Interactive Fuzzy Decision Support to Adjust Human Resource Structures

Peter Rausch and Michael Stumpf
Technische Hochschule Nürnberg Georg Simon Ohm, Keßlerplatz 12, 90489 Nuremberg, Germany

Keywords: Human Resource Planning, Human Resource Management, Manpower Planning, Fuzzy Decision Support, Fuzzy Linear Optimization, Uncertainty, Fuzzy Set Theory.

Abstract: Human resource planning plays a key role for enterprises' and organizations' sustainable success. This paper focuses on issues and challenges in the field of human resource planning in hierarchical organizations. Due to current challenges, like digital transformation, progress in artificial intelligence, etc., a fundamental structural transformation of workforce is initiated in many companies and organizations. Especially, huge enterprises in many industries and the service sector as well as organizations in the public sector have to review their mid-term and long-term desired human resource (HR) target structures. Based on an organization's target structure, a strategy to transfer the actual HR structure to a desired new target structure is needed. This step is a big challenge because of many uncertainties of system parameters and complex structures of the planning approaches with many constraints and conflicting goals. To bridge gaps in this field, an interactive fuzzy approach which supports the development of strategies for actual-target structural adjustments (ATSA) in big organizations will be presented. This approach manages conflicting goals and is based on experience gained in an organization of the public sector, but it can also be transferred to non-governmental industry and service companies.

1 INTRODUCTION

Digital transformation, progress in artificial intelligence, globalization and process reengineering trigger fundamental structural transformations of workforce, both in enterprises and in the public sector. Considering that human resource planning is a key factor for enterprises' and organizations' sustainable success, this issue is a serious challenge. Thus, especially, huge enterprises in many industries and service sectors as well as organizations in the public sector, like public authorities, the army, and the police, have to manage transformation processes of their human resource (HR) structures. For this reason, decision support systems in the field of HR planning are essential. Despite all progress in research, some serious issues have not been addressed in an appropriate manner yet. For instance, the complexity of staff planning issues causes a lot of effort since all the necessary data for the planning tools has to be gathered. Especially in case of medium- and long-term oriented planning, approaches additionally struggle with uncertainties of planning parameters. Most tools are not able to cope with a lack of data precision and reduce vague data to (unrealistic) crisp values. Moreover, procedures to manage conflicting goals, for instance, minimizing costs versus fast staffing of open positions, have to be provided, which is not always the case.

To analyze these issues in detail, the paper is arranged as follows: At first, we give a brief survey on HR planning. We will outline the issue of actual-target structural adjustments (ATSA) and classify it in the field of HR planning. Afterwards, related work and open challenges will be discussed. The presented approach addresses open issues and provides interactively generated strategies for future staff alignments. It is designed for medium-sized or big organizations and can be used by industry and service companies as well as by other organizations. We will briefly describe the sources of data input, namely, an HR system providing the actual headcount and a decision support system, which computes an HR target structure. Subsequently, the interactive fuzzy approach to explore the solution space and to identify actual-target adjustment strategies is presented. Details of the related planning procedure will be given, including a solution to solve conflicting goals. Finally, we discuss the impacts of our approach and provide conclusions for further developments.

Rausch, P. and Stumpf, M.
Interactive Fuzzy Decision Support to Adjust Human Resource Structures.
DOI: 10.5220/0006765204410447
In *Proceedings of the 20th International Conference on Enterprise Information Systems (ICEIS 2018)*, pages 441-447
ISBN: 978-989-758-298-1

2 OPEN ISSUES, CHALLENGES, AND RELATED WORK

Since HR planning covers a broad range of issues, it is important to classify the subject of this research. There are many different interpretations of the term HR planning with varying scope. For instance, Geisler regards HR planning as a ”process including forecasting, developing and controlling by which a firm ensures that it has the right number of people and the right kind of people at the right places at the right time doing work for which they are economically most useful” (Geisler, 1967). Others like Koltnerová et al. follow Geisler and explicitly emphasize the aspect of forecasting the future manpower requirements respectively the number and the type of employees required by an enterprise in the near future (Koltnerová et al., 2013). Stainer defines HR planning ”as a strategy for the procurement, development, allocation, and utilization of an enterprise's human resources” (Stainer, 1971). Kachaňáková et al. distinguish a wider view in terms of planning the personnel development and a narrow meaning covering plans of employees and plans of staffing jobs (Kachaňáková et al., 2008).

