Improving activity-based costing heuristics by higher-level cost drivers

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Abstract

Activity-based costing (ABC) tries to allocate overhead costs to cost objects more accurately than traditional cost systems. However, since ABC proportionalizes overhead costs it is a heuristic. The paper uses simulations and mixed-integer programming to analyze the extent of the sub-optimality incurred by ABC-heuristics. While previous research has focused on ABC systems with a simple set of cost drivers, thereby restricting the potential of ABC as a heuristic, the paper analyzes the effects of establishing a cost driver corresponding to a higher cost level. Specifically, a portfolio-based cost driver captures the demand heterogeneity triggered by the portfolio. This heterogeneity driver is then used to proportionalize all costs due to inflexible overhead resources. One of the main findings is that such a heterogeneity driver improves the quality of ABC-heuristics significantly.

Keywords: Activity-based costing; Heuristics; Simulation; Mixed-integer programming

1. Introduction

Activity-based costing (ABC) tries to assign overhead costs to cost objects more accurately than traditional cost systems. Therefore it is often argued that ABC can support medium- and long-term decisions, such as make-or-buy, pricing and special orders decisions, or product portfolio decisions. ABC is even considered as a strategic cost system (see, e.g., Cooper and Kaplan, 1988). So far, however, it is not at all clear whether ABC is really an adequate instrument for decision making. Also it is an open question how the quality of decisions supported by ABC depends on the cost drivers of the underlying ABC system. These are the questions that the paper wants to address.

Our paper contributes to a recent strand of literature analyzing cost-based decision rules for planning purposes (see Balakrishnan and Sivaramakrishnan (2002) for a recent overview). Within this strand there are several publications which analyze the problems of using ABC for decision making. Noreen (1991) and Christensen and Demski (1995) investigate the general conditions under which ABC provides accurate cost information for decision making. Their main result is that costs must be separable into cost pools each of which corresponding to a single cost driver.

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Furthermore, the cost of a cost pool must be proportional to the volume of the relevant cost driver resulting in a linear cost function for each cost pool. This linear behavior of overhead costs is often not fulfilled in real-world applications. A paper providing empirical evidence against proportionality is Noreen and Soderstrom (1994). They test for the proportionality of overhead costs to activity using hospital data and reject proportionality. The reason for this result is obvious. When overhead resources are not perfectly flexible, under or over capacities as well as costs for adjusting capacities will result. Since these factors are not taken into account precisely, ABC has to be viewed as a heuristic, generally yielding sub-optimal decisions.

Several papers provide special situations for which ABC yields acceptable or even optimal results. For instance, Banker and Hughes (1994) provide a setting in which ABC supports optimal pricing decisions. The reason for their ABC decision rule to be optimal is that their model is based on a single period of time and soft capacity constraints only. If necessary, resource capacity can be extended to any desired level in the short-run.

An other paper analyzing cost-based heuristics is Hansen and Magee (1993) who find out that the use of sunk capacity costs to evaluate product profitability tends to be justified when the number of possible products is large. Banker and Hansen (2000) show that cost-based heuristics yield a surprisingly good performance when being applied for a situation involving multi-period capacity adjustments with soft capacity constraints. One important reason for this is that due to the soft capacity constraints the overall problem is separable into a sequence of periodic sub-problems.

In contrast, Balakrishnan and Sivaramakrishnan (1996) analyze the consequences of proportionalizing capacity costs when hard capacity constraints apply. Using a simple example with two periods the authors illustrate that proportionalizing capacity costs as it is done in ABC generally results in sub-optimal production decisions. Balachandran et al. (1997) use simulations to analyze the performance of several cost-based heuristics for capacity planning, one of which can be interpreted as ABC. The authors show that the performance of the various cost-based decision rules within their simulation study depends on the extent to which products interact. Schneeweiss (1998) also uses simulations to investigate the quality of ABC as a decision rule and finds out that ABC may lead to a considerable economic loss which increases with the inflexibility of overhead resources.

Like Balachandran, Balakrishnan, Sivaramakrishnan and Schneeweiss the following investigation uses simulations to analyze the extent of the sub-optimality incurred by applying ABC for decision making. The quality of ABC will be compared with the optimal solution to a mixed-integer program which takes precisely into account the dynamic adjustments of capacities. In light of the complexity required to formulate and solve such a model, ABC can be justified as a simple heuristic. Previous research has focused on ABC systems using only a simple set of cost drivers, thereby restricting the potential of ABC. In contrast, the paper analyzes the effects of establishing a cost driver corresponding to a higher cost level. A higher level cost driver does not apply to single cost objects but to the portfolio of cost objects. Hence, such a cost driver is used to allocate those overhead costs for which there are no cause-and-effect relationships with respect to single cost objects. For instance, one can think of the opportunity cost due to excess or idle capacity that cannot be traced to single products but only to the product portfolio as a whole. Another example is given by the firm's suppliers. Here a higher level cost driver might measure the heterogeneity of the suppliers' electronic order systems. If the firm's suppliers differ substantially in there software standards the firm is likely to bear high software costs not traceable to just a single supplier.

