Modelling Processes in Fractalized Hospitals with Multiagent Systems and Data Analytics

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Abstract: Most approaches for modelling processes neglect the high degree of distributed decision making in the hospital domain where processes are coordinated by local authorities. The paradigm of fractal organizations combined with the decentralized characteristics of distributed Artificial Intelligence may help to understand and model the problem. This paper presents ongoing research and contributes a meta-model for modelling processes in hospitals with multiagent systems as fractals of a logistics supply network and incorporates data analytics methods to identify dependencies between different fractals. The presented approach is evaluated by analyzing a hospital scenario involving multiple fractals in a patient-centric process.

1 INTRODUCTION

With a constant change towards profit maximization, hospitals are forced to apply new methods. To cope with the increasing cost pressure, approaches from industrial enterprises seem appropriate and, thus, more and more hospitals start to make use of process-orientation on their internal workflow (Cleven et al. 2014). Applications in hospitals have to face complex relationships and dependencies of several departments that follow locally optimized processes. Clinical pathways are a first approach to cope with the interrelations of multiple departments, but neglect the limited suggestibility of intra-departmental processes (Vanberkel et al. 2010). In hospitals, lasting organizational structures are established that partly show a high degree of autonomy on some levels. As hospital units structure their internal processes without external intervention, these local decisions may influence the inter-department processes and lead to a suboptimal efficacy. To address this issue, the decentralized decision making process of hospitals has to be included in process models to form the basis for analyzing dependencies between multiple departments (i.e. process fractals). A well-suited approach to model and analyse such systems with distributed decision making processes comes with the concept of intelligent, cooperative software agents, and multiagent systems (MAS). We further propose data analytics methods to identify interdependent process fractals and predict time-based parameters to improve cooperation among these.

The goal of this paper is (i) to develop a meta-model for modelling interdependent process fractals that is suitable for scenarios in hospitals and (ii) to incorporate data analytics methods to identify the dependencies between multiple process fractals and to predict execution times as a basis for improved cooperation and higher efficacy. The suggested meta-model is based on two major abstractions: (i) logistics (the right material in the right quantity, at the right time and the right place) as well as (ii) the paradigm of fractal companies introduced by Warnecke (1993). The paper presents ongoing research and is based on previous work (Premm & Kirn 2015).

The remainder is structured as follows. Section 2 discusses related work on process management in hospitals and organizational theory. Section 3 develops a logistics-based meta-model to model fractal processes. Section 4 presents a data analytics approach for identifying process fractal dependencies and predicting execution times. Section 5 presents a scenario-based evaluation. Section 6 concludes.

2 STATE OF THE ART

This section presents the state of the art on (i) process management in hospitals, (ii) organizational para-

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digms that are used in distributed artificial intelligence and may help to structure processes in hospitals, (iii) the concept of fractal organizational units to better understand hospital processes, and (iv) the systematics of logistics tasks and organizational fractals.

2.1 Process Management in Hospitals

In the past, counteracting delays has been performed by adding additional resources. However, a lack of resources is in many cases not the cause for delays in hospitals, but the organization of inter-departmental processes (Haraden & Resar 2004). Decisions are made on a local basis and the actors are not aware of the consequences on other departments or parallel processes. Haraden and Resar (2004) examine this problem and evaluate processes of several hospitals in the United States and the United Kingdom. The authors focus on elective surgeries as well as the surrounding units and found that an overall view on hospital processes may increase the resource efficiency and thus also the financial performance. However, the paper is restricted to an overview on possible improvements and does not suggest how to enforce processes involving multiple units considering the decentralized character of decision making in hospitals.

Vanberkel et al. (2010) survey similar approaches that encompass multiple departments in hospitals focusing clinical pathways, which aim at eliminating the ambiguity of patient care trajectory. While other modelling approaches optimize all patient types in one department, the scope of clinical pathways is one patient type with all relevant departments. However, this point of view neglects different types of patients competing for the same resources. For Vanberkel et al. (2010), the optimization of clinical pathways is the first step before quantitatively optimizing the internal processes of single departments.

