9780 PRINT #5,"------------------------------------------------------------"
9810 PRINT #5," job statistics of unloaders "
9815 PRINT #5," day trucks workT operationT overT"
9830 FOR I=0 TO TOTALDAYS
9840 IF I=0 THEN PRINT #5," sum"; ELSE PRINT #5,USING "#####";I;
9850 PRINT #5,USING "#########";JOBUNLOAD(I,0);
9860 FOR J=1 TO 3:PRINT #5,USING "##########.###"; JOBUNLOAD(I,J);:
     NEXT J: PRINT #5,""
9870 NEXT I
9880 PRINT #5,"=============================================="
9890 RETURN
```

```
11000 REM: CASE 1 SUBROUTINE - ARRIVAL AT IZONE TO LOAD
11010 'KEVENT(1)=KEVENT(1)+1
11020 IF LDLEN(IZONE)>=0 THEN LDLEN(IZONE)=LDLEN(IZONE)+1:
      EVENT(IITRUCK,2)=10000+IZONE:GOTO 11200
11030 LDLEN(IZONE)=LDLEN(IZONE)+1
11040 FOR I=1 TO LOADER(IZONE)
11050 IF ILOADER(IZONE,I)=0 THEN ILOADER(IZONE,I)=1:
      EVENT(IITRUCK,2)=100*IZONE+I:EVENT(IITRUCK,0)=2:GOTO 11200
11060 NEXT I
11200 RETURN
```

```
12000 REM: CASE 2 SUBROUTINE - START LOADING
12010 'KEVENT(2)=KEVENT(2)+1
12020 WIZONE=INT(EVENT(IITRUCK,2)/100):WILOADER=
      (EVENT(IITRUCK,2) MOD 100):GOSUB 12500:REM duration of loading
12030 EVENT(IITRUCK,0)=3
12040 EVENT(IITRUCK,1)=EVENT(IITRUCK,1)+WTLOAD
12100 RETURN
```

```
12500 REM: SUBROUTINE TO DETERMINE THE DURATION OF LOADING
12515 Rem: INPUT WIZONE OUTPUT WTLOAD
12520 U1=RND(1):U2=RND(2):ALPHA=22:THETA=4.5:a=1/sqr(2*ALPHA-1):
```

```
      b=ALPHA-LOG(4):q=ALPHA+1/a:d=1+LOG(THETA)
12525 V=a*LOG(U1/(1-U1)):Y=ALPHA*EXP(V):Z=U1^2*U2:W=b+q*V-Y
12530 IF W+d-THETA*Z>=0 THEN WTLOAD=LT(IS2)*Y ELSE GOTO
      12536:REM Gamma
12536 IF W>=LOG(Z) THEN WTLOAD=LT(IS2)*Y ELSE GOTO 12530 :
      REM: Gamma
12550 RETURN
```

```
13000 REM: CASE 3 SUBROUTINE - DEPARTURE FROM LOADING ZONE
13010 'KEVENT(3)=KEvENT(3)+1
13020 U1=RND(1):U2=RND(2):ALPHA=53:THETA=4.5:a=1/SQR
      (2*ALPHA-1): b=ALPHA-LOG(4):q=ALPHA+1/a: d=1+LOG(THETA)
13025 V=a*LOG(U1/(1-U1)):Y=ALPHA*EXP(V):Z=U1^2*U2:W=b+q*V-Y
13026 IF W+d-THETA*Z>=0 THEN TTL=DIST(ZONE)/(VT(IS1)*Y) ELSE
      GOTO 13027
13027 IF W>=LOG(Z) THEN TTL=DIST(ZONE)/(VT(IS1)*Y) ELSE GOTO
      13020: REM Gamma
13030 EVENT(IITRUCK,0)=4:TDEPART=EVENT(IITRUCK,1)
13040 EVENT(IITRUCK,1)=EVENT(IITRUCK,1)+TTL
13050 WIITRUCK=IITRUCK:GOSUB 7000:IF WIZONE<>IZONE THEN STOP
13060 WILOADER=(EVENT(IITRUCK,2) MOD 100)
13070 LDLEN(IZONE)=LDLEN(IZONE)-1:EVENT(IITRUCK,2)=0
13071 ILOADER(IZONE,WILOADER)=0
13090 TRUCKI=0:FOR I=1 TO IZONE-1:TRUCKI=TRUCKI+TRUCK(I):NEXT I
13100 IF LDLEN(IZONE)>=0 THEN ILOADER(IZONE,WILOADER)=1:
      GOSUB 13500:ELSE GOTO 13160:REM reload
13160 RETURN
```

```
13500 REM: SUBROUTINE TO SCHEDULE NEXT LOADING
13510 'KEVENT(2)=KEVENT(2)+1
13520 TCU=1E+37
13530 FOR I=TRUCKI+1 TO TRUCKI+TRUCK(IZONE)
13540 IF EVENT(I,1)<TCU AND EVENT(I,2)>10000 THEN IITRUCK=I:
      TCU= EVENT(I,1)
13550 NEXT I
13555 EVENT(IITRUCK,1)=TDEPART:EVENT(IITRUCK,0)=2:
      EVENT(IITRUCK,2)=100*IZONE+WILOADER
13560 WIITRUCK=IITRUCK:GOSUB 7000:IF IZONE<>WIZONE THEN STOP
13565 CASE=2:GOSUB 33240:CASE=3
13570 GOSUB 12000
```

```
13580 RETURN
-----------------------------------------------------------------------------------------
14000 REM: CASE 4 SUBROUTINE - ARRIVAL AT UNLOADING SITE
14010 'KEVENT(4)=KEVENT(4)+1
14020 IF LDLEN(0)>=0 THEN LDLEN(0)=LDLEN(0)+1: EVENT(IITRUCK,2)
      = 10000:GOTO 14200
14030 LDLEN(0)=LDLEN(0)+1
14040 FOR J=1 TO UNLOADER
14050 IF ILOADER(0,J)=0 THEN ILOADER(0,J)=1:EVENT(IITRUCK,2)=J:
      EVENT(IITRUCK,0)=5:GOTO 14200
14060 NEXT J
14200 RETURN
-----------------------------------------------------------------------------------------
15000 REM: CASE 5 SUBROUTINE - START UNLOADING
15010 'KEVENT(5)=KEVENT(5)+1
15020 WIZONE=0:WIUNLOADER=EVENT(IITRUCK,2):GOSUB 15500:REM:
      duration of unloading
15030 EVENT(IITRUCK,0)=6
15040 EVENT(IITRUCK,1)=EVENT(IITRUCK,1)+WTUNLOAD
15100 RETURN
-----------------------------------------------------------------------------------------
15500 REM: SUBROUTINE TO DETERMINE THE DURATION OF UNLOADING
15525  ' INPUT WIZONE, OUTPUT WTUNLOAD
15530 U1=RND(1):U2=RND(2):ALPHA=10:THETA=4.5:a=1/SQR
      (2*ALPHA-1): b=ALPHA-LOG(4):q=ALPHA+1/a:d=1+LOG(THETA)
15532 V=a*LOG(U1/(1-U1)):Y=ALPHA*EXP(V):Z=U1^2*U2:W=b+q*V-Y
15535 IF W+d-THETA*Z >=0 THEN WTUNLOAD=UT(IS3)*Y ELSE GOTO
      15540
15540 IF W>=LOG(Z) THEN WTUNLOAD=UT(IS3)*Y ELSE GOTO 15530:
      REM Gamma
15550 RETURN
-----------------------------------------------------------------------------------------
16000 REM: CASE 6 SUBROUTINE - DEPARTURE FROM UNLOADING SITE
16010 'KEVENT(6)=KEVENT(6)+1
16020 TDEPART=EVENT(IITRUCK,1)
16030 IF EVENT(IITRUCK,1)>=SHIFT+OVERTIME-TRIPTIME(IZONE)
      THEN EVENT(IITRUCK,0)=-1:GOTO 16250
16225 U1=RND(1):U2=RND(2):ALPHA=53:THETA=4.5:a=1/SQR
      (2*ALPHA-1): b=ALPHA-LOG(4):q=ALPHA+1/a:d=1+LOG(THETA)
16226 V=a*LOG(U1/(1-U1)):Y=ALPHA*EXP(V):Z=U1^2*U2:W=b+q*V-Y
```

```
16227 IF W+d-THETA*Z >=0 THEN TTE=DIST(ZONE)/(1.2*VT(IS1)*Y)
