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Eliminating Knowledge Bottlenecks Using Fuzzy Logic

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In the formation of new processes, innovations generated by people possessing the right knowledge and talent play a crucial role. Our starting point was the fact that every new change in processes can alter the knowledge structure of a work position or work role. This means that a person can become a knowledge bottleneck in the process. If this person is found on a critical path, the process cannot produce the output in a desired form, extent or quality, unless the bottleneck is removed. For this reason, we developed a decision model founded on fuzzy logic. The result of the fuzzy model is knowledge estimation based on deviation between the required and actual knowledge. For faster decision making, we made a presentation of allocated people on desired roles using the heat map technique. Therefore, the employers make better decisions on actual knowledge allocation, acquiring missing knowledge, or defining knowledge required for the future, which makes them more competitive.

Keywords: knowledge allocation, knowledge management, business processes, business intelligence, fuzzy logic

1 Introduction

In an era of human potential, there is a struggle for the best people to know that they are true value creators (Guillory, 2009). When business success or failure depends on talented people (Michaels et al., 2001), it is crucial for organisations to achieve their goals and realise that the most fundamental problem is uncertainty. This results in a need for more rapid responses to changes in competitive environments, since the nature of work across all industries has become increasingly project-oriented and less routine (Wang and Salunga, 2008). Employers respond to customer demands, competitor innovations, regulatory changes and outside factors with changes in business processes that must be interconnected. It is also essential to change strategic and operational goals so they can successfully meet the business measurements (Ballard et al., 2005). The developments driving these responses are difficult to predict, and mistakes in responding are costly. There are inherent mismatches of employees and skills (not enough talent to meet business demands, or too much, leading to layoffs or a poor fit between individual attributes and requirements); additionally, there are costs of losing investments in talent through the failure to retain employees (Cappelli, 2009). Discussions regarding human capital are extremely valuable whenever strategic personnel planning and development take centre stage in times of great uncertainty. Both the current and the future requirements in human capital have to become the focal point of the analysis and must be seen as a strategic competitive advantage for the company (McCall, 1998; Nahapiet and Sumantra, 1998).

The most influential internal driver of change is process change (Mühlbacher et al., 2011). Every new change in business processes can change the knowledge structure of a work position, because knowledge requirements aggregate on work positions (Meglič et al., 2009). Therefore, a current employee is not sufficiently educated, with regards to process and knowledge requirements (Roblek et al., 2011). This is a so-called knowledge gap (Kern et al., 2005), which can be often seen in engineering-to-order (ETO) production processes, in which a set of unique products is produced for the first and probably the only time (Roblek and Zajec, 2012).

When it is desirable to allocate a person with the right knowledge to a work position, there is a need for a number of wide educated employees (generalists), who are expensive from the investment point of view. As a result, to be competitive businesses have few widely educated employees and many cheaper specialists. From the knowledge point of view, widely educated employees are rarely bottlenecks; from the time availability perspective they always are (Roblek et al., 2011). If these employees (bot-

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tlenecks) are on a critical path of a process, that process cannot yield the expected output, quantity or quality (as if there had been no bottlenecks). Process execution normally stops when someone has to retrieve knowledge that has not been provisioned for them to use. When this occurs in a customer-facing process, the cost to execute the process skyrockets (Russell Records, 2005).

Businesses relying on the knowledge of their employees are not most concerned with the financial distribution amongst a set of (R&D) opportunities, but rather with the allocation of human capital. However, available expertise determines whether a project, process or innovation may turn into a success or if it is doomed to fail because of a lack of critical intellectual capabilities (Gutjahr et al., 2008). Hitt et al. (2001) and Zupan and Kaše (2006) agree that intangible resources rather than tangible ones are vital for achieving competitive advantages. Therefore, investments in intellectual capital are critical, so managers are forced to find an appropriate balance between their investments in tangible and intangible resources (Čater and Čater, 2009). Škerlavaj and Dimovski (2006) argued that higher-level organisational learning (intangible resources) has a strong positive impact on both return on assets and value added per employee. It even has a stronger positive influence on better relationships with customers, suppliers and the lower net turnover of employees.

