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AN OPTIMIZATION APPROACH INTEGRATING TECHNICAL AND FINANCIAL OBJECTIVES

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Abstract

The interdependence of technical and financial considerations poses a major problem for the development of appropriate decision support systems in business practice. In this paper, an application - with strategic importance for outsourcing providers in information technology - is described employing a two-dimensional operations research model and an interactive solution approach finally leading to a PC-based system which could also serve as a prototype for other strategic applications requiring financial <u>*and*</u> *technical expertise.*

1. Introduction

A large variety of business decisions is affected by the inherent interdependence of technical and financial aspects. The development of appropriate decision support methods and tools for this kind of problem requires not only coping with the isolated tasks of evaluating the "one-dimensional" impacts of decisions, but, moreover, asks for an integrated analysis of each decision alternative covering both aspects. Often, even "one-dimensional" decision support is hard to establish - particularly when technical problems are concerned. Therefore, it does not seem to be surprising that in practice such decisions mostly have to be made in the absence of helpful integrated methods and tools. Instead, decision makers have to resort to consulting experts (or tools) for each problem area separately, and somehow evaluate the different aspects of the problem. In this paper, we will show how state-of-the-art information technology may be applied to design and implement decision support systems that are able to cope with interdependent technical and financial objectives. The application described proves not only to solve the problem satisfactorily from a scientific point of view, but above all to serve as a prototype for providing adequate and easy-to-use support for a variety of strategic problems in business practice.

A typical example for the kind of complex decision environment mentioned above is the planning of hardware investments in the area of information technology. Here, the technical characteristics of computing systems substantially determine their utility and strategic value for the company. On the other hand, the financial impacts of investment decisions have to be carefully analyzed in detail to guarantee an investment policy consistent with the profitability goals of the company. The two-dimensionality of the problem is usually reflected in the organizational processes that are put into place: Computer experts start out to develop investment scenarios from a basically technical point of view which then have to be approved or - more frequently - be disapproved by financial staff. Since almost ever the technical and financial objectives turn out to be contradictory, the essence of the investment decision is to find a suitable compromise between them. Unfortunately, the decision process is rather unstructured and can hardly be based on sound decision models.

Although this problem exists for virtually all companies running computing facilities, it obviously is of particularly vital importance to those companies that offer *outsourcing* services like facility and system management to their customers: Here, the problem of determining in which computing facilities to invest may be of high strategic importance. Investing in products that e.g. best suit the customers' applications to be run, provide a high degree of flexibility and may be upward compatible to newly emerging hardware and software technologies, does not only affect the ability of the company to fulfil current outsourcing contracts, but substantially determines its competitive position in the future. At the same time, the capital investments and operating costs associated with these decisions represent a major influence factor of the present and future financial performance of the company. For these service-providers in the outsourcing business an application rendering integrated technical and financial support is even more a necessity than it is for those customers supplying information technology just for themselves:

- The investment decision is particularly *important*: Whereas information technology is generally regarded as an area of strategic importance for virtually all companies, it is the core business for the suppliers of outsourcing services and thus the main subject of strategic considerations.

- By managing computing facilities for a variety of customers, the size and complexity of their computing facilities exceeds by far the level to be handled in other companies. Therefore, the investment problem as such is more *difficult* to be solved "manually" with - e.g. - more decision alternatives and/or interdependencies between them.

- The fast and thorough analysis of investment decisions represents an indispensable prerequisite to succeed in the bidding contests within a tough outsourcing market. Thus, speed in providing customized bids may put the company ahead of competition without foregoing economically sound pricing. Therefore, the investment problem must be solved *within short time*.

In this paper, we will show how for this particular investment problem an operations research approach can be taken to provide a decision model and, moreover, a PC-based tool to assist the decision makers. Two features of the application developed might be of particular interest: First, a *knowledge based system* is used to handle the technical analysis of decisions[1], and is thus coupled with an operations research model. Second, the kind of *interactive* decision support offered enables the decision maker to gradually create and explore "reasonable" compromises between the conflicting goals. This should be seen as a contribution for a new generation of decision support which has been outlined by Mitra a few years ago: "Computer assisted decision making falls in a very sensitive area where new developments in information technology, artificial intelligence and mathematical modelling play key roles in problem solving in business and industry. All the trends in research, development and experience of product implementation indicate that these methodologies will come closer together and will continue to exploit hardware, software and man machine communication tools to produce progressively refined decision support products[2]".