More specifically, the investigation focuses on a portfolio-based cost driver that captures the demand heterogeneity triggered by the portfolio as a whole. Typically demand heterogeneity cannot be assigned to single cost objects. This heterogeneity driver is then used to proportionalize all costs due to inflexible overhead resources. Using simulations the performance of this extended decision rule is evaluated in comparison to the benchmark as well as to ABC with simple drivers.
The primary finding is that when the portfolio level is established as an additional cost hierarchy ABC shows a considerable quality and robustness. In particular simple ABC is out-performed, though a significant gap to the benchmark model remains. These results are checked for a variety of resource situations covering highly flexible to highly inflexible overhead resources.

The paper is organized as follows: Section 2 introduces a mixed-integer program as a benchmark model yielding optimal results. In Section 3 it is shown how ABC can be used as a heuristic for the benchmark model. A simple and an extended ABC system are distinguished. In Section 4 simulations are used to compare simple and extended ABC relative to one another and relative to the benchmark model. Section 5 concludes.

2. Exact decision making using a mixed-integer program

ABC is often applied for strategic or tactical decisions with a ‘zero-one character’, for instance, including a product in the portfolio or not, make-or-buy, accepting or rejecting a special order, accepting or rejecting a contract, working together with a new customer or supplier etc. Therefore, in the investigation a vector \( x = (x_i) = (x_1, \ldots, x_I) \) of ‘zero–one decisions’ is considered. In what follows, \( x \) is called the firm’s portfolio. Note, that \( x \) might define a portfolio of products, orders, suppliers, customers etc. It is assumed that given \( x \) the capacity demand with respect to the firm’s overhead resources is specified over the entire planning horizon \( T \) and the firm is assumed to know this capacity demand. For some of the decisions mentioned above the latter assumption might seem to be too restrictive. First, however, it is a necessary simplification for our analysis. Furthermore, one can think of a variety of situations where \( x \) indeed specifies the capacity demand with certainty. For example, when \( x_i \) is an accept/reject decision on a contract specifying future order quantities a perfectly informed firm is realistic.

Once \( x \) is determined, the triggered resource demand must be fulfilled in all \( T \) periods. Furthermore, the firm is supposed to be a price taker. Hence, with \( E_i^T \) denoting the contribution margin over \( T \) periods caused by setting \( x_i = 1 \), the portfolio \( x \) yields an overall contribution margin of

\[
\sum_{i=1}^{I} E_i^T \cdot x_i
\]

which is independent of any pricing decision of the firm.

Of course, since by assumption under-capacity is not an option, the firm faces a complex (overhead) resource decision. In our model capacities can be adjusted dynamically from period to period. The complexity of the corresponding dynamic decision problem is, however, reduced by the assumption that the firm has got perfect information with respect to the resource demand triggered by a portfolio \( x \) over the entire planning horizon \( T \). Therefore the portfolio and the resource capacity necessary to fulfill the corresponding market demand can be determined simultaneously in \( t = 0 \). The decision problem described so far can be adequately reflected by the following (deterministic) mixed-integer program:

\[
\max \sum_{i=1}^{I} E_i^T \cdot x_i - \sum_{s=1}^{S} \sum_{t=1}^{T} (c_s \cdot k_{st} + c^o_s \cdot o_{st}) - \sum_{s=1}^{S} \sum_{t=1}^{T} (c^+_{s} \cdot k^+_{st} + c^-_{s} \cdot k^-_{st}),
\]

subject to

\[
\sum_{i=1}^{I} A_{ist} \cdot x_i \leq k_{st} + o_{st}
\]

\forall s = 1, \ldots, S; \ t = 1, \ldots, T, \ (2)

\[
k_{st} = k_{st-1} + k^+_{st} - k^-_{st}
\]

\forall s = 1, \ldots, S; \ t = 1, \ldots, T + 1, \ (3)

\[
k^+_{st} \leq v^+_{s} \cdot k_{st-1}
\]

\forall s = 1, \ldots, S; \ t = 1, \ldots, T + 1, \ (4)

\[
k^-_{st} \leq v^-_{s} \cdot k_{st-1}
\]

\forall s = 1, \ldots, S; \ t = 1, \ldots, T + 1, \ (5)

\[
k_{st} = k_{st+1} \quad \forall s = 1, \ldots, S, \]

\( a_{st} \leq o_{st} \cdot k_{st} \) \forall s = 1, \ldots, S; \ t = 1, \ldots, T, \ (6)

\[
k_{st}, k^+_{st}, k^-_{st}, o_{st} \geq 0
\]

\forall s = 1, \ldots, S; \ t = 1, \ldots, T + 1, \ (8)

\[
x_i \in \{0,1\} \quad \forall i = 1, \ldots, I,
\]

(9)
with the decision variables

\[ x = (x_t) \] portfolio decision,
\[ k_{st} \] capacity of resource \( s \) in period \( t \),
\[ k_{so} \] initial capacity of resource \( s \),
\[ k_{st+1} \] final capacity of resource \( s \),
\[ o_{st} \] short-term capacity expansion of resource \( s \) in period \( t \),
\[ k_{st+} \] medium-term capacity expansion of resource \( s \) in period \( t \),
\[ k_{st-} \] medium-term capacity reduction of resource \( s \) in period \( t \),

and the parameters

\[ E_i^T \] contribution margin over \( T \) caused when setting \( x_i = 1 \),
\[ c_s \] cost of providing one unit of resource \( s \),
\[ c_s^o \] cost of a short-term capacity expansion of resource \( s \) by one unit,
\[ c_s^+ \] cost of a medium-term capacity expansion of resource \( s \) by one unit,
\[ c_s^- \] cost of a medium-term capacity reduction of resource \( s \) by one unit,
\[ A_{ist} \] consumption for resource \( s \) in period \( t \) triggered when \( x_i = 1 \),
\[ v_s^+ \] maximum factor by which resource \( s \) can be expanded from one period to another through a medium-term expansion,
\[ v_s^- \] minimum factor by which resource \( s \) can be reduced from one period to another through a medium-term expansion,
\[ \alpha_s \] factor defining the maximum short-term expansion of resource \( s \).

