Detailed Cost Modelling: A Case Study in Warehouse Logistics

Article *in* International Journal of Physical Distribution & Logistics Management · April 2007

DOI: 10.1108/09600030710742416

Detailed cost modelling: a case study in warehouse logistics

Mikko Varila
Institute of Industrial Management, Cost Management Center, Tampere University of Technology, Tampere, Finland
Marko Seppänen
Institute of Industrial Management, Center for Innovation and Technology Research, Tampere University of Technology, Tampere, Finland, and
Petri Suomala
Institute of Industrial Management, Cost Management Center, Tampere University of Technology, Tampere, Finland

Abstract

Purpose – The purpose of this paper is to examine the applicability of different drivers for assigning activity costs to products in warehouse logistics environment.

Design/methodology/approach – An action research case study in the warehouse logistics of an electronics wholesaler. Data were collected from a single activity which was analysed in depth.

Findings – The study illustrates that there may be significant variation in activity costs that cannot be traced with any single transaction-based driver. Automatic data collection methods can be used to support cost accounting in such a situation. It was clearly demonstrated that in certain environments it is possible to significantly increase the accuracy and versatility of accounting by measuring the actual durations together with other variables.

Research limitations/implications – The results are derived from a single company and activity.

Practical implications – Gives accountants in environments where data is rich and plentiful examples of methods for analysing the data for obtaining a deeper understanding of the cost behaviour of activities and products.

Originality/value – Complements the discussion on activity cost drivers and logistics costing.

Keywords Cost accounting, Warehousing, Distribution management, Automation, Data collection, Regression analysis

Paper type Case study

Increasing the visibility of logistics costs

Cost accounting is a discipline that assists decision making, planning and control by determining the cost of the processing of a cost object (e.g. product, service, customer or project). This is done as accurately as possible within given time and cost frames. Logistics is an example of an environment in which the cost efficiency of processes is a necessity, thus making the accuracy of cost accounting especially important. In a recent logistics survey, as many as 71 per cent of those responding ranked "cost control/cost reduction" as their top concern (Cooke, 2002). The firms seem to have an understanding of how to accomplish this goal, since the need to utilise and optimise information technology was cited by 40 per cent of the respondents. Despite the potential benefits of advanced

International Journal of Physical Distribution & Logistics Management
Vol. 37 No. 3, 2007
pp. 184-200

0960-0035
DOI 10.1108/09600030710742416

technology, cost accounting systems in companies often lag behind (Lahikainen *et al.*, 2000; Sievänen *et al.*, 2004).

Proper cost control requires sufficiently accurate monitoring of logistics processes. Reaching this level of accuracy will largely depend on the ability of the firm's cost accounting system to trace costs to cost objects (Pohlen and La Londe, 1994). Traditional accounting methods are based on assumptions of a stable and predictable market, long product life-cycles, large production runs, and a large portion of direct variable costs in total product costs. This is rarely the case in today's logistics environment. Especially, wholesalers/retailers have the need for an instrument capable of linking logistics process information to financial information (van Damme and van der Zon, 1999). In general, increased visibility of costs is required in logistics (Kemppainen and Vepsäläinen, 2003). This would provide information necessary to assist in making pricing decisions, to identify potential targets for cost reductions, to assess new technology investments and to focus on the general management of all assets. Enterprise solutions that simply manage transactions are not sufficient and thus more versatile data are needed (Graham, 2003).

Increased accuracy does not often come for free. The extensive data collection that would be required is rarely conducted due to the fear of increased costs (Kaplan, 1992). At the same time, today's information technology provides a variety of means for replacing manual data collection with automatic applications. Advanced identification methods, e.g. bar codes and RFID, have been important landmarks in a relationship for recording even the smallest phases of the processes. They have been used for manifold purposes in managing operations in warehouse environments (Yao and Carlson, 1999). Concurrently, they pose a challenge to cost accounting. As the data become available and the costs of acquiring data decrease, a more accurate cost accounting becomes possible. In addition, automatic data collection (ADC) produces plentiful information for analysing activities. Thus, increased visibility helps in assigning costs to activities and improving the cost efficiency of activities.

This study forms part of a development project to produce an accounting system for an electronics wholesaler. One characteristic of this industry is that the gross margin is extremely low, which makes cost effectiveness one of the cornerstones of the business. Owing to the demand for cost effectiveness, the logistics process must be smooth, and no mistakes can be tolerated. The number of different items ranges in the tens of thousands, with very short product life cycles varying typically from a few months to one year. Because of the large and continually changing product assortment, it has not been possible to control costs intuitively. In order to increase the visibility, more data must be collected and it must be analysed with more effective methods. During the project, a sophisticated cost accounting system was designed which utilises automatically collected, accurate, rich data. The data produced by this cost accounting system are used to find new perspectives in the behaviour of logistics activities and, especially, in assigning activity costs to products.

