AN AGENT-BASED APPROACH TO IMPROVING RESOURCE ALLOCATION IN THE DUTCH YOUTH HEALTH CARE SECTOR

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Abstract

We show how agent-based simulation is used for analyzing different queuing strategies in the youth health care sector. The simulation model represents an authentic business case and is parameterized with actual market data. We discuss the differences between four queuing strategies which are based on push/pull allocation and centralized/decentralized queuing strategies. The model incorporates, among others, a withdrawal and return mechanism, a non-stationary Poisson arrival process, and a preference algorithm to include a care provider's case preference. The investigated system accommodates extensive waiting lines which are currently solely judged on their length. We have identified that performance measurement in youth health care should not be focused on queue lengths alone, but should include a case urgency parameter as well. The simulation results, together with contextual data obtained from stakeholder interviews, indicate that a push strategy with a centralized queue suites the sector best. Most related research in health care focuses on queuing theory which fails to address the complexity of the case. Our simulation approach incorporates additional complexities of the case at hand which turn out to be relevant for the queuing strategy decision. We validate the model and strategies by comparison with real market data and field expert discussions.

Keywords: Agent-based simulation, resource allocation, youth health care, queuing strategies, scenario analysis

1 INTRODUCTION

The Dutch youth health care sector aims to provide care to children on demand. Children can enter the system at the institution for youth health care at their own initiative and obtain an indication for professional help. A formal indication includes a diagnosis and entitles the child to receive care at a care provider of its own preference. The system is publicly funded and enforced by the law on youth health care since 2003. The national system is subdivided in multiple regional systems which cover provinces or urbanized regions. These local systems implement their own structures, including local offices of youth health institutions, care provider agreements, and financial systems (Figure 1).

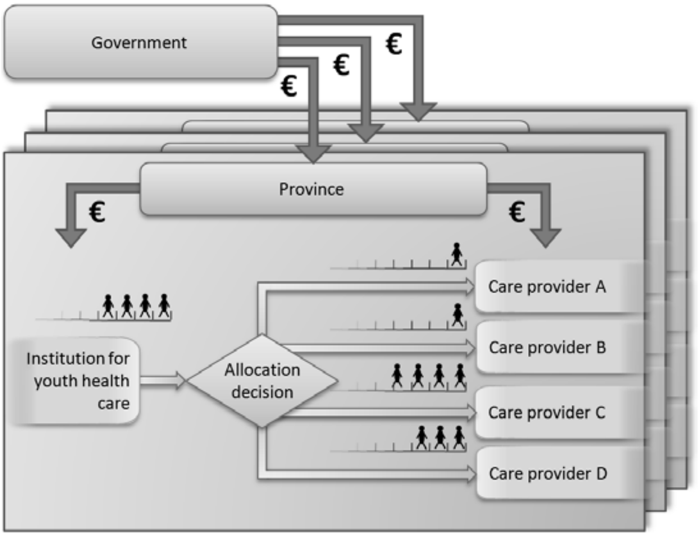

Figure 1 Overview of the allocation mechanism in the Dutch youth health care system.

Over the last few years, the Dutch youth care sector has faced long waiting lists and long waiting times, a problem that has received a lot of media attention. The government has provided funding on several occasions, which did not result in a permanent solution. Hiring interim managers to reorganize internal operations at for instance a local office of the institution for youth health care turned out to be unsuccessful as well. The approach taken in this research starts with the observation that the real problem is not solely the waiting list length or waiting time as such. We claim that it is rather a problem of the current strategy of allocating cases to care providers in general. In our opinion, methods that solely address the symptom of long waiting lists will be ineffective in the long run. We shall consider solution directions that not only focuses on the handling of contemporary waiting lists, but that may require structural changes in the system.