      ELSE GOTO 16228
16228 IF W>=LOG(Z) THEN TTE=DIST(ZONE)/(1.2*VT(IS1)*Y) ELSE GOTO
      16225
16230 EVENT(IITRUCK,0)=1
16240 EVENT(IITRUCK,1)=EVENT(IITRUCK,1)+TTE
16250 LDLEN(0)=LDLEN(0)-1:WIUNLOADER=EVENT(IITRUCK,2):
      EVENT(IITRUCK,2)=0
16255 ILOADER(0,WIUNLOADER)=0
16300 IF LDLEN(0)>=0 THEN ILOADER(0,WIUNLOADER)=1:GOSUB 16500
      ELSE GOTO 16360:REM REUNLOAD
16360 RETURN
---------------------------------------------------------------------------
16500 REM: SUBROUTINE TO SCHEDULE NEXT UNLOADING
16510 'KEVENT(2)=KEVENT(2)+1
16520 TCU=1E+37
16530 FOR I=1 TO NTRUCK
16540 IF EVENT(I,1)<TCU AND EVENT(I,2)=10000 THEN IITRUCK=I:
      TCU=EVENT(I,1)
16550 NEXT I
16555 EVENT(IITRUCK,1)=TDEPART:EVENT(IITRUCK,0)=5:
      EVENT(IITRUCK,2)=WIUNLOADER
16560 WIITRUCK=IITRUCK:IZONE=0
16565 CASE=5:GOSUB 33240:CASE=6
16570 GOSUB 15000
16580 RETURN
---------------------------------------------------------------------------
22000 REM: SUBROUTINE TO ASSIGN TRUCKS AND LOADERS TO EACH
      ZONE
22010 W1=0:W2=0:WW1=0:WW2=0:
22015 RR0=0:FOR I=1 TO ZONE
22025 ATT(I)=DIST(I)/VL:ATT2(I)=DIST(I)/VE
22026 TRIPTIME(I)=ATT(I)+ATT2(I)+LMD(1,0)+LMD(0,0)+0.333
22030 RR(I)=GROSS(I)/TRIPTIME(I):RR0=RR0+RR(I)
22040 NEXT I
22050 FOR I=1 TO ZONE:RR(I)=RR(I)/RR0:NEXT I
22060 FOR I=1 TO ZONE
22070 TRUCK(I)=INT(NTRUCK*RR(I)+.5):IF TRUCK(I)<1 THEN TRUCK(I)=1
22080 LOADER(I)=INT(NLOADER*RR(I)+.5):IF LOADER(I)<1 THEN
      LOADER(I)=1
```

```
22085 W1=W1+TRUCK(I):W2=W2+LOADER(I)
22090 IF TRUCK(I)>WW1 THEN WW1=TRUCK(I):II1=I
22100 IF LOADER(I)>WW2 THEN WW2=LOADER(I):II2=I
22110 NEXT I
22120 TRUCK(II1)=TRUCK(II1)+NTRUCK-W1:IF TRUCK(II1)<1 THEN
      PRINT"trucks not enough":STOP
22130 LOADER(II2)=LOADER(II2)+NLOADER-W2:IF LOADER(II2)<1 THEN
      PRINT"loader not enough":STOP
22140 RETURN
-----------------------------------------------------------------------------------------
22150 REM: SUBROUTINE TO SET START TIME
22160 FOR I=1 TO ZONE:T=0:W=0
22170 FOR J=1 TO LOADER(I):W=W+1:START(I,W)=T:IF W>=TRUCK(I)
      THEN GOTO 22200
22180 NEXT J:T=T+LMD(1,0):GOTO 22170
22200 NEXT I
22250 RETURN
-----------------------------------------------------------------------------------------
25000 REM: SUBROUTINE FOR PRINT RESULTS OPTIONS
25010 CLS
25020 PRINT"":PRINT "-----results output sub menu-----":PRINT""
25030 PRINT "   1. print all job summary(the results)"
25040 PRINT "   2. print job report"
25050 PRINT "   3. print daily report"
25060 PRINT "   4. print event report"
25065 PRINT "   5. print all input constants, parameters and actions"
25070 PRINT "   0. return to main menu"
25080 'INPUT "choice( 3 or 3job5 or 3job5 to filename)";CH: IF CH<0 OR CH>5
      THEN GOTO 25080
25082 INPUT "choice(eg. 3 or 3job5 or 3job5 to filename)"; CH$: CH=VAL(CH$)
25084 FOR I=1 TO LEN(CH$):W=ASC(MID$(CH$,I)):IF W>64 AND W<91
      THEN MID$(CH$,I,1)=CHR$(W+32)
25086 NEXT I :W=INSTR(CH$,"job"):W1=INSTR(CH$,"to")
25090 IF W1=0 THEN GOTO 25095
25091 CH1$="": FOR J=W1+2 TO LEN(CH$): W$=MID$(CH$,J,1): IF
      W$<>"" THEN CH1$=CH1$+W$
25092 NEXT J:OPEN "o",#2,CH1$
25095 IF W>0 THEN CH$="job("+STR$(VAL(MID$(CH$,W+3))) ELSE CH$=""
25100 IF CH<>1 THEN GOTO 25120
25110 NAM$=NAMESUM$:GOTO 25300
```

```
25120 IF CH<>2 THEN GOTO 25150
25130 NAM$=NAMEJOB$:IF JOBREP$<>"Y" THEN PRINT "job report not
      saved": GOTO 25030
25140 GOTO 25300
25150 IF CH<>3 THEN GOTO 25180
25160 NAM$=NAMEDAY$:IF DAYREP$<>"Y" THEN PRINT "daily report not
      saved": GOTO 25030
25170 GOTO 25300
25180 IF CH<>4 THEN GOTO 25210
25190 NAM$=NAMEEVE$:IF EVEREP$<>"Y" THEN PRINT "event report not
      saved" :GOTO 25030
25200 GOTO 25300
25210 IF CH=0 THEN GOTO 25350
25215 IF CH<>5 THEN GOTO 25080
25220 LPRINT "interface:":LPRINT "loading zones=";ZONE
25225 FOR I=1 TO ZONE:LPRINT "distance to loading zone(";I;")="; DIST(I);
      "gross loads in loading zone(";I;")=";GROSS(I):NEXT I
25230 LPRINT "duration of a shift=";SHIFT;"(hours);"overtime limit=";
      OVERTIME; "(hours)"
25236 LPRINT "cost of a truck per hour=";CTR:"$"; cost of a loader per hour=";
      CLD;"$";"cost of a unloader per hour=";CUNLD;"$": LPRINT"overtime
      rate=";COVER
25240 LPRINT "set of input parameters:":LPRINT "average speed of rucks=";VT$:
      LPRINT "average loading time of one truck load)="; LT$:LPRINT "average
      unloading time of one truck load=";UT$
25250 LPRINT "actions:":LPRINT "total trucks #=";AT$: LPRINT "total loaders
      #="; AL$:LPRINT "total unloaders #=";AU$
25260 IF JOBREP$="Y" THEN LPRINT "job report file name=";NAMEJOB$
25261 IF DAYREP$="Y" THEN LPRINT "daily report file name=";NAMEDAY$
25262 IF EVEREP$="Y" THEN LPRINT "event report file name=";NAMEEVE$
25270 GOTO 25010
25290 REM: To get output
25300 OPEN "i",#1,NAM$
25306 IF CH$<>"" THEN GOTO 25400
25310 IF EOF(1) THEN CLOSE #1,#2:GOTO 25010
25320 LINE INPUT #1,A$
25330 IF W1=0 THEN LPRINT A$ ELSE PRINT #2,A$
25340 GOTO 25310