The research method used was action research, which is a common method for identifying and tackling often unstructured real-world problems. Action research involves spending significant amount of time within the organization and participating in its problem solving in a role of an "interventionist" (Westbrook, 1995; Coughlan and Coghlan, 2002). Therefore, it often offers access to fruitful and in-depth data and advances both science and practice. There have recently been hopeful expectations to see this method in logistics environment (Näslund, 2002). Action research approach was reasoned in this case, because the level of cost awareness in the company was initially not at a satisfactory level. That is why interventionist role of the researchers was needed in finding ways to improve the company's cost accounting practices.

There are many sources of variation that can affect the cost of performing activities. Examples of these are machinery, labour, environment, methods and products. This study concentrates on variation that is product-related. The research problem is to determine how the consumption of an activity is affected by different products and product-related variations in the working methods. The main objective of this paper is to examine the applicability of different drivers for assigning activities to products. Particularly, alternative, transaction-based drivers are compared with duration-based drivers. Large amounts of automatically collected data is analysed in order to understand the effects of product-related variation on activity costs. This study shows how an activity can be broken down into subtasks and analysed in the light of related variables. The effects of enhanced data on the accuracy of accounting and the applicability of costing methods in practice are considered.

Theoretical background

Assignments of logistics activities

Cost accounting aims at assigning costs to cost objects as accurately as is economically reasonable. Activity-based costing (ABC) has been utilised for almost two decades to achieve better accuracy. In ABC, many drivers are typically utilised to reach as fair assignments of costs as possible. ABC aims especially at improving the assignments of overhead costs, which are often allocated on the basis of direct costs or direct labour hours (Johnson and Kaplan, 1987; Cooper, 1988, 1989). Sometimes, however, even the treatment of direct costs may prove to be problematic. For example, logistics often uses simple transaction data and averaging for allocating direct costs. This may be especially disadvantageous in those circumstances when products do not consume resources equally.

The key innovation of ABC systems are activity cost drivers, which are quantitative measures of the outputs of activities. Three factors should be considered in selecting suitable drivers:

(1) their effect on behaviour;

(2) reliability of measurement; and

(3) the costs of measurement (Geiger, 1999).

Driver information may be utilised to reduce costs, thus guiding interest to the right targets. At its best, a good driver provides the motivation to reduce costs; however, in the worst case, it can direct employees toward undesired behaviour. Nevertheless, Johnson *et al.* (1991) point out that decision-makers should not only look at the driver information, but should also search for other ways to improve processes. Increasing the number of drivers can in most cases lead to more accurate results. On the other hand, at the same time, the costs of acquiring driver information grow, especially if the information is acquired and entered manually. Thus, the selection of drivers reflects a subjective trade-off between accuracy and the cost of measurement. According to Gunasekaran *et al.* (1999), the level of desired accuracy should be based on a company's strategic objectives. Many companies underestimate the laboriousness of acquiring information required for an ABC system. Defining activity cost drivers is in many cases the most expensive and difficult part of the whole ABC project (Kaplan and Atkinson, 1998; Lahikainen and Paranko, 2001).

Kaplan and Atkinson (1998) have classified activity drivers into three classes: transaction, duration and intensity drivers. The aim is to select an appropriate driver which reflects as closely as possible the real consumption of resources. Warehousing activities incur a remarkable part of the costs in a logistics process. On a general level, these activities are:

- receiving;
- put-away;
- storage;
- order picking;
- packing, marking and staging; and
- shipping (Roth and Sims, 1991).

Depending on the accounting context, it is possible to use a finer or coarser classification. In logistics activities, a transaction driver (e.g. the number of products or rows handled) is typically used (Fernie *et al.*, 2001). Although transaction drivers are the least expensive type of cost drivers, they could be the least valid, as they assume that the same quantity of resources is required each time an activity is performed (Kaplan and Atkinson, 1998). In real life, such is very seldom the case. Cooper (1989) warns that in environments where different products consume very unequal amounts of activities, activity cost drivers should be selected very carefully. A driver which treats all products equally may dramatically undermine the accuracy of accounting. Similarly, Noreen (1991) and Christensen and Demski (1995) have argued that averaging should be strictly limited to cases where the relationship between the driver and the resource consumption is actually linear.

If products consume different amounts of resources, using weight indexes is a simple way to increase the accuracy of the cost assignment phase (Kaplan and Atkinson, 1998; Lahikainen and Paranko, 2001). In this approach, an individual activity is divided into different levels and weighted using weight factors that indicate the time required by each of the levels. This approach simulates an intensity driver when the actual data is unavailable. In a logistics environment, where the number of different items and alternative ways to handle different products is large, even weight indexes may oversimplify the situation. Moreover, updating the weight indexes for thousands of items would be an overly laborious task. Themido *et al.* (2000) suggest using simple statistical techniques in order to correlate output with alternative activity drivers. This offers features of a surrogate driver, which means a driver that is not descriptive of an activity, though closely correlated and easy to measure (Raffish and Turney, 1991).