However, there are several ways to allocate the right person with the right knowledge to the right role or work position. In the search for an optimal solution, we want to review classic allocation models, such as linear programming (Gärtner, 2006), and heuristic solution algorithms, such as Ant Colony Optimization (Dorigo and Stützle, 2004) and Genetic Algorithm (Turban et al., 2007). Linear programming is used in the PKA model (Roblek et al., 2011), in which the knowledge structure of a work position is compared with the knowledge structure of all employees. In that case, the model is used to measure how large the knowledge gap is. The gap can be determined with an optimal function, which is based on minimum shortage (deficit) or maximum excess (surplus) of knowledge. If the difference is too high (knowledge deficit), then we presume that the work is done less effectively. In that case, businesses train their employees, and if they do not have enough time they have to find the right person outside of the business. For those cases in which an exact solution by means of linear programming is no longer possible, either on account of nonlinearity or because of an excessively large number of input variables, heuristic solution algorithms should be used. The Ant Colony Optimization algorithm uses an incremental solution construction procedure so that the generation of unfeasible solutions can be avoided during the construction process. The genetic algorithm constructs a complete solution and then uses a repair function if the constructed solution is not feasible, which may be extremely time-consuming in the presence of restrictive constraints. The genetic algorithm seems to be slightly superior, except in those cases where the solutions space is highly constrained, in which case the Ant Colony Optimization yielded better results (Gutjahr et al., 2008). Regardless, we must be aware of unsure and partial information that is inherently human in nature (knowledge) and can cause bias in the final estimation. When we are dealing with knowledge-based systems, the classical set becomes inflexible in terms of real world problems (Virant, 2003). The fuzzy set theory can be best used in such cases, because it offers a paradigm of working with the graduation, uncertainty and ambiguity described by linguistic expressions when sharply defined classification criteria could not be created. It supports overlapping boundaries between sets and permits the gradation of the membership of the element in a set. This gradation is described by a membership function valued in the interval [0, 1]. The main advantage of a fuzzy classification compared to a crisp one is that an element is not limited to a single class but can be assigned to several classes (Hudec and Vujošević, 2010). For that reason, we developed a decision model based on fuzzy logic with which we can allocate people, according to their knowledge availability.

2 Method

The research was based on a model (Kern et al., 2005) in which business processes and competence profiles of employees were combined. After a literature review of this field, we decided to use the term ‘knowledge’; unlike other terms (e.g. competence, talent etc.) it had the clearest definition. The model shows how to define the required knowledge of business processes and how to assess actual knowledge (360-degree method). This data can be used for allocating employees to work positions, but it is limited to certain values whereby the slightest difference means that the employee is no longer suitable for a work position.

This problem can be solved with fuzzy logic, with which we can define membership functions. These can help us clearly see how each knowledge value is mapped to a membership value (degree of membership). We have to be aware of knowledge estimation subjectivity, which cause deviations right at the input of any system.

Our model will give the estimation of employee suitability to each role according to his/her knowledge. It is based on following steps:

- Defining required knowledge from selected process;
- Defining actual knowledge from 360-degree method;
- Setting allocation criteria;
- Knowledge allocation using fuzzy logic.

2.1 Defining required knowledge definitions

For a demonstration of our model, we wanted to allocate five employees to nine roles according to their knowledge. Our starting point was a process with five activities and with one AND operator (Figure 1), modelled in Aris Business Designer 7.1.

The required knowledge definitions were derived from process activities. At that point, the company experts helped us define which knowledge was essential to achieve the best performance in a specific process activity and what

strength it must be. That strength was defined on a scale from 1 to 5, where:
- 1 = very low important knowledge,
- 2 = low important knowledge,
- 3 = medium important knowledge,
- 4 = very important knowledge,
- 5 = most important (key) knowledge.