In the following sections we address the issue of planning a series of steps to eliminate differences between the actual and desired quantitative and qualitative HR structure of an organization on a medium-term or a long-term timeline. This includes process steps to determine how an organization should move from its current manpower position to its desired manpower position which can be called manpower planning according to Vetter (Vetter, 1967). The presented approach can also be used to support gap analysis which aims to asses human capital readiness in an organization (Snell et al., 2016).

As already mentioned in the introduction, big companies and organizations have to cope with profound structural transformations of the workforce. In our case, we consider an organization in the public sector which also tries hard to manage this issue. In terms of above mentioned HR planning subjects which are being analyzed here, the planning of actual-target structure adjustments (ATSA) of the regarded organization was challenging. Due to confidentiality reasons we can only outline the basic requirements here. Nevertheless, we will see that the challenges and issues are also representative for other huge organizations and enterprises. In our case, a linear optimization approach was used which should be part of the new solution. In general, huge organization's workforce planning involves many constraints and is based on complex planning approaches (Spengler, 2006). Thus, it is generally almost impossible to anticipate all effects of ATSA strategies, for instance, the impacts of adjustment strategies to digest a merger.

Additionally, many HR planning parameters and their relationships cannot be represented by deterministic elements. For instance, in a huge organization it is usually not mission-critical to be slightly understaffed in a certain department for a limited time. Hence, the amount of the necessary headcount for this department is fuzzy. If a planning system is only capable of handling crisp data, it is likely that valid options in the solution space which might be appreciated by the decision maker are not considered. Meanwhile, the issue of fuzziness in the field of HR planning is already recognized. A lot of scientific research can be found, for instance (Jana et al., 2017a), (Jana et al., 2017b), (Doka et al., 2015), (Xu et al., 2005), and (Nobari et al., 2012). Nevertheless, these approaches do not cover the aspect of planning actual-target structure adjustments. Yamchi et al. compare deterministic and fuzzy approaches in the field of manpower planning, but they just provide a deterministic equivalent of a model which represents a fuzzy system according to their statement (Yamchi et al., 2016). The original fuzzy model is not described and procedures to explicitly manage conflicting goals are not regarded. For instance, rapid actual-target adjustments can cause higher expenses for redundancy pay-outs in case of headcount reductions. Therefore, in our case, it was necessary to develop a new solution which addresses all the above mentioned issues.

Before a detailed presentation of the interactive fuzzy solution, we will briefly outline the necessary data sources of the approach as far as it serves comprehension.

3 ACTUAL HEADCOUNT DATA AND ORGANIZATIONAL TARGET STRUCTURE (OTS)

Most enterprise resource planning systems contain an HR component which can be used to provide actual headcount data accessible via software interfaces. The provided data can also include information about the expiration of contracts. Other companies or organizations deploy standalone HR software which is more or less integrated with other components. In our case, the necessary headcount data for actual-target adjustments is generated by a tailor-made software.

Another custom software component supports the calculation of an organization's target structure, namely, the quantitative and qualitative structure of the staff depending on the function, educational background (professional trainings) and the (sub-) organization. The staff structure of organizational units and their age-specific compositions are determined. The results are based on decision makers' specifications, for instance, required unit volumes or replenishment needs as well as educational and professional backgrounds.

Based on the computed results and the data of the HR administration system, actual-target adjustment strategies can be derived like described in the next sections.

4 ACTUAL-TARGET STRUCTURAL ADJUSTMENTS (ATSA)

To analyze adjustment strategies in terms of transferring the actual HR structure to the target structure within a certain timespan the planning model has to reflect:

- Flows from one hierarchy level to another
- Opportunities in terms of "the chance to graduate from one level to the next is x %"
- Constant relations between headcounts in certain units of the organization
- Objectives minimizing the target-actual distance within a certain timespan

As already mentioned in Section 2, challenges such as potentially conflicting goals, for instance, "rapid actual-target adjustments versus higher expenses for swift promotions", have to be considered. Additionally, fuzziness of planning parameters has to be anticipated. For example, future headcount volumes of organizational units, flow coefficients, opportunities and failure rates (regarding trainings as prerequisite for a promotion) often can't exactly be quantifiable in advance. With the help of fuzzification decision makers get a certain degree of freedom which can be used to find a good solution according to the linear equation system, the conflicting goals and the subjective appreciation of compromises.

