Service Productivity Optimization Using Genetic Algorithm

GJCST Computing Classification
H.3.4

[1]S. Tackenberg, [2]S. Duckwitz

Abstract- **The efficient development and prospective evaluation of valid service scenarios is a critical success factor for companies. With an increasing complexity of service provision the planning process gains importance. But the process of planning a service and optimizing the underlying service plan still lacks adequate knowledge and support. Existing approaches are not suitable for an optimization of services with regard to productivity prior to their implementation. To achieve efficient services, the concepts for service productivity are reviewed and novel aspects of a developed Genetic Algorithm (GA) for solving the resource constraint service scheduling problem are presented. The GA is verified and validated based on a case study in the German chemical industry. Due to the extensive documentation of this company, detailed information about task structure and workload could be gathered and used for model development. The results of the validation study confirm the structural and external validity of the developed project model. Therefore, the proposed GA-based optimization method has demonstrated its validity and utility in this particular application domain.**

Keywords- optimization, Genetic Algorithm, Service Productivity, Service Management.

I. Introduction

Service science focuses on studying the characteristics of service processes intending to simultaneously reduce service lead-times, reduce cost, and improve quality. Several formal theories of service management have been published (Koumpis, 2010). While the relevant authors fail to agree on a single theory of best service processes as a benchmark for a service enterprise, four facts in terms of planning service operations are generally regarded as important: (1) Uncertainties regarding the duration of activities are a typical characteristic of service projects (Blackburn, 1991), (2) predecessor constraints of tasks within a (service) project are not strictly specified and are therefore often refined with respect to the situation and the person (Eppinger et al., 1994), (3) the assignment of actors and resources (tools, facilities) to tasks is a complex resource constraint scheduling problem whose solution determines the service lead-time (Hildum, 1994), (4) iterations are a characteristic of complex services as well as a major source of unexpected rework and budget overruns (Reijers, 2003). Due to these facts, both the prospective evaluation of uncertainty and the consideration of complexity have become central issues in developing a service organization. Research in this field has shown that modeling provides an avenue to improved understanding and optimization of service operations (Barnard, 2006). Optimization of a service organization and the underlying service processes can be achieved in several ways:

Improving the sequence of activities to streamline the workflows, which directly determine the service provision (Eppinger et al., 1994); developing simulation models to describe, evaluate and minimize uncertainty of a service process due to adding actors and resources to bottle neck tasks (Yassine & Braha, 2003). Instability can be reduced by reordering tasks and considering alternative options so that the effects of delayed activity processing and feedback are minimized. Thereby, an ideal work organization is defined as one with no iterations (Yassine et al., 2007) and which fully achieves the planning objectives. However, in real complex service projects, an optimal sequence of activities as well as assignment of actors and resources is unlikely to be uncovered. Thus, a heuristic for the development of an optimal service provision is still missing. Therefore this paper focuses on a genetic optimization heuristic to improve the productivity of service projects. The approach has to be suitable for decision support in the context of developing a service plan.

II. Service productivity

A theoretical concept or a procedure model to evaluate the effectiveness of services is missing. To close the lack of knowledge the German Federal Ministry of Education and Research set up the research program ―productivity of services" in 2009 to identify the success parameters of efficient services. The incentive for such a research program was the missing of a general theory for service productivity. Existing definitions of service productivity are based on elements of definitions for production processes. In the context of production, the term productivity is understood as the alignment between the entire output and the input used (Ojasalo, 1999). A measurement of the input parameters, e.g. labor, capital, energy, material and information (Sink, 1985) is a central challenge for service science. But also the definition of a valuation baseline is compared to the evaluation of a production processes difficult to achieve due to weakly structured service operations and a high impact of actors' behavior (Ojassalo, 1999). In particular for service providers, the dependence on superordinate workflows leads