If resource consumption is directly proportional to time, it might be more convenient to use duration drivers instead of transaction ones. Kaplan and Anderson (2004) have recently advocated time-driven ABC, in which the actual time for performing an activity is estimated instead of using percentage of total time spent on it. Time-driven ABC is partly an effort to overcome the labour and costs often associated with implementing and maintaining ABC systems. The capacity of most resources is measured in terms of time availability, which helps in distinguishing between used and unused capacity. Time-driven ABC also makes it possible to use time equations, which help in differentiating between the complexity of different products. Information for time equations can be easily available from the company's ERP system, which makes updating also easier. Despite the obvious benefits of duration-based drivers in many environments, transaction-based drivers are still more commonly used. The problem has been that the measurement of durations has been too laborious or even impossible. Therefore, when seeking to optimise accuracy and costs of measurement, a coarse driver has been selected.

Towards more accurate accounting

The laborious nature of data collection and analysis may diminish the usefulness of cost management. In this section, we present different approaches which may ease operational cost management, especially in a logistics environment.

Determining the cost of performing a certain activity is very close to the objectives of traditional work measurement. Work measurement is used in many industries to eliminate inefficiency, to reduce operational costs, and to increase productivity. It also offers a means for finding objective reasoning to determine the cost of a single work stage. Work measurement involves many techniques, including time-studies and engineered approaches that typically split tasks into very small parts, which are examined in detail (Michaels, 1989). The drawbacks of these techniques are that they can be time-consuming and costly (Failing *et al.*, 1988). For example, Lee and Lye (2003) have examined packaging activity and determined standard times by recording stopwatch readings. They even calculated the standard times for performing a variety of subtasks for a limited number of different products on the basis of their difficulty. Particularly, for those environments in which the number of items is large and the consumption of resources can vary for different items, work measurement of this kind may become impossible. Furthermore, the standards may quickly become obsolete because of the ever-changing set of product mixes. Gray (1992) has proposed an alternative to a proper time-study which includes recognising the related variables at different stages and using these key variables to examine the total time of a task. However, even this data may be overly time-consuming to collect manually.

In today's logistics, it is common to utilise a variety of technologies for collecting data (Faber *et al.*, 2002; Kemppainen and Vepsäläinen, 2003). ADC is a common term used for methods which help in collecting information from processes with minimum manual efforts. Today's information systems ease the collection of information. Bar codes and RFID technology enable products in the material flow to be individually recognised (Smith and Offodile, 2002). In addition, ADC enables large-scale information collection without human errors. The benefits of ADC include improved data accuracy, more rapid availability, better managerial decisions, improved job performance and improved response rate to changes in production schedules (Christoph *et al.*, 1991). Rossetti and Clark (2003) offered an example of how to utilise automatically collected time data to aid scheduling and capacity planning by collecting time stamps from machine centre arrival and departure events. They also used regression analysis in estimating cycle-times on the basis of product and batch characteristics. ADC can similarly be utilised in assisting cost accounting.

ADC allows real-time process information to be linked to cost information, resulting in automatic, easy cost accounting. However, there often exists a desire to know logistics costs in advance, to determine objective cost standards or to examine the effects of different variables on costs. For instance, this real-time information is not sufficient for the needs of pricing. Determining standards could be problematic if the product is new and there is no experience of its behaviour. In such cases, the time must be estimated on the basis of parameters. This is where statistical analyses, e.g. multiple regression analysis, can offer a solution. Multiple regression analysis can be used to examine how independent variables affect a dependent variable. Regression analysis provides estimates for the coefficient vector, thus minimising the forecasting error of the model. The coefficient vector is then used to estimate new values for the dependent variable. Rather than breaking tasks into smaller elements, regression analysis utilises variables to create a predictive model of total time. This implies that the work needed for measurement is reduced, as are the costs of measurement.

Other methods for cost estimation have also been introduced. For example, neural networks as extremely flexible tools often produce better estimates. Their disadvantage, however, is that the model is completely a "black box" which gives decision makers no chance to argue logically about whether the result is reasonable (Smith and Mason, 1997). For this reason, regression analysis seems to be more convenient when promoting comprehension. Although many studies have examined the use of regression analysis in cost estimation (Smith and Mason, 1997), no previous research has explored the use of cost estimation modelling in connection with operational cost accounting systems.

Case study

Producing data with an automatic time-based costing system

In the case company, a project was initiated with the aim of building an accounting system to monitor costs at the level of individual product ID codes. This was made possible using the company's advanced information system, which is able to track the material flow accurately.

Data can be recorded in the log file in connection with many tasks: scanning a bar code, pressing a button or clicking a mouse with a computer and starting or ending a transfer through the automation system. An essential piece of information which can be attained is the time of the event. These time data were utilised by the accounting system for assigning activities to products.

The logistics process was divided into 30 activities. For defining an activity, it was important that each activity was bounded by transaction points for gathering information. The total cost per time period for each activity was calculated using activity-based costing. Since, the idea of the system was to utilise time as a cost driver, a practical capacity in seconds was defined for each activity. For example, in an activity where labour is a bottle-neck resource, the activity's capacity was set to the available labour (in seconds) for a time period. On the basis of this information, the cost per second was calculated for each activity.

