

2. Simulation research framework

For this thesis, a simulation approach is used as opposed to analytical models or empirical methods such as survey or archival data. This chapter pursues three goals: Laying a common understanding of simulations, discussing the adequateness of the approach in the field of management accounting research and introducing a research framework to conduct simulation based experiments.

2.1 A basic introduction to simulations

This thesis follows the simulation definition by Kleijnen (2015), defining a simulation model as “a mathematical model that is solved by means of experimentation” and further relates to simulations solved by means of computer algorithms.⁹ Hence, a simulation experiment in the scope of this definition can be synonymously seen as a computer experiment. Kleijnen (2015) further differentiates between deterministic vs. random and static vs. dynamic experiments. In contrast to deterministic models, random models incorporate variables based on probability functions. Dynamic models differ from static simulations in modelling time as an independent variable. Both characteristics can be mixed, e.g. a random, static or a deterministic, static model. The term random needs to be explained in detail. Since computer algorithms are deterministic, they are incapable of creating random numbers.¹⁰ Therefore, the terms pseudo random numbers and pseudo random number-generators (PRN) are used. Without laying down the concrete methodology of PRNs, a “good” quality of a PRN is measured upon its capability to generate, firstly uniform, i.e. equally probable and secondly

⁹ Kleijnen (2015), p. 4.

¹⁰ It should be noted that by the usage of externally applied devices, e.g. measuring radioactive decay, true random number series could be used. The problems are the partially unknown and most-probably not fitting probability distributions, as well as the time to create a fitting series of random numbers, since many of these appliances create random events only by several years. See Niederreiter (2003), p. 2.

independent numbers, meaning that there is “no” relation between drawn values. There exist various generators fitting both prerequisites.¹¹

Even deterministic simulations may incorporate (pseudo-)random components and underlie random effects.¹² While the underlying optimization function itself includes only non-random inputs at the time of optimization, the used solver and the input itself can lead to uncertain results. This is the case, when the solution can only be found by approximate procedures and/or the inputs are generated by PRNs.¹³

A simulation is usually embedded in a decision context. Schneeweiß (1992) abstractly models such a decision context, distinguishing between a real world problem, an abstracted real model and a decision generator.¹⁴ A real world problem could be a planning context of a firm. A real model would abstract from this complex problem, e.g. uncertain effects would be modelled by PRNs. The underlying probability distributions of such generators and further simplifications would be evaluated by empirical tests against the real world problem. Since the real model is most likely still not solvable by quantitative measures, a further relaxation – in other words a second simplification – leads to the decision generator. Such a relaxation could be the usage of opportunity costs instead of modelling capacity constraints.¹⁵ Such a decision generator could be implemented as a simulation, solving e.g. an optimization problem. The simulation itself follows an input-process-output model.¹⁶ The simulation input usually consists of parameters to steer the simulation variables, e.g. environmental conditions as firm size, inflation, product range etc. The parameters control hereby the sampling of values from a prior defined distribution function. The process stage is the execution of the simulation yielding the simulation output. It encompasses the relaxed model, which in this case could be based upon a quadratic

¹¹ See Gentle (2003), p. 63.

¹² See Picheny et al. (2013), p. 3.

¹³ See Kleijnen (2015), p. 4.

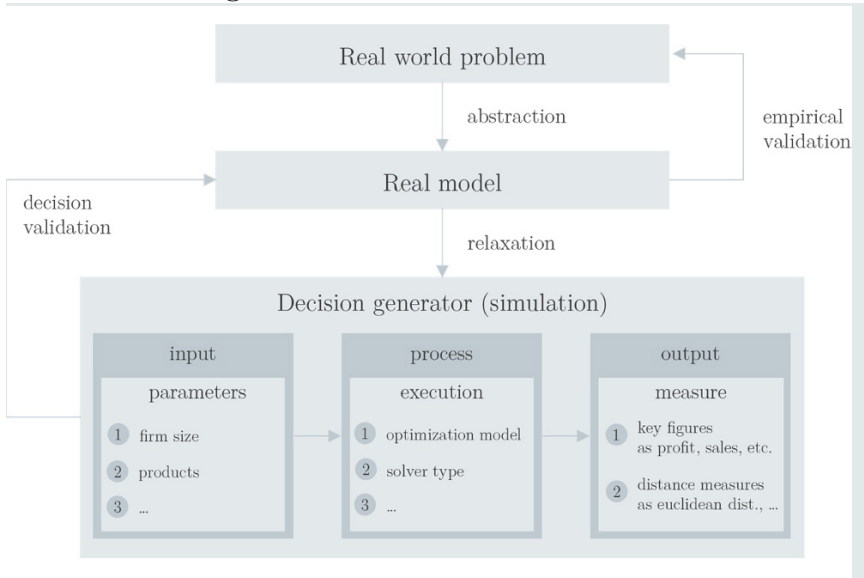
¹⁴ See also Schneeweiss (2003) for an example of an abstract decision model.

¹⁵ See Homburg (2001b), pp. 51 and 52.

¹⁶ See Hocke, Meyer and Lorscheid (2015), p. 141.

optimization function and a suitable solver. For a given combination of parameters, the underlying model is then subsequently solved. In the introduced planning context, a relaxed model could be a firm's portfolio and pricing decision based on opportunity cost. The decision could be whether to produce, out of two products (a , b), both or only one product (a or b) and the respective quantities based on a given product price. The yielded output would be the profit for each portfolio combination. According to a set of environmental parameters, one is now able to take a decision on the portfolio question, i.e. take the portfolio with the highest profit. The decision would subsequently be validated against the real model. Referring to the relaxation example of using opportunity costs instead of capacity restrictions, it needs to be checked whether the underlying firm has the capacity and the resources needed to produce the portfolio and the respective quantities.

Figure 1: Abstract simulation model



Based on Schneeweiß (1992), p. 4 and Hocke, Meyer and Lorscheid (2015), p. 141.

In addition, the prices set in the simulations could be challenged against market prices, to ensure that such prices would be accepted by customers.

Figure 1 illustrates the previously defined abstract model of a simulation in a decision context. The illustration of the decision generator will be used as a template for the simulation models in chapters 3 and 4.

