Resource Planning of Industrial Product-Service Systems (IPS²) by a Heuristic Resource Planning Approach

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Abstract

Industrial Product-Service-Systems (IPS²) are specified by delivering value in use to the customer while both product and service shares occur integrative over the whole life cycle. Thus they comprise several degrees of freedom, such as the partial substitution of product and service shares or the integration of customers' resources, which the operational resource planning of IPS² deals with. Furthermore it has to optimize the schedule regarding several aims like costs or constant work load. This article describes the Heuristic Resource Planning Approach for IPS² which combines e.g. randomized search heuristics and evolutionary algorithms.

Keywords

Industrial Product-Service Systems (IPS²), advanced planning and scheduling, process planning

1 INTRODUCTION

Already at the end of the 1960s Theodore LEVITT [1] made a statement that is still valid for current industrial applications: „People don't buy products; they buy the expectation of benefits". Therefore a comprehensive customer orientation is essential and thus a shifting from product sales to value sales will be realized.

The requirements and demands from the customer are rising and an upward trend towards customized solutions can be recorded; customers not only request products of high quality and high technology. They want to be placed in a position to operate these products optimally and request for a complete service offer [2]. This demanding attitude at the customer side though presupposes an efficient service design at the machine or service provider. The requirements of customers and providers are met by consequently offering Industrial Product-Service Systems (IPS²) with integrated services for all phases of the product life cycle [3, 4], what justifies the increasing meaning of industrial services by focusing on the customer use [5],

This solutions providing will also shift the relationship to a risk sharing between the customer and the provider. Focusing on the value provision Industrial Product-Service Systems enable innovative, life cycle spanning customer-provider relationships and new business models. In the context of innovative business models, the provider undertakes more and more responsibility for individual process steps up to the responsibility for the complete operation of a plant [6]. Hence the customers are freed from the control of the highly-complex processes and are able to focus on their actual core competences. The customer-provider relation will develop to an integrative cooperation, where the established separation between provider and customer will be dissolved more and more, depending on the business model.

1.1 Problem and purpose of the IPS² resource planning

The intangible service shares of Industrial Product-Service Systems provide a value to the customer via the complete life cycle; thus the detailed planning of service processes along the entire life cycle gains importance.

The resources linked with the services are a critical factor for the successful service execution; achieving the necessary availability is based on them. The planning of these resources has to be considered not only in the phase of service delivery but already in the phase of service design; all further products and services are designed in advance together with the product core during the integrated development of an Industrial Product-Service System.

Great impact of IPS² on the planning's complexity is their dynamic behavior over the life cycle: Within the designed solution space the occurrence of an IPS² can change over time due to changing customer demands and provider abilities; this dynamic of cause effects the use phase with its relevant processes. Other requirements are flexibility and real time capability to allow high work load. This is reached by evolving the service delivery from randomness to planning based on operating experience: The continuous optimization of service processes during their repeated execution (ramp up) allows faster and cheaper service execution overall; depending on the number of installed IPS² also the knowledge increases over the use phase.

The required resources for all processes have to be analyzed, planned and optimized. The capacity planning primary has to analyze the resource needs and make a first scheduling with respect to the numerous specifics of Industrial Product-Service Systems: In the first planning step all the single resource needs are analyzed and combined the best way. Therefore all customer specific restraints of all processes as well as their relevant data have to be carried along [7]; furthermore the IPS² specifics (see next chapter) have to be considered. Afterwards the total resource requirement can be calculated and optimized continuously by the operational resource planning, while in the short term it has to deal with emergencies and unscheduled jobs (such as repairing machine break-downs); therefore its methods and approaches have to operate in real-time.

The strategic capacity planning has a relatively long term planning horizon; hence the degrees of freedom are wide. But this variety of possibilities also implies the optimization regarding several aims. On the other hand, the operational resource planning especially has to deal with unscheduled jobs, which leads to changing priorities.

Regarding the resource planning at first a quick solution for a planning problem is needed to balance between calculation time and performance of the optimization result. Afterwards, or for example during an overnight replanning run, the more complex variances' applications can be examined for further optimization. As a planning problem in most cases means the dissatisfaction of a customer it should be solved as soon as possible; in this case the optimization aims are changed to enable the execution of all necessary processes; i.e. costs become second most important on this short term issue.

The basic scheduling is similar to classical travelling salesman problems and the transition times can be reduced by using algorithms specialized therefore. But there are several resources and processes at several places all connected via numerous interrelationships. This implies inner constraints due to the structure of all Industrial Product-Service Systems to be planned.

A process in this context means every action to be done by the provider, e.g. the execution of a service process as well as the delivery of a spare part or sending a software update. A resource means all required machines, material, personnel, tools et cetera. A critical resource in this case is a resource running above or significantly below their maximum capacity; a critical process is a process that cannot be executed until its deadline due to a lack of resources (i.e. it uses one or more critical resources). A solution in this context means a certain combination of resources and processes including the whole scheduling (i.e. the complete planning) for all Industrial Product-Service Systems to be planned.