From the information system's point of view, an activity refers to everything that is done between two transaction points. Each time an item passes an activity, an event row is recorded in the information system. An event row can include the starting and ending time of an event, thus enabling its duration to be calculated. Each consecutive pair of transaction points represents an activity that has a cost per second. An event is also linked with information on the product ID codes and the number of items being handled. A product ID code thus provides access to other product information, such as weight, volume and product group. The basic idea of the system is shown in Figure 1.

Picking was chosen as a case activity for further research. It is performed at five picking stations in two shifts. Picking starts after products are automatically transferred to picking stations by a conveyor in plastic boxes. The number of items indicated by the information system is picked, receipted into the system, padded if needed and packed into customer boxes. Picking was chosen, because it includes a relatively large amount of manual work and is for that reason a potential source of variation in a very automatic environment. Furthermore, it is one of the most expensive activities, thus making it a natural focus of interest in the case company.

Monitoring the causes and effects of variation in an activity can be done at the level of subtasks. Even a simple activity like picking can be divided into several subtasks, in which case-specific variation takes place. Each subtask depends on how or whether the task is done and the amount being handled. The products can be receipted in various ways. At its simplest, all the products are receipted by either scanning one common EAN code or pressing a button and feeding the amount into the system. Alternatively, a unique serial number may have to be scanned from the side of each item. Different products also have different requirements for packing: some must be carefully padded and wrapped, while others do not need such actions at all. Moving products can be more or less difficult, intuitively based on the weight, volume and shape of the items. Finally, an employee may receive a note on his/her screen for additional handling. This may mean, for example, that the products must be supplied with additional parts or handled with extra features.

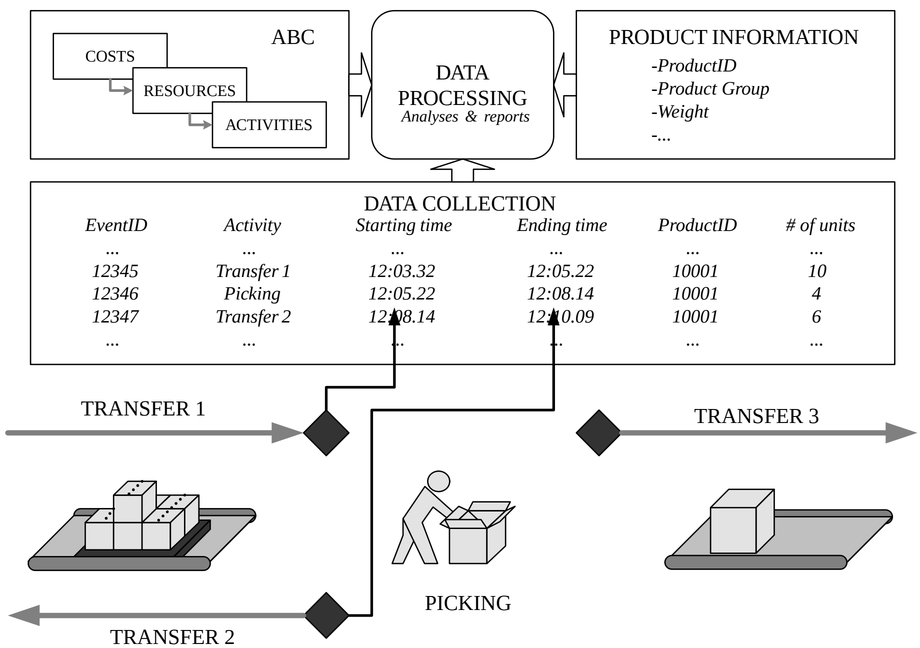

Figure 1.
The basic idea of collecting data automatically to support cost accounting

Following the duration of each subtask would be technically demanding and costly, and would unacceptably complicate the actual work. Instead of measuring the times bottom-up, we take a top-down approach. In other words, we can examine the subtasks by measuring the total duration required to perform the activity, as well as a set of variables, and thus use this information to try to explain the duration of the task. Every variation in an activity is recorded in the data as a different combination of variables, depending on the characteristics of the products that are handled. Overall, the variables in Table I were included in the data, each representing a part of the information content of a subtask.

Why is not a transaction driver enough?

Data consisting of the above mentioned variables were collected from the picking activity. The number of events totalled 1,449, where one event denotes picking items from one plastic box into one or several customer boxes. Since, one plastic box can contain only one type of product, each item handled in an event is similar and is also handled similarly. Naturally, each event was also linked with its duration, which was calculated from the difference between the starting and ending times. A starting transaction of a picking event occurs when the plastic box arrives at the picking station, and an ending transaction occurs when the plastic box leaves. It is supposed that the time between the transactions consists mainly of effective work. The distribution of event durations proved to be far from the normal distribution, being emphasised by short time events (Figure 2). The average picking time was approximately 45 seconds, with the minimum being 6 and the maximum 645 seconds. Standard deviation was high (58 seconds) in proportion to the average duration, thus explaining significant variation.