25350 RETURN
```

```
25400 REM: SUBROUTINE TO PRINT SELECTED JOBS
25410 IF EOF(1) THEN CLOSE #1:GOTO 25010
25420 LINE INPUT #1,A$
25430 IF INSTR(A$,"job(")=0 THEN GOTO 25410
25440 IF INSTR(A$,CH$)=0 THEN PRINT ".";:GOTO 25410
25450 IF W1=0 THEN LPRINT A$ ELSE PRINT #2,A$
25460 IF EOF(1) THEN CLOSE #1:GOTO 25010
25470 LINE INPUT #1,A$
25480 IF INSTR(A$,"job(")>0 THEN CLOSE #1,#2:GOTO 25010
25490 GOTO 25450
25550 RETURN
-----------------------------------------------------------------------------------------
33240 REM: SUBROUTINE FOR PRINTING
33260 IF EVENT(IITRUCK,0)>0 THEN U=U+1 ELSE GOTO 33650
33500 REM: To record event sequence
33510 EVESEQ(U,0)=IITRUCK:EVESEQ(U,1)=EVENT(IITRUCK,1):
      EVESEQ(U,2)= EVENT(IITRUCK,0)
33520 IF CASE=2 OR CASE=5 THEN EVESEQ(U,3)=EVENT(IITRUCK,2)
      ELSE EVESEQ(U,3)=0
33650 RETURN
-----------------------------------------------------------------------------------------
34000 REM: SUBROUTINE FOR SORTING
34005 PRINT "wait for sorting ..."
34010 CHANGE=0:K=K+1:PRINT ".";
34020 FOR I=1 TO MAXI-1
34030 FOR J=0 TO 2
34035 IF EVESEQ(I,J)<EVESEQ(I+1,J) THEN GOTO 34090
34040 IF EVESEQ(I,J)>EVESEQ(I+1,J) THEN GOTO 34060
34050 NEXT J:GOTO 34090
34060 FOR J=0 TO 3:WWE(J)=EVESEQ(I+1,J):EVESEQ(I+1,J)=EVESEQ(I,J):
      EVESEQ(I,J)=WWE(J):NEXT J:CHANGE=1
34090 NEXT I
34100 IF CHANGE=1 THEN GOTO 34010
34110 PRINT "----"
34180 IF EVEREP$<>"Y" THEN GOTO 34220
34200 FOR WI=1 TO MAXI:FOR WJ=0 TO 3:PRINT #3,EVESEQ(WI,WJ);:
      NEXT WJ: PRINT #3,"":NEXT WI
34210 REM: To record eventseq per day FOR WI=1 TO MAXI:FOR WJ=0 TO 3:
      PRINT #2,EVESEQ(WI,WJ);:NEXT WJ:PRINT #2,"":NEXT WI
```

```
34220 RETURN
------------------------------------------------------------------------------------
35000 REM: SUBROUTINE FOR MAKING OUTCOME TABLES
35005 WIDTH "lpt1:",255
35010 D$(1)="day trips":D$(2)="truck work time":D$(12)= "other outcome"
35020 D$(3)="truck over time":D$(4)="loader work time":D$(5)=
      "loader over time"
35030 D$(6)="unloader work time":D$(7)="unloader over time"
35040 D$(8)="total cost":D$(9)="truck cost":D$(10)="loader cost":D$(11)="
      unloader cost"
35050 NJOB=ATRUCK*ALOAD*AUNLD*STRUCK*SLOAD*SUNLD
35060 PRINT "       make outcome table"
35070 FOR I=1 TO 12:PRINT USING "######";I;:PRINT "."+D$(I):NEXT I
35080 PRINT USING "######";0;:PRINT ". return to main menu"
35090 INPUT "choice";CH:CH=INT(CH):IF CH<0 OR CH>12 THEN GOTO
      35090
35095 IF CH=0 THEN RETURN
35100 IF CH=1 THEN COL=7
35110 IF CH>1 AND CH<12 THEN COL=CH+10
35120 IF CH=12 THEN INPUT "column number=";COL
35130 OPEN "i",#1,NAMESUM$:OPEN "o",#2,"outcome."+MID$(STR$(COL),2)
35140 LINE INPUT #1,W$:LINE INPUT #1,W$
35150 IF CH<12 THEN LPRINT "   "+D$(CH) ELSE LPRINT "column=";COL
35160 LPRINT"------------------------------------------------------------"
35170 PRINT #2," T L U|V-tr";
35180 LPRINT " T L U|V-tr";
35190 FOR J1=1 TO STRUCK:FOR J2=1 TO SLOAD:FOR J3=1 TO SUNLD:
      PRINT #2 USING "#######.#";VT(J1);:NEXT J3:NEXT J2:NEXT J1:
      PRINT #2,""
35200 FOR J1=1 TO STRUCK:FOR J2=1 TO SLOAD:FOR J3=1 TO SUNLD:
      LPRINT USING "#######.#";VT(J1);:NEXT J3:NEXT J2:NEXT J1:
      LPRINT ""
35210 PRINT #2," K D N|T-ld";
35220 LPRINT " K D N|T-ld";
35230 FOR J1=1 TO STRUCK:FOR J2=1 TO SLOAD:FOR J3=1 TO SUNLD:
      PRINT #2, USING "######.##";LT(J2);:NEXT J3:NEXT J2:NEXT J1:
      PRINT #2,""
35240 FOR J1=1 TO STRUCK:FOR J2=1 TO SLOAD:FOR J3=1 TO SUNLD:
      LPRINT USING "######.##";LT(J2);:NEXT J3:NEXT J2:NEXT J1:
      LPRINT ""
35250 PRINT #2," N N N|T-un";
35260 LPRINT " N N N|T-un";
```

```
35270 FOR J1=1 TO STRUCK:FOR J2=1 TO SLOAD:FOR J3=1 TO SUNLD:
      PRINT #2,USING "######.##";UT(J3);:NEXT J3:NEXT J2:NEXT J1:
      PRINT #2,""
35280 FOR J1=1 TO STRUCK:FOR J2=1 TO SLOAD:FOR J3=1 TO SUNLD:
      LPRINT USING "######.##";UT(J3);:NEXT J3:NEXT J2:NEXT J1:
      LPRINT ""
35290 LPRINT"------------------------------------------------------------"
35300 PRINT #2,"------------------------------------------------------------"
35310 FOR I1=1 TO ATRUCK
35320 FOR I2=1 TO ALOAD
35330 FOR I3=1 TO AUNLD
35340 PRINT #2,USING "###";AT(I1);AL(I2);AU(I3);:PRINT #2,"     ";
35350 LPRINT USING "###";AT(I1);AL(I2);AU(I3);:LPRINT "     ";
35360 FOR J1=1 TO STRUCK
35370 FOR J2=1 TO SLOAD
35380 FOR J3=1 TO SUNLD
35390 FOR J=0 TO 21:INPUT #1,EVENT(J,0):NEXT J
35400 LPRINT USING "######.##";EVENT(COL,0);
35410 NEXT J3:NEXT J2:NEXT J1:PRINT #2,"":LPRINT ""
35420 NEXT I3:NEXT I2:NEXT I1
35425 LPRINT"------------------------------------------------------------"
35426 PRINT #2,"------------------------------------------------------------"
35430 CLOSE #1
35440 CLOSE #2
35450 GOTO 35060
35460 RETURN
```

APPENDIX IIa

Simulation output based on deterministic average values estimated with large sample equal to 0.45 hours for loading time, 0.29 hours for unloading time, and 65 km/hr for travel speed.

