DEVELOPING A MODEL FOR QUANTIFYING THE QUALITY AND VALUE OF TRACKING INFORMATION ON SUPPLY CHAIN DECISIONS

(Research Paper, IQ Metrics, Measures, Models, and Methodologies, IQ Assessment)

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Abstract: Supply chain tracking information has always been an enabler for effective and efficient business operations. In this paper we propose a way to model supply chain tracking information in order to determine its quality with regard to its ability to support business decisions. The analysis provides insights on the way that tracking information accuracy and timeliness affect decision effectiveness. A way to measure the value of the information provided by the tracking system as well as a way to measure the overall system performance are proposed. The results reveal the potential that automatic identification and data capture (AIDC) technologies offer for improved tracking systems' performance.

Key Words: Supply Chain, Tracking, Information Quality, Decision Effectiveness, Performance, RFID

INTRODUCTION

The intense market competition at an international level has created an imperative need for companies to optimize business operations, streamline processes and minimize costs in order to be competitive. For companies that are, in some way, part of a supply network, information regarding the location of products is the cornerstone for effective and efficient business operations. Critical processes, such as inventory management, distribution planning and production planning include important decisions to be made, which depend on the quality of product location information. The effectiveness of these decisions is directly linked to the quality information that the decision maker has access to, regarding the location of products across the supply network.

The emergence of new technologies that can enhance the quality of product location information provides a new potential for the supply chain tracking information systems. The use of Global Positioning System (GPS) in combination with automatic identification (auto-id) technologies such as barcode and more recently radio frequency identification (RFID) technologies promise the improvement of product location information quality in many aspects. Researchers and practitioners have already proposed a number of ways in which these technologies can be used under different architectures in order to deliver high quality product location information [9, 13]. Moreover, the expected benefits and information quality improvements stemming from the use of these technologies have been analyzed; however only at a qualitative level. There has not been proposed any quantitative method that will assess the quality of product location information across a supply network, with regard to its ability to support business decisions and operations.

The aim of this paper is to propose a method that can be used to quantitatively measure the quality of product location information across a supply chain, in an objective and normalized manner. In order to achieve this, the paper's objectives are

- To provide a formal way to model product location information in a supply network
- To provide a way to measure product location information quality and quantify its value
- To provide a way to measure the overall performance of a supply network tracking system.

The remaining of this paper is structured as follows: the next section provides some existing background. The third section describes the rationale behind this research. The fourth section presents the proposed model and the fifth section describes the proposed information quality metrics. The sixth section includes a discussion on our findings. Finally we state the limitations of this research and we conclude this paper.

BACKGROUND

The terms *tracking* and *tracing* are being used interchangeably by both the industrial and the academic community, many times referring to the same activity. We adopt the definition of *supply chain tracking* as the ability to determine the on-going location of a product during its way through the supply chain [7, 20]. The term *tracing* mainly relates to a product's composition information and refers to the ability to identify and locate products that have either been produced using a specific product lot (forward traceability) or have used to produce a specific product (backward traceability) [7, 19]. This study focuses on the quality of tracking information; however it can be extended to also address the quality of tracing information.

Researchers have proposed many different information system architectures to enable supply chain tracking [9, 13]. Each of the different architectures has its own advantages and disadvantages with regard to the quality of tracking information provided, considering many different quality dimensions as defined by Wand and Wang [22]. Karkkainen [8] and van Dorp [19] analyze the importance of automatic identification and data capture (AIDC) technologies for the effectiveness and efficiency of tracking applications. Sahin et al [17] propose a qualitative way to evaluate the performance of a tracking application, highlighting the importance of the use of auto-id systems. Despite the intense research interest in the role of AIDC in supply chain tracking, a formal quantitative approach to assess the quality of tracking information and the impact of auto-id technologies on that is clearly missing.

IQ background

There has been extensive research on the information quality dimensions (or attributes) that play an important role in determining its value. There are a number of studies that analyze the importance of specific information quality dimensions in a qualitative manner. The works of DeLone and McLean [6], Wang and Strong [25] and Boritz [5] are examples of classifications of IQ dimensions. Wang et al. [24] also provide an extensive list of information quality attributes that should be considered when assessing the effectiveness of an information system. The works of Strong et al. [18] and Wand and Wang [22] provide a contextual framing for some of the proposed information quality dimensions. Our model adopts the definitions and framing suggested by the aforementioned work and focuses on specific IQ dimensions that affect the value of tracking information.

Researchers have proposed quantitative measures for some information quality dimensions. Ballou and Pazer [3] have suggested a form of a utility function that can be used to optimize the trade-off between accuracy and timeliness in an information system, depending on the importance of each of the two dimensions for the end user. The same authors have suggested ways to calculate the timeliness and quality of data as these evolve in an information system [2] and a way to model the impact of completeness and consistency in decision problems. Raghunathan [16] takes a different approach; he uses belief networks to model information accuracy and decision-maker quality. He suggests that the improvement of information quality leads to information system performance improvement only when the decision maker has perfect knowledge over the decision variables and the relationships between them. In a different case, there is no monotonic relation between the information accuracy and the system's performance.