An example of a logical driver for this kind of an activity could be the number of units being picked. Figure 2 (right) reveals that this is not the case: the correlation between time and number of units is poor ($R^2 \approx 11$ per cent) and there seems to be a weak connection between the two. What is notable in this data is the large number of events containing only a few units, but yet resulting in quite a long duration. Despite the intuitive assumption that the picking time is dependent on the number of units

Variable name	Description	Possible values
Number of units	Number of units being picked	N (1, 2, 3, ...)
Total weight	Total weight of products being picked	R^+ (positive integer)
Total volume	Total volume of products being picked	R^+ (positive integer)
Additional handling?	Indicates whether additional handling is required	Yes, no
Receipt method	Indicates the way the products are receipted	Button (= receipted by pressing a button), EAN (= receipted by scanning one common EAN code), SN (= receipted by scanning each serial number)
Number of receipts	Number of receipts made during picking	N (1, 2, 3, ...)
Product group	The product group determined in the information system	Product group 1, ... product group 10

Table I.
The variables included in the data

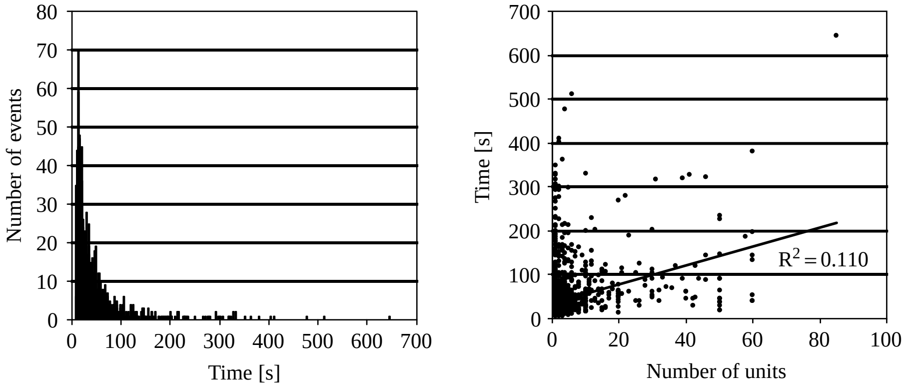

Figure 2.
The frequency of event duration and its distribution (left). The picking time as a function of number of units (right)

being handled, it does not explain much of the variance. Therefore, it is clear that number of units does not predict picking time very well and, thus, the activity must be further explored.

The key to understanding the behaviour of the activity is the interaction between different variables. Therefore, the number of units must be examined with other variables that determine whether a certain subtask is done or how it is done. An independent variable can have not only a so-called main effect on the dependent variable itself, but also interaction effects with other independent variables. An interaction effect means that the impact of one independent variable on the dependent variable is influenced by the level of another independent variable (Aiken and West, 1991, pp. 1-8, 116-38). An interaction between a categorical and continuous variable can be described by plotting a regression line for each category. If the lines are parallel, categorical variables have only a main effect on the dependent variable. If the slope of lines is different, an interaction effect is indicated.

The first categorical variable, receipt method, explains how the products are receipted into the information system. The selection of the method is completely product-dependent and is performed similarly for all the products of the same type. Pressing a button or scanning one EAN bar code are non-recurring tasks, with the number of units having no significant effect on the duration of the receipting task. Scanning a serial number from each item, however, must be repeated for each item. It can be seen in Figure 3 that the effect of number of units on duration is strongly dependent on the receipting method. The second variable examined relates to additional handling. The larger the number of units is, the greater the increase that the additional handling will have on the duration of the activity. This means that additional handling also has an interaction effect with the number of units on picking time.

Probably the most interesting findings were made between different product groups. A product group approximates the need of padding and the difficulty of moving and generally handling the items. Figure 4 shows that there are differences in both the setup times between different product groups, as well as in the times per unit. With respect to the activity cost driver hierarchy, these results reveal that an activity can be a unit-level or a batch-level one, depending on the type of product being handled. Compared to the other categorical variables under examination, the differences between product groups are the largest. This implies that the product