About 1st author: Sven Tackenberg completed an apprenticeship as Electronician in the German electronics industry in 2000. He studied industrial engineering at the Technical University of Kaiserslautern, Oita University and received his degree from Paderborn University in 2006. Since June 2007 he is research assistant at the Institute of Industrial Engineering and Ergonomics at RWTH Aachen University.
(telephone: +49 241 80 99462 email: s.tackenberg@iaw.rwth-aachen.de
About 2nd author: Sönke Duckwitz received the Dipl.-Ing. and the Dipl.-Wirt.Ing. degrees from RWTH Aachen University, Germany, in 2003 and 2006, respectively. He is currently a research assistant at the Institute of Industrial Engineering and Ergonomics at RWTH Aachen University.
(telephone: +49 241 80 99461 email: s.duckwitz@iaw.rwth-aachen.de)

to a close cooperation between different actors (Cerasale, 2004). Similar to the lack of methods for a precise measurement of the input parameters, an approach for the evaluation of output parameters is missing. Apart from the quantitative parameters (quantity of service per time period, costs, utilization of the workforce) especially the ―soft" parameters for the evaluation of service productivity are of high relevance, e.g. customer satisfaction, workload of employees (Karapidis, 2005). Although, the comprehension of the term ―service productivity" is related to the definition of production productivity (Johnston & Jones, 2003) a general approach to determine a service specific basis of valuation is missing. On the basis of experience with simulation models for the development of production processes a simulation based evaluation of service productivity seems promising. Therefore, the following aspects have to be considered:

i. The measurement of productivity is distorted due to physical distinction during the analysis of inputs and outputs, which are scaled in most cases in different units (Johnston & Jones, 2003).
ii. The high number of combinations between different characteristic of outputs and inputs as well as missing restriction of productivity ratios does not provide valid indicators of performance (Sink, 1985; Johnston & Jones, 2003).
iii. The significance of the productivity ratio is limited due to the insulated view from other performance factors (e.g. the demanded productivity or internal bench marks) (Sink, 1985).
iv. The characteristics of elements (activities, actors etc.) and relations (iterations, overlapping of activities etc.) of a service organization are fraught with uncertainty. Groenross (2000) describes a service provision as an open process by which changes in the input variables (such as employees, systems, physical resources and technologies, and customer participation) influence the efficiency of the process.
v. The behavior and the decision making of actors have a high impact on service productivity (Cerasale, 2004). This must take into account that services operations are not exclusively designed and implemented by the service provider due to the fact that there are strong interrelations to the customers as well as the suppliers (Edvardsson & Olsson, 1996).

Ojasalo (1999) assumes that existing economic approaches cannot adequately describe or measure service productivity. In this context (Groenross & Ojasalo, 2004) asserted that the comprehensive analysis of service productivity is still at the beginning. Due to the fact that only a few papers about service productivity were published during the last five years, a research gap can still be identified. Therefore, only a few detailed models can be found in literature that explain the complexity and multidimensionality of service productivity, e.g. Corsten & Stuhlmann (1998), Groenross & Ojasalo (2004), and Johnston & Jones (2003). However, all these models are very generic and limited with regard to their applicability by service managers. Thus, an efficient design of service operations and the application of the methods to real service processes are missing.

The approach presented in this paper focuses on a simulation based model to measure service productivity. It is suitable for the decision support in the context of service design and considers the cooperation of enterprises, suppliers and subagents. Thereby, retrospective methods of analysis are not accessible for the prospective evaluation of different service scenarios (Winkelmann & Luczak, 2006) and are not considered for the development of an optimization heursitic.

III. Genetic Algorithm for the Optimization of Service Productivity

Genetic Algorithms (GA) are robust stochastic search algorithms inspired by the process of biological evolution and are often used for scheduling problems (Koza et al., 2003). This class of optimization heuristics considers a set of population of solutions as opposed to only one solution throughout local search. Following an initial population with several individuals through a random generation, new individuals are produced by mating two existing ones (crossover operation) and/or by altering an existing one (mutation operation). Thereby, an individual represents a solution to the optimization problem. Selection scheme determines which individuals survive via evaluating fitness or objective function. The fittest individuals take over next generation while the others are deleted. This optimization process finishes with a convergence to an optimal or near-optimal solution. The structure and the operations of Standard Genetic Algorithms (SGA) for scheduling problems are widely mentioned in literature (Koza et al., 2003) and are not further covered in this paper. The novelty of the presented GA is the characteristic of a chromosome, the transformation of the modified chromosomes into a detailed, feasible service organization model and the evaluation of the service plan quality. These three aspects allow the initial description of uncertainty and stochastic events within a service organization.