2.2 On the adequacy of simulations in management accounting research

A comprehensive overview and an analysis of the impact of simulation research in management journals is provided by Harrison et al. (2007) or Reiss (2011). On one hand, both surveys indicate that on average over 10 years only up to 8 percent of the published articles in the evaluated management journals are based on simulations.¹⁷ Labro (2015) critically states that an important factor of the low usage of simulations in management accounting literature, is the general “unfamiliarity of the readership (and of journal editors, and sometimes even referees) with simulation methods”.¹⁸

On the other hand (Balakrishnan and Sivaramakrishnan (2002); Harrison et al. (2007); Reiss (2011); Labro (2015)) highlight the benefits of simulations, especially “because organizations are complex systems and many of their characteristics and behaviors are often inaccessible to researchers, especially over time, simulation can be a particularly useful research tool for management theorists”.¹⁹ In regard to this thesis, Labro's (2015) argument, that particularly by lacking internal information of a company, simulations offer a valuable research alternative, weighs the most: Cost allocation and internal cost data are not as accessible as e.g. external accounting figures

¹⁷ See Reiss (2011), p. 246: The proportion of publications using “simulation” or “simulate” either in title or abstract in the field of economic literature for 2005 was less than 3%.

¹⁸ Labro (2015), p. 5.

¹⁹ Harrison et al. (2007), p. 1243.

provided by various databases such as COMPUSTAT²⁰ or I/B/E/S²¹.

In addition, Balakrishnan and Penno (2014) discuss the role of analytical models and the advantages of numerical experiments. They also conclude that simulations belong to the managerial research toolkit, enabling research where analytical approaches are limited. They stress that this might be more useful than a literature based analysis of reality. The biggest advantage they see is that simulation and numerical computation are able to scale: They show that the number of models grow exponentially with the amount of model factors.²² Hence, given a certain degree of complexity only computational solutions are applicable.

At the same time, this complexity seems to be one of the root causes for the low leverage of simulations. The complexity of such models (numbers of input parameters / variables, justification of variable manifestations, i.e. variable values, statistical distributions, etc.) and the vast output of data tends to mislead research: Labro (2015) states that research tends to go for trees instead of the wood. Each step (input, process, and output) needs to be planned, documented and objectified. Shortcomings in these activities may lead to misunderstandings or rejection of the research method.²³

There exist various different frameworks (e.g. Sacks et al. (1989); Santner, Williams and Notz (2003); Lorscheid, Heine and Meyer (2012); Kleijnen (2015)). A central method discussed in all approaches is the design of experiments (DOE) framework, which was introduced for farming experiments in the early 20th by Ronald Aylmer Fisher.²⁴ It typically consists of planning, designing, conducting and analyzing phases to structure

²⁰ Standard & Poor's COMPUSTAT contains financial and price data for active and inactive publicly traded companies.

²¹ The Institutional Brokers' Estimate System (I/B/E/S) by Thomson Reuters encompasses mostly (earnings) forecasts.

²² See Balakrishnan and Penno (2014), p. 532.

²³ See Labro (2015), pp. 3–4.

²⁴ Fisher documented his approach in his book “The Design of Experiments”, see Fisher (1935).

experiments, thereby trying to ensure the quality of experimental data.²⁵ Whereas Kleijnen (2015) argues that physical experiments differ essentially from computer experiments and calls for a new approach, Sacks et al. (1989) argue that DOE can be applied to computer experiments for two reasons. First, the choice of simulation input is a design question comparable to DOE. Second, the statistical methods applied to physical experiments are also applicable to computer experiments.²⁶ Lorscheid, Heine and Meyer (2012) extend DOE for computational experiments. Their approach has been chosen deliberately, since the most influential and related research articles leading to this thesis can be structured and thus compared on the basis of the their extended DOE process.²⁷

The preceding discussion underlines the necessity to use a standardized and structured approach to enable easier access to the research method and a sound understanding of the simulation process. The discussion revealed that by using DOE the drawbacks of simulations can be mastered and the research method is applicable.

2.3 The underlying research framework

Lorscheid, Heine and Meyer (2012) consider simulations as a state of the art methodology. As introduced in the last section, they develop a methodology to overcome these obstacles based on the systematic design of experiments. Their abstract framework is the subject of this chapter and will be used subsequently in the research chapters (3 & 4).

In general Lorscheid, Heine and Meyer (2012) follow the typical DOE setup but additionally in their approach, each step is linked to either a central objective, which the respective simulation approach can be benchmarked

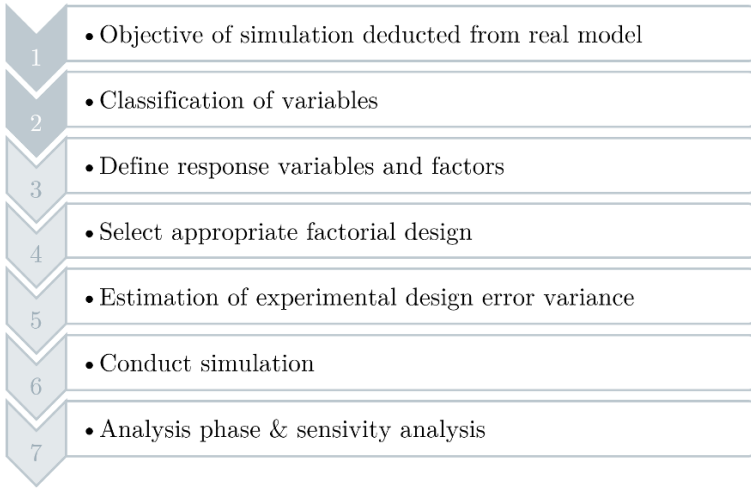
²⁵ See Antony (2014), p. 40.

²⁶ Sacks et al. (1989), p. 411.

²⁷ See Hocke, Meyer and Lorscheid (2015), evaluating among others Labro and Vanhoucke (2007) and Balakrishnan, Hansen and Labro (2011).

against or it is linked to a (statistical) method, used to objectify the experimenter's considerations.

Figure 2: DOE design process



Based on Lorscheid, Heine and Meyer (2012), p. 30.

In this thesis the approach is, as introduced in the previous chapter, embedded into the decision generator model by Schneeweiß (1992). The adjusted DOE design by Lorscheid, Heine and Meyer (2012) as illustrated in Figure 2 consists of the following:

- (1) The process of abstraction and relaxation of the real model by Schneeweiß (1992) already takes into account a considerable feedback mechanism to align the decision generator or more precisely enable the simulation to solve the given problem. In addition, Lorscheid, Heine and Meyer (2012) consider theoretical model behaviors such as performance and possible model configurations in their first process step. As stated before, the variety of parameters is positively correlated with the complexity of the model. Hence, the research should focus only on reduced and value creating parameter sets. For the illustration of the adjusted DOE process, let us come back to our portfolio

optimization problem. As illustrated in Figure 1, firm size is such a possible parameter. It needs to be decided if this is a parameter for the simulation, or if it can be neglected because it does not add any insights to the subsequent analysis.

