Track and Trace Performance Measurement

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Report Abstract: Automatic identification technologies are enablers for enhanced supply chain tracking and tracing performance. This report proposes a way to measure track and trace performance in an objective, comparable and normalized manner.

The case studies carried out revealed that the following factors affect the ability of a company to determine the ongoing location of a product: identification accuracy, product processing delays, aggregation information accuracy and the configuration of checkpoints along the supply chain. This report analyzes how each of the above affects tracking performance. Further, the quantitative metrics for each of the factors are defined using a model to represent supply chain tracking. In addition, a way to combine the individual metrics into an overall tracking performance metric, which represents the amount of tracking information that the system can communicate, is also suggested.

It had been earlier identified that the usefulness of lifecycle tracing information is affected by its quality, timeliness and the cost for obtaining it. Based on these, this report proposes a method to model the way lifecycle information evolves throughout the lifecycle of a product in order to estimate the quality, timeliness and cost of the final lifecycle information available to the decision maker. Also suggested here is a way to estimate the information value of the final information product as a function of the aforementioned properties and the intrinsic value of perfect information.

Finally, the report analyzes the way that the proposed tracking and tracing assessment methods should be applied in a company, and demonstrates their use through examples. To conclude, the report suggests how the above could be used for a return on investment (ROI) study for a tracking solution.

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1. Introduction

1.1. Aims

The aim of this report is to provide a way of measuring tracking and tracing performance in a company in a normalized and objective manner. Apart from describing the individual and overall metrics, this report aims at analyzing the process of measuring tracking and tracing performance and provides illustrative examples of how a company can carry out such an assessment.

1.2. Rationale

Case studies carried out so far in the context of the Aerospace-ID technologies programme have revealed that supply chain tracking and tracing are enablers for effective and efficient business operations and decision making [1, 2]. As a consequence, good performance in these areas is a prerequisite for a successful business.

In order to achieve good performance in tracking and tracing applications, one must first be able to monitor and measure it. A tool is needed that can generate objective and normalized performance measures, which will enable comparison of tracking and tracing practices and will stimulate improvement. Furthermore, a performance measurement tool will enable prediction of the impact of new technologies and innovative practices on tracking and tracing operations. Finally, a way to measure tracking and tracing performance can act as a basis for a return on investment (ROI) study, which will quantify the impact of auto-id technologies on business operations through improved tracking and tracing.

1.3. Report structure

This report is structured as follows: section 2 defines and analyzes the performance metrics and overall performance measures. Section 3 describes the process that should be followed in order to measure tracking and tracing performance in a company. Section 4 includes examples of applying the proposed performance measurement method. Section 5 concludes the report. The report's structure is shown in Figure 1.1.

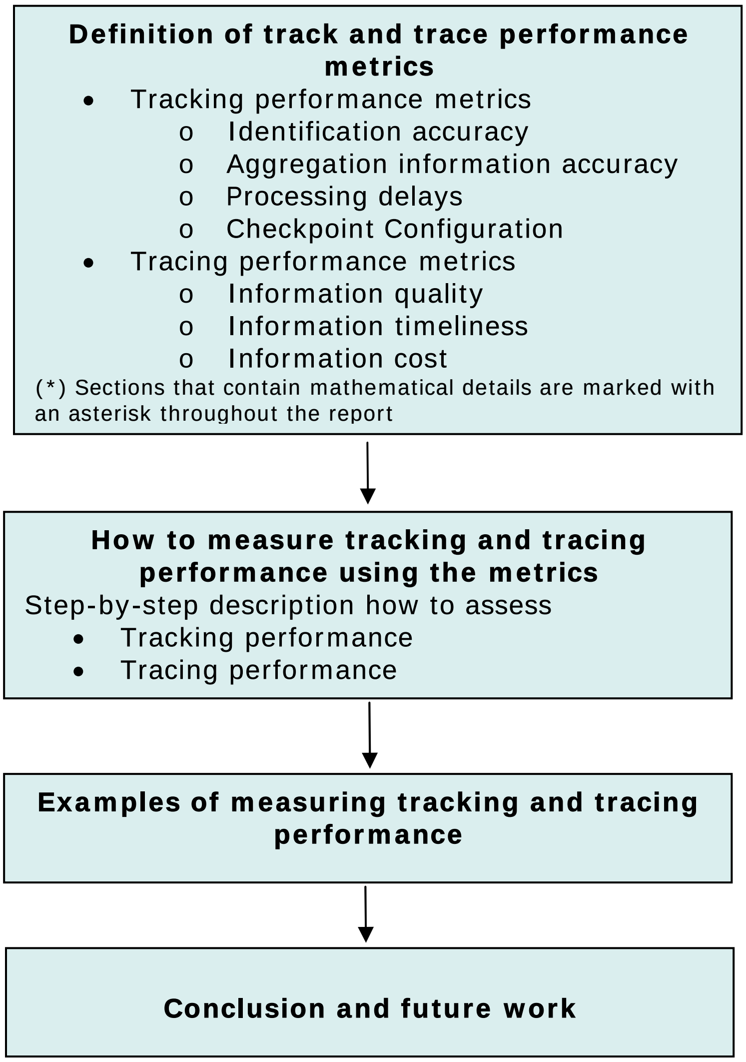

Figure 1.1: Report overview

2. Track and Trace Performance Metrics

2.1. Aim

The aim of this section is to define quantitative metrics for each of the factors that have been identified to affect the ability of a company to effectively track and trace an item's state through its lifecycle. Further, these metrics will be combined into measures that reflect a company's (or a system's) overall tracking and tracing performance. Finally, this section will provide some qualitative description of the implications that tracking and tracing performance can have on business decisions and operational efficiency.

We first analyze the measures for tracking performance (sub-section 2.2) and then we proceed with tracing performance (sub-section 2.3). In each of the sub-sections we provide an overview of the proposed metrics before analyzing them analytically and proposing quantitative measures.

Note: The sections that contain the mathematical details are marked with an asterisk (*) and can be skipped by the reader who does not wish to go into this level of analytic depth.

2.2. Tracking performance

The term tracking performance refers to a company's ability to determine an item's ongoing state (for example, the location) and the usefulness of this tracking information for the company. As a consequence, the report aims at assessing the degree to which the tracking system reflects the actual state of an item. Before analyzing the performance metrics, the model used to represent supply chain tracking is described.

The case studies undertaken revealed that there are four factors that affect tracking effectiveness in a supply network and in turn the quality of tracking information. These are as follows:

- Identification accuracy: It refers to the ability of the system to correctly identify items at different checkpoint along the supply chain.
- Detection delays: It refers to the delay between the moment that an item's state changes and the moment this is detected/observed by the system.
- Aggregation information accuracy: It refers to the accuracy of the information that indicates what items are included in an aggregated shipment (for example, pallet, container, etc.).
- Location/Configuration of checkpoints: It refers to the location of checkpoints along the supply chain.

In the following sub-sections we will analyze the way these factors affect tracking performance and we will propose quantitative metrics for them. We incorporate the measure of the impact of checkpoint configuration in the overall tracking performance metrics presented in section 2.2.3.

2.2.1. Modelling supply chain tracking

The overall objective of a tracking system is to represent the ongoing state of an item. The state could not only mean location information but other information as well, such as quality, etc. For simplicity, at this point we will assume that state represents location and an item can be found in any of the n locations from the set $\boldsymbol{S} = S_1, S_2, \ldots, S_n$

Let $S(\alpha,t)= S_i$ denote that the real world state of item α at time t is S_i , $i=1,2,\ldots,n$. Similarly, let $s(\alpha,t)= s_i$ denote that the state of item α represented by the tracking system at time t is s_i, $i=1,2,\ldots,n$. We assume that we have a correct representation from S_i to s_j when $i=j$. Note that capital S denotes the real world state while small s denotes the state represented by the tracking system.

In order to define the performance metrics, we also need to establish the following definitions:

- Timestamp: It is the moment when a detection took place.
- Identity: It is a set of alphanumeric characters which uniquely identifies an item.
- Tracking record: It is a triplet consisting of an item's identity, a timestamp and the state that the item is detected to be at that moment (typically a code indicating the location of the detection).
- Detection: It is a process under which an item is 'seen' at a checkpoint and a tracking record is created for it in the system. We assume that the time between the moment an item is detected and the moment the system is updated to reflect the item state change is negligible.
- Checkpoint: It is a point in the supply network where items are detected and a tracking record is created for them each time the system detects each of them.
- State change: It denotes an item's transition from one state into the next one.

Figure 2.1 illustrates an item's state evolution in the real world and in the tracking system using the notation of our tracking model.

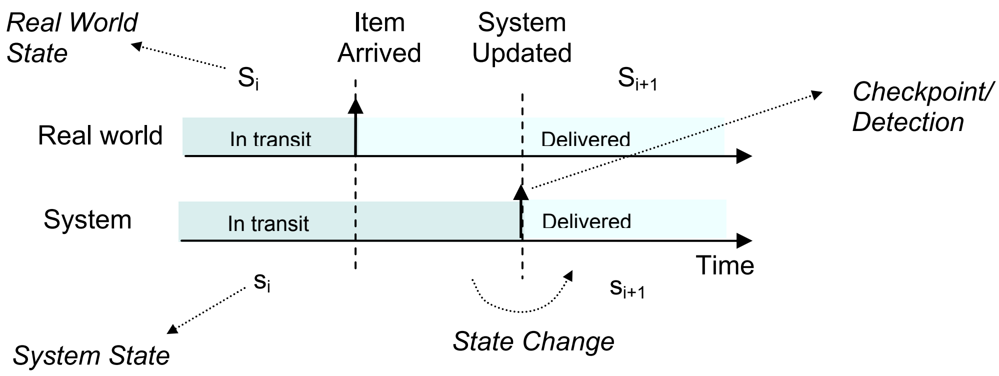

Figure 2.1: Supply chain tracking modelling

2.2.2. * Tracking performance metrics

2.2.2.1. * Measuring 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. We define as a measure of identification accuracy the probability P_{ID} of an item α being accurately identified when being at state S_i, and therefore the system correctly representing that the item is at state s_i. We note that at this point we assume there are no detection delays and no problems because of package aggregation. Therefore, the probability of correct state representation because of identification accuracy will be equal to the percentage of accurate reads at a specific checkpoint, which can be expressed as:

$$P_{ID}(s(\alpha,t)= s_i \mid S(\alpha,t)= S_i) = P_{ID}(s_i \mid S_i) = \text{Percentage of accurate reads}/100 \quad (1)$$

It is worth noting that this probability might be different for each checkpoint along the supply chain, as different identification methods might be in use.