The objective function (1) maximizes the profit over a planning horizon of \( T \) periods. Profit is calculated as the difference of the overall contribution margin and the overall resource costs incurred by the portfolio \( x \). Besides the costs of providing normal resources \( k_{st} \) there are costs of expanding these resources by short-term capacities \( o_{st} \). In what follows the latter costs \( c_s^o \) will be interpreted as overtime costs. An additional cost is incurred by medium-term capacity adjustments \((k_{st+} \text{ and } k_{st-})\) of normal resources from one period to another. These capacity adjustments cause adjustment costs \((c_s^+ \text{ and } c_s^-)\). In contrast to overtime medium-term adjustments refer, in general, to a change in capacity for more than a single period. A typical example for medium-term adjustment costs are costs for hiring or firing manpower. Apart from overtime manpower capacity will generally not be changed for only one period. Constraint (6) requires that the initial and the final capacities of the normal resources are identical. Allowing for an infinite cyclical repetition of \( x \) this constraint avoids a bias due to the finite planning horizon of \( T \) periods. It leads to the term for \( t = T + 1 \) in the objective function (1) to represent the costs of adapting the capacity at the end of the planning horizon to the initial value.

Once the portfolio \( x \) is determined, the triggered resource demand must be fulfilled. In that sense constraint (2) ensures the feasibility of a portfolio \( x \) in terms of the resources available after short- and medium-term capacity adjustments. Note that since the firm is assumed to have perfect information, already in \( t = 0 \) the resource demand values \( A_{ist} \) in (2) are deterministic.

The further model constraints capture the inflexibility of resources. The capacity balance equation (3) reflects the dynamics of capacity adjustments with the coupling of initial and final capacities in (6). Restrictions in adjusting capacities are accounted for in (4) and (5) corresponding to a medium-term adjustment, and in (7) corresponding to overtime. While in one period the extent of medium-term adjustments is restricted to a certain percentage of the previous period’s normal resource capacity, the extent of overtime in a period is restricted to a certain percentage of the same period’s normal resource capacity. To reduce complexity the possibility of smoothing demand e.g. by producing for inventory is not considered. This makes the issue of under/over capacities more severe which typically reflects the situation of a firm in the service industry.

For a manufacturer the model might capture the following decision problem: The manufacturer is offered a long-term contract for several products \((i = 1, \ldots, I)\) at a pre-fixed price and quantity. Then, the manufacturer must contemplate which part of the order to manufacture \((x_i = 1)\) and which to outsource \((x_i = 0)\), with zero profit on the out-sourced products. Note that such an outsourcing decision is a typical ABC-application.
In the mixed-integer program (1)–(9) capacity constraints vary between completely hard and completely soft, reflecting the real-world character of overhead capacities and covering the range of resource situations considered in the literature. Throughout the investigation the optimal solution to model (1)–(9) will be considered as the benchmark. The quality of the ABC-heuristics will be compared with the optimal solution to this complex to solve mixed-integer program. Evaluating a heuristic requires to specify all the parameters of the benchmark model (1)–(9). In what follows a situation with \( I = 6 \) zero–one decisions, \( S = 3 \) different resources, and \( T = 5 \) periods is considered. The focus will be on covering a variety of different scenarios with respect to the portfolios’ resource demand. To this end the consumption values \( A_{ist} \) in (2) will be generated randomly. Specifically,

\[
A_{ist} = x_{is} \cdot \beta_{it} \quad \text{for all } i, s, t, \tag{10}
\]

where \( x_{is} \) will be drawn from a uniform distribution with support over \([0.5, 1.5]\) and \( \beta_{it} \) will be drawn from a (symmetric) beta distribution with form parameters \((2, 2)\) and support \([50, 250]\). Generating the resource demand according to (10), i.e., by combining a uniform and a beta distribution is in line with Balachandran et al. (1997). While \( \beta_{it} \) is used to model effects caused by \( x_{i} = 1 \) concerning all resources, \( x_{is} \) reflects the fact that \( x_{i} = 1 \) will influence the resources \( s \) differently. Note, however, that generating \( A_{ist} \) randomly does not change the assumption of a firm with perfect information.

It will be assumed that the overall contribution margin caused by \( x_{i} = 1 \) depends on its resource consumption (10) through

\[
E_{it}^T = e_{i} \cdot \sum_{s=1}^{T} \sum_{s=1}^{S} c_{s} \cdot A_{ist}, \tag{11}
\]

where \( e_{i} \geq 0 \) can be interpreted as a profitability factor. By (11) it is ensured that the contribution margin \( E_{it}^T \) increases when the resource demand triggered by \( x_{i} = 1 \) increases. Note that (11) means that the contribution margin is proportional to the normal resource costs which will turn out to be the activity-based costs of \( x_{i} = 1 \). This means that the market is supposed to be willing to pay for an increase in a cost object’s capacity demand. This is a reasonable assumption as long as the increased capacity usage is not due to non-value adding activities. The profitability factors \( e_{i} \) in Table 1 are chosen such that the decisions \( x_{1} = 1 \) and \( x_{2} = 1 \) yield a contribution margin which is 10% higher than their activity-based costs while \( x_{3} = 1 \) and \( x_{4} = 1 \) (\( x_{5} = 1 \) and \( x_{6} = 1 \)) yield slightly lower (slightly higher) contribution margins. It might seem inconsistent that cost objects with profitability factors significantly lower than one are not considered. However, due to their low contribution margin such cost objects would simply be irrelevant since they would not be chosen for the portfolio by any of the decision rules.

