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A Methodology to Assess Changes in Healthcare Infrastructure in Stockholm

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Abstract. Designing major shifts in complex systems such as healthcare requires a combination of approaches and perspectives. A considerable change in healthcare infrastructure is due to occur in Stockholm with a major emergency department being closed. As this change impacts operations as well as governance, multiple methods are needed to assess it. In this paper, we present an approach combining simulations and data mining of healthcare data to assess the changes to healthcare system in Stockholm; and discuss the opportunities and challenges of doing so.

Introduction

The opening of the New Karolinska hospital (NKS), a super specialty hospital has raised many questions regarding the distribution of care in region of Stockholm county. The access rules to the emergency care will be changed in order to conserve resources for specialized care for those required. Patients who used to choose the Emergency Department (ED) of NKS will need to adjust to other alternatives within Stockholm County (SLL), unless they need special care.

This complex shift affects the overall healthcare system of Stockholm. Healthcare system, being a complex adaptive system contains self-organizing layers of people and processes, from people directly involved in patient care to management and administration. The healthcare system in a city is even more complex as authorities and politicians are also involved and are stakeholders in this system.

This shift raises many questions at various levels of the healthcare system. Apart from changes in capacities at the operational level at individual hospitals in the region, there is also a need for development of new governance strategies for the entire health care system. An investigation of the same problem was undertaken by SLL(Martling 2016). The report identifies technical aids to sort patients into the right level of care, process for developing governance strategies, common electronic health records to make clear communication possible and guidance to redistribute patients as main topics to be investigated. This sets the context for the research questions to be addressed.

While there are various theories that address socio-technical complexity of the health care system, no individual method can sufficiently address all the questions raised in such a case study(Raghothama and Meijer 2015) . An economical or physiological model of the system might be fundamentally correct, but that does not depict the behavior of the patients themselves. Patient behavior and preferences can be mined from healthcare data, but that does not depict how patients could behave after a relatively radical change in the system.

In this paper we introduce the combination of approaches. Simulation models and data mining can depict more thoroughly the change in system and patient behavior, so that more of the complexity of the health care system is captured, thus generating more knowledge of the system for the design process.

Background

Healthcare systems have evolved from a collection of components to Complex Adaptive Systems (Rouse 2008). The approach to study of healthcare as a hierarchical system of systems has facilitated in tracing the flows of patients, information and economy through the healthcare system(Kopach-Konrad et al. 2007). This has aided development of processes and efficient utilization of resources by providing insights into design of hospitals, special departments or services, looking into patient waiting-times, occupancy rates or scheduling issues (Comas et al. 2008; Giesen, Ketter, and Zuidwijk 2015; Mutlu et al. 2015).

Conceptual modeling of healthcare using Systems Dynamics (SD) models has also aided in focusing on aspects under study and figuring out causes and feedback loops in the processes and to hence make better decisions(Brailsford et al. 2004; Koelling and Schwandt 2005; Lane and Husemann 2008). Approaches that combine different simulation paradigms have also been successful at addressing process and workflow aspects with the that of patient behavior (Djanatliev and German 2013; Kittipittayakorn and Ying 2016).

Data in healthcare sector is being generated on a large spectrum, from genetics data to patient record data, all amounting to big data in healthcare (Schneeweiss 2014; Zhang et al. 2015). While much of the data in healthcare is used extensively for diagnostic purposes (Yoo et al. 2012), it has also been used study performance of healthcare infrastructure (Barnes et al. 2015; Peck et al. 2013). There are also examples of data being used for gathering insights and patterns within clinical processes, to identify patient groups and predicting readmissions and discharges (Barnes et al. 2015; Bates et al. 2014)

Simulation approaches have been successful in characterizing processes in the healthcare system and aided in design and management. However, translating these insights from simulations to actual hospital has been hard (Peck et al. 2014). Data driven approaches have been accurate at predictions and capturing needs. A change in the structure of a system that generates the data, changes its meaning and problem description itself. It is therefore beneficial to combine these approaches to capture needs and then study the structural changes to healthcare infrastructure in Stockholm.

Approach

The nature of healthcare provision in SLL makes it a unique case of a highly connected network of hospitals and primary care centers communicating flows of patients and information across the region.

The decision to close the ED in NKS will have an effect on demand to EDs in other major hospitals in the region. As the demand for different hospitals in Stockholm will change, the capacities and flows of the healthcare system in Stockholm will need to adapt.