Past research on information quality assessment includes proposals of methods for systematic assessment of the information quality that a system produces. The papers of Wang [23] and Ballou et al. [2] propose similar methods for assessing the quality of information produced by a system. They model information as a product that undergoes a number of operations, which affect different quality dimensions. The system user's payoff can be a function of the quality dimensions of the final information product. Ahituv [1] suggests another method for assessing the value of an information system, in which the evaluator should construct a utility function according to the critical quality attributes that affect the information value for the system user. The effectiveness of the aforementioned assessment methods depends heavily on the selection of the right weighting factors and other critical parameters which lie on the subjective judgment of the system evaluator or the inevitable inaccuracy of the response from interviewees.

Taking into account the above, in this paper we suggest a way to assess the quality of tracking information and to measure the performance of tracking information system, focusing on the accuracy and timeliness of the provided information and the impact that these have on the system value.

Decision Theory

As this research builds heavily on previous work in the field of decision theory, we briefly review existing works that define the underlying principles of decision theory. We adopt the expected utility model and its associated axioms, as defined by von Neuman and Morgenstern [21]. We model the information system's output as a set of information signals and we define the system's accuracy in accordance with the definitions provided by the well known works of Blackwell [4] and Marschak and Miyasawa [14]. Lawrence [12] provides a comprehensive review of existing work in the field of information value. The concepts of system accuracy and its relation with the system value, as well as other core concepts of information value are well analyzed in Lawrence's work. Of course, the literature of decision theory and information theory includes numerous other pieces of work that relate to the concepts we will use, however a comprehensive listing of them is out of this paper's scope.

RATIONALE

The rationale behind this research lies in two dimensions. From an academic perspective, this paper aims at delivering a method for measuring the performance of a supply chain tracking system. It provides a basis for modeling tracking information, taking into account its intrinsic uncertainty. Moreover, the proposed method aims to provide a way to quantify the value of tracking information for the supply chain decision maker, as a function of its quality. The proposed method reveals the critical determinants of a tracking system that make it successful.

On the other hand, from an industrial perspective, this research provides a tool which can help companies to assess the performance of their tracking systems and estimate the benefits these are delivering to the company. Monitoring the performance of the system is crucial as it enables the company to point out shortcomings that need to be addressed. Moreover, delivering a robust return on investment (ROI) study for future tracking systems has always been a difficult challenge for companies. The proposed method can be used to estimate - in monetary terms - the benefits that a tracking system can deliver to a company regarding the improved effectiveness of decisions. The analysis of benefits at the decision effectiveness level can give a more accurate picture of the benefits that a system is/will be delivering.

THE MODEL

Let a product be moving across a supply chain as shown in Figure 1. The aim of a tracking system is to detect and record the presence of the product at specific checkpoints across the chain. These detection records are available to the system users. A decision maker needs to make a decision by choosing among a number of actions, based on the location of the product at the time of the decision. However, the only available information is the latest observation record, rather than the actual current location of the product. The quality of the information provided by the system has a direct impact on the effectiveness of the decisions. Case studies [10, 11] have revealed the following sources of noise in supply chain tracking information 1) Product identification accuracy 2) Processing delays (during product detection) and 3)Aggregation information accuracy. Considering the above, the model presented in this section aims to describe the aforementioned decision problem, to describe the quality of the generated information and to provide a way to measure the performance of the tracking system.

We first define the elements of the model, which describe the state of a product in the supply chain, the framing of the decision problem and the way that a tracking system records the ongoing location of a product. Based on these, in the next subsection we then define the information and estimation signals that a tracking information system provides to the decision maker; we also analyze how noise is introduced to the tracking information and the way this is modeled.

The Model Elements

Product State

Let X be the variable that describes the location of a product across the supply chain. For example, this could be the distance from the start, or the end of the supply chain, or a set of coordinates which defines the exact location of a product.

Actions

The decision maker needs to make a decision D based on the location of the product. Let $A = \{a_1, a_2, ..., a_k\}$ be the set of feasible actions that are available for this decision and the decision maker needs to choose from. Also, let C be a set of possible consequences that an action can lead to. Each action a maps X into C

$$a(x) = c \tag{4.1}$$

Two distinct states x and x' may be such that $a(x) = a(x'), \forall a \in \mathrm{A}$. We will call these states *equivalent with respect to A* [14]. According to this, we define a partition Z_x^A on X of equivalent sets of the form

$$z_x^A \equiv \{x, x' \in X : a(x) = a(x'), \forall a \in A\} \tag{4.2}$$

Payoffs and State Partitions

In order to represent the preference of the decision maker for some consequences compared to some others, we introduce the concept of the utility of a consequence *u(c)*, $u: C \rightarrow \Re$, in many cases the utility is represented in monetary terms. We can now define the *payoff function* $\omega: X \times A \rightarrow \Re$

$$\omega(x,a) \equiv u(a(x)) = u(c) \tag{4.3}$$

Using the payoff function ω we can define a new partition on *X*. This new partition will have sets of the form

$$z_x^{\omega} \equiv \{x, x' \in X : \omega(x,\alpha) = \omega(x',\alpha), \forall a \in A\} \tag{4.4}$$

We will call z^{ω}, a typical equivalence set in $Z^{\omega} = \{z_1, z_2, ..., z_m\}$, a state, relevant with respect to the payoff function ω, or briefly an ω-relevant state [14]. The partitioning we have defined allows us to define ω in the discrete set Z^{ω} rather in the continuous space *X*.

