FLEXIBLE COMPLETION OF WORKFLOW ACTIVITIES

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Abstract: Over the last twenty years business process management has become a central approach to maintaining the competitiveness of companies. However the automation of the business processes utilizing workflow systems have often led to over-structured solutions that lack of the flexibility inherent in the underlying business model. Therefore there is a need to develop flexible workflow management systems that easily and quickly adapt to dynamically changing business models and processes. Lin and Orlowska (2005) introduced partly complete-able activities as one way to make workflow systems more flexible. In our paper, we extend the concept of partly complete-able activities by recognizing separate probability and fuzzy dimensions and by introducing process memory.

1 INTRODUCTION

Since its appearance twenty years ago, business process modelling has become one of the core methods to organizationally develop companies with the objective of improving their performance (van der Aalst and van Hee 2002). In the implementation and support of processes using information technology, workflow systems are of special importance.

However, after a period of high expectations in workflow system technology in the middle of nineties, a period of disappointment followed around the millennium. Currently it is experiencing a revival, as a core element of the new generation of ERP systems based on middleware technology.

One of the areas of disillusionment around the millennium was where workflow systems replaced human-oriented processes that are characterized by high flexibility: a simple transfer of the rigid concepts of manufacturing to service processes delivers suboptimal outcomes or results in failure.

Interactive or semi-automated workflows need to adapt to their human participants, and therefore need to support high degrees of flexibility.

However, examples of workflow systems that cater well for flexibility still mostly occur in research laboratories rather than in commercial products. Examples are Adept (Reichert 1998) or Chameleon (DSTC Praxis Project 2004, Sadiq 2000). A range of dimensions of flexibility was also discussed by Tagg (2003).

One example for flexibility is the ease with which an individual workflow instance (or business case) can be allowed to diverge from the general pattern. This is typically required because processes fall behind schedule and need to be got back on track by such means as increasing resources or taking agreed short cuts. One specific type of short cut is to allow progression of the workflow before some activities have been fully completed. But in virtually all commercial workflow systems, an activity is only considered as completed when all its post-conditions have been fulfilled. Lin and Orlowska (2005) suggested the concept of *partly complete-able activities* to relax this constraint (please note, we use *activity* in the sense of Carter et al. (2004): we do not differentiate between *task* and *activity*).

The objective of our paper is to extend the concept of partly complete-able activities by

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distinguishing *fuzzy* and *probability* dimensions. Besides that we introduce a memory component to such processes, in order to further increase flexibility. Last but not least we briefly analyze the potential of partly complete-able activities for current workflow systems.

The paper is organized as follows. In section 2 we describe the concept of partial completion of activities (Lin, Orlowska 2005). In the following section we introduce the probability and fuzzy dimensions to partly complete-able activities; furthermore we investigate some implications of memory to a process with partly complete-able activities. The paper concludes with a summary.

2 PARTIAL COMPLETION OF ACTIVITIES

2.1 Partly Complete-able Activities

Without loss of generality let us assume a sequential workflow. A central prerequisite to start activity A_n is that its predecessor, the activity A_{n-1}, has been completed. As long as the post-conditions of A_{n-1} are not fully completed the workflow system cannot continue to the next activity. This behaviour can be characterized as *all-or-nothing* strategy. It leads to a somewhat inflexible behaviour of the workflow system (Lin, Orlowska 2005).

To achieve more flexibility in the completion of activities Lin and Orlowska introduced the concept of *partly complete-able activities*. The possible states of a classic activity *not-completed* or *completed* are augmented by a third state, *partly completed*. Allowing partial completion of activities can lead to a higher flexibility of the process and a better alignment to real life situations. According to Lin and Orlowska, the main advantages obtained by this concept are a reduced processing time and an earlier release of resources for other activities.

Partly complete-able activities are characterized by the following property. The objective of an activity is decomposable: the activity can be completed on different levels denoted as $L_1,\ldots,L_M,\ldots,L_N$, where L_M defines the minimum requirements and L_N indicates full completion.

This property implies that the absolute completion of the activity is not critical for the process. As long as all activities are partly completed at least on the level L_M, the process outcome still meets at least its minimum objectives.

