ZESZYTY NAUKOWE WYŻSZEJ SZKOŁY TECHNICZNEJ W KATOWICACH
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Mariusz Topolski
WSB University in Wrocław, Institute of Logistics
mariusz.topolski@wsb.wroclaw.pl

COMPUTER ALGORITHMS PROBABILISTIC SUPPORTING INTELLIGENT TRANSPORTATION MANAGEMENT OF INTERNAL

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ABSTRACT

This paper presents a probabilistic model in managing intelligent internal transport based on decision making risk. The term reliability of an internal transport denotes failure-free operating time of internal transport as compared to the entire time particular transport is supposed to operate correctly. This paper illustrates a model of risk evaluation in internal transport operation based on probability that the system will reliably function within particular time, in a particular environment for specific purposes. Building probabilistic models used to calculate the risk of production planning is based on a reliable analysis of all possible aspects of producing a particular economic good. Modelling evaluates strengths and weaknesses of an enterprise which would like to complete a transport task, plans a transport processes based on the most important goals originating from the transport process.

KEYWORDS

Intelligent transport system, recognition Bayes

INTRODUCTION

Internal transport is an important aspect of a production enterprise which often poses a problem for numerous industrial plants. It is especially vital when time as well as production costs are considered.

Thanks to optimization of internal transport and internal roads we may count on lowering manufacturing costs.

Transport in factories may play a significant role in the production mechanism. Depending on the type and the nature of a particular enterprise, transport costs may be ranked highly in the hierarchy of costs incurred by a company. Well organized internal transport involves not only decreasing costs but also time and denotes the quality of production.

The literature is familiar with soft methods of supporting transport systems management, forecasting sales and analysing various transport problems [4,5,6]. This paper shows two methods, the first one supports the selection of intelligent transport systems depending on various decision criteria. The other model focuses on choosing the shortest route in internal transport between numerous destination points minimizing an overall length of the route.

1. THEORETICAL BASIS OF TRANSPORT

Internal transport ,or in other words in-house transport, belongs to handling which takes place within a plant whose borders divide the transport.

It is a company activity directly related to production logistics which refers to short distance transportation depending on the size of a particular production enterprise.
In-house transport is also defined as internal transport, handling or industrial and refers to one type of movements.
Production transport consists in moving cargo connected to production processes. It comprises inter-divisional transport or movement between e.g. warehouses as well as departmental transport e.g. transportation in a production hall.
Warehouse transports involves transporting cargo and putting it in warehouses and storerooms.
Inter- divisional transport is one of elements of production transport and comprises transport between departments, warehouses or orchard fields.
Divisional transport takes place in a work station.
Intelligent transport consists of a transport system being able to organize and control itself unaided directly by an operator.