I. Genetic Representation Of A Service Organization

The chromosome consists of a number of genes corresponding to the number of activities in a service project or a multi service portfolio of a company. More precisely, a gene represents an activity and has therefore a unique identification number (ID). By the use of an ID, the loci of genes do not necessarily have to be fixed. Each gene consists of several attributes (Fig. 1):

i. Status Of Activity- The boolean value (true, false) indicates if the activity is an integral element of the service plan. Due to this construct the alternative execution of activities or a sequence of activities can be described.
ii. Starting time ti- The value defines the starting time of the activity i and describes the work on predecessor activities j completed by that time.

iii. Within a predetermined range [0, 2.5] the value zi is randomly selected during the optimization process:
zi < 1; Overlapping of activities i and j,
zi = 1; Starting time of activity i and end time of activity j are identical.
zi > 1 Pause between the end time of activity j and the starting time of activity i.

iv. Actor: The value references to the characteristic of at least one actor who has to execute the activity. Thereby, the assigned actor fulfills the formal qualifications required by the task.

v. Duration of Activity di: The attribute describes the duration of the activity i. The stochastic parameters (variance of estimation errors, random events etc.) and deterministic parameters (effect of complexity of task etc.) are integrated in this value.

vi. Events: The attribute ―events" describes the occurrence and the structure of an iteration. The information about the characteristic is stored in the gene which triggers the event.

vii. Additional Information: The information on the probability of the occurrence of this specific activity characteristic is stored in the gene. This information is used during the optimization process to calculate the probability for the occurrence of the generated service process.

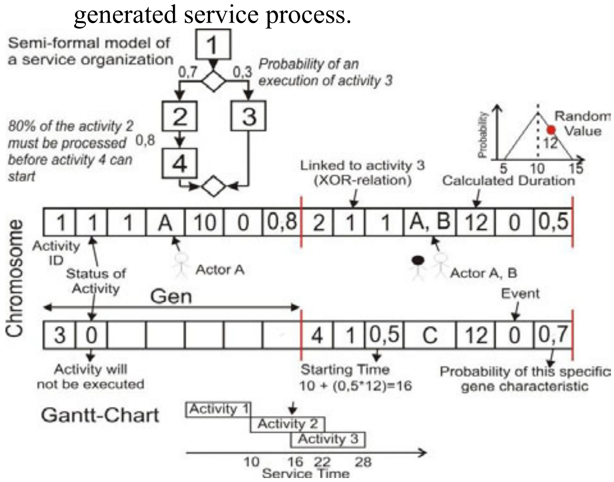

Fig.1. Gene structure

The values of starting time t_i and duration d_i are used to clearly assign the activity into a plan for service provision. Except the gene's ID, which is internally stored by the data structure, the attributes of the gene are subject to crossover and mutation operations and will be changed during evolution. Based on the description of the most important and widely used types of genetic representation by Rothlauf (2006), the developed encoding can be characterized as a real-valued messy representation. The position of genes and the corresponding real value are coded together in the string. Thereby, the encoding is independent of the position of the alleles in the chromosome.

II. Gp Mapping

A chromosome (genotype) represents an individual and is a blueprint for a service organization. Based on the information of varied, unvaried chromosomes and data base entries the genotype-phenotype mapping fg (GP-mapping) is used to generate a feasible, detailed service process for an individual. Information about the characteristics of actors and activities is stored in a central data base and is not varied during optimization. The developed algorithm therefore concerns only for the attributes of the genes of an individual. A mapping results in a description of a detailed service organization which includes information about the sequence of activities, the assignment of actors to tasks as well as further characteristics of the service scenario, i.e., the starting time and the durations of activities, the probability of the occurrence of the service scenario, etc. Uncertainties within a service organization are modeled by stochastic variables and are interpreted during the optimization process by the GA. Within a population the stochastic elements of the service model lead to a variety of heterogeneous individuals. Although uncertainties of service projects have been considered in the approach, due to the novel genotype structure and fg, the mapping of a specific characteristic of a genotype into a phenotype always generates an identical service organization. The steps for the GP mapping process are as follows:

Step 1-A gen (activity i) is randomly chosen from the set of genes of an individual. At the same time the algorithm verifies whether the activity i is already a part of the developed service organization and its predecessors activities have been sufficiently processed. If not, step 1 is continued until an activity i is found.

Step 2-Assignment of actor(s) to the activity i according to the ID of an actor stored in the gene.