5 INTERACTIVE FUZZY SOLUTION FOR THE ATSA PROBLEM

To solve the problem outlined in Section 4 an iterative solution finding technique named FULPAL (FUzzy Linear Programming based on Aspiration Levels) is used. FULPAL allows decision makers to explore the vast solution space step by step regarding multiple objectives. In each iteration decision makers are able to adjust their subjective aspiration levels concerning goals and also regarding the adherence of fuzzy constraints. For this purpose, they are allowed to modify the underlying model parameters of the planning problem step by step. The idea of this procedure is to find a satisfying solution in the sense of bounded rationality, see (Simon, 1955) and (Becker and Siegel, 1958). The underlying theory is acknowledged by recent research, see (Senf, 2017) and (Shinkle, 2012), and is useful to manage complexity in our case. Due to the complexity of the decision problem, it is assumed that the decision maker's value system can change when the solution space is explored.

Before the iterative planning process is thoroughly explained, it is necessary to understand the model and its parameters in detail.

5.1 Modeling the Hierarchical HR Structure with FULPAL

In order to model the planning problem the domain has to be described. To reduce complexity in our case and to simplify our example some assumptions will be made:

- The hierarchical organization consists of N hierarchy levels and only aggregated headcounts per level are considered.
- The planning period covers T periods.
- In order to be promoted to a higher level training over Y years has to be completed.
- Hierarchy levels cannot be skipped.
- Demotion is not allowed.
- Entire hiring starts at the lowest level.
- Discharges are not allowed in training.

Taking these assumptions into account, variables to represent the states (headcount) for all possible permutations of planning periods, hierarchy levels, and training years are required. So, a state variable $\mathrm{L}\,[n]_y^t$ represents the headcount in the model for planning period t and hierarchy level n with y years of training.

Flow variables have to be introduced to represent finished training steps and promotions. $\mathrm{UP}[n]_y^t$ denotes the number of employees which flow after planning period t from hierarchy level n with y years of training towards their next state variable. This can either be the next year $y+1$ in training or a promotion to the next hierarchy level $n+1$ with training year $y=0$. Additional flow variables are needed to represent external influences, either inbound for hiring in the lowest hierarchy level A: $\mathrm{IN}[A]_0^t$ or outbound for discharges $\mathrm{OUT}[n]_0^t$ in planning period t for hierarchy level n without being in training ($y = 0$).

An example illustration of the hierarchic structure is depicted in Figure 1, where the different variables are shown. To model the structure of the hierarchical problem over multiple periods relationships between state and flow variables have to be established. This is done by adding constraints to the linear program.

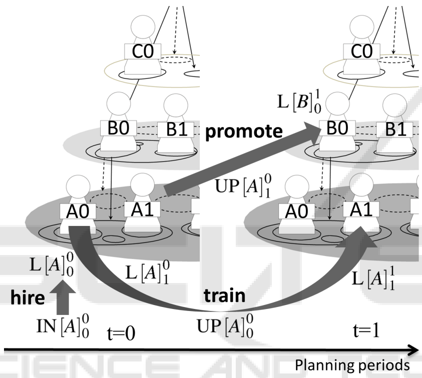

Figure 1: Example Illustration for $n = \{A, B, C, \dots\}$, $Y = 1$.