ACTIONS	Trucking time (hrs) Total working	Trucking time (hrs) Wait[1]	Trucking time (hrs) Wait[2]	Trucking time (hrs) Over-time	Loading (hrs) Total working	Loading (hrs) Over-time	Loading (hrs) Idle	Unloading (hrs) Total working	Unloading (hrs) Over-time	Unloading (hrs) Idle	Total working days[3]
5,3,1	6.63	0.37	0.31	0.00	5.04	0.00	3.54	7.43	0.00	4.53	18.18
5,3,2	6.40	0.39	0.06	0.00	4.84	0.00	3.34	7.14	0.00	5.69	18.18
5,4,1	6.53	0.09	0.49	0.00	5.10	0.00	3.97	7.11	0.00	4.21	18.18
5,4,2	6.22	0.12	0.14	0.00	4.82	0.00	3.69	6.69	0.00	5.24	18.18
5,5,1	6.53	0.00	0.58	0.00	5.20	0.00	4.30	7.11	0.00	4.21	18.18
5,5,2	6.19	0.00	0.23	0.00	4.80	0.00	3.90	6.53	0.00	5.08	18.18
10,3,1	6.66	0.54	0.76	0.00	6.19	0.00	3.49	7.98	0.00	2.76	10.53
10,3,2	6.64	0.57	0.11	0.00	5.64	0.00	2.64	7.59	0.12	4.69	9.53
10,4,1	6.37	0.36	0.94	0.00	5.82	0.00	3.91	8.27	0.27	3.34	11.11
10,4,2	6.53	0.36	0.22	0.00	5.46	0.00	3.21	7.11	0.00	4.21	9.53
10,5,1	6.66	0.32	0.99	0.00	5.96	0.00	4.34	8.27	0.27	3.05	10.53
10,5,2	6.55	0.33	0.27	0.00	5.47	0.00	3.67	7.27	0.00	4.37	9.53
20,3,1	8.05	1.31	2.58	0.05	6.19	0.00	1.99	10.81	2.81	2.69	6.45
20,3,2	6.88	1.37	0.15	0.00	6.65	0.00	1.25	8.33	0.33	3.11	5.13
20,4,1	7.73	0.94	2.77	0.00	5.82	0.00	2.79	10.52	2.52	2.69	6.67
20,4,2	6.66	0.94	0.36	0.00	6.33	0.00	2.28	8.27	0.27	3.05	5.13
20,5,1	7.76	0.83	2.91	0.00	5.78	0.00	3.35	10.52	2.52	2.69	6.67
20,5,2	6.68	0.85	0.47	0.00	6.14	0.00	2.90	8.43	0.43	3.21	5.13

[1] waiting time of trucks at loading zones.
[2] waiting time of trucks at unloading sites.
[3] total working days required for hauling 200 truck loads.

APPENDIX IIb

Simulation output based on deterministic average values estimated with small sample equal to 0.54 hours for loading time, 0.36 hours for unloading time, and 78.5 km/hr for travel speed.

ACTIONS	Trucking time (hrs)				Loading (hrs)			Unloading (hrs)			Total working days[3]
	Total working	Wait[1]	Wait[2]	Over-time	Total working	Over-time	Idle	Total working	Over-time	Idle	
5,3,1	6.92	0.43	0.40	0.00	5.80	0.00	3.82	8.31	0.31	4.35	16.67
5,3,2	7.18	0.47	0.07	0.00	6.48	0.00	4.32	8.31	0.31	6.15	15.38
5,4,1	6.81	0.11	0.61	0.00	5.66	0.00	4.17	8.31	0.31	4.35	16.67
5,4,2	6.97	0.14	0.18	0.00	5.99	0.00	4.37	8.31	0.31	6.15	15.38
5,5,1	6.81	0.00	0.72	0.00	5.65	0.00	4.46	8.31	0.31	4.35	16.67
5,5,2	6.93	0.00	0.29	0.00	5.70	0.00	4.40	8.31	0.31	6.15	15.38
10,3,1	7.27	0.65	1.64	0.00	6.32	0.00	3.08	8.89	0.89	2.41	10.53
10,3,2	6.92	0.68	0.14	0.00	6.66	0.00	2.70	8.31	0.31	4.35	8.70
10,4,1	6.55	0.43	1.69	0.00	5.51	0.00	3.35	8.17	0.17	2.41	11.76
10,4,2	6.81	0.43	0.29	0.00	6.08	0.00	3.11	8.31	0.31	4.35	8.70
10,5,1	6.91	0.38	1.82	0.00	5.81	0.00	3.98	8.53	0.53	2.41	11.11
10,5,2	6.83	0.40	0.34	0.00	5.91	0.00	3.54	8.31	0.31	4.35	8.70
20,3,1	9.07	1.65	3.54	1.07	6.41	0.00	1.37	12.49	4.49	2.41	6.45
20,3,2	7.17	2.03	0.30	0.00	7.15	0.00	0.85	8.89	0.89	2.59	5.26
20,4,1	8.35	1.16	3.59	0.35	5.51	0.00	2.00	11.77	3.77	2.41	6.90
20,4,2	6.91	1.22	0.98	0.00	6.14	0.00	1.55	8.53	0.53	2.41	5.41
20,5,1	8.71	1.03	3.94	0.71	5.81	0.00	2.90	12.13	4.13	2.41	6.67
20,5,2	6.87	1.06	1.11	0.00	6.03	0.00	2.36	8.53	0.53	2.41	5.41

[1] waiting time of trucks at loading zones.