While the resource demand values are generated randomly, the other parameters are given in Table 1 defining a reasonable base-situation. Of course there is a considerable freedom in choosing the model parameters. However, overtime should be more expensive than providing normal capacity \((e_{i}^{o} > c_{i})\). Furthermore, adjustment costs for the three resources are chosen such that for the first resource \((s = 1)\) an extension of normal capacity for a single period is less expensive than overtime \((c_{1} + c_{1}^{o} + c_{1}^{y} < c_{1}^{o})\), for the second resource \((s = 2)\) one is indifferent between an extension of normal capacity for a single period and overtime \((c_{2} + c_{2}^{o} + c_{2}^{y} = c_{2}^{o})\), and for the third resource \((s = 3)\) an extension of normal capacity for a single period is more expensive than overtime \((c_{3} + c_{3}^{o} + c_{3}^{y} > c_{3}^{o})\). Note that an adjustment of

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**Table 1**

Parameter values of the base-situation

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( I )</td>
<td>6</td>
</tr>
<tr>
<td>( S )</td>
<td>3</td>
</tr>
<tr>
<td>( T )</td>
<td>5</td>
</tr>
<tr>
<td>( x_{it} )</td>
<td>Uniformly distributed on ([0.5, 1.5])</td>
</tr>
<tr>
<td>( \beta_{it} )</td>
<td>Beta-distributed on ([50, 250]) with parameters ((2, 2))</td>
</tr>
<tr>
<td>((e_{1}, \ldots, e_{6}))</td>
<td>((1.1, 1.1, 0.99, 0.99, 1.01, 1.01))</td>
</tr>
<tr>
<td>((c_{1}, c_{2}, c_{3}))</td>
<td>((10.0, 9.0, 11.0))</td>
</tr>
<tr>
<td>((c_{1}^{o}, c_{2}^{o}, c_{3}^{o}))</td>
<td>((4.0, 4.0, 5.0))</td>
</tr>
<tr>
<td>((c_{1}^{y}, c_{2}^{y}, c_{3}^{y}))</td>
<td>((4.0, 4.0, 4.0))</td>
</tr>
<tr>
<td>((c_{1}^{<em>}, c_{2}^{</em>}, c_{3}^{*}))</td>
<td>((20.0, 17.0, 19.0))</td>
</tr>
<tr>
<td>((\theta_{1}, \theta_{2}, \theta_{3}))</td>
<td>((0.5, 0.5, 0.5))</td>
</tr>
<tr>
<td>((e_{1}^{y}, e_{2}^{y}, e_{3}^{y}))</td>
<td>((0.5, 0.5, 0.5))</td>
</tr>
</tbody>
</table>
normal resources for just a single period is less expensive than overtime as long as the overall cost of the relevant capacity provision is lower. This means that one has to account for the cost \( c_{i}^+ \) of extending the capacity, then the cost \( c_{i} \) of providing the capacity, and finally the cost \( c_{i}^- \) of reducing the capacity to the original value.

Both possibilities of adjusting capacities in a time period are restricted to 50% of the previous and the same period’s capacity amount, respectively \((v_i^+ = v_i^- = 0.5\) and \(\delta_i = 0.5\)). This percentage is crucial for the firm’s flexibility in adjusting capacities. The choice of 50% for the base case might be considered as a medium degree of flexibility. The choice of 50% for the base case might be considered as a medium degree of flexibility. The consequences of a lower and a higher flexibility, respectively, will be analyzed in additional simulations. Hence, the base case will not be the only situation for which the ABC-heuristics will be used mitigating the more or less arbitrary definition of a base case. Furthermore, to avoid the choice of any arbitrary starting values favoring the choice of specific portfolios, the initial capacities \( k_{i0} \) are assumed to be decision variables that can be adjusted in \( t = 0 \) without any cost. All the ABC-heuristics that will be discussed benefit from this flexibility so that it does not bias their relative performance.

3. Activity-based costing as a heuristic

In this section ABC is considered as a heuristic for the benchmark model. Two different ABC systems are distinguished. In the first system, termed simple ABC, the highest cost hierarchy established is the ‘\( x \)-level’. This means that simple ABC only considers those costs that can be traced to the specific decision of setting \( x_i = 1 \). For instance, when \( x \) is a decision on the firm’s suppliers then the system only accounts for the costs that can be traced to specific suppliers of the portfolio. The previous literature on the performance of ABC as a decision rule has focused on this form of ABC. However, as pointed out by Cooper (1990) it is consistent with the ABC framework to account for cost drivers corresponding to higher cost levels as well. Therefore the second system, termed extended ABC, accounts for the possibility of assigning overhead costs not only up to the \( x \)-level but also on the portfolio level. To this end an additional cost driver corresponding to the portfolio level is established.

