Uncertain Analysis Based on Milk-Runs Systems Using Bayesian Networks

Roberto Murillo-Ramirez and Giovanni Lizarraga-Lizarraga

Abstract For several years, the role of original equipment manufacturers (OEM) has been changing. Now, their primary operations focus on design, assembly systems, and marketing. Considering that component suppliers provide more than 95% parts of a light vehicle, the complexity of the logistics is high. Seeking to comply with the Just in Time (JIT) philosophy and thus avoid the shortage of components on assembly lines, the companies use the inbound logistics to perform these operations from suppliers to OEMs. The Milk-run concept refers to carrying out the consolidated supply of components to OEMs through the planning of routes considering xed and cyclical time windows. Currently, Milk-run (MR) systems suffer from interruptions in component deliveries; this can produce monetary losses per minute of delay in the assembly line of OEM. Problems in MR have been approached from the perspective of optimization models with variations within them, and there are a few studies about variability and uncertainty in MR operations. The results of this research are favorable because not only uncertainty is quantified; the causes of optimistic and pessimistic scenarios are also quantified.

Keywords Milk-runs · Bayesian networks · Uncertainty

1 Introduction

The automotive industry has been a forerunner in important areas such as global economic structures and manufacturing systems. This industry has moved its manufacturing plants to different parts of the world, which benefits the economy of the countries in which they move [1, 2].

R. Murillo-Ramirez (✉) · G. Lizarraga-Lizarraga
Universidad Autonoma de Nuevo Leon, San Nicolas de los Garza, Mexico
e-mail: roberto.murillorm@uanl.edu.mx

G. Lizarraga-Lizarraga
e-mail: giovanni.lizarragalz@uanl.edu.mx

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Another significant contribution has been the implementation of lean manufacturing systems, and its objective is to eliminate processes that do not add value to a company. One of the most representative tools of these systems is the Just In Time (JIT) manufacturing philosophy, which supports the correct coordination of the actors in a supply chain system [3, 4].

The role of Original Equipment Manufacturers (OEM) has changed over time; in the past, car manufacturing was carried out entirely within OEM's. Today, their main functions focus on the design, marketing, and assembly systems of vehicles. The current models of light vehicles assembled by the OEM's are composed of an average of 3,500 to 7,000 parts and components. The suppliers' status takes total relevance since they are responsible for supplying 95% of the vehicle components [5]. Inbound logistics in OEM's refers to the articulation of the supply of components, following established parameters, correct quantities, and specific components in the right order. The modes of transportation that used to carry out the logistics may be the following:

(a) point-to-point transportation, (b) expedited transportation, (c) Milk-run round-trip and (d) Milk-run open [6]:

(a) This kind of transportation is planned and based on the monthly requirement of components.
(b) This mode is activated by a variation in the demand for components.
(c) Component collection system that begins at the plant taking empty equipment to suppliers.
(d) Component collection system that begins at a supplier on the route.

In the literature review, these systems are called Milk-Runs (MR) and present specific characteristics such as cyclical and xed scheduling of routes and collection times previously defined and coordinated by the OEMs [7].

MR freight transport operations are carried out by outsourcing services companies, which seek to establish efficient and pro table transportation routes, thus minimizing losses of time and money [6].

2 Problem Statement

It is known that variations and interruptions may occur within the operations of an MR. Disruptions in freight transport are associated with errors in daily work and their execution. However, minimal they may seem, these interruptions can cause changes in everyday practices and, therefore, lead to disturbances in a network [8]. Thus, the disruptions presented in transport are showed. We explain how these interruptions can affect the mobility of goods, in such a way that the entire flow of a transport network suffer alterations. In [9], the author mentions the effects caused by the uncertainty in such operations.

One of OEM's main goals is to speed up the entry of components to the assembly lines, thus reducing the number of delays and low inventory levels. Delays result in monetary losses per unit of time [3]. Interruptions in MR generate uncertainty and to face the uncertainty presented in component delivery delays, expedited freight transport is used. This is an alternative currently used by OEMs to avoid delays in production lines. Consequently, this represents a higher inherent cost and more complexity in logistics operations.