1.2 IPS² specifics impacting the planning

Industrial Product-Service Systems are especially characterized by delivering value and fulfilling customer demands without stating clearly with exactly what combination of products and services this is done. Thus Industrial Product-Service Systems imply some specific variances [8]; the main are:

- variance in time;
- variance of resources;
- variance of processes;
- variance of allocation time;
- service distribution;
- partial substitution of product and service shares;
- integration of customers' resources;

The **variance in time** describes the possibility to reschedule a process, e.g. a regular maintenance, within a certain time span. It is a specific variance of IPS², as all processes are developed with an individual due date and a possible time span around, which can be used by the provider without reconsulting the customer; e.g. a regular maintenance has a great variance in time, while a break down repair has to be executed immediately. In general there is the possibility to reschedule a delayed process itself or one of the other processes planned for the critical resource at that time.

The **variance of resources** characterizes the opportunity to perform a process with several resources optionally; using the variance of resources means to shift the delayed process or another process to their alternative resource. For example a maintenance process can be rapidly executed by an expert or more slowly by a lower skilled worker.

The **variance of processes** specifies the existence of different processes reaching the same aim of customer satisfaction; those alternative processes are principally different and require different resources. For example a weak part can be replaced repeatedly or substituted by an improved part once.

The **allocation time** can be varied by making the technician or the spare part use different means of transportation, i.e. drive by car or use a plane.

Service distribution is the sourcing of certain resources or the outsourcing of entire processes within the network; it is a specific variance as Industrial Product-Service Systems are highly complex and will be offered in dynamic networks.

The **partial substitution of product and service shares** is a major characteristic of Industrial Product-Service Systems, as the only aim is to fulfil the customers' requests independent from a certain combination of products and services. For example in case of a machine breakdown you can either send a replacement part to the customer (mainly product) or you can repair the existing part on-site (mainly service); both processes allow to restart the machine afterwards. From the planning's point of view this variance is only a special kind of the variance in processes: the processes to be planned as well as the required resources are changed by choosing another product-service combination.

Another degree of freedom is the possibility of **using customer's resources**, e.g. maintenance personnel; this appears due to the high level of collaboration associated with Industrial Product-Service Systems. The customer is an essential part of the IPS²-network; like every other network partner his resources can be requested and used by the provider. Thus from the planning point of view the service distribution and the integration of customers' resources coincide to one variance: requesting processes or resources to the network.

If for one resource sometime the maximum capacity is exceeded (critical resource), at that point in time not all planned processes can be executed; there is at least one process that will be delayed. In this case the variances can be used to solve the planning problem.

The rescheduling or shifting of processes might be illustrated in a Gantt chart; nevertheless nothing of the complex consequences of those process alterations can be visualized thereby. Furthermore the classical visualizations of a planning problem are only able to cope with the less complex variances, as there are many interrelations between the different resources by being linked via several processes: Replanning a process always impacts all other processes and resources, even those ones far away from the considered process.

1.3 Resource planning for IPS²: a multi-dimensional and multi-objective optimization problem

The resource planning of Industrial Product-Service Systems is an optimization problem such as classical scheduling problems or the travelling salesman problem. When starting the planning all process-resource-combinations are chosen best regarding costs etc., so reducing transition times is the main possibility of optimization. But when there are delayed processes or additional processes to be executed in short time, the resource planning can make use of the specific variances to solve this problem under real time conditions.

There are several parameters to be adjusted within the resource planning's optimization according to the specifics and variances of Industrial Product-Service Systems. The numerous variances each induce possibilities to solve a problem. In addition these variances can be applied to several processes and resources. Due to this wide scope of variables the IPS² resource planning is a multi-dimensional optimization problem, becoming even more complex by the interrelations and dependencies between the variables.

Based on that, there are multitudinous possible solutions for an optimization problem. Applying variances or combinations generates various solutions concerning costs, efficiency, and so on. So solutions have to be compared regarding the current aims of the planning.

The three main objectives of the IPS² resource planning are:

- delivery reliability (towards the customer);
- costs;
- work load of the resources;

The quality though has to be kept on the original level by using only the variances specified during the development of the IPS².

There are at least three objectives and depending on the planning horizon the priorities of the planning are changing; hence the resource planning is multi-objective.

Additionally it is an optimization problem that cannot be assessed by mathematical methods: The relationship between two planning solutions can be described by applying the IPS²-specifics, but the relation between planning changes and solution improvements (if → then) cannot be modelled mathematically. Thus a heuristic approach was chosen.

2 ANALIZIS OF RELATED ALGORITMS

When looking at the details of the IPS²s planning it can be seen that it is a combination of several optimization problems.

The underlying basic problems of the combinatorial optimization are, among others:

- bin packing;
- travelling salesman;
- resource allocation;
- vehicle routing;
- course timetabling;
- job shop scheduling;

All these basic problems cannot be easily assessed by mathematical optimization techniques. For complex real cases of these problems mainly randomized search heuristic are applied, as they are able to cope with problem specifics and constraints [9-14].

The IPS²s planning features several objectives, many constraints and a multi-dimensional solution space. Thus no directly applicable optimization algorithm exists and the application of an individual hybrid metaheuristic is essential.