The outline of the paper will follow the solution of the investment problem that will finally be moulded into an application system. Part 2 will first model the problem in question and close with the formulation of a two-dimensional optimization problem. Part 3 will be devoted to deriving a solution approach, while part 4 will present an algorithm to solve the problem. Part 5 introduces an application - developed by the authors for IBM Germany - which is based on the operations research approach described before. Part 6 sums up the results.

2. The decision model

The problem at hand consists of finding an *investment program* for a certain capacity demand in a computing facility[3]. This program may be composed of several *investment alternatives* with individually different technical and financial characteristics. These alternatives include e.g. purchasing new and used hardware, upgrading existing systems and or continuing the use of existing systems[4]. The range of investment alternatives is enlarged if the hardware systems are distinguished by the features they incorporate, e.g. the size of central or extended storage, the number of input/output channels and the like. To enable the modelling of all these alternatives, we choose the following notation:

(A1) $N := \{1, ..., n\}$ denotes the set of existing computer systems, while
$M := \{1, ..., m\}$ denotes the set of computer systems that might be installed after
the investment decision is made.

(A2) The set of investment alternatives is characterized by

$A := \{ (i,j) \;/\; i=0(1)n$ und $j=0(1)m\}$
with the following interpretation of its elements (i,j)[5]:

(0,j) Purchase of an additional system $j \in M$

(i,j) Upgrade of system $i \in N$ to system $j \in M$, with $i = j$ denoting the continued use of an unchanged system $i \in N$.

(i,0) Sale of system $i \in N$.

(A3) The (pure integer) *decision variables* are the extent to which these alternatives are realized:

$$x_{ij} := x((i,j)) \in N_0 \quad \text{for each } (i,j) \in A$$

These decision variables may be limited by upper bounds $\bar{x}_{ij} \in N_0$ characterizing e.g. the limited availability of new or used systems. Therefore, any feasible investment program has to adhere to the following *availability restrictions*:

$$x_{ij} \leqq \overline{x}_{ij} \quad \text{for each } (i,j) \in A$$

Furthermore, it must be guaranteed that each existing system is included in exactly one investment alternative, i.e. for each existing system it must be decided whether it will be de-installed and sold, upgraded or used unchanged. This leads to the following *feasibility restrictions*:

$$\sum_{j=0}^{m} x_{ij} = 1 \quad \text{for each } i \in N$$

An investment program may be denoted as a vector

$$x = (x_{ij}) \quad \text{for } i=0(1)n,\ j=0(1)m \text{ and } x_{00} := 0$$

(A4) The capacity provided by the finally installed systems $j \in M$ is known as $c_j > 0$. If a feasible investment program is to yield a minimum capacity[6] of $C > 0$ and we let the capacity of disinvestments be $c_0 := 0$, we get the following *capacity restriction*:

$$\sum_{i=0}^{n} \sum_{j=0}^{m} c_j x_{ij} \geq C$$

(A5) Each investment alternative $(i,j) \in A$ is characterized by a financial evaluation $f_{ij} \in R$ and the results of a technical analysis $t_{ij} \in R$ reflecting the suitability for the applications to be run and the capacity it renders[7]. If the decision maker is interested in maximizing both the financial and technical evaluations of an investment program, this will be denoted by the two *objective functions*[8]:

$$F(x) := \sum_{i=0}^{n} \sum_{j=0}^{m} f_{ij} x_{ij}$$

$$T(x) := \sum_{i=0}^{n} \sum_{j=0}^{m} t_{ij} x_{ij}$$

With these assumptions, our (two-dimensional)[9] hardware investment optimization problem can be summarized as follows:

$$\text{Maximize} \quad \begin{cases} F(x) := \sum_{i=0}^{n} \sum_{j=0}^{m} f_{ij} x_{ij} \\ T(x) := \sum_{i=0}^{n} \sum_{j=0}^{m} t_{ij} x_{ij} \end{cases} \tag{1}$$

subject to:

$$\sum_{i=0}^{n} \sum_{j=0}^{m} c_j x_{ij} \geq \mathrm{C} \tag{2}$$

$$\mathrm{x}_{ij} \leq \overline{\mathrm{x}}_{ij} \qquad \text{for each (i,j)} \in \mathrm{A} \tag{3}$$

$$\sum_{j=0}^{m} \mathrm{x}_{ij} = 1 \qquad \text{for each i} \in \mathrm{N} \tag{4}$$

$$\mathrm{x}_{ij} \in N_0 \qquad \text{for each (i,j)} \in \mathrm{A} \tag{5}$$

In the following we will try to find an adequate approach to deal with this multiple criteria problem.