The literature also provides work that specifically addresses the distributed nature of the decision problem: Murray et al. (Murray et al. 2014) take a patient-centric perspective and suggest to use software agents representing relevant actors of patient care trajectory (e.g. patient, physician, unit). The agent interaction protocol takes over the coordination of resources as well as involved actors while coping with the decentralized nature of the processes. The distributed nature of the decision making process as well as the huge dynamic caused by the mixture of planned and emergency instances of numerous individual tasks lead to a high complexity of the process landscape in hospitals. The organizational units as well as the processes in their responsibility can be considered as fractals of the organization. Agent-based approaches from Distributed Artificial Intelligence (DAI show great potential to cope with this complexity.

2.2 Organizational Metaphors in Multiagent Systems

In the last decades, researches in DAI have developed a paradigm called MAS, which is suitable for scenarios with multiple actors deciding about their actions on a local knowledge basis. The main focus of research has been on an increased flexibility facing previously unknown environmental circumstances. However, there are also approaches that cope with organizational stability required in hospital scenarios. According to DAI/MAS researchers with backgrounds in management science, “organization” is a metaphor that can be useful in helping to describe, to study, and to design distributed software systems (Malone 1987; Fox 1981). Compared to organizational theories in management, however, MAS/DAI still lacks similar fine-grained concepts and instruments for describing, analyzing, thus understanding and designing organizational phenomena within agent-based systems.

Approaches from DAI that involve single problem solving experts can be compared with the perspective of management science, in which organizations are systems that pool individual resources in order to gain additional benefits for all of their members. From an organizational perspective this approach implements the concept of dividing labor among a set of individuals each possessing a particular capabilities profile (Gasser 1992). As an immediate consequence, distributed problem solving leads us to role concepts – e.g., the role concept of the C-Net system (Davis & Smith 1983), in which manager and contractor roles coordinate the execution of tasks. However, the definition of roles in DAI is quite different to organizational theories in management science. The latter refers to a role as a precise definition of expected behavior of a particular member of an organization.

Management science considers organizations mainly from a social science perspective. This perspective builds upon the basic assumption that humans form an enterprise in order to fulfill a concrete market demand (e.g., production of autonomous cars). Organizational rules and definitions (e.g., definition of positions) are required to coordinate the division of labor, the behavior of employees, and all operational processes to produce, sell, and maintain goods and services. It is well understood, that enterprises need stability with respect to their suppliers and customers, to their employees, and to their infrastructural, technical and financial production factors. It is well understood, too, that the increased dynamics of their environments (e.g., changing consumer behaviors, changing market demand, changing market structures, changing market coordination, etc.) does also require an increase of organizational flexibility. Approaches from distributed artificial intelligence may serve this kind of flexibility, but lack stability in terms of organizational structures. In the healthcare domain, however, both principles are necessary to fulfill patient care. The paradigm of fractal organizations by Warnecke (1993) enables using these two approaches simultaneously.

2.3 From Fractal Processes to Fractal Organizational Units

It has been argued that the enterprise of the future will be radically decentralized, in order to meet the challenges of the increasing complexity of its environment, and the dynamics of world-wide competition. Decentralization involves the allocation of autonomy, resources, and responsibilities to deeper levels of the organizational hierarchy (for instance, see work of Tapscott & Caston (1993) or Warnecke (1993)). This requires enterprises to replace hierarchical planning by more decentralized concepts of coordination like the MAS paradigm introduced above. In turn, autonomous organizational departments need to exhibit improved capabilities in terms of intelligence and self-reference than they do today. This has given rise to the notion of organizational fractals (Warnecke 1993). Organizational fractals are characterized by the following major criteria (Warnecke 1993): (i) self-organization and self-optimization, (ii) goal orientation, (iii) dynamic, as well as (iv) self-similarity.