Metaheuristics refer to a class of optimization techniques including stochastic optimization and black-box optimization. They are able to cope with complex problems that cannot be assessed by mathematical optimization as there is too less knowledge about the solution space. On the other hand they can be used for large scale problems where brute-force search does not work. If the quality of a random solution can be quantified by a fitness function, it is possible to compare solutions and to move towards the optimal one.

A hybrid metaheuristic furthermore is a combination of several metaheuristics [15].

2.1 Basic metaheuristics and algorithms for the optimization of real problems

In the following the relevant basic metaheuristics / algorithms are characterized; according to their applicability for the IPS² resource planning the main advantages and disadvantages are shown. For details about the general algorithms' principles please refer to [16-20].

Evolutionary Algorithm

As a main characteristic of Evolutionary Algorithms the quality of the solution depends on the topology of the search space. If no exact solution is needed, it is a very fast algorithm, as the near-optimal point can usually be reached in a very short time; the longest time is spent in the evaluation of all chromosomes. Evolutionary Algorithms are stochastic and mostly there are no guarantees to reach an optimum. They can be applied to problems of various natures, and are adaptable for hybrid metaheuristics; e.g. the combination with Simulated Annealing (see below) allows passing local maxima in the process of evolution. [21, 22]

Genetic Algorithm

Genetic Algorithms are a particular class of Evolutionary Algorithms using the mutation of chromosomes in addition to the evolutionary recombination. They mainly feature the same advantages and disadvantages. The solution quality and speed can be better than with Evolutionary Algorithms, although the optimal solution is usually determined by going through a number of generations. The application to the IPS² resource planning is not easy, as the chance for circular movements probably outweighs the faster covering of the search space. [23]

Simulated Annealing

Simulated Annealing helps to improve the performance of simple search algorithms. As with other metaheuristics there are no guarantees to reach an optimum. Especially with noisy fitness functions Simulated Annealing helps to find the global optimum. [24, 25]

Tabu Search

In applying a tabu search technique to the problem, neighbourhood structure and search strategy are elaborated to improve solution quality and to reduce computation time. They generally find pretty good solutions very early in the search, but must be combined with another algorithm to find a first solution from where the optimization could start. Tabu Search heuristics are capable of integrating constraints and boundary conditions by declaring tabus in a short-term memory of the search (tabu lists). They only apply well on discrete problems. [26]

Greedy Algorithm

A Greedy Algorithm creates a small amount of interim solutions to be compared by choosing the best variables. That is not applicable for the IPS² resource planning, as there is no causal relationship between the costs etc. of a variance and the quality of the referring solutions. [27]

Ant Algorithm

The Ant Algorithm or Ant Colony Optimization uses the historical quality (pheromones) of components to create new solutions. It works well on complex problems and is quite established on large Travelling Salesman Problems. However it is a totally different approach, difficult to hybridize, and normally requires long calculation times. [28]

2.2 Comparison of applicability

When comparing those basic metaheuristics (see table 1), the Evolutionary Algorithm fulfils the most requirements; the second evolutionary approach (Genetic Algorithm) features problems with the application on the IPS² resource planning, as the mutation of solutions easily causes circular movement.

The next compatible approach is Simulated Annealing; the combination with an Evolutionary Algorithm is purposeful. In case of the IPS² resource planning the fitness function abruptly increases if an additional process becomes realizable. Therefore Simulated Annealing enhances the possibility to cope with local optima of this discontinuous (noisy) fitness function.

	Implementation of restrictions	cope with noisiness	initial solution	speed	solution quality	possible hybridization	applicability
Evolutionary Algorithm	o	o	+	+	o	++	++
Genetic Algorithm	o	+	+	+	o	+	o
Simulated Annealing	+	++	--	o	+	++	++
Tabu Search	+	o	--	+	+	+	+
Greedy Algorithm	o	o	-	++	+	+	--
Ant Algorithm	++	+	+	-	+	-	+

++ very good, + good, o moderate, - bad, -- very bad

Table 1: Comparison of basic metaheuristics

Another alternative would be the integration of Tabu Search techniques, as they are easily implementable and work well on discrete, combinatorial problems. In order not to complicate the hybrid metaheuristic to be developed, the Tabu Search was not implemented additionally, but that could be done easily when larger problems justify an extensive hybrid metaheuristic.

3 THE HEURISTIC RESOURCE PLANNING APPROACH FOR IPS²

The Heuristic Resource Planning Approach for IPS² (HRPA-IPS²) consists of a hybrid metaheuristic (Figure 1) structuring the variances' application and defining the exit conditions. Within this metaheuristic the variances are applied independent from each other while including the intelligent use of the variances' specifics.

3.1 Hybrid metaheuristic

The optimization of an existing scheduling to integrate an additional job makes use of the IPS²-specific variances. The reasonable way to generate solutions for evaluation is the selective application of these variances consecutively to the relevant resources and processes.

These variances have to be structured according to their effectiveness and efficiency. Therefore the strategy of application ranks the variances according to the caused costs, preferring low cost variances. Additionally it ranks the resources and processes according to their optimization potential; those directly linked to a problem are preferred.