The decision whether an activity is completed or not goes as follows. For levels of completion lower than L_M and for full completion (L_N) the decision process is the same as in classic workflow systems. If the level of completion is lower than L_M the workflow systems treats the activity as not completed and therefore does not proceed to the consecutive activity. If the full completion level L_N is reached the workflow system automatically continues with the next activity.

However, if the activity is completed at least to the level L_M but less than L_N the workflow system presents the activity to an external decision maker, in most cases probably the process owner, who decides whether or not the activity can be considered as completed. If yes, the workflow system closes the activity and continues with the next process step.

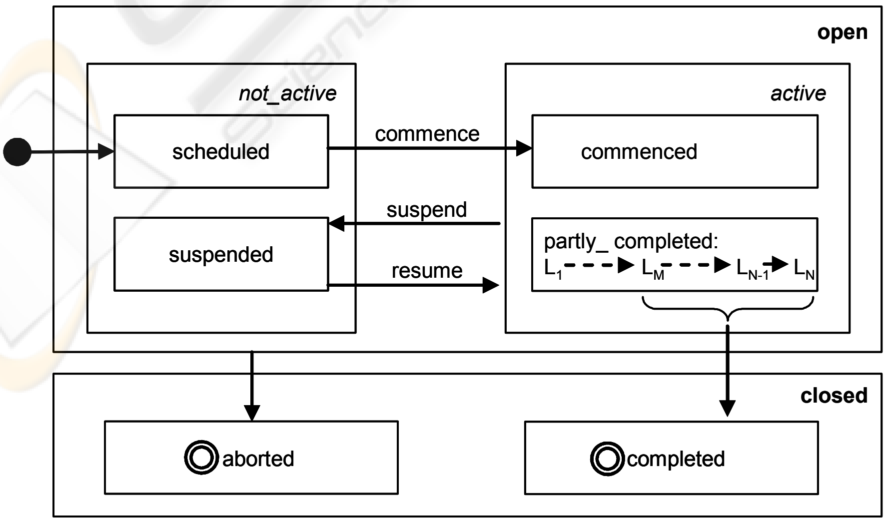

Figure 1: Enhanced Activity State Machine (according to (Lin and Orlowska, 2005)).

2.2 Finite State Machine

To formally model the concept of partial completion, Lin and Orlowska developed an enhanced activity finite state machine (Fig. 1) as a generalization of the state model of the WFMC (1995):

An activity can have the states *open* and *closed*. In the open state it is *scheduled* and therefore not active: *open.not_active.scheduled*. When the performer picks the activity out of a work-item list it changes its state to *open.active.commenced*. If a sub-objective of the activity is completed the state changes to *open.active.partly_completed*.

As already defined above the level of completion is indicated by L_1, L_2, …, L_M, …, L_N with L_N the level of full achievement of the objective of the activity and L_M the minimum requirements. If the activity reaches the levels L_M, … L_{N-1} the process owner can decide that the activity is sufficiently completed. In that case the activity changes to its final state *closed.completed*. This state will also be reached when the level L_N is achieved since the workflow engine automatically closes the activity.

Anytime during the activity is *open.active.commenced* it can be set on "Wait": *not_active. suspended* and *resumed* accordingly. The activity also can be aborted (*closed.aborted*) at any time.

3 AN ENHANCED MODEL OF PARTIAL COMPLETION

3.1 Probabilistic and Fuzzy Enhanced Finite State Models

3.1.1 Fuzzy and Probability Concepts

Lin and Orlowska introduced a model of partly complete-able activities without specifying the phenomena that can lead to the different levels of completion. We will distinguish between the fuzzy sets and probability as two possible reasons for the partial completion.

The relationship of *fuzzy sets* (Zimmermann 2001) and *probability* has been intensively and controversially discussed (e.g. Klir 1989, Zadeh 1983, 1995) since Zadeh introduced fuzzy sets in 1965. Recently, it has become accepted that they can be considered as independent and complementary to each other. Fuzzy sets are indicators for similarities or *neighbourhood relations* while probability is related to *probabilistic uncertainty*.

Note, that fuzziness is often also regarded as one form of uncertainty (Klir 1989, Zimmermann 2001). However this uncertainty is related to e.g. linguistic variables. What does the term "rich" mean: \$1million, \$10million or \$100million? Therefore linguistic variables are described as membership functions. To avoid confusing this with fuzzy uncertainty we explicitly refer to *probabilistic uncertainty* when we are in the field of probability theory.