For hiring and discharges the state change for training year $y = 0$ can be written as Equation 1. This means, that headcounts at hierarchy level n in period t are equal to headcounts at the same hierarchy level of the previous period $t-1$ minus the number of employees which began a training after the previous period plus the number of hired employees minus the number of discharged employees in period t.

$$\begin{aligned} \mathrm{L}[n]_0^t \;=\; & \mathrm{L}[n]_0^{t-1} - \mathrm{UP}[n]_0^{t-1} \\ & + \mathrm{IN}[n]_0^t - \mathrm{OUT}[n]_0^t \end{aligned} \quad (1)$$

To model trainings for subsequent training years $y \geq 1$ Equation 2 is introduced. $\mathrm{L}[n]_y^t$ is determined by the state variable of the previous year minus the employees which advanced one year in training after the previous period (away from this state variable) plus the employees which advanced one year in training after the previous period (towards this state variable).

$$\mathrm{L}[n]_y^t \;=\; \mathrm{L}[n]_y^{t-1} - \mathrm{UP}[n]_y^{t-1} + \mathrm{UP}[n]_{y-1}^{t-1} \quad (2)$$

To represent promotions, only state variables with $y = 0$ are considered. Equation 3 establishes the connection between different periods. As denoted in Equation 3, the state variable in period t is equal to the corresponding state variable in period $t-1$ minus the employees which advanced one year in training after the previous period plus $\mathrm{UP}[n-1]_Y^{t-1}$ which represents the number of promoted employees from hierarchy level $n-1$ to n minus discharges in hierarchy level n in period t.

$$\begin{aligned} \mathrm{L}[n]_0^t \;=\; & \mathrm{L}[n]_0^{t-1} - \mathrm{UP}[n]_0^{t-1} + \mathrm{UP}[n-1]_Y^{t-1} \\ & - \mathrm{OUT}[n]_0^t \end{aligned} \quad (3)$$

By means of this part of the model, the flows from one hierarchy level to the next are established, see Section 4. Since this just represents the deterministic version of the constraints, we will look at fuzzy parameters for the constraints and the objective functions of the linear program in the following sections.

5.2 Fuzzy Parameters

To put the model into action, actual data from HR components, see Section 3, for the headcount at different hierarchy levels has to be added. This can be achieved by adding further constraints which attach actual values to the corresponding state variables $\mathrm{L}[n]_0^0$, see Equation 4.

$$\mathrm{L}[n]_0^0 = \text{Actual value for hierarchy level } n \quad (4)$$

Usually, these numbers will be crisp values. However, values for the target structure after T years, are uncertain and can be specified as fuzzy parameters. So, instead of adding crisp constraints to the model fuzzy constraints are used, see Equations 5 and 6.

$$\mathrm{L}[n]_0^T \;\; \widetilde{\leq} \;\; \widetilde{\mathrm{b}_i}[n]_0^T \quad (5)$$
$$\mathrm{L}[n]_0^T \;\; \widetilde{\geq} \;\; \widetilde{\mathrm{b}_{i+1}}[n]_0^T \quad (6)$$

The first fuzzy constraint, see Equation 5, represents the upper bound for the headcount in hierarchy level n in the last period T as a fuzzy constraint border $\widetilde{\mathrm{b}_i}[n]_0^T$, where i denotes the i-th fuzzy parameter. To do this, a good subjective representation for the upper bound (denoted as $\overline{\mathrm{b}_i[n]_0^T}$ in Figure 2) has to be defined. Afterwards, the decision maker has to determine a higher value which isn't a good representation for the upper bound anymore (denoted as $\underline{\mathrm{b}_i[n]_0^T}$ in Figure 2).

To control the planning process the decision maker is able to adjust the aspiration level $\mathrm{AL}_i[n]_0^T$ to these bounds. It has to be an element of the interval $\left[\overline{\mathrm{b}_i[n]_0^T}, \underline{\mathrm{b}_i[n]_0^T}\right]$ and represents an acceptable level of utilizing a resource. Equation 6 represents a lower bound accordingly.

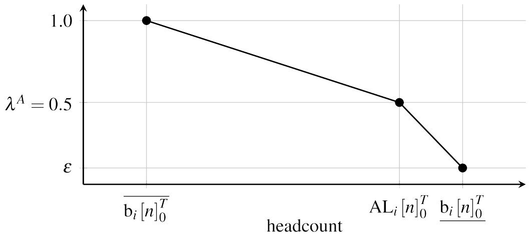

Figure 2: Fuzzy constraint border with aspiration level of target value for $y = 0$.

If intermediate milestones are needed it is possible to add more constraints to the model. For example, if a specific target value in period $\frac{N}{2}$ is desired, a fuzzy constraint with $\widetilde{\mathrm{b}_{i+2}}\left[\frac{N}{2}\right]_0^T$ can be added to meet this requirement.