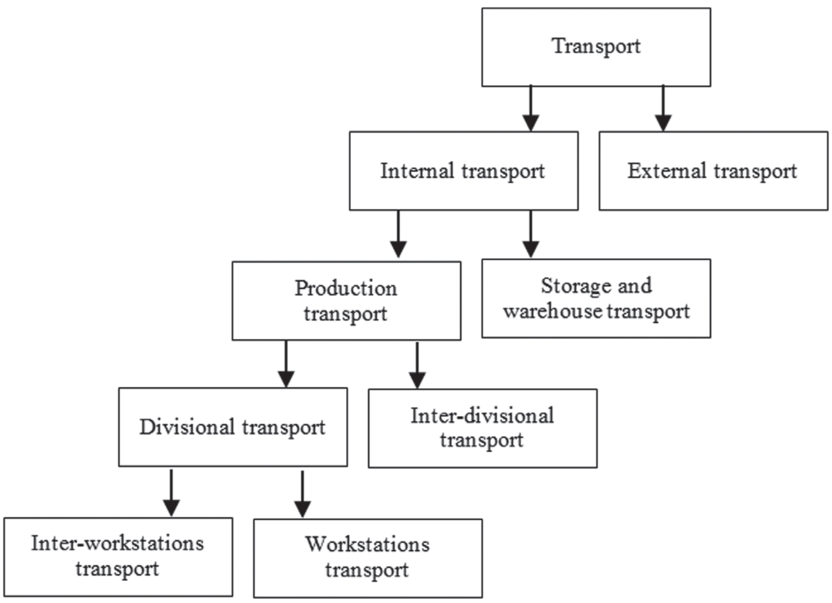

Fig. 1. Division of transport

In order to have the best transport organization, we should remember about a few important principles such as a short transport way maximizing the use of transportation means at the lowest wear and tear.

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Thanks to optimization of internal transport, transportation means may be used in a better way, work time of operators and warehousemen may be better organized. Optimization is also related to reduction of transport costs which is vital to entrepreneurs. It also eases transport shortages and simplifies its organization.

Ways of optimizing transport:

1. Creating a one-flow stream of materials avoiding turning back and crossroads. It should flow straight, along a circle or in S, U or Z shape.
2. Decreasing the number of transport operations and removing those unnecessary
3. Decreasing the distance between transshipment place will result in shortening transport routes leading to less time and lower transport costs. We can make better use of the production space.
4. Application of a continuous material flow and elimination of transshipment operations. Each transshipment break is tied up to production delays resulting in stoppages or additional transport operations.
5. Making use of physics in internal transport systems to relieve workers e.g. sliding, dropping materials provided they do not break.
6. A full use of space in buildings will improve work efficiency.
7. Appropriate maintenance of transport devices and transport routes.
8. Securing safety where transport operations may pose a threat to employees.

2. PROBABILISTIC MODEL

A random experience shall refer to an experiment, a physical phenomenon whose course of action depends on a coincidence and fulfilment of the two conditions:
1. Set Ω_δ of all possible results is at most countable.
2. It is possible to define a priori and estimate a posteriori the probability of a result that the experiment will end with.

A random experiment shall be marked with δ.
The outcome of a random experiment must consist of at least two elements. When it comes to a set which is at most countable we then talk about a grainy random experiment. Out of them we can differentiate experiments which occur in stages. We will call them multi-stage. There may be experiments with random number of stages. They shall be called random experiments with a random number of stages.
Probability space (Ω,) shall be referred to as a probabilistic model or in other words a model of random experiment δ if Ω is a set of all outcomes of experiment δ which is possible. Whereas function shall assing a probability with which experiment δ may end.
Transport optimization is a key element in companies and there are numerous methods of creating the best solution for companies and production plants. For these purposes probability may be used by calculating which route and method will be the best solution for a particular enterprise.
For event A and a series of events $B_1, B_2, \ldots, B_n$ meeting the conditions as follows:
1. $P(B_i)>0$ for each i {1,2,...,n}
2. B_i are disjoint pairs
3. $B_1 \cup B_2 \cup \ldots \cup B_n = \Omega$

the total probability may be calculated using a total probability theorem expressed by the formula [2]

$$P(A)=P(B_1)\cdot P(A|B_1)+P(B_2)\cdot P(A|B_2)+\cdots+P(B_n)\cdot P(A|B_n)$$

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For each probability distribution there is function referred to as a cumulative distribution function. In case of a discrete distribution this function fulfils the following five conditions:

1. $\lim_{x\to-\infty)} F(x)=0$
2. $\lim_{x\to+\infty)} F(x)=1$
3. F is a non-decreasing function
4. F is a left-continuous function
5. F is a piece-wise constant function [2]

Letter d stands for a discrete probability distribution. We deal with a discrete probability distribution when the following three conditions are met:

1. There is a sub-set of set R,X={r_n,n∊N_0}
2. There is a series of numbers p_n∊(0,1),n∊N_0 which adds up to one
3. The function d:R→{p_n,n∊N_0}, takie że d(r_n)=p_n, for each, n∊N_0, gdzie N_0≤N [2]