We elaborate on such structural changes by presenting an overview of multiple allocation strategies, based on a combination of push/pull strategies and centralized/decentralized queuing strategies. The push and pull strategies define the party which ultimately makes the actual allocation decision. This could either be the institution for youth health care that pushes specific cases towards care providers, or the care provider that pulls the specific demand for care towards its resources. Centralized and decentralized queuing strategies define the moment at which the actual allocation will take place. A centralized strategy postpones allocation of children until the moment they can instantly get care; in other words, at the moment a care position has become available at a care provider and can be dedicated to the specific case. This strategy results in waiting lines at the institution for youth health care. A decentralized strategy allocates cases immediately as much as possible when they arrive in the system; this will result in waiting lines both at the institution for youth health care and at the care providers. Allocation decision problems, as presented by the youth health care case, suit very well a multi-agent simulation approach, as the allocation decisions depend on communication between the different parties in the system. Furthermore, institutions and persons have their own objectives and the coordination thereof needs to be addressed explicitly. The actual clientflow through the system is the result of a negotiation process between several parties in the supply chain. Indeed, a case allocation procedure requires input from other parties in the sector on which the final decision can be based. Since a multi-agent simulation is built of individual agents that pursue a specific personal goal, it is fairly easy to configure and study alternative allocation strategies in a simulation environment.

Our objective is to provide insights into the allocation problem and to advice on possible improvements by discussing and evaluating a variety of allocation strategies. The analyses are supported by an agent-based simulation model. The model simulates the allocation process in the youth care sector as well as the directly coupled processes of case indication and the actual treatment. The parameters of the model are loaded with stochastic distributions which are based on actual data taken from one province in the youth care sector. While it is difficult to play around with the actual system itself, the simulation model provides a rich but risk free environment for testing varying resource allocation strategies. A simulated environment has the advantage that multiple decision algorithms and coordination structures can be used for experiments. This approach enables analyses on long term effects of certain strategies while maintaining focus on inter-agent interaction. Such studies would be hard, if not impossible, to perform in the real world system, because one cannot make structural changes in the real world system just to study a certain long term effect. Our approach contributes to the research in information systems and agent-based simulation, since it proves the usability of an agent-based approach in a real world environment by not only matching the current decision making process but also by studying varying alternatives. The model is loaded with an extensive amount of stochastic distributions based on actual market data and successfully matches the performance of the real world system. This research contributes to the research in resource allocation in health care by providing a currently unused approach to counter queuing related issues. Simulation of the resource allocation process helps to understand and test long term effects of varying allocation strategies and coordination decisions. We contribute to research in information systems by improving the human decision-making process. Our study on the different strategies on the youth health care system decreases the information overload which increases the rate of fair child allocations. This will improve socially responsible welfare decision-making.

2 LITERATURE REVIEW

Waiting lines in the health care sector have received little attention in the scientific literature, although hospitals and general health care face similar problems with waiting lines. A common approach taken by governments to tackle these problems is the injection of capital which is used to increase capacity. This provides a short term solution, as available capacity and queue lengths reach a new equilibrium after a short while (Hurst & Siciliani 2003; Postl 2006). Saulnier, Shortt & Gruenwoldt (2004) identified five popular approaches to decrease waiting times: monitoring of procedures, using priority scoring tools, setting waiting time targets, using an external advisory body, and registering online. However, Rachlis (2005) argues that such methods do not work by themselves; better coordination and flow control should increase performance at the public sector. Waiting lines in health care feature withdrawals when clients have to wait for an extended amount of time. Several studies have shown that the amount of time that a client is willing to wait for care is related to the urgency of the problem (Goodacre & Webster 2003, Goldman et al. 2005). More urgent problems are difficult to treat elsewhere, while they genuinely require attention. These cases will therefore accept longer waiting times. The converse holds for less urgent problems. Most literature on waiting line management in health care are based on the mathematical approach described by queuing theory (Torgerson & McIntosh 2006). These studies focus mainly on utilization of resources and calculations of the minimum required amount of treatment positions while maintaining a high service rate (Gorunescu, McClean & Millard 2002a & 2002b; McManus et al. 2004). These studies show how queuing theory struggles with phenomena like seasonal effects and withdrawals. These issues are also identified by

Brown et al. (2003) who argue that traditional queuing theory has a series of shortcomings like, among other things, the absence of customer withdrawal behaviour, time-dependent parameters or customer heterogeneity. These three characteristics are all notably present in a health care system. Mandelbaum & Shimkin (2000) tried to construct a model for withdrawal. They acknowledged that a lot of work needs to be done to achieve practical usability of queuing theory.