This uncertainty has not yet been incorporated and analyzed within the MR scenarios, decisions to either to expedite or not to expedite components are made empirically or by intuition without considering a decision statement-making [10].

In this research, we identify, describe, and document the problems related to MR's uncertainty and how these factors affect decision-making regarding expedited component transportation. We analyze the operating scenarios to observe the uncertainty involved in the MR.

3 Literature Review

This section describes the problems that some authors have associated with MR. MR's have pick-up and delivery time windows. There are also a limited number of cargo units with specific capacities that make them a candidate to be solved by a vehicle routing problem (VRP) [11]. It is essential to mention that the MR's have specific characteristics and the VRP models only contribute in a part of the design and planning of the MRs, but do not adequately contemplate the logistics operations involved.

Usually, the main target of optimizing VRP models is to obtain the minimum total travel distance using heuristic algorithms or linear programming. For component pick-up systems MR, a tool known as the vehicle routing problem with MRVRP dairy routes is used. In this model, two approaches are considered: minimizing the distance or the total costs [12]. According to [13], VRP models can present one of the following strategies: minimize aspects such as total cost of operation, full transport time, total distance traveled, and waiting time. You can also look for pro t maximization, customer service, vehicle utilization, etc.

In [6], the authors solved the Periodic Vehicle Routing Problem with Service Choice (PVRPSC) using mixed-integer programming. Among its results, they provided a basis for the decision regarding the selection of the transport mode and a 15% reduction in annual operating costs. In another paper, [3] explains the VRP model and its implications for the management of parts collecting systems. They mentioned that this model has variants that may consider factors such as time windows or dynamic order processing, and for both cases, there are modifications to the model. The author also mentions that as the size of the problem grows, the calculation time will be longer.

These authors modify the classic VRP problem and seek to adapt certain needs of their case studies, as can be seen in Table 1, in which the VRP can include factors of time windows, dynamism and include CRS costs. These models present specific objectives to be achieved. Still, models do not contemplate any behavior that implies uncertainty, which means that the values in established parameters are not usually the most appropriate.

There is a stochastic approach of the VRP's. This variant is known in the literature as SVRP and includes non-deterministic factors since, in real life, the variables considered present some degree of uncertainty. These variables include, usually, service and travel times, customers, and the most crucial factor is the demand. These variants are widely studied in the literature [14], and can help make partial decisions because the real performances of these variables are not frequently measured.

The generation of cost structures is one of the approaches found in the literature. These investigations contemplate implicit costs in the design, planning, and execution of MRs, and are mostly used to examine hidden costs and future scenarios. Another perspective of the investigations associated with the term Milk-Runs is the MR in the plant (MRIP), which refers to the design of component pick-up systems. The main target is to design and plan the implementation of MR tours in manufacturing plants, with the help of automatic or semi-automatic equipment, to reduce operating times and human mistakes.

In our literature review, we did not found published works related to levels of uncertainty in MR. In the next section, we introduce some of the tools used to analyze scenarios where uncertainty is incorporated as a preamble to understand the objective of this research. Uncertainty refers to the least possible or null understanding of a scene that requires inquiries or answers that the standard models do not work contemplate. There are tools used in the quantification of uncertainty [15]. One of them is the Monte Carlo method, which consists of generating a series of numbers using a random sampling of probability distributions and can give approximate solutions by experimenting with real phenomena [16]. Within these tools, there are also

Table 1 Overview of problems related with Milk-run systems

Authors	Problems					
	VRP	VRPTW	DVRP	Cost	MRIP	Uncertainity
Du 2007	x	x	x	–	–	–
Aragao 2016	x	–	x	–	–	–
Meyer 2018	x	–	–	x	–	–
Kluska 2018	–	–	–	–	x	–
De 2016	–	–	–	x	–	–
Guner 2017	x	–	x	–	–	–
Staab 2016	–	–	–	–	x	–
Bocewicz 2019	x	–	–	–	x	–
Fedorko 2018	–	–	–	–	x	–
Lin 2015	x	–	–	–	–	–
Ma 2013	x	–	–	–	–	–
Novaes 2015	x	–	x	x	–	–
Ranjbaran 2020	–	–	–	x	–	–

fuzzy sets in which a linguistic label is used to determine a membership function and helps to represent the ambiguity or vagueness of real phenomena [4]. One more quantification method for uncertainty is the polynomial chaos method.