In the same way, we can partition the set of possible actions *A* by defining sets of actions that have the same payoff for all states *x* in *X*,

$$u(a(x)) = u(a'(x)) \Leftrightarrow \omega(x,a) = \omega(x,a') \tag{4.5}$$

In this way we define a partition D^{ω} of *A* into equivalence sets of the form

$$d_a^{\omega} \equiv \{a, a' \in A : \omega(x,a) = \omega(x,a'), \forall x \in X\} \tag{4.6}$$

In simple words, equation (4.6) defines a partition on *A,* such that all actions $a \in d_i^{\omega}$ lead to the same payoff for all states in *X*. From this point on, with no ambiguity, we can define ω in the domain $Z^{\omega} \times D^{\omega}$ instead of $X \times A$, therefore writing *ω(z,d)* instead of *ω(x,a)*.

Observations

Let $C = \{c_1, c_2, ..., c_m\}$ be the set of checkpoints along the supply chain. We will use $c_i \prec c_j$ to denote that a checkpoint c_j is further down/later in the supply chain than checkpoint c_i. Same for the ω-relevant states, $z_i \prec z_j$. When an item with identity code ID is observed at a checkpoint c_j at time t_j an observation record is created for it. At any time *t* we can define an observation vector for an item with a specific ID, $V(ID,t) = ((c_1,t_1),(c_2,t_2),....,(c_m,t_m))$ where

$$(c_j,t_j) = \begin{cases} (c_j,0), \text{Item not yet seen at } c_j \\ (c_j,t_j), \text{Item was seen at } c_j \text{ at } t_j < t \end{cases} \tag{4.7}$$

Information System

Vector $V(ID,t)$ describes the checkpoints and the respective times that the item has been observed for all $t_j < t$. Let t_l be the latest time that the item was observed at any checkpoint. We then define an information signal $y_j(ID)$ as the observation record that corresponds to the latest observation of the item with the specific identity $y_j(ID) = (c_j,t_j),\ (c_j,t_j) \in V(ID,t) : t_j = t_l$. For simplicity, the identity parameter will be omitted from this point on. In simple words, information signal y_j indicates that the item was last observed at checkpoint c_j at time t_j. According to the above, the allocation of checkpoints across the supply chain, creates a set of possible information signals $Y = \{y_1, y_2, ..., y_m\}$ as shown in Figure 1. *Y* is a partition of *X* in a way defined by the checkpoints.

Based on the latest information signal y_j, the tracking system will produce an estimation $\hat{z}_i$ of the current state of the product. The set of estimated states $\hat{Z}_x^{\omega}$ will be the same partition of X as the set of ω-relevant states Z^{ω}.

Figure 1 shows an example of an ω-relevant state partition, the respective state estimation partition and information signals for a tracking system that tracks a product from one end of a supply chain to the other. It should be noted that the checkpoints c_i are not always at points where the ω-relevant states change.

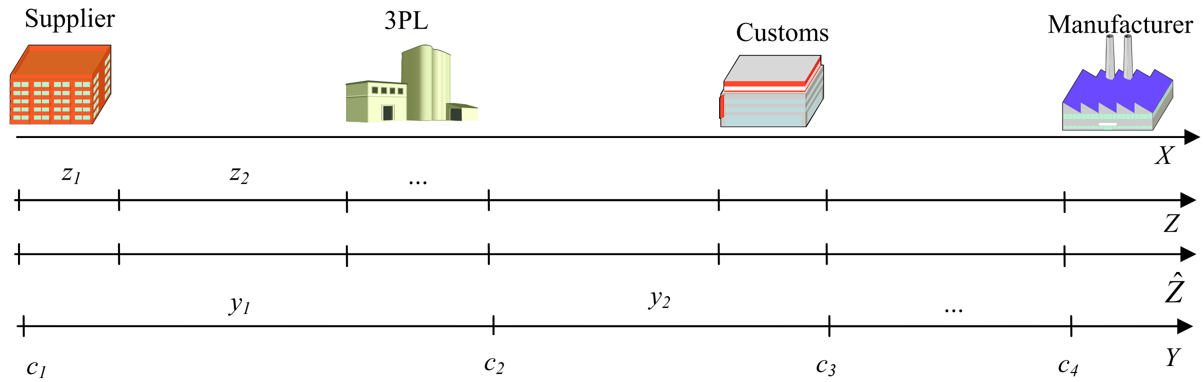

Figure 1, Example of an ω-relevant partition, state estimation partition and information signals

Noiseless Tracking Information

When the information system sends information signal y_j (as a response to a tracking query), this indicates that the item is in some ω-relevant state between the checkpoint it was last observed at, and any next checkpoint along the supply chain (if we assume that the system is accurate). Let $Z_{y_j}^{\omega}$ denote the set of ω-relevant states that an item can be between checkpoint c_j and any next one. Note that the possible ω-relevant states that an item might be in, after a checkpoint, can form a tree structure rather than a linear structure, however the above definitions are still valid. In the example of Figure 1 it is $Z_{y_1}^{\omega} = \{z_1, z_2, z_3\}$. In the same way we define $\hat{Z}_{y_j}^{\omega}$ as the set of estimation states between checkpoint j and any next one.

At time $t > t_j$ the estimated product's state will be described by a time-dependent probability distribution $f(x,t)$ over the set $Z_{y_j}^{\omega}$. For example, assuming that a transition from c_1 to c_2 takes on average 5 hours in the example of Figure 1, then a possible probability distribution over the ω-relevant states given signal y_1 for different times is displayed in Figure 2.