Fuzzy Concept

For example, a bank wants to classify its customers into two groups: rich and poor customers. Obviously there is no crisp separation between rich and poor - e.g. in a way that customers that own less than \$ 1 million are poor while people with a fortune of \$ 1 million and more are rich. It is more intuitive that a person with a wealth of – let's say – \$ 1.1 million is considered as reasonably rich but still a little bit poor.

The indicator for similarity in fuzzy sets is called membership degree μ=[0,…,1]. A membership degree μ=1 indicates that an object fully belongs to a set while a membership degree μ=0 shows a total dissimilarity between an object and a set.

In our example, the customer with \$ 1.1 million may have membership degrees of e.g. μ_{RICH}(\$1.1M)=0.6 to the set rich and μ_{POOR}(\$1.1M)=0.4 to the set poor (Fig. 2). This indicates that the customer is rich but not extremely wealthy. However a person possessing \$ 50 billions would surely have memberships of μ_{RICH}(\$1B)=1.0 and μ_{POOR}(\$1B)=0.0.

Note that there is probabilistic uncertainty neither about the fortune of the customer (he *has* \$ 1.1 million) nor about the rules for how to classify him into one or other of the two sets (*determined* by the functions given in Fig. 2). Therefore the membership degrees do not indicate any *probability* of belonging to the sets, but *similarities* of values to those sets.

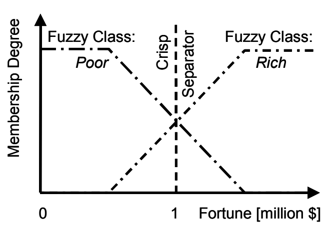

Figure 2: Fuzzy Concept.

Probability Concept

The same bank may face probabilistic uncertainty about the wealth of a customer. For example, a new customer driving up with an old bicycle might be considered of having a fortune of , say, $ 10 while it might be assumed that a customer chauffeured to the bank in a big limousine could have a million dollars. However, these are only the guesses of the bank employees. The vehicles of the customers are indicators for the wealth but no proof. Therefore the bank clerks have to act under probabilistic uncertainty. The biker could be a crazy billionaire while the chauffeured customer might be a debt-ridden conman.

The biker (BI) might have a fortune of $ 10 with a *probability* of $P_{BI}(\$10)=0.9$ and a fortune of one million dollars with a probability of $P_{BI}(\$1M)=0.1$ while the limousine customer (LI) has the following probabilities: $P_{LI}(\$10)=0.2$ and $P_{LI}(\$1M)=0.8$.

Note, that in the example only probabilistic uncertainty is taken into account. In contrast to the fuzzy concept as shown in the previous section the amounts of money ($ 10 and $ 1 million) are not examined with respect to their similarity to the sets poor and rich.

Joint Fuzzy and Probability Concept

Since the fuzzy and probability concepts are independent they can be combined. For simplicity let us consider here only the bike rider.

First the bank clerks estimate the fortune of the new customers: the biker might have a fortune of $ 10 with a *probability* of $P_{BI}(\$10)=0.9$ and a fortune of one million dollars with a *probability* of $P_{BI}(\$1M)=0.1$. Second the given amounts of money are examined with respect to their similarity to the sets *rich* and *poor*. Ten dollars may be classified with the following *membership degrees:* $\mu_{POOR}(\$10)=0.95$ and $\mu_{RICH}(\$10)=0.05$. For one million dollars we may get: $\mu_{POOR}(\$1M)=0.02$ and $\mu_{RICH}(\$1M)=0.98$.

Combining probably and fuzziness we finally get: The biker belongs with a probability of $P_{BI}=0.9$ and to a membership degree of $\mu_{POOR}=0.95$ to the set *poor* as well as to the set *rich* with $\mu_{RICH}=0.05$. With a probability of $P_{BI}=0.1$ he belongs to the set *rich* with a membership degree of $\mu_{RICH}=0.98$. as well as to the set *poor* with $\mu_{POOR}=0.02$.

3.1.2 The Enhanced Finite State Models

The application of the fuzzy and probability concepts leads to enhanced finite state models.