In this method, an uncertainty propagation is performed on the model predictions and reduces the complexity in computational resolution compared to the Monte Carlo method [17]. The last uncertainty method we reviewed was the Bayesian model, based on the conditional probabilities between variables according to Bayes' theorem. This tool has proven to be efficient in the correct quantification of uncertainty in highly complex scenarios.

4 Methodology

The selected tool to quantify the uncertainty, among the existing methods, was the Bayesian networks because they have the following advantages:

- Ideal for situations where there is a few data or imperfect knowledge, which cannot be solved by rigorous probabilistic models [18].
- This tool is based mainly on intuition, which is formalized in certainty factors [18].
- General reasoning is used under uncertainty with in-depth knowledge [18].

Due to these aspects, Bayesian networks promise to be a good option to quantify the uncertainty in MR and also provide an important guideline in terms of literature contribution.

Bayes' method is the inverse effect of the total probability. Given two mutually independent events, the result in the calculation of the total probability is the probability of the intersection of one event to the other and is expressed in the following way:

$$\mathrm{P(A \cap B) = P(A) * P(B)} \tag{1}$$

Where $\mathrm{P(A \cap B)}$ is the probability of the intersection of event A and event B.

In this way, it is easier to understand how Bayes' theorem works; it is the inverse form of the previous equation since prior evidence of one event is required. This is the probability of occurrence of an event since another has happened and is expressed as follows:

$$\mathrm{P}(\mathrm{A}_i|\mathrm{B}) = \frac{\mathrm{P}(\mathrm{A}_i|\mathrm{B})}{\mathrm{P(B)}} \tag{2}$$

Where: $\mathrm{P}(\mathrm{A}_i|\mathrm{B})$ is the probability that event A occurs knowing that event B occurred.

As we mentioned before, a scenario is structured to better outline the MR operations, where we exemplify the behavior of the independent variable A, concerning a dependent variable B.

We try to explain how realiced the estructure of MR scenario with the Fig. 1, where:

C = Complete scenario of operation MR.

A_i = Independent variables of MR, the subscript i show the count to each event.

B = Dependent variable that represents the probability of expediting components.

The developed methodology is based on MR scenarios that are schematized for their analysis using Bayes' theorem. The next step is establishing the variables type Ai to proceed with the creation of the directed acyclic graph and the calculation of the conditional probabilities. Bayesian networks have two parts, one qualitative and the other quantitative. The qualitative component is made based on the experience of the people involved in MR operations [19]. The methodology developed arises from the application of models that use Bayesian networks. The authors [20–22] adjusted the variables of their models to be able to predict the events in their corresponding scenarios. The following is the assignment of variables to the scenario.

These variables require a probabilistic value based on the possible states they can take. For example, the states that these variables can have can be expressed as follows:

- True—false
- Complete—incomplete
- In time—delated.

These statements are analyzed by the expert people consulted, in order to obtain the values of the probability of occurrence of each sentence according to their experience. It is essential to mention that the sum of the percentages in the possible states of a variable must be equal to one hundred percent in all cases (see Fig. 2).

Once the conditional probabilities for the scenario are determined, we will continue with the creation of the graphical model that will help in the probabilistic reasoning and is represented by the directed acyclic graphs formed by nodes and arcs. Each variable represents the nodes with its respective probabilities, and the arches are the direct dependency relationships between variables. The purpose of Bayesian networks is to know the posterior probability of the variables of the network. These probabilities arise when specific evidence is given that some variable has taken a certain state, while no evidence is given to the variables, the network will take values of the a priori probability distribution, in which only the probability of an event occurring without prior evidence is considered. The following steps are required to create the graph:

- Determination of the relationship between variables, identify the parent nodes and the child nodes.
- Validate the interdependence or conditional dependence between variables.