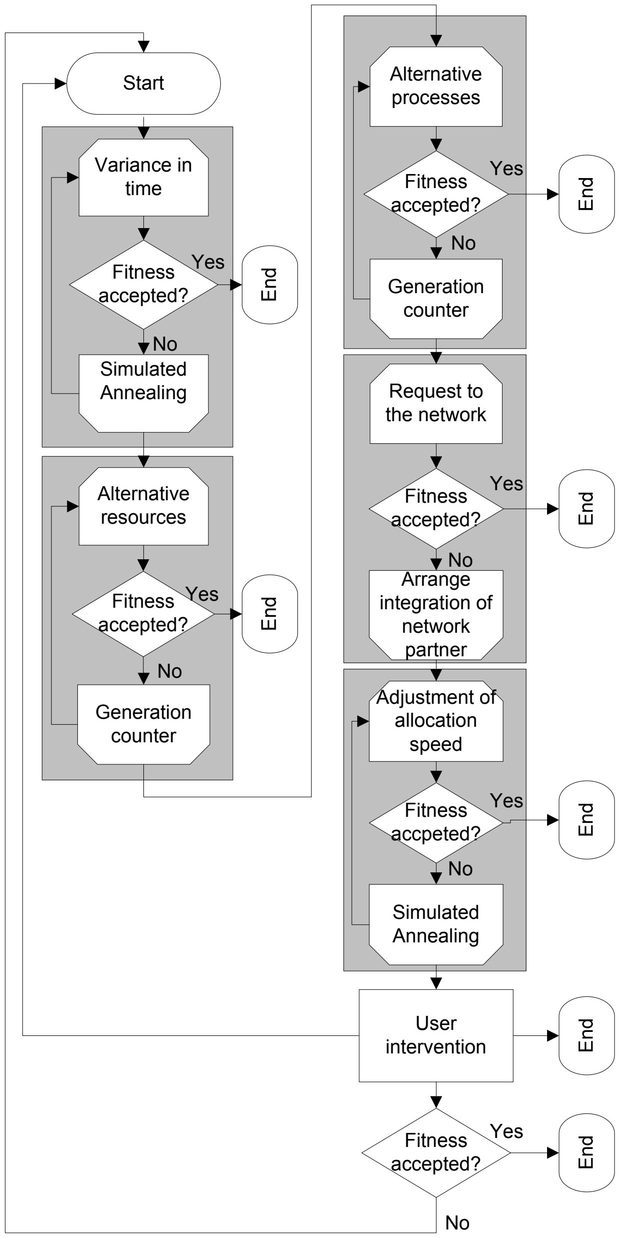

Figure 1: Structure of the hybrid metaheuristic

The variances are mainly categorized by the direct costs they cause. The application of the **variance in time** (i.e. postponement of processes) does not cause any direct costs. The use of **alternative resources** also causes no direct costs, if only unused, existing resources are considered; however it will cause some indirect costs, because e.g. an alternative worker is not as familiar with the job and thus takes longer. The use of **alternative processes** might cause some direct and indirect costs, as during the development already the most cost effective process was chosen for each task. To **request necessary resources to the network** will cause a significant amount of costs, as the external partners have to be included, coordinated and supported as well; also it is a very direct but slow way to replace a necessary resource. At least the **adjustment of the allocation speed** is considered; it often causes direct costs by using faster but more expensive means of transportation.

After each variance's application the fitness is checked to finally stop the complete optimization if the necessary fitness is reached.

Additionally break conditions are added to the inner loop of each variance to switch over to the next one. According to the complexity of the variances' application, these break conditions consider how broad and how deep one variance is used: how many applications of this variance are executed consecutively and up to which level of complexity (range of alterations) an improvement of the solution is supposable.

The application of the variance in time is easy to apply on the one hand, but comprises two degrees of freedom: the selection of the process to be rescheduled and the amount of time it is postponed. The consecutive postponement of several processes will be more effective in many cases, but along the variance's application the improvement of the solution becomes less supposable over time while making the overall scheduling more and more inefficient. Thus an evolutionary algorithm is combined with simulated annealing (see next chapter); the HRPA-IPS² makes use of the advantages of consecutive evolutionary algorithms but allows for passing local optima by a dynamic adjustment of the exit condition.

The same applies to the alteration of the allocation speed which keeps two more degrees of freedom besides the selection of the resource to be accelerated: resources can be accelerated by several means of transportation, additionally that can be applied to each journey of this resource. Again the consecutive acceleration of several resources might be more effective. Thus also an evolutionary algorithm is combined with simulated annealing. Nevertheless it is a much more cost-intensive variance and thus it is not evaluated as deep as the variance in time.

The last part of the hybrid metaheuristic includes the request to the user as a kind of interactive optimization. The user in some cases can decide beyond the initially planned variances and thereby enable a kind of optimization the approach itself cannot achieve. For example the user can phone to a customer to arrange an exceptional increase of the time variance and enable the further postponement of this process. Moreover he can raise the available maximum capacity for a resource (i.e. instruct overtime).