- (2) In line with Field and Hole (2003), Lorscheid, Heine and Meyer (2012) see a major advantage in the clustering of variables into dependent, independent and control variables. The dependent variables are the variables of interest. The whole purpose of the simulation is to measure these variables, hence they represent the simulation output. The independent variables should drive the relevant effect on the dependent variables, whereas control variables rather have minor or no effect at all. Additionally control variables are usually not linked to the research question. Independent and control variables are steered via the input parameters of the simulation. To continue with the previously introduced market variable example, consider a parameter, by which the experimenter is able to switch between an initial market size of small, medium and large markets.
- (3) The third step includes the transformation of dependent and control variables into factor levels, depending on how the respective variable was modelled in step 2. A possible example could be a market maturity variable, which could be transformed into two factor levels for saturated and growing markets.
- (4) The factorial design reflects the possible factor level combinations with the simulation, taking into account also interactional effects between factors.²⁸ Following Box, Hunter and Hunter (1978) factorial design can be separated in full and fractional. A fractional design limits the degree of interaction between factors. Usually main effects outweigh two-factor effects, and subsequently two-factor effects outweigh three-factor effects and so forth. The idea therefore is to focus only on the important effects.²⁹ Lorscheid, Heine and Meyer (2012) propose that

²⁸ The term „factorial design“ originates back to Fisher (1935), arguing that experimenters should focus on isolated, elementary factors in an experiment and laying out a structured approach to design experiments.

²⁹ See Box, Hunter and Hunter (1978), p. 374.

the experimenter should use design points – a minimum set of factor levels – for each factor defined in step 3.³⁰

A full-factorial experimental design can be coded as l levels to the power of k factors.³¹ A common approach is to indicate a high level of a factor as “+” and his low level as “–” respectively. If more than two levels are used, additional levels are subsequently coded as “+ +” or “– –”. If the number of parameters is uneven, “o” indicates the level between “-” and “+”. The signs do not necessarily indicate an order of levels, but an indicator of levels, to better separate the levels.

By limiting these factors the model complexity can be reduced, also aiding the runtime of the simulation, because each level combination equals at least one simulation run.

Each iteration to solve the underlying model is also referred to as a “run”. Assuming each run is very time consuming (e.g. 30 minutes), a design resulting in a total of e.g. 6 factors each having 2 levels would accumulate to a total of at least 2 to the power of 6 combinations, taking aside multiple runs of the same combination to control for stochastic effects. This would mean the complete simulation would last for at least 32 days.³² Interaction effects between factors would increase the complexity exponentially.³³ Usually a 2-factor design is a good starting point to obtain a first data-set. From this sparse data-set one is able to decide whether factors are important or if they could possibly be neglected. Computational power is a curse and a savior at the same time. Even if a computer-based simulation can handle high varieties of input factors and model parameters, the size of resulting datasets may become a problem (datasets easily exceed many gigabytes limiting statistical analysis). Additionally, the vast numbers of possible data slices and subsets may add more confusion, than understanding, of the underlying problem.³⁴

³⁰ See Lorscheid, Heine and Meyer (2012), pp. 32–33.

³¹ See Antony (2014), p. 63.

³² 32 days = 2^6 combinations * 30 minutes. See Kleijnen et al. (2005), p. 274 for further considerations on efficiency of simulations.

³³ See Sacks et al. (1989), p. 418, stressing that the high cardinality of input factors and interactions needs to be addressed to achieve efficient design and analysis.

³⁴ Labro (2015), p. 4.

- (5) This step aims at measuring the design error: As stated earlier the usage of PRNs and approximate solutions may lead to an unwanted variance in results. To control for this effect, multiple runs by stable inputs need to be conducted. Together with the initial 2-factor design, this leads to a first idea of necessary total simulation runs. A metric to identify the best tradeoff between variance and simulation runs, is considered to be the *coefficient of variance*.

$$CV = \frac{s}{\mu} \quad (1)$$

The *CV*, calculated by dividing the standard deviation (s) by the mean of the simulation results (μ), is measured for a small set of simulation runs. Subsequently the number of runs is raised until the *CV* stabilizes.³⁵

- (6) Having defined design points in the former steps and chosen a fitting number of simulation runs to control for experimental variance, step 6 considers conducting the simulation, where each design point equals a separate experiment.
- (7) The final step is the analysis, incorporating sensitivity tests of input parameters. This is achieved by comparing the yielded data for each design point to choose a final set of factors for the experiment and to illustrate the sensitive behavior of the simulation itself. Lorscheid, Heine and Meyer (2012) focus on the application of analysis of variance (ANOVA) for this task.³⁶

Based on these findings, adjustments of the model could lead to an iterative procedure of adjusting level choices in step 4. This would also include, adjusting the 2-factor design to a multi-factor design. Coming back to the planning example it could be beneficial to control for more than two levels of market maturity. Santner, Williams and Notz (2003) lay special focus on the analytical methods and robustness tests. The

³⁵ See Lorscheid, Heine and Meyer (2012), pp. 33. They also discuss the downsides of the *CV* application.

³⁶ See Lorscheid, Heine and Meyer (2012), p. 35.

authors suggest using descriptive tests and regression modelling next to ANOVA.³⁷ This thesis will focus on the first two methods.

2.4 Relevant simulation models in management accounting – A theory review

Whereas DOE lays the foundation for a sound understanding of the methodical approach, the understanding is best supported by non-abstract ‘real-life’ examples. As a counterpart to the methodical introduction of the last chapter, the proceeding discussion of selected simulation approaches should foster the understanding of the implementation of simulations.

In a way the fundament for state of the art simulations in the field of management accounting has been laid by Balakrishnan and Sivaramakrishnan (2002). The authors investigate a basis model upon which future research can build its simulations and formulate research questions taken up by Balakrishnan, Hansen and Labro (2011); Anand, Balakrishnan and Labro (2013) and this thesis respectively. Since these articles also create the foundation for the developed model in chapter 3 & 4, they are presented subsequently in detail.

2.4.1 The Grand Model

Balakrishnan and Sivaramakrishnan (2002) analytically deduct their ‘grand model’ for a joint decision upon optimal prices and capacity in an iterative approach. **In short**, with each iteration they extend a basic profit optimization model. The starting point is a simple one-period model, only adjusting the produced quantity based on given prices and variable costs and within the constraints of a given demand and a given capacity. The next extension replaces the given demand, by a demand function dependent on price and price-elasticity. The third extension introduces capacity on a need basis, hence in addition to the given capacity, more expensive flexible capacity can be purchased. The fourth extension enables planning for a

³⁷ See Santner, Williams and Notz (2003), pp. 199.

multi-period instead of a one-period setting. While all prior extensions used a deterministic optimization function, the grand model adds a stochastic demand, therefore implementing imperfect information on market behavior.³⁸

The grand model derivation by Balakrishnan and Sivaramakrishnan (2002) **in detail**: In this thesis the indexes i , j and t will be used consistently to indicate products ($i \in I$), resources ($j \in J$) and time ($t \in T$), capital letters indicating the total of units.