In the same way other restrictions can be imposed, for instance, opportunities, see Section 4, are established by adding constraints as in Equation 7. $\widetilde{\omega_{i+3}}$ represents a minimum percentage as fuzzy value for those who are able to graduate from one hierarchy level (state variables $\mathrm{L}\,[n]_Y^t$) to the next (via flow variables $\mathrm{UP}\,[n]_Y^t$).

$$\widetilde{\omega_{i+3}} \cdot \mathrm{L}\,[n]_Y^t \;\widetilde{\geq}\; \mathrm{UP}\,[n]_Y^t \tag{7}$$

As mentioned in Section 4 constant relations between headcounts of different hierarchy levels can also be modeled in this manner. To make sure that a particular ratio between two hierarchy levels is maintained in all periods constraints like Equation 8 can be added. For this purpose, it has to be considered that employees who take part in a training are also members of this hierarchy level. So, the ratio $\widetilde{\omega_{i+4}}$ between two different ($n_1 \neq n_2$) hierarchy levels relates the sums of all state variables for each hierarchy level ($\sum_{j_1=0}^{Y} \mathrm{L}\,[n_1]_{j_1}^t$ and $\sum_{j_2=0}^{Y} \mathrm{L}\,[n_2]_{j_2}^t$) to another one. For every period t this ratio should hold a constraint and has to be added separately.

$$\widetilde{\omega_{i+4}} \cdot \sum_{j_1=0}^{Y} \mathrm{L}\,[n_1]_{j_1}^t \;\widetilde{=}\; \sum_{j_2=0}^{Y} \mathrm{L}\,[n_2]_{j_2}^t \tag{8}$$

5.3 Objective Functions

Concerning the constraints, the regarded organization intends to minimize the cost of the overall ATSA, see Equation 9. The cost factors for each hierarchy level can also be fuzzy values.

$$\sum_{n=0}^{N}\sum_{t=0}^{T}\sum_{y=0}^{Y} \widetilde{\mathrm{Cost}}\,[n]_y^t \cdot \mathrm{L}\,[n]_y^t \rightarrow min \tag{9}$$

Furthermore, FULPAL allows to specify multiple objectives which can be contradictory. As an example for a conflicting goal it could be desired, that a specific hierarchy level is staffed as fast as possible. For instance, setting up the middle management before a massive hiring initiative can be necessary. This is contradictory to the objective minimizing costs.

Options to handle conflicting objectives by means of aspiration levels are described in the next section.

5.4 Iterative Planning Process

The planning process, see Figure 3, begins with importing the actual data and the target structure from the HR systems as described in Section 3. Afterwards the decision maker can specify his subjective aspiration levels and an overall value λ^* is computed. λ^* represents the achieved result, namely the maximized minimal degree of satisfaction concerning all constraints and the goals (Rausch et al., 2013). The goal for the decision maker is to reach a solution with λ^* slightly above λ^A where λ^A is arbitrarily set to 0.5 in FULPAL and represents the assigned membership value for the aspiration levels. Details on the assignment of aspiration levels to membership values can be found in (Rausch et al., 2013). In case a solution does not satisfy the aspiration level concerning at least one objective or constraint, a λ^A value below 0.5 occurs, and the solution is not acceptable. The decision process does not necessarily end at this point. The decision maker is allowed to explore the solution space further and may modify his aspiration levels for a new iteration. In case λ^* surpluses 0.5 significantly, planning parameters may be tightened for a new iteration. If the decision maker does not want to use this freedom, he can also accept the solution, and the planning process ends.

6 EVALUATION

The interactive solution process based on the concept of satisfying aspiration levels ensures that the subjective preferences and goals of the decision maker, which can dynamically change during the decision process, are met. It turned out that this approach is congruent with human thinking while testing the system. Besides, the complexity of the planning problem could be significantly reduced. The decision maker can start the planning process without a fully developed or only vaguely describable system of objectives and information about the planning parameters. Imprecise system parameters, for instance, headcount limits for departments, can be entered fuzzy in accordance to reality, and no artificial level of precision is enforced to provide system inputs. By anticipating real world's fuzziness a wider range of valid options of the solution space which may be interesting for the