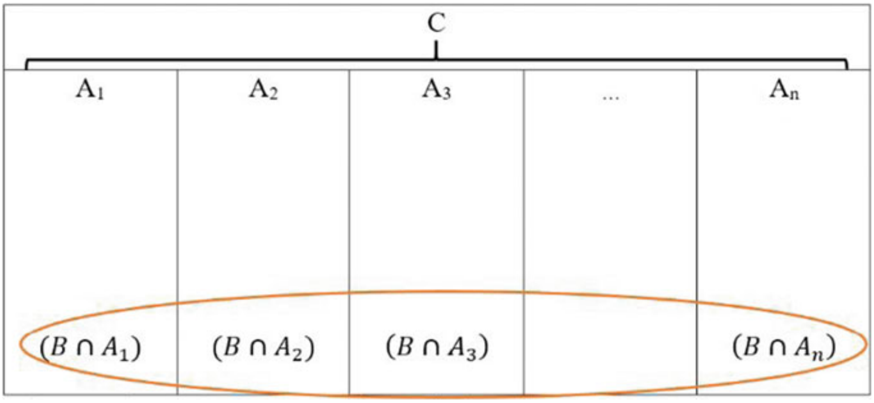
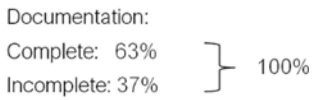


Fig. 1 Venn diagram with respect to the Bayes theorem scenario [20]

Fig. 2 Values of variables



The first part is determined by calculating the dependency probabilities, which are developed by the following equation:

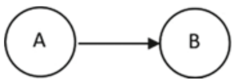
$$P(B|A_1 \ldots A_n) = (B|A_i) \tag{3}$$

The resulting probability for each variable $(B|A_i)$ produced by this equation serves as a statement for the creation of the graph. If they determine the dependency or independence relationship for the nodes, these relationships are expressed within the graph, as shown in Fig. 3.

These graphical representations are used in the creation of a graph based on the structure of Bayesian networks. Within the graphs, the relationships between nodes can have several behavior patterns: convergent behavior, that happens when a parent node has two children (see Fig. 4); divergent behavior, when a variable has two parents; and sequential behavior, in which there is a relationship between a parent node and a child node that in turn is the parent of another node.

Once the graph is created, the next step is the calculation of the conditional probabilities. This step is di cult and extremely laborious because each probability is calculated with the following equation:

Fig. 3 Structure of graph model



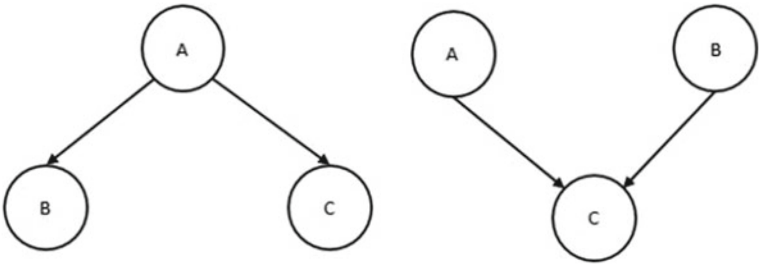


Fig. 4 Types of structure in graph models

After the creation of the graph, the calculation of the conditional probabilities is difficult and the manual process is extremely laborious, because include each probability spread following equation:

$$P(A_i|B) = \frac{P(A_iB)}{P(B)} = \frac{P(B|A_i)}{\sum_{i=1}^{n} P(A_i)P(B|A_i)} \tag{4}$$

Where $P(A_i|B)$ is the conditional probability of an event A_i given that there was an event B of an expedition of components. The calculations are made for each relationship between parent and child node, in such a way that they can be shown in result matrices that will help to inference the causes and probabilities of the operational scenarios. Considering the last part, this research pretends to obtain a basis given the calculation of the probabilities and causes that influence the events where component expediting occurs. The inferences about the event studied will serve as a statement for decision-makers regarding two types of planning:

- Seek the possible integration of the expediting of components in the MR planning knowing the probability that these events will happen given certain findings and
- Identify the processes that negatively influence the MR's execution and seek their improvement; these MR operations involved can be seen in Table 2.