3. A solution approach for multiple criteria optimization

The basic problem of multiple criteria optimization consists of identifying the *efficient* out of the range of *feasible* solutions, i.e. solutions that are not dominated by other feasible solutions, and, therefore, represent Pareto-optima. An example for the efficient set of our hardware investment problem is depicted in figure 1.

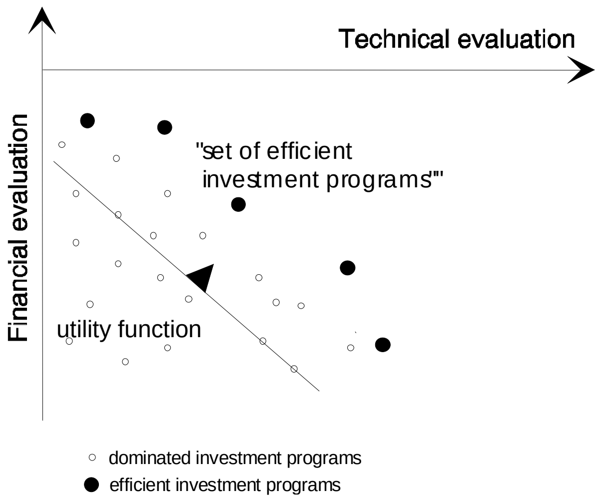

Figure 1. Dominated and efficient investment programs.

Since usually a perfect solution, i.e. a solution that simultaneously maximizes both objective functions, does not exist, we have do deal with conflicting objectives. The solution methods that are proposed in the multiple criteria optimization literature can roughly be categorized into three groups[10]:

- *Enumeration of the efficient solutions*: By listing all efficient solutions to the decision maker, he should be able to identify the efficient solution maximizing his utility. These methods are only of very limited importance particularly for pure integer problems since the number of efficient solutions may be considerable. Therefore, neither can this set be determined with reasonable effort nor does it sufficiently limit the number of alternatives for the decision maker.

- *Compromise models*: These approaches make explicit assumptions about the preferences of the decision maker and thus incorporate his utility function into the approach. Usually this results in transforming the multiple criteria problem into a one-dimensional problem: This might be done

  - by directly using the utility function of the decision maker as an objective function,
  - by assuming solutions with maximum utility and trying to minimize the deviation from them (goal programming),
  - by ranking the objectives and optimizing the most important one first, then - if necessary - the second one and so on (lexicographical approaches).

- *Interactive approaches*: A variety of methods exist that do not ex ante require the specification of the decision maker's preferences. Instead, these interactive methods propose solutions and let the decision maker indicate the "direction" further solutions should be sought in. Thus, the decision maker reveals step by step parts of his implicit utility function.

Since optimization problem (1) - (5) is pure integer and we cannot expect to ex ante identify the decision maker's preferences, the solution approach will neither consist in enumerating all efficient solutions nor can a compromise model be applied. We, therefore, focus on developing an interactive approach.

We will derive an approach from three axioms[11] that characterize some plausible value preferences and thus the type of utility function (not the utility function itself). For this purpose we assume that the decision maker acts according to the relative values f(x) and t(x) of the objective functions rather than their absolute ones[12]:

$$\begin{aligned} f(x) &:= \frac{F(x)}{f^*} \text{ with } f^* := \max\left\{ \left| f_{ij} \right| / (i,j) \in A \right\} \\ t(x) &:= \frac{T(x)}{t^*} \text{ with } t^* := \max\left\{ \left| t_{ij} \right| / (i,j) \in A \right\} \end{aligned} \qquad (6)$$

The decision maker's utility function U: $R^2 \rightarrow R$ transforms these relative values f(x) and t(x) to a scalar value u(f(x),t(x)). The requirements of a typical decision maker will lead to the following axioms describing the utility function[13]:

(P1) *Translation Property:*

If a constant is added to both the financial and technical evaluations, the utility should also change by that constant. Formally:

$$U(f + b, t + b) = U(f,t) + b \qquad \text{for all } b \in R \qquad (7)$$

(P2) *Proportionality Property:*

If the technical evaluation is equal to zero, the utility should only depend on the financial evaluation and be proportional to f. Formally:

$$U(f, 0) = \lambda f \qquad \text{for } \lambda \geq 0 \qquad (8)$$

(P3) *Mean Value Property:*

The utility lies somewhere in between minimum and maximum financial and technical evaluations. Formally:

$$\min \{f,t\} \leq U(f,t) \leq \max \{f,t\} \qquad (9)$$

These value judgements are only reflected in a very special type of utility function, as the following theorem shows:

<u>*Theorem:*</u> A function U: (f,t) $\rightarrow$ U(f,t) satisfies axioms (P1) - (P3) if and only if it can be stated in the following form:

$$U(f,t) = \lambda f + (1 - \lambda) t \quad \text{with } \lambda \in [0,1]. \qquad (10)$$

Proof:

"$\Rightarrow$":

$$U(f,t) = U((f-t)+t, 0+t) \overset{(P1)}{=} U(f-t,0)+t$$

$$\overset{(P2)}{=} \lambda(f-t)+t = \lambda f + (1-\lambda)t$$

(P3) requires that $0 \leq \lambda = U(1,0) \leq \lambda$.

"$\Leftarrow$":

Every function of the form (10) satisfies equations (7) - (9). ■

Therefore, the objective function of the decision maker adheres to the following form with $\lambda \in [0,1]$ characterizing his individual and ex ante unknown preference structure:

$$\text{Maximize}^{14} \quad \lambda \frac{F(x)}{f*} + (1-\lambda)\frac{T(x)}{t*} \qquad (11)$$

The theorem shows that the plausible axioms (P1) - (P3) imply a linear utility function of the decision maker. Using this formulation the two objective functions are combined to one objective function that can be solved by methods of pure integer programming. Though the existence of a utility function is assumed neither explicitly nor implicitly, the objective functions corresponding to the weights λ and (1-λ) can be interpreted as a linear approximation[15] of the decision maker's utility function. Therefore, an interactive optimization approach has to assist the decision maker to gradually close in on his individual preference parameter λ by solving a sequence of optimization problems with objective functions (11). The objective function(s) corresponding to the relevant individual preference parameter(s) can be understood as linear *approximation(s)* of the decision maker's utility function *in the relevant domain.*

The next part will first propose a heuristic algorithm to solve this pure integer problem for one fixed preference parameter λ. Part 5 will then introduce the interactive approach chosen for generating the sequence of solutions in the hardware optimization problem.

4. A heuristic approach for solving the pure integer optimization problem

Based upon the discussion in the previous part on how to deal with the two-dimensional optimization problem, we will now turn to the question of how to solve the optimization problem (11) for a fixed parameter λ and the objective function formulated for the original decision variables (see (1)):

$$\text{Maximize} \qquad \lambda\sum_{i=0}^{n}\sum_{j=0}^{m}\frac{f_{ij}}{f^*}x_{ij}+(1-\lambda)\sum_{i=0}^{n}\sum_{j=0}^{m}\frac{t_{ij}}{t^*}x_{ij}:=\sum_{i=0}^{n}\sum_{j=0}^{m}b_{ij}\,x_{ij} \;{}^{16} \qquad (12)$$

This problem can - due to restriction (2) - be categorized as a binpacking and, therefore, as a NP-hard optimization problem[17]. Since we need to solve the problem for a variety of parameters λ within the interactive approach, we resort to a (fast) heuristic algorithm which will be outlined below[18]. Using the heuristic to solve hardware investment problems in practice, we found that for small problems - where the results could be compared with the ones of an exact algorithm - the generated solutions represented optima in roughly 95% of all cases. In most of the remaining cases they did not deviate more than 2% from the optimum.

The heuristic is based upon simple approaches known from production planning in the presence of a capacity restriction. The problem can be solved by ranking products according to their profit margins relative to its consumption of the limited resource[19].

In our optimization problem the relative profit margins are replaced by the objective function coefficients b_{ij}. However, we have to modify the simple heuristic in order to deal with two further characteristics:

- *Dependency of investment alternatives*: The decision variables in our problem are not only dependent due to the common capacity constraint, but moreover due to restriction (2) requiring an investment decision for all existing systems.