3.1. Simple ABC

Suppose that the \( S \) resources in the benchmark model of Section 2 are overhead resources needed for the activities of a firm with \( c_{i} \) denoting the unit cost of providing resource \( s \). Furthermore, let us assume that \( j = 1, \ldots, J \) cost drivers are used to measure the activities to be performed by using the overhead resources.

Within ABC, for each cost driver \( j \) a cost driver rate \( \pi_j \) must be established showing the cost that is assigned for consuming one unit of cost driver \( j \). To determine \( \pi_j \), the capacity demand \( n_{js} \) of a cost driver unit for resource \( s \) has to be known. This knowledge is provided by an activity analysis. In general a particular activity \( j \) requires several resources giving

\[
\pi_j = \sum_{s=1}^{S} c_s \cdot n_{js}.
\]  

On the other hand, in calculating the activity-based cost of \( x_i = 1 \) \((i = 1, \ldots, I)\) one needs to determine the cost driver consumption triggered when setting \( x_i = 1 \). To be in line with the situation underlying the benchmark model, the activity-based costs are considered for the case that the capacity demand for all \( x_i = 1 \) is fulfilled. Let therefore \( M_{ijt} \) denote the overall consumption for cost driver \( j \) in period \( t \) with respect to \( x_i = 1 \), given that the capacity demand is fulfilled. Then for a planning horizon of \( T \) periods setting \( x_i = 1 \) causes activity-based costs of

\[
C_i^T = \sum_{i=1}^{T} \sum_{j=1}^{J} \pi_j \cdot M_{ijt}.
\]  

According to (13) overhead resource costs are proportionalized on the basis of the cost driver consumptions. Substituting (12) in (13) yields

\[
C_i^T = \sum_{i=1}^{T} \sum_{j=1}^{S} c_j \cdot \sum_{j=1}^{J} n_{js} \cdot M_{ijt}
\]  

for the activity-based cost of \( x_i = 1 \). The term \( \sum_{j=1}^{J} n_{js} \cdot M_{ijt} \) is the overall consumption of \( x_i = 1 \)
for resource \( s \) in period \( t \). Hence, considering the resources of the benchmark model as overhead resources to perform activities gives

\[
A_{ist} = \sum_{j=1}^{J} n_{ist} \cdot M_{ijt}
\]

for the consumption values \( A_{ist} \) in (2). Furthermore, over a planning horizon of \( T \) periods the activity-based cost for fulfilling the capacity demand for \( x_i = 1 \) turns out to be

\[
C^T_i = \sum_{s=1}^{S} \sum_{t=1}^{T} c_s \cdot A_{ist}.
\]

When no cost hierarchy higher than the \( x_i \)-level is established, ABC evaluates each \( x_i \) decision separately, i.e., the resource consumption of the remaining portfolio is ignored and overhead costs are proportionalized by (16). This results in the ABC-heuristic of setting \( x_i = 1 \) if and only if the difference between its contribution margin \( E_i^T \) and its activity-based costs \( C_i^T \), both taken over a planning horizon of \( T \) periods, is positive. Hence, using simple ABC yields the ABC-heuristic of determining the portfolio \( x = (x_i) \) by

\[
x_i = \begin{cases} 
1 & \text{if } E_i^T - C_i^T > 0, \\
0 & \text{otherwise.} 
\end{cases}
\]

Once the portfolio is fixed by the heuristic (17) the corresponding cost-optimal normal and short-term capacities \((k_{si} \text{ and } o_{si}, \text{ respectively})\) have to be determined for the planning horizon \( T \). This is done by solving the benchmark model (1)-(9) with \( x \) being set to the ABC-portfolio. As a result one gets the highest profit (1) that can be accomplished with the (sub-optimal) ABC-portfolio. Note that though according to (2) satisfying capacity demand is required there are no infeasible ABC-portfolios. Infeasibilities are avoided because the initial capacities \( k_{s0} \) in the benchmark model are defined as decision variables. Hence, to fulfill the ABC-portfolio’s capacity demand it is always possible to choose adequate initial capacities.

3.2. Extended activity-based costing

In the simple ABC-heuristic (17) the \( x_i \)-level is the only level on which overhead costs are allocated. However, it is consistent with the ABC framework to use cost drivers corresponding to higher cost levels, resulting in more sophisticated ABC-heuristic. In what follows the portfolio level is established as an additional cost hierarchy, allowing to account for the heterogeneity triggered by a portfolio. To this end a cost driver of the portfolio level is introduced. Being a measure of the portfolio’s heterogeneity this cost driver shows how well the resource demands caused by the various \( x_i \)-decisions fit together. Since in addition all previous cost drivers are taken into account with the same cost driver rates \( \pi_i \), the resulting ABC-heuristic is termed extended ABC in contrast to simple ABC (17).

