A note on optimal cost driver selection in ABC

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In implementing an activity-based costing (ABC) system the selection of cost drivers is a major issue since accuracy must be traded off against the complexity of the ABC-system. On the one hand, a high accuracy in allocating overhead costs often requires a high number of cost drivers. On the other hand, a small number of cost drivers is desirable to achieve acceptable information cost and to make the ABC-system easier for management to understand. In this paper a mathematical model to support optimal cost driver selection is developed. While existing approaches consider only the possible replacement of one cost driver by just one other cost driver, the model takes into account that cost drivers can also be replaced by combinations of cost drivers. This approach yields a more accurate cost allocation with the same ABC-system complexity.

Key words: activity-based costing; cost driver accuracy; cost driver selection; cost driver combinations.

1. Introduction

Activity-based costing (ABC) has become a well-known method for more accurately assigning overhead costs to cost objects, such as products, special orders, and customers, than traditional cost systems (Cooper and Kaplan, 1988). In assigning overhead costs to cost objects, ABC determines cost drivers to measure the utilization of overhead resources by cost objects. Overhead costs are then allocated to cost objects in proportion to their cost driver demand. In contrast to conventional cost systems, ABC also considers non-volume related cost drivers such as the heterogeneity of the product portfolio.

In practice, the number of cost drivers of an ABC-system is particularly important (Cooper, 1989; Babad and Balachandran, 1993; Schniederjans and Garvin, 1997). Often a high number of cost drivers is needed to measure the utilization of overhead

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resources accurately. However, an ABC-system of low complexity, i.e. a system with a small number of cost drivers, is not only less costly but also easier for management to understand (Merchant and Shields, 1993). Furthermore, it is often desirable to focus management attention on only a few main cost drivers (Hiromoto, 1988).

This research focuses on the selection of cost drivers. After defining a set of available cost drivers, complexity constraints are established which have to be fulfilled by the ABC-system. Hence, the set of available cost drivers must be reduced to a subset of cost drivers which are actually implemented to allocate the future overhead costs. Since the selected cost drivers are used to allocate overall overhead costs, they must also bear the overhead costs corresponding to non-selected cost drivers.

A model to optimally select cost drivers from a set of available cost drivers is proposed. In contrast to existing approaches the model does not only consider the possible replacement of one cost driver by just one of the selected cost drivers, but takes into account that a cost driver can also be replaced by a combination of the remaining cost drivers. Hence, instead of allocating the overhead costs corresponding to a non-selected cost driver on the basis of only one of the selected cost drivers one is able to allocate them on the basis of all the selected cost drivers. This means that, in general, the overhead costs corresponding to a replaced cost driver are allocated on the basis of several selected cost drivers. Given the complexity constraints of the ABC-system, the model dominates the approach of simple replacements since it contains this simple approach as a special case. Furthermore, the use of cost driver combinations reduces the danger of overweighting selected cost drivers.

In the next section it is first analyzed how a cost object’s activity-based costs change when overhead costs are allocated on a reduced cost driver basis. Using this analysis, a model to support the selection of cost drivers is developed. To reduce complexity the model uses the possibility of replacing cost drivers by combinations of the selected cost drivers. A restricted version of this model reflects the special case where only simple replacements are allowed. In Section 3 the advantages of the new approach are illustrated with a numerical example in which the model of cost driver combinations is compared with its restricted version of simple replacements. It will turn out that using cost driver combinations outperforms the simple approach considerably. The last section gives some concluding remarks.

2. Replacing cost drivers

Implementation of an ABC-system begins with the identification of activities that use overhead resources and pooling the respective activity costs into cost pools. Second, cost drivers are determined to measure the amount of activities that are required by different cost objects. Finally, overhead costs are allocated to the cost objects in proportion to their respective cost driver demand.

The two-stage allocation of ABC is often not consistent with real-world behavior of overhead costs since it requires separability and proportionality (Noreen, 1991; Christensen and Demski, 1995). For example, overhead capacities that can only be adapted in discrete steps result in non-proportional capacity costs (Salafatinos, 1996). Thus, ABC must be viewed as an approximation (Balakrishnan and Sivaramakrishnan, 1996; Balachandran et al., 1997; Schneeweiss, 1998). However, this investigation does
not focus on inaccuracies caused by the simplifying assumptions of ABC. Rather, it analyzes the inaccuracies that are caused by using only a subset of the available cost drivers. Also, in what follows any kind of errors in measuring overhead costs or cost driver demand are neglected. As demonstrated by Datar and Gupta (1994) such measurement errors might favor the use of simple ABC-systems that have a small number of cost pools and corresponding cost drivers. In contrast, a situation is considered where eliminating possible cost drivers does always reduce accuracy. Any strategic advantages which might result from biased cost data (Banker and Potter, 1993; Wagenhofer, 1996) are out of the scope of the analysis as well.