5 Case of study

We worked in collaboration with a company dedicated to the management of type C components. This classification includes materials such as adhesives, plugs, fuses, indicators, led accessories, security seals, wires, hardware, and terminals for wires, among others. Within the manufacturing industries, all components' importance is kept in mind, no matter their size and volume, they are essential for a manufacturing process. At this point, the importance of managing these components is rectified.

The company carries out management to guarantee its clients solutions based on the challenges that manufacturing companies present. These challenges are the reduction of total ownership costs without risking factors such as product quality and inventory levels in parts consumption.

It is valuable for the company to contemplate that hidden costs are commonly omitted in the management of class C components. Only 15% of the total value of a component is known, while the other 85% is unknown or ignored. These hidden costs impact areas such as logistics, inventory management, engineering, quality, and finance.

It will be advantageous for the company to provide a specific supply chain for class C components, which will improve the consolidation of suppliers in a single operating figure, reduce the degree of uncertainty, decrease delivery times, and increase productivity. The following are the company's value-added services: risk minimization, inventory optimization, operations improvement, and quality improvement.

It is important to mention that the company carries out projects according to the requirements of each specific client. These requirements can be diverse and varied because the company has clients from different industries, such as automotive and household appliances, among other sectors.

6 Results and Analysis

For this investigation, the company provided information related to twenty-one MR routes. The creation of the scenario was based on the operations in Table 2. These operations were taken as the scenario variables. First, we assign probabilities of occurrence to these variables. These probabilities were determined by consulting the company's expert group through an online form that was shared. We sent the form to the experts so they can familiarize them-selves with the tool, then an online meeting was held with all the participants in which the probabilities were assigned by consensus.

In Fig. 5, we can see the structure of the directed acyclic graph and how the variables are related to each other. We can see that the network has a total of twelve nodes, whose output variable is the node "Expediting", which has as parent nodes "Load time", "Road accident", and "Change model" variables.

The propagation of probabilities in the network is shown in Fig. 6 and we can see that values showed in each node represent the "a priori" probabilities of the

Table 2 Variables of MR scenario

Variables		
Supplier	3PL transport	OEM
Shipping documentation	Vehicle arrives	Forecast production
Load time	Vehicular traffic	Stowage plan
Complete pallets	Maintenance	Change of model
Quality	Road accident	