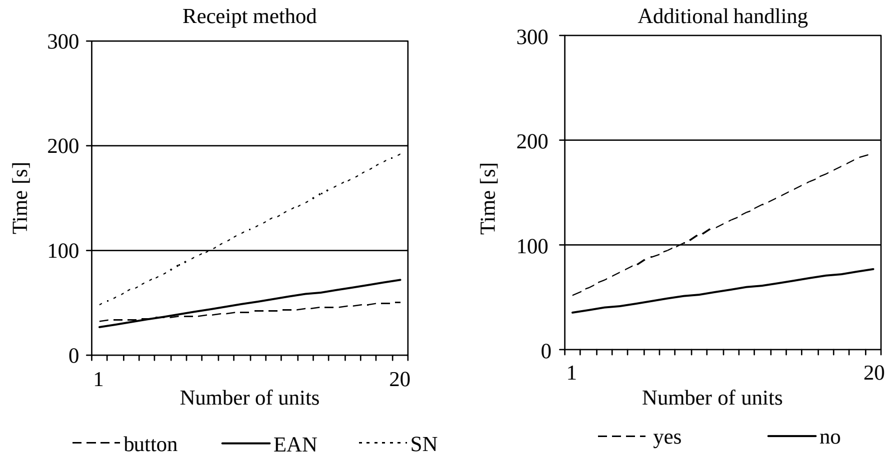

Figure 3.
The effects of the receipt method (left) and additional handling (right) on picking time as a function of the number of units

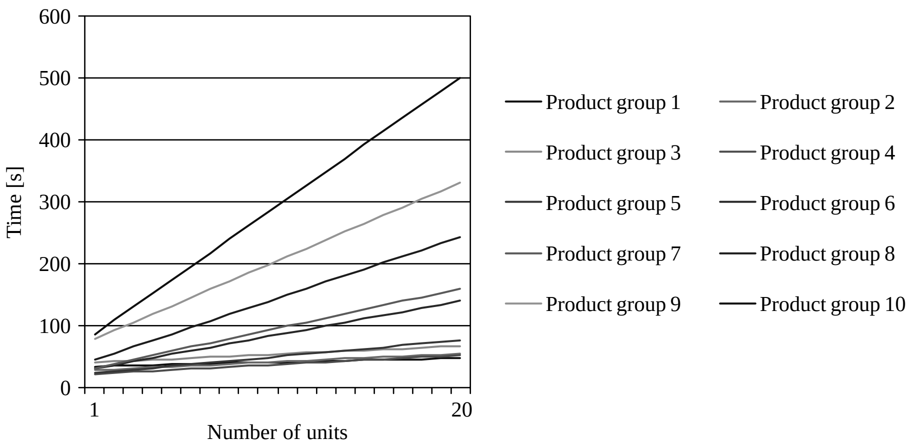

Figure 4.
The effects of the product groups on the picking time as a function of the number of units

group-related subtasks, such as padding, have a significant role in determining the activity's duration.

Based on the aforementioned figures, it is reasonable to assume that there are interactions between the variables which make even a simple activity like picking more complicated than expected. Variation is caused by both the different types of products and different types of methods used. A preliminary observation is that there seems to be no single variable that could sufficiently explain the variability in activity duration. Instead, multiple variables are needed.

Comparing transaction drivers with duration drivers

Regression analysis was used in further analyses for two purposes. First, regression analysis makes it possible to compare alternative drivers with duration and to examine their accuracy. Second, multiple regression enables multiple variables to be combined in creating a model for estimating duration based on transaction data. Creating such a model may be necessary due to an inability to measure the duration when performing an activity on a certain batch of products or, for example, when the product is new. For this reason, it is essential that easily available transaction data be used for estimations.

In addition to each separate variable, a forecasting model was built, which takes into account the interactions between the variables. Although seven original variables were collected from the case activity, additional variables were added due to the categorical nature of some variables and the interactions. The most frequently used procedure for representing categorical variables in regression is dummy variable coding (Aiken and West, 1991, pp. 116-27). For a categorical variable containing k options, $k - 1$ dummy variables are created. A dummy representing category A is given the value 1 if A exists and 0 otherwise. In order to avoid singularity of the data matrix, one category must stand as a reference for others and have no dummy variable at all. In case of interaction between a categorical and a quantitative variable, an additional term must also be added for interaction. Only the interactions of two variables were included. The final number of variables was 28 altogether and they are presented in Table II.

The results of the regression analyses for all the models are summarised in Table III. It can be seen that no single variable model produces sufficient estimations. The number of receipts, total weight and number of units are the best estimates, but

Description	Variables	Number of variables
Main effects of numerical variables	[# of units], [total weight], [total volume], [# of receipts]	4
Dummy variable for additional handling	[Additional handling]	1
Interaction effect between additional handling and number of units	[Additional handling]*[# of units]	1
Dummy variables for receipt methods	[Receipt method i]	2
Interaction effects between receipt methods and number of receipts	[Receipt method i]*[# of receipts]	2
Dummy variables for product groups	[Product group j]	9
Interaction effects between product groups and number of units	[Product group j]*[# of units]	9
		28

Table II.
The variables included in the model with all variables

Model		R	R^2	Adjusted R^2	Standard error
All variables		0.707	0.500	0.490	29.841
Single variable models	Number of receipts	0.416	0.173	0.172	52.569
	Total weight	0.401	0.161	0.160	52.954
	Number of units	0.332	0.110	0.110	54.521
	Product group	0.299	0.089	0.084	55.310
	Total volume	0.182	0.033	0.033	56.831
	Receipt method	0.134	0.018	0.017	57.300
	Additional handling?	0.083	0.007	0.006	57.599

Table III.
Summary of the models – single variables vs the model with all variables

even for these the explanatory powers remain almost meaningless. On this basis, it is justifiable to criticise the use of a single variable as a cost driver for an activity of this type.