Then the user can abort the optimization, make use of his new variances by starting the same metaheuristic again, or switch over to the extended one. If there has not been found a solution yet, the metaheuristic is started again but extended by implementing the next stages of deepness in the variances' application. Therefore the intended number of generations is increased, the simulated annealing is slowed down and the Resource Identifying Heuristic (RIH, see next chapter) additionally examines one more degree of relationship.

3.2 Identifying the source of the problem

For the application of the variances within the hybrid metaheuristic (see next chapter) the sources of the planning problem have to be identified first. Therefore two heuristics are used:

The Process Identifying Heuristic (PIH) defines the search space for process related variances. It selects the critical processes as follows (pseudocode):

```
procedure PIH
    if resourceRequirement > resourceCapacity
    then resource ← "critical"
    if processEnddate > processDuedate
    then process ← "critical"
    if resource ∈ critical process
    then resource ← "critical"
    if process ∈ critical resource
    then process ← "critical"
end PIH
```

In that way it tags all delayed process, those processes using one or more critical resources, as well as the connected processes that also use a resource involved in a delayed process. To step over to the next degree of relationship to the initial problem source, this procedure can be applied twice (see recent chapter).

The search space for resource related variances is defined by the Resource Identifying Heuristic (RIH):

```
procedure RIH
    if resourceRequirement > resourceCapacity
    then resource ← "critical"
    if resource ∈ alternatives (critical resource)
    then resource ← "critical"
    if processEnddate > processDuedate
    then process ← "critical"
    if resource ∈ critical process
    then resource ← "critical"
end RIH
```

It selects the overloaded resources, their direct alternatives and all resources involved in critical processes. If a resource is less related to the critical resources, its replacement or acceleration has too low chance to solve the problem. To step over to the next degree of relationship to the initial problem source (see recent chapter), this procedure can be applied after the PIH.

3.3 Variances' application

All variances' applications are large scale optimization problems themselves, as each application step includes a whole scheduling (see chapter 1.1) and thereupon impacts all other processes and resources. So the search within each step also needs for individual metaheuristics.

Variance in time

The Process Identifying Heuristic (PIH) defines the search space. Afterwards an evolutionary algorithm optimizes this scheduling: For candidate solutions it chooses one of these processes and shifts it for a certain amount of time (within its variance in time). The EA stops if the necessary fitness or a predefined number of generations is reached. After this single optimization, the overall scheduling and thus the critical resources have changed. To deal with this the application of the variance in time is started again (inner loop). The break condition for the inner loop is modified by simulated annealing (SA), as ongoing shifting of processes becomes less effective during calculation but without SA the EA would not be able to pass local optima. Therefore the allowed fitness worsening is decreased by degrees. In addition the inner loop stops, when the delivery reliability or the overall efficiency becomes unacceptably bad. (Figure 2a)

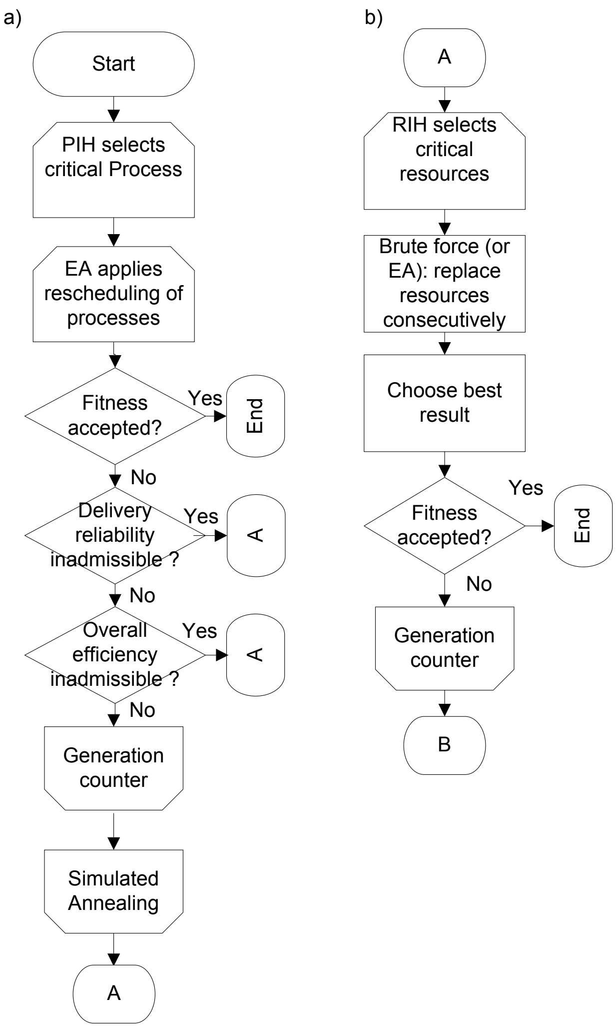

Figure 2: Application of the variance in time and the variance of resources

Variance of resources

Following to the search space definition by the Resource Identifying Heuristic (RIH) the combinations of replaceable resources are checked according to the achievable fitness. For normal scale problems and few available calculation time (of the overall optimization) the possible combinations are examined consecutively (brute force). If the main loop was already executed unsuccessfully and more alternatives have to be evaluated in depth, as well as for very large scale problems, that is done by an evolutionary algorithm instead.