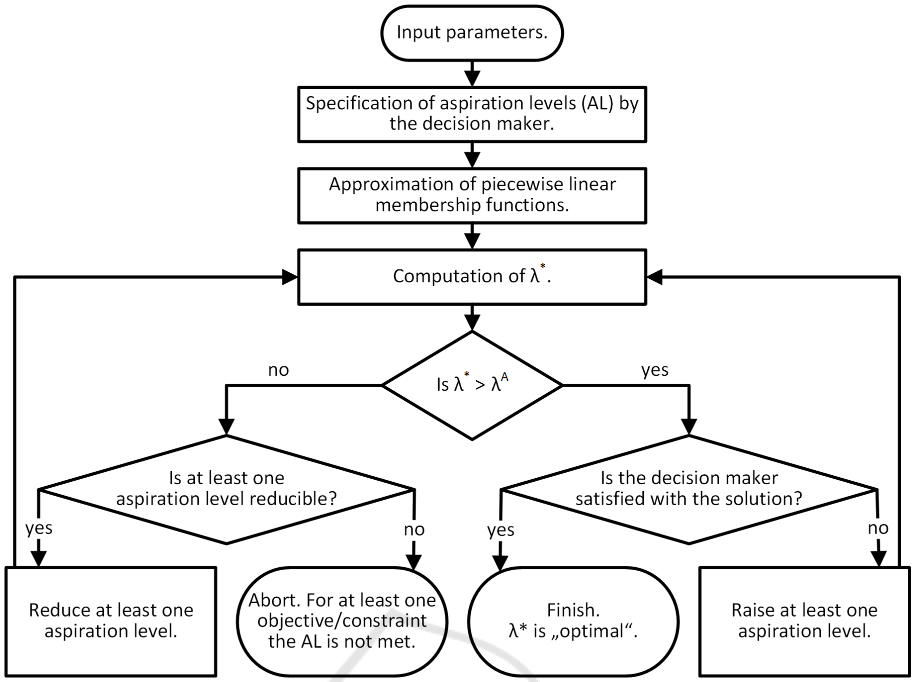

Figure 3: Iterative planning process with FULPAL, based on (Rausch et al., 2012).

decision maker are taken into account during the planning process. Thus, it is likely that the quality of the planning results is better in many cases. This effect is also enforced by taking the decision makers' internal knowledge during the planning process into account. If necessary, implicit knowledge can be made explicit by adding additional constraints or objectives to a model during the interactive process. So, the interactive exploration fosters also the acceptance of the generated solutions and helps the decision maker to cope with the complexity of the system and its solution space. The presented approach is also useful in terms of managing conflicting goals in the field of ATSA problems.

7 CONCLUSIONS AND FUTURE WORK

It has been shown that fuzzy optimization models significantly contribute to manage uncertainties in the field of human resource planning. Of course, the presented approach cannot handle unforeseen disruptive events. Nonetheless, it is resilient regarding stress which influences system parameters, for instance, in case of workforce bottlenecks due to external factors. Additionally, by allowing fuzziness more or less valid solutions can be taken into account. This can be beneficial, because a compromise solution, which violates a constraint slightly could be better from a decision maker's point of view in terms of all goals and constraints. At first sight, the impression can emerge that more effort is needed for setting up the fuzzy model compared to modeling a crisp system. But in our case, we had a different impression. System parameters can be entered in accordance with reality and there were no discussions how to reduce fuzzy values to a crisp number.

The verification of this observation and analysis of the general effects on modeling effort would be an interesting subject for a future study. In particular, it should be examined to what extent users can change model parameters, like constraint borders, between individual steps in practice, for instance, to externalize their implicit knowledge. Furthermore, it would be interesting to deploy the presented approach in other sectors and to get more experience with different industries. Since in our case a linear optimization approach had to be a part of the new solution, a comparison with other approaches like fuzzy soft computing could be also an interesting subject for further research.

In summary, the presented fuzzy approach provides a powerful instrument to manage structural transformations of the workforce and to master the related challenges. Organizations in the public sector, big companies as well as large institutions, like churches, can benefit from the approach and become more successful in the important field of human resource planning.

REFERENCES

Becker, S. and Siegel, S. (1958). Utility of grades: level of aspiration in a decision theory context. *J. Exp. Psychol.*, 55:81–85.