- *Pure integer decision variables*.

In order to solve this more complicated problem heuristically, the investment alternatives x_{ij} will be ranked according to their relative objective function values rel_{ij}[20] obtained by dividing by the capacity. We then add alternatives to our solution starting with the alternative yielding the maximum rel_{ij} until the required capacity C is exceeded by adding the next investment alternative (*marginal system*). Such a marginal system is then re-evaluated dividing by the difference between the required capacity and the capacity provided by the ranked alternatives without the marginal system yielding a smaller (negative) rel_{ij}. Then the ranking process continues. The algorithm stops, if either the required capacity is reached exactly or an investment alternative is added to the solution the second time[21]. In each step dependent alternatives (i.e. alternatives where only one of two or more is feasible) might be re-evaluated and re-ranked, as outlined in the following example.

Example: In a computer center, a capacity C of 70 units (e.g. MIPS) is needed. There are 4 different investment alternatives providing capacity units of 20, 40, 50 and 60, respectively, out of which the following two are dependent: System A is a base machine and A -> B is describing the upgrade of system A to system B. The corresponding objective function values given in table 1 are determined by financial and technical evaluations; based on these data, table 1 illustrates the heuristic approach generating the heuristic investment program:[22]

investment alternative	objective function value b_{ij}	capacity c_j	relative objective function value $rel_{ij} := \frac{b_{ij}}{c_j}$	actions to generate an investment program
A	-400	40	- 10	* add to solution cap := 40 * re-evaluation of A -> B: b_{ij} := -550 - (-400) = -150 c_j := 50 - 40 = 10 $\rightarrow$ rel_{ij} := - 15
A -> B	-550	50	-11 -15	* add to solution: cap := 50 * remove dependent alternative A
C	-720	40	-18 -36	* mark as "marginal" system * re-evaluation: rel_{ij} := -36
D	-500	25	-20 -25	* mark as "marginal" system * re-evaluation rel_{ij} := -25 * add to solution: **cap := 75** * stop of algorithm with cap > C

Table 1. Generation of an investment program

In this case the algorithm generates
the optimal solution by choosing investment alternative D and upgrade of system A to system B (A -> B). The efficient solution provides an actual capacity of 75 units with an objective function value of -1050.

While in the example above the technical and financial objectives were both hidden in the b_{ij}, in what follows the conflicting nature of the objectives becomes obvious.

5. An application: The decision support system MIPS

In this chapter we will describe the interactive approach that was used to solve the hardware investment problem. This approach has been implemented in the decision support system MIPS[23] developed in a joint project with IBM Germany.

As described in part 1 in general terms, the MIPS system was designed to support hardware investment decisions particularly for mainframe computers. Solving the optimization problem formulated in part 2, however, has been just one of several functions that had to be performed by the system. For the sake of completeness, we will first give a brief overview of these functions[24] before we demonstrate the optimization approach in more detail.

- Initially the investment alternatives had to be generated requiring the availability of a variety of data, e.g. the current equipment of computing facilities, available upgrades or used systems on stock or offered in the market. Also the data necessary to perform the following analysis had to be collected and made available.

- Each investment alternative (i.e. (i,j) in the notation of part 2) had to be analyzed financially - taking into account, e.g., the cash flows for the initial investment, operating and maintenance costs, resale values and the tax effects. This rendered the coefficients f_{ij} usually in the form of after-tax net present values.

- In analogy to the financial analysis, each investment alternative had to be thouroughly evaluated from a technical point of view in order to attach coefficients t_{ij}. Due to the large number of alternatives an automated process had to be established. This was possible by developing a knowledge based system that was fed with the knowledge of the computer experts and heavily relied on its ability to propagate uncertain and vague knowledge[25]. The normalized coefficients t(x) were generated - by using the suitability factors $t_{ij} \in [0,1]$ - as values denoting that an alternative was not at all ($t_{ij} = 0$) or ideally suited ($t_{ij} = 1$) to perform the tasks in question. The strategic technological direction of the company would, e.g., favor/disfavor certain technology platforms, while backup or availability objectives would favor/disfavor certain processor complexes. Using a knowledge based system allowed for automated generation of suitability factors for a variety of application scenarios.