After this single optimization, the overall scheduling and thus the critical resources have changed and the application of the variance of resources is started again (inner loop). The break condition for the inner loop is a predefined number of generations, as ongoing replacement of resources carries the risk of moving in a circle during calculation. (Figure 2b)

Variance of processes

In this case the PIH again defines the search space. Thereafter all combinations of alternative processes are checked according to the achievable fitness (brute force).

That is repeated for a small number of generations only (inner loop) as it has a wide and complex impact on the whole planning, and deeper analysis would cause extremely long calculation times without necessarily improving the result. (Figure 3a)

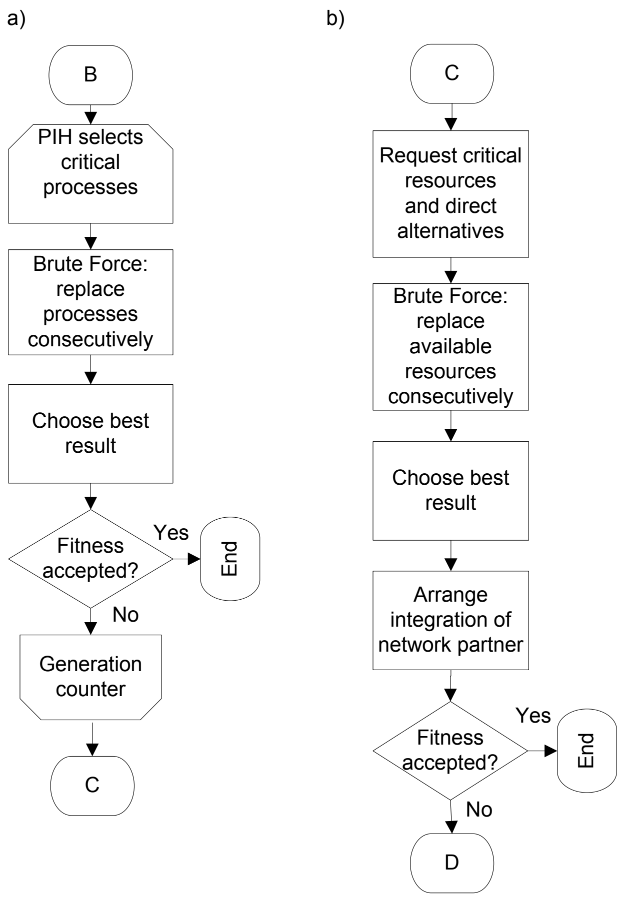

Figure 3: Application of the variance of processes and the service distribution

Service distribution

Here again the RIH is applied. Then all critical resources and their direct alternatives are requested to the network which includes e.g. customers, suppliers or sub suppliers. Further on all combinations of available resources are examined (brute force).

Requesting more resources less related to the critical ones would involve too much coordination effort while being to slow to enable the required real-time solution. Also this variance is not started again afterwards (no inner loop), as this would cause too long response time, too. (Figure 3b)

Variance of allocation time

Finally the adjustment of the allocation speed is executed for a reasonable calculation time.

The RIH at first tags the promising resources for acceleration. Afterwards an evolutionary algorithm optimizes the scheduling: For candidate solutions it chooses one of these resources, a journey between two processes and shifts it to another way of transportation. The EA stops if the necessary fitness or a predefined number of generations is reached. After this single optimization consequently the overall scheduling and the critical resources have changed. So an inner loop is implemented applying the variance of allocation time again. The break condition for the inner loop is modified by simulated annealing to pass local optima; therefore the allowed fitness worsening is decreased by degrees, whereas ongoing acceleration of resources becomes less effective but much more costly during calculation. (Figure 4a)

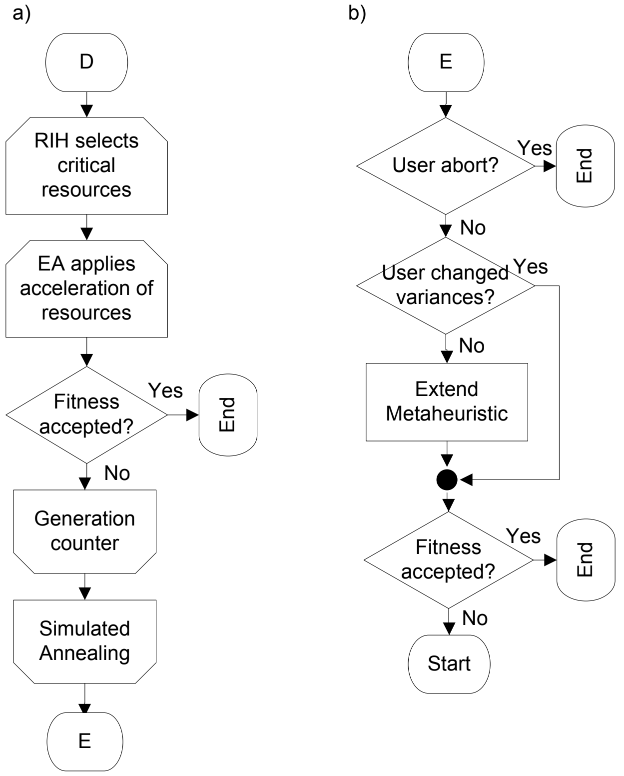

Figure 4: Application of the variance of allocation time and user intervention

After the application of all variances the user comes into action: He can abort the optimization manually or can modify some parameters / variances and start the same metaheuristic again. Alternatively he can start an extended metaheuristic on the same data. Therefore the intended number of generations is increased, the simulated annealing is slowed down; furthermore the PIH is applied before each RIH to additionally examine those resources involved in indirectly critical processes. (figure 4b)