Fuzzy Enhanced Finite State Model

In a fuzzy enhanced finite state model (Fig. 3) the similarity between the actual output of an activity and a given post-condition is determined. A membership degree μ=1 indicates that the output fully satisfies the required post-condition while μ=0 shows a total dissimilarity between output and post-conditions. Membership degrees between these extreme values indicate partial compliance between the actual output and the post-conditions.

The membership degrees can be utilized to

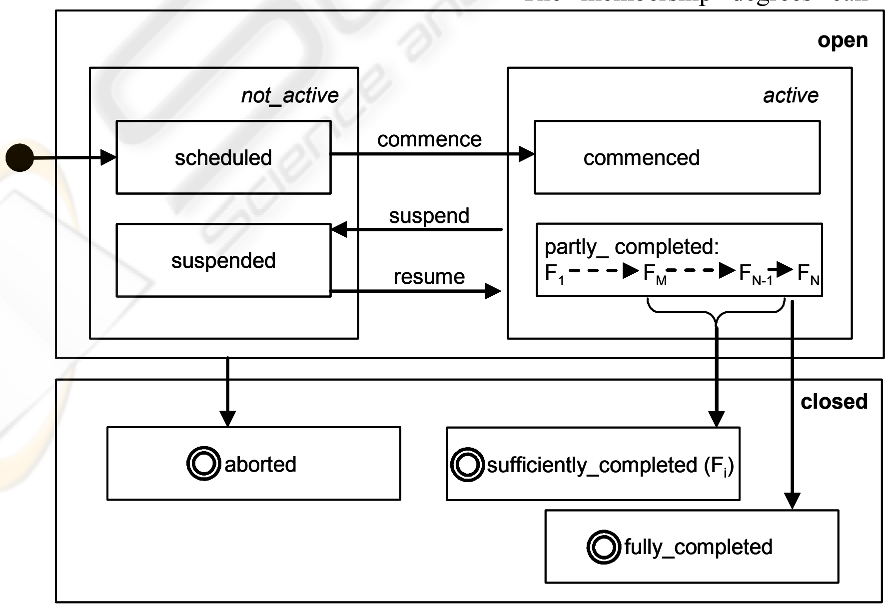

Figure 3: Fuzzy Enhanced Activity Finite State Machine.

describe the states of completion in a more detailed way than in the basic model as introduced in Section 2.2. The states can be added by a label F_i ($F_M \le F_i \le 1$) which indicates the level of completion of the activity: *closed.completed* (F_i). Obviously the label equals the membership degree of the actual output to the post-condition as defined above. An activity with the *state closed.completed (0.8)* shows that it belongs to the set completed with a membership degree of μ=0.8.

Furthermore we suggest explicitly distinguishing between fully and only partly completed activities. So we finally get the following states:

- state: *closed.completed* (F_i) with $F_M \le F_i < 1.0$: *sufficiently_completed* (F_i)
- state: *closed.completed* (F_i) with F_i=1.0: *fully_completed*

This leads to the fuzzy enhanced activity finite state machine as shown in Fig. 3. The fuzzy enhanced model now clearly separates the levels of completion and therefore has a finer granularity in comparison to the model of Lin and Orlowska.

Furthermore fuzzy set operators now easily allow us to aggregate multi-dimensional post-conditions. Let us extend our example of Section 3.1.1. Besides the vehicles the bank clerks also take into account the number of credit cards the new customer presents to the bank. Zero credit cards would result in a membership degree of μ_{RICH}(CC=0)=0 to the set while ten credit cards lead to μ_{RICH}(CC=10)=1.

A customer possessing one million dollars and seven credit cards then has the following membership degrees: μ_{RICH} (\$1M)=0.98 and μ_{RICH} (CC=7)=0.7. To obtain the membership degree of the combined decision the single memberships can be summed up by a fuzzy aggregation operator, for example the basic min-operator: $\mu_{aggregated}$=min{0.98, 0.7}=0.7.