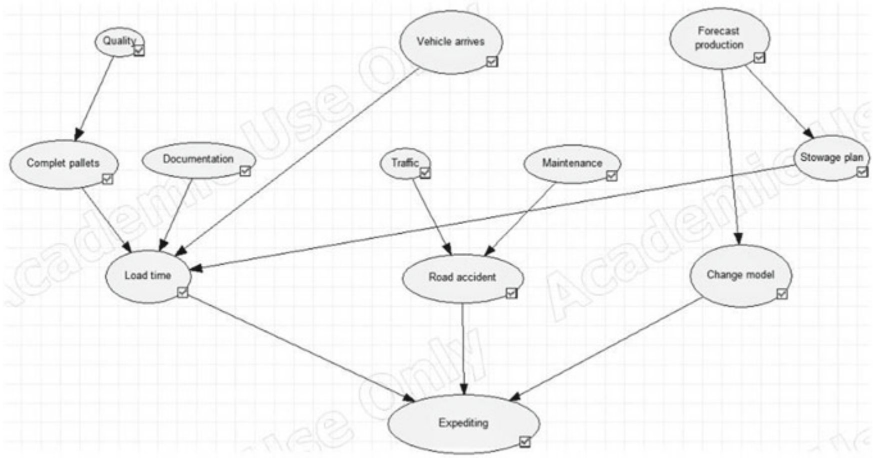


Fig. 5 Graphic model of MR systems

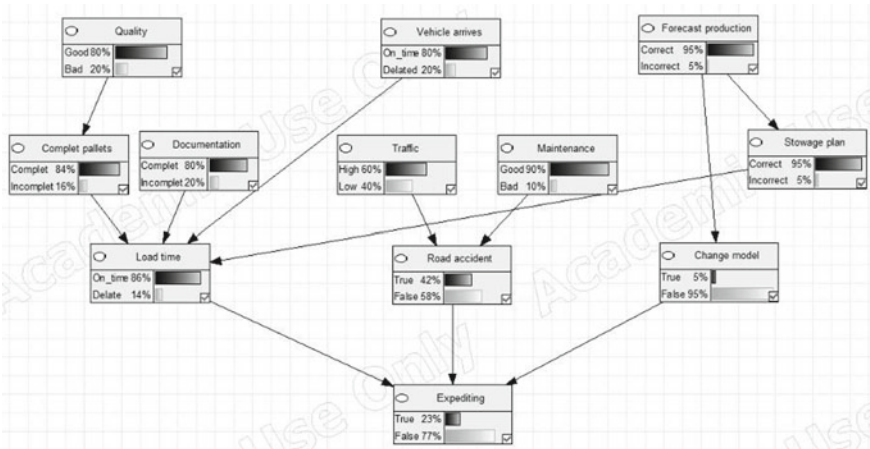


Fig. 6 Graphic model of probabilities a priori of MR systems

network. When we introduce the probabilities values gived from experts the target node "Expediting" take the value 77%, means that it is not required to expedite components versus 23% otherwise.

When obtaining the probability of occurrence, the acyclic directed graphic was created using the Genie version 2.4 software. The calculation of the "a priori" probabilities distributions and their respective conditional probability tables were obtained. In this sense, by providing evidence to the network's nodes, the conditional probabilities spread is carried out throughout the network, giving an estimation of the "a posteriori" probabilities.

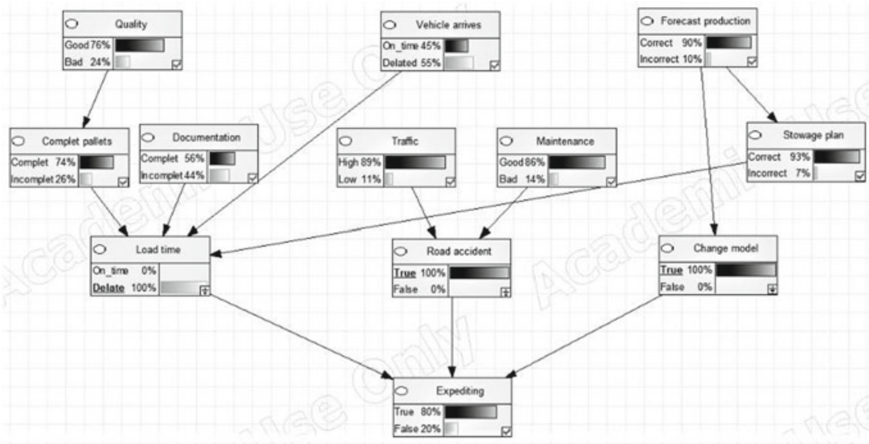


Fig. 7 Graphic model of negative scenario of MR systems

In the first part of the “a priori” probabilities, it is probability of occurrence is shown based on the experts’ values. The second part, where realiced inferences, is made when certain evidence is given to the middle nodes, the probabilities spread are not only shown on the target node, but also affect the nodes probabilities on top and bottom positions creating an upstream and downstream effect. To exemplify this part, two scenarios were elaborated, one with favorable conditions for the MR’s execution, and the other with negative conditions.

The first scenario is shown in Fig. 7, in which negative evidence was given to the “Load time”, “Road accident”, and “Change model” middle nodes and in this way, the network’s values were modificated. The “a posteriori” probability changes its value, and the target node “Expediting” changes its probabilities of occurrence, now the probability that will be occurr as 80% true against 20% false.