With these prerequisites of the optimization approach the decision maker can now interactively work with the efficient set of solutions and find compromises between financial and technical values which correspond to his preferences. Figure 2 shows an example[26] of an investment decision problem with the three steps described above having already been completed: In the upper right hand window a list of efficient investment programs is shown each corresponding to one value parameter λ. More information on this investment program is included, e.g. the MIPS capacity required[27] and the financial and technical evaluation[28] for the investment program. Note that with increasing emphasis on the financial aspects (i.e. larger λ) the financial evaluation improves yielding larger (negative) net present values, while the technical suitability deteriorates. This represents the conflict inherent in the objectives of the decision maker. The highlighted investment program with $\lambda = 0.5$ provides a minimum capacity of 350 MIPS[29], its realization (and use) will cause a net present value of roughly 10.7 million Deutschmarks and yield a technical evaluation of 693.

Figure 2. Example of a MIPS consultation

The window at the bottom shows the composition of the investment program highlighted above. Here, the individual investment alternatives forming the program are listed. We see that two existing systems ("Nr. 36" and "Nr. 42") should be used unchanged and one new system ("Nr. 57") should be purchased. We also get the part of the net present value attached to each alternative [30].

Thus, the decision maker can choose among these investment programs while he is always able to simultaneously spot their detailed composition. Important for its practical applicability is the variety of functions that the MIPS system offers to the user in order to generate and refine this list of investment programs: Initially performing a *standard optimization*, he will get a rough structure of the set of efficient investment programs[31] by generating solutions for some selected λ's out of the interval [0,1]. Using the option *interval optimization*, he might refine the list of solutions: By indicating two λ's of "adjacent" solutions already found, he will obtain further solutions for three more λ's in between. Finally, he might choose to generate an investment program for a distinct λ by selecting the option *single optimization*. Since optimizations are required frequently, a (fast) heuristic algorithm (outlined in part 5) is used to obtain approximately optimal solutions. Selecting the option *exact optimization* the decision maker may verify the efficiency of any solution by starting an exact optimization algorithm.

Most important with respect to the acceptance of the system in practice was the option to manually compose investment programs and compare them to the ones suggested by MIPS. These would be included in the list and identified by a special symbol in column "Weight".

The experience with the MIPS system has shown that an interactive approach like the one chosen is a highly accepted vehicle for creating and evaluating investment proposals - particularly in this complex area with substantial interdependencies of financial and technical impacts of investments. Thus, the quality of decision support could be raised to a higher level, and the productivity within the hardware planning process could also be increased. In addition one might note the improved communication between financial and technical experts made possible by the common use of the MIPS system.

6. Conclusions

In this paper it was shown how an optimization approach can be used to solve problems with both financial and technical objectives using an example from hardware investment planning[32]. Important was the use of operations research as an integrative approach being based on the results of detailed analyses in other areas, namely well-founded evaluations from the field of investment theory and the judgements of technical experts made available through knowledge based system technology. Particularly interesting might be the combination of operations research and knowledge based systems put forward in this article. While the cooperation of these fields has long been a subject of discussion[33], there seems to be a lack of applications combining the methods of both areas to *solve* the problems in question. Up to now, approaches seem to prevail that offer knowledge based access to and interpretation of operations research methods only.

The application of the optimization model and methods developed has led to a strategically important decision support system that offers a new quality of decision support by integrating financial and technical considerations. Moreover, the interactive solution approach has left the decision maker with enough independence as to his final decision. The use of operations research models and methods within integrative decision support approaches may indicate a very promising direction for further research and application.

Appendix Footnotes

1 The knowledge based system itself, however, will not be the focus of this paper. For this and other parts of the solution see [3], [5], [19] and [21].

2 [16, p. xix].

3 In this paper we will focus on CPUs (central processing units); these investments usually account for a substantial part of total hardware costs.

4 It might be interesting to note that even the continued use of an existing system should be seen as an investment alternative since it implies to forego the cash inflow from the sale of the hardware equipment.

5 For reasons of simplification of illustration we also admit the "do nothing"-alternative (0,0).

6 It should be noted that single capacity measures, e.g. MIPS (millions instructions per second) are subject to controversial discussions, but nevertheless heavily relied on in practice (see e.g. [12, p.4]

and [19, p. 21]). Thus, MIPS were used in the IBM cooperation project described in this paper. If application software is to be considered in the investment problem, for measuring capacity one might also use software-oriented performance measures, e.g. the number of SAP-transactions.