The area below the probability distribution function and between the boundaries of each state z_i (denoted by $\underline{z}_i$ and $\overline{z}_i$) defines the probability that the product is at that state at that time t.

$$p(z_i, t) = \int_{\underline{z}_i}^{\overline{z}_i} f(x,t)dx \tag{4.8}$$

The estimated product state $\hat{z}_t$ at time t is the state with the greater probability at that time.

$$\hat{z}_t = \arg\max_{z_i} \int_{z_i}^{\bar{z}_i} f(x,t)dx \tag{4.9}$$

For the example of Figure 2, at time $t = t_1 + 1.5\text{hours}$, the estimated state is $\hat{z}_2$ since the area of the probability distribution between the boundaries of z_2 is greater than the other states. Before proceeding, based on the above we derive the following definitions:

Definition 1: A tracking system is called *noiseless* when the set of possible information signals Y is a partition of the set Z^{ω} [15], that is

- Every ω-relevant state z^{ω} is indicated by a signal y, and
- No ω-relevant state z^{ω} is indicated by more than one signal y

Definition 2: A tracking information signal y_j is called *accurate* if the product is actually in a state $z_i \in Z^{\omega}_{y_j}$ at the time t that the information signal is received by the decision maker. That is $p(Z^{\omega}_{y_j} \mid y_j, t) = \sum_i p(z_i \mid y_j, t) = 1, z_i \in Z^{\omega}_{y_j}$.

Definition 3: An estimation $\hat{z}_i$ is called *accurate* if the product is actually in state z_i at the time t that the estimation is received by the decision maker. That is $p(z_i \mid \hat{z}_i) = 1$.

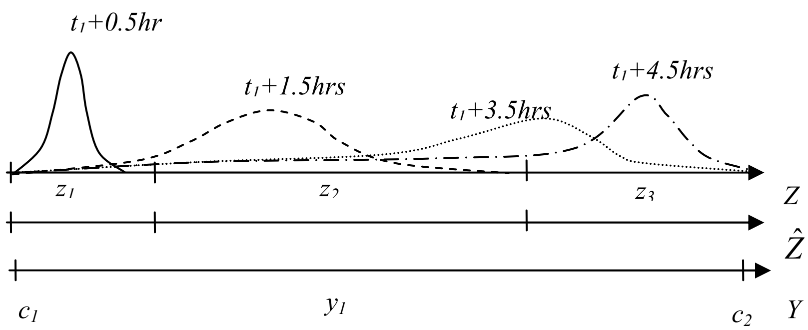

Figure 2, Noiseless probability distribution over ω-relevant states for different times

In a noiseless tracking system, given an information signal y_j, there will be an estimated state $\hat{z}_j$ and an associated time-dependent posterior probability distribution over the ω-relevant states in the set $Z^{\omega}_{y_j}$. The distribution can be represented by a n×n matrix $\Pi(t)$, in which the *ij*-th element represents the conditional probability that the product is at state z_i given that the system estimates state $\hat{z}_j$. Equation (4.10) shows a posterior distribution for the example of Figure 1. Note that, given y_j, the distribution for states $z^{\omega} \notin Z^{\omega}_{y_j}$ is zero. Also, the matrix is column stochastic: $\sum_i p(z_i \mid \hat{z}_j, t) = 1$.

$$\Pi(t)=\begin{bmatrix} p(z_1\,|\,\hat{z}_1,t) & p(z_1\,|\,\hat{z}_2,t) & p(z_1\,|\,\hat{z}_3,t) & 0 & 0 & 0 \\ p(z_2\,|\,\hat{z}_1,t) & p(z_2\,|\,\hat{z}_2,t) & p(z_2\,|\,\hat{z}_3,t) & 0 & 0 & 0 \\ p(z_3\,|\,\hat{z}_1,t) & p(z_3\,|\,\hat{z}_2,t) & p(z_3\,|\,\hat{z}_3,t) & 0 & 0 & 0 \\ 0 & 0 & 0 & p(z_4\,|\,\hat{z}_4,t) & p(z_4\,|\,\hat{z}_5,t) & 0 \\ 0 & 0 & 0 & p(z_5\,|\,\hat{z}_4,t) & p(z_5\,|\,\hat{z}_5,t) & 0 \\ 0 & 0 & 0 & 0 & 0 & p(z_6\,|\,\hat{z}_6,t) \end{bmatrix} \quad (4.10)$$

Noisy Tracking Information

The real world is not perfect and information signals contain noise. Therefore, even though an information signal y indicates that an item should be in some state between two checkpoints, it may actually be anywhere in the supply chain. In this case, the posterior distribution matrix Π will be in the general form of (4.11), still being column stochastic.

$$\Pi(t)=\begin{bmatrix} p(z_1\,|\,\hat{z}_1,t) & \cdots & p(z_1\,|\,\hat{z}_n,t) \\ \vdots & p(z_i\,|\,\hat{z}_j,t) & \vdots \\ p(z_n\,|\,\hat{z}_1,t) & \cdots & p(z_n\,|\,\hat{z}_n,t) \end{bmatrix} \quad (4.11)$$

Matrix Π can be written as a function of the *age* τ_j (instead of the absolute time *t*) of the respective information signal that resulted in the estimation $\hat{z}_j$. The age of an information signal at any time *t* is $\tau_j = t - t_j$ (This is in accordance with Ballou et al. [2], assuming that the age of the signal when recorded into the system is zero).

We briefly analyze the factors that introduce noise in tracking information.