Step 3-The exact duration of activity i is listed in the gene. The calculation of the value is done before the GP-mapping by the mutation operator and is based on:

i. Basic effort de(i) of activity i estimated by experts
ii. Qualification q of assigned actor
iii. Random value h, to consider the estimation errors of the requested durations – probability distribution, e.g., Gaussian, right- or left-skewed β-distribution.
The duration d of activity i is calculated: di = de(i) • q • h.

Step 4- Calculation of the absolute starting time tj of activity i, based on:

i. Time period related to the end time of predecessor activities tj (variable factor zi, stored in gene)
ii. Starting time and duration of the predecessor(s).
iii. The absolute starting time t_i is calculated as follows:
$t_i = t_j + (z_i \cdot d_j)$. For activities with more than one predecessor: $t_i = max\ \{ t_j + (z_i \cdot d_j) \mid j = 1, \ldots, n\}$

Step 5- In this step it is verified if the assigned actor executes an activity j, j≠i at any particular time of the period pi:

i. Status of the actor (employed, unemployed) during: $p_i = t_i + d_i$

If the actor is unemployed during pi the assignment leads to a change of the status (employed). If an actor is employed, the starting time of the activity i is modified under consideration of the predecessor constraints. For the identification of a valid placement the starting time is iteratively modified: ti = max { tj + 1 + (zi • dj) | j = 1, …, n} until a valid solution is found.

Step 6- Activity Freeze – the parameters of the activity are defined (global starting time, duration etc.) and the activity is placed in the plan.

Step 7- The steps 1 to 6 are repeated until all tasks of a chromosome have been placed for the development of a comprehensive service organization.

III. *Evaluation Of Plan Quality*

The development of efficient service organizations has to be characterized as a multi-criteria optimization problem. Thereby, the planning objectives are often complementary or conflicting. This can result in a plurality of optimal solutions, but only according to a specific objective or a target combination. Therefore, one optimal plan can only be identified if a prioritizing of objectives is given. Otherwise a pareto front with different optimal solutions must be approximated. In subject to the personal preferences of the planner a solution can be situation-related selected.

The planning problem considered here has a two-dimensional targeting vector (minimization of service budget and service duration). Two-dimensional targeting vectors are partially ordered, i.e. two vectors are incomparable if each of them contains a more advantageous component. A vector dominates another one if at least one component shows a better value and is not concurrently worse in any other component. For example, the Individual No. 1 is dominated with regards to time- and cost-targets by five individuals (Fig. 2). To quantify the performance of the generated individuals, the S-metric by Zitzler et al. (2006) was implemented for the GA. This metric has been deemed one of the fairest and most useful existing methods for the evaluation of multi-criteria solutions (Zitzler et al., 2006). The metric measures the dominated hyper volume. The volume describes the area of a solution space and those vectors which are worse than at least one individual of the set. The S-metric value is to be maximized, which can graphically be regarded as the conquest of the solution space. It is further necessary to distinguish between two sets of individuals non-dominated and dominated vectors. If a population contains dominated individuals, the one with the highest dominance value is removed. The value describes the number of individuals which are dominated by a solution. If a population contains only non-dominated individuals, the one with the lowest s-metric value (hyper volume) is deleted. Thereby, the hyper volume is the sub-space which is only dominated by a single individual (Fig. 2). To minimize the loss of quality the GA selects in a case of exclusive non-dominated individuals the one with the smallest s-metric value. For the dominated individuals a further VS-metric value is calculated. This value describes the smallest distance of a dominated solution to a non-dominated pareto-optimal solution. Thus apart from the non-dominated individuals, the dominated individuals are sequenced in an ascending order.

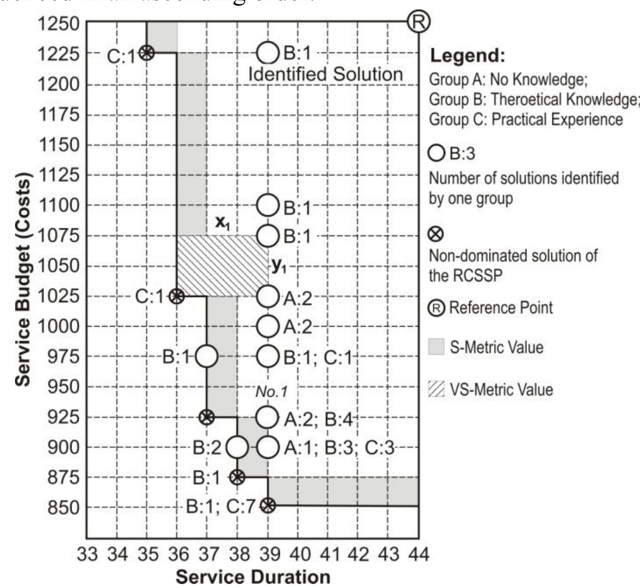

Fig. 2. Pareto front with optimal solutions and solutions identified by participants