In assigning a part of the overhead costs on the basis of a heterogeneity driver it is necessary to find an adequate measure of heterogeneity. In what follows the focus is on the portfolio’s heterogeneity with respect to the resource demand over the entire planning horizon. As will be shown, a suitable measure of the (resource demand) heterogeneity \( h(x) \) of a portfolio \( x = (x_1, \ldots, x_i) \) over the planning horizon of \( T \) periods is given by

\[
h(x) = \frac{\sum_{s=1}^{S} (c_s^+ + c_s^- + c_s^0 - c_s)}{\sum_{i=2}^{T} |\sum_{i=1}^{I} (A_{ist} - A_{ist-1}) \cdot x_i|}.
\]

The heterogeneity cost driver \( h(x) \) reflects that resource costs depend on the variation of the demand for all \( S \) resources over the entire planning horizon. The term \( \sum_{i=2}^{T} |\sum_{i=1}^{I} (A_{ist} - A_{ist-1}) \cdot x_i| \) in (18) measures the variation for a particular resource \( s \). Variations are summed over all resources, where the weighting factors \( c_s^+ + c_s^- + c_s^0 - c_s \) reflect that the demand variations for resources with high adjustment costs (\( c_s^+ \) and \( c_s^- \), respectively) and/or high additional costs for overtime (\( c_s^0 - c_s \)) are weighted relatively high.

The aim of establishing the cost driver (18) is to account approximately for those resource costs that are totally neglected when evaluating portfolios by the simple ABC-heuristic (17) where only cost drivers of the \( x_i \)-level apply. The exact overhead cost to be allocated by (18) on the portfolio level is the difference \( \Delta C(x) \) between the exact cost
function (1) calculated by solving the benchmark model with the portfolio being fixed to \( x \) and the activity-based cost (16) of the simple ABC-heuristic, also being calculated for a specific portfolio \( x \):

\[
\Delta C(x) = \frac{s}{s} \sum_{i=1}^{s} \sum_{t=1}^{T} \left( c_s \cdot k_{st}(x) + c_s^+ \cdot \alpha_{st}(x) \right) \\
+ \frac{s}{s} \sum_{i=1}^{s} \sum_{t=1}^{T} \left( c_s^- \cdot k^+_s(x) + c_s^- \cdot k^-_s(x) \right) \\
- \frac{s}{s} \sum_{i=1}^{s} \sum_{t=1}^{T} c_s \cdot A_{st} \cdot x_t.
\]  

To stay in the ABC framework one can only try to account for the heterogeneity cost \( \Delta C(x) \) by a linear cost function with the heterogeneity driver (18) being the argument. Therefore, a first question is whether at all a linear cost function makes sense. To analyze this question a linear regression with the heterogeneity driver \( D \) to account for the heterogeneity cost is whether at all a linear cost function makes sense. Therefore, a first question is whether at all a linear cost function with the heterogeneity driver (18) being the argument. Therefore, a first question is whether at all a linear cost function makes sense. To analyze this question a linear regression with the heterogeneity driver \( D \) to account for the heterogeneity cost is justified, the slope \( \pi_h \) of the linear regression line can be considered as a reasonable cost driver rate of heterogeneity. Within the extended ABC-heuristic the cost driver rate \( \pi_h \) is then the cost that is assigned to a portfolio \( x \) for one unit with respect to heterogeneity \( h(x) \) in (18).

The linear regression is based on the parameters of Table 1. To get a data base that covers a reasonable range of heterogeneity 10 patterns of consumption values are generated for each possible portfolio different to the ‘no-production case’ \( x = (0, \ldots, 0) \). This means that the data correspond to \( (2^6 - 1) \times 10 = 630 \) different sets of demand scenarios drawn from (10). For a given portfolio \( x \) defining a single resource demand scenario for all resources in all periods requires to draw \( \sum x_i \cdot S \) values for the \( x_i \) from the uniform distribution and \( \sum x_i \cdot T \) values for the \( \beta_n \) from the beta distribution.

After the demand scenario for a portfolio \( x \) has been generated, the demand heterogeneity \( h(x) \) is calculated according to (18). Furthermore the corresponding heterogeneity cost \( \Delta C(x) \) is calculated according to (19). Note that to determine \( \Delta C(x) \) one must determine the capacity adjustments which are optimal for fulfilling the demand triggered by portfolio \( x \). This requires to solve the benchmark model with the portfolio being fixed to \( x \). The bottom line are 630 data points each consisting of a heterogeneity value and the corresponding heterogeneity cost. The scatter diagram in Fig. 1 illustrates the outcome of the linear regression. It indicates that assuming linearity seems to be justified. Also, \( R^2 = 0.845 \) reveals an acceptable goodness of fit for the linear model. The slope of the linear regression line is \( \pi_h = 0.2261 \) (significant at the 0.05 level) and can be considered as the cost driver rate of heterogeneity.

Once the cost driver rate \( \pi_h \) for the heterogeneity driver \( h(x) \) is fixed, the calculus of the extended ABC-heuristic to determine the portfolio is given by

\[
\max_x \left( \sum_{i=1}^{I} (E_i^T - C_i^T) \cdot x_i - \pi_h \cdot h(x) \right),
\]

where the activity-based costs \( C_i^T \) of the \( x_i \)-level are given by (16). This calculus differs from the calculus of simple ABC in that a certain part of the overhead costs, \( \pi_h \cdot h(x) \), is allocated on the portfolio level. In contrast to (17) the calculus (20) evaluates \( x_i \)-decisions not only separately but also in their combined effects on overhead costs.

4. Comparison of simple and extended activity-based costing

Of course the extended ABC-heuristic (20) is more complex than the simple heuristic (17).
Hence, the question is whether the increased complexity incurred by using a cost driver like (18) is actually justified by improved profits. This question is analyzed by a simulation study in which demand scenarios are generated randomly according to (10) to compare the outcomes of the ABC decision rules and the outcome of the benchmark model. 