Product Identification Accuracy

It is clear that the accuracy of the identification process directly affects the quality of tracking information, since the item's identity is one of the variables of a tracking record. Let an item be in a state $z_i \in Z^{\omega}_{y_j}$ and the system actually reflecting that by an information signal y_j. The item moves from z_i through a checkpoint c_k onto another state $z_k \notin Z^{\omega}_{y_j}$. If the item is not accurately identified at c_k then the system will keep on sending information signal y_j, which will be inaccurate from the moment t_k the item passes checkpoint c_k and thereafter.

Processing Delays

The case studies [11] have revealed that in many cases there is a significant amount of time between the moment an item actually changes state, the moment this change is observed by either a person or the system and the moment the change is updated in the tracking system through a tracking record. This results in the system representing an inaccurate state of the item for this period of time. Figure 3 illustrates the processing delay in the case of an item arriving in the receiving dock of the freight forwarder in our example.

The moment the item's state changes in this case is the moment that the item physically arrives at the receiving dock. The moment of physical observation is the moment that either a person or a machine detects and identifies the item. The moment of system update is the moment that a tracking record is created in the tracking information system for the item. When the observation is manual (for example using human readable identifiers), there is usually a significant amount of time between observation and system update. However, when automatic identification technologies are used (for example barcode), typically there is no delay between the observation and the moment the system is updated, as identification information is passed automatically into the system. In this paper it is assumed that the period between physical observation and system update is zero.

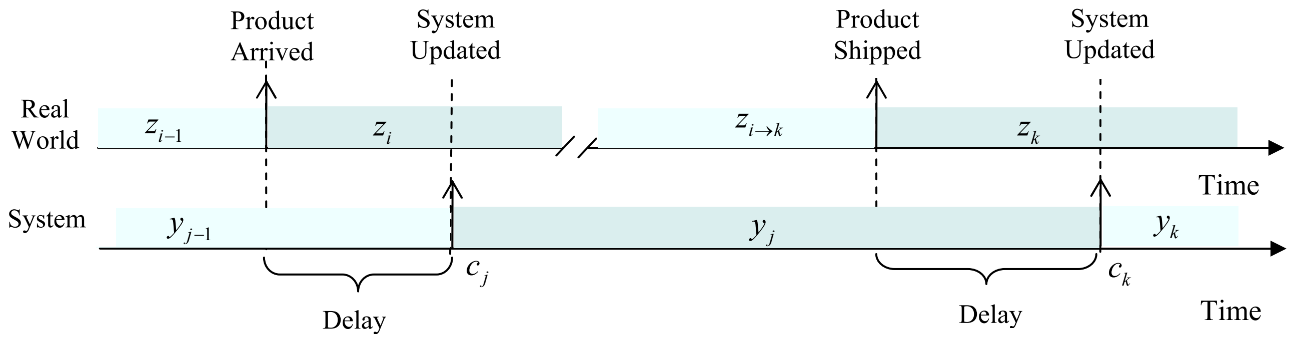

Figure 3, Processing delays during product state changes

Note that the accuracy of information signal y_j does not depend on the processing delay at checkpoint c_j but only on that of checkpoints c_k, as shown in Figure 3. Indeed, when the system update at checkpoint c_j takes place, information signal y_j is accurate (disregarding other sources of inaccuracy). The signal might become inaccurate only when the item arrives at any of the checkpoints c_k, because of the processing delay.

Aggregation Information Accuracy

There are many cases in which the ID of an aggregated package (e.g. a pallet) is used to track products that are registered to be in it. When the package reaches a checkpoint c_j its ID is recorded and a tracking record is created for all products that are expected to be in it. However, if, for any reason, a product is not in the package, this creates an inaccuracy in the tracking system for that product.

Overall Tracking Information Accuracy

The above reveal the reasons of noise in tracking information. Figure 4 demonstrates the differences between an accurate and an inaccurate information signal at a time *t*. In the case of accurate signal, as defined by Definition 2, the posterior probability distribution is spread over the states that correspond to signal y_1, $Z^{\omega}_{y_1} = \{z_1, z_2, z_3\}$. On the other hand, in the case of the noisy information signal, a part of the distribution spreads before checkpoint c_1 and after checkpoint c_2. The part before checkpoint c_1 corresponds to possible inaccuracies because of inaccurate aggregation information. That is, the product might have been left in earlier states, although the aggregated package that it is expected to be in has reached c_1. The part of the distribution after checkpoint c_2 corresponds to possible inaccuracies due to identification errors or processing delays. The product might have already reached state z_4, but the system might not be updated because of processing delays or because there was an error during the scanning of the products ID.