The fundament for all succeeding models is **model 1**: Prices (P_i) are dictated by the market thus the firm is focused on optimizing production output (Q_i), given a positive marginal income ($P_i - v_i$), v_i being the variable costs per product:

$$\begin{aligned} & \max_{Q_i} \sum_{i=1}^I (P_i - v_i) Q_i \\ & \text{subject to } \sum_{i=1}^I m_{ij} Q_i \leq L_j \quad \forall j \\ & 0 \leq Q_i \leq D_i \quad \forall i \end{aligned} \tag{2}$$

See Balakrishnan and Sivaramakrishnan (2002), p. 9.

Setting focus on modelling **demand** and **capacity**: In this model, the simplest way to implement demand (D_i) and capacity (L_j) has been chosen, both being fixed. Obviously, a company's production output (Q_i), is only limited by demand and supplied capacity.³⁹ The link between quantity and capacity is modeled by the resource consumption matrix (m_{ij}), which maps

³⁸ See Balakrishnan and Sivaramakrishnan (2002), p. 13.

³⁹ Presuming an absence of stock keeping of inventories.

the needed resources j for a product i . The needed resources $Q_i m_{ij}$ must not exceed supplied resources L_j .

$$D_i = A_i - b_i P_i \quad (3)$$

By focusing on a monopolistic setting, the given company becomes a price setter and is thus able to adjust the **demand** (D_i): As illustrated in eq. (3) the demand is now modeled as a function of market size (A_i), price elasticity (b_i) and price (P_i).⁴⁰ Price elasticity is the responsiveness of demand on price changes. In this thesis only non-luxury goods are considered, hence an increase in prices directly decreases the demand.⁴¹

By modeling the demand as time-dependent (A_{it}) the question arises, whether the firm has complete knowledge of the demand throughout the planning horizon. The final evolution of the demand function is therefore to incorporate demand uncertainty, expressed by an error term ε_{it} . The error term offsets the expectations of the firm per product and period (see Table 1).

Capacity (L_j) – being the resources supplied – has been neglected as a decision variable so far. Taking a multi-period setting into account Balakrishnan and Sivaramakrishnan (2002) further distinguish between two terms of capacity: long-term capacity (L_j) and capacity on a need basis (R_{jt}). Long-term capacity is available throughout the complete planning horizon (T -periods), whereas short term capacity is only build up and available for period t .

⁴⁰ See Balakrishnan and Sivaramakrishnan (2002), p. 10.

⁴¹ See Mankiw and Taylor (2006), p. 88.

Table 1: Evolution of models (cont'd)

Evolution steps	Demand	Capacity
Initial model	$\max_{Q_i} \sum_{i=1}^I (P_i - v_i) Q_i$	$\sum_{i=1}^I m_{ij} Q_i \leq L_j \quad \forall j$
<ul style="list-style-type: none"> Translates from quantity to demand Demand depends on prices 	$\Rightarrow D_i = A_i - b_i P_i$	
<ul style="list-style-type: none"> Time-dependency Resource costs Differentiate between long- and short-term capacity 	$\Rightarrow D_{it} = A_{it} - b_i P_{it}$	$L_j \begin{cases} \nearrow T \sum_{j=1}^J c_j L_j \\ \searrow \sum_{t=1}^T \sum_{j=1}^J c_j \phi_j R_{jt} \end{cases}$
<ul style="list-style-type: none"> Demand uncertainty 	$\Rightarrow D_{it} = A_i + \varepsilon_{it} - b_i P_{it}$	
\Rightarrow Grand Model:		
$\max_{P_{it}, R_{jt}, L_j} E \left[\sum_{t=1}^T \left(\sum_{i=1}^I (P_{it} - v_i) (A_i + \varepsilon_{it} - b_i P_{it}) - \sum_{j=1}^J \phi_j c_j R_{jt} \right) \right] \quad (4)$ $- T \sum_{j=1}^J c_j L_j$		
$\text{subject to} \quad \sum_{i=1}^I m_{ij} (A_i + \varepsilon_{it} - b_i P_{it}) - R_{jt} - L_j \leq 0 \quad \forall j, t$		
$(A_i + \varepsilon_{it} - b_i P_{it}) \geq 0 \quad \forall i, t \quad (5)$		
$P_{it} \geq 0 \quad \forall i, t.$		

Table 1: Evolution of models (cont'd)

Decision variables:		Non-decision variables:	
P_{it}	Price for product i in period t	A_i	Market size per product i and period t
		$D_i/(D_{it})$	Demand per product i (and period t)
		$Q_i/(Q_{it})$	Quantity per product i (and period t)
L_j	Initial long-term capacity for resource j (available every period)	ε_{it}	Error term per product i and period t
R_{jt}	Flexible short-term capacity for resource j and period t	b_i	Price elasticity of product i
		v_i	Variable cost of product i
		c_j	Resource costs of resource j
		ϕ_j	Premium price for one capacity of unit j
		m_{ij}	Resource consumption matrix for product i and resource j

See Balakrishnan and Sivaramakrishnan (2002), p. 13.

In this setting both resources become decision variables, since an optimal trade-off between initial setup of resources, in other words the capital employed over the planning horizon and short term investments, due to a heterogeneous demand needs to be found. Now being part of the decision context, capacity costs are no longer sunk.

Therefor resources (j) need to be valued by a cost-price of c_j , identical for short- and long-term resources. Since short-term capacity needs to be purchased on a need basis, a cost-price premium of $\phi_j > 1$ needs to be paid. The premium reflects additional costs, such as higher rates for interim staffing or renting/leasing of production facilities over time. Additionally, a lack of price premium or a premium factor of one, would lead to investments

only in short-term capacity.⁴² The grand model (see eq. (4)), in comparison to its deterministic predecessors, no longer maximizes the profit itself, but its expectation.⁴³ Table 1 illustrates the evolution steps from initial to grand model.

The advantage of the grand model is that it can be decomposed into different models and planning scenarios. This is leveraged by Balakrishnan and Sivaramakrishnan (2002) to analytically identify the economic loss of simplified planning approaches in comparison to the grand model. They address simplifications such as separating capacity and price planning, using full costing for capacity approximation, and modeling either hard- or soft-capacity constraints. They also indicate that simulations may enrich the understanding of open research questions such as the influence of cost-pool and cost-allocation design on capacity and pricing issues.