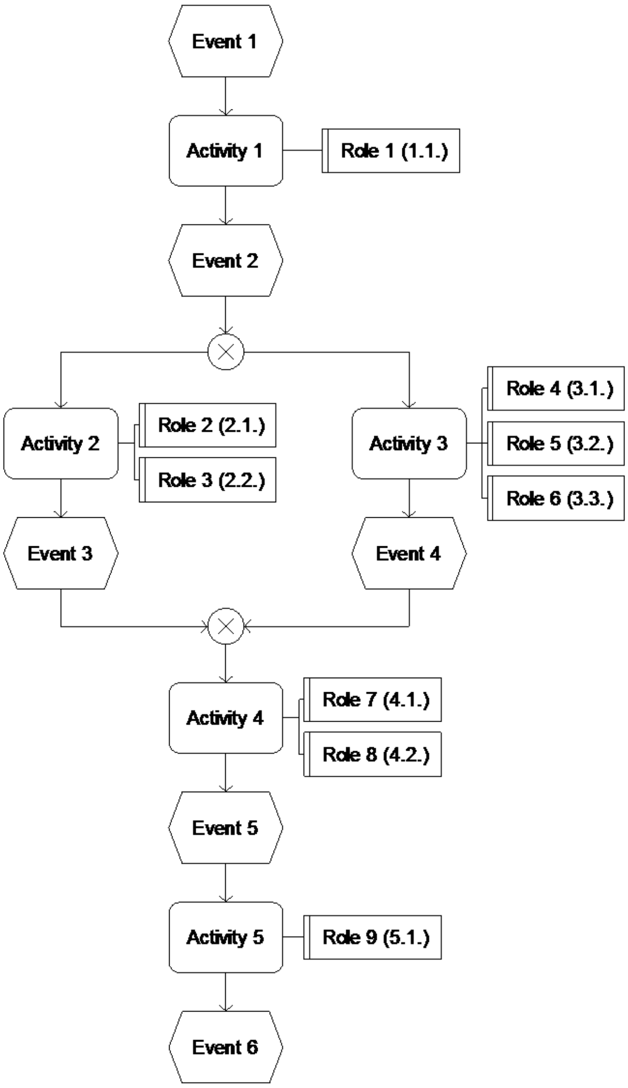

Figure 1: The starting process

If the knowledge was not needed for a specific activity, we marked this with 0.

2.2 Defining actual knowledge definitions

After defining required knowledge definitions for specific activities and their strengths, we assessed five employees using the 360-degree method (Maylett, 2009).

Because there could be at least one role on one activity, we marked each role with two numbers (see Figure 1). The first number shows the connection between activity and role, while the second number indicates the importance of the role (e.g. ‘1’ represents the highest importance for activity execution). An activity without the role with a last number of ‘1’ cannot be executed. In our case, we had five activities and nine roles:

1 **Activity #1**
   1.1 Role 1
2 **Activity #2**
   2.1 Role 2
   2.2 Role 3
3 **Activity #3**
   3.1 Role 4
   3.2 Role 5
   3.3 Role 6
4 **Activity #4**
   4.1 Role 7
   4.2 Role 8
5 **Activity #5**
   5.1 Role 9

Because of growing complexity in modelling the fuzzy decision model, we decided to take the five most important types of knowledge for each role. The way of defining this knowledge is not part of this research. The knowledge definitions were specified according to chosen role, since there were no extended specifications on which role is executing which activity.

We measured the difference between required knowledge of a specific role and the actual knowledge of each employee where ‘0’ means no gap between required and actual knowledge. In that case, we have the most suitable person for our role. If the employee received number ‘-4’, this means that he/she does not have knowledge according to the required knowledge definition (underqualified). In contrast, a person with number ‘4’ shows overqualification and this state is also undesirable because this knowledge is more beneficial when used for another activity inside the process, or opportunity could be found somewhere else outside of our process. Therefore, the employee with a number ‘-4’ or ‘4’ is unsuitable for chosen role.

2.3 Setting allocation criteria

To determine which employee had the best knowledge distributions for a required role, we had to define:
- **input variables,**
- **output variables**, and
- **base mechanism**, which translates input variables to output variables using ‘if-then’ rules. These rules are valued parallelly, i.e. the sequence is not important. They use variables and adjectives for those variables.