IV. VALIDATION STUDY

An experimental study and a case study in a medium-sized enterprise in the German chemical industry were conducted to verify and validate the developed GA.

The goal of the experimental study was to compare service plans generated by the GA with solutions developed by humans. Therefore, an existing measure of problem solving- and planning competencies (Arling, 2006) was refined. The study was conducted as a web-based planning game and could be executed by multiple participants simultaneously. The advantage of a decentralized execution – due to independence regarding time and place – was that experienced service managers could be recruited for the two-hour participation. On the other hand, the decentralization of the test procedures limited the significance of the test due to a missing control of the framework conditions. A total of 34 participants, 9 female and 25 male between 18 and 56 years of age participated in the study (average 28.03 years, SD=6.85). For the experimental task a typical computer-aided development of a service plan, such as the definition of predecessors and successors for activities or the parameterization of activities (starting time, duration, costs etc) had to be completed by the participants. The task the subjects had to deal with was the development of a project plan for the service —organization of an event” consisting of 34 activities. Each subject received a graphical model indicating the sequence of activities and further information about their characteristics. The web-based experimental environment is similar to MS Project. In parallel to these investigations, the corresponding service model for the GA was developed and the multi-criteria optimization was carried out. The goal was the simultaneous minimization of service costs and time and therefore the approximation of the pareto front for this specific RCSSP.

The analysis of the planning results of the participants shows a significant deviation of the solutions from the optima, identified by the GA (Fig. 2). For the multiple criteria planning game (cost versus service duration) 5 non-dominated solutions exists. The matrix shows all solutions of the participants in relation to the pareto front. With regard to the information about the classification of the subjects regarding their project planning knowledge/experience the graphical visualization allows a comprehensive evaluation to what extent the subjects were able to identify optimal solutions.

The case study in a medium-sized enterprise involves the service of a facility for the production of polymer. Due to complex interrelations between service projects within the company, only one project and acquired accurate time and cost data was considered. The essential information to build up a service organization model was enquired from the service manager of the enterprise. Finally, the most efficient work organization relating to the fulfillment of predefined planning objectives was compared to the historical data of the enterprise. Identified similarities as well as differences regarding the key project performance indicators (duration, costs, utilization of workers etc.) and the progression of services were discussed with the project manager and project team members. The validation procedure chosen in this study ensures by the separation of data ascertainment (interview and experience-based organizational modeling), the development of the project simulation model and the analysis of the existing project documentation an objective evaluation of the planning quality achieved.

The service project consisted of 62 development tasks, from the identification and analysis of customer specifications of the chemical process, to the commissioning of the installation. Thereby, the service organization was comprehensively modeled through the characterization of internal organizational units of the company, as well as external actors (engineering service providers, maintenance enterprises etc.). The characterization of organizational units included the modeling of qualifications and experiences of the employees, as well as resource descriptions. The tasks have been processed in several projects, so that deviations from the arithmetic mean could be identified by the project manager. Because the task predecessor constraints were deterministic and stochastic, and there were many degrees of freedom in assigning actors to tasks, the considered service process in this particular company was a good candidate for evaluating the performance of the GA. The identification of the global optimum implies an efficient parameterization of the population size and the mutation rate. Based on previous work of Zhuang and Yassine (2004), the correlation between the arithmetic mean of the fitness value and the population size were investigated. The fitness function was a weighted accumulation function with a strong emphasis on the minimization of project lead-time and cost. The weighting of each objective was based on project manager‘s individual preferences concerning the investigated process engineering project. Fig. 3 shows the progress of the arithmetic mean of the fitness influenced by population size and mutation probability pmc. An individual that passed into the next generation is chosen randomly (probability pmc) and it genes are than accidentally selected for mutation. As the population size (number of individual) increases, the fitness increases in value. The results revealed a clear influence of the mutation probability pmc and the fitness. For low values of pmc fitness values become stable when the population size reaches the number of genes of an individual (number of tasks: 62). For higher values of pmc the continuous modification of a high proportion of partial efficient individuals lead to an oscillation of the fitness. These results are consistent with the findings of Zhuang and Yassine (2004). Therefore, it can be assumed that with an adequate population size, good schemes for the project planning problem can be located within the search space.