3.4 Comparing optimization results

Basic requirement for every heuristic optimization is a calculable fitness function to compare solutions and move towards the optimum. Therefore the quality of a planning solution has to be measured by calculating key performance indicators (KPI). According to the three main objectives (delivery reliability, costs, work load, see chapter 1.3) at least three KPIs are needed.

Punctuality

The delivery reliability from the planner's point of view is represented by the punctuality. The punctuality z_p for each job is calculated by the ratio of process end date (end_p) and due date (due_p), each related to the current point in time t_i (equation 1a); in the best case z_p is 1, early finishing results in smaller, finishing too late in greater values. When combining these to the total punctuality z, the single punctualities are weighted by an exponential function to put strength on large delays and reduce earliness effects (equation 1b). As z_p>0, the first term is between 1 and ∞ (Optimum=e). Thus the total punctuality z is greater than 0 and has the optimum 1.

$$z_p = \frac{end_p - t_i}{due_p - t_i} \quad \text{(1a)}$$

$$z = \frac{1}{\left| \frac{\sum e^{z_p}}{n_p} - e \right| + 1} \quad \text{(1b)}$$

Costs

As comparable relative costs the ratio of planned total costs c and the total costs of a new planning solution c_i are calculated (eq. 2):

$$ce = \frac{c}{c_i} \quad (2)$$

Work load

The activity of all resources a is calculated by the ratio of cumulative process time (t_p) for all resources and the total possible resource working time (t_r), related to the current planning horizon and implying equal weighting of all resources. In the best case it is 100% (full use, no waiting); smaller values represent a lower work load. The overload of single resources is initially inadmissible; as an exception the planner can increase the maximum capacity of some resources and enable a work load > 1.

$$a = \frac{\sum t_p \forall r}{\sum t_r} \quad (3)$$

Total fitness: weighted sum approach

After calculating the single KPIs they are combined to an overall KPI for the optimization result. The single terms normally tend to the optimum 1, while lower values represent worse KPIs.

$$f_i = w_1(t_i) \cdot z_i + w_2(t_i) \cdot ce_i + w_3(t_i) \cdot a_i \quad (4)$$

The summation of the weights is 1. Furthermore the weights are adjusted dynamically according to the position within the planning horizon t_i: When the planning problem to be optimized is situated far in the future, so e.g. building up capacities is possible, costs are the main objective of the optimization. The absolute work load on the other hand has secondary importance, beyond costs, for the valuation of the optimization result, because the capacities can be adjusted to the workload. During the operative planning, which has to react on short-term tasks, e.g. due to a machine breakdown the delivery reliability for all jobs including the short-term tasks is much more important than costs or work loads.

Thus the planner can vary the focus of the planning between punctuality, costs and work load. The total fitness f is always > 0 and normally < 1; the greatest f represents the best solution. Only exceptionally a fitness > 1 can occur.

This situational combination of the three main KPIs allows reducing the optimization complexity as there is now only one objective: the optimization of the overall KPI.

4 SUMMARY

To deal with the multidimensional and multiobjective planning of service processes within Industrial Product-Service-Systems a real-time capable optimization strategy is needed. Therefore the related basic optimization problems and optimization metaheuristics were analyzed. This paper describes an approach of using an individual hybrid metaheuristic to optimize the resource planning. Therefore a combination of Evolutionary Algorithms, Simulated Annealing and Brute Force Search is used in conjunction with the structured application of the IPS²-specific variances.

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6 REFERENCES

[1] Levitt, T., 1969, The Marketing Mode, Pathways to Corporate Growth

[2] Cunha, P. F., Caldeira Duarte, J. A., 2004, Development of a Productive Service Module Based on a Life Cycle Perspective of Maintenance Issues, Annals of the CIRP, Vol 53/1, 13-16, ISSN: 0007-8506

[3] Tan, A. R., McAloone, T. C., 2006, Characteristics of strategies in Product/Service-System Development, International Design Conference – Design 2006, Dubrovnik – Croatia, May 15-18

[4] Matzen, D., Tan, A. R., Myrup Andreasen, M., 2005, Product/Service-Systems: Proposal for Models and Terminology, 16. Symposium “Design For X”, Neukirchen, October 13-15,

[5] Arai, T., Shimomura, Y. 2005, Service CAD System – Evaluation and Quantification, Annals of the CIRP, Vol 54/1, 463-466

[6] Meier, H., Kortmann, D., 2007, Leadership – From Technology to Use, 14th CIRP Conference on Life Cycle Engineering, 159-163