Our final estimation of an employee’s knowledge is based on processing input data (differences between required knowledge of a specific role and actual knowledge of each employee). We had 5 input variables (top 5 knowledge) which were defined as [-4, 4]. If we had required knowledge marked with a strength of ‘5’ and actual knowledge with a strength of ‘1’, then we marked the difference

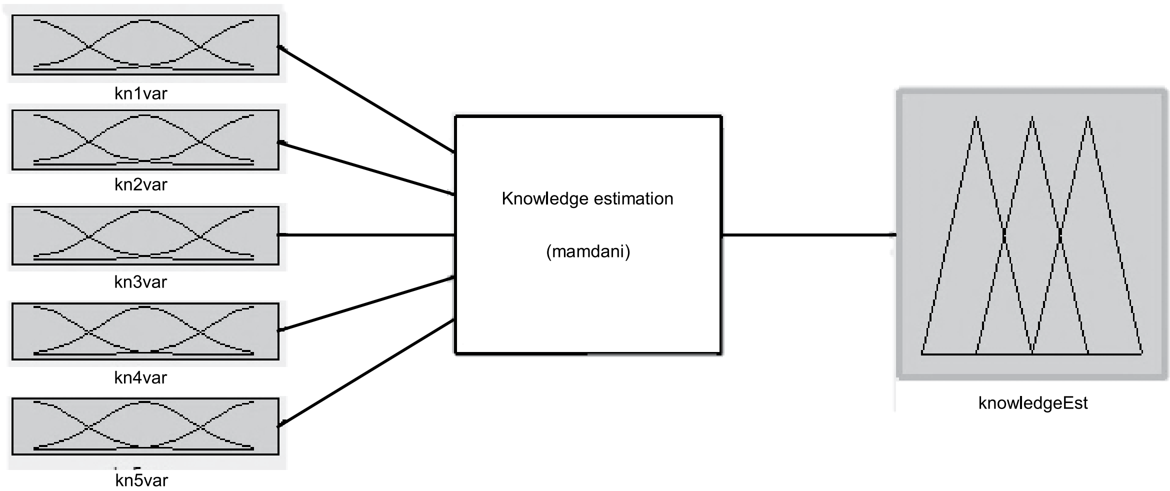

Figure 2 shows our base model structure

with '-4' and vice versa. Required knowledge marked with '0' was not taken into consideration because we selected the top five types of knowledge.

We then defined membership functions for input and output variables. We chose a Gaussian membership function because of its softness (Schmid, 2005) and the suitability of nonlinear systems (Mitaim and Kosko, 2001). In our opinion, this is the best choice when operating with knowledge. However, when assessing employees using the 360-degree method deviations are encountered due to different perceptions of the assessors. The usage of fuzzy logic should eliminate this bias and the employee can occupy one or more membership functions with different degree.

For every **input variable**, we set membership functions with linguistic variables according to knowledge differences. The linguistic variables were:

- *maximal negative difference (max_neg_diff)* with parameters [0.8494, -4][1];
- *negative difference (neg_ diff)* with parameters [0.8494, -2];
- *no difference (no_ diff)* with parameters [0.8494, 0];
- *positive difference (poz_ diff)* with parameters [0.8494, 2];
- *maximal positive difference (max_poz_diff)* with parameters [0.8494, 4].

The **output variable** 'knowledge evaluation' was defined on [-1, 1] and had 5 linguistic variables:

- *underqualified* with parameters [0.21, -1];
- *partly qualified* with parameters [0.21, -0.5];
- *qualified* with parameters [0.21, 0];
- *partly overqualified* with parameters [0.21, 0.5];
- *overqualified* with parameters [0.21, 1].

After the input variables and output variables were defined, we created 'if-then' rules with the use of AND/OR operators. When we use an AND operator, the system takes the minimum of the stated values, and when we use OR operator the system takes maximum. Although determining these rules is intuitive, it is important to include all cases in these rules. The rules for knowledge estimation are the following:

1. IF (kn1diff = max_neg_diff) OR (kn2diff = max_neg_diff) OR (kn3diff = max_neg_diff) OR (kn4diff = max_neg_diff) OR (kn5diff = max_neg_diff) THEN (knowledge_evaluation = underqualified)
2. IF (kn1diff = no_diff) AND (kn2diff = no_diff) AND (kn3diff = no_diff) AND (kn4diff = no_diff) AND (kn5diff = no_diff) THEN (knowledge_evaluation = qualified)
3. IF (kn1diff = pos_diff) AND (kn2diff = pos_diff) AND (kn3diff = pos_diff) AND (kn4diff = pos_diff) AND (kn5diff = pos_diff) THEN (knowledge_evaluation = partly_qualified)
4. IF (kn1diff = neg_diff) AND (kn2diff = neg_diff) AND (kn3diff = neg_diff) AND (kn4diff = neg_diff) AND (kn5diff = neg_diff) THEN (knowledge_evaluation = partly_qualified)
5. IF (kn1diff = max_pos_diff) OR (kn2diff = max_pos_diff) OR (kn3diff = max_pos_diff) OR (kn4diff = max_pos_diff) OR (kn5diff = max_pos_diff) THEN (knowledge_evaluation = overqualified)