The last criterion of self-similarity describes the structural characteristics of the organization as well as the modalities of generating added value. The self-similarity between different fractals enables resource sharing especially for informational resources and thus is especially interesting as it enables to build complex systems on simple and reoccurring modules. In the case of hospitals, one can think of several logistic tasks that have to be fulfilled for patient care. Whereas the patient itself undergoes multiple different process steps that show self-similarity in their internal structure. Findings from logistics may be transferred to the hospital domain and may serve to improve processes in hospitals with their fractal organizations.

2.4 Systematics of Logistics Tasks and Organizational Fractals

Logistics aim at supplying a requesting entity with the right good (quantity and quality), at the right time and the right place at minimal costs. The spatiotemporal transformation of goods is the rudimental capability of logistics systems. The involved processes can be distinguished into the following categories (Pfohl 2004): (i) Core processes of goods flow (transport, transshipment and storage processes), (ii) supporting processes, e.g. packaging processes and (iii) order transmission and processing processes. A generic example from the manufacturing industry would be the storage of a resource (temporal transformation) that has to be prepared for pickup (transshipment), transported to the targeted destination (spatial transformation), prepared for further processing (transshipment), physically adapted (production), again prepared for pickup (transshipment) and so on. This elementary example shows that the core logistics processes occur continually

The widespread visualization as a graph is domain-independent and enables also logistics networks as an extension of a logistics supply chain (Domschke 2008). Dependent on the specific modelling goal, there are numerous approaches for formalizing logistics tasks. Besides business driven approaches like the Architecture of Integrated Information Systems (ARIS), which provides general means for business process modelling (Scheer & Nüttgens 2000) and the Supply Chain Operation Reference (SCOR) Model, which is an industry-independent framework for evaluation and improvement of supply chains (Stewart 1997) a huge range of quantitative decision models exist in literature. Quantitatively parameterized mathematical models are mainly used for planning and decision making, but usually involve only a restricted number of parameters (Scholl 2008). With these mathematical models numerous variants of supply chain optimization problem can be addressed. However, these models generally assume some central designer that is able to enforce a production plan to all instances of the supply chain. In real-world scenarios this is usually not the case, especially in hospital scenarios in which single departments remain highly autonomous in their internal processes.

The organizational fractals involve a maximum degree of local autonomy, self-control, and self-organization skills. Aiming to maximize their local utility (for instance, in terms of profit), organizational fractals decide on their own whether they are willing to cooperate, or to collaborate with other organizational units. There is no direct means by which fractals can be compelled to behave in a certain manner. The single acceptable way to control the behavior of an organizational fractal, or of a group of cooperating fractals, is through designing a globally consistent system of aims and objectives (Warnecke 1993). However, due to bounded rationality, organizations are, in most cases, not able to establish consistent goal hierarchies. Instead, the different goals that exist within an organization are more or less inconsistent, the knowledge about goals and relationships between them remains necessarily incomplete, uncertain, fuzzy, and sometimes even wrong.

Organizational fractals form organizationally stable parts of an enterprise and have well-defined interfaces to their environments. They execute locally well-defined production functions (transformations), and they are supposed to guarantee a maximum of internal stability in terms of, e.g., their operations and processes, their requests for resources, their availability, and their responsiveness. Their flexibility results from their capability to cooperate, and even merge with other fractals in order to create a more complex fractal, if required.

3 MODELLING FRACTALS WITH MULTIAGENT SYSTEMS

To address the complex nature of organizing processes in hospitals, this section combines the paradigm of organizational fractals from management science with MAS from DAI and proposes a meta-model for modelling fractals from a supply network perspective.

3.1 A Fractal Supply Network Perspective

The transportation of goods and the systematics mentioned in section 2.4 are independent of a certain domain and the mentioned types of processes show similar characteristics: Goods have to be transported, handled and stored. In general, this is even independent of the fact, whether the good in question is physical or informational. For information goods the border between these core processes and the order transmission or processing might diminish as no physical good is present. In this case, the core process is an information flow just like the order processes.

