ASSET SIMULATION AND AUTOMATIC ASSET OPTIMIZATION

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ABSTRACT

Asset managers are challenged to find sustainable mid and long term strategies which meet regulatory, technical and business constraints. These complex decisions have been supported by asset simulation in the past to estimate the consequences of different alternative asset strategies. Despite these increasing supports given by asset simulation tools, asset managers still have to define several hundred parameters to determine a certain strategy. Therefore the remaining complexity is still overwhelming. In this paper we propose a further extension of the simulation paradigm by introducing a combination with evolutionary optimization techniques. These approaches allow, after the formulation of an appropriate optimization model, an automatic identification of nearly optimal asset strategies. Using such an approach, asset managers are now able to concentrate on their domains and background knowledge while leaving the time consuming task of adjusting strategy parameters to a computer. First applications of such an approach prove much higher efficiency and show improved results.

INTRODUCTION

Since the beginning of deregulation asset management capabilities have reached a new level. The main challenge for the asset manager is to balance conflicting targets over time. General targets are for instance defined by:

- save revenue, minimize costs and increase profits
- ensure asset availability
- obey regulatory constraints
- reconsider maintenance strategies

DYNAMIC ASSET SIMULATION

Asset simulation is an understandable and well regarded method, which makes the resulting complexity controllable and helps thus to derive sustainable and sound asset strategies. In the first step, the target dimensions, accompanying parameters, possible measures of the asset management and the dependence existing between these dimensions in a cause-effect diagram will be gathered and displayed.

In the second step deterioration chains will be defined for the single asset segments or resources groups by means of continuance diagrams and flowcharts, which describe the life cycle. By doing that every deterioration chain will be divided into single state classes, which characterize the state of the resource means located within them. In dependence of the state class the effects of the measures of the asset management on the resources located in the state class will be described. The various back couplings, delays and non-linear connections between the different influence and target dimensions will be made transparent that way.

Based on the description of the mathematical context and consolidation of cause-, effect-, continuance- and flow diagrams, a dynamic asset-simulation model will be developed in the third step (see display 2). Based on the resulting model different asset-strategies can be calculated, valued, analyzed in detail and interpreted. By starting the simulation the entire amount of defined target dimensions of every resource groups will be calculated within the shortest time.

The simulation results of the target dimensions will be displayed in the form of a diagram or a value table. Besides, the determining set screws can be identified by parameter variations and sensitivity analyses. Thus, the asset management creates - as it were without any negative side effects - a substantially better understanding about the possible long-term effects of its planned measures, and therefore will be put into the position to formulate and implement sound and sustainable asset-strategies.

In order to achieve these objectives the asset manager has to take into account and to adjust hundreds of decision parameters. To get a grip on these complex problems the asset manager uses dynamic simulation tools. This enables him to understand the outcomes' sensitivity to changes in different decision parameters, but finding an optimal solution is still a cumbersome try-and-error process. This means: for every slight change in the chosen strategy or the underlying constraints this process has to be started all over again. Thousands of decision parameters have to be adjusted "manually" to achieve an acceptable result.

STATUS QUO

The asset manager is confronted with overwhelming complexity, Figure 1.

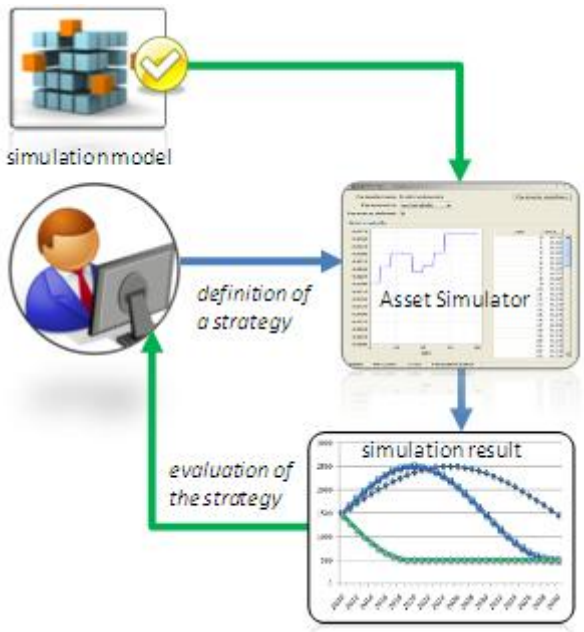


Figure 1

Once the simulation model has been identified the asset manager has to define the asset strategy by choosing the rate of new construction and the replacement rate for each class of asset for each year under investigation for example.