The next step is processing the 'if-then' rules within the fuzzy inference system (FIS) from MATLAB software for the calculation of an optimal solution. We chose a Mamdani inference system in which an aggregation method (maximum) and defuzzification method (centroid calculation) were selected. Therefore, the output of the Mamdani inference system is a fuzzy set, so a defuzzification method of the output fuzzy set is required to extract a crisp value that best represents an obtained fuzzy set.

1 The first number is standard deviation while the second number shows arithmetic mean.

Table 1: Knowledge estimation by person

		Knowledge estimation by person				
Activity by role	**Role**	**1**	**2**	**3**	**4**	**5**
1.1.	Role 1	-0.0525	-0.0526	-0.771	-0.771	-0.771
2.1.	Role 2	-0.771	-0.771	-9.50E-18	-0.771	-0.771
2.2.	Role 3	-0.0525	-0.217	-0.0526	-0.771	-0.771
3.1.	Role 4	-0.771	-9.50E-18	-0.771	-0.771	-0.771
3.2.	Role 5	1.15E-04	1.15E-04	-0.217	-0.771	-0.771
3.3.	Role 6	-0.0525	-9.50E-18	-0.217	-0.771	-0.771
4.1.	Role 7	-0.656	-0.656	-0.828	0.0526	-0.828
4.2.	Role 8	0.771	0.771	0.712	0.712	0.771
5.1.	Role 9	-0.656	-0.656	-0.828	-0.771	-0.0525

2.4 Knowledge allocation using fuzzy logic (results)

With the fuzzy reasoning, we compared every person to a role in a particular activity. In Table 1, we show results where we can see which person is the most suitable for each role.

When we have a small number of knowledge and roles (variables), we can quickly determine what is an optimal solution concerning knowledge and role requirements. In that case, the results can be seen in MATLAB software, as the knowledge of employees is defined by the degree of membership functions. In other cases, when we have to assess a large number of employees, activities and roles, there can be a problem with the visibility of results. Therefore, the employers must use business intelligence to clearly see all the knowledge bottlenecks in a usable and understandable form. We would like to examine a heat map technique that offers the possibility of filtering employees according to their knowledge in descending or ascending