[2] waiting time of trucks at unloading sites.
[3] total working days required for hauling 200 truck loads.

APPENDIX III

Total cost of alternative actions with deterministic average values: for large sample, loading time = 0.45 hours, unloading time = 0.29 hours and travel speed = 65 km/hr; and for small sample, loading time = 0.54 hours, unloading time = 0.36 hours and travel speed = 78.5 km/hr

ACTIONS	Total cost (in '000$)	
	For large sample	For small sample
5, 3, 1	44.61	44.71
5, 3, 2	49.47	50.27
5, 4, 1	48.78	48.72
5, 4, 2	52.30	53.08
5, 5, 1	53.87	53.38
5, 5, 2	56.18	56.44
10, 3, 1	42.03	45.82
10, 3, 2	40.57	40.22*
10, 4, 1	45.97	48.67
10, 4, 2	42.08	41.73
10, 5, 1	48.22	51.89
10, 5, 2	44.90	44.07
20, 3, 1	53.43	61.67
20, 3, 2	37.76*	41.02
20, 4, 1	54.57	61.35
20, 4, 2*	38.21	41.41
20, 5, 1	56.59	64.30
20, 5, 2	39.80	42.77

[1] total cost incurred for hauling 200 truck-loads.

* minimum total cost.

APPENDIX IV

A SAMPLE OF SIMULATION OUTPUT FOR DEVELOPMENT OF RESPONSE FUNCTIONS FOR ACTION 1 (5, 3, 1)

β_l	β_{ul}	β_{ts}	WaitTL (hrs/day)	WaitTUNL (hrs/day)	IdleTL (hrs/day)	IdleTUNL (hrs/day)	No of Trips/day
0.01	0.06	1.4	0.06	1.02	4.48	2.55	10.87
0.03	0.06	1.4	0.30	0.69	3.62	3.39	9.43
0.05	0.06	1.4	0.52	0.41	2.82	4.02	8.47
0.07	0.06	1.4	0.78	0.20	2.08	4.84	7.53
0.09	0.06	1.4	1.05	0.13	1.16	5.50	6.23
0.11	0.06	1.4	1.30	0.13	0.94	6.78	5.83
0.06	0.01	1.4	0.75	0.01	2.49	6.90	8.90
0.06	0.03	1.4	0.66	0.09	2.66	5.75	8.90
0.06	0.05	1.4	0.68	0.20	2.60	4.77	8.47
0.06	0.07	1.4	0.67	0.38	2.19	4.14	7.63
0.06	0.09	1.4	0.63	0.70	1.70	3.37	6.87
0.06	0.11	1.4	0.67	1.09	1.29	3.04	6.43
0.06	0.06	0.6	0.54	0.28	2.18	6.22	5.93
0.06	0.06	1.0	0.58	0.26	1.52	4.56	6.23
0.06	0.06	1.4	0.68	0.32	2.33	4.46	7.80
0.06	0.06	1.8	0.69	0.38	2.39	3.54	8.87
0.06	0.06	2.2	0.75	0.47	2.17	3.14	9.67

APPENDIX Va

REGRESSION COEFFICIENTS OF THE RESPONSE FUNCTIONS FOR THE AVERAGE WAITING TIME AT LOADING ZONES

	INDEPENDENT VARIABLES										
ACTION	k^*	β_1^*	β_1^2	β_1^3	β_{ul}^*	β_{ul}^2	β_{ul}^3	β_{ts}^*	β_{ts}^2	β_{ts}^3	R^2
	Coefficient values										
5, 3, 1	-0.13	10.61	23.46	-73.89	-4.57	52.67	-191.48	0.13	0.03	-0.01	0.997
5, 3, 2	-0.07	14.76	-41.30	276.02	-6.90	79.65	-311.64	0.30	-0.24	0.09	0.998
5, 4, 1	-0.27	3.16	11.25	-50.02	1.55	-32.11	180.78	0.42	-0.26	0.05	0.999
5, 4, 2	-0.16	2.09	33.46	-157.14	-0.85	6.90	-21.81	0.31	-0.18	0.04	0.995
5, 5, 1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.000
5, 5, 2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.000
10, 3, 1	0.40	33.25	-99.88	507.29	-14.85	118.40	-257.14	-0.89	0.82	-0.17	0.998
10, 3, 2	0.52	34.64	-80.11	84.15	-14.45	125.32	-394.29	-1.38	1.17	-0.22	0.999
10, 4, 1	-0.19	11.66	131.05	-742.33	-13.95	189.34	-862.46	0.84	-0.51	0.12	0.998
10, 4, 2	-0.31	19.80	-8.20	69.63	-2.94	-18.99	244.93	0.54	-0.35	0.10	0.999
10, 5, 1	0.03	13.35	36.69	-194.38	-15.86	240.89	-1151.59	0.20	-0.02	0.00	0.998
10, 5, 2	-0.15	16.97	34.64	188.35	-9.37	102.39	-367.38	0.55	-0.39	0.12	0.998

Appendix Va. (Continued)

ACTION	INDEPENDENT VARIABLES										
	k^*	β_l^*	β_l^2	β_l^3	β_{ul}^*	β_{ul}^2	β_{ul}^3	β_{ts}^*	β_{ts}^2	β_{ts}^3	R^2
	Coefficient values										
20, 3, 1	0.84	77.68	96.46	-1162.69	-9.35	-75.54	851.90	-5.07	5.02	-1.22	0.996
20, 3, 2	1.41	104.65	-369.12	899.92	-5.76	-74.00	543.75	-8.26	7.63	-1.81	0.997
20, 4, 1	0.16	80.27	-552.03	2427.18	-27.68	106.70	264.09	0.11	0.25	-0.07	0.998
20, 4, 2	0.34	93.60	-739.56	3039.91	-17.93	-51.04	968.26	-1.63	1.60	-0.33	0.995
20, 5, 1	0.49	69.84	-569.55	2559.00	-38.43	311.44	-818.78	0.90	-0.72	0.18	0.987
20, 5, 2	-0.60	79.39	-677.39	2808.90	-12.72	-148.67	1444.00	2.11	-1.62	0.43	0.988

k^* constant.
β_l^* parameter (β) for gamma distributed loading time.
β_{ul}^* parameter (β) for gamma distributed unloading time.
β_{ts}^* parameter (β) for gamma distributed travel speed.