Independent of the physical presence of a good, it can be observed that supply chains are in many cases divided into different fractals. These fractal are autonomous and cannot be fully controlled from a macro perspective. Depending on the context, these fractals might be whole enterprises (e.g. in a manufacturing supply chain) or different departments (e.g. in a hospital) that show a certain amount of autonomy. Hence, the overall process cannot be planned in detail against the motivation of the single fractals.

3.2 Multiagent Systems

With its focus on distributed decision making, the paradigm of MAS seems well suited for the local authorities in the hospital domain. Since the emergence of the multiagent paradigm numerous MAS have been developed for various domains, e.g. manufacturing and logistics, and in most cases the design is focused on specific issues (Stockheim et al. 2004). Although developed independently, the different MAS cannot be viewed as separated autarkic systems as they interrelate with each other in many ways. The organizational structure between two or more independently developed MAS usually involves the relations between the represented real world organizations. The technical as well as the organizational question has been addressed by the platform Agent.Enterprise in a logistic scenario (Woelk et al. 2006). Agent.Enterprise is not restricted to intra-organizational value chains already represented by MAS, but integrates multiple instances of these into inter-organizational supply chains. This combination of multiple MAS is called a multi-multiagent system and works cross-organizational. Each MAS remains locally controlled, but obtains features of inter-organizational communication and cooperation to further increase flexibility and decrease costs. In Agent.Enterprise each MAS plans and optimizes its logistic and production processes individually, but informs other systems of unforeseen and potentially disturbing events. On the basis of this information exchange, plans of other MAS may be adapted or inter-organizational contracts may be renegotiated (Woelk et al. 2006).

3.3 Meta-Model

In logistics supply chains one can find different levels of organizational structure, e.g. in a manufacturing supply chain, there are usually different companies that work together for one final good. Thus, we can distinguish between intra- and inter-organizational structures, e.g. the intra-organization structure of a company is embedded into the inter-organizational structure of the supply chain that involves various other companies whose behavior is not controllable, but has to be motivated. Analogously, processes in hospitals are characterized by highly autonomous departments that can only be limitedly controlled by the central hospital process management. This leads to

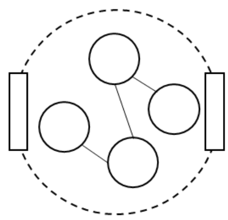

Figure 1: Organizational fractal.

fractal processes within the hospital where each department again can be represented by a single MAS.

Independent of a certain domain, network-wide processes consist of flexibly coordinated fractals being under local control of complex agents, e.g. a single MAS. Two dependent organizational problems evolve: (i) the intra-organizational structure of each MAS that may differ significantly and (ii) the overall inter-organizational structure that aims at a final product and that is not able to fully control the single process fractals. Each fractal has a logistics task based on domain independent types: (i) spatial transformation in form of a transportation process, (ii) temporal transformation in form of storage as well as (iii) physical transformation in form of a production process. The single fractals are represented by a MAS with interfaces to form a supply chain.

The internal workflow of each process fractal is only in a small extent influenceable from an external position. The operational sequences performed by the involved actors may be affected by incentives, but cannot be controlled directly. Hence, for modelling process fractals in logistic processes, it is necessary to have a modelling language that allows to abstract from the internal workflow within a process fractal. Table 1 shows the meta-model for modelling domain independent logistic process that show characteristics of fractalization. Figure 1 shows an example of a process fractal involving the modelling elements described above. The elements are arranged to represent a process fractal with a number of interacting actors and two interfaces.

Table 1: Meta-Model.