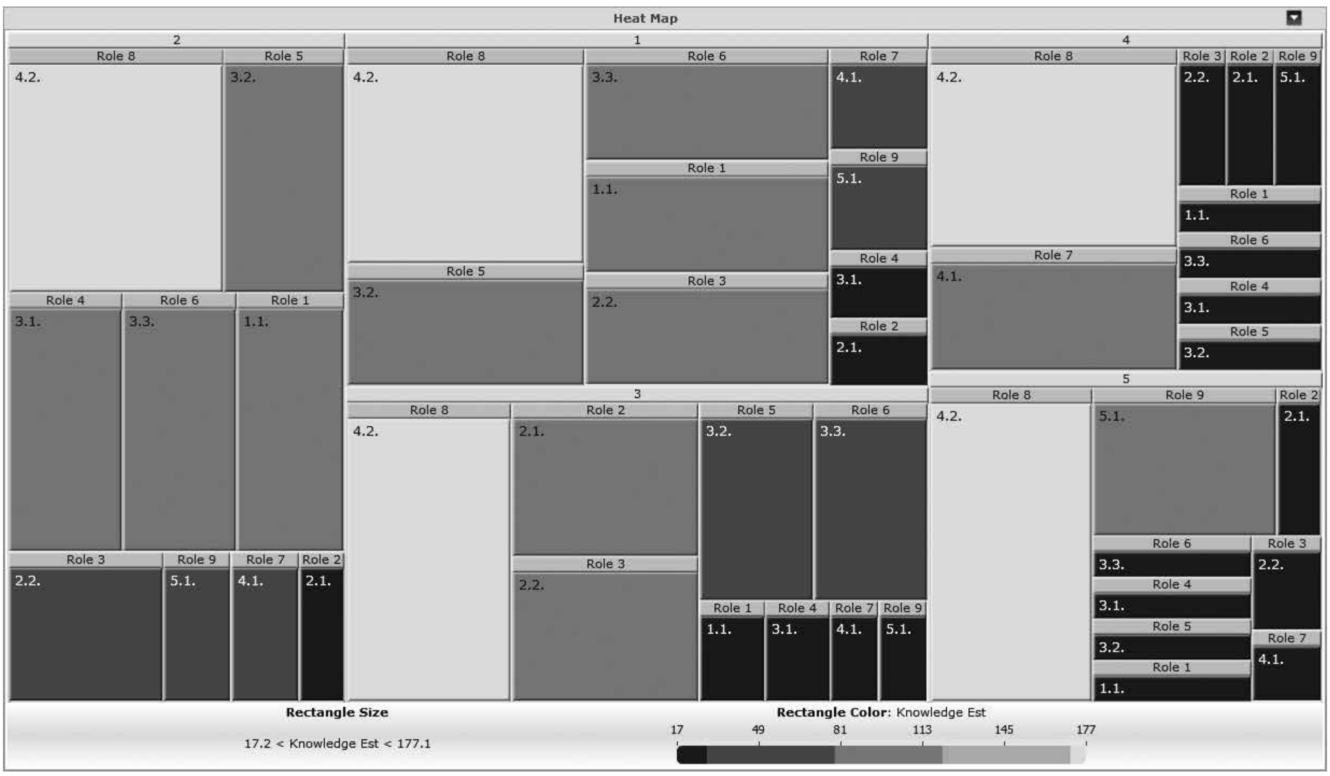

Figure 3: Role classification by person and activity according to knowledge estimation

order. It gives a good overview with a colour scale and helps us recognise the degree of knowledge redundancy.

Although the optimal solution can be seen in the Table 1, it may require too much time for the employer to make a final decision. The problem escalates with the number of employees, activities and roles. Therefore, we provided results in a usable and understandable form by using business intelligence. We decided to use MicroStrategy Cloud Express because of its highly interactive dashboard, with which we can easily recognise trends, deviations and undiscovered insights that would otherwise remain buried in the data.

Employees and roles were sorted by knowledge estimation in descending order (Figure 3). For faster decision making, the rectangle colours were also based on knowledge estimation values. However, the colour scale was generated automatically when importing data and customised according to our qualification values (underqualified, partly qualified, qualified, party over qualified, and overqualified, respectively).

From the heat map, we can clearly and easily see that the most educated employee was Person 2 (largest rectangle size) and the least educated was Person 5 (smallest rectangle size). Therefore, we could also see knowledge redundancy for Role 8, for which every employee was overqualified. The lowest redundancy was observed for those roles where we had only one person with the right knowledge.

As already mentioned, we started with the process in which two activities were running in parallel, which could lead to a capacity problem. Our final decision can be represented by activities:

- **Activity #1**
  – **Person 1** can occupy Role 1.1.
- **Activity #2**
  – **Person 3** can occupy Role 2.1.
  – **Person 1** can occupy Role 2.2.
- **Activity #3**
  – **Person 2** can occupy Role 3.1.
  – The most suitable person for Role 3.2. is Person 1, but he/she could not be allocated because he/she is working in parallel on other activity (see Activity #2). The second option would be Person 2 but could also not be allocated because he/she is allocated for Role 3.1., which plays a crucial role in this activity. The third option is Person 3 who also works in parallel on another activity (see Activity #2). According to these facts, the manager must use his knowledge and decide on his own. He could use scheduling or (in the worst case scenario) find a new employee or outsource the work.
- **Activity #4**
  – **Person 4** can occupy Role 4.1.
  – Role 4.2. can be occupied by any person in our selection, but we had chosen that person who was the least overqualified. We could choose Person 3 or 4, but we decided for **Person 3** because Person 4 is already allocated to this activity (Role 4.1.).
- **Activity #5**
  – Only **Person 5** can occupy Role 5.1.