[7] Meier, H., Krug, C. M., 2008, System for Planning of Resources in IPS²-Delivery, 41st CIRP Conference on Manufacturing Systems, Tokyo, Japan

[8] Meier, H., Krug, C. M., 2006, Strategische Kapazitätsplanung hybrider Leistungsbündel, PPS Management 11, 48-51

[9] Klamroth, K., 2009, Discrete Multiobjective Optimization, Evolutionary Multi-Criterion Optimization 5th International Conference, EMO 2009, Nantes, France, April 7-10, Proceedings ISBN 978-3-642-01019-4, 4

[10] Sathe, M., Schenk, O., Burkhart, H., 2009, Solving Bi-objective Many-Constraint Bin Packing Problems in Automobile Sheet Metal Forming Processes, Evolutionary Multi-Criterion Optimization 5th International Conference, EMO 2009, Nantes, France, April 7-10, Proceedings ISBN 978-3-642-01019-4, 246-260

[11] Datta, D., Deb, K., Fonseca, C. M., 2007, Multi-objective Evolutionary Algorithms for Resource Allocation Problems, Evolutionary Multi-Criterion Optimization 4th International Conference, EMO 2007, Matsushima, Japan, March 5-8, Proceedings ISBN 978-3-540-70927-5, 401-416

[12] Hutzschenreuter, A., Bosman, P., La Poutré, H., 2009, Evolutionary Multiobjective Optimization for Dynamic Hospital Resource Management, Evolutionary Multi-Criterion Optimization 5th International Conference, EMO 2009, Nantes, France, April 7-10, Proceedings ISBN 978-3-642-01019-4, 320-334

[13] Garcia-Najera, A., Bullinaria, J., 2009, Bi-objective Optimization for the Vehicle Routing Problem with Time Windows: Using Route Similarity to Enhance Performance, Evolutionary Multi-Criterion Optimization 5th International Conference, EMO 2009, Nantes, France, April 7-10, Proceedings ISBN 978-3-642-01019-4, 275-289

[14] Geiger, M. J., 2009, Multi-criteria curriculum based course timetabling - A comparison of a weighted sum and a reference point based approach, Evolutionary Multi-Criterion Optimization 5th International Conference, EMO 2009, Nantes, France, April 7-10, Proceedings ISBN 978-3-642-01019-4, 290-304

[15] Raidl, G. R., 2006, A Unified View on Hybrid Metaheuristics, Hybrid Metaheuristics, Third International Workshop, HM 2006 Gran Canaria, Spain, October 13-15, Proceedings ISBN 978-3-540-46384-9, 1-12

[16] Glover, F., Kochenberger, G. A. (eds.), 2003, Handbook of Metaheuristics, International Series in Operations Research & Management Science, Vol. 57, Springer, ISBN 978-1-4020-7263-5

[17] Blum, C., Roli, A., 2003, Metaheuristics in combinatorial optimization: Overview and conceptual comparison, ACM Computing Surveys 35(3), 268-308.

[18] Crescenzi, P., Kann, V., 1997, Approximation on the web: A compendium of NP optimization problems, Randomization and Approximation Techniques in Computer Science, International Workshop RANDOM'97, Bologna, Italy, July 11-12, Proceedings ISBN 978-3-540-63248-1, 111-118

[19] Talbi, E. G., 2009, Metaheuristics: from design to implementation, Wiley, ISBN 978-0-470-27858-1

[20] Vöcking, B.; Alt, H.; Dietzfelbinger, M.; Reischuk, R.; Scheideler, C.; Vollmer, H.; Wagner, D. (Ed.), 2008, Taschenbuch der Algorithmen, Springer, ISBN: 978-3-540-76393-2

[21] Zitzler, E., Laumanns, M., Bleuler, S., 2004, A tutorial on evolutionary multiobjective optimization, Metaheuristics for Multiobjective Optimisation, Springer, ISBN: 978-3-540-20637-8, 3-38

[22] Eiben, A. E., Smith, J. E., 2003, Introduction to Evolutionary Computing, Springer, ISBN: 978-3-540-40184-1

[23] Konaka, A., Coitb, D. W., Smithc, A. E., 2006, Multi-objective optimization using genetic algorithms: A tutorial, Reliability Engineering & System Safety, Vol. 91, Issue 9, 992-1007

[24] van Laarhoven, P. J., Aarts, E. H., 1987, Simulated Annealing: Theory and Applications, Springer, ISBN: 978-90-277-2513-4

[25] Martin, O. C., Otto, S. W., 1996, Combining simulated annealing with local search heuristics, Annals of Operations Research 63 (1), Springer Netherlands, ISSN 0254-5330

[26] Gendreau, M., 2003, An introduction to tabu search, Handbook of Metaheuristics, International Series in Operations Research & Management Science, Vol. 57, Springer, ISBN 978-1-4020-7263-5, 37-54

[27] Cormen, T., H., 2001, Introduction to algorithms, MIT Press, ISBN 0262032937

[28] Dorigo, M., Stützle, T., 2004, Ant colony optimization, MIT Press, ISBN 0-262-04219-3