When the definition of a certain strategy is finished the asset simulation tool is used to calculate the development of the assets under investigation within the periods which have to be observed. These results are then analyzed by the asset manager again for instance by comparing the characteristics of the new strategy with strategies already known. Usually the user then starts to adjust the strategy parameters again and begins to run through the simulation cycle another time [1,3,4,6].
The main area for improvement in such an approach is that the search for a satisfying asset strategy should be supported by a systematic guidance. It is useful to understand given asset strategies but novel solutions should be derived in a systematical way. The asset manager is kept in a repetitive task while his core competencies of understanding the inner relationships within his asset structure cannot be fully included.

COMBINED APPROACH

This dilemma can now be solved by combining dynamic simulation tools with an optimization technique called evolutionary algorithms [2,5]. The evolutionary algorithm automates the optimization process. Simulation and optimization are complementing one another [7], see Figure 2: The Optimizer uses the Asset Simulator to “try” a large variety of different asset strategies.

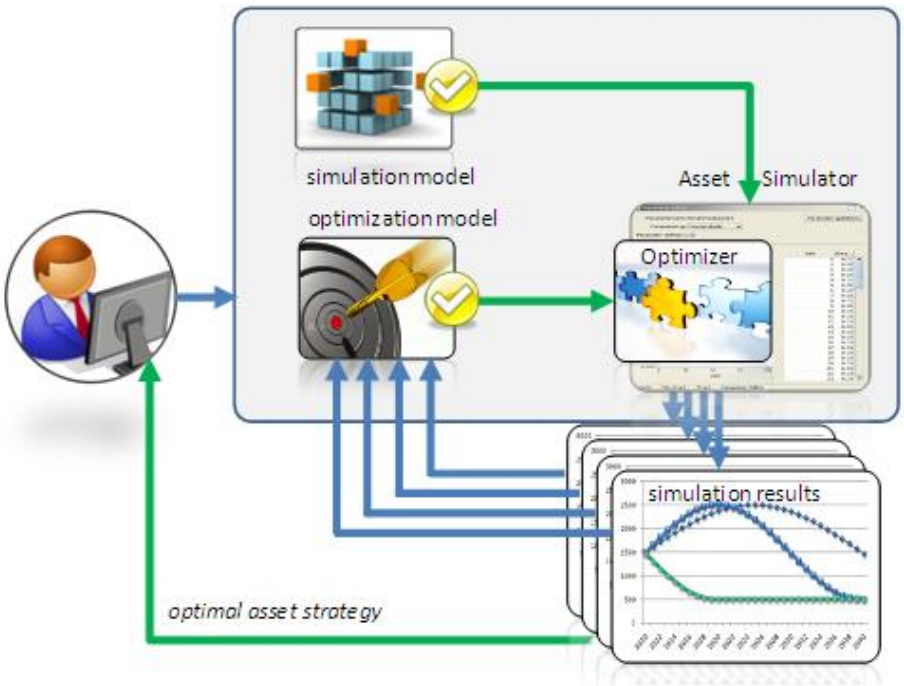


Figure 2

So that the Optimizer is able to select the most promising strategies and can improve these further, first of all an optimization model has to be defined. This model tells the Optimizer which solutions are valid under the given constraints and which fulfil the objective function better than others. These criteria are applied to a group of simulation results which exclude some of these solutions. The best solutions are taken by the Optimizer as candidates for further adaptation. In this manner several thousand loops of generation of new strategies, simulation and evaluation are executed until a feasible, quasi optimal and stable solution has been identified. This solution is given to the asset manager as the optimal asset strategy respecting the constraints and objectives of the optimization model.