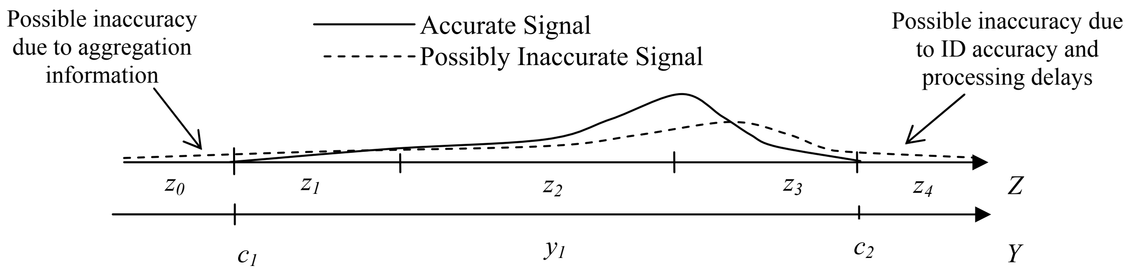

Figure 4, Comparison of accurate and inaccurate tracking information signals

The overall posterior probability distribution over the ω-relevant states will result by taking into account the errors due to the aforementioned reasons and combining them into a unified distribution. The probability of inaccuracy due to aggregation information errors is not dependent on time. However, the probability of inaccuracies due to identification errors or processing delays does depend on the age of the estimation signal. The accuracy of the signal is almost certain at the moment t_j that the product is detected (disregarding errors due to aggregation information). However, the probability of the signal being inaccurate because of identification errors or processing delays should increase as the age of the signal increases. Figure 5 shows a noisy probability distribution for the example of Figure 2. Note that a small part of the distribution is assigned at states $z \prec z_1$ for all t (due to aggregation information inaccuracies) and for $t >> t_1$ a part of the distribution is assigned to states $z_3 \prec z$ (due to identification inaccuracies and processing delays).

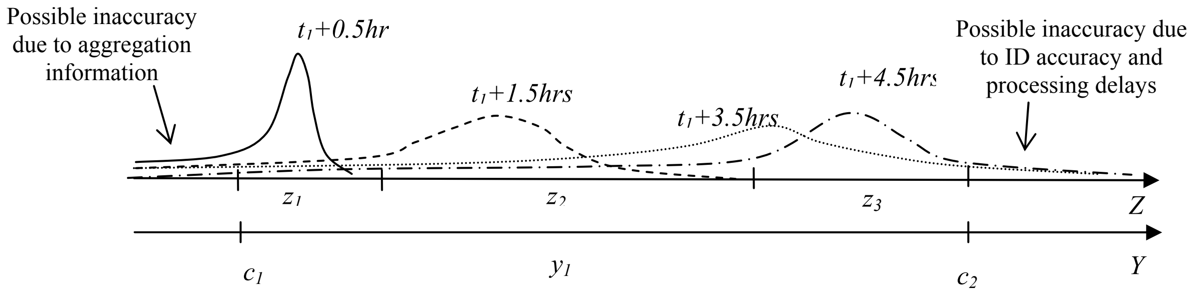

Figure 5, Noisy probability distribution over ω-relevant states for different times

Due to the aforementioned reasons of possible inaccuracies, when the decision maker receives an estimation $\hat{z}_i$ about the product's state, the actual state will result from a time-dependent posterior probability distribution described by (4.11).

METRICS

Based on the model that describes the decision problem and tracking information quality, we will now define the value of tracking information for the decision maker and a measure of overall performance for the tracking system.

Information Value

We adopt the maximum expected utility axiom in order to define the information value. Under this axiom, the decision maker will choose the action that maximizes his expected payoff [12, 15]. At time *t,* let $p(z_i,t)$ denote the prior probability distribution over the *ω*-relevant states. When no information is available, at time *t* the decision maker will choose action d_0 that maximizes his expected payoff

$$d_0 = \arg\max_d \sum_i p(z_i,t)\omega(z_i,d) \tag{5.1}$$

and the expected payoff under no information will be

$$\Omega(D,t) \equiv \max_d \sum_i \omega(z_i,d)p(z_i,t) = \sum_i \omega(z_i,d_0)p(z_i,t) \tag{5.2}$$

When tracking information is available, at time *t* the decision maker will have a state estimation $\hat{z}_j$ available from the system and taking into account the posterior probability distribution Π(t) (4.11) he will choose the action $d_{\hat{z}_j}$ that maximizes his expected payoff given the estimation $\hat{z}_j$

$$d_{\hat{z}_j} \equiv \arg\max_d \sum_i \omega(z_i,d)p(z_i \mid \hat{z}_j,t) \tag{5.3}$$

The decision maker's expected payoff when using the tracking system described by (4.11) will be

$$\Omega(D,Y,t) = \sum_j \sum_i \omega(z_i,d_{\hat{z}_j})p(z_i,\hat{z}_j,t) = \sum_j p(\hat{z}_j,t)\sum_i \omega(z_i,d_{\hat{z}_j})p(z_i \mid \hat{z}_j,t) \tag{5.4}$$

The *gross normative* value [1] of tracking information would be the difference between the expected payoff under prior and informed decision making. The gross value of information $V^g(Y,t)$ at time *t* is given by (5.5)

$$V^g(Y,t) = \Omega(D,Y,t) - \Omega(D,t) \tag{5.5}$$

Let *C(Y)* denote the cost for obtaining information described by (4.11). The *net normative* value $V^n(I)$ of tracking information will be

$$V^n(Y,t) = \Omega(D,Y,t) - \Omega(D,t) - C(Y) \tag{5.6}$$

Tracking System Performance Measurement

We measure the performance of a tracking system by comparing it to the perfect tracking system for the decision problem in question.