Label	Symbol	Description
Process Fractal		A self-contained and self-organized series of activities with a permanent nature that involves a certain number of actors and is available via interfaces
Actor		Smallest organizational entity in a process fractal that has the competency to make decisions with a given scope
Interface		Coupling point of a process fractal that allows for incoming or outgoing products, services or humans from or to another process fractal
Interaction Path		Bidirectional communication link between two actors of a process fractal
Process Flow		Transition of a product, service or human from one process fractal to another one

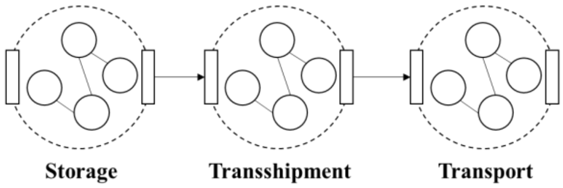

Figure 2: Combination of process fractals.

As described in section 2.4, logistic processes in many domains show self-similarity and can be reduced to three types of processes: (i) storage, (ii) transshipment, and (iii) transport. From a logistic perspective production processes can be interpreted as storage processes, as the product or service has no influence on the logistic system for a certain time and, thus, is transformed in a temporal manner.

3.4 Formalizing Logistics Tasks

The combination of different process fractals is a central feature of the proposed meta-model. The combination of process fractals that are independent from a decision making perspective allows to form logistic supply chains. While each fractal only performs simple tasks the combination of different fractals may serve to solve tasks with a higher complexity. **Error! Reference source not found.** shows an example of a combination of different process fractals: Between transport and storage process fractals, usually, a transshipment process fractal has to be involved to achieve compatibility. In a flow of goods scenario this might be the forklift that allows for transshipping goods in a high-bay warehouse to the transporting truck. However, these process fractals also match for scenarios in a hospital domain, e.g. the patient has to be repositioned (transshipped) from the transportation bed to the surgical table before surgery (see section 5).

These process fractals can be arranged to different kind of processes. Figure 3 shows three elementary types: (i) the single-tier system with only two connected fractals are involved, (ii) the multi-tier system with different interconnected tiers, as well as (iii)

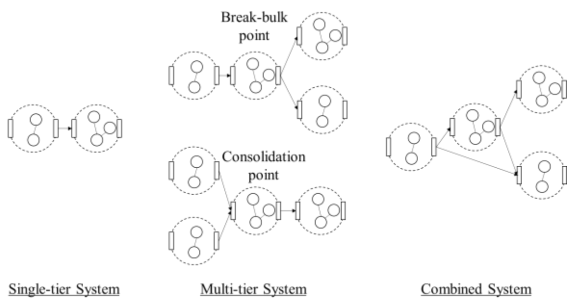

Figure 3: Basic structures of logistics systems.

combined systems that also have connections between non-consecutive tiers. Processes may also split up at break-bulk points and may be joint at consolidation points.

4 DATA ANALYTICS FOR FRACTALIZED PROCESSES

For modelling and better coordinating and supporting logistic processes among fractals with MAS, methods for data analytics can be used to (1) identify fractals in the first place, and (2) predict parameters of the fractals such as the start, duration, and end of individual logistic tasks of different types. The identified fractals can be used for modelling the logistics of an organization with MAS. The predicted parameters can be used by MAS that represent fractals to support and improve coordination among fractals by better anticipating logistic tasks. The most important prerequisite for applying data analytics to the described respect is the availability of large amounts of data that allows describing and predicting the fractals' parameters. Nowadays, this seems less of a problem as more and more data emerges and becomes available due to new types of sensor systems and information systems used in the scope of logistics, e.g. electronic healthcare records and advanced medical devices (Manyika et al. 2011).

For identifying fractals from data, the traces of the logistic tasks within an organization have to be collected and made available for analysis. The data should comprise time stamps and locations of each individual logistic task (i.e., events of starting and completing a logistic task) and a unique reference to the logistic goods across an organization. By sorting the tasks by the time stamps of starting and completing events, the routing of goods can be identified and the duration of tasks can be measured. Aggregating the (most frequent) routes in a graph-based model can help to identify the most important routes and also waiting bottlenecks across fractals can be identified. For conducting this type of data analytics, several software tools are available. For instance, the tool proM can be used (Van Der Aalst et al. 2009).