What is interesting is that even though the model with all variables produces remarkably better estimates than do single-variable models, the explanatory power (R^2) of the model remains at 50 per cent. In this case, the result was expected, as the study concentrated only on the variation caused by different product characteristics and the methods dependent on them. In other words, this is the variance that can with good reason be assigned to products as costs that vary from one product to another. In addition, the variance caused by other factors – for example, labour and environment – is significant in such a short-time activity. According to preliminary estimations, the differences in labour productivity may well explain the remaining 50 per cent of the variation. Although the other sources of variation are worth examining for process improvement purposes, this variation cannot be traced to different products.

Another explanation for poor estimates could result from errors in the data. Even though the data were quite accurately collected, an event may be interrupted for many reasons. In the case of the picking activity, possible sources of interruptions may have included the malfunctioning of automation and information systems and short breaks taken by labourers. Because of the typically short duration of the case activity, interruptions may cause severe distortion in the data. These diverging observations, often called outliers, may seriously weaken the explanatory power of the model based on historical data. Detecting and filtering outliers from regression data has been a widely researched topic (Srivastava and von Rosen, 1998). For example, residual analysis and robust regression have been suggested as possible solutions to this problem.

The coefficients for the model incorporating all the variables are presented in Appendix. The model yielded some coefficients that did not only seem to be uninformative, but some of these were not even statistically significant. Particularly, the product group variable seemed to partly explain some of the other variables, such as the need for an additional handling or receipting method. Thus, the coefficients are biased and their values do not reflect the actual effects of the variables. Examining the effect of one variable requires making a separate analysis for each variable, as was done in section Why is not a transaction driver enough? However, for forecasting purposes, using all the variables would be justifiable.

The numerical example in Table IV illustrates the ability of two alternative models to estimate picking times based on either a complete set of the variables available or number of units only. Estimation was carried out on a batch of 20 units of products to be handled. When all the variables are considered, the difference in picking times can rise almost tenfold depending on the characteristics of the product. Conversely, when only the number of units forms the basis for estimation, the result is the same for each product regardless of its characteristics. The latter estimation particularly underestimates the laboriousness of difficult products.

When considering the practical applicability of using multiple variables in cost estimations, it must be remembered that one of the main objectives of cost accounting systems is to increase comprehension. Using multiple variables will inevitably weaken the traceability of costs. If the collecting of data were automatic, analysing and interpreting it would nevertheless be challenging and time-consuming.

Table IV.
An example of estimations of the picking time. Number of units-based estimation underestimates difficult products

Model	Product type	Variables	Estimated duration (s)
All variables	Easy product	[# of units] = 20, [total weight] = 1,000, [total volume] = 1,000, [# of receipts] = 1, [product group 7] = 1	26
	Moderate product	[# of units] = 20, [total weight] = 3,000, [total volume] = 3,000, [receipt method EAN] = 1, [# of receipts] = 2, [product group 2] = 1	52
	Difficult product	[# of units] = 20, [total weight] = 10,000, [total volume] = 10,000, [additional handling] = 1, [receipt method SN] = 1, [# of receipts] = 20, [product group 10] = 1	254
Number of units only	Any product	[# of units] = 20	78

In a dynamic environment, such as the wholesale electronics field, an accounting system needs constant updating. A new analysis should be made each time changes are made in the product assortment or the way an activity is performed. However, this kind of an analysis provides at least an interesting benchmark value of what the variation in costs might be.

Conclusions and discussion

In the wholesale environment, where the gross margin is extremely low, every penny is worth accounting for. Owing to the wide variety of products with different characteristics and needs, transaction-based drivers may not be accurate enough in assigning costs of certain activities in warehouse logistics. For most resources in logistics, time drives costs, and time should also be used as a driver in activity assignment. Although the time usage of a large and constantly renewable product assortment is impossible to monitor manually, ADC can provide a useful tool for building a time-based accounting system. Particularly in a logistics environment, where the process is straightforward and identification is recurrent, data are easily available for cost accounting purposes. RFID technology may provide interesting possibilities for accounting in the future. It remains to be seen whether it is possible to even more easily and accurately follow the products' paths, as well as record cost information to radio-frequency tags in real time.

When time drives costs, the key question for accounting should be what drives time. Collecting information provides excellent opportunities for a more profound analysis of activities. Identifying and measuring related variables makes it possible to trace the causes and effects of variation in activity duration. Data containing activity durations and related variables were collected from a case activity, picking products and packing them into customer boxes. The data were analysed and some interesting observations were made. Products vary in the use of the subtasks and thus require the use of different working methods. This causes significant variation in picking times at both the batch and unit level. For some product groups, the picking time seemed to be almost independent of the number of units handled, while for others the growing number increased picking times dramatically.