7 The systematical derivation of such suitability factors from the complex technical characteristics of the alternatives on the one hand, and of the strategic and technological objectives of the company on the other, can be achieved by applying knowledge based techniques: Their ability to represent and reason with uncertain and vague knowledge of the experts as well as to handle qualitative strategies and objectives make them ideal means to perform automated technical analyses (see also the application in part 5). The technical evaluations t_{ij}, therefore, describe the results of a knowledge based qualitative analysis, while the financial coefficients f_{ij} represent the results of a financial analysis, e.g. the net present values of the investment alternatives. Here, the f_{ij} are calculated from hardware payments. In general, they might also include software payments tied to the hardware. If in addition to hardware selection software *allocation* is to be optimized, the analysis is much more complex and not covered by the optimization approach presented here.

8 To simplify the notation, we assume $f_{00} := 0$ and $t_{00} := 0$.

9 If additional aspects are to be taken into account, the approach presented here can easily be extended to more than two objectives. This of course requires that these aspects are quantifiably tied to the single investment alternatives.

10 See e.g.[8], [13], [19]and [22].

11 For the derivation of functions from axioms see also [1].

12 This is motivated by the observations that the different scaling of objective function values is not adequately reflected by decision makers in their value judgements (see [17]) and that certain desirable preference structures can only be formulated using relative values (see [2]).

13 To simplify the notation, we write $f := f(x)$ and $t := t(x)$.

14 The generalization of (11) to functions of more than two arguments can easily be done.

15 Particularly in interesting - user-defined - financial or technical areas.

16 Because of the financial evaluation $f_{ij} < 0$ the objective function value b_{ij} of an hardware investment will usually be negative for sufficiently larger λ's. This negativity is important for the quality of the heuristic solutions.

17 See e.g. [7, p. 97] or [15 ,p. 213]. Algorithms for pure integer problems in general can e.g. be found in [10], [11] or [13].

18 We will not continue the search for further optima once an optimum is found.

19 See e.g. [8].

20 rel_{ij} is usually negative, too.

[21] For details see [22]. It is easy to show, that once a marginal system has been dropped before it is added the second time, then all systems added in between can be removed from the solution. This is due to the fact that the rel_{ij} has been better the first time and because of marginality the capacity constraint is satisfied.

[22] Note that the objective function value of alternative (A -> B) = 550 contains the financial evaluation for both the base machine A and the upgrade separately while the technical evaluation is determined by the upgraded base machine B as a whole. In the financial evaluation identical base machines A, A' with identical market prices may differ due to tax reasons if, e.g., one is already installed in the computer center while the other one can be bought in the market; thus it also makes a difference which one is upgraded (for details see [4]).

[23] MIPS is short for Mainframe Investment Planning System. The allusion to the underlying capacity measure (millions instructions per second) was deliberately chosen.

[24] For more information on the system MIPS see [18] and [21].

[25] For details of the reasoning approach used which is based on evidence theory, see [19] or [3].

[26] The example shown includes fictitious systems and data.

[27] An important feature of the MIPS system is its ability to simultaneously show efficient programs for different minimum capacities C. This enables the decision maker to evaluate the consequences of capacity growth that, e.g., would be needed to handle an additional outsourcing contract (see part 1).

[28] This corresponds - using the general notation from part 2 - to the parameters C, F(x) and T(x) for each investment program x. It might be noted that the technical evaluation was transformed to the interval [0;1000] from [0;1] because this scale appeared to be more intuitive to the decision makers.

[29] It is interesting to note that the actual capacity provided by this program amounts to 373 MIPS, and therefore, is substantially larger than the required 350 MIPS. This piece of information could be obtained by scrolling the window containing the investment programs.

[30] The difference of the sum of net present values of the alternatives and the net present value of the total investment program (10.7 million) represents the effect of the sale of other currently existing systems. These disinvestment alternatives are not explicitly shown in the bottom window to restrict the information to those systems that *will* be installed.

[31] Speaking now about efficient solutions represents solutions that are generated by the heuristic approach.

[32] As mentioned in footnotes 6, 7, 9 and 14, the approach is extendable to account for both consideration of (application) software and for more than two objectives.

[33] See e.g. [14] or [9].

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