The following simulation runs are performed for the parameter values depicted in Table 1 specifying the base-situation with respect to the benchmark model (1)–(9). To analyze the performance of simple and extended ABC 100 runs are calculated with each run being based on different resource consumptions $A_{it}$ drawn from (10). A single simulation run requires to draw $I \cdot S = 18$ values for the $a_{it}$ from the uniform distribution and $I \cdot T = 30$ values for the $\beta_{it}$ from the beta distribution. As described above, the resulting ABC-portfolios are evaluated on the basis of the exact benchmark model (1)–(9) with the parameter values of Table 1. This yields 100 profit values for the ABC-portfolios suggested by (20) as well as 100 profit values for the ABC-portfolios suggested by (20). The profits account for the minimum resource costs triggered by the portfolios since they are calculated by solving (1)–(9) with the portfolios being fixed to the ABC-portfolios. Furthermore, within each run the benchmark model is solved optimally, i.e., without setting $x$ to any pre-specified portfolio, yielding 100 benchmark profits. 

It turns out that for the base-situation of Table 1 accounting for heterogeneity in evaluating portfolios yields a considerable improvement of ABC. By using the extended calculus (20), the mean relative profitability loss is only 1.28% (significant at the 0.001 level) instead of 10.04% (significant at the 0.001 level) for the simple calculus (17). Thereby the difference between the relative profitability losses of the two decision rules is significantly different from zero (significant at the 0.001 level). Note that since the firm is assumed to have perfect information, the profitability losses hold for the expected value of perfect information associated with the ABC heuristics as compared to the benchmark model (1)–(9). 

To use the extended ABC decision rule (20) one first must determine a cost driver rate $\pi_h$ evaluating the heterogeneity $h(x)$ of a portfolio $x$. Within the simulation study $\pi_h$ is set to 0.2261. As explained above, this value is calculated by a linear regression with data being generated on the basis of model (1)–(9) using the parameter values of Table 1. However, in practice neither model (1)–(9) nor all the parameter values will be known precisely. Hence, one will have to estimate $\pi_h$ on the basis of past data, generally yielding a cost driver rate different to the one calculated as described above. Therefore, the extended ABC decision rule is analyzed in the best possible light assuming that a good estimate for $\pi_h$ is available. This assumption seems to be justified since the focus of the investigation is on the potential of using a portfolio-level cost driver for decision making. 

For the base-situation of Table 1 the extended ABC-heuristic shows a significantly better performance than the simple ABC decision rule. Before generalizing this result further simulations based on different parameters are necessary. First, the performance of the two ABC-heuristics is evaluated in light of different overtime costs. For all $S = 3$ resources, overtime costs are increased simultaneously from the $c_s$ values of Table 1 (no additional cost for overtime) to $c_s^o + (c_s^o - c_s)$ (twice the additional cost of Table 1). Specifically overtime costs are modified according to 

$$c_s^{o'} = c_s^o + \delta \cdot (c_s^o - c_s), \quad s = 1, 2, 3, \quad \text{where} \quad \delta = -1, -0.8, -0.6, \ldots, 1.$$ 

Obviously, $\delta = -1$ means a 100% reduction of the additional overtime cost. Hence for such a reduction one has a maximum resource flexibility allowing to provide short-term resources for the price $c_s$ of normal resources. Notice, that when cost parameters are changed, the cost of heterogeneity changes too. Hence, for $\delta \neq 0$ the cost driver rate of $\pi_h = 0.2261$ calculated for the base-situation of Table 1 becomes obsolete. Therefore before calculating 100 runs for each $\delta$ individual cost driver rates corresponding to heterogeneity $h(x)$ (s (18)) are determined. The way in which $\pi_h$ is updated for each $\delta$ is the same as described above (linear regression with data generated from 630 different scenarios) except that the new overtime costs $c_s^{o'}$ apply.
Fig. 2 illustrates the impact of overtime costs on the quality of the heuristics relative to one another and relative to the benchmark provided by the optimal solution to model (1)–(9). It turns out that the quality of extended ABC relative to the benchmark is much more robust against increasing overtime costs than the quality of simple ABC. The reason for this observation is that accounting for the heterogeneity cost driver \( h(x) \) (s (18)) allows to fit the extended ABC-heuristic to a change in overtime costs. In contrast, the simple ABC decision rule does not at all react to increased overtime costs. Therefore when the flexibility of adjusting capacities is reduced due to increased overtime costs, the relative optimality gap of the simple ABC-heuristic (17) tends to increase while the relative optimality gap of the extended ABC decision rule (20) remains almost constantly low. When no additional overtime costs apply (\( \delta = -1 \), i.e., \( c_s^{\prime\prime} = c_s \)) both heuristics yield the same performance which, in this special case of an extreme resource flexibility, is identical to the benchmark performance. With overtime costs passing a certain bound (\( \delta \geq 0 \), i.e., \( c_s^{\prime\prime} \geq c_s^{\prime} \)) the simple ABC decision rule does no longer show a clear trend in terms of its relative performance. The reason for this is that with overtime costs becoming extremely high this instrument becomes unattractive for fulfilling demand. Hence, with an optimal resource management, overtime is nearly no longer used so that an additional increase in overtime cost does not have much impact on the relative performance of ABC.