Note, that the basic min-operator has no compensatory power. E.g. Hamacher (1978) introduced a class of intersection operators with compensatory power:

$$\mu_{\tilde{A}\cap\tilde{B}} = \frac{\mu_{\tilde{A}}(x)\mu_{\tilde{B}}(x)}{\gamma + (1-\gamma)(\mu_{\tilde{A}}(x) + \mu_{\tilde{B}}(x) - \mu_{\tilde{A}}(x)\mu_{\tilde{B}}(x))}.$$

More compensatory operators can be found in e.g. Dubois, Prade (1982), Werners (1988), Yager (1980) or Zimmermann, Zysno (1980).

The introduction of the fuzzy sets leads to a finite state model quite similar to that suggested by Lin and Orlowska (also note the relationship to fuzzy Petri Net approaches e.g. Rapso et al. (2001)) The main advantage is that one can use this well established theory with its tools to formulate the partial completeness of the activities.

Probabilistically Enhanced Finite State Model

The probabilistically enhanced finite state engine (Fig. 4) deals with the probabilistic uncertainty over whether or not the outcome actually matches the intended post-conditions of the activity.

In our example the bank clerks have to decide under probabilistic uncertainty whether the approaching customer is rich or poor. Generally they have two different policies when their decision turns out to be wrong (e.g. the limousine customer has no

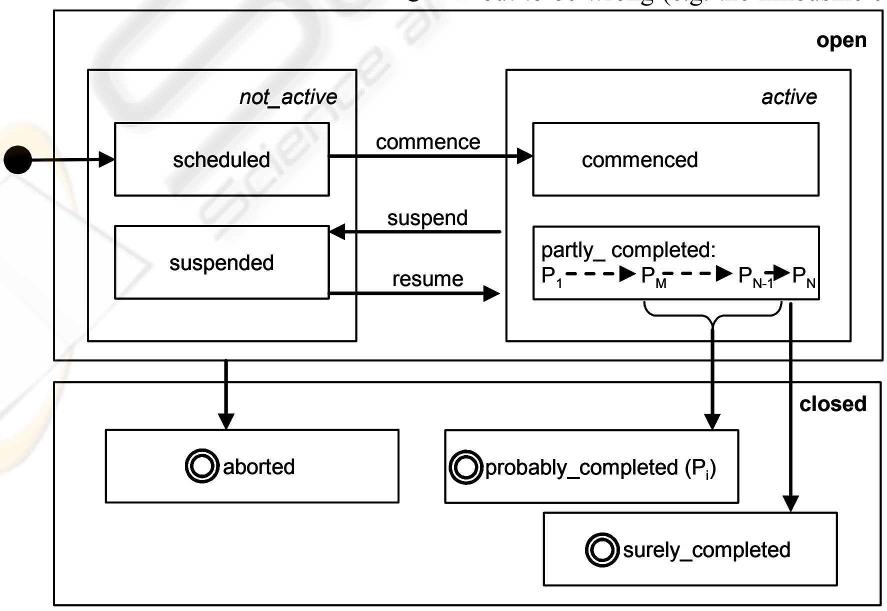

Figure 4: Probabilistically Enhanced Activity Finite State Machine.

money at all):

- Policy 1. The bank clerks do not revise their decision and continue to service the customer as if he were rich: e.g. an approval for a home loan will not be withdrawn. The process continues memory-free, that means that once a decision is taken it will never be corrected. The workflow system does not require any roll-back strategies.
- Policy 2. The drive up with the limousine is accepted only as first proof for wealth. The customer gets an approval for a home loan under the reserve that he proves to be rich within a given time period. Here the workflow system needs roll-back strategies in case that the customer turns out to be poor. This policy needs an advanced transaction management (e.g. Leymann, Roller 2000).

To distinguish between a *surely* completed activity and an activity that is only completed *with a certain probability* the following states are introduced:

- state*: closed.completed (P_i)* with $P_M \leq P_i < 1.0$: *probably_completed (P_i)*
- state: *closed.completed (P_i)* with P_i=1.0: *surely_completed*

The nomenclature parallels the one we have already presented for the fuzzy dimension. The corresponding probability enhanced activity finite state machine is show in (Fig. 4).

Along the lines of the discussion on fuzzy trade-offs we introduce a compensation between outcomes on different levels of certainty or probabilistic uncertainty. Now, in our example the vehicles as well as the credit cards are taken into account.