[*] The sub-section may be skipped by the reader who does not wish to go into this level of analytic depth.

2.2.2.2. * Measuring detection delays

The timeliness of tracking information is another important factor that affects its quality. The case studies have revealed that in many cases there is a significant amount of time between the moment an item actually changes state and the moment this is reflected by the tracking system. This results in the system representing an inaccurate state of the item for this period of time. Figure 2.2 illustrates the detection delay in the case of an item arriving in a receiving dock.

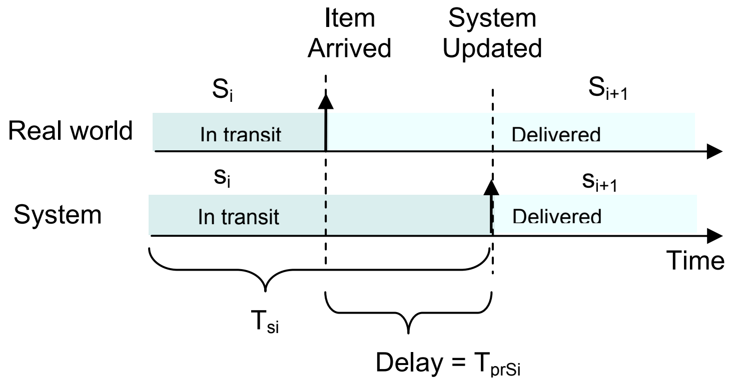

Figure 2.2: Item detection delay

We measure the system's performance with regard to detection delay in terms of the probability that that system represents the correct item's state at any time. This can be expressed as the fraction of time that the system represents an accurate state over the overall time that the state is represented. Let $P(s_j|S_i)$ be the probability that the system indicates that an item is at state s_j while it is at state S_i. We assume that the representation is correct when i=j.

Let T_{si} be the total time that the item appears in the system to be at state s_i and T_{prSi} the processing delay during state transition $S_i \rightarrow S_{i+1}$. Then the conditional probability $P_{pr}(s_i|S_i)$ that the system actually represents the correct state, because of processing delays, can be defined as:

$$P(s_i \mid S_i) = \frac{T_{s_i} - T_{prS_i}}{T_{s_i}} \qquad (2)$$

This probability might be different for each state, as the delay might be different at each checkpoint due to different identification practices.

2.2.2.3. * Measuring aggregation information accuracy

There are many cases in which aggregation information is used to track items in the supply chain. In specific, items are registered to be contained in a case or pallet. When the pallet is detected at a checkpoint, one can infer that items that are registered to be contained in it are also detected at the checkpoint and therefore a tracking record should be created for them. There are cases however that items that are registered to be in a container are not in it, which results in the tracking records, based on this aggregation information, to be inaccurate.

In order to measure aggregation information accuracy we measure the probability that an item, which is regarded to be in an aggregated packaging (a container, for instance), is actually in a specific state when the package is observed to be at this state. That is, if a container is detected in a receiving dock, what is the probability that the items that are expected to be in it are actually there.

Let '*ag'* be the aggregated package of item α. We define as aggregation information accuracy the probability $P_{ag}(s(a,t) = s_j \mid S(a,t) = S_i)$ that the system indicates that an item is at state s_j while it is at state S_i (we will denote this as $P_{ag}(s_j \mid S_i)$ for simplicity). This equals the probability that the system indicates that the aggregated packing is in state s_j^{ag} while the item is in state S_i , $P_{ag}(s(ag,t) = s_j^{ag} \mid S(a,t) = S_i)$ *or* $P_{ag}(s_j^{ag} \mid S_i)$. Assuming that the state of the aggregated packing is always accurately represented, the previous probability can be rewritten as $P_{ag}(S_j^{ag} \mid S_i)$. Therefore we have:

$$P_{ag}(s_j \mid S_i) = P_{ag}(s_j^{ag} \mid S_i) = P_{ag}(S_j^{ag} \mid S_i) \qquad (3)$$

For items that are not identified using aggregated information, we can assume that $P_{ag}(s_j \mid S_i)$ =1. We note that when we calculate aggregation information accuracy we ignore inaccuracies due to other reasons (for example, identification). Therefore, when an aggregated package is detected at state s_j^{ag} , we assume that its real state is indeed S_j^{ag} and that is why we have $P_{ag}(s_j^{ag} \mid S_i) = P_{ag}(S_j^{ag} \mid S_i)$ in (3).

Aggregation information accuracy can be measured by the amount of errors in aggregation information that a company is handling. For instance, if 3% of the items that are supposed to be contained in pallets are not actually there when the pallet is processed then we can assume that $P_{ag}(s_j \mid S_i) = P_{ag}(S_j^{ag} \mid S_i)$ =0.97

2.2.3. * Overall tracking performance measure

The overall tracking performance depends on the ability of the tracking system to accurately represent the item's state at any time and on the number and distribution of checkpoints along the supply chain, which affect the number and kind of states that the system can actually capture.

The ability of a tracking system to represent is affected by the factors analyzed in sections 2.2.2.1 to 2.2.2.3. In particular, the probability of the system representing the correct real world state will be:

$$P(s_i \mid S_i) = P_{id}(s_i \mid S_i) P_{pr}(s_i \mid S_i) P_{ag}(s_i \mid S_i) \tag{4}$$

The way that checkpoints are arranged throughout the supply chain also affects tracking effectiveness. The number of checkpoints and the states that these provide information about are factors that should be taken into account when measuring tracking performance. Initially we assume that we have a perfect system, which indicates the correct state S_i at all times, therefore, $P(s_i \mid S_i) = 1$.

We will define an overall measure of tracking performance in terms of the amount of tracking information the system communicates to the end user. According to information theory, the amount of information gained when the system indicates that the item is at state S_i is:

$$I_i = \log_2 \frac{1}{P(S_i)} = -\log_2 P(S_i) \text{ bits per state indication } S_i \tag{5}$$

Therefore, the average information gained from the system over a long period of time will be:

$$I_{av} = -\sum_{i=1}^{n} P(S_i) \log_2 P(S_i) \text{ bits per state indication} \tag{6}$$

In the case of the imperfect systems, from Bayes rule we can find the probability $P(S_i \mid s_j)$ of an item actually being in state S_i when the system indicates it is in state s_i:

$$P(S_i \mid s_j) = \frac{P(s_j \mid S_i) P(S_i)}{P(s_j)} \tag{7}$$

$$\text{where } P(s_j) = \sum_{i=1}^{n} P(s_j \mid S_i) P(S_i) \tag{8}$$

When there is a state indication s_i, the probability that the actual item's state is S_i changes from its prior value $P(S_i)$ to the posterior value $P(S_i|s_j)$. The change in information is:

$I(S_i \mid s_j)$ = Information embedded in state occurrence – Additional initial information available

or Information gained about state S_i when system indicates s_j:

$$I(S_i \mid s_j) = \log_2 \frac{1}{P(S_i)} - \log_2 \frac{1}{P(S_i \mid s_j)} = \log_2 \frac{P(S_i \mid s_j)}{P(S_i)} \tag{9}$$

The average information gained from system state indication s_j about the actual state S_i is:

$$I_{av} = \sum_{j=1}^{n}\sum_{i=1}^{n}\left[P(s_j)P(S_i \mid s_j)\log_2 \frac{P(S_i \mid s_j)}{P(S_i)}\right]$$

or

$$I_{av} = -\sum_{i=1}^{n} P(S_i)\log_2 P(S_i) + \sum_{j=1}^{n} P(s_j)\sum_{i=1}^{n} P(S_i \mid s_j)\log_2 P(S_i \mid s_j) \text{ bits per state indication} \quad (10)$$

or $I_{av}=I(S_i)-I(S_i|s_j)$

Formula (10) will produce a measure of information content of the current tracking system. In order to get a relative measure of tracking information we should compare this to the desired operation of the tracking system. Based on the decisions that a company needs to make taking into account tracking information, one can define the desired levels of identification accuracy, detection delays and accuracy of aggregation information. Also, the decisions to be made will indicate the desired number and location of checkpoints along the supply chain. The above should be sufficient to redo the calculations (4)–(10) for the desired values and produce the optimum information content for the specific system $I_{opt}(S_i \mid s_j)$.

Having the actual and optimum information content we define the relative information content (RIC) of the tracking system, which is a dimensionless and comparable measure

$$RIC = \frac{\text{Actual Information Content}}{\text{Optimum Information Content}} = \frac{I(S_i) - I(S_i \mid s_j)}{I_{opt}(S_i \mid s_j)} \quad (11)$$

It should be noted that the method proposed above is a first approach to measuring tracking performance and therefore has a number of limitations. Most importantly, the calculation of the actual information content does not take into account the business decisions that are based on tracking information. These could affect the importance of the location of checkpoints and the importance of the probability of the system representing the correct state at different points in the supply chain. A weighed calculation of the overall information content, based on the importance of tracking information at different points, might produce a more realistic measure of tracking performance. We intend to address this issue in the next steps of this research.

2.2.4. Business benefits resulting from good tracking performance

The benefits a company can gain from an effective tracking system are related to the effectiveness of the decisions that are based on tracking information. The decisions may lie in different application areas such as:

- Inventory replenishment
- Production planning

- Distribution scheduling
- Manufacturing control

The availability and accuracy of information about the state of an item at any time can significantly change the decisions and therefore impact on the utilities and costs associated to them. As mentioned earlier, the next step of this research aims to address the way tracking information impacts on decision effectiveness and quantify this impact.

2.3. Tracing performance

The term 'tracing performance' refers to the ability of a company to record and communicate lifecycle information about an item to the decision makers who need it. In the aerospace industry in specific, part lifecycle information is highly critical and it passes through various stages from the moment of recording it until it is made available to the final decision maker.

In the case of tracking information there is only one step of capturing, recording tracking data to the tracking system and making it available to the decision maker. On the other hand, in the case of tracing information it is required to model the complete evolution of information from the moment it is generated until the moment it is used by the decision maker as there might be multiple steps involved in this process. This may have an impact on the quality of information and consequently on its usefulness for the decision.

2.3.1. Modelling supply chain tracing

Our modelling approach is based on the work of Ballou et al. [3] who defined a way to model "information manufacturing systems". Their mode enables modelling the way information evolves through the system and estimating its value at the system's output. In order to model the way tracing information evolves we define five types of blocks that represent components of the overall system that handles lifecycle information. As shown in Figure 2.3, the blocks are:

- Data vendor block: It represents the various sources of raw input data.
- Processing block: It adds value to the data by manipulating or combining different data units.
- Data storage block: It models the placement of data units in files or databases where they are available as needed for additional processing.
- Quality block: It enhances data quality so that the output data stream has a higher quality than the input stream.
- Customer block: It represents the output and typically the information consumer that will use the final information product.