OPTIMIZATION MODEL

An Optimizer would identify trivial solutions if the solution space is not restricted by constraints derived from expert knowledge. For example an ideal solution for minimizing asset costs would be that all assets are deconstructed. This behaviour must be avoided by introducing constraints, for instance that the value of all assets have to remain above a certain threshold.
On the other hand the Optimizer would get lost during its search if it was not be guided by an objective function, for example to minimize breakdown times.
Such kind of criteria are summarized within an optimization model which is used as the base for the optimization process. In order to build such an optimization model expert knowledge of an asset manager and an optimization specialist is needed.

OPTIMIZATION RESULTS

The evolutionary optimization approach which has been chosen here shows excellent convergence behaviour. Figure 3 shows the sequence of an optimization run. The y-axis depicts the value of the objective function which is minimized here. The x-axis represents iteration steps during the optimization. Blue dots indicate valid strategies while red dots show solutions which violate restrictions

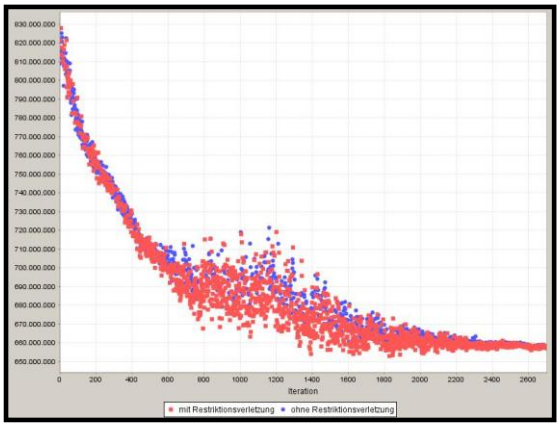


Figure 3

defined by the optimization model.
Computation times vary due to the complexity of the given optimization task from several minutes to several hours. Due to the fact that evolutionary algorithms can be easily reformulated to a parallel architecture this will be a natural step in further development.

CASE STUDY 1

The method described here has been applied to assets of a large German electricity distribution network. The strategy includes the adaptation of 42 different types of equipment. The Optimizer is instructed to use the parameters "maximum amount of replacements" and the "maximum amount of conversion". The objective function is given by minimization of equipments in bad or critical states and by minimization of breakdown times. Investments are restricted by 10% over time.

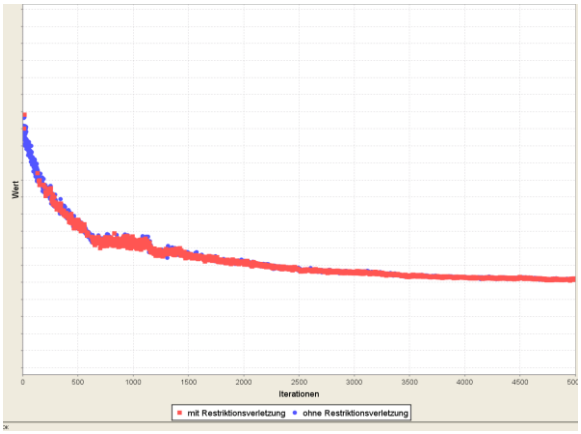


Figure 4

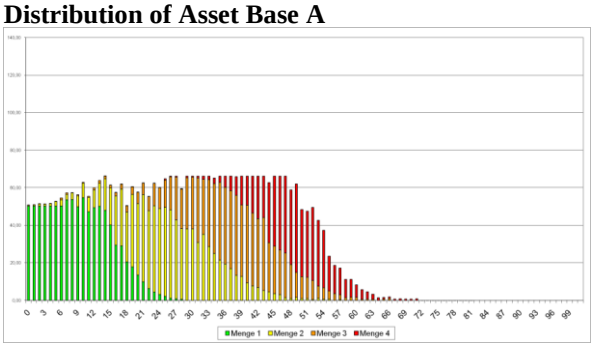
Figure 4 shows the improvement in minimization of breakdown times identified automatically by the Optimizer in 5.000 optimization iterations.
The application of the proposed paradigm:

- shows possibilities to apply the budget in an optimal way
- fast and effective checking of thoughts and considerations about sustainability and practicability
- finds attempts for optimizing the adaption of the budget planning to new restrictions.