APPENDIX Vb

REGRESSION COEFFICIENTS OF RESPONSE FUNCTIONS FOR AVERAGE WAITING TIME AT UNLOADING SITES

ACTION	INDEPENDENT VARIABLES										
	k^*	β_l^*	β_l^2	β_l^3	β_{ul}^*	β_{ul}^2	β_{ul}^3	β_{ts}^*	β_{ts}^2	β_{ts}^3	R^2
	Coefficient values										
5, 3, 1	0.85	-19.35	47.42	358.80	2.63	15.63	474.54	-0.56	0.39	-0.07	0.999
5, 3, 2	0.37	-15.71	204.03	-868.06	-2.30	60.15	-300.93	0.08	-0.05	0.01	0.972
5, 4, 1	0.31	-8.26	-140.05	1238.43	5.43	118.04	-162.04	0.77	-0.62	0.18	0.997
5, 4, 2	0.27	-1.84	-55.05	451.39	-4.36	120.21	-486.11	-0.25	0.26	-0.07	0.978
5, 5, 1	0.65	-20.12	215.28	-1041.67	-2.30	365.28	-1747.69	-0.52	0.59	-0.14	0.997
5, 5, 2	-0.02	-3.68	0.19	81.02	-1.91	102.34	-358.80	0.38	-0.24	0.07	0.993
10, 3, 1	4.09	-70.86	123.99	1342.59	-30.23	1065.90	-4861.11	-2.04	1.85	-0.42	0.999
10, 3, 2	1.68	-60.83	757.66	-3090.28	1.92	-66.44	868.06	-0.26	0.19	-0.04	0.999
10, 4, 1	3.31	-57.62	68.93	1053.24	-18.80	1027.53	-4895.83	-1.95	1.80	-0.38	0.999
10, 4, 2	1.38	-45.74	433.83	-1365.74	-3.55	80.76	185.19	0.44	-0.05	0.01	0.997
10, 5, 1	3.94	-64.63	256.88	69.44	2.76	594.41	-2523.15	-4.16	3.46	-0.76	0.997

Appendix Vb. (Continued)

ACTION	INDEPENDENT VARIABLES										R^2
	k*	β_l*	β_l^2	β_l^3	β_{ul}*	β_{ul}^2	β_{ul}^3	β_{ts}*	β_{ts}^2	β_{ts}^3	
	Coefficient values										
10, 5, 2	1.49	-40.02	360.57	-1087.96	-8.19	192.00	-289.35	-0.45	0.43	-0.10	0.997
20, 3, 1	7.21	-111.34	-496.63	7442.13	-84.07	2286.14	-9641.20	0.27	-0.03	0.00	0.995
20, 3, 2	5.50	-200.86	2402.44	-9340.28	0.32	-63.96	1134.26	-0.13	0.07	-0.01	0.998
20, 4, 1	5.20	-71.54	-377.88	3831.02	-38.64	2056.62	-9699.07	-2.76	2.66	-0.59	0.997
20, 4, 2	4.59	-144.26	1258.14	-3298.61	-23.30	444.02	-682.87	0.73	-0.33	0.04	0.988
20, 5, 1	5.09	-100.05	557.93	-1539.35	-30.60	2182.31	-11331.00	-3.67	3.75	-0.87	0.997
20, 5, 2	4.85	-123.62	969.23	-2210.65	-29.55	666.69	-1759.26	-1.49	1.47	-0.35	0.993

k* constant.
β_l* parameter (β) for gamma distributed loading time.
β_{ul}* parameter (β) for gamma distributed unloading time.
β_{ts}* parameter (β) for gamma distributed travel speed.

APPENDIX Vc

REGRESSION COEFFICIENTS OF RESPONSE FUNCTIONS FOR AVERAGE IDLE TIME FOR LOADERS

	INDEPENDENT VARIABLES										
ACTION	k*	β_l*	β_l^2	β_l^3	β_{ul}*	β_{ul}^2	β_{ul}^3	β_{ts}*	β_{ts}^2	β_{ts}^3	R^2
	Coefficient values										
5, 3, 1	7.75	-30.55	-359.47	2870.37	29.94	-651.93	2731.48	-11.06	9.25	-2.28	0.979
5, 3, 2	7.65	-11.88	-588.58	3761.57	23.15	-467.36	1689.82	-10.96	9.34	-2.36	0.949
5, 4, 1	10.52	-39.61	-444.80	4363.43	46.35	-1281.97	6805.56	-13.37	10.36	-2.36	0.985
5, 4, 2	8.66	31.02	-1463.1	8692.13	57.34	-1237.52	5729.17	-14.93	12.54	-3.09	0.962
5, 5, 1	12.23	-18.20	-889.14	6643.52	58.67	-1741.63	9756.94	-18.01	14.03	-3.18	0.982
5, 5, 2	9.47	70.03	-2207.8	12210.65	79.55	-1799.46	8738.43	-18.41	15.54	-3.79	0.967
10, 3, 1	8.81	-153.45	1528.46	-4861.11	4.43	-23.37	-115.74	-5.65	3.33	-0.69	0.996
10, 3, 2	8.83	-181.07	2023.66	-7372.69	6.28	-96.02	439.81	-4.40	2.27	0.43	0.999
10, 4, 1	8.75	-91.57	340.03	1250.00	30.29	-648.68	3229.17	-7.67	5.28	-1.16	0.991
10, 4, 2	8.73	-98.75	457.77	613.43	27.73	-528.66	2361.11	-7.58	5.44	-1.26	0.990
10, 5, 1	9.47	-60.67	-15.79	2465.28	52.13	-1148.08	5763.89	-11.55	8.71	-1.99	0.993
10, 5, 2	9.32	-55.44	-198.19	3483.80	39.53	-765.16	3206.02	-11.41	9.00	-2.16	0.980
20, 3, 1	8.60	-203.33	3012.29	-13865.70	-4.54	36.72	11.57	-5.26	2.65	-0.46	0.968

Appendix Vc. (Continued)

ACTION	INDEPENDENT VARIABLES										R^2
	k^*	β_l^*	β_l^2	β_l^3	β_{ul}^*	β_{ul}^2	β_{ul}^3	β_{ts}^*	β_{ts}^2	β_{ts}^3	
	Coefficient values										
20, 3, 2	9.01	-226.39	3409.17	-15856.50	-5.77	47.54	11.57	-5.29	2.66	-0.46	0.957
20, 4, 1	8.20	-186.73	2571.94	-11169.00	-4.49	73.36	-335.65	-4.00	1.78	-0.27	0.994
20, 4, 2	9.22	-222.72	3141.55	-13888.90	0.51	-62.21	532.41	-4.92	2.47	-0.43	0.991
20, 5, 1	7.77	-145.89	1601.46	-5474.54	13.44	-265.02	1319.44	-3.73	1.85	-0.35	0.989
20, 5, 2	9.11	-175.24	2041.63	-7581.02	5.72	-112.67	543.98	-5.31	3.02	-0.61	0.995

k^* constant.
β_l^* parameter (β) for gamma distributed loading time.
β_{ul}^* parameter (β) for gamma distributed unloading time.
β_{ts}^* parameter (β) for gamma distributed travel speed.