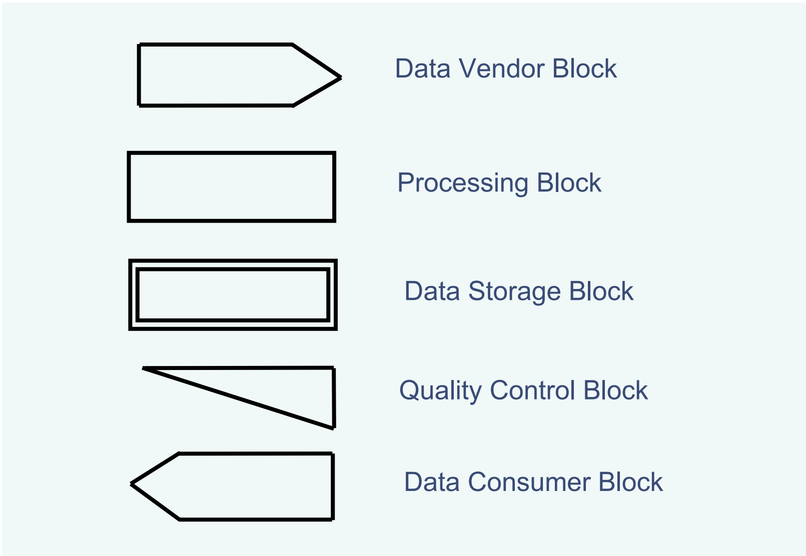

Figure 2.3: Components of information handling

Using the above blocks we can model the way information evolves through the steps of a business process. For example, Figure 2.4 demonstrates how the above model can be used to represent the evolution of maintenance information from the moment it is generated until it is used by a technician at a repair shop. The 'Job Log Recording' task gets input from the actual maintenance task, which generates maintenance data, and the part manual. The output of this processing is stored on a log card. The data on the log card is visually inspected to check for errors and then entered in the information system through a manual data entry process. The technician at the repair shop can access the information from the system to make the correct decision on the way to repair a part.

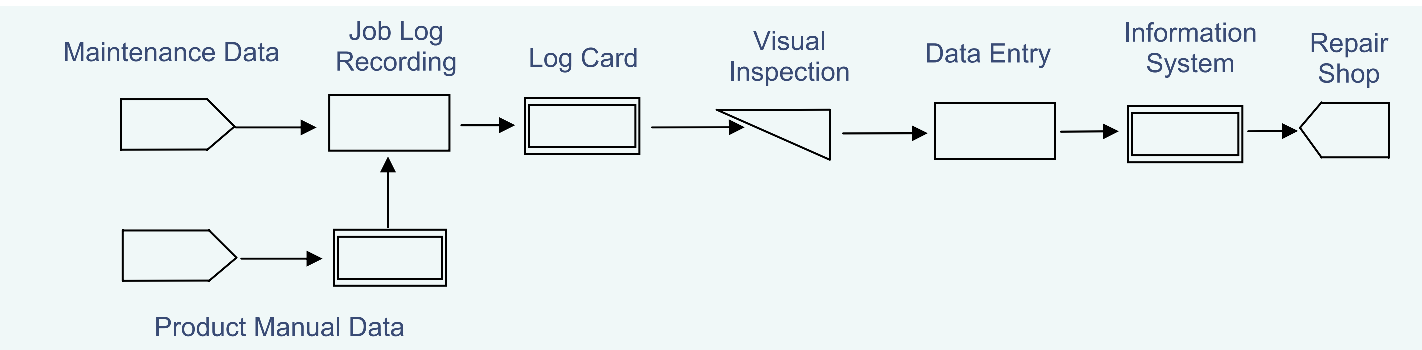

Figure 2.4: Maintenance information handling

The critical factors that we need to study about the lifecycle information are:

- Information timeliness
- Information quality
- Cost of information
- Value of information for final information consumer

In order to estimate the timeliness, the quality and the cost of the final information product, we need to define how each block affects these. In this way we will be able to estimate the usefulness and cost of information for the final consumer. In the following sub-sections we describe how each block impacts on the above-listed critical factors.

2.3.2. * Tracing performance metrics

2.3.2.1. * Tracing information timeliness

The timeliness of data depends on two factors. The first, currency, refers to the age of data units. The second, volatility, refers to how long the data remains valid, which depends on how fast the state that the data represents changes. It is emphasised here that data timeliness depends on the moment that this is used by the data consumer and its currency at that point. This determines the timeliness of the primitive data units. The overall timeliness of the final information product will result from the combination of the individual timeliness measures as explained in the following sub-sections.

Data vendor – Primitive data units

The currency of a data unit can be defined as:

$$\text{Currency} = (\text{Delivery time} - \text{Input time}) + \text{Age} \qquad (12)$$

The term in the parentheses represents how long the data have been in the system and *Age* represents the time difference between the moment the real-world event occurred and the moment the data were entered into the system.

Volatility represents how fast the state of the real world is changing and therefore data becomes outdated. We can view volatility as the 'shelf life' of data. According to the above, we can define timeliness of data as a function of data currency and volatility on a continuous scale from 0 to 1 as:

$$\text{Timeliness} = \max\left[(1 - \text{currency} / \text{shelf life}), 0\right]^{s} \qquad (13)$$

The exponent s is a parameter that allows us to control the sensitivity of timeliness to the currency/shelf life ratio. Note that the above definition of timeliness allows us to measure data timeliness the moment the data reach the decision maker, accumulating data currency up to that moment.

Processing blocks

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Processing blocks may use more than one data unit to produce their output data unit as shown in Figure 2.5. The objective is to be able to estimate the timeliness of each of the outputs of a processing block. We will define the timeliness T(y) of the output of a processing block as a weighted average of the timeliness of the individual input data units.

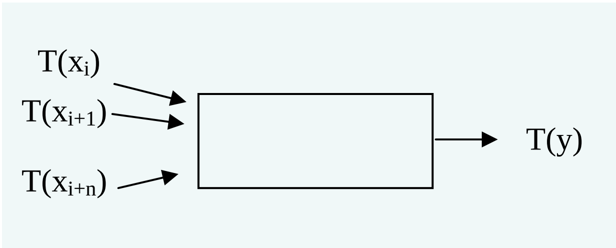


Figure 2.5: Timeliness of processing block output

$$T(y) = \frac{\sum_{i=1}^{n} w_i T(x_i)}{\sum_{i=1}^{n} w_i} \tag{14}$$

The weights used in (14) depend on the nature of the data and the way these are used to produce the output. For example, if the processing operation is an arithmetic operation then the weights should be proportional to the degree that each input affects the output function *y*, as shown in (15).

$$w_i = \left|\frac{\partial y}{\partial x_i}\right| |x_i| \tag{15}$$

For non-arithmetic operations, the weights in (14) should be assigned according to the way data are used to produce the output. For example, if the operation is merging of records from two files and the first file is twice as big as the second one, then it should be w_1=2 and w_2=1.

Apart from the impact on the timeliness of the data, processing blocks (as well as quality and storage blocks as we will present in the next sub-section) take some time to execute, which should be accumulated to calculate the total currency of data the moment this is received by the information consumer. In order to estimate the overall timeliness of the information that the final consumer receives, one should follow a two-step process: firstly, one should accumulate the total currency of each data unit and calculate the timeliness of the original data units fed into the system using (13); and secondly, according to the structure of the information system one should calculate the overall timeliness using (14) and (15) when necessary.

The above makes clear that to calculate the timeliness of data we should first know when this is used by the consumer in order to calculate the currency of primitive data units used for the production of the final information product. The example in section 4 of this report will illustrate the above process.

Quality and storage blocks

The timeliness of the output of quality and storage blocks is the same as the timeliness of the data units provided as input. This is so even though quality and storage may consume time (which should be accumulated in the overall currency of data in the output). The justification is that all timeliness measures ultimately depend upon the point in time when the consumer uses the information product. As a consequence, we should define the amount of time needed for quality control and storage operations to complete in order to be able to calculate the overall currency of the data used by the consumer.

In each of the block types, we should also define the delay before the actual operation starts, if any, as this affects the time the data will become available to the next operation and finally to the information consumer. The above enables us to estimate the timeliness of the final information product.

2.3.2.2. * Tracing information quality

The second factor we need to be able to asses is the quality of the final information product. Again, we represent this using a scale from 0 to 1.

Data vendor – Primitive data units

We assume that each data unit x_i has an initial quality level $DQ(x_i)$. $DQ(x_i) = 0$ means that the data quality is intolerable, while $DQ(x_i) = 1$ means that there is no problem with the quality of data unit x_i. The initialization of the data quality level of primitive data units resides with the analyst. Historical information about the accuracy and completeness of the data units produced should be used to assign a value to the quality of primitive data units. In our maintenance log example in Figure 2.4, this would refer to the accuracy, completeness and usefulness of the maintenance data that a technician would usually record in a log card.

Processing blocks

As in the case of timeliness, our aim is to be able to estimate the quality of the output data units of a processing block. The quality of the output DQ(y) depends on two factors:

- the quality of the data provided as input for processing;
- the processing effectiveness (PE) of the operation.

We will refer to the quality of the input data units as the data component (DC) of the quality estimation. The DC will depend on the individual quality levels of the input data units $DQ(x_i)$. As in the case of timeliness estimation, we can calculate the data component quality as a weighted average of the input data units' quality.

$$DC = \frac{\sum_{i=1}^{n} w_i DQ(x_i)}{\sum_{i=1}^{n} w_i} \tag{16}$$

where the weights w_i could be assigned in a similar way as in the case of timeliness estimation, using for example (15) for arithmetic operations.

The second factor that affects the quality of the output data units is the processing effectiveness (PE) of the operation. This can be represented as a real number in the scale 0 to 1–0 representing that the operation corrupts the quality of the input to such a degree that the data quality measure for the output should be 0; and 1 representing that the processing never introduces errors.

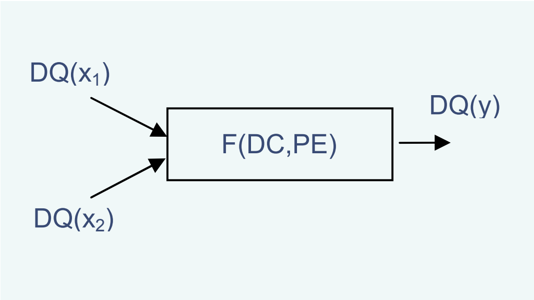


Figure 2.6: Output data quality of a processing block

The overall quality of the output DQ(y) should be a function of the DC and PE of the processing block, as shown in Figure 2.6.

$$DQ(y) = f(DC, PE) \tag{17}$$

An example could be:

$$DQ(y) = \sqrt{DC * PE} \tag{18}$$

In this way we can estimate the output data quality of a processing block, given the quality of input data units, its processing effectiveness and the function that represents how these two contribute to the output data quality.