Perfect Information

Perfect information occurs when the information system provides categorical direct messages that identify precisely and unequivocally the state that the item is in [12]. Under perfect information the set of information signals is identical to the state set, $Y = Z^{\omega}$, and the posterior probability that a product is in a state z_i given the estimation $\hat{z}_i$ is one, $p(z_i \mid \hat{z}_i) = 1$.That is, all entries in the diagonal in (4.11) equal one and all other entries equal zero. Let us denote the information signal set that corresponds to perfect information as $Y\uparrow$. In the case of perfect information, given an estimation $\hat{z}_j\uparrow$, the decision maker will choose action $d_{\hat{z}_j\uparrow}$ that maximizes his expected payoff

$$d_{\hat{z}_j\uparrow} \equiv \arg\max_d \sum_i \omega(z_i,d)p(z_i,\hat{z}_j\uparrow,t) = \arg\max_d \omega(z_j,d) \tag{5.7}$$

and the expected payoff under perfect information will be

$$\Omega(D,Y\uparrow,t) = \sum_j p(\hat{z}_j\uparrow,t)\sum_i \omega(z_i,d_{\hat{z}_i\uparrow}) \tag{5.8}$$

In the same way, the value of perfect information (assuming it comes at no cost) will be

$$V^g(Y\uparrow,t) = \Omega(D,Y\uparrow,t) - \Omega(D,t) \tag{5.9}$$

Having defined the value of perfect information, we now define the tracking system performance (*TSP*)

$$TSP(t)=\frac{V^n(Y,t)}{V^g(Y\uparrow,t)}=\frac{\Omega(D,Y,t)-\Omega(D,t)-C(Y)}{\Omega(D,Y\uparrow,t)-\Omega(D,t)} \tag{5.10}$$

and replacing the expected payoffs from (5.2),(5.4) and (5.8) we get

$$TSP(t)=\frac{\sum_j p(\hat{z}_j,t)\sum_i \omega(z_i,d_{\hat{z}_j})p(z_i\mid\hat{z}_j,t)-\sum_i \omega(z_i,d_0)p(z_i,t)-C(Y)}{\sum_j p(\hat{z}_j\uparrow,t)\sum_i \omega(z_i,d_{\hat{z}_i\uparrow})-\sum_i \omega(z_i,d_0)p(z_i,t)} \tag{5.11}$$

Note that $V^g(Y\uparrow,t)\geq V^n(Y,t)\geq 0$ [12, 15]. In the case where $V^g(Y\uparrow,t)=V^n(Y,t)=0$ the *TSP* is not defined, as there is no need for a tracking system anyway.

Example

Let us consider the supply chain depicted in Figure 1. In this example we will use cost figures, which were captured during a case study undertaken in a manufacturer, based in Brazil. The probabilities resulted from interviews with the company managers. We assume that the checkpoints are installed at the places where the *ω*-relevant states z_1, z_2, z_3 and z_4 change. At time *t* a shipment should have reached the 3PL centre. The manufacturer needs to choose one of the following actions based on the location of the shipment d1: send the shipment by sea, d2: send the shipment by air or d3: send the shipment by air and reschedule production in order to make up for the lost time. Table 1 shows the payoffs per action per state. Let the prior distribution over the states at time *t* be: $p(z_1)=0.05, p(z_2)=0.4, p(z_3)=0.4, p(z_4)=0.15$. Also let the posterior distribution $p(z\mid\hat{z})$ at time *t* be as shown in Table 2. Assuming that $C(Y)$=\$30 then using (5.1)-(5.6) we get $V^n(Y,t)=\$85.2$. At time *t+Δt* the prior distribution is $p(z_1)=0.03, p(z_2)=0.3, p(z_3)=0.5, p(z_4)=0.17$ and the posterior distribution will be as shown in Table 3. We then get $V^n(Y,t+\Delta t)=\$69$. For this decision problem, using (5.7)-(5.9), we get $V^g(Y\uparrow,t)=\$142$ and $V^g(Y\uparrow,t+\Delta t)=\$141.9$. The system performance for the two time instances will be $TSP(t)=60\%$ and $TSP(t+\Delta t)=48\%$.

	d1	d2	d3
Z1	-1100	-870	-670
Z2	-700	-270	-770
Z3	-100	-340	-720
Z4	-100	-340	-870

Table 1, Action payoffs (\$) per state, ω(z,d)

$p(z\mid\hat{z})$	Z_1	Z_2	Z_3	Z_4
$\hat{z}_1$	0.53	0.47	0	0
$\hat{z}_2$	0.01	0.88	0.11	0
$\hat{z}_3$	0	0.09	0.87	0.04
$\hat{z}_4$	0	0	0	1

Table 2, Posterior distribution at time *t*

$p(z\mid\hat{z})$	Z_1	Z_2	Z_3	Z_4
$\hat{z}_1$	0.36	0.64	0	0
$\hat{z}_2$	0.01	0.68	0.31	0
$\hat{z}_3$	0	0.06	0.86	0.08
$\hat{z}_4$	0	0	0	1

Table 3, Posterior distribution at t+Δt

The example shows that the accuracy of tracking information, the information timeliness and the cost of information have a direct impact on the value of information and the system performance.

DISCUSSION

The model and metrics presented in the previous sections reveal the importance of the following determinants of the quality and value of tracking information: accuracy, timeliness, checkpoint configuration and cost. The following paragraphs provide a qualitative analysis of how each of the above factors affects the value of information. The exploration of the behavior of the value of information as a function of these factors, as well as the quantification of their impact is one of the next steps of this research, which will enable a more explicit comparison regarding the importance of each of them in different business context.