Following Babad and Balachandran (1993), to analyze the effects of replacing cost drivers let us consider a situation with \( J \) activities (cost pools) which are measured by \( J \) cost drivers. Suppose that the total use \( P_j \) of cost driver \( j \) causes overhead costs of \( D_j \). Hence, the cost driver rate of cost driver \( j \) is \( \pi_j = D_j / P_j \).

ABC allocates overhead costs to cost objects in proportion to their respective cost driver demand. Let \( \bar{V}_{ij} \) be the (estimated) use of cost driver \( j \) by cost object \( i \). Then, with \( I \) cost objects, the total use of cost driver \( j \) is \( P_j = \sum_{i=1}^{I} \bar{V}_{ij} \), and the activity-based costs of cost object \( i \) are

\[
U_i = \sum_{j=1}^{J} \pi_j \cdot \bar{V}_{ij} = \sum_{j=1}^{J} \frac{D_j \cdot \bar{V}_{ij}}{P_j} = \sum_{j=1}^{J} D_j \cdot V_{ij},
\]

(1) (Babad and Balachandran, 1993, p. 565) where

\[
V_{ij} := \frac{\bar{V}_{ij}}{P_j} : \text{(estimated) relative use of cost driver } j \text{ by cost object } i.
\]

To calculate activity-based costs, equation (1) makes use of the available \( J \) cost drivers. However, for the above-mentioned reasons one often wants to reduce the number of cost drivers, while maintaining acceptable accuracy in cost allocation. In analyzing this problem first the situation of Babad and Balachandran (1993) is considered where a cost driver is replaced by just one of the selected cost drivers. Second, in considering the use of cost driver combinations a more general approach is established.

To eliminate cost driver \( m \) by using only simple cost driver replacements, overhead costs \( D_m \) must be allocated by one of the remaining \( J - 1 \) cost drivers. If cost driver \( k \neq m \) is chosen as the respective allocation basis, its overhead costs increase from \( D_k \) to \( D_k + D_m \) and its new cost driver rate is \( \pi'_k = \pi_k + D_m / P_k \). Hence, with \( U_{im}^\lambda \) denoting the new activity-based costs of cost object \( i \), the accuracy loss for cost object \( i \) is

\[
\Delta_{im}^\lambda := U_i - U_{im}^\lambda = D_m \cdot (V_{im} - V_{ik})
\]

(2) (Babad and Balachandran, 1993, p. 566).

Instead of using only a single cost driver to allocate the overhead costs \( D_m \), the idea is to use all selected cost drivers. More precisely, a combination of the remaining \( J - 1 \) cost drivers is calculated to replace cost driver \( m \). In this combination each cost driver is assigned a certain weight determining the portion of \( D_m \) to be allocated on the basis of this cost driver. If in allocating overhead costs \( D_m \), a weight of \( \lambda_{mk} \geq 0 \) is assigned to cost driver \( k \neq m \), its new overhead cost is \( D_k + \lambda_{mk} \cdot D_m \), yielding the new cost driver rate \( \pi'_k = \pi_k + \lambda_{mk} \cdot (D_m / P_k) \). Hence, the accuracy loss of the new
activity-based costs $U_i^m$ of cost object $i$ is

$$
\delta_i^m := U_i - U_i^m = D_m \cdot \left( V_{im} - \sum_{k=1}^J \lambda_{mk} \cdot V_{ik} \right),
$$

where

$$
\lambda_{mk} \geq 0: \text{ weight of cost driver } k \text{ in replacing cost driver } m.
$$

To have weights that are consistent with the replacement of cost driver $m$, one must set $\lambda_{mm} = 0$. Furthermore, requiring convex combinations,

$$
\sum_{k=1}^J \lambda_{mk} = 1,
$$

ensures that precisely the overhead costs $D_m$ are allocated.