Nowadays, predicting logistic tasks in an organization is often accomplished by human estimates. Theses are often too coarse-grained and the resulting imprecision leads to bad coordination among fractals and frustration in the implementation of fractalized logistic tasks. Methods for data analytics can be used to more effectively predict all three types of logistic tasks of process fractals.

Predictive data analytics is to create a prediction model in a data-driven way, which maps several predictive variables to the variable to be predicted (here: parameters of logistic tasks). Finding the optimal mapping can be well accomplished by machine learning methods. Machine learning is the ability to improve performance on a task with increasing experience (Mitchell 1997). Performance is measured in terms of the error of the prediction model's output vs. actual outcomes as described in a historic dataset. In the last decade the performance of Machine learning has strongly increased due to the availability of sufficient training data, computational resources and theoretical improvements (Vapnik 2000).

Figure 4 outlines the principle approach of machine learning (Vapnik 2000): the explanatory or predictive input variables created by the *generator* are transformed. The vector transformation makes sure that variables are represented as real numbers. Further types of transformations are also possible that might improve the ability of the method to create an accurate prediction model. The input variables are paired with the variable to predict, which is to be provided by a *supervisor*, e.g. a human annotator. These pairs are used by a so called *learning machine* to create a prediction model, which maps the input variables to the variable to predict $\hat{y}$. With the created model, new data of the input variables can be used to predict the variable of interest.

For the data-driven creation of prediction models, the machine learning method Support Vector Regression (SVR) can be used (Drucker et al. 1997). The SVR method is a Support Vector Machine (SVM; Boser et al. 1992) for regression tasks. The input and output variables are real numbers. But also textual input can be incorporated by means of n-gram based text representations (Joachims 1998). Textual documents are transformed into a vector space representation by means of determining the frequency of occurrence of each n-gram of words within a document and within a whole corpus of documents. Typically, unigrams or bigrams are used.

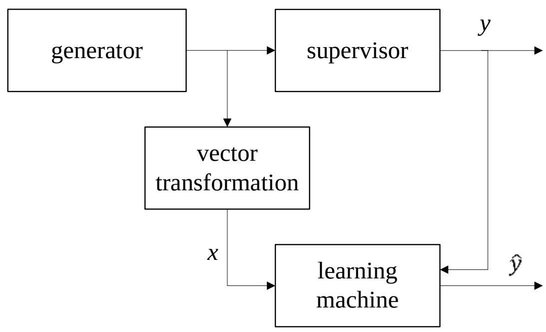

Figure 4: Machine Learning (Vapnik 2000).

The following introduction to SVR is based on Smola & Scholkopf (2004). Given training data $\{(x_1, y_1), \ldots, (x_l, y_l)\} \subset X \times \mathbb{R}$, where X is the input space. SVR determines a function f(x) that is as flat as possible and has at most ε distance from the actual target y_i. To allow a higher distance than ε this algorithm is extended by incorporating a cost parameter (Smola & Scholkopf 2004). For putting in place data analytics for the fractals of an organization, a respective data handling and software architecture is required. The architecture needs to support the desired analytic tasks. Analytics can be conducted either in an offline or online fashion. Offline analytics means to sample large amounts of data, comprising predictive variables and also the variables to predict. The data is used to create the prediction model, which is then applied unchanged on new data. The online approach would try to continuously improve the model once new data becomes available.

5 EVALUATION

Outlined below is a scenario of a patient process, which evaluates the effectiveness of our approach for the improvement of the cooperation among hospital process fractals to improve the overall efficacy. Note that such a process might arise during emergency and regular operations and therefore follows the patterns of reoccurring fractals as described in section 2.4.