Only a limited amount of literature studied the waiting line problem by means of event-based simulation (Ridge et al. 1998, Bagust, Place & Posnett 1999). While these studies include stochastic processes and basic withdrawal schemes, they still solely focus on utilization issues and capacity planning. To the knowledge of the authors, agent-based approaches have not yet been used in this context. Event-based simulation is able to include an extensive level of complexity in the model like withdrawal & return behaviour, seasonal arrivals and client heterogeneity. An agent-based model in addition is also suited to quickly implement and experiment with alternative strategies and coordination flows. These experiments are difficult, if not impossible, to implement with queuing theory. Research on waiting lines and times by means of simulation is rarely used in the health care sector in general. While other sectors with comparable cross organisational networking structures like container ports were studied with agent-based approaches (Moonen et al 2005), an agent based approach in health care is even unique in its kind. This study will therefore provide a first example of the usability of agent-based methods for improving performance in the health care sector. It will contribute to scientific research in studying an agent based simulation approach on a genuine and new business case in practice with a significant amount of market data in the youth health care sector. Unfortunately, research is not able to provide a clear definition of what an agent is. While most researchers agree on certain aspects of an agent, it seems not easy to integrate all views in one grant perspective (Lang et al 2008). The four and most appreciated aspects are autonomy, social ability, reactivity, and pro-activeness, this set has become known as the weak notion of agency (Wooldridge & Jennings 1995). The authors state that an agent is a hardware, or software based computer system, or both, displaying the properties of autonomy, social adeptness, reactivity, and pro-activity.

3 THE SIMULATION MODEL

The agent-based model extends the Distributed Simulation Object Library (DSOL) simulation environment (Jacobs and Verbraeck 2005) and was run on a conventional desktop computer with settings as shown in Table 1. This environment provides the discrete event simulation engine, the theoretical distributions and a toolkit to design a simulation model as a set of loosely coupled objects. Because of the latter, the suite is ideal for implementing an agent-based model since it enables the design of agent who are physically disconnected from each other. While the simulation environment provides all the elementary building blocks of a simulation, the model itself only concerns the agent specific parts. Other research studied agent-based simulation architectures and the required components for building an agent-based model (Ketter et al 2009, Collins et al 2002).

System	
System	Dell Vostro 200
CPU	Intel Penrium E2140
RAM	2GB DDR2 (PC2-5300)
OS	Windows Vista Ultimate 32bit

Simulation model	
Java version	JDK 1.6.0.11
Java VM arguments	-jar -Xms512m -Xmx1024m -server
Format	Access database
Data per replication[1]	± 70-77MB
CPU time per replication[2]	± 10 minutes

Table 1 Technical information of system used for analysis.

[1] The total amount of data used for the study was about 20 GB from 256 replication runs.
[2] The model runs on one processor core, therefore the model can be ran on both processor cores simultaneously without drastic influence on the average processing time. The given value is based on the average processing time while running the model twice in parallel on the same machine.

There are several types of information identified in the model. First, there are parameters which define fixed values like agent names, the theoretical distributions and the geographical home location of an agent. These parameters are mined from real world health care data. Second, there are dynamic data stores which hold process information upon which an agent can make decisions. This group of information can be divided in two groups; the transactional data store and the decision data store. The transactional data store holds records of the overall process of an agent. For instance, the agents of the institution for youth health care maintain an internal database of care lines which holds all relevant information of a case. The care provider agent hold a similar database, however holding only information which is relevant and accessible for these agent. The transactional data store in such is factual information which represents historical record keeping. The decision data stores, on the other hand, hold short term information which is relevant in executing the allocation strategy on a certain moment in time. The appraisal of this data decays over time since its trustworthiness decreases as time passes by. For instance, the institution for youth health care who decides on the best location for allocating a case based on known data and estimates of dated data.