Quality blocks

As the aim of quality blocks is to check and potentially improve the quality of input data units, the output data units' quality should typically be higher than that of the input. We can represent this by expressing the quality of an output data unit DQ(y) as a function of the input data units' quality. For example the function in (19) indicates that the quality block eliminates 75% of the data quality problems in the input before producing the output.

$$DQ(y)=[1-((1-DQ(x_i))*0.25)] \tag{19}$$

Storage blocks

Storage blocks have no impact of the quality of the data units stored in them.

2.3.2.3. * Tracing information cost

The last important factor we should take into consideration is the cost of obtaining the final information product which will be used to make a decision. This is the cost that is incurred in each of the blocks that a data unit is processed in before reaching the final information consumer. As a consequence, for each of the blocks that we use to model our system we should define the cost per data unit incurred in that. In this way, by accumulating all costs from the blocks a data unit has passed through its lifetime, we can calculate its total cost when reaching the final information consumer.

2.3.3. Overall tracing performance measure

Table 2.1 summarizes the required information needed to define for each of the block types in order to be able to estimate the timeliness, the quality and the cost of the final information product when this reaches the information consumer, who typically is the decision maker.

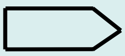
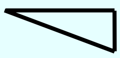
	Cost	Quality	Time	Timeliness Function	Delay
	For obtaining	Intrinsic	Currency, volatility	How important is it for this data	-
	For processing	Processing effectiveness and function of output quality	For processing	Weighted average	To start
	For storing	-	To retrieve	-	To retrieve
	For improving quality	Improvement percentage	To complete check	-	To start

Table 2.1: Tracing information production modelling

The next step is to define the value of this information for the decision maker as a function of its timeliness and its quality, as we have assumed that these directly affect information usefulness. As a first step, let us assume that the final information product is of perfect quality and timeliness (i.e. T=1 and DQ=1). This is also called *perfect information*. Appendix A describes how one can calculate the intrinsic value V_I of perfect information for a decision through a simple example. The actual value of information V_A for the decision maker should be a function of the intrinsic value of the information, its timeliness and its quality.

$$V_A=f\,(V_I,\ T,\ DQ) \qquad (20)$$

Since the timeliness and data quality are measured in the scale 0 to 1, a functional form of the actual value of information could be:

$$V_A=V_I\,(w\,T^{\,a}+(1-w)\,DQ^{\,b}) \qquad (21)$$

Where a, b and $0 \le w \le 1$ depend on the decision maker and the nature of the decision. The weight w captures the relative importance of information quality and timeliness to the customer. The exponents *a* and *b* reflect the decision maker's sensitivity to changes in DQ and T.

The values of overall timeliness and quality of the information that the decision maker receives are the primary measures of the effectiveness of the system to provide useful information that can optimize decision making. The value of this information is another measure that reflects the performance of the information system in a financial dimension. Comparing the actual value of this information with the total cost for obtaining it (which is accumulated through the different blocks along its lifetime) will reveal the net value of the final information product for the decision maker and whether recording and accessing the information is worthwhile in the first place.

2.3.4. Business benefits resulting from tracing performance

As in the case of benefits stemming from tracking performance, the benefits that result from good lifecycle information tracing performance relate to the effectiveness of the decisions that are based on this information. Appendix A provides an example of a decision that is facilitated with lifecycle information (that is, warranty information) and quantifies the benefit of having this information when making the decision. The benefits of good product lifecycle tracing performance would be similar in the cases of:

- Maintenance and repair decisions
- End of life decisions
- Product recall and service bulleting incidents

3. The Process of Measuring Track and Trace Performance

This section describes the approach for measuring tracking and tracing performance. As we have decided that assessing tracking performance is a different process from assessing tracing performance, we describe the steps for carrying out this assessment separately for these processes.

3.1. A method for measuring tracking performance

Before describing in detail the steps one should take in order to measure tracking performance we provide an overview of the measuring process in the following sub-section.

3.1.1. Tracking performance measurement: Overview

The tracking performance measurement process includes four phases, as shown in Figure 3.1. The scoping phase involves identifying the products that a company wishes to track, understanding the structure of the supply network and understanding the decisions that are based on tracking information. The next two phases run in parallel. The current system analysis phase aims at understanding the current configuration of checkpoints along the supply network and the way items are detected at them. Based on these data, we calculate the performance metrics for specific performance factors (as described in section 2.2.2). The final step of the current system analysis is an assessment of the effectiveness of the decisions based on current tracking information; however, this will be addressed at a later stage of this research. On the other hand, the required system analysis phase aims at defining the checkpoint configuration and desired performance for item detection and system booking based on the requirements that the decisions pose. The required configuration and performance will generate a new set of ‘required’ performance metrics. Again, as a last step of this phase, the effectiveness of the decisions under the required tracking performance should be assessed. The final phase of the tracking performance measurement process includes the comparison of the performance metrics and decision effectiveness between the current and the required tracking process.

In the next sub-section we describe each of the steps of the process. We will refer to the person conducting the performance assessment as the ‘analyst’.

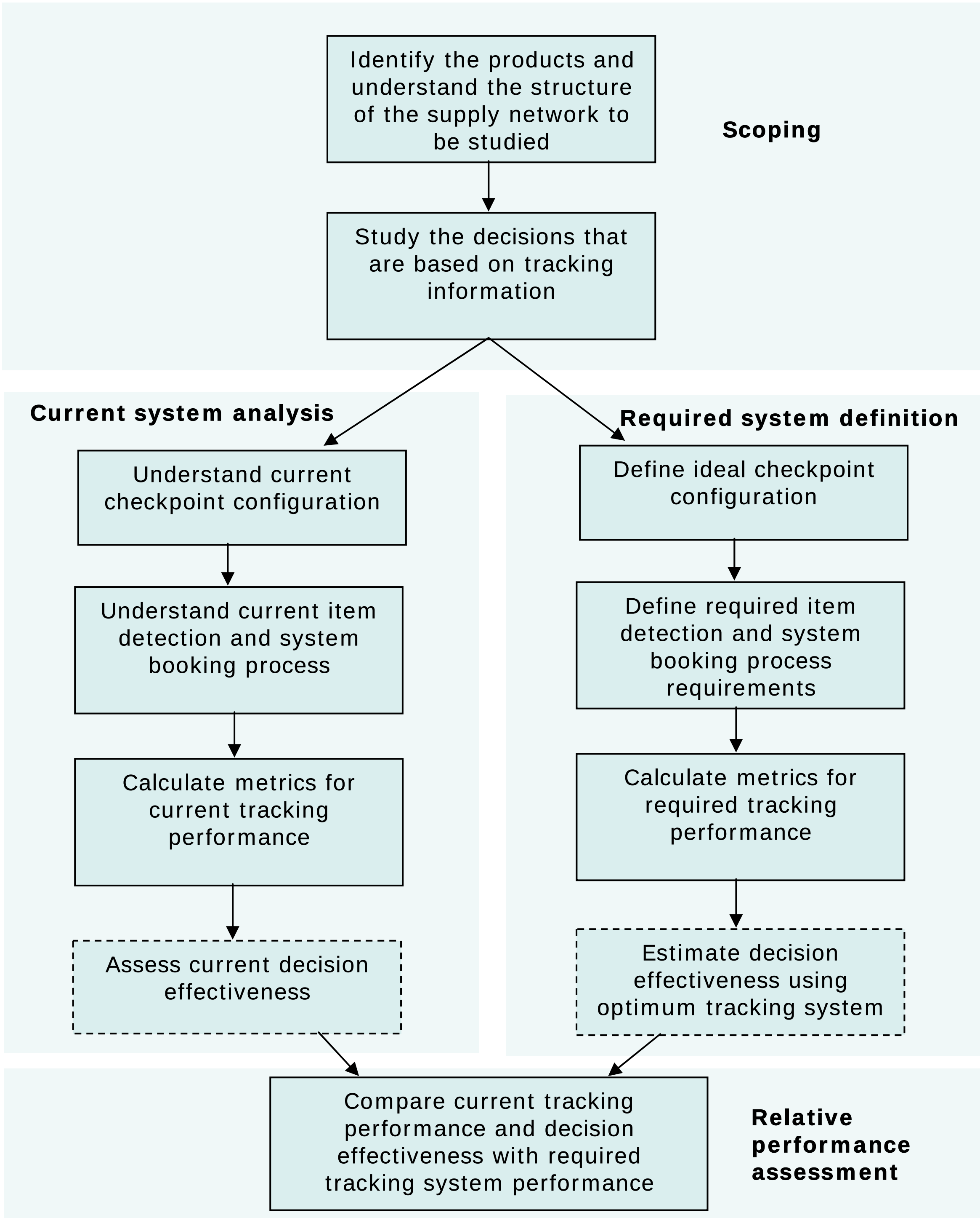


Figure 3.1: Tracking performance measurement process overview

3.1.2. Tracking performance measurement: Process steps

Phase 1: Scoping

1.1 Products and supply network study: At this step the products, for which the tracking performance will be assessed, should be identified and any relevant information should be collected, such as cost of each product, criticality and packaging information. Also, the structure of the supply network should be analyzed. The analyst should define the distinct locations along the supply network that a product might be at any time and what the possible routes between them are.

1.2 Decisions based on tracking information: At this step the critical decisions that are based on tracking information should be identified for each checkpoint. For each decision, the analyst should understand how tracking information quality affects the decision and what are the costs involved.

Phase 2: Current tracking system analysis

2.1 Current checkpoint configuration: The analyst should identify the locations along the supply chain at which products are currently detected and a tracking record is created for them. The space between two checkpoints defines a location state that a product could be at any point.

2.2 Product detection and booking process: For each checkpoint the analyst shall study the process of identifying and booking an item into the information system (we call this a detection event). The analyst shall find out the identification technology used and, in particular, the following data should be collected: a) the accuracy of data capture (that is, the percentage of items correctly identified); b) the delay (if any) involved between the moment an item changes location (state) and the moment the change is actually booked into the system; c) whether items are booked based on their aggregated packaging and what is the accuracy of aggregation information. The above information will be used to calculate the performance metrics as these are defined in section 2.2.2.