The process comprises the following steps: (1) a patient is brought from the ward to the operation section, (2) the patient is moved to a bed in the surgery section, (3) the patient is transported to the operating room, (4) the patient is repositioned to a surgical table, (5) the surgery takes place, (6) the patient is repositioned again to a hospital bed and (7) moved to a postanesthesia recovery.

Figure 5 shows the mapping of the procedural steps into the fractal constructs. The dashed circle represents a fractal, i.e. an autonomously-organized hospital unit. The solid interconnected circles indicate interchangeable agents of the organization. The solid boxes between the fractals represent their interfaces. The procedural steps of the scenario are mapped to following fractal constructs: (1) transport, (2) transshipment, (3) transport, (4) transshipment, (5) storage, (6) transshipment, and (7) transport.

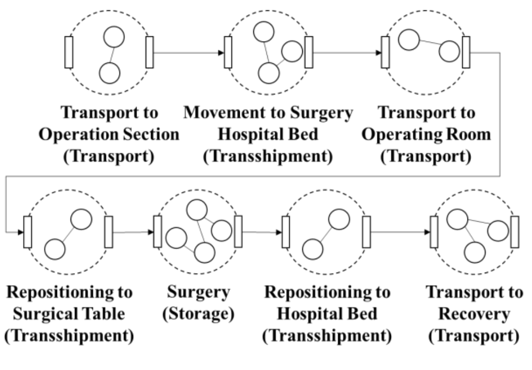

Figure 5: Fractal model of hospital scenario.

In this scenario several problems occur if the prediction of the process time is imprecise. First, all steps are subsequent and therefore an imprecise prediction of the duration of a step will directly suspend the earliest initiation of the following steps. Second, interdependencies of resources like specialized surgeons, medical devices and operating rooms further delay surgeries in this or other operating rooms. Third, due to the previously named problems, the planning of the hospital time is difficult due to the high variance in the actual execution of plans, which leads to the allocation of fewer resources to planning and also decreases commitment of the staff to the plan, which further increases the prediction error.

By means of the fractal based modelling approach it is possible to understand the limits of process planning. One can easily recognize that processes may only be planned on a certain level of abstraction. On a more detailed level, the process execution is always performed by a certain set of involved agents and, thus, can only be indirectly influenced. However, these fractals contain dependencies among each other that have to be recognized to optimize process execution, e.g. the execution time of process steps within a fractal may also be relevant for process steps within other fractals.

The usage of data analytics for the prediction of process times improves the hospital organization by following aspects. First, due to machine learning the start and end time of the fractals can be predicted with low prediction error. Therefore, the planning error is directly reduced. Second, the confidence for the prediction can be estimated. This information allows scheduling surgeries with low prediction confidence in spots that have as few as possible interdependencies with other surgeries. Third, process times can be predicted up to the minute. These predicted process times can be communicated to other affected process fractals without involvement of a human, which allows the automatic updating of process times of emergency and regular surgeries when new information becomes available.

6 CONCLUSION

This research contributes a meta-model for fractalized organizations from a logistics perspective, which is used for modelling hospital processes. The proposed meta-model forms the basis for data analytic methods aiming to identify dependencies between multiple fractals. The contribution has been evaluated by a scenario-based evaluation and is planned to be validated in a field study in future work. However, first results show great potential for modelling hospitals with the paradigm of fractal organizations. With mostly independently organized units, hospitals show a high level of fractalization and, thus, are predestined for modelling processes following the paradigm of organizational fractals.

Together with data analytics focused on hospital needs, the dependencies between different fractals can be identified and parameters of fractals such as process duration can be predicted for the benefit of increasing patient throughput as well as to improve patient care significantly. A detailed investigation will be subject to further research.

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REFERENCES

Van Der Aalst, W.M.P. et al., 2009. Prom: The process mining toolkit. In *Business Process Management Demonstration Track*.