The core model is constructed around a strict path which all cases in the system will follow. This flow is used in all four strategies. The white box indicates that the used allocation strategy might differ, while the remaining parts stay the same. Each child or case will be created at the top-left. The model includes mechanisms for the allocation process, the waiting phase and the treatment itself. Further it includes withdrawals during the waiting phase and returns after treatment or withdrawal. A core concept in this model is the use of a case selection process for treatment at the care providers. An overview of this process is shown in Figure 2. When a care provider selects the next case for treatment, he will judge the cases in his queue on certain characteristics for fitting with the available treatment location. This is modelled as an fit with the age of the child which results is a potential list of cases for treatment. While the order of these cases should be on 'first come, first serve' basis, this rule is violated by the care providers when possible because they prefer easier cases. More easy cases means more throughput which increases profit for the care providers. The political influenced decision algorithm, which is shown in Figure 2, will order the potential cases by preference of the care provider. The political influenced decisions are responsible for the major part of the differences in performance between the allocation strategies. Without this algorithm all strategies would perform roughly similar because the selection procedure would maintain a strict 'first come, first serve' order.

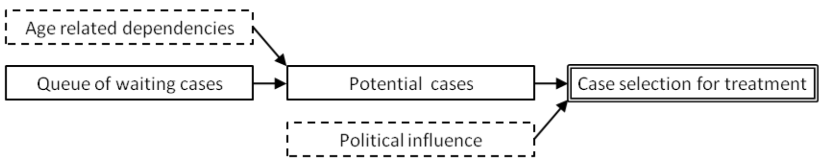

Figure 2 *Overview of the case selection process for treatment at the care providers. The dashed boxes represent factors which set restrictions on the set of potential cases The single lined boxes represent the set of cases which can potentially be selected while de last (double lined) box represents the final case selected for treatment.*

Equation 1 is responsible for the political influenced ordering of the cases which has been developed by use of a balanced scorecard technique (Kaplan & Norton, 2005) based on interviews with field experts and the evaluation of real world data. The matter at hand is intangible, complex and hard to express in words; often these issues live in one's mind rather than being written down in some kind of procedures, therefore the interviews were of an unstructured kind in order to manoeuvre the discussion into the most fruitful directions during the interview. Among the experts are: a youth health care consultant with a high level of experience in the sector, a case manager at the institution of youth health care with operational experience, a financial director at a care provider with operational experience and some strategic experience, a director at a care provider with strategic experience and some operational experience. The results of these interviews are translated into a set of constraints which the equation should obey. These constraints are parameterized into the resulting equation which consists out of two parts; the influence of a case's waiting time (left) and the influence of the expected treatment time (right). Waiting time is estimated to influence the decision mainly in the first weeks; a case which is waiting just a few days cannot precede a case which is already waiting a long time because the care provider will not be able to justify such a decision to the institution for youth health care. This effect is estimated to be decelerating decreasing with the turning point at the threshold value[3]. This simulates the effect of a rapid increase in preference in the first weeks of waiting while it flattens out afterwards. The second part represents the expected treatment time by a care provider. Cases with below average treatment times are preferred in any case, however the higher the treatment time, the lesser the preference which is expected to be exponentially increasing. The threshold value is related to the average treatment time in order to set the estimated steepness of the preference line. The graph in Figure 3 shows an example of four potential cases after making a subset for age characteristics of the open treatment position. The cases differ on waiting time and expected treatment time. It can be seen that the waiting time order (when solely looking at the waiting value in decreasing order; B-C-E-G) differs from the preference order (looking at the acceptance value in decreasing order; C-E-B-G).When solely looking at the waiting time, child B should be selected, however the preference function will prefer child C.

$$acceptance\_factor = \frac{threshold\_waiting}{waiting\_time + 1} + \frac{treatment\_time^2}{2 \cdot threshold\_treatment^2} \qquad (1)$$