Doka, K., Ahmad, F., Shamsuddin, S., Awang, W., and Ghazali, N. (2015). Integrated decision support system for human resource selection using topsis based models. *Applied Mathematical Sciences*, 9:6403–6414.

Geisler, E. (1967). *Manpower planning: An Emerging Staff Function*. American Management Association, New York.

Jana, R., Sanyal, M., and Chakrabarti, S. (2017a). Binary fuzzy goal programming for effective utilization of it professionals. In Mandal, J., Satapathy, S., Sanyal, M., and Bhateja, V., editors, *Proceedings of the First International Conference on Intelligent Computing and Communication*, volume 458 of *Advances in Intelligent Systems and Computing*, pages 395–405. Springer.

Jana, R., Sanyal, M., and Chakrabarti, S. (2017b). Multi-objective it professionals' utilization problems using fuzzy goal programming. In Satapathy, S., Bhateja, V., Udgata, S., and Pattnaik, P., editors, *Proceedings of the 5th International Conference on Frontiers in Intelligent Computing: Theory and Applications*, volume 526 of *Advances in Intelligent Systems and Computing*, pages 199–208. Springer.

Kachaňáková, A., Nachtmannová, O., and Joniaková, Z. (2008). *Personnel management*. IURA Edition.

Koltnerová, K., Chlpeková, A., and Samáková, J. (2013). Personnel planning reflecting the requirements of sustainable performance of industrial enterprises. In Semmelrock-Picej, M. and Novak, A., editors, *ECMLG 2013: The Proceedings of The 9th European Conference on Management Leadership and Governance*, pages 136–143. Academic Conferences and Publishing International Limited.

Nobari, S., Jabrailova, Z., and Nobari, A. (2012). Using fuzzy decision support systems in human resource management. In *ICIIM 2012: International Conference on Innovation and Information Management*, volume 36, pages 204–207. IACSIT Press.

Rausch, P., Rommelfanger, H., Stumpf, M., and Jehle, B. (2012). Managing uncertainties in the field of planning and budgeting - an interactive fuzzy approach. In Bramer, M. and Petridis, M., editors, *Proceedings of AI-2012, The Thirty-second SGAI International Conference on Innovative Techniques and Applications of Artificial Intelligence*, Research and Development in Intelligent Systems XXIX, pages 375–388. Springer.

Rausch, P., Stahl, F., and Stumpf, M. (2013). Efficient interactive budget planning and adjusting under financial stress. In Bramer, M. and Petridis, M., editors, *Proceedings of AI-2013, The Thirty-third SGAI International Conference on Innovative Techniques and Applications of Artificial Intelligence*, Research and Development in Intelligent Systems XXX, pages 375–388. Springer.

Senf, N. N. (2017). *Organisationale Anspruchsniveaus*. SpringerGabler, Wiesbaden.

Shinkle, G. A. (2012). Organizational aspirations, reference points, and goals: Building on the past and aiming for the future. *Journal of Management*, 38:415–455.

Simon, H. (1955). Behavioral model of rational choice. *Q. J. Econ.*, 69:99–118.

Snell, S., Morris, S., and Bohlander, G. (2016). *Managing Human Resources*. Cengage Learning, Boston, 17 edition.

Spengler, T. (2006). Modellgestützte Personalplanung, working paper no. 10, url: http://tinyurl.com/y7sybvpx, last access: 2017-11-20.

Stainer, G. (1971). *Manpower planning: The Management of Human Resources*. Heinemann, London.

Vetter, E. (1967). *Manpower Planning for High Talent Personnel*. Michigan Univ., Ann Arbor.

Xu, Z., Song, B., and Chen, L. (2005). Fuzzy logic experience model in human resource management. In Khosla, R., Howlett, R., and Jain, L., editors, *KES 2005: Knowledge-Based Intelligent Information and Engineering Systems*, volume 3682 of *Lecture Notes in Computer Science*, pages 204–207. Springer.

Yamchi, H. G., Azar, A., Alvani, M., and Javadin, R. S. (2016). Comparison of the deterministic and fuzzy approaches in HR planning. *Journal of Industrial Strategic Management*, 1:39–50.