3 Discussion and conclusions

The developed model for knowledge allocation on roles is based on the employee‘s strengths. It was developed using the FIS tool in MATLAB software and tested on a real process. With the use of this model, businesses can benefit significantly and thereby greatly increase their competitiveness. The use of a fuzzy decision model gives employers a complete view of employees‘ knowledge and knowledge bottlenecks. Therefore, it supports better use of employees’ full potential.

The advantage of this model is allocating employees to more than one role whereby we can compare employees with each other according to their knowledge. This leads to better business results that are achieved by better processes (higher output) and productive employees using their strengths and knowledge. The model can be tested on the PKA model (Roblek et al., 2011) in which linear programming is used. In this case, there is a crisp classification in which two employees with remarkably similar values, near the boundary value, may be classified into different classes, which causes a greater difference between the required knowledge and the obtained resources. When employers accept less accurate systems and want to include approximate reasoning, fuzzy logic is the right choice (Kuncheva, 2000).

From the perspective of the end user, the disadvantage can be seen in the complexity of fuzzy system software products (e.g. MATLAB software). When we have a small number of types of required knowledge and roles (variables), we can quickly see what an optimal solution concerning knowledge and role requirements is. In that case, the results can be seen in MATLAB software whereby the knowledge of employee is defined by degrees of membership functions. In other cases, when we have to assess a large number of employees, activities and roles, there can be a problem with visibility of results. Therefore, the employers must use business intelligence to clearly see all knowledge bottlenecks in a usable and understandable form. We review a Microstrategy Cloud Express heat map technique that offers the possibility of filtering employees according to their knowledge in descending or ascending order. It gives a good overview with colour scale and aids in recognising the degree of knowledge redundancy. However, the decision maker may also need an operational research expert to set appropriate functions for aggregation, implication, aggregation and defuzzification in FIS. The FIS tools usually offer a variety of functions, so a fuzzy model may become unreliable if inappropriate functions are chosen (Hudec and Vujošević, 2010).

The fuzzy decision model makes a hard decision making easier but cannot replace the autonomy and final judgement of the decision maker. However, in comparison with crisp approaches, it can allocate employees' knowledge more precisely to each role according to knowledge requirements.

The fuzzy model can be further developed by adding more input variables that will bring higher accuracy to the final result. We could use knowledge management systems in which intelligent agents help define employees' knowledge profiles and compare them with process requirements. In this way, we could obtain a wider set of needed and alternative types of knowledge. Based on those data, the employer can decide whether to train employees, compensate them, outsource the work or search for new human resources.

References

Ballard, C., White, C., McDonald, S., Myllymaki, J., McDowell, S., Goerlich, O. & Neroda, A. (2005). *Business Performance Management ... Meets Business Intelligence*. International Business Machines Corporation.

Cappelli, P. (2009). A Supply Chain Model for Talent Management, *People & Strategy*, 32 (3). Retrieved July 25, 2013, from http://connection.ebscohost.com/c/opinions/44933254/supply-chain-model-talent-management

Čater, T. & Čater, B. (2009). (In)tangible resources as antecedents of a company's competitive advantage and performance, *Journal for East European Management Studies*, 14 (2), 186-209, http://dx.doi.org/10.1688/1862-0019_jeems_2009_02_cater

Dorigo, M. & Stützle, T. (2004). *Ant colony optimization*. Cambridge: MIT Press.

Gärtner, B. & Matoušek, J. (2006). *Understanding and Using Linear Programming*. Berlin: Springer.

Guillory, W. A. (2009). *The Age of Human Potential – Talent Management*. Salt Lake City: Innovations International Inc.