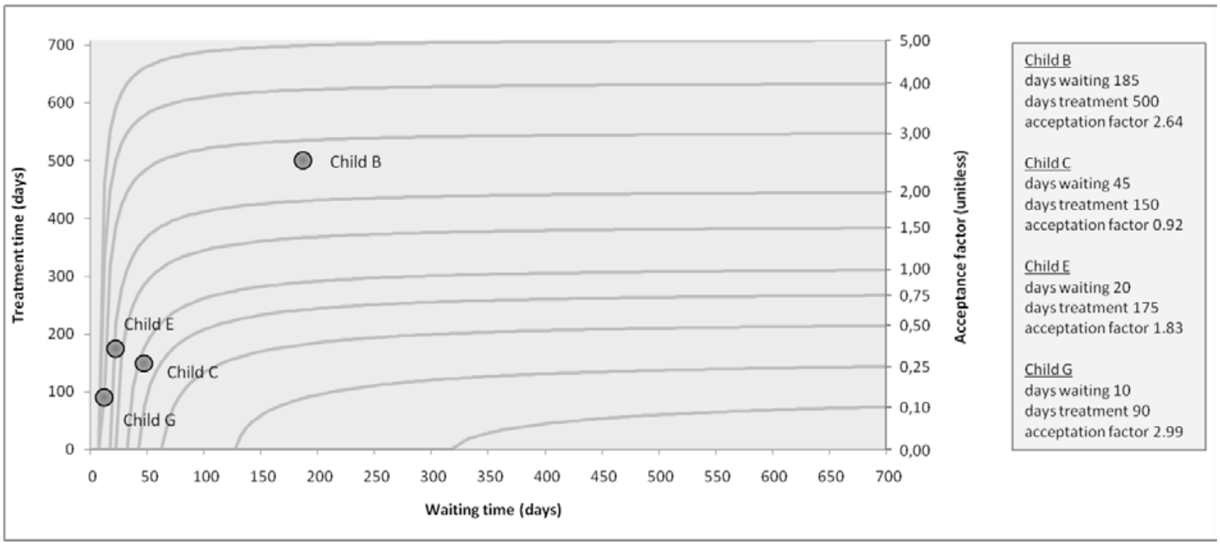

Figure 3 Indifference curves of the political influenced decision algorithm for specific acceptance factors including a example subset of children ready for allocation.

This core model, including the political influenced decision algorithm, is the same for all four strategies. The difference will be in the process which performs the actual allocation. While the current allocation strategy in the youth care sector is based on pushing cases towards the care providers at the moment they receive an indication for care needs, it is considered that a push can be postponed until the moment that a care position becomes available. This centralizes the queue at the institution of youth healthcare which will enable the supply chain to more effectively match cases to care positions. Such an system would reduce the ability of care providers to make preference based selections since the institution of youth healthcare has a much better view and control on final case selection which increases fairness in the system. Care providers are likely better in estimating the actual treatment plan for a child than the institution of youth healthcare since they are the party

[3] Threshold_waiting is set to 32 days, threshold_treatment is set to the average treatment time of the care provider in question. These settings are based on interviews with field experts and evaluation of real world data.

providing the actual care to the children. Therefore it would increase the efficiency of the system when the care provider would also decide which child should be treated next. This strategy changes the push system into a pull system in which the care providers select cases from a pool of children requiring treatment. Note that the moment of selection still enables the possibility of maintaining centralized or decentralized queues, therefore we will address the following four types of allocation strategies.