Obviously, since $\lambda_{mk} = 1$ for $k = k'$ and $\lambda_{mk} = 0$ for $k \neq k'$ are feasible weights in (3) it turns out that (2) is a special case of a cost driver combination. Therefore using cost driver combinations will generally yield a better accuracy than simple replacements when the same cost drivers are eliminated. In particular, if the overhead cost corresponding to a replaced cost driver must be fully allocated by only one of the remaining cost drivers, it is likely that the cost driver selected as the new allocation base is overweighted. Hence, management attention is focused too much on a specific driver. Cost driver combinations reduce this bias by allowing for a ‘smoother’ allocation of overhead costs belonging to a replaced cost driver. In other words, the whole set of remaining cost drivers will often better capture the cause-and-effect between the overhead cost of an eliminated cost driver and its corresponding cost driver volume.

The first step in developing a mathematical model to replace cost drivers rationally is to establish an adequate overall measure for the accuracy of a reduced ABC-system. Summing up the inaccuracies of the activity-based costs of different cost objects does not yield an adequate measure because inaccuracies neutralize each other. Therefore, in evaluating the accuracy of a reduced ABC-system its detailed cost allocation must be taken into account. The detailed cost allocation of an ABC-system is captured by a matrix that shows in its $i$th row ($i = 1, \ldots, I$) and $j$th column ($j = 1, \ldots, J$) how much of the overhead cost $D_j$ is allocated to cost object $i$. The accuracy of a reduced ABC-system can then be measured by the Euclidean distance of its cost allocation matrix from that of the original system.

Note, that if several cost drivers are replaced, inaccuracies can neutralize each other for a single cost object. To illustrate this offsetting effect (Gupta, 1993) consider a situation in which cost drivers $m$ and $m'$ are replaced by cost drivers $k$ and $k'$, respectively. If the two corresponding accuracy losses, $\Delta_{ikm}$ and $\Delta_{ik'm'}$, are different in sign, the resulting activity-based costs of cost object $i$ might be accurate even though the wrong overhead costs are assigned to cost object $i$. However, using ABC one is in general not only interested in receiving adequate cost values. From the more general perspective of activity-based management (ABM), to improve activities or cost objects one also needs adequate information about the extent to which particular activities cause the cost objects’ cost. This information might be extremely biased by exploiting the offsetting effect to yield accurate activity costs with a small number of
A Note on Optimal Cost Driver Selection in ABC

cost drivers. Therefore the proposed accuracy measure does not consider an ABC-
system as accurate when it yields accurate activity costs by offsetting inaccurate
allocations.

To obtain an optimal cost driver selection one must trade off accuracy against com-
plexity. In what follows ABC-system complexity is operationalized by information
cost and the number of cost drivers, taking into account aspiration levels \( \bar{C} \) and \( \bar{J} \)
for information cost and the maximum number of selected cost drivers, respectively.
Information costs are a result of gathering, storing, and processing data concerning
cost drivers. Like in Babad and Balachandran (1993) it is assumed that different cost
drivers result in different information costs and that the aspiration levels \( \bar{C} \) and \( \bar{J} \)
are given exogenously. One should be aware though that these aspiration levels result
from a complex decision process.

Considering the use of cost driver combinations, one must determine binary
variables

\[
x_m := \begin{cases} 
1 & \text{if cost driver } m \text{ is to be replaced by a} \\
0 & \text{otherwise} 
\end{cases} 
\]

for all cost drivers \( m = 1, \ldots, J \). In addition, for an eliminated cost driver \( m \), one must
determine weights \( \lambda_{mk} \geq 0 \) for combining the selected cost drivers. With \( C_j \) denoting
the information cost of cost driver \( j \), both can be done by using the following model:

\[
\begin{align*}
\min & \left( \sum_{m=1}^{J} \sum_{i=1}^{I} (\delta_{ij}^m)^2 \cdot x_m \right)^{1/2} \\
\text{s.t.} & \\
\sum_{m=1}^{J} C_m \cdot (1 - x_m) & \leq \bar{C} \\
J - \sum_{m=1}^{J} x_m & \leq \bar{J} \\
\sum_{k=1}^{J} \lambda_{mk} & = x_m \quad \text{for all } m = 1, \ldots, J \\
0 & \leq \lambda_{mk} \leq 1 - x_k \quad \text{for all } m, k = 1, \ldots, J \\
x_m & \in \{0; 1\} \quad \text{for all } m = 1, \ldots, J.
\end{align*}
\]