2.3 Performance metrics calculation: In this step the performance metrics should be calculated and the analyst should produce values for the metrics defined in (1)–(4) and (10). The calculation should be based on data collected in the previous step.

2.4 Current decision effectiveness: The final step of this phase aims at assessing decision effectiveness under the current configuration of the tracking system. As mentioned before, we aim to propose a formal approach for this process at a later stage of this research. However, the output of this step should be a measure of the overall expected utility of decisions based on current tracking information.

Phase 3: Required tracking system definition

3.1 Required checkpoint configuration: Based on the outcome of step 1.2, the analyst should identify the locations along the supply chain at which the products should be detected and a tracking record should be created for them. This will be driven by the decisions to be made based on tracking information that will indicate which item states the tracking system should capture.

3.2 Required product detection and booking process: For each of the required checkpoints the analyst shall define the required performance characteristics of the item detection process. The analyst should define the identification technology that should be used for item detection. Finally, the analyst should set the performance requirements of the detection process with regard to the performance metrics that have been defined: a) the accuracy of data capture; b) the delay between the moment an item changes location and the moment the change is actually booked into the system; c) whether items should be booked based on their aggregated packaging and what the accuracy of aggregation information should be.

3.3 Required performance metrics calculation: As in step 2.3, in this step the analyst should calculate the performance metrics for the required tracking system operation and the analyst should produce values for the metrics defined in (1)–(4) and (10). The calculation should be based on data collected in the previous step.

3.4 Required decision effectiveness: The final step of this phase aims at estimating decision effectiveness under the required configuration of the tracking system. Again, the output of this step should be a measure of the overall expected utility of decisions based on required tracking information.

Phase 4: Relative performance assessment

4.1 System performance and decision effectiveness comparison: In order to produce a normalized, comparable and dimensionless measure, the analyst should compare the results of the calculated metrics from phases 2 and 3. These should produce relative performance measures in the respective operations and a relative overall performance measure. Moreover, by comparing the decision effectiveness measures we should have a relative decision effectiveness measure, which could provide a basis for a cost-benefit assessment of the system in financial terms.

The tracking performance measurement process described in this section will produce measures that will enable the company to monitor its tracking effectiveness and point out areas that should be improved in order to achieve the desired decision and operational effectiveness.

3.2. A method for measuring tracing performance

This section describes the approach for measuring tracing performance in a company, that is, the ability of a company or an individual process to deliver lifecycle information about a product to a person who needs it for a decision. Before analyzing the steps, we provide an overview of the process.

3.2.1. Lifecycle information tracing performance measurement: Overview

The process of measuring lifecycle information tracing performance consists of three phases.

In the first phase, the aim is to identify the data that need to be traced and the way these evolve until the moment they reach the decision maker. For this purpose, the analyst should identify the business steps that take place for the data to become available for the decision maker. The complete process should be modelled using the model we have proposed in section 2.3.1 and for each block the analyst should define the respective operational parameters regarding the impact of the step on the quality, timeliness and cost of the processed data as defined in Table 2.1. This should enable the analyst to calculate the quality, timeliness and cost of the final information product.

The second phase of the process refers to understanding the decisions that are based on tracing information and quantifying the value of perfect information. The analyst should identify and analyze the different options for each decision and, using the approach described in Appendix A, he/she should calculate the value of the perfect information for the decision maker. Moreover, depending on the nature of the decision, the analyst should define how the value of information is affected by the data quality and data timeliness.

The final phase refers to the calculation of the actual value of information for the decision maker. Having defined how this is affected by data quality and timeliness and using the estimations for these measures from the model, the analyst should be able to calculate the value generated by the tracing system for the decision maker. The overview of the process described above is depicted in Figure 3.2. In the next section we analyze each of the process steps.

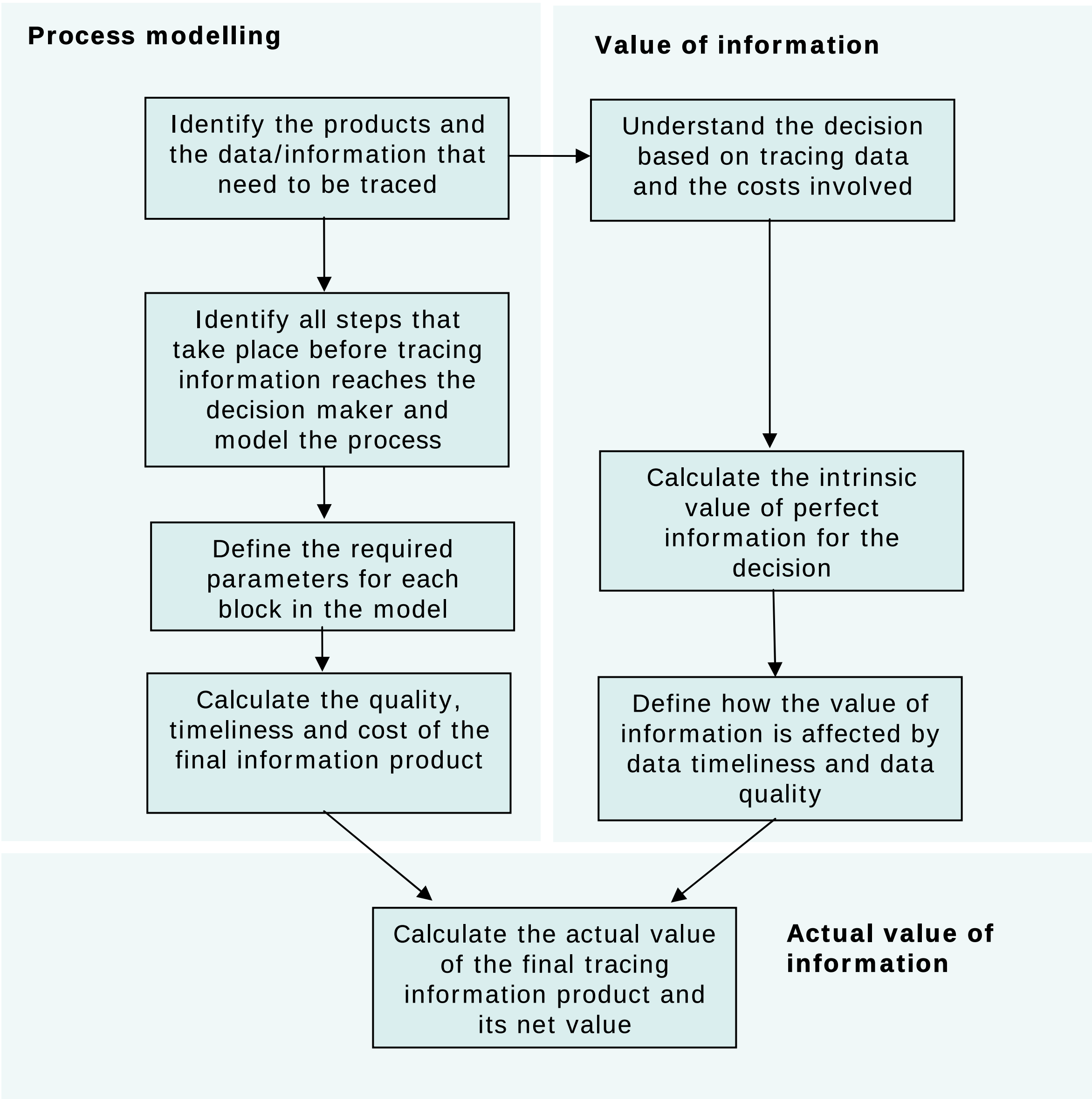


Figure 3.2: Lifecycle information tracing performance measurement process overview

3.2.2. Lifecycle information tracing performance measurement: Process steps

Phase 1: Tracing process modelling

1.1 Products and data to be traced: As a first step, the analyst should identify the products for which tracing information is recorded. Secondly, the analyst should clearly define the exact set of data that need to be recorded and made available to the decision maker. The data should be split in data units, so that the analyst can treat each part of the data separately if this becomes necessary. Each data unit should include data that refer to a specific variable, for example, date of maintenance or part number.

1.2 Information processing steps and process modelling: In this step the analyst should identify all business operations that the data go through before they reach the decision maker. These steps include the data sources, data storage, data processing operations, data quality control operations and finally information consumers. Having identified the data-flow steps before reaching the decision maker, the analyst should be able to model the complete flow using the model proposed in section 2.3.1.

1.3 Data processing parameters definition: For each of the identified data management blocks, the analyst should define the processing parameters that refer to the cost, the required time and delay, the impact on timeliness and quality of each block, as these are described in Table 2.1. The value of the above parameters for each block depends on the nature of the operation the block executes and how it affects the data. The parameters should be carefully selected so that they reflect the actual system operation as accurately as possible. The values of the parameters are critical for the accuracy of the final outcome of the performance-assessment process.

1.4 Final product quality, timeliness and cost calculation: Given the processing parameters for each block, the analyst should calculate the quality, timeliness and cost for each data unit when this reaches the decision maker. These values will be used in the third phase to calculate the actual value of the information. However, they are good performance metrics by themselves, as they provide an indication of how the system impacts on the overall data quality, timeliness and cost, which are the components that affect the overall performance in the first place.

Phase 2: Value of information

2.1 Decisions based on tracing data: Before calculating the intrinsic value of perfect information for the decision maker, the analyst should understand what the decisions to be made are. Furthermore, the analyst should identify the different options for each decision and the costs/utilities that relate to each option. These will provide input to the next step of the process.

2.2 Value of perfect information calculation: Given the decisions and their options along with the associated costs/utilities, the analyst should calculate the intrinsic value of perfect information for each decision using the approach described in Appendix A. In case the decision maker has to make more than one decision, this step should be repeated for all distinct decisions. The output of this step should be a figure of the value of perfect information for each decision.

2.3 Impact of timeliness and quality on value of information: In this step the analyst should study how the decision is affected by the timeliness and quality of data. For example, identify which of the two attributes is more critical for an effective decision and what is the sensitivity of the actual value of information with regard to data timeliness and quality reduction. The above analysis should provide enough information so that the analyst is able to produce a formula similar to (21) and assign values to the weight *w* and the exponents *a* and *b*, so that these reflect the actual behaviour of the value of information with regard to timelines and quality.

Phase 3: Actual value of information

3.1 Actual value of information calculation: The previous two phases should have produced the following data to be used in this step:

- The intrinsic value of information
- The way the value of information is affected by changes in data timeliness and quality (a formula similar to (21))
- The values of quality, timeliness and cost for each data unit that reaches the decision maker

Using the above, the analyst should be able to calculate the actual value of the information that the system generates. The equation that the analyst has defined (according to (20) or (21)) will give a final figure of the actual value of the information for the decision maker, based on its intrinsic value and the impact that data quality and timeliness have on it. Comparing this with the overall cost for the decision maker to obtain this information, one can calculate the net value of information and judge whether collecting this information, given its quality and timeliness levels, is worthwhile.