2.4.2 Cost Model

Balakrishnan, Hansen and Labro (2011) take up the idea of investigating the influence of cost-system design on the error of reported costs. The basic idea is to compare a company having full information on cost-consumption with entities only using approximations of the real cost-consumption by products.

In general, full costs of a product can be calculated as the sum of variable costs (v_i) and the costs of consumed capacity ($\sum_{j=1}^J m_{ij}c_j$).⁴⁴ In the context of Balakrishnan, Hansen and Labro (2011), the central variables are the resource consumption matrix (m_{ij}) and the corresponding cost vector (c_j). In the following, variable costs are neglected. Therefore, following Balakrishnan, Hansen and Labro (2011) the term product cost (PC) is used.

⁴² See Banker and Hughes (1994), p. 481.

⁴³ See Balakrishnan and Sivaramakrishnan (2002), p. 13.

⁴⁴ See Balakrishnan and Sivaramakrishnan (2002), p. 14.

In an ideal world, a company has full information on resource consumption and resource costs. In reality both information are biased (see Table 2, as indicated by the index $bias$ for $m_{ij}^{bias} / c_j^{bias}$). The impact of partial and/or biased information on cost reporting, in theory, the delta between both product costs, unbiased (BM) and biased, indicates the quality of an implemented cost system design (see eq. (6) in Table 2).

Where does the bias come from? Naturally, cost systems lack complete information on resource consumption and therefore use algorithms to apply (activity) costs to products. Hence, the resulting product costs are only approximate. In other words, inherit sources of erroneous cost allocation. Cost systems classically use two stage cost allocation processes: on the first stage, costs are allocated to cost pools. On the second stage, the costs accumulated on these pools are allocated to products. The effectiveness of such cost systems is limited by aggregation, measurement and specification errors while pooling and allocating costs.⁴⁵

Aggregation errors usually originate from failures on first layer, i.e. pooling wrong resources into the same cost pools. Specification errors occur on both levels, based on cost driver rates not reflecting the consumption pattern of resources. That could for example be the usage of the labor cost rates for energy overhead, when both are possibly not interrelated. Measurement error – as the last error group – is straightforward: while setting up rates for cost allocation, wrong assumptions of the amount of resource/activity usages are made. E.g. storing inventory lasts not 10 but 15 minutes. If the allocation of overhead costs was based on these time assumptions, the reflected costs would not meet actual process usage.⁴⁶


There exist different basic cost system designs (volume based costing, activity based costing, resource based costing, etc.).⁴⁷

⁴⁵ See Datar and Gupta (1994), p. 568.

⁴⁶ See Labro and Vanhoucke (2007), p. 941.

⁴⁷ See Balakrishnan, Labro and Sivaramakrishnan (2012a), p. 4.

Table 2: Derivation of the BHL⁴⁸ simulation model

benchmark model		biased model	
1) full information on resource consumption and resource costs	$\sum_{j=1}^J m_{ij}^{BM} c_j^{BM} = PC_i^{BM}$	$\sum_{j=1}^J m_{ij}^{bias} c_j^{bias} = PC_i^{bias}$	2) biased information on resource consumption and resource costs
$\Rightarrow \Delta PC_i = PC_i^{BM} - PC_i^{bias}$			
noisy model			
	$c_j \xrightarrow{h1} ACP_k$	3) transformation of resource costs into activity cost pools	(7)
	$m_{ij} \xrightarrow{h2} ad_{ki}$	4) transformation of resource into activity consumption	(8)
	$\sum_{k=1}^K ad_{ki} ACP_k = PC_i^{NM}$	5) product costs based on activity based costing	(9)
	$\Rightarrow \Delta PC_i = PC_i^{BM} - PC_i^{NM}$		
h1	heuristic 1: set of algorithms to transform the cost vector of size j into k -activity cost pools	h2	heuristic 2: set of algorithms to transform the resource consumption matrix of size i, j into a matrix mapping activities (k) to products (i) activity driver: maps the costs of activity (k) to a product (i)
ACP_k	activity cost pool: costs to perform an activity (k)	ad_{ki}	

⁴⁸ The abbreviation BHL identifies in the following the paper Balakrishnan, Hansen and Labro (2011). See also Homburg, Nasev and Plank (2013) p. 9ff.

As already discussed in the introduction, activity based costing is considered one of the best performing alternatives.⁴⁹

Instead of using an abstract “bias” to model the information deficit of cost system designs (see “biased model” in Table 2), Balakrishnan, Hansen and Labro (2011) implement a comparable approach to activity based costing.

The “noisy model” (NM) (see Table 2) simplifies the allocation process in contrast to the “benchmark model” (BM). While the BM allocates resource-costs to products directly, the NM first pools the resource costs on k activity cost pools (ACP_k). Hence, only aggregated costs need to be allocated successively in the second step. The second step accordingly facilitates the allocation process: while the BM has a maximum of I times J allocation rules, the NM only has I times K . It can be expected that the amount of activity cost pools is notably lower than the total resources (J) available. By analogy with eq. (6) the impact of the non-optimal allocation process can be expressed by the delta between BM and NM product costs (see eq.(10))

As introduced in Table 2 the pooling and allocation rules follow specified algorithms. The pooling is defined by heuristic 1 (see eq. (7)), already indicating that the process is only approximate. Likewise, the cost-allocation step is defined by heuristic 2 (see eq. (8)). In the following, the abstract heuristics are illustrated.

2.4.2.1 First-stage heuristics

In detail, the first stage heuristics encompass the following five heuristics:⁵⁰ The **random method** (—) randomly assigns resources to cost pools. This

⁴⁹ For a comprehensive comparison of different cost-systems and ABC evolutions see Balakrishnan, Labro and Sivaramakrishnan (2012b), p. 24.

⁵⁰ See Balakrishnan, Hansen and Labro (2011), p. 527 and also Homburg, Nasev and Plank (2013) in the appendix section p. 26.

method represents the simplest method because it needs information neither about resource costs nor about resource consumption patterns.

In a cost system with, e.g., six activity cost pools, the **size random method** (–) first assigns the six largest resources (in terms of per unit resource costs) to the six cost pools. Subsequently, the remaining resources are randomly assigned to the six cost pools.

In a cost system with six activity cost pools, the **size misc method** (o) assigns the five largest resources (in terms of unit resource costs) to five of the six cost pools. The remaining resources are lumped in the sixth cost pool.

The **correlation random method** (+) groups resources with similar consumption patterns into one cost pool. First, one resource – the base resource – is randomly assigned to each activity cost pool. Then the remaining resources are assigned to activity cost pools based on their correlation with the base resource. The number of resources per cost pool is chosen such that every cost pool has approximately the same number of resources. As this method requires data on consumption patterns, it is informational demanding.