APPENDIX Vd

REGRESSION COEFFICIENTS OF RESPONSE FUNCTIONS FOR AVERAGE IDLE TIME FOR UNLOADERS

	INDEPENDENT VARIABLES										
ACTION	k*	β_l*	β_l^2	β_l^3	β_{ul}*	β_{ul}^2	β_{ul}^3	β_{ts}*	β_{ts}^2	β_{ts}^3	R^2
	Coefficient values										
5, 3, 1	11.16	72.87	-1015.00	6890.66	-87.90	583.90	-1784.29	-9.71	5.93	-1.35	0.978
5, 3, 2	13.93	57.21	-861.34	6491.16	-66.60	693.65	-3569.22	-15.23	9.85	-2.11	0.962
5, 4, 1	13.21	72.63	-833.29	3500.57	-62.25	-155.44	3278.00	-16.08	10.78	-2.42	0.979
5, 4, 2	12.38	56.48	-616.92	2352.47	-35.65	68.90	-472.34	-16.58	12.85	-3.14	0.868
5, 5, 1	13.53	36.40	-177.98	-55.18	-60.63	-177.89	3462.66	-15.88	10.69	-2.42	0.980
5, 5, 2	12.27	68.09	-695.13	1088.20	-15.70	-289.63	1530.86	-18.24	14.43	-3.54	0.845
10, 3, 1	17.41	54.87	-1194.66	10402.13	-261.92	3029.08	-11485.30	-14.36	8.14	-1.61	0.992
10, 3, 2	15.41	71.52	-852.30	7437.74	-100.92	385.15	35.75	-16.30	9.89	-2.01	0.988
10, 4, 1	15.45	33.17	-507.69	4183.03	-257.17	3267.95	-13500.60	-11.05	5.69	-1.04	0.994
10, 4, 2	12.34	56.17	-583.01	4784.39	-116.86	682.58	-1095.91	-9.19	5.19	-1.08	0.982
10, 5, 1	15.71	30.62	-427.28	3428.64	-264.47	3443.62	-14480.00	-11.51	5.99	-1.11	0.994
10, 5, 2	12.71	65.59	-901.51	6958.47	-121.20	705.73	-935.80	-9.13	4.84	-0.95	0.974

Appendix Vd. (Continued)

	INDEPENDENT VARIABLES										
ACTION	k^*	β_l^*	β_l^2	β_l^3	β_{ul}^*	β_{ul}^2	β_{ul}^3	β_{ts}^*	β_{ts}^2	β_{ts}^3	R^2
	Coefficient values										
20, 3, 1	19.66	0.42	-782.45	17021.67	-411.64	4596.79	-19732.90	-11.41	8.24	-2.06	0.964
20, 3, 2	21.35	-142.20	4383.28	-14604.00	-247.33	3018.70	-16238.40	-30.93	25.27	-6.13	0.965
20, 4, 1	19.84	51.24	-909.08	6465.60	-440.72	5591.98	-22857.30	-10.59	5.23	-0.91	0.996
20, 4, 2	18.61	2.46	233.31	3646.80	-259.98	1693.68	-2494.76	-8.14	3.24	-0.51	0.984
20, 5, 1	20.36	43.05	-678.22	4555.18	-465.66	6173.97	-26245.90	-11.55	6.01	-1.11	0.995
20, 5, 2	17.10	-3.67	300.81	3128.44	-244.30	1343.50	-449.50	-3.29	-0.75	0.40	0.982

k^* constant.
β_l^* parameter (β) for gamma distributed loading time.
β_{ul}^* parameter (β) for gamma distributed unloading time.
β_{ts}^* parameter (β) for gamma distributed travel speed.

APPENDIX Ve

REGRESSION COEFFICIENTS OF RESPONSE FUNCTIONS FOR AVERAGE NUMBER OF TRIPS

	INDEPENDENT VARIABLES										
ACTION	k*	β_1*	β_1^2	β_1^3	β_{ul}*	β_{ul}^2	β_{ul}^3	β_{ts}*	β_{ts}^2	β_{ts}^3	R^2
	Coefficient values										
5, 3, 1	12.8	-61.8	-28.9	1111.1	33.1	-1150.9	6041.7	-7.6	8.2	-2.0	0.989
5, 3, 2	13.8	5.0	-1960.9	12569.4	22.4	-614.4	2361.1	-13.6	3.6	-3.4	0.994
5, 4, 1	16.9	-64.8	-192.3	2951.4	-38.7	-491.3	4282.4	-12.2	11.0	-2.5	0.992
5, 4, 2	15.4	42.1	-2516.4	15104.2	62.7	-1742.6	8726.9	-18.7	17.5	-4.2	0.996
5, 5, 1	19.0	-48.4	-623.2	5648.2	-93.2	175.2	1851.9	-14.1	12.5	-2.9	0.991
5, 5, 2	16.7	45.2	-2444.9	14259.3	104.1	-2940.1	15902.8	-21.8	20.0	-4.8	0.994
10, 3, 1	21.0	-40.9	-872.0	6990.7	-57.0	-283.0	3634.3	-8.1	8.1	-1.9	0.988
10, 3, 2	25.5	-120.9	-1011.0	10520.8	55.8	-1720.9	8888.9	-17.1	16.3	-3.9	0.997
10, 4, 1	25.4	-84.6	-62.5	2847.2	-123.7	410.3	1354.2	-13.0	11.9	-2.8	0.995
10, 4, 2	28.8	-73.7	-1874.4	15219.9	-21.7	-893.9	5914.4	-21.0	18.9	-4.3	0.998
10, 5, 1	24.3	-60.2	-490.4	5034.7	-161.0	668.8	1145.8	-7.0	7.0	-1.6	0.997
10, 5, 2	29.3	-108.5	-1408.1	13159.7	-5.0	-1677.6	10960.7	-17.9	16.3	-3.6	0.993

Appendix Ve. (Continued)

	INDEPENDENT VARIABLES										
ACTION	k*	β_l*	β_l^2	β_l^3	β_{ul}*	β_{ul}^2	β_{ul}^3	β_{ts}*	β_{ts}^2	β_{ts}^3	R^2
	Coefficient values										
20, 3, 1	34.8	-50.2	-631.1	5590.3	-68.7	-176.4	3333.3	-11.9	11.1	-2.6	0.997
20, 3, 2	34.9	-93.6	-1598.0	13159.7	137.9	-2422.9	10358.8	-17.1	16.2	-3.8	0.994
20, 4, 1	34.8	-43.7	-501.6	4282.4	-155.7	939.0	-1261.6	-7.5	7.7	-1.8	0.994
20, 4, 2	37.8	-102.6	-1258.1	11724.5	118.7	-3035.6	15937.5	-20.3	18.7	-4.3	0.999
20, 5, 1	38.6	-46.9	-664.2	5775.5	-240.2	2214.9	-7268.5	-11.6	10.7	-2.5	0.997
20, 5, 2	39.6	-113.0	-1028.4	10266.2	95.8	-3280.4	18553.2	-20.4	18.9	-4.3	0.996

k* constant.
β_l* parameter (β) for gamma distributed loading time.
β_{ul}* parameter (β) for gamma distributed unloading time.
β_{ts}* parameter (β) for gamma distributed travel speed.