If is finite, such a distribution is called a finite probability distribution.
A two-point distribution is the simplest example of a discrete distribution:

X=(0,1}, d(0)=q, d(1)=p, dla p∊(0,1), q=1-p

A cumulative distribution function of a discrete distribution is expressed by the following formula:

$$F(x)=\sum_{x_n<x} p_n \tag{1}$$

A cumulative distribution function of a two-point distribution assumed the following form:

$$F(x) = \begin{cases} 0, when\ x \le 0 \\ q, when\ x \in (0,1] \\ 1, when\ x > 1 \end{cases} \tag{2}$$

We deal with a continuous probability distribution when there is a cumulative distribution function: meeting the conditions as follows:

1. $\lim_{x\to-\infty)} F(x)=0$
2. $\lim_{x\to+\infty)} F(x)=1$
3. F is a non-decreasing function.
4. F is left-hand continuous [2].

Before defining a normal distribution we need to define a density function of probability distribution.
"a random variable of a continuous nature shall have a derivative of a cumulative distribution function called a density probability function written as follows: $f_X=F'_X \cdot$ "[2]

Normal distribution N(0,1) is characterised by density represented by Gaussian curve expressed by the formula:

$$f(x) = \frac{1}{\sqrt{2\pi}} \cdot e^{-\frac{x^2}{2}} \tag{3}$$

+

A cumulative distribution N(0,1) function of random variable X which has a normal distribution is marked with Φ. The cumulative distribution function of such random variable is not an elementary function i.e. its value must be read in the table of normal distribution.

Bayer classifier is one the basic classifiers enabling us to establish a probability density function *a-posteriori* on the basis of *a-priori* probability.
We may assume that the data refers to the probability of belonging to classes representing a particular means of transport or a transshipment system of internal transport respectively $P(C_1),P(C_2),...,P(C_n)$ examples of a certain classification. So based on a certain value x an appropriate means of transport is selected for providing internal transport. Let us also assume density of probability distributions of observation vector x occurring in particular classes of examples $p(x|C_1),p(x|C_2),...,p(x|C_n)$. This way we have achieved a-priori probability. We use the same denomination as in case conditional probability however we substitute the symbol of probability with a small letter "p".
Using Bayes' theorem we may establish density of a-posteriori probability distribution of class *k* occurring in relation to observation vector x. In the equation of transport management we will consider random value x being a parameter deciding about using a particular means of transport:

$$P(C_k|x) = \frac{p(x|C_k)\cdot P(C_k)}{p(x)} \tag{4}$$

in the denominator denotes distribution density of values of the observation vector and it is a sum of density after all classes. It may be illustrated by means of the following formula:

$$p(x) = \sum_{k=1}^{n} p(x|C_k). \tag{5}$$

The most important property of a-posteriori probability is illustrated by the fact that all classes (means of transport) add up to one in the entire field of changeability of the observation vector.
The last step is to assign a class (means of transport) to each classified observation vector so that this assignment is a function assigning a maximum value of a-posteriori probability:

$$f(x) = \underset{C}{\operatorname{argmax}}\, P(C|x) \tag{6}$$

Bayes' classifier in optimal in terms of minimizing a generalization error on condition that the used probability and density of probability distribution are true. It is confirmed by density of values distribution of the observation vector, namely the sum of density after all classes mentioned before.. It results from the error classification function:

$$P(err) = \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j \neq i}}^{n} P(x \in R_i, C_i)\, f(x)$$

$$= \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j \neq i}}^{n} P(x \in R_i|C_j) P(C_j) f(x)$$

$$= \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j \neq i}}^{n} \int_{R_1} p(x|C_j) P(C_j) f(x) dx \tag{7}$$