Gutjahr, W. J., Katzensteiner, S., Reiter, P., Stummer, C. & Denk, M. (2008). Competence-driven project portfolio selection, scheduling and staff assignment, *Central European Journal of Operations Research*, 16 (3), 281-306, http://dx.doi.org/10.1007/s10100-008-0057-z

Hitt, M. A. (ed.) (2001). Direct and moderating effects of human capital on strategy and performance in professional service firms: A resource-based perspective, *Academy of Management Journal*, 44 (1), 13-28, http://dx.doi.org/10.2307/3069334

Hudec, M. & Vujošević, M. (2010). A fuzzy system for municipalities classification, *Central European Journal of Operations Research*, 18 (2), 171-180, http://dx.doi.org/10.1007/s10100-009-0105-3

Kern, T., Roblek, M., Mayer, J. & Urh, B. (2005). *Business processes and human resources competence profiles*, Khosrowpour, Mehdi (ed.). 2005 Information Resources Management Association, International Conference, San Diego, California, USA, May 15-18,. *Managing modern organizations with information technology*. Hershey [etc.]: Idea Group, 1202-1204.

Kuncheva, L. (2000). *How good are fuzzy if-then classifier*, IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics 30 (4), 501-509, http://dx.doi.org/10.1109/3477.865167

Maylett, T. (2009). 360-Degree Feedback Revisited: The transition from development to appraisal, *Compensation & Benefits Review*, SAGE Publications, 41 (5), 52-59. http://dx.doi.org/10.1177/0886368709337922

McCall, M. W. (1998). *High flyers, developing the next generation of leaders, Boston*: Harvard Business School Press.

Meglič, J., Kern, T., Urh, B., Balkovec, J. & Roblek, M. (2009). Influence of polyvalence professionals on product development process efficiency, *Strojarstvo*, 51 (2), 105-121,

Michaels, E., Handfield-Jones, H., Axelrod, B. (2001). *The War for Talent*. Boston Massachusetts: Harvard Business School Press.

Mitaim, S. & Kosko, B. (2001). The Shape of Fuzzy Sets in Adaptive Function Approximation, *IEEE Transactions on Fuzzy Systems*, 9 (4), 637-656, http://dx.doi.org/10.1109/91.940974

Mühlbacher, J., Nettekoven, M. & Kovac, J. (2011). Competency management in Slovenia: Paradoxes between development trends and drivers of change, *Journal for East European Management Studies*, 16 (1), 75-90.

Nahapiet, J. & Sumantra, G. (1998). Social capital, intellectual capital, and the organizational advantage, *Academy of Management Review*, 23 (2), 242-266, http://dx.doi.org/10.2307%2F259373

Roblek, M., Zajec, M. & Kern, T. (2011). *The Lack of Knowledge? Change the Way you Work*, Proceedings of the Forty-Fourth Hawaii International Conference on System Sciences HICSS-44, Kauai, HI. Los Alamitos, CA: IEEE Computer Society Press.

Roblek, M. & Zajec, M. (2012). *ETO Production knowledge based reverse engineering*, 31. International Conference on Organizational Science Development. Quality. Innovation. Future. Portorož, 2012, 1022-1030.

Russel Records, L. (2005). *The Fusion of Process and Knowledge Management*. Retrieved July 25, 2013, from http://www.bptrends.com/publicationfiles/09-05%20WP%20Fusion%20Process%20KM%20-%20Records.pdf

Schmid, C. (2005). *Membership Functions*. Retrieved July 25, 2013, from http://www.atp.ruhr-uni-bochum.de/rt1/syscontrol/node117.html

Škerlavaj, M. & Dimovski, V. (2006). Study of the mutual connections among information-communication technologies, organisational learning and business performance, *Journal for East European Management Studies*, 11 (1), 9-29.

Turban, E., Aronson, J. E., Peng Liang, T. & Sharda, R. (2007). *Decision Support and Business Intelligence Systems*. New Jersey: Pearson Prentice Hall.

Virant, J. (2003). *Svet mehkega računanja, sklepanja in delovanja; Novo znanje za mlade in strokovnjake vseh strok [The world of soft computing, reasoning and functioning; The new knowledge for young people and professionals of all disciplines]*. Radovljica: Didakta.

Wang, R. R. & Salunga, A. (2008). *Trends 2008: Project-Based Solutions*. Enterprise solutions for a Project-Based World: Forrester Research.

Zupan, N. & Kaše, R. (2006). Assessment of intellectual capital management in European transition economies: Building a conceptual model on the case of Slovenia, *International Journal of Human Resource Management*, 16 (6), 882-906. http://dx.doi.org/10.1080/09585190500120525

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