CASE STUDY 2

In the following example it is recognizable that the age distribution of the asset base of company A and B is (with respect to almost constant quantities) significantly differing in one or even more resource groups: while the asset inventory of company A shows an almost equally distributed aging structure, the asset inventory of company B has significant maxima in its inventory aging structure (see Figure 5). For both asset bases the start values of the renewal rate is set at of 0% in state 3 and 20% in state 4.

Distribution of Asset Base A



Distribution of Asset Base B

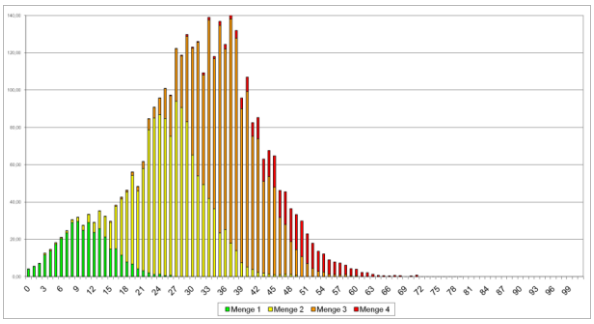
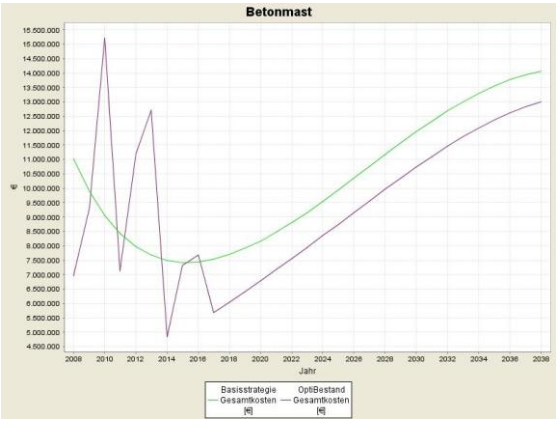


Figure 5

Total Costs Asset Base A



Total Costs Asset Base B

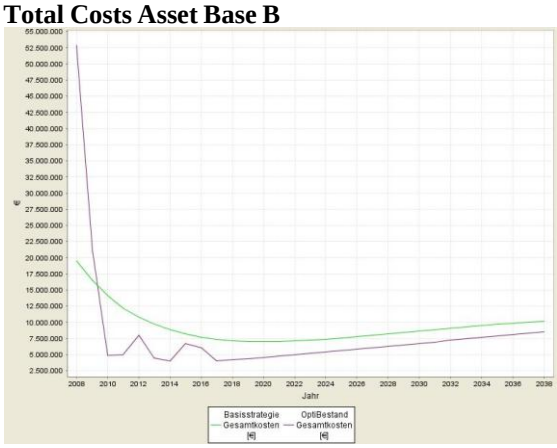


Figure 6

For both asset bases the requirements for optimization are considered as: the total costs needs to be minimized, while a non-availability limit at the same level is set. 5000 iterations will be carried out in each case. The result reveals that many different strategy attempts for the considered age diversifications of the resource groups will be derived from the cost optimization.

In the end, this shows that a sustained and sound asset strategy only results in the context of the age distribution of the asset bases mentioned above. The combination of dynamic asset simulation and evolutionary optimization leads, besides a considerable work relief, to substantially better results in terms of stability. The technical asset management has therefore reached a next level. Standardized solutions or recipes, which do not respect the detailed individualistic circumstances, do not lead to the target.

CONCLUSION

The approach we have presented here not only reduces the workload of the asset manager but leads to better and more stable results. The approach presented here helps to identify critical control parameter over the entire asset lifecycle. Asset managers are able to focus on their core competencies: the right balance between conflicting targets over time. Technical asset management has now truly reached a new dimension.

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