Similarly to classical Bayes' classifier, this one is also based on Bayes' theorem but it may be used for solving problems related to numerous input possibilities. Moreover this method is much easier and often works better than other classification methods.
This classifier is called „naïve" because of the assumption made before solving the problem. Namely, a mutual independence of independent variables is assumed [1]. Establishing an a-posteriori value of probability by means of this classifier is quicker and easier. In order to establish values of a-posteriori probability out of set we use Bayes' theorem:

$$p(C_j|x_1,x_{-2},\dots,x_n)=p(x_1,x_2,\dots,x_n|C_j)\cdot f(x)p(C_j) \tag{8}$$

As we already know is a-posteriori probability of belonging to a class in other words .
Then using our assumption of mutual independence of independent variables we may describe it by means of the product:

$$p(C_j|X)=p(C_j)\prod_{(k=1)}^{n}p(x_k|C_j)f(x) \tag{9}$$

X is a new case we consider. This case is called a chance. Using the same assumption we may describe our Chance in the form of the product:

$$p(X|C\_j)=\prod_{k=1}^{n} p(x_k,C_j)f(x) \tag{10}$$

By means of Bayes' theorem the choice of transport means is assigned to class which has the highest a-posteriori probability.
The designed probabilistic model allows us to select the best transportation means on the basis of a criterion e.g. distance x. It is time to choose the most favourable transport route. Let us take time $t_{a,b}$ and distance $o_{a,b}$ (a = 0,...,B; b = 0,1,2...,B) to all points in an enterprise (a production hall or a warehouse). Let us assume that a transportation order is marked as zam_b expressed by distance. We provided a load of transport means v expressed by the distance of the route. Thanks to the above assumptions we will determine:

- number of trips
- products carried on each trip
- duration of trips
- destination points
- a route of each transportation means

The problem of reducing the transport time to a minimum needs solving as it constitutes a criterion for optimizing the problem. Firstly we must define a stage of the decision process and functions of generating subsequent stages. The stage of the decision making is as follows:

$$C = [c_{b,a}] \qquad b = 1,\dots,B \qquad a = 1,2. \tag{11}$$

The first column of the matrix (11) is defined as follows:

$$C_{b,1} = tr \tag{12}$$

where *tr* - routes (trips) of a transport means determined by algorithm (10) (tr=1,2,...,TR) whereas the number of *TR routes* (trips) is unknown.

The second column of the matrix (11) is defined as follows:

$$C_{b,2} = st \tag{13}$$

where *st* – sequence number (consecutive) of *b-th* point of a delivery on the t*r-th* route whereas *st=1,2,...St*$_{tr}$ and *St*$_{rtr}$ is the number of delivery points on t*r-th* route.

Assuming that each line corresponds to a b-th delivery point, b=1...B we may assume that in the first column we put down the number of trip tr which delivered a product to a b-th delivery point, in the other column we put down a subsequent st-th delivery point on tr-th route. The initial state of G^0 is a matrix with zero elements, the final state G^N is unknown – it is a matrix with all positive elements. The final stage illustrates a permissible (optimal) solution to an internal transport issue. The trajectory is subject to an appropriately defined procedure of generating stages.
Initial stage C^0 is a matrix of zero elements. The final stage C^B is unknown – it is a matrix with all positive elements. It represents a permissible solution. The algorithm must consider:

- a current location of a transport means $^{d-1}$, on each trip a truck starts from location 0 and it goes back to 0 at the end. .
- the number of metres covered e^{d-1} on tr-th route whereas at the beginning of each route e^{d-1}=0;
- the number of products k^{d-1} delivered to destination points on the tr-th route whereas at the beginning of each route ^{e}d-1=0 and at the end of each route the following condition must be met

$$k_{tr}^{d-1} \le v. \tag{14}$$

The procedure of generating permissible stages must take up the form:

$$\underset{b}{\forall}\left(x_{b,1}^{d-1}=0\right)\Rightarrow\left[C^{d}=F\left(C^{d-1},b\right)\right]p\left(X\middle|C_{j}\right). \tag{15}$$