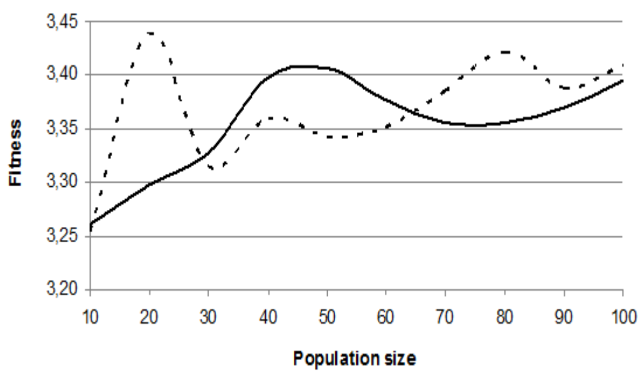

Fig. 3. Arithmetic mean of the fitness value over the chromosomes of all 50 generations for different population size and mutation probability pmc

The validity of the results was further confirmed by analyzing the service lead-time and cost for several generations. This requires the transformation of the genotypes of each generated individual into a detailed service plan. Two scenarios with different actor competences were investigated in detail: (1) The actors involved in the project have a medium competence (value: 1.0). (2) The actors have different values for their competences (0.8 to 1.2). The competence of an actor is negatively correlated with the makespan of a specific task and positively correlated with the cost per time unit. Both correlations are based on estimates of the service managers. The curve progression (Fig. 4) concisely describes the correlation of assigning ―competent" actors to tasks to reach a minimization of the service lead-time. In particular, the steep negative slope for the lead-time of scenario 2 until generation 30 indicates the high degrees of freedom regarding the improvement of the service organization. With an increasing number of generations the lead-time converges due to precedence constraints of tasks. The stopping criterion of optimization was set to 100 generation. A further reduction of the makespan of single tasks through the assignment of actors to tasks with a higher competence has no influence and only the service budget increases.

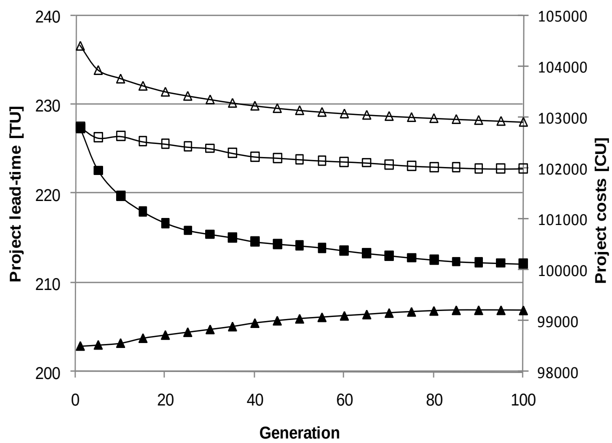

Fig. 4. Arithmetic mean of the service lead-time and costs

V. CONCLUSION

In the previous sections, a GA was introduced to describe and optimize service productivity. Determining the sequence of tasks with given and indefinite predecessor constraints as well as uncertainty regarding the time-on-task is a NP-hard scheduling problem. The objective was to minimize the service lead-time and costs through the improvement of activity sequences, assignment of actors, and resources under certain constraints (availability; qualification etc.). The GA structure and operations allow the identification and evaluation of optimal service organizations under uncertainty. Furthermore, the transformation of a modified gene resulted in time-grained and valid project plans despite several stochastic influences.

In future papers additional optimization studies of more complex project organizations with a larger number of coupled activities and more organizational units will be presented. A scientific focus is the integration of individual human behavior into the project model. In conclusion, the GA enables manager to develop more efficient service organizations. In the long term, an effect on the service productivity due to a comprehensive identification and evaluation of valid service organizations within a short time will take place.