The above analysis should reflect the performance of the tracing system with respect to the actual value it is delivering to the information consumer. The outcome of the analysis should be used to identify any problems in data quality, timeliness and cost that affect either the data's value for the decision or make them too expensive to obtain. These findings should be used to take action that would increase data usefulness and decrease its production cost.

In the next section we demonstrate how the approaches analyzed in this section can be applied in two simple examples of tracking and tracing performance measurement.

4. Examples of Measuring Track and Trace Performance

In this section we will demonstrate the use of the proposed method to measure tracking and tracing performance through two examples. The first one demonstrates the way tracking performance is measured in a supply chain, while the second one illustrates how lifecycle information tracing performance is measured in the case of recording maintenance/repair information of an aircraft part which is sent back to the repair agent for repair.

4.1. Measuring tracking performance: An example

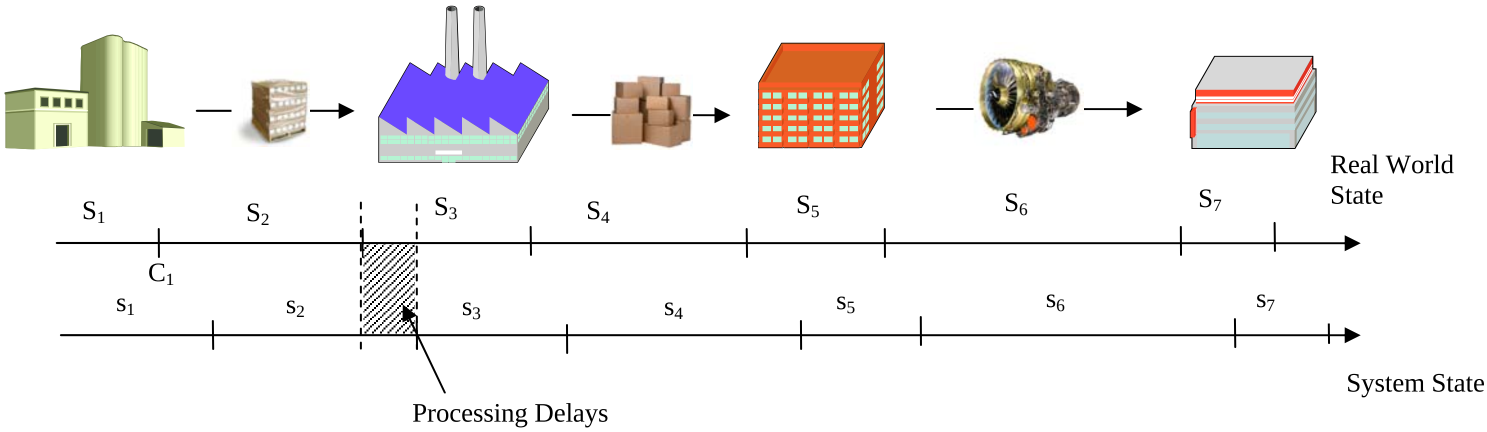


Figure 4.1: Item tracking across the supply chain

We will demonstrate how to measure tracking performance through a simple example using a hypothetical supply chain shown in Figure 4.1. In this scenario the supply chain includes four nodes. We follow the steps outlined in section 3.1.

Phase 1: Scoping

1.1 Products and supply network study: In this example the product to be tracked are high-value aircraft components. The structure of the supply chain is depicted in Figure 4.1.

1.2 Decisions based on tracking information: We assume that the decisions to be made in this example refer to logistics and distribution decisions. The only important thing to notice at this point is that we assume that according to the decisions along the supply chain, two more checkpoints would be needed. This will be further analyzed in phase 3 of this analysis.

Phase 2: Current tracking system analysis

2.1 Current checkpoint configuration: Figure 4.1 shows what the checkpoints along the supply chain are at the current state (real world state axis). In a real case this would result from the study of the supply chain and the current tracking practice. The current checkpoints define seven distinct states (S_1–S_7) that an item could be at any point in the supply chain. The hypothetical analysis of the supply chain revealed the time periods that items spend at each state and their respective prior probabilities of occurring as these appear in Table 4.1.

State	State duration (days)	$P(S_i)$
S_1	10	0.204082
S_2	5	0.102041
S_3	20	0.408163
S_4	5	0.102041
S_5	6	0.122449
S_6	1	0.020408
S_7	2	0.040816

Table 4.1: State durations and prior probabilities

2.2 Product detection and booking process: The analysis of the item detection and booking process at each checkpoint in the supply chain revealed the following information: at checkpoints C1 and C2 the items are identified using pallet content information which is accurate in 98% of the cases. Similarly, at checkpoints C3 and C4 the items are identified using the case identifiers. The accuracy of this aggregation information is 98.5%. Finally, at checkpoints C5, C6 and C7 the products are identified at item level. The accuracy of the identification technology used throughout the supply chain is 99% for each checkpoint. Also, the detection process is subject to the following delays per state transition:

State	Processing Delay during $S_i \rightarrow S_{i+1}$ (days)
S_1	2
S_2	1.5
S_3	2
S_4	1
S_5	0.5
S_6	0.5
S_7	0.1

Table 4.2: Item detection delays

2.3 Performance metrics calculation: Based on the information collected so far we are able to calculate the metrics that refer to (1)–(4), which are described in Table 4.3 per state.

State	Probability of accurate representation due to:			Overall probability of accurate representation
	Identification accuracy	Processing delays	Aggregation information accuracy	
	$P_{ID}(s_i \mid S_i)$	$P_{pr}(s_i \mid S_i)$	$P_{ag}(s_i \mid S_i)$	$P(s_i \mid S_i)$
S_1	0.99	0.8	0.98	0.77616
S_2	0.99	0.7	0.98	0.67914
S_3	0.99	0.9	0.985	0.877635
S_4	0.99	0.8	0.985	0.78012
S_5	0.99	0.916667	1	0.9075
S_6	0.99	0.5	1	0.495
S_7	0.99	0.95	1	0.9405

Table 4.3: Intermediate state representation metrics

Using (7)–(9) we can calculate the intermediate conditional probabilities before we calculate the actual information content of the tracking system as shown in Table 4.4. The second column $P(s_i|S_i)$ contains the overall probability of accurate representation by the system, while column $P(s_i|S_{i+1})$ is its complementary value, that is, the system representing a previous state while the item is at the next one. Column $P(s_i)$ contains for each state the overall probability of the system indicating that an item is at state s_i using formula (8). Finally, using (7) we calculate the conditional probability of item being at state S_i given indication s_i and its complementary value.

State	Overall probability of accurate representation	Overall probability of inaccurate representation	Probability distribution of system indicating state s_i (Results from (8))	Conditional probability of item being at state S_i given indication s_i (Results from (7))	Conditional probability of item being at state S_{i+1} given indication s_i (Complementary to $P(S_i\|s_i)$)
	$P(s_i\|S_i)$	$P(s_i\|S_{i+1})$	$P(s_i)$	$P(S_i\|s_i)$	$P(S_{i+1}\|s_i)$
s_1	0.77616	0.22384	0.181241	0.873975	0.126025
s_2	0.67914	0.32086	0.200263	0.346044	0.653956
s_3	0.877635	0.122365	0.370705	0.966318	0.033682
s_4	0.78012	0.21988	0.106528	0.747259	0.252741
s_5	0.9075	0.0925	0.11301	0.983296	0.016704
s_6	0.495	0.505	0.030714	0.328904	0.671096
s_7	0.9405	0.0595	0.038388	1	0

Table 4.4: Intermediate conditional probabilities for calculating actual information content

Having calculated all the above, we are now ready to calculate the actual information content of the system using (10), which will be:

$$I_{av} = -\sum_{i=1}^{n} P(S_i)\log_2 P(S_i) + \sum_{j=1}^{n} P(s_j)\sum_{i=1}^{n} P(S_i \mid s_j)\log_2 P(S_i \mid s_j) = 1.848 \text{ bits/state indication} \quad (22)$$

In this phase we have calculated the intermediate performance metrics (Table 4.3) and the overall information content of the system (22). In the next phase we will do the same for the required system operation and at the end we will compare these values to come up with an overall relative performance measure.

Phase 3: Required tracking system definition

3.1 Required checkpoint configuration: The analysis of the decisions revealed that two additional checkpoints are needed to support business decisions and operations. The first one is in the second supply chain node and will therefore split state S_3 to S_{31} and S_{32}. The second additional checkpoint is needed in the third supply chain node, therefore splitting state S_5 to S_{51} and S_{52}. The required distinct states resulting from the addition of the two checkpoints along with the duration of states are listed in Table 4.5. The last column in Table

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4.5 shows the maximum accepted state update delays. Note that these are shorter than those observed in the current operation of the system, listed in Table 4.2.

State	State duration (days)	$P(S_i)$	Delay for $S_i \rightarrow S_{i+1}$ (days)
S_1	10	0.204082	1
S_2	5	0.102041	1
S_{31}	15	0.306122	1.5
S_{32}	5	0.102041	0.5
S_4	5	0.102041	0.5
S_{51}	3	0.061224	0.5
S_{52}	3	0.061224	0.3
S_6	1	0.020408	0.3
S_7	2	0.040816	0.1

Table 4.5: Required states, transition delays and prior probabilities

3.2 Required product detection and booking process: The identification accuracy of the current system is regarded acceptable (99%). However, the aggregation information accuracy is required to be 99% for all checkpoints that aggregated packaging is used to track items. According the above requirements, the new version of Table 4.3 will be:

State	Probability of accurate representation due to:			Overall probability of accurate representation
	Identification accuracy	Processing delays	Aggregation information accuracy	
	$P_{ID}(s_i \mid S_i)$	$P_{pr}(s_i \mid S_i)$	$P_{ag}(s_i \mid S_i)$	$P(s_i \mid S_i)$
S_1	0.99	0.9	0.99	0.88209
S_2	0.99	0.8	0.99	0.78408

S_{31}	0.99	0.9	0.99	0.88209
S_{32}	0.99	0.9	0.99	0.88209
S_4	0.99	0.9	0.99	0.88209
S_{51}	0.99	0.833333	1	0.825
S_{52}	0.99	0.9	1	0.891
S_6	0.99	0.7	1	0.693
S_7	0.99	0.95	1	0.9405

Table 4.6: Required state representation metrics

3.3 Required performance metrics calculation: The data in Table 4.6 are the first indication of required performance. Using these data we can again calculate the conditional probabilities for the required operation of the system, shown in Table 4.7.