Function *F* is defined as follows:

for *i ≠ b* we receive:

$$x_{i,a}^{d} = x_{i,a}^{d-1}, \tag{16}$$

for *i=b* we receive:

$$\begin{aligned} x_{i,1}^{d} &= R^{d-1}, && \mathit{if} \quad k_{r}^{d-1}+z_{b} \le v \\ x_{i,1}^{d} &= R^{d-1}+1, && \mathit{if} \quad k_{r}^{d-1}+z_{b} > v \\ x_{i,2}^{d} &= St^{\,d-1}+1, && \mathit{if} \quad k_{r}^{d-1}+z_{b} \le v \\ x_{i,2}^{d} &= 1, && \mathit{if} \quad k_{r}^{d-1}+z_{b} > v \end{aligned} \tag{17}$$

where:
TR^{d-1} – number of a current (last) route,
ST^{d-1} – number of the last destination point on T*R*$^{d-1}$ point.
Numbers T*R*$^{d-1}$ and *ST*$^{d-1}$ may be easily established for stage *B*$^{d-1}$. Moreover, when generating stages of transport we define the following parameters:

$$car^d = b$$
$$k^d_{tr} = k^{d-1}_{tr} + t_{sam,b}$$

$$\begin{aligned} k_{r}^{d} &= k_{r}^{d-1}+z_{b}, && \mathit{if} \quad k_{r}^{d-1}+z_{b} \le v \\ k_{r}^{d} &= z_{b}, && \mathit{if} \quad k_{r}^{d-1}+z_{b} > v. \end{aligned} \tag{18}$$

CONCLUSION

The paper discussed methods of planning a selection of internal transport means as well as planning routes. In case of selection of an appropriate means of transport Bayes' classifier was used. The selection of an optimal route was made by means of a heuristic method of a-posteriori probability. Contemporary transport systems are mostly attendance-free. The elaborated methods may be used in software systems for work automation, management of the use and maintenance of means of transport. Automated floor transportation in the internal materials flow and in the production integrated with the automated system of tacking more often replaces old servicing systems. The author's mathematical model is presented in one article. The model will help solve, for example, the problem of reducing time or selecting the optimization criterion. The methods elaborated may be used in optional controlling by means of tracking system to secure flexible routing i.e. automated fork-lifts make it possible to collect and put away pallets, baskets or other containers.

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KOMPUTEROWE ALGORYTMY PROBABILISTYCZNE WSPOMAGAJĄCE ZARZĄDZANIE INTELIGENTNYM TRANSPORTEM WEWNĘTRZNYM

STRESZCZENIE

Artykuł przedstawia model probabilistyczny w zadaniu zarządzania inteligentnym transportem wewnętrznym bazującym na ryzyku związanym z podejmowaniem decyzji. Poprzez termin niezawodności systemu transportu wewnętrznego rozumie się czas bezawaryjnego działania transportu wewnętrznego w stosunku do całości czasu, w którym dany transport powinien działać poprawnie. Artykuł przedstawia model oceny ryzyka działania transportu wewnętrznego na bazie prawdopodobieństwa z jakim system będzie bezawaryjnie funkcjonował w zadanym okresie czasu, przy pracy w określonym środowisku i dla określonego celu. Budowanie modeli probabilistycznych służących do wyznaczania ryzyka planowania produkcji opiera się na rzetelnej analizie wszystkich możliwych aspektów produkcji danego dobra gospodarczego. W modelowaniu poddaje się ocenie mocne i słabe strony przedsiębiorstwa, które chce podjąć się zadania transportowego, dokonuje się planowania samego procesu transportowego w oparciu o najważniejsze cele wynikające z procesu transportowego.

SŁOWA KLUCZOWE

inteligentny system transportowy, rozpoznawanie Bayesa