VI. REFERENCES

1) Arling, V.S. (2006). Entwicklung und Validierung eines Verfahrens zur Erfassung von Planungskompetenz in der beruflichen Rehabilitation: „Der Tour-Planer―. Ph.D. dissertation, psychology program, RWTH Aachen University, Aachen, Germany.
2) Barnard, J.H. (2006). A Multi-View Framework for Defining the Services Supply Chain Using Object Oriented Methodology. PhD Thesis, University of Central Florida.
3) Blackburn, J.T. (1991). New Product Development: The New Time Wars. In J.T. Blackburn (Ed.), Time-Based Competition: The Next Battleground in Manufacturing. Homewood, IL: Business One Irwin Publishers.
4) Cerasale, M. (2004). Business Solutions on Demand. London: Kogan Pages.
5) Corsten, H., & Stuhlmann, S. (1998). Capacity management in service organizations. Technovation, 18(3), 163-178.
6) Edvardsson, B., & Olsson, J. (1996). Key Concept for New Service Development. The Service Industries Journal, 16(2), 140-164.
7) Eppinger, D., Whitney, D. E., Smith, R.P., & Gebala, D.A. (1994). A model-based method for organizing tasks in product development. Research in Engineering Design, 6(1), 1-13.
8) Groenroos, C. (2000). I Did It My Way. In R.P. Fisk, S.J. Grove, & J. John (Eds.). Service Marketing Self-Portraits: Introspections, Reflections, and Glimpses from Experts. Chicago: American Marketing Association, 71-108.
9) Groenroos, C., & Ojasalo, K. (2004) Service Productivity. Towards a Conceptualization of the Transformation of Inputs into Economic Results in Services. Journal of Business Research, 54(4), 414-423.
10) Hildum, D.W. (1994). Flexibility in a knowledge-based system for solving dynamic resource-constrained scheduling problems. UMass CMPSCI Technical Report 94-77, Department of Computer Science, University of Massachusetts.
11) Johnston, R., & Jones, P. (2003). Service Productivity – Towards Understanding the Relationship between Operational and Customer Productivity. presented in the Workshop Service Productivity, IAO, Stuttgart.
12) Karapidis, A. (2005). Service Management in Production Companies. In G. Zülch, H.S. Jagdev, & P. Stock (Eds.). Integrating Human Aspects in Production Management. Proceedings of the International Conference on Human Aspects in Production Management. New York: Springer: 375-385.
13) Koumpis, A. (2010). Service Science for Socio-Economical and Information Systems Advancement. Hershey: Information Science Publishing.
14) Koza, J.R., Keane, M.A., Streeter, M.J., Mydlowec, W., Yu, J., & Lanza, G. (2003). Genetic Programming IV: routine human-competitive machine intelligence. Newell, MA: Kluwer Academic Publishing.
15) Ojasalo, K. (1999). Conceptualizing productivity in services. Thesis (doctoral). Svenska handelshögskolan, Helsingfors: Swedish School of Economics and Business Administration.
16) Reijers, H.A. (2003). Design and Control of Workflow Processes – Business Process Management for the Service Industry. Berlin: Springer.

17) Rothlauf, F. (2006). Representations for Genetic and Evolutionary Algorithms, 2nd ed. Berlin: Springer.
18) Sink, S. (1985). Productivity Management: Planning, Measurement and Evaluation, Control and Improvement. New York: John Wiley & Sons Inc.
19) Winkelmann, K., & Luczak, H. (2006). Modelling, simulation and prospective analysis of cooperative provision of industrial services using coloured petri nets. International Journal of Simulation, 7(7), 10-26.
20) Yassine, A. A., & Braha, D. (2003). Four Complex Problems in Concurrent Engineering and the Design Structure Matrix Method. Concurrent Engineering Research & Applications, 11(3), 165-176.
21) Yassine, A. A., Meier, C., & Browning, T.R. (2007). Design Process Sequencing With Competent Genetic Algorithms. Transaction of the ASME, 129, 566-585.
22) Zhuang, M., & Yassine, A. A. (2004). Task Scheduling of Parallel Development Projects using Genetic Algorithm. Proceedings of ASME 2004 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, Salt Lake City, Utah USA, September 28-October 2. 1-11.
23) Zitzler, E., Deb, K., & Thiele, L. (2000). Comparison of multiobjective evolutionary Algorithms: Empirical Results. Evolutionary Computation, 8(2), 173-195.

Global Journals Guidelines Handbook 2010

www.GlobalJournals.org