Fig. 3 shows similar results for varying costs \( c_s^{+} \) and \( c_s^{-} \) of medium-term capacity adjustments. The rules according to which the relevant cost parameters are modified (simultaneously) are given by

\[
\begin{align*}
c_s^{+\prime\prime} &= c_s^+ + \delta \cdot c_s^+; \quad s = 1, 2, 3, \quad \text{and} \\
c_s^{-\prime\prime} &= c_s^- + \delta \cdot c_s^-; \quad s = 1, 2, 3,
\end{align*}
\]

where \( \delta = -1, -0.8, -0.6, \ldots, 1 \).

In interpreting Fig. 3 one has to notice that \( \delta = -1 \) means \( c_s^{+\prime\prime} = c_s^{-\prime\prime} = 0 \), i.e., resources are highly flexible. While simple ABC performs only well when resources are flexible (low \( \delta \)), the extended ABC-heuristic shows a considerable robustness with respect to different resource flexibilities. Its performance tends to decrease only slightly with higher adjustment costs (higher \( \delta \)). In contrast the optimality gap of simple ABC increases extensively.

Finally, Fig. 4 analyzes the influence of the extent to which capacities can be adjusted from one period to another. The corresponding parameters are varied according to

\[
\begin{align*}
v_s^{+\prime\prime} &= v_s^+ + \delta \cdot v_s^+; \quad s = 1, 2, 3, \\
v_s^{-\prime\prime} &= v_s^- + \delta \cdot v_s^-; \quad s = 1, 2, 3,
\end{align*}
\]

where \( \delta = -1, -0.8, -0.6, \ldots, 1 \).

While for \( \delta = -1 \) it becomes impossible to adjust resources (except through overtime), \( \delta = 1 \) means that from one period to another resources can be decreased or increased by 100% (i.e., \( v_s^{+\prime\prime} = 2v_s^+ = 1 \) and \( v_s^{-\prime\prime} = 2v_s^- = 1 \)). Hence, the higher \( \delta \) the more flexible are the resources and the
better the simple ABC-heuristic (17) tends to perform relative to the benchmark. In contrast the extended ABC-heuristic (20) shows an acceptable performance more or less independent of the resource flexibility.

To check the robustness of the results additional sensitivity analyses were performed. For instance, resource consumptions (10) were drawn from left-skewed and right-skewed beta distributions (form parameters \( (2, 4) \) and \( (4, 2) \), respectively, with unchanged support \( [50, 250] \)). Also, further scenarios in terms of the resource flexibility and cost parameters were examined. However, none of these configurations led to substantial changes in the qualitative results of the simulation study. Therefore a detailed report is not given.

In addition, heterogeneity drivers different to (18) were investigated to reflect the demand heterogeneity of a portfolio over the planning horizon. Several drivers were able to provide acceptable linear approximations for the heterogeneity costs \( \Delta C(x) \) in (19). Yet, the driver (18) performed best and was therefore chosen for the extended ABC-heuristic (20). Note that (18) measures demand heterogeneity \( h(x) \) of a portfolio over all \( S \) resources. It turned out, however, that using \( S \) separate heterogeneity drivers by establishing (18) for each resource separately, i.e., without summing over the resources, could not significantly improve the performance of the extended ABC-heuristic (20). Therefore the aggregate heterogeneity driver (18) requiring only a single cost driver rate \( \pi_s \) seemed to be appropriate.

5. Concluding remarks

The investigation focused on analyzing the performance of ABC for determining the portfolio when overhead resources are not perfectly flexible. A mixed-integer program reflected the inflexibility of overhead resources precisely and provided an adequate benchmark throughout the investigation. It turned out that the severe linearity assumption of ABC can result in a significant optimality gap. This gap increases with a decreasing flexibility of the involved overhead resources. These results are in line with previous investigations on ABC performance.

However, in evaluating ABC as a heuristic to make portfolio decisions previous research has not used all the opportunities provided by the ABC framework. Rather, ABC was reduced to a simple cost system though it is one of the major points of ABC to use complex cost drivers as well. Hence, the primary finding of the investigation is that implementing higher-level cost drivers might improve the quality of ABC as a heuristic considerably. The reason for this is that higher-level cost drivers are able to adequately reflect interdependencies by a linear approximation. In particular only higher-level cost drivers allow to adjust an ABC decision rule to a change in the flexibility of overhead resources. In contrast, within simple ABC major interdependences are neglected completely, often resulting in an unacceptable optimality gap.

Of course, generalizing the results of the investigation is an issue. The simulations are based on simplified scenarios which will not precisely reflect the situation of a real-world firm determining its portfolio. None the less, the results provide some insight as to the quality of ABC for decision making. In particular, extensive sensitivity analyses indicate that it is important to account for higher-level cost drivers whenever the resource flexibility becomes an issue. Before using simple ABC a manager should therefore have a clear understanding of the importance of capacity adjustments for the problem at hand.

In practice, proportionalizing overhead costs is not the only approximation ABC is making use of. For instance, the number of cost drivers of an
ABC-system plays an important role (see, e.g., Babad and Balachandran, 1993; Schniederjans and Garvin, 1997). An ABC-system of low complexity, such as a system with a small number of cost drivers, is not only easier to handle but also easier to understand by management (see, e.g., Merchant and Shields, 1993). Therefore, in many practical situations the cost drivers do not yield an accurate explanation of the utilization of overhead resources. However, these approximations were out of the scope of the paper. The focus was on the sub-optimality resulting when the proportionalization of overhead costs is the only approximation underlying the ABC system. It seems to be an interesting next step to analyze how ABC decision rules perform when several approximations apply.

References