The biker (index BI)has a probability of P_{BI}($10)=0.9 that he owns $ 10 (see above). However he possesses ten credit cards (index CC) which leads to a following probability of P_{CC}($10)=0.2 that he owns $ 10 and P_{CC}(1M)=0.8 that he has one million dollars. For simplicity's sake let us assume that the probabilities related a) to the vehicle and b) to the number of credit cards are statistically independent. Then the overall probability that he has $10 is: P_{BI}($10)* P_{CC}($10)=0.18.

Fuzzy and Probabilistically Enhanced Finite State Model

As discussed above the fuzzy and probability dimensions are independent from each other. Therefore they can be combined. The resulting probabilistic-fuzzy completion states can be derived straightforwardly from the models introduced in the previous Sections. They are defined as follows:

- state: *closed.completed (F_i, P_i)* with ($F_M \leq F_i$ and $P_M \leq P_i$) and (F_i<1.0 and/or P_i<1.0): *sufficiently_completed (F_i, P_i)*
- state: *closed.completed (F_i, P_i)* with F_i=1.0 and P_i=1.0: *fully_completed*

3.2 Processes with Memory

Up to now we have considered a memory-free process: the level of completion of an earlier activity (process step) is not recorded and therefore has no influence on any later process step. In particular no compensation between process steps is possible.

However, we have already introduced the possibility of fuzzy and probabilistic compensations within one process step (in our example between the kind of vehicle and the number of credit cards). We can easily generalize this construct to compensations between different process steps (activities) by introducing a process memory. In such a generalized model the degree of completion has an impact on future decision spaces within the process.

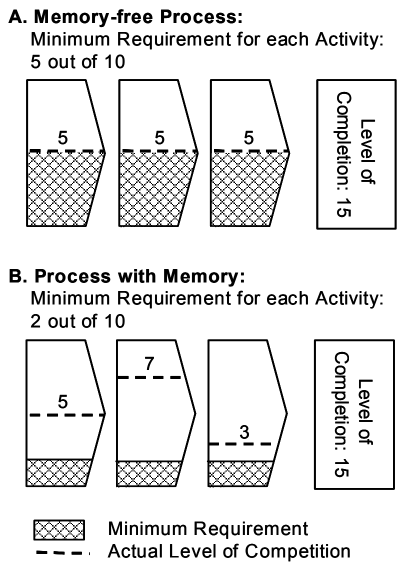

Figure 5: Process Memory.

In a *memory-free* process every step of the process must meet minimum requirements independently from the other process steps (Fig. 5A). Once the minimum requirements of an activity are met the process owner is free to define it as completed and continue with the next activity. The overall objective of the process can only be taken into account indirectly since no trade-off between the levels of completion of the single activities is possible. In the case of a memory-free process one always has to assume the worst case scenario - this is when all activities just reach their minimum requirements. However these minimum requirements must meet higher standards in comparison to a process with memory where compensations between high and low performing activities are possible (Fig. 5B).

When only one activity is completed on a higher level then the process objective is also accomplished at a higher degree than needed. Generally this leads to a waste of resources and a reduced flexibility in a memory-free process. In the process shown in Fig. 5B for example, the good performances of the process in the first two steps allow the last activity to completed on a low level without endangering the overall process output.

The increased flexibility of a process with memory in comparison to a memory free process is counterbalanced by the following drawbacks:

- Processes with memory can only applied when trade-offs between the objectives of the activities are present. In particular, designing such a process is more complex than designing a memory-free process since the trade-offs must be specified. In the running phase the workflow system must additionally monitor and record the degrees of completion of each activity.
- The possible trade-off between low and high accomplishment of activities might encourage performers of early activities to meet only the minimum requirements. This could result in stricter requirements and less flexibility in later process steps (even stricter than in a process without memory). However it could be more likely that the later process steps require greater flexibility than the earlier ones.

Therefore the use of such processes needs to be carefully deliberated to ensure that the performance meets the expectations of the process owner.

4 CONCLUSION

In this paper we extended the concept of partly complete-able activities by distinguishing two independent dimensions (fuzziness and probability) and introducing a process memory. The two dimensions allow us to describe the reasons for the partial completion of activities in more detail. The process memory allows us to formulate trade-offs on the level of completion between earlier and later activities, and make it easier to meet the overall process goal in comparison to a memory-free approach.