Tracking Information Accuracy

The impact of accuracy on decision effectiveness and the value of information are well established by existing research in the field of decision theory. Blackwell [4] has shown that the value of information is monotonically linked to the *"Blackwell accuracy"* of an information system. The accuracy of the tracking system is reflected by the posterior distribution of (4.11). The more the probabilities of the main diagonal are close to one, the more accurate the system. Figure 6 shows how the value of information behaves as a function of the accuracy of an estimation signal $\hat{z}_1$, at a specific time *t*. The graph shows that there is a threshold of the posterior probability $p(z_1 \mid \hat{z}_1) \approx 0.71$ below which the estimation signal $\hat{z}_1$ adds no value to the system. This is because the signal in not accurate enough so that the decision maker can trust it and change his prior decision. Note that the system value in Figure 6 up to $1750 is due to other estimation signals. On the contrary, when $p(z_1 \mid \hat{z}_1) > 0.71$, the decision maker changes his decision when he receives estimation $\hat{z}_1$ and the signal starts to add value. The more accurate it gets the more the value it delivers to the decision maker. Following the above analysis, it becomes evident that the accuracy of the tracking system at any time is directly linked to its performance and the value it delivers.

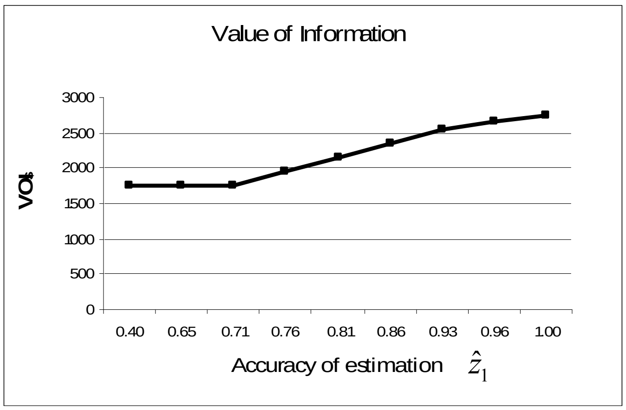

Figure 6, Value of information as a function of estimation accuracy

Tracking Information Timeliness

The posterior probability distribution, described by (4.11), is time-dependent and could be expressed as a function of the age τ_j of the information signal y_j (which is assumed to be the same as the age of the estimation signal $\hat{z}_j$). As shown in Figure 5, as the age of the estimation signal grows, the probability distribution is more spread over the possible states that the product could be in. For example, immediately after a product has been detected at a checkpoint, the probability that it still is at the state after the checkpoint is very high. On the contrary, some time after the last detection, this probability will be spread over more states. This is translated into decreased accuracy, as defined in the previous sub-section. Consequently, the age of the estimation signal affects its accuracy and in turn the effectiveness of the system in a way analyzed earlier on. Indeed, as described by (5.10) and (5.11) the performance of the tracking system is time-dependent. One would expect the performance of the system to increase for *t* soon after a product detection has taken place at a checkpoint (since the accuracy of the system would be high) and decrease after that, until the next detection time when it would again rise. As a result, the performance of the system would have oscillations defined by the information signal times t_j.

Checkpoints Configuration

The configuration of checkpoints across the supply chain directly affects the quality of tracking information provided. As discussed earlier, the accuracy of the information is affected by the age of the signals. Moreover, the identification technology used in each checkpoint also affects the accuracy of tracking information in terms of accurate and complete identification of products as they arrive at a checkpoint. As a consequence, the distribution and density of checkpoints along the supply chain, along with the identification technology used has a direct impact on the posterior probability distribution of (4.11) and the performance of the overall system.

Cost of Information

The cost at which tracking information can be accessed impacts on the performance of the tracking system, as defined by (5.10). The decision maker has to position himself in the trade-off of having more accurate information, which usually comes at a higher cost. The value that this information delivers for the decision maker will determine the performance of the tracking system. The aim of the decision maker should be to optimize the overall performance of the system, by finding the right balance between the value and cost of tracking information.

RFID Potential

The emergence of RFID technology provides great potential for improving the quality of information provided by supply chain tracking systems. RFID can promise high read accuracy at checkpoints and minimization of processing delays. Moreover, the fact that no human intervention is required for a detection to take place, enables the installation of additional checkpoints along a supply chain, without disturbing existing operations. Finally, the significant reduction in labor costs for scanning products reduces the cost of information. In a nutshell, RFID technology provides an opportunity for significantly improving the performance of a tracking system, as defined in this paper, in an economically efficient way .

LIMITATIONS

We have represented the accuracy of the tracking system by the time-dependent posterior probability distribution of (4.11). However populating this distribution, in a systematic manner, can be a challenging task. Researchers have proposed ways in which one could populate this distribution [12]. The model we have proposed refers to decision effectiveness with regard to decisions that are based on the current state of a product in the supply chain. Very often, decisions in a supply chain are based on the estimated future state of a product (for example: "when will a shipment arrive in my warehouse?"). In this respect, our model needs to be extended to address this important decision class. Our research team is currently working to address the aforementioned issues and explore in greater depth the impact of the determinants of tracking system performance.

CONCLUSION

We have proposed a model that describes the quality of information provided by a supply chain tracking system and the way this affects decision effectiveness. Based on this model, we have proposed a method for quantifying the value of tracking information for a decision maker and a way to measure the overall tracking system performance. The analysis of results demonstrated the importance of tracking information accuracy as well as its timeliness for the system performance. It was also shown that the configuration of checkpoints along the supply chain directly affects the quality of information. Moreover, the cost of tracking information is another factor affecting the performance of the system, which, together with the system's accuracy, defines trade-off that the decision maker needs to balance. All the above provide a way to analyze the potential that RFID technology offers for improving the effectiveness and efficiency of tracking applications. Further research is currently undertaken to extend the proposed model and explore the potential of this new technology in greater detail.

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