The objective function (6) minimizes the Euclidean distance between the reduced
and the original ABC-system’s cost allocation matrices where \( \delta_{ij}^m \) is defined by
equation (3). There is a tradeoff between overall accuracy, information cost, and the
number of cost drivers. Constraints (7) and (8) set aspiration levels for information
cost and the number of cost drivers. Constraint (9) requires that the combination
of cost drivers replacing a non-selected cost driver \( m \) (\( x_m = 1 \)) fully allocates the
relevant overhead costs \( D_m \) (see also equation (4)). Furthermore, if cost driver \( m \)
not eliminated (\( x_m = 0 \)) it guarantees that the weights \( \lambda_{mk} \) (\( k = 1, \ldots, J \)) are set to
zero. Note that choosing \( \lambda_{mm} = 0 \) for a non-eliminated cost driver \( m \) is only a question
of definition which does not influence the optimal cost driver selection in any way.
Constraint (10) reflects that a replaced cost driver \( k \) (\( x_k = 1 \)) must have zero weight in
any cost driver combination. In particular this constraint requires $\lambda_{kk} = 0$ for a non-selected cost driver $k$.

Obviously the square root in the objective function (6) can be neglected in the optimization. Hence, for fixed binary variables $x_m$, model (6)–(11) is a quadratic convex optimization problem with linear constraints and can be solved exactly. In practice, the number of relevant cost drivers will allow a complete enumeration of the binary variables, yielding the overall optimum. The simple case in which a cost driver can be replaced by just one of the selected cost drivers can be seen as a restricted version of model (6)–(11) resulting by requiring that the weights of the cost driver combinations are either zero or one ($\lambda_{mk} \in \{0, 1\}$).

When only simple cost driver replacements are considered the model is similar to an approach of Babad and Balachandran (1993). However, even for this simple case it differs in that it uses a more reasonable measure of accuracy. Also, unlike Babad and Balachandran, the objective function does not directly trade off information cost and accuracy. Rather, the model is based on aspiration levels which can be adjusted according to the decision maker’s preferences. Finally, Babad and Balachandran use a greedy heuristic to select cost drivers. In general this is not necessary for real-world problems, since the number of relevant cost drivers does not prohibit finding an optimum.

However, besides these rather technical differences, our main point is that using only simple replacements of cost drivers ($\lambda_{mk} \in \{0, 1\}$) is an unnecessary restriction, which might result in a high accuracy loss. Hence, considering all remaining cost drivers to allocate the overhead costs of a replaced cost driver (model (6)–(11)) is the more reasonable approach.

Obviously, to select cost drivers with model (6)–(11), estimates for all possible cost drivers must be available. These estimates can be viewed as information about the general relationship between possible cost drivers. However, cost driver selection is done in the implementation phase of an ABC-system. Once the system is implemented cost drivers are fixed at least for a medium-term horizon and activity-based costs are calculated without estimating the use of replaced cost drivers. Therefore, from time to time it might be necessary to determine a new cost driver selection.

3. Numerical example

To illustrate the advantages of using cost driver combinations, model (6)–(11) and its restricted version ($\lambda_{mk} \in \{0, 1\}$) are compared for an example given by Cooper (1988), where a situation with five cost drivers and four cost objects is considered. Table 1 shows the (estimated) relative utilizations ($V_{ij} = \bar{V}_{ij}/P_j$) of five cost drivers ($J = 5$) by four cost objects ($I = 4$). Furthermore, it shows the overhead costs $D_j$ and the information costs $C_j$ corresponding to the cost drivers. The same example is used by Babad and Balachandran (1993) to illustrate their approach of simple cost driver replacements. However, because of the various above-mentioned differences, our approach produces different results even for the case of simple replacements.

Let us first consider a situation where only an aspiration level for the maximum number of cost drivers selected and not for information cost applies. The resulting information costs are calculated from the optimal cost driver selection. Table 2
A Note on Optimal Cost Driver Selection in ABC

Table 1
Hypothetical cost driver data

<table>
<thead>
<tr>
<th>Cost object $i$</th>
<th>Relative use $V_{ij}$ of cost driver $j$</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$i = 1$</td>
<td>$j = 1$ (labor hours)</td>
<td>0.0227</td>
<td>0.0588</td>
<td>0.1250</td>
<td>0.1250</td>
</tr>
<tr>
<td></td>
<td>$j = 2$ (machine hours)</td>
<td>0.2273</td>
<td>0.2353</td>
<td>0.2500</td>
<td>0.3750</td>
</tr>
<tr>
<td></td>
<td>$j = 3$ (setups)</td>
<td>0.0682</td>
<td>0.1176</td>
<td>0.1250</td>
<td>0.1250</td>
</tr>
<tr>
<td></td>
<td>$j = 4$ (orders)</td>
<td>0.6818</td>
<td>0.5882</td>
<td>0.5000</td>
<td>0.3750</td>
</tr>
<tr>
<td></td>
<td>$j = 5$ (parts)</td>
<td>2,464</td>
<td>3,400</td>
<td>960</td>
<td>1,200</td>
</tr>
<tr>
<td>Overhead costs $D_j$</td>
<td></td>
<td>2,500</td>
<td>1,500</td>
<td>2,000</td>
<td>2,000</td>
</tr>
<tr>
<td>Information costs $C_j$</td>
<td></td>
<td>2,500</td>
<td>1,500</td>
<td>2,000</td>
<td>2,000</td>
</tr>
</tbody>
</table>