While the correlation random method randomly chooses the base resource, the **correlation size method** (++) chooses the largest resource (in terms of per unit resource costs c_j) as the base resource. The remaining resources are assigned to the cost pools based on their correlation with the base resource. The advantage of this method is the combination of size-based and correlation-based criteria to assign resources to cost pools. It is also informational demanding.

2.4.2.2 Second-stage heuristics

The second-stage heuristics encompass the following four heuristics:⁵¹ According to the **Big Pool Method** (–) the activity driver of a cost pool is the resource consumption coefficient of the largest resource (in terms of per unit resource costs) in the cost pool. The advantage of this method is that it is simple and that the costs of the largest resources are accurately assigned to the products. The disadvantage is that the remaining resources are inaccurately assigned.

For the **Average Method** (+ +) the activity driver of a cost pool is the average of the resource consumption coefficients of all resources in the cost pool. Compared to the big pool method, this method leads to more accurate product costs because it considers more resource consumption information. Nevertheless, the method is associated with relatively high information costs.

The Intermediate Methods Num(2) (–) to Num(4) (+) set the activity driver of a cost pool as the average of the resource consumption coefficients of the largest resources in the cost pool. For example, the activity driver according to the Num(4) method is the average of the consumption patterns of the four largest resources (in terms of per unit resource costs) of a cost pool. While intermediate methods require more information than the big pool method – resource consumption of a single resource vs. resource consumptions of four resources – they require less information than the average method which requires consumption patterns of all resources in a cost pool.

2.4.2.3 Simulation approach

This chapter discusses the general design layout by Balakrishnan, Hansen and Labro (2011). The central research question is the accuracy loss of product costs, by using approximate cost-system designs. Eq. (10) expresses

⁵¹ See Balakrishnan, Hansen and Labro (2011), p. 528 also Homburg, Nasev and Plank (2013) in the appendix section p. 27.

this loss per product, in terms of the delta of product costs ΔPC_i between the benchmark and the noisy model.

To measure the total reported error of such a system, Homburg (2001a) and Balakrishnan, Hansen and Labro (2011) use the Euclidean Distance ($EUCD_s$), as displayed in eq. (11). The subscript s indicates the identifier of the corresponding simulation run. The simulation embeds a catalogue of different environments. Each environment defines the simulation input. In total three parameters (resource cost variation, density of the consumption matrix and correlation of resource consumption) form 48 different environments.

Table 3: BHL simulation process

$EUCD_s = \sqrt{(\Delta PC_i)^2}$ $s \in S \text{ (simulation runs)}$ $i \in I \text{ (products)}$			(11)
Simulation	Input (environment)	Process	Output
	<ol style="list-style-type: none"> 1. Resource cost variation (RCV, 3 level) 2. Density of the consumption matrix ($DENS$, 4 level) 3. Correlation of resource consumption (COR, 4 level) \Rightarrow 48 environments 	<ol style="list-style-type: none"> 1. Calculate product costs in the benchmark model \Rightarrow 20 samples 2. For each BM calculate product costs in the noisy model for a combination of <ol style="list-style-type: none"> a. Heuristic 1 (5 level) b. Heuristic 2 (4 level) c. ACP (6 level) d. Measurement error (ME) (3 level) \Rightarrow 360 samples 	\Rightarrow $EUCD_s$ $S =$ 345,600
Example run ($s=1$)	<ol style="list-style-type: none"> 1. Low dispersion (–) 2. High sharing (+) 3. Similar consumption pattern (+) 	<ol style="list-style-type: none"> 1. Calculate PC^{BM} 2. Calculate PC^{NM} for <ol style="list-style-type: none"> a. Random (– –) b. Big Pool (–) c. 2 ACP (– –) d. ME at 50% (+ + +) 	\Rightarrow $EUCD_1$

To cope with the stochastic effect of random number generation, 20 samples of each environment leading to a total number of 960 benchmark models are drawn.⁵² A noisy model definition consists out of four parameters (heuristics 1 & 2 combination, the number of activity cost pools, a systematic cost system error and the measurement error) leading to a total number of 360 noisy models, for each BM. The simulation process is summarized in Table 3.

The following paragraph explains the introduced (see Table 3) input parameters used to build the environment. In accordance to the factorial design, the levels for each factor are coded to better visualize the state of the respective factor.⁵³ The generic design of the parameters works as follows: For each input factor, a distribution function is modeled. The factor level is used as a parameter to steer the distribution, e.g. the boundaries, skewness, etc. Subsequently from this adjusted distribution, a set of random numbers is drawn.

In case of the resource cost variation, a uniform distribution is applied. The level of resource sharing changes the boundaries of the distribution. A low level of cost dispersion limits e.g. the possible drawn random numbers to a corridor of 0 to 0.2 instead of 0 to 1 of the standard uniform distribution. The drawn random numbers are considered the proportion of used costs by each resource of total resource costs. Hence the biggest spread in a low dispersion setting is 20%, in other words each resource will consume approximately the same portion of total resource costs. In a final step, the drawn numbers are normalized. Obviously, only 100% of resource costs are allocable.⁵⁴ Table 4 summarizes the interaction between parameters, factors and variables.

⁵² See DOE design step 6 on page 16 and Lorscheid, Heine and Meyer (2012), pp. 33.

⁵³ See also step 3 in the DOE process on page 14.

⁵⁴ This is an arbitrary example. For the exact algorithm, see the working paper version of BHL, Balakrishnan et al. (2009).

Table 4: BHL Input factors for variables

Factor	Levels & Coding	Functionality	Variable
RCV: Resource cost variation	- Low dispersion 0 Med dispersion + High dispersion	The resource cost variation defines how disperse the total resource costs are distributed over resources. A low dispersion equals a setting where the total resource costs are almost equally distributed. At high dispersion, a small set of resources accounts for a majority of resource costs.	c_j
DENS: Density of the consumption matrix	- Little sharing 0 Medium sharing + High sharing + Very high + sharing	Despite from the complex naming the density parameter is straightforward: The resource consumption matrix is adjusted in a way that settings from little to very high resource sharing are controllable. The most extreme “little sharing” outcome would be a 1:1 mapping between resources and products. On the other side a very high sharing could lead to completely filled matrix m_{ij} , where each	m_{ij}

Table 4: BHL Input factors for variables (cont'd)

Factor	Levels & Coding	Functionality	Variable
		product consumes each resource.	
COR: Correlation of resource consumption	+ Similar consumption 0 Intermediate consumption - Dissimilar consumption -- Very dissimilar consumption	The most complex parameter. It also adjusts the resource consumption matrix. In simple terms, it steers how resource consumption of product $i=1$ correlates with product $i=2$. Where DENS steers if two products consume the same resource j (binary condition), COR steers if both consume the same amount of j , in respect to the chosen level (e.g. similar +).	m_{ij}

See Balakrishnan, Hansen and Labro (2011), p. 525.