Both our extensions lead to an increase in process flexibility in comparison to the approach of Lin and Orlowska and classic workflow systems. However partly complete-able workflow systems (both fuzzy and probabilistic) with memory require very detailed information in the design phase to customize the levels of completion and the trade-offs between the activities. This information would be very difficult to determine in real life. Therefore it will be difficult to implement - and economically operate - such a workflow system in the near future. However in the longer term, further progress in artificial intelligence and automated learning might provide methods to overcome these obstacles.

Our opinion is that these compensation structures and process memory are very common when humans conduct any kinds of processes that are not supported by information technology. Therefore we think that it is important to recognize and describe these phenomena, since they might provide reasons why an IT-supported workflow may not perform in the expected way. Knowing the reasons might provide strategies for workarounds until more sophisticated, human like, technologies are developed to further bridge the gap between technology and human thinking.

REFERENCES

Carter, B.M.; Lin, J.Y.C; Orlowska, M.E., 2004: Customizing Internal Activity Behaviour for Flexible Process Enforcement. *Proceed. 15th Australasian Database Conference*, Dunedin, New Zealand

DSTC Praxis Project 2004: Chameleon Website, www.dstc.edu.au/Research/Projects/praxis/ chameleon/index.html

Dubois, D.; Prade, H., 1982: A class of fuzzy measures based on triangular norms. *International Journal of General Systems*, 8, 43-61

Hamacher, H., 1978: *Ueber logische Aggregationen nicht-binaer expliziter Entscheidungskriterien*. Rita G. Fischer Verlag, Frankfurt, Main, Germany

Klir, G., 1989: Is there more Uncertainty than some Probability Theorist might have us believe? *International Journal of General Systems*, 15, 347-378

Leymann, F.; Roller, D., 2000: *Production Workflow: Concepts and Techniques*. Prentice-Hall, Upper Saddle River, NJ, USA

Lin, J.Y.C.; Orlowska, M.E., 2005: Partial completion of activity in business process specification. *Proceed. IRMA 2005*, San Diego, CA, USA, 186-189

Raposo, A.B.; Coelho, A.L.V.; Magalhães, L.P.; Ricarte, I.L.M., 2001: Using Fuzzy Petri Nets to Coordinate Collaborative Activities. *Proceed. 9th IFSA World Congress & 20th NAFIPS Intern. Conf.*, Vancouver, Canada, 1494-1499

Reichert, M.; Dadam, P., 1998: ADEPT*flex* - supporting dynamic changes of workflows without losing control. *Journal of Intelligent Information Systems*, 10, 93-129

Sadiq, S. 2000: Handling Dynamic Schema Change in Process Models. www.dstc.edu.au/ Research/Projects/praxis/publications/ssadiq_adc_2000.pdf (accessed 08.07.2005)

Tagg, R.M. 2003: Dimensions of Flexibility in Workflow Management, *EURO/INFORMS Conference, Istanbul*, 2003

van der Aalst, W.; van Hee, K. 2002: *Workflow Management - Models, Methods, and Systems*. MIT Press, Cambridge, MA, USA

Werners, B. 1988: Aggregation models in mathematical programming. In Mitra, G.: *Mathematical Models for Decision Support*. Springer Verlag, Berlin, 295-319

Workflow Management Coalition 1995: Workflow Management Coalition - The Workflow Reference Model. Doc. # WFMC-TC1003

Yager, R.R. 1980: On a general class of fuzzy connectives. *Fuzzy Sets and Systems*, 4, 235-242

Zadeh, L. 1965: Fuzzy Sets. *Information and Control*, 8, 338-353

Zadeh, L. 1983: Is Possibility different from Probability? *Human Systems Management*, 3, 253-254

Zadeh, L. 1995: Probability Theory and Fuzzy Logic are Complementary Rather Than Competitive. *Technometrics*, 37, 271-276

Zimmermann, H.J. 2001: *Fuzzy sets and its applications* (4th edition). Kluwer Academic Publishers, Boston, MA, USA

Zimmermann, H.J.; Zysno, P. 1980: Latent connectives in human decision making. *Fuzzy Sets and Systems*, 4, 37-51