APPENDIX VIa
SIMULATION OUTPUT WITH BAYES APPROACH ("ONE-LOADING ZONE" POLICY)
LOADING ZONE 1 or 2

ACTIONS	Trucking time (hrs)				Loading (hrs)			Unloading (hrs)			Total working days[3]
	Total working	Wait[1]	Wait[2]	Over-time	Total working	Over-time	Idle	Total working	Over-time	Idle	
5,3,1	6.75	0.11	0.58	0.00	6.32	0.00	4.20	7.51	0.00	2.91	3.16
5,3,2	6.55	0.13	0.09	0.00	5.98	0.00	3.76	7.05	0.00	4.67	3.09
5,4,1	6.86	0.04	0.61	0.00	6.42	0.00	4.79	7.62	0.00	3.00	3.14
5,4,2	6.50	0.04	0.14	0.00	5.90	0.00	4.26	7.08	0.00	4.73	3.11
5,5,1	6.83	0.00	0.68	0.00	6.36	0.00	5.06	7.59	0.00	3.14	3.16
5,5,2	6.50	0.00	0.14	0.00	5.95	0.00	4.61	7.06	0.00	4.70	3.09
10,3,1	7.19	0.44	2.02	0.00	6.50	0.00	3.18	8.59	0.57	1.58	2.13
10,3,2	6.75	0.49	0.19	0.00	6.58	0.00	2.31	7.74	0.00	3.23	1.64
10,4,1	7.14	0.25	2.20	0.01	6.53	0.00	4.06	8.55	0.55	1.54	2.08
10,4,2	6.81	0.27	0.33	0.00	6.55	0.00	3.27	7.71	0.00	3.04	1.61
10,5,1	7.15	0.16	2.32	0.00	6.45	0.00	4.47	8.51	0.51	1.55	2.09
10,5,2	6.79	0.15	0.44	0.00	6.48	0.00	3.90	7.65	0.00	3.00	1.61
20,3,1	8.67	1.26	4.06	0.67	6.45	0.00	1.73	11.57	3.57	1.57	1.39
20,3,2	7.20	1.90	0.74	0.00	7.04	0.00	0.64	8.70	0.70	1.84	1.06
20,4,1	8.65	0.78	4.51	0.65	6.49	0.00	2.93	11.60	3.60	1.54	1.40
20,4,2	7.18	0.80	1.70	0.00	6.63	0.00	1.72	8.67	0.67	1.67	1.03
20,5,1	8.75	0.56	4.76	0.75	6.50	0.00	3.59	11.71	3.71	1.52	1.37
20,5,2	7.15	0.56	1.92	0.00	6.57	0.00	2.63	8.66	0.66	1.65	1.03

[1] waiting time of trucks at loading zones.
[2] waiting time of trucks at unloading sites.
[3] total working days required for hauling 200 truck loads.

APPENDIX VIb
SIMULATION OUTPUT WITH BAYES APPROACH ("ONE-LOADING ZONE" POLICY)
LOADING ZONE 3

ACTIONS	Trucking time (hrs) Total working	Wait[1]	Wait[2]	Over-time	Loading (hrs) Total working	Over-time	Idle	Unloading (hrs) Total working	Over-time	Idle	Total working days[3]
5,3,1	6.36	0.07	0.47	0.00	5.41	0.00	3.91	7.15	0.00	4.11	9.03
5,3,2	5.88	0.08	0.05	0.00	4.88	0.00	3.42	6.41	0.00	4.92	9.15
5,4,1	6.26	0.02	0.48	0.00	5.28	0.00	4.18	7.03	0.00	3.93	9.03
5,4,2	5.90	0.02	0.08	0.00	4.85	0.00	3.77	6.39	0.00	4.82	9.12
5,5,1	6.25	0.00	0.48	0.00	5.29	0.00	4.41	7.03	0.00	3.88	9.09
5,5,2	5.82	0.00	0.10	0.00	4.72	0.00	3.86	6.24	0.00	4.68	9.12
10,3,1	6.49	0.37	0.99	0.00	6.04	0.00	3.45	7.92	0.00	2.47	5.33
10,3,2	6.38	0.40	0.17	0.00	5.73	0.00	2.80	7.32	0.00	4.11	4.76
10,4,1	6.50	0.22	1.09	0.00	6.04	0.00	4.02	7.97	0.00	2.40	5.32
10,4,2	6.28	0.22	0.27	0.00	5.46	0.00	3.26	7.16	0.00	4.05	4.75
10,5,1	6.46	0.12	1.24	0.00	6.10	0.00	4.55	7.98	0.00	2.38	5.25
10,5,2	6.26	0.11	0.35	0.00	5.49	0.00	3.76	7.18	0.00	4.03	4.76
20,3,1	7.96	1.04	2.94	0.00	6.06	0.00	2.05	10.96	2.96	2.23	3.21
20,3,2	6.40	1.14	0.35	0.00	6.29	0.00	1.27	8.01	0.01	2.70	2.65
20,4,1	7.91	0.72	3.16	0.00	6.03	0.00	2.97	10.83	2.83	2.24	3.21
20,4,2	6.41	0.71	0.62	0.00	6.20	0.00	2.33	7.99	0.00	2.56	2.61
20,5,1	8.06	0.50	3.50	0.06	6.07	0.00	3.61	11.14	3.14	2.21	3.18
20,5,2	6.41	0.49	0.84	0.00	6.14	0.00	3.07	7.99	0.00	2.49	2.54

[1] waiting time of trucks at loading zones.
[2] waiting time of trucks at unloading sites.
[3] total working days required for hauling 200 truck loads.

APPENDIX VII
SIMULATION OUTPUT FOR THE APPLICATION OF THE METHOD FOR A DIFFERENT UNLOADING MACHINE

	Trucking time (hrs)				Loading (hrs)			Unloading (hrs)			
ACTIONS	Total working	Wait[1]	Wait[2]	Over-time	Total working	Over-time	Idle	Total working	Over-time	Idle	Total working days[3]
5,3,1	6.65	0.22	0.46	0.00	5.18	0.00	3.71	7.63	0.00	3.94	17.86
5,3,2	6.27	0.25	0.05	0.00	4.90	0.00	3.39	7.12	0.00	5.33	18.30
5,4,1	6.74	0.05	0.60	0.00	5.29	0.00	4.17	7.69	0.00	3.94	17.65
5,4,2	6.20	0.04	0.09	0.00	4.86	0.00	3.72	7.10	0.00	5.28	17.75
5,5,1	6.67	0.00	0.64	0.00	5.25	0.00	4.35	7.66	0.00	3.97	17.75
5,5,2	6.10	0.00	0.14	0.00	4.69	0.00	3.82	6.85	0.00	5.06	17.86
10,3,1	6.98	0.41	1.39	0.00	5.99	0.00	3.44	8.61	0.61	2.31	10.75
10,3,2	6.76	0.50	0.22	0.00	5.88	0.00	2.84	8.02	0.02	4.28	9.35
10,4,1	7.00	0.25	1.66	0.01	5.93	0.00	4.02	8.74	0.74	2.37	10.74
10,4,2	6.62	0.28	0.30	0.00	5.60	0.00	3.33	7.88	0.00	4.25	9.33
10,5,1	7.20	0.22	1.66	0.00	5.94	0.00	4.35	8.87	0.87	2.35	10.53
10,5,2	6.63	0.25	0.36	0.00	5.46	0.00	3.65	7.90	0.00	4.18	9.26
20,3,1	8.97	1.14	3.69	0.97	6.17	0.00	2.03	12.46	4.46	2.25	6.46
20,3,2	7.12	1.23	0.74	0.00	6.57	0.00	1.50	8.92	0.92	2.57	5.26
20,4,1	8.91	0.76	4.09	0.91	5.83	0.00	2.84	12.55	4.55	2.22	6.56
20,4,2	7.07	0.82	1.07	0.00	6.33	0.00	2.45	8.89	0.89	2.49	5.25
20,5,1	8.76	0.68	4.06	0.76	5.90	0.00	3.50	12.25	4.25	2.21	7.59
20,5,2	7.20	0.70	1.14	0.00	6.35	0.00	3.16	8.96	0.96	2.40	5.04

[1] waiting time of trucks at loading zones.
[2] waiting time of trucks at unloading sites.
[3] total working days required for hauling 200 truck loads.

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