State	Overall probability of accurate representation	Overall probability of inaccurate representation	Probability distribution of system indicating state s_i (Results from (8))	Conditional probability of item being at state S_i given indication s_i (Results from (7))	Conditional probability of item being at state S_{i+1} given indication s_i (Complementary to $P(S_i\|s_i)$)
	$P(s_i\|S_i)$	$P(s_i\|S_{i+1})$	$P(s_i)$	$P(S_i\|s_i)$	$P(S_{i+1}\|s_i)$
S_1	0.88209	0.11791	0.19205	0.937352	0.062648
S_2	0.78408	0.21592	0.146106	0.547603	0.452397
S_3	0.88209	0.11791	0.282059	0.957344	0.042656
S31	0.88209	0.11791	0.097228	0.925752	0.074248
S_4	0.88209	0.11791	0.097228	0.925752	0.074248
S_5	0.825	0.175	0.054082	0.933962	0.066038
S51	0.891	0.109	0.059	0.924594	0.075406
S_6	0.693	0.307	0.026673	0.530222	0.469778
S_7	0.9405	0.0595	0.038388	1	0

Table 4.7: Intermediate conditional probabilities for calculating the required information content

Having calculated the above data and using (10) we can calculate the required information content for the optimum system operation:

$$I_{av} = -\sum_{i=1}^{n} P(S_i)\log_2 P(S_i) + \sum_{j=1}^{n} P(s_j)\sum_{i=1}^{n} P(S_i \mid s_j)\log_2 P(S_i \mid s_j) = 2.37 \text{ bits/state indication} \quad (23)$$

Phase 4: Relative performance assessment

4.1 System performance and decision effectiveness comparison: The previous two phases have provided us with the individual performance metrics for specific operations (for example identification accuracy) and with the overall information content of the actual and the required system operation. In this step we can compare the respective measures to get a relative performance measure, which will show the performance of our current system compared to the optimum. Using (11) to calculate the relative information content of the system we get:

$$RIC = \frac{1.848}{2.37} = 78\% \quad (24)$$

which is an indication that our system currently operates at nearly the 80% of the performance that it should in order to support our business decisions in the ideal way.

4.2. Measuring lifecycle information tracing performance: An example

In this section we will demonstrate the use of the proposed method for measuring lifecycle information tracing performance in the case of recording maintenance/repair information of an aircraft part which is sent back to the repair agent for repair. We follow the steps of the approach we proposed in section 3.2.

Phase 1: Tracing process modelling

1.1 Products and data to be traced: In this example we will study the maintenance and repair information of a hypothetical aircraft component which has failed. A failure reason and a description should be recorded and made available to the final repair technician who will decide on the way to treat the failed part. We assume that the failure description is one data unit which needs to be communicated to the repair technician in order for him to make a decision.

1.2 Information processing steps and process modelling: The analysis of business operations revealed that the data go through a number of operations from the moment they are generated until they reach the repair agent. The sequence of these operations, which is depicted in Figure 4.2, is as follows:

- **VB1, Maintenance data:** This block represents the generation of data which are important for maintenance operations. In our case this refers to the data regarding the failure reason and description of problem for the part. This data is generated by the visual observation of the problem by the field engineer and, in our diagram, is represented by data unit DU1.

- **VB2, Product manual data:** This block represents the data retrieved from the part's manual of use/maintenance that the engineer might refer to in order to fill in the log card.
- **PB1, Job log recording:** This block represents the process of manually recording the observed data into a log card. This operation has a significant impact on the quality of the data which is finally stored on the log card, which is represented by data unit DU3.

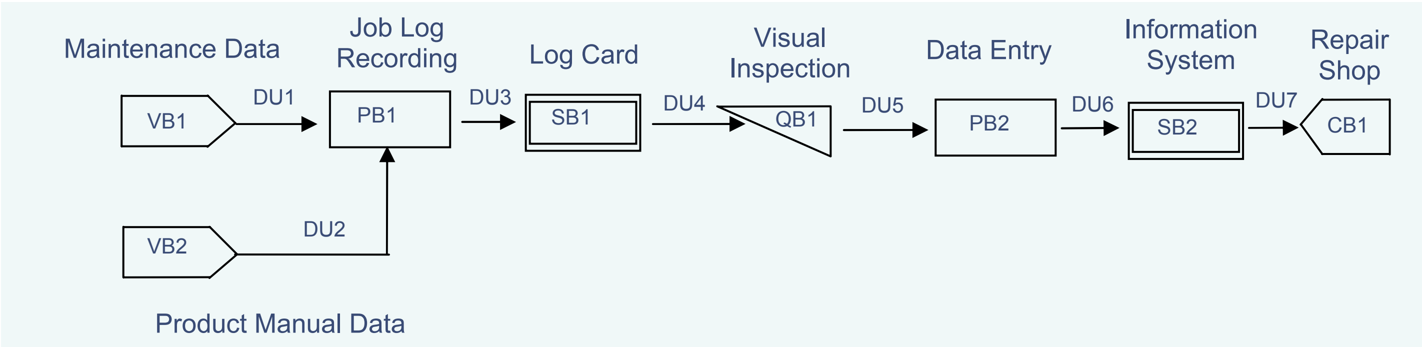

Figure 4.2: Maintenance information handling operations modelling

- **SB1, Log card:** The data is then stored on a log card from which it will be copied into the information system.
- **QB1, Visual inspection:** The data are read from the log card (DU4) and a data quality inspection takes place. The result of this process (DU5) will be the input of the next operation.
- **PB2, Data entry:** After the quality control, the data from the log card are manually entered into the information system through a data entry process.
- **SB2, Information system:** The lifecycle data are stored in the system until a technician requests for them.
- **CB1, Repair shop:** The final information consumer is the repair shop technician who will read the information about the failed part and, based on that, will make the best repair decision.

1.3 Data processing parameters definition: For each of the identified data-management blocks, we define the required processing parameters.

VB1, Maintenance data

1. *Cost*: The cost of obtaining failure information and description is estimated about £15, based on the average time a technician will need to assess the state of a failed part.

2. *Quality*: The quality of the data that the technician will capture depends on the quality and the level of detail of the visual inspection. Moreover, the way information will be recorded also affects its quality, since the descriptiveness will affect the usefulness of the information for the final decision making. The analysis showed that in 10% of the cases, the information captured was not helpful or was inconsistent with the actual fault of the part. As a consequence, we assume that the quality of DU1 is 0.9.

3. *Input time*: The collection of failure information takes place at the beginning of the process; therefore the input time of DU1 will be zero.

4. *Age*: The collection of failure information takes place on average 1–2 days after a part has failed. Therefore we assume that the age of information is 1.5 days.

5. *Shelf life*: The analysis showed that unless the repair agent received the data within 30 days, these are useless, as the part needs to be repaired even without available information approximately after a month. Of course, in some cases the data are required to arrive earlier than that.

6. *Timeliness function*: Since information becomes less useful towards the end of the 30-day period, an exponent of less than one for the timeliness function is required. An exponent of 1/3 indicating that 55% of the parts are repaired in the period 25–30 days (and therefore failure information should be available by then) proved satisfactory.

VB2, Product manual data

1. *Cost*: The cost of obtaining product manual data refers to the cost of searching and retrieving the relevant files and the time consumed in that. The analysis showed this is about £2 per failed part.

2. *Quality*: We assume that there is no quality problem with part manual data.

3. *Input time*: The collection of failure information takes place at the beginning of the process; therefore the input time of DU2 will be zero.

4. *Age*: The age of part manual data is calculated from the first time the manual was generated. An average value is 5 years.

5. *Shelf life*: The part manual data are valid until a next version of the manual is issued. Therefore the shelf life should be assumed to be infinite.

6. *Timeliness function*: Since the shelf life of part manual data is infinite, a linear timeliness function would be appropriate to indicate that timeliness of part manual data does not decrease.

PB1, Job log recording

1. *Cost*: The cost of recording part failure information on a log card refers to the labour costs involved in this process. This is regarded to be approximately £10 per failed part.

2. *Time*: The expected time required for this operation is small compared to the overall timescale. We will denote this by 0.01 days.

3. Quality function: Given that the filling of the log card takes as input both DU1 and DU2, the data component of the output data quality will result from the weighted average of DQ(DU1) and DQ(DU2). Given that the quality of the actual failure data (DU1) is much more important than the quality of part manual data quality, we take the weight for DU1 to be w_1=4 and the weight for DU2 w_2=1. The processing effectiveness of this operation refers to the effectiveness of the manual information recording. The analysis showed that in 10% of the cases the manual recording introduced errors that made the information useless. Therefore, the processing effectiveness will be 0.9.

4. Delay: Log cards are filled with failure information on average 1–2 days after the part has been inspected.

5. Timeliness function: The output timeliness could be calculated as a weighted average of the input timeliness, using the same weights as in the case of output data quality.

SB1, Log card

1. Cost: The cost of storing data on the log card is estimated at £3, which includes the time to retrieve the data and paper storage cost.

2. Time: This is the time to retrieve a log card from the file, which is relatively short, 0.005 days.

3. Delay: Assuming that all log cards are available at any time, there is no delay for retrieving log card information.

QB1, Visual inspection

1. Cost: The cost of visual inspection is regarded to be £3, including the time to inspect and correcting and data errors.

2. Time: The time for the inspection to take place is relatively short, 0.005 days.

3. Quality function: We assume that the quality inspection captures and corrects 80% of the quality problems. Therefore the quality function should be DQ(DU5)=(1-(1-DQ(DU4))0.2).

4. Delay: The data quality control might be delayed for 5–10 days on average before data are entered into the information system.

PB2, Data entry

1. Cost: The cost of entering data into the information system refers to the labour costs involved in this process. This is regarded to be approximately £10 per failed part.

2. Time: The expected time required for this operation is small compared to the overall timescale. We will denote this by 0.01 days.

3. Quality function: Given that this process takes only one data unit as input, the output data quality will depend on the input data quality, and mainly on the processing effectiveness of the operation. The analysis showed that the manual data entry introduced errors that made data meaningless in 7% of the cases. Therefore the processing effectiveness of PB2 is 0.93.

4. Delay: Data are typed into the information system typically 1–2 days after the log card has passed quality control.

SB2, Information system

1. Cost: The cost of storing data in the information system refers to system maintenance and administration. This is approximately £0.5 per failed part.