2.4.2.4 Results

As proposed in the DOE framework by Lorscheid, Heine and Meyer (2012), Balakrishnan, Hansen and Labro (2011) use an ANOVA regression to analyze the results. In general, the results suggest that more sophisticated

allocation methods yield product costs closer to the benchmark, than less advanced methods.⁵⁵

The number of activity cost pools has a marginal effect on the error of product costs. Using more than a moderate number of cost pools only adds a small added value in terms of product cost accuracy. One of the main contradictory findings is, that the more the resource consumption of products varies (i.e. factor COR levels “—“ or “— —“, see Table 4), the more correlation based methods outperform size based methods.⁵⁶

Important findings, in regard to this thesis, are the influences of cost structure on the performance of the noisy model: for one, even a small reduction of specification errors result in significantly lower reporting errors. For the other, the highest environmental effect originates from the distribution of resource costs.⁵⁷

2.4.3 Margin Model

The *cost model* simulation disconnects from the synchronous profit and capacity optimization problem of the *grand model*, by focusing on optimal product cost determination. Nevertheless, it does not only shed light on one of the research proposals by Balakrishnan and Sivaramakrishnan (2002), identifying the criticality of cost pool design, but also lays the fundament for the *margin model*.

As discussed, a central requirement of cost reporting is the accordance of reported and realized costs. According to Anand, Balakrishnan and Labro (2013), a reporting system is tidy if both figures equal. Obviously, profit-planning tools are only fully reliable by being based on tidy costs. Considering that cost systems are approximations of true cost consumption, in practice cost systems are seldom completely tidy. A central objective of management accounting divisions is therefore to review planned costs based

⁵⁵ See Balakrishnan, Hansen and Labro (2011), p. 540.

⁵⁶ See Balakrishnan, Hansen and Labro (2011), p. 537.

⁵⁷ See Balakrishnan, Hansen and Labro (2011), p. 541 and the results of this thesis on page 66.

on true cost consumption on a regular basis and to adjust allocation methods to close the existing gap.

Leveraging a numerical example / simulation approach Anand, Balakrishnan and Labro (2013) review the heuristics introduced by Balakrishnan, Hansen and Labro (2011) on their capability of yielding tidy costs and the time frame needed to align reported and realized product costs. The underlying model implements a product margin-optimizing firm, given predetermined, static capacity. Different to Balakrishnan and Sivaramakrishnan (2002) and this thesis, the respective optimized company therefore is a price taker and not a (monopolistic) price setter. Price optimization is therefore neglected, as is respectively the quantity produced.⁵⁸

2.4.3.1 Simulation approach

The used profit functions are illustrated in eq. (12) & (16) in Table 5. There is no optimization process because all required variables are known prior to planning. Additionally, the planning process is sequential. This means that at first the product mix is defined and, based on this decision, the capacity L_j^{BM} is set.

As input for the simulation, environmental parameters are used comparative to the *cost model*. Therefore, only the two new parameters for steering markup and quantity are discussed: Anand, Balakrishnan and Labro (2013) calculate the respective product margin (μ_i) leveraging a random number generator using the parameters “average markup” and “variance in markup”. The steering concept of the first parameter is straightforward: for the given set of i -products, it models the average margin over the portfolio. Comparable to the cost variance parameter (RCV), the variance in markup triggers portfolios with heterogeneous or homogeneous products. For both, 2-levels (high/low) are defined. Quantities (Q_i) are drawn from a uniform

⁵⁸ See Anand, Balakrishnan and Labro (2013), p. 7,

distribution.⁵⁹ Table 6 illustrates the complete process, while Table 5 describes in detail the underlying model.

Table 5: ABL Margin model definition⁶⁰

BM	$Profit^{BM} = \sum_{i=1}^I \mu_i \lambda_i^{NM} Q_i - \sum_{j=1}^J c_j L_j^{BM} \quad (12)$	
	$L_j^{BM} = \sum_{i=1}^I m_{ij} \lambda_i^{NM} Q_i \quad \forall_j \quad PC_i^{BM} = \sum_{j=1}^J m_{ij} c_j \quad \forall_i$ $\lambda_i^{NM} = \begin{cases} 1 & \mu_i > 0 \\ 0 & \mu_i \leq 0 \end{cases} \quad \forall_i \quad TC^{BM} = \sum_{j=1}^J c_j L_j^{BM}$	
NM	<div>Initial period⁶¹</div> $TC^{BM} \xrightarrow{h1} ACP_k^{total} \quad (13)$ $m_{ij} \xrightarrow{h2} ad_{ki} \quad (14)$ $\frac{ACP_k^{total}}{L_j^{BM}} = ACP_k^{pl} \quad j \subseteq J \quad (15)$	
	<div>Succeeding periods</div> $TC^{NM} \xrightarrow{h1} ACP_k^{total}$ $\frac{ACP_k^{total}}{L_j^{NM}} = ACP_k^{pl} \quad j \subseteq J$ <p><i>ad_{ki} is identical for all periods</i></p>	
	$PC_i^{NM} = \sum_{k=1}^K ad_{ki} ACP_k^{pl} \quad \lambda_i^{NM} = \begin{cases} 1 & P_i^{NM} > PC_i^{NM} \\ 0 & P_i^{NM} \leq PC_i^{NM} \end{cases} \quad \forall_i$ $P_i^{NM} = (1 + \mu_i) PC_i^{NM} \quad TC^{NM} = \sum_{i=1}^I PC_i^{NM} \lambda_i^{NM} Q_i \quad \forall_j$	
	$Profit^{NM} = \sum_{i=1}^I \mu_i \lambda_i^{NM} Q_i - TC^{NM} \quad (16)$	

⁵⁹ See Anand, Balakrishnan and Labro (2013), p. 11.

⁶⁰ The model is not illustrated straight away in Anand, Balakrishnan and Labro (2013), but is derived from various information given in the paper, especially out of the Appendix. ABL will be used as an abbreviation for Anand, Balakrishnan and Labro (2013).

⁶¹ For simplification reasons the time index is neglected.

In the following, both views on the paper are combined: Having used the described inputs, in the process stage firstly the BM profit ($Profit^{BM}$), and secondly the noisy model profit ($Profit^{NM}$) are calculated. This is achieved by initially taking over information from the benchmark model into the noisy model: based on benchmark portfolio (λ_i^{BM}) and benchmark capacity (TC^{BM}) heuristics taken over from the *cost model* are used to allocate costs. ⁶² Next, building upon these product costs (PC_i^{NM}) the noisy model portfolio (λ_i^{NM}) is derived. Corresponding to this new portfolio, the total costs of the NM are calculated.