1. **Pushing cases to decentralized queues [Decentralized Pushing].** When a case is indicated at the institution for youth health care, it is immediately pushed to one of the care providers. The push is performed by the institution for youth health care. This strategy is currently implemented in the youth care sector. In this case the care providers maintain and control their own queues while the institution of youth health care only tracks the development of a case. The political influenced decision algorithm can significantly influence the order of treatment because this strategy positions all cases at the care providers. The allocation itself is performed by the institution of youth health care which makes the decision based on a estimated 'shortest queue' algorithm. Each institution agent maintains a list of known queue lengths to support this decision. The value of each item in the list however decays when time passes by. The algorithm estimates the current queue length at a care provider by judging the available information while it gets maximal three requests for an updated queue length per case. The agent therefore makes the final decision on partially uncertain information.
2. **Pushing cases from a centralized queue [Centralized Pushing].** When a case is indicated at the institution for youth health care, it is held in a centralized queue until a fitting treatment position becomes available. The institution for youth health care maintains and controls the central queue while the care providers have no queue at al. The care provider announces that treatment positions become available and the institution of youth health care pushes the next case for treatment. The political influenced decision algorithm at the care providers is blocked in this strategy since there are no cases to choose from except for the case pushed by the institution for youth health care.
3. **Pulling cases from a centralized queue [Centralized Pulling].** When a case is indicated at the institution for youth health care, it is held in a centralized queue until it is pulled by a care provider which offers an open treatment position. The institution for youth health care publishes the waiting list on a bulletin board for evaluation by the care providers. The care providers do not maintain own queues. The institution for youth health care monitors selection behaviour by maintaining 'first come, first serve' order on comparable cases. Care providers anticipate on this rule by applying the political influenced decision algorithm to choose between multiple fitting, but incomparable cases on the bulletin board to select the following case.
4. **Pulling cases to decentralized queues [Decentralized Pulling].** When a case is indicated at the institution for youth health care, it is published on the bulletin board until it is selected by a care provider which promises to offer a treatment position in the future when it becomes available. Both the institution for youth health care and the care providers maintain queues in this strategy. A care provider prefers easy cases but must also select the comparable preceding cases if it wants the preferred case. Postponing a preferred selection however increases the chance that another care providers selects the case while it also increases the chance of ending up with an empty queue. An empty queue means that a care provider cannot find a fitting case for a treatment position which is considered worse than treating a unprofitable case. The care provider will evaluate the trade-off between the inclusion of less easy cases in the allocation and the chance on running his own queues empty. This selection behaviour by care providers is simulated by the function from Equation 2. The equation shows the algorithm used to judge cases on the bulletin board. The equation consists out of three parts; influence of current queue length (left), influence of estimated treatment time (middle) and the influence of the interaction between these two factors (right). The equation is based on interviews with field experts[4] which prescribed a set of constraints; When a care provider faces a low queue length for a given treatment type, he is likely more easily willing

[4] Threshold_queue, threshold_treatment and treshold_steep are based on interviews with field experts in order to create the desired effect of decision making for this allocation strategy.

to accept new cases in order to ensure full utilization of resources (i.e. bedrooms). The longer his queue, the less willing he is to accept new cases which will decrease exponentially as the queue increases. The expected treatment time of a case will also influence the decision because the care provider will try to avoid the most difficult and therefore unprofitable cases. Ultimately these two factors interact with each other which weaknesses the willingness to accept cases even further if at least one of the two dimensions scores rather high.

$$acceptance\_factor = \frac{queue\_length^2}{threshold\_queue} + \frac{treatment\_time^2}{(2 \cdot threshold\_treatment)^2} + \sqrt{\frac{queue\_length \cdot treatment\_time}{threshold\_steep}} \tag{2}$$

4 MODEL ANALYSES

The model is parameterized, verified and validated with real world data during three months of full-time analyses. The model is initiated with 7 youth care institutions and 8 care providers which have a capacity and a geographical location in the studied region. These will be unchanged during the entire simulation. The children are generated during the time of the simulation by a non-stationary Poisson distribution to include a seasonal influenced arrival effect. The age of the arriving children is included in the simulation to include the non-uniform division of age over the generated children. The age of a child is important for the age related aspect of the treatment positions. Further a distinction is made on the crises level of a case. Some cases are remarked a crises which means that these cases are allocated and get treatment at once. These cases bypass the allocation strategy but do influence the usage of capacity in the model. Note that a ‘crisis’ denotes a case of extreme urgency and that its level of difficulty can be of any kind. Each generated child will be indicated with a varying amount of care needs. These needs can be indicated simultaneously at the first indication or re-indicated after a withdrawal or a successful treatment. This also involves the analyses for withdrawal chances during the waiting phase and return chances when withdrawing or ending care. A return further involves a return interval since the child will not return immediately but after a varying amount of time. Since a child cannot be geographically allocated at random due to practical distance limitation, the analyses include a set of chances for maximal allocation distance from the view of the child’s home location. A case is provided with a identifier which represents an attribute for a case’s difficulty. The difficulty of a case cannot be analysed but is considered to be uniform distributed for the purpose of this research. The treatment time distributions differ among the care providers, the treatment time is therefore coupled to the difficulty identifier and the care provider. Table 2 lists the parameters and types of distributions as they are used in the model.