As shown in Fig. 7, it can be observed that now the probability that the “Vehicle arrives” is delayed is 55% and that the “Documentation” of MR’s could be 44% wrong. In comparison, there is an 89% probability that the traffic is high. With these observations, one of the advantages of Bayesian networks is fulfilled. It not only shows the probability of occurrence of the target variables but also quantifies the possible causes for these states in the variables, this prove the upstream and downstream effect.

The behavior of this network is similar to the previous one, by giving positive evidence to the network the upstream and downstream effect will repeat, now the probability that components will be expedited is 90% false (view Fig. 8), which is favorable for the company. Besides, it is also observed how should the values be so that the probability that the “Load time” is on time should present a “Vehicle arrives” with 86% on time, and that the “Documentation” of the SRC should be correct by 84%. In comparison, there is a 61% probability that the traffic was low. This scenario

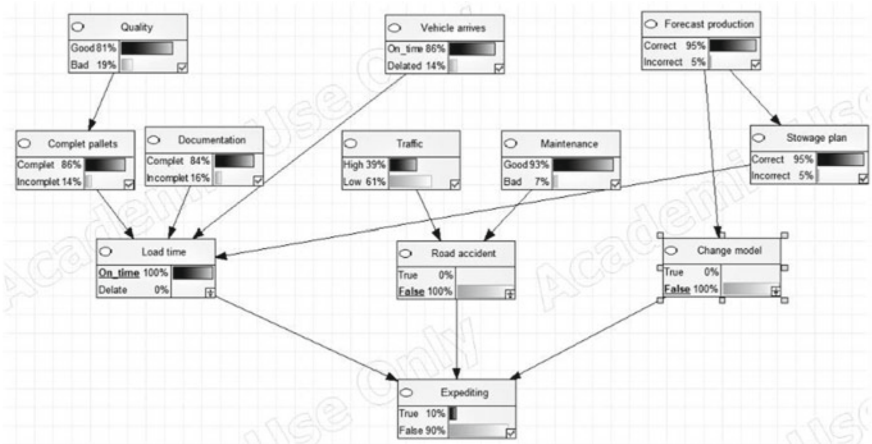


Fig. 8 Graphic model with positive evidence of MR systems

could be as a strategic guide for decision makers because shown the occur probability use minime of expediting transport and how to reduce the use of this.

7 Conclusions

This paper addresses a logistics issue related to the business structures commonly used by the automotive industry, the Milk-run systems. We reviewed the literature, and by studying the applications of these systems in the cases of study, we found that MRs are not exclusive to the automotive industry. Industries such as household appliances have adopted these systems to reduce inventories and achieve more agile and lean manufacturing. Also, we observed that in the current approaches in the literature related to MR, there are many guidelines to develop these systems. We can conclude that MRs is a topic that has not been studied so extensively, since these systems can be associated with other types of transport structures.

In the uncertainty part in the MR, the closest that could be found to the literature is the approach to the vehicle routing problem using stochastic variables. As mentioned before, the VRPs only manage to solve a part of the planning and design of MR, while there is still uncertainty in the other parts. It is convenient to mention that by relating the term" Uncertainty" with the term "milk-runs" the literature search is reduced to a minimum, which indicates that more studies can be carried out on this topic.

In the part of the uncertainty quantification tool, the Bayesian networks showed their effectiveness, not only in their maximum expressiveness of the probability distributions in the nodes using the directed acyclic graph, but it was also possible to weight causality of nodes given some evidence. It was possible to show to the company the probability of an event of expedited transport of components to happen and what are the possible causes that propitiate it.

7.1 Future Work

As mentioned before, as we did not have historical data on MR's execution, it was decided to consider the company's staff's expert opinion to calculate the probabilities of the variables. For this, the company was informed that the network could be fed in the future with historical operating data. The Bayesian network has an advantage over other probabilistic tools since it can work with little information or incomplete information.

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