The accuracy of different activity-cost drivers was examined by comparing a set of variables with the actual durations measured. A regression model was built for each variable separately. In addition, a multiple regression model with all variables available and their interactions was created. Regression was used because of its suitability for situations in which plenty of historical data are available. Single-variable models were able to explain 17 per cent of the variation at the highest, while the model incorporating all variables could reach an explanatory power of 50 per cent. No single variable alone could provide sufficient estimations for the costs of the case activity. Although the model utilising multiple variables was able to differentiate between batches of products of varying difficulty, duration was a superior driver for the case activity. Based on these results, it can be argued that using a single variable as a transaction driver in this kind of an environment may result in biased cost estimations.

This study clearly demonstrates that in certain environments, it is possible to significantly increase the accuracy of accounting by measuring the actual durations. In addition, collecting more data with more variables enables a much deeper understanding of the cost behaviour of an activity and products to be achieved. The question still remains whether this result is meaningful. One issue to be resolved is the magnitude of the cost differences in those activities with significant variations relative to other costs, such as the purchase prices of items. In the case company, the purchase prices vary from cheap bulk to high-end specialty products. It does not follow that an expensive product would necessarily require higher processing costs. Although this study considered only a single activity, a typical product in the case company would consume around ten activities. The cumulative effect of rather small variations could result in dramatic differences in total costs. An effort should, therefore, be made to examine this variation in the total product costs and compare it with the purchase prices of the same items.

Completely automatic accounting is not yet commonplace. Even if data were collected automatically, much work would still remain before the raw data could be transformed into intelligible cost information. Despite these challenges, an accounting system based on ADC can nevertheless provide the potential for more accurate accounting and tracing of the underlying causes and effects of variability.

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Appendix

Variable name	Unstandardized coefficients *B*	Std error	Standardized coefficients β	Sig.
(Constant)	26.417	13.522		0.051
[# of units]	0.114	0.466	0.024	0.806
[Total weight]	0.002	0.001	0.082	0.052
[Total volume]	0.000	0.000	−0.007	0.767
[Additional handling]	38.522	8.253	0.241	0.000
[Additional handling]*[# of units]	−9.908	2.779	−0.227	0.000
[Receipt method SN]	3.718	11.602	0.043	0.749
[Receipt method EAN]	−10.069	12.028	−0.119	0.403
[# of receipts]	5.558	10.639	0.239	0.601
[Receipt method SN]*[# of receipts]	−1.085	10.324	−0.042	0.916
[Receipt method EAN]*[# of receipts]	9.381	10.642	0.312	0.378
[Product group 2]	−8.661	6.003	−0.076	0.149
[Product group 3]	−5.059	7.015	−0.037	0.471
[Product group 4]	−15.514	6.801	−0.107	0.023
[Product group 5]	−14.786	5.888	−0.151	0.012

(*continued*)

Table AI.

Variable name	Unstandardized coefficients B	Std error	Standardized coefficients β	Sig.
[Product group 6]	−43.424	12.075	−0.225	0.000
[Product group 7]	−7.500	7.849	−0.060	0.339
[Product group 8]	−4.221	8.162	−0.033	0.605
[Product group 9]	21.727	9.021	0.114	0.016
[Product group 10]	14.745	10.713	0.055	0.169
[Product group 2]*[# of units]	1.021	0.501	0.100	0.042
[Product group 3]*[# of units]	0.533	0.829	0.029	0.521
[Product group 4]*[# of units]	0.381	1.839	0.006	0.836
[Product group 5]*[# of units]	0.975	0.468	0.183	0.037
[Product group 6]*[# of units]	10.514	3.369	0.211	0.002
[Product group 7]*[# of units]	−0.137	1.787	−0.003	0.939
[Product group 8]*[# of units]	3.504	2.527	0.055	0.166
[Product group 9]*[# of units]	6.634	2.992	0.075	0.027
[Product group 10]*[# of units]	12.713	3.113	0.141	0.000

Table AI.

Table AII.
The variables and their coefficients used in the regression model based on the number of units only

Variable name	Unstandardized coefficients B	Std. error	Standardized coefficients β	Sig.
(Constant)	35.178	1.605		0.000
[# of units]	2.148	0.160	0.332	0.000

About the authors

Mikko Varila holds MSc in Industrial Management and Engineering. He works for Cost Management Center (CMC) research team at Tampere University of Technology. His current research interests are cost accounting systems and cost management in industrial companies. Mikko Varila is the corresponding author and can be contacted at: mikko.varila@tut.fi

Marko Seppänen holds MSc in Industrial Management and Engineering. He works for Center for Innovation and Technology Research (CITER) at Tampere University of Technology. His current research interest is business models in competitive environments. E-mail: marko.seppanen@tut.fi

Petri Suomala holds PhD in Industrial Management and Engineering. He is the Director of Cost Management Center (CMC) research team at Tampere University of Technology. His current research interests are (life cycle) cost management and management accounting and their utilization in industrial companies and other organizations. E-mail: petri.suomala@tut.fi