In order to evaluate the changes over the whole system, there are three major questions that need answering.

- Which factors are affecting the choice of patients to choose a kind of care?
- Provided those factors, what effects are expected on the capacities of SLL major hospitals?
- How can this knowledge be further utilized to design processes to handle this change?

30 million anonymized records of patient visits over eight years are accessible to this study. The records consist of codes (nominal data) for departments and hospitals visited, symptoms and diagnosis. Using these features, profiles for hospitals as well as patients can be constructed. This could be achieved through data science approaches, by framing the hypothesis as a supervised machine learning problem, by using classification or recommender system algorithms. Through this, relevance of various features of the hospitals - such as staff, size, location, distance – to care choice can be discovered. Thus, by creating a space for exploration through data it could be possible to further understand patient behavior, through his/her visits to different hospitals.

Scenario based simulation taking into account the majors factors influencing healthcare in Stockholm can then explore further the healthcare system behavior after it undergoes the changes. Simulation can provide a tool to test the capacities and services of hospitals to different level of demands resulting for the transition to NKS. Potential solutions for problematic scenarios can be tested or even emerge from the use of the simulation.

Simulations allow particularly visualizing and understanding simple effects of some factors in isolation. In fact, simulation through simple models such as agent-based models can provide insight to decision-makers on the effect of possible behavioral changes of the population facing the new healthcare system. Agent based models, being best at describing emergence of behaviors from simple interactions between the population simulated and their environment, are used to investigate how interaction between patients and the new environment provided by the opening of NKS affects the whole system. At this point, two agent based models are already under development.

The first model tests the capacities of emergency departments in other hospitals in SLL against an increase of flow due to NKS being a super specialty hospital only. This model allows testing for different capacities and demands. It assumes that patients seeking an ED will choose the hospital that is closest to their residence. If the condition of the patient cannot be treated at that hospital, the patient moves on to the next closest hospital. This assumption, as well as the data used to run the model, can be modified depending on further data analysis.

Another agent based model being developed provides insight into the effect of having information systems for patients to know the length of queues as well as travel-times to different ED before choosing the hospital to go to. This model will provide decision-makers a space to explore the possibilities such an information system can provide.

The simplicity of these models allows particularly understanding in isolation effects of factors such as capacities or information. The hybrid approach of this work will enable simulations to rely on data to pick up scenarios of interest and provide tools of to verify models and increase their realism. The outcomes of the data-mining exploration can also identify other areas or factors into which theory driven-models can provide complementary of different insight.

Conclusion

The assessment of changes in healthcare infrastructure in Stockholm asks for a hybrid approach due to the behavioral and structural component of the issue at hand. This paper presented an approach to combine simulation and data mining that addresses the uncertainty of behavioral change and the volume of care data available. By combining the outcomes of both methods a richer assessment on design of new processes can be obtained. The main challenge for this work is validation of the hybrid approach, as validity will have to be ascertained at level of simulation, data mining and the combination itself. Future work will also validate the hybrid approach by following up the actual closure of the ED at NKS.

References

Barnes, Sean, Eric Hamrock, Matthew Toerper, Sauleh Siddiqui, and Scott Levin. 2015. “Real-Time Prediction of Inpatient Length of Stay for Discharge Prioritization.” *Journal of the American Medical Informatics Association*, ocv106.

Bates, D. W., S. Saria, L. Ohno-Machado, A. Shah, and G. Escobar. 2014. “Big Data In Health Care: Using Analytics To Identify And Manage High-Risk And High-Cost Patients.” *Health Affairs* 33 (7): 1123–31. doi:10.1377/hlthaff.2014.0041.

Brailsford, Sally C., V. A. Lattimer, P. Tarnaras, and J. C. Turnbull. 2004. “Emergency and on-Demand Health Care: Modelling a Large Complex System.” *Journal of the Operational Research Society* 55 (1): 34–42.

Comas, Mercè, Xavier Castells, Lorena Hoffmeister, Rubén Román, Francesc Cots, Javier Mar, Santiago Gutiérrez-Moreno, and Mireia Espallargues. 2008. “Discrete-Event Simulation Applied to Analysis of Waiting Lists. Evaluation of a Prioritization System for Cataract Surgery.” *Value in Health* 11 (7): 1203–1213. doi:10.1111/j.1524-4733.2008.00322.x.