If the total costs (TC^{NM}) of the noisy model equal total costs (TC^{BM}) of the benchmark model, i.e. the cost system is tidy, finally the noisy model profit $Profit^{NM}$ is derived, as illustrated in eq. (16).⁶³ If $TC^{NM} \neq TC^{BM}$, in other words the cost system is untidy, then for t periods, the product costs are refined until either both costs equal or a maximum of T periods is reached.⁶⁴

As metrics for the research (see Table 6, output), the profit efficiency (PF^{eff} , eq. (17)) and mean product cost error (\overline{PCE} , eq. (18)) are used. The former being the quality of the noisy model profit estimation, measured upon its relative closeness to the benchmark model. The latter, measuring the mean fit of NM product costs in regard to the benchmark product costs.

⁶² A subset of heuristics from Balakrishnan, Hansen and Labro (2011) is used.

⁶³ Different from Balakrishnan, Hansen and Labro (2011) the decision context by Anand, Balakrishnan and Labro (2013) is on product and not on portfolio level. This becomes relevant especially while calculating $Profit^{NM}$: As illustrated in Table 5, corresponding to the *cost model* (see eq. (7) & (9)), the sum of all costs pooled in the activity cost pools (ACP_k^{total}) initially equal the total costs (TC^{BM}) of the benchmark model. Since the *margin model* assesses product costs on item level, the activity costs need to be brought down to this level as well. Eq. (15) documents this process: The total activity costs (ACP_k^{total}) are divided by the total amount of resources j , i.e. the capacity L_j^{BM} of resources j assigned to activity cost pool k . Therefore, the costs ACP_k^{pl} are applicable on product level, expressed by the superscript *pl*.

⁶⁴ The „break condition“ has been simplified in this summary. For details refer to the appendix of Anand, Balakrishnan and Labro (2013)

Table 6: ABL simulation process

Input	Process	Output	
1. μ_i – For each product, a random	Benchmark Model	$PF_s^{eff} = \frac{Profit^{NM}}{Profit^{BM}}$	(17)
2. markup is generated. (2×2 levels)	1) Corresponding to the given quantity and markup, capacity L_j^{BM} and $Profit^{BM}$ are calculated. In each	$\overline{PCE_s} =$	(18)
3. Q_i – For each product a maximum production quantity is drawn.	period, the benchmark profit is constant. \Rightarrow 1,000 samples	$\frac{1}{I} \sum_{i=1}^I \frac{ PC_i^{BM} - PC_i^{NM} }{PC_i^{BM}}$	
4. The environmental parameter and factors equal the <i>cost model</i> and are neglected in this synopsis. They are only used to build the simulation, but are not used as independent or control variables. \Rightarrow 4 environments	Noisy Model 2) Initial period a) To calculate period one noisy model $Profit^{BM}$, as an initial information the noisy model is calculated based on the benchmark portfolio (λ_i^{BM}) and the benchmark capacity (TC^{BM}). b) Calculate difference between TC^{BM} and TC^{NM} .	<i>convergence rate</i> (CR_s) = <i>percentage of NM, where $TC^{BM} \sim TC^{NM}$</i> S = 32,000	(19)

Additionally for each simulation run, i.e. the combination of input parameters and cost system designs, the rate and time of convergence of total costs between noisy and benchmark model is measured. Hereby the t periods needed until TC^{NM} equals TC^{BM} are determined. If a given time barrier is hit or a level of accuracy is met, the cost system refinement is aborted (CR_S , eq. (19)).

The simulation consists out of $S = 32,000$ simulation runs. For each market setting (markup average/variance) 1,000 samples are drawn, resulting in 4,000 BM. In line with the cost model, one set of NM is mapped to exact one BM. In the margin model, this leads to 8 NM samples. Instead of using all heuristics known from the cost model Anand, Balakrishnan and Labro (2013) only focus on heuristics on the second stage. For these they reduce the heuristics variation to the big-pool and NUM(2) methods. The number of cost pools is varied by 4 levels (1, 3, 6 and 10).⁶⁵

2.4.3.2 Results

In general Anand, Balakrishnan and Labro (2013) find that the approximate cost-systems (NM) perform quite well in comparison to the BM: They show that on average a convergence rate (CR_s) of approximately 30% to 55% can be reached and that profit efficiency levels PF_s^{eff} of almost 70% are possible.⁶⁶

Counterintuitive is the outperformance of big-pool method compared with the NUM(2) method in 1-pool scenarios. Raising the number of cost-pools leads to a more intuitive result, that superior cost-system design yields better results.⁶⁷ Anand, Balakrishnan and Labro (2013) explain this behavior by aggregation errors offsetting specification errors. This explanation is not based on model behavior, but on the findings by Datar and Gupta (1994). This finding can be challenged by reviewing the model characteristics: Big-

⁶⁵ See Anand, Balakrishnan and Labro (2013), p. 12 and 14.

⁶⁶ For the definition of the CR see eq. (19). The range of convergence depends on the accuracy level requested. See Anand, Balakrishnan and Labro (2013), pp. 15–16.

⁶⁷ See panel A by Anand, Balakrishnan and Labro (2013), p. 26.

pool and NUM(2) are almost equal. Both select allocation rates based on the biggest and on the average of the two biggest resources in the cost-pool respectively. Considering environments where the total spread of total resource costs is low and the resource sharing equals between products, both methods should lead to identical decisions. Both, the spread in total resource costs (RCV) and the density (DENS) only vary by 30 percentage-points.⁶⁸ Hence, one would assume that both methods would yield comparable results. A detailed analysis on DENS and RCV is not given by Anand, Balakrishnan and Labro (2013).

The mean product cost error ($\overline{PCE_s}$) is reported to be rather high throughout all scenarios: Intuitively, higher markups lead to lower product cost errors and vice-versa. High variance leads to lower product cost errors.⁶⁹ While being reported, this finding is not further explained. In light of the markup variable being constructed out of two parameters (variance and average) it is questionable to separate the effects from each other.

Further the markup, following Anand, Balakrishnan and Labro (2013), matters more than cost system design. This is supported by the ANOVA regression. Here, the markup explains more than 30% of mean profit efficiency $\overline{PF^{eff}}$, whereas the cost system design ($ACP + \text{Heuristic2}$) only amounts for approximately 16%.

⁶⁸ See Anand, Balakrishnan and Labro (2013), p. 29.

⁶⁹ See Anand, Balakrishnan and Labro (2013), p. 17.

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