2. Time: The time to retrieve data from the information system is regarded negligible.

3. Delay: Assuming full availability of the system, there is no delay for obtaining maintenance information.

	Cost	Quality	Time (days)	Timeliness function	Delay (days)
VB1	£15	0.9	Input Time=0 Age=1.5 Shelf Life=30	max(1-currency/30,0)$^{1/3}$	-
VB2	£2	1	Input time=0 Age=3000 Shelf Life=infinite	1	-
PB1	£10	0.9([4DQ(DU1)+ DQ(DU2)]/5)	0.01	4DT(DU1)+ DT(DU2)]/5	1.5
SB1	£3	-	0.005	-	0
QB1	£3	1-(1-DQ(DU4))0.2	0.005	-	7.5
PB2	£10	0.93(DQ(DU5)	0.01	DT(DU5)	1.5
SB2	£0.5	-	0	-	0

Table 4.8: Data block processing parameters for example 4.2

Table 4.8 summarizes all processing parameters for the blocks in Figure 4.2. These will be used to calculate the final quality, timeliness and cost of the information that reaches the repair agent.

1.4 Final product quality, timeliness and cost calculation: In this step we calculate the quality, timeliness and cost of the final product.

Data quality: Applying the data collected from the previous step, we find that the respective data quality levels for data units along the process depicted in Figure 4.2 are DQ(DU3)= DQ(DU4)=0.828, DQ(DU5)=0.965 and DQ(DU6)= DQ(DU7)=0.898.

Timeliness: In order to calculate the timeliness, we first need to calculate the currency of the data when these reach the final data consumer. The overall aggregated delay of data in the system is 10.5 days. According to (12) the currency of failure information will be 12 days. Similarly the currency of the part manual data will be 3010.5 days. Given the currency, shelf life and timeliness function of the two primitive data units we can calculate their timeliness:

$DT(DU1)=\max(1-12/30,0)^{1/3}=0.85$ and $DT(DU2)=1$

The final timeliness of the data provided to the repair agent will be:

$DT(DU7)=0.88$

(after applying the weighted average of PB2, since it is the only operation that affects the timeliness of data until the end of the process)

Cost: The overall cost for managing part failure information and delivering it to the final decision maker is £43.5.

Phase 2: Value of information

2.1 Decisions based on tracing data: The part failure information is needed to support maintenance decision making at the repair shop. When a failed part is received, the options are either to overhaul it or to repair it selectively according to the failure description. These two options incur different costs and result in different decision utilities depending on the state of the part.

2.2 Value of perfect information calculation: In the previous step we identified that the two decision options are to repair or overhaul the part. The possible states of the part are 'needs overhaul' or 'needs specific repair'. The repair agent might take any decision for any part resulting in different costs and decision utilities for the repair agent. An analysis similar to that in Appendix A can reveal the intrinsic value of perfect information for the decision maker. Let us assume that in our case it is V_I=£100.

2.3 Impact of timeliness and quality on value of information: We decided to use formula (21) to represent the value of information as a function of data quality and timeliness. The analysis of the decision process revealed that quality of information was approximately four times more important than timeliness, therefore we picked w=0.2. Moreover, the analysis showed that small data quality problems significantly decrease the value of information. As a consequence, we should pick a quality exponent b greater than one. It was estimated that an error probability of 10% reduced the value of information by half, while an error probability of 50% made the data useless. In order to reflect this relation we set b=7. The impact of timeliness in value of information was analyzed in step 1.3 and was modelled in the timeliness function of the primitive data units. As a consequence, at this point we will use a linear function to relate timeliness to value of information.

According to the above, the actual value of information is given by the formula:

$$V_A=V_I\,(0.2\,T+0.8\,DQ^{\,7}) \qquad (25)$$

Phase 3: Actual value of information

3.1 Actual value of information calculation: Using the data we have calculated in the previous two phases and using (25) we can calculate the final actual value of the information that the current lifecycle tracing system generates. This will be:

$\boldsymbol{V_A=V_I\,(0.2\,T+0.8\,DQ^{\,7})}$ **= £100(0.2*0.88+0.8*0.898^7) = £100(0.176+0.376) = £35.2**

If we compare the actual value of information that the system produces with the cost incurred for producing it, we conclude that **the company loses £35.2- £43.5=- £8.3** for every failed part that failure information is recorded and communicated to the repair agent (this is also called net value of information). In order to make the above process beneficial for the company and make the overall revenue positive, there should be a significant improvement in the quality of the information that finally reaches the decision maker, as this is the factor that radically decreases the actual value of information. Indeed, if the quality of the final information product is increased from 0.898 to 0.95, the actual value of information will become £73.4 and the net value of information will be £29.9, thus making the process beneficial for the company. The improvement in the quality of the final information product can be achieved, for example, by reducing the data errors introduced in the job log recording process (PB1) and the data entry process (PB2). Automatic identification technologies, such as RFID, can be used to automate these processes by storing and communicating data in electronic form.

5. Conclusion and Future Work

In this report we have proposed a way to measure tracking and tracing performance in a company. We have defined the individual metrics that should be used for this purpose as well as the overall measures that reflect the general tracking or tracing performance. We have proposed a way to model supply chain tracking and we have showed that a company's tracking performance can be measured using a normalized and comparable measure of the tracking information content that the system communicates to the end user. Likewise, we have proposed a way to measure the attributes that affect the value of traceability information. We have suggested a way to model a tracing system, which enables studying how the system operations affect the usefulness of the final information product and its value for the decision maker. For both tracking and tracing performance measurement we have proposed a detailed step-by-step approach, describing what the data that should be collected are, how they should be collected, how to calculate the performance metrics and how to interpret them. Finally, we have described two illustrative examples in which we apply the suggested method to measure tracking and tracing performance.

Our work so far has a number of open issues and limitations that need to be addressed. As we have mentioned during our discussion on tracking performance measurement, we should further study the importance of the business decisions that are based on tracking information. The importance of these decisions should be incorporated into our model in order to take them into account when measuring tracking performance. Once the decisions are included into the performance measurement, the measurement output will reflect the real business needs in a more accurate manner.

The next step of this research will be to build on top of the proposed tracking and tracing performance measurement method in order to deliver a method for quantifying the benefits of automatic identification technologies deployment for improving tracking and tracing. This will require understanding and modelling the decisions and operations that are affected by tracking and tracing information in order to quantify the potential benefits. This will provide a firm basis for a generic ROI calculation tool that could be used for assessing investments in tracking and tracing infrastructure.

6. Appendix A: Value of Perfect Information

The aim of this appendix is to briefly describe a way of quantifying the value of perfect information for a decision maker. We use as an example the case of deciding whether a failed item should be sent to its original supplier for repair or should be sent to a repair agent based on whether it is under supplier warranty or not.

Let W be the variable representing that an item is under supplier warranty. Also, let M be the variable representing whether the product is repaired/replaced using supplier's warranty or (M') it is sent for repair/replacement at a repair agent at the decision maker's cost. Let us also assume that usually 1/3 of products that fail are under supplier warranty, therefore the prior probability of an item being under warranty is P(W)=0.33.

Decision / Warranty status	Repair or replace with supplier who provides warranty (M)	Repair or replace with new at own cost (M')
Item under warranty (W)	–£50	–£1500
Item is not under warranty (W')	–£1000	–£750

Table A.1: Utilities for different warranty states and repair decisions

The decision that needs to be made is whether a failed product should be sent for repair/replacement to the supplier and the cost claimed under the warranty or should it be repaired/replaced with a new one at the decision maker's cost (usually at a repair agent). The utility of each of the two decision options is different depending on whether the product is under warranty or not. Table A.1 gives the utilities for the four combinations expressed in the costs that the decision maker will have to pay in each case. We briefly explain the utilities:

- U(W,M)= –£50 : It is the cost of sending the product to the supplier to repair/replace it (shipment, management, etc). There is no cost for the repair/replacement itself since the item is under warranty.
- U(W',M)= –£1000 : It is the cost of sending the product to the supplier to repair/replace it when is it is not under warranty. The repair/replacement incurs a cost. We assume this cost is higher than repairing/replacing the product at own cost (£750) because the decision maker might be able to achieve a better agreement repair agents other than the original supplier.
- U(W,M')= –£1500 : It is the cost of sending the product for repair/replacement at the decision maker's own cost, while the product is under warranty. This includes the cost of shipment, cost of repair and the cost of lost opportunity since the product is under warranty which has been obviously paid for.

- U(W',M')= –£750 : It is the cost of sending and repairing the product while it is not under warranty.

For a failed product, there is a probability p* of being under warranty such that it is indifferent to send it to its original supplier for repair or repair at own cost [4]. That is,

p*U(W,M)+(1–p*)U(W',M) = p*U(W,M')+(1–p*)U(W',M')

or $$p^* = \frac{C}{C+B} \tag{1}$$

where, C = cost of decision = U(W',M') – U(W',M)

and, B = benefit of decision = U(W,M) – U(W,M')

In our case this is p*=0.147

Since the prior probability of an item being under warranty P(W)=0.33 is higher than p*, if the decision maker has no evidence of whether a product is under warranty, he will treat the item as being under warranty and send it to supplier for repair/replacement. Therefore the expected utility of having no evidence will be:

EU(Ø) = P(W) U(W,M) + (1–P(W)) U(W',M) = 0.33 * (–£50) + 0.66 * (–£1000) = –£676.5 (2)

Now we want to explore the value of making a query (Q) to ask whether the product is under warranty. This query will be based on information provided by the tracking solution and the auto-id technologies deployed along the supply chain. Let the accuracy of this information be 95%. That is, in 95% of the cases that the system indicates a product is under warranty, it actually is. The expected utility of gathering this information Q will be:

EU(Q) = p(W) EU(Q|W) + (1–p(W)) EU(Q|W') (3)

But the expected utility of making the query when the item is actually under warranty (which is not known in advance) is:

EU(Q|W) = 0.95 U(W,M) + 0.05 U(W,M') = –£122.5

And the expected utility of making the query when the item is NOT under warranty (which is not known in advance) is:

EU(Q|W') = 0.05 U(W',M) + 0.95 U(W',M') = –£762.5

Therefore from (3) we have that the expected utility of making the query is:

EU(Q) = p(W) EU(Q|W) + (1–p(W)) EU(Q|W') = 0.33 (–£122.5) + 0.66 (–£762.5) = – £543.67

The value of warranty information will be the difference between the utility of the decision with no evidence and the utility of the decision after the warranty query:

Value of information = EU(Q) – EU(Ø) = –£543.67 – (–£676.5) = £132.82(4)

This is the value of warranty information for a single decision instance for one failed product.

7. References

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