Boser, B., Guyon, I. & Vapnik, V., 1992. A training algorithm for optimal margin classifiers. In *5th Annual ACM Workshop on Computational Learning Theory*. pp. 144–152.

Cleven, A.K. et al., 2014. Process management in hospitals: an empirically grounded maturity model. *Business Research*, 7, pp.191–216.

Davis, R. & Smith, R.G., 1983. Negotiation as a metaphor for distributed problem solving. *Artificial Intelligence*, 20(1), pp.63–109.

Domschke, W., 2008. *Grundlagen der Betriebswirtschaftslehre – Eine Einführung aus entscheidungsorientierter Sicht* 4th ed., Springer.

Drucker, H. et al., 1997. Support vector regression machines. *Neural Information Processing Systems*, 9, pp.155–161.

Fox, M.S., 1981. An organizational view of distributed systems. *IEEE Transactions on Systems, Man and Cybernetics*, 11(1), pp.70–80.

Gasser, L., 1992. DAI Approaches to Coordination. In N. M. Avouris & L. Gasser, eds. *Distributed Artificial Intelligence: Theory and Practice*. Kluwer, pp. 31–51.

Haraden, C. & Resar, R., 2004. Patient flow in hospitals: understanding and controlling it better. *Frontiers of health services management*, 20(4), pp.3–15.

Joachims, T., 1998. Text categorization with support vector machines: Learning with many relevant features. In *10th European Conference on Machine Learning*. Lecture Notes in Computer Science. pp. 137–142.

Malone, T.W., 1987. Modeling Coordination in Organizations and Markets. *Management Science*, 33(10), pp.1317–1332.

Manyika, J. et al., 2011. *Big data: The next frontier for innovation, competition, and productivity*,

Mitchell, T., 1997. *Machine Learning*, McGraw Hill.

Murray, J., Widmer, T. & Kirn, S., 2014. Agent-based process coordination among hospital units. In *Multikonferenz Wirtschaftsinformatik*. pp. 763–774.

Pfohl, H.-C., 2004. *Logistiksysteme – Betriebswirtschaftliche Grundlagen* 7th ed., Springer.

Premm, M. & Kirn, S., 2015. From Cooperating Agents to Cooperating Multiagent Systems: A Survey. In *Proceedings of the 13th German Conference on Multiagent System Technologies*. Springer.

Scheer, A.-W. & Nüttgens, M., 2000. ARIS Architecture and Reference Models for Business Process Management. In *Business Process Management: Models, Techniques, and Empirical Studies*. pp. 376–389.

Scholl, A., 2008. Grundlagen der modellgestützten Planung. In D. Arnold et al., eds. *Handbuch Logisitk*. Heidelberg: Springer.

Smola, a J. & Scholkopf, B., 2004. A tutorial on support vector regression. *Statistics and Computing*, 14, pp.199–222.

Stewart, G., 1997. Supply Chain Operations Reference Model (SCOR): the First Framework for Integrated Supply-Chain Management. *Logistics Information Management*, 10(2), pp.62–67.

Stockheim, T. et al., 2004. How to build a multi-multi-agent system the agent.enterprise approach. In *ICEIS 2004 - Proceedings of the Sixth International Conference on Enterprise Information Systems*. pp. 364–371.

Tapscott, D. & Caston, A., 1993. *Paradigm Shift: The New Promise of Information Technology*, New York: McGraw Hill.

Vanberkel, P.T. et al., 2010. A Survey of Health Care Models that Encompass Multiple Departments. *International Journal of Health Management and Information*, 1.

Vapnik, V.N., 2000. *The nature of statistical learning theory*, Springer.

Warnecke, H.-J., 1993. *Revolution der Unternehmenskultur* 2nd ed., Heidelberg: Springer.

Woelk, P.-O. et al., 2006. Agent.Enterprise in a Nutshell. In S. Kirn et al., eds. *Multiagent Engineering – Theory and Applications in Enterprises*. Heidelberg: Springer.