Table 2
Cost driver selection and replacement for the restricted and the non-restricted model

<table>
<thead>
<tr>
<th>Max. number of cost drivers</th>
<th>Model</th>
<th>Remaining cost drivers</th>
<th>Optimal binary variables and weights</th>
<th>Information costs $\bar{C}$</th>
<th>Accuracy loss $\lambda_{mk}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$J = 4$</td>
<td>restricted</td>
<td>1; 2; 4; 5</td>
<td>$\lambda_{32} = 1$</td>
<td>8,500</td>
<td>107.05</td>
</tr>
<tr>
<td></td>
<td>non-restricted</td>
<td>1; 2; 4; 5</td>
<td>$\lambda_{31} = 0.54; \lambda_{34} = 0.11; \lambda_{35} = 0.35$</td>
<td>8,500</td>
<td>16.90</td>
</tr>
<tr>
<td>$J = 2$</td>
<td>restricted</td>
<td>2; 5</td>
<td>$\lambda_{12} = 1; \lambda_{32} = 1; \lambda_{45} = 1$</td>
<td>4,000</td>
<td>421.64</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1; 5</td>
<td>$\lambda_{21} = 0.79; \lambda_{25} = 0.21$</td>
<td>5,000</td>
<td>195.76</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2; 5</td>
<td>$\lambda_{12} = 1$</td>
<td>2,000</td>
<td>333.89</td>
</tr>
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</table>

shows the optimal cost driver selections and replacements for model (6)–(11) and its restricted version ($\lambda_{mk} \in \{0; 1\}$). For instance, if we require an ABC-system with a maximum number of four cost drivers, using only simple replacements one eliminates setups. The corresponding overhead costs are fully allocated on the basis of machine hours. This yields an overall accuracy loss of 107.05. For a maximum number of four cost drivers, using cost driver combinations one replaces the same cost driver, setups. However, allocating 54% of the corresponding overhead costs on the basis of labor hours, 11% on orders, and 35% on parts, yields a better accuracy. Moreover, one reduces the danger of overweighting just one specific cost driver demand triggered by a cost object.

Let us now consider the second situation shown in Table 2, where only two of the five cost drivers are used. In this case different cost drivers are selected for model (6)–(11) and its restricted version ($\lambda_{mk} \in \{0; 1\}$), with the non-restricted model yielding the better accuracy. However, not requiring an aspiration level for information cost allows the non-restricted model to choose the more expensive cost driver 1 instead of cost driver 2. To yield the same information cost as in the restricted model one simply sets an aspiration level of $\bar{C} = 4,000$. Table 2 shows that this results in the same cost driver selection as for the case of simple replacements. However, the accuracy loss for the case where only simple replacements are feasible is still higher.
4. Concluding remarks

In this paper a model to support cost driver selection was proposed. In contrast to existing approaches the model reflects the possibility of replacing a cost driver by a combination of the selected cost drivers. A restricted version of the model is similar to an approach proposed by Babad and Balachandran (1993) where only simple replacements of cost drivers are feasible. As has been shown our more general model extends this simple approach substantially. Given the ABC-system complexity, it yields a better accuracy than the simple approach. In addition, it reduces the danger of overweighting selected cost drivers.

Though a situation is considered in which ABC is able to provide precise (marginal) costs, our model might also be helpful when this is no longer the case. For example, when diseconomies of scale are present, proportionality between activity cost and cost driver volume is violated and ABC tends to underestimate marginal costs. However, one could try to compensate this effect by increasing the activity costs of some of the available cost drivers (Christensen and Demski, 1997). Then the most accurate ABC-system would use all available cost drivers to allocate these systematically adjusted activity costs and the accuracy measure (6) would simply measure the distance from this modified benchmark system.

References

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A Note on Optimal Cost Driver Selection in ABC