Djanatliev, A., and R. German. 2013. “Prospective Healthcare Decision-Making by Combined System Dynamics, Discrete-Event and Agent-Based Simulation.” In *2013 Winter Simulations Conference (WSC)*, 270–281. doi:10.1109/WSC.2013.6721426.

Giesen, Erik, Wolfgang Ketter, and Rob Zuidwijk. 2015. “Dynamic Agent-Based Scheduling of Treatments: Evidence from the Dutch Youth Health Care Sector.” In *Multiagent System Technologies*, 173–199. Springer, Cham. doi:10.1007/978-3-319-27343-3_10.

Kittipittayakorn, Cholada, and Kuo-Ching Ying. 2016. “Using the Integration of Discrete Event and Agent-Based Simulation to Enhance Outpatient Service Quality in an Orthopedic Department.” *Journal of Healthcare Engineering* 2016 (March): e4189206. doi:10.1155/2016/4189206.

Koelling, P., and M. J. Schwandt. 2005. “Health Systems: A Dynamic System - Benefits from System Dynamics.” In *Proceedings of the Winter Simulation Conference, 2005.*, 7 pp.–. doi:10.1109/WSC.2005.1574393.

Kopach-Konrad, Renata, Mark Lawley, Mike Criswell, Imran Hasan, Santanu Chakraborty, Joseph Pekny, and Bradley N. Doebbeling. 2007. “Applying Systems Engineering Principles in Improving Health Care Delivery.” *Journal of General Internal Medicine* 22 (S3): 431–37. doi:10.1007/s11606-007-0292-3.

Lane, D C, and E Husemann. 2008. “System Dynamics Mapping of Acute Patient Flows.” *Journal of the Operational Research Society* 59 (2): 213–24. doi:10.1057/palgrave.jors.2602498.

Martling, Claes-Roland. 2016. “Patientuppdrag För Akutmottagningen Vid NKS.”

Mutlu, Serpil, James Benneyan, John Terrell, Victoria Jordan, and Ayten Turkcan. 2015. “A Co-Availability Scheduling Model for Coordinating Multi-Disciplinary Care Teams.” *International Journal of Production Research* 53 (24): 7226–7237. doi:10.1080/00207543.2015.1018452.

Peck, Jordan S., James C. Benneyan, Deborah J. Nightingale, and Stephan A. Gaehde. 2014. “Characterizing the Value of Predictive Analytics in Facilitating Hospital Patient Flow.” *IIE Transactions on Healthcare Systems Engineering* 4 (3): 135–43. doi:10.1080/19488300.2014.930765.

Peck, Jordan S., Stephan A. Gaehde, Deborah J. Nightingale, David Y. Gelman, David S. Huckins, Mark F. Lemons, Eric W. Dickson, and James C. Benneyan. 2013. “Generalizability of a Simple Approach for Predicting Hospital Admission From an Emergency Department.” Edited by Mark Hauswald. *Academic Emergency Medicine* 20 (11): 1156–63. doi:10.1111/acem.12244.

Raghothama, Jayanth, and Sebastiaan Meijer. 2015. “Gaming, Urban Planning and Transportation

Design Process." In *Planning Support Systems and Smart Cities*, 297–312. Springer International Publishing.
Rouse, William B. 2008. "Health Care as a Complex Adaptive System: Implications for Design and Management." *Bridge-Washington-National Academy of Engineering-* 38 (1): 17.
Schneeweiss, Sebastian. 2014. "Learning from Big Health Care Data." *New England Journal of Medicine* 370 (23): 2161–2163.
Yoo, Illhoi, Patricia Alafaireet, Miroslav Marinov, Keila Pena-Hernandez, Rajitha Gopidi, Jia-Fu Chang, and Lei Hua. 2012. "Data Mining in Healthcare and Biomedicine: A Survey of the Literature." *Journal of Medical Systems* 36 (4): 2431–2448.
Zhang, Yin, Meikang Qiu, Chun-Wei Tsai, Mohammad Mehedi Hassan, and Atif Alamri. 2015. "Health-CPS: Healthcare Cyber-Physical System Assisted by Cloud and Big Data." *IEEE Systems Journal*, 1–8. doi:10.1109/JSYST.2015.2460747.