Parameter	**Valid**	**Type of distribution**
Capacities	+	Absolute value
Arrival distribution	++	Non-stationary Poisson distribution
Age distribution	0	Empirical distribution
Crises distribution	++	Absolute chance value (%)
Parallel tracks	++	Absolute chance value (%)
Repeating tracks	0	Absolute chance value (%)
Difficulty	++	Uniform distribution
Geographical arrival distribution	++	Uniform distribution within the borders of the region
Geographical range limitations	++	Absolute chance value (%)
Care duration	0	Empirical distribution
Withdrawal ratios	++	Calculated chance value (%)
Return rate	++	Calculated chance value (%)

Table 2 Model parameters with validation and type of distribution remarks. The validity results range from bad to good, respectively; --, -, 0, +, ++.

The model is initiated as a non-terminating system since decisions and performance measures depend on long lasting developments. The model is pre-filled at start in a fully utilized state at the care providers while there are no waiting lists. This procedure will decrease the required warm-up length of the model. Warm-up time has been determined by the method of Welch (1981, 1983) which resulted in a warm-up time of 4 years simulation time. The replication length has been set to 20 years simulation time in total.

The verification of the model is split in two groups; first, the introduction of state-transition control and the implementation of numerous checks during the simulation which ensure a correct flow of cases through the system. Second, in-depth source review by others who didn't participate in the design of the model verified the correct coding of the model. These two types of verification resulted in the acceptance of the model as technically correct.

The validation process is split in three groups; first, the results for the input parameters of the model are compared to the expected values which are based on the real world data which was used for the input analysis. The comparison of chance variables is performed by matching the average results with the expected value. The theoretical and empirical distributions are visually compared with the results. The results are split into multiple independent sections which enables the comparison with a specific certainty. This procedure is required to avoid biased judgement due to the stochastic nature of the parameters in question. The results of this comparison phase are listed in Table 2; the column 'valid' represents the result of the validation process of a particular parameter in the simulation model. Second, two of the most important but less understood parameters of the model are analysed for sensitivity. The determination of a case's fit by comparing the age of the child to the preferred age of the treatment position depends on a certain range which is considered acceptable. The results showed low sensitivity on this setting. The other value for sensitivity analyses is the political influenced decision algorithm. The results showed moderate sensitivity on these values. The third validation group is the user validation by field experts (1 youth health care consultant with a high level of experience in the sector, 1 case manager at the institution of youth health care with operational experience, 1 financial director at a care provider with operational experience and some strategic experience, 1 director at a care provider with strategic experience and some operational experience). The results show that the model mimics expected behaviour accurately. The field experts recognized much of the real world system in the model's output. For example, the arrival distribution including seasonal effects and the construction of treatment trajectories including crises, parallel and repeating cases were found realistic representations of reality. The model has been found valid on almost all aspects and is therefore assumed sufficiently accurate for this research.

5 RESULTS AND DISCUSSION

The strategies are judged on a set of 5 Key Performance Indicators (KPIs); 1) Ratio of (difficult) cases that are taken into care, 2) Ratio of (difficult) case withdrawals from the waiting lines, 3) Amount of (difficult) cases on the waiting lines, 4) Aggregated waiting times for the (difficult) cases and 5) Utilization of care positions at the care providers. The KPIs are developed by discussion with field experts, publications from the youth care sector and evaluation of real world data which indicate the importance of these measures. Interviews with field experts indicated that a major shortcoming of the current system is the neglecting of difficult cases. The law on youth care indicates that children in need of care should be able to receive it. However Andriessen and Besseling (2008) argue that there are many cases which receive help via the institution for youth health care are not genuine cases requiring professional help. The authors indicate that these cases shouldn't enter the system because either the indication of a problem is falsely recognized or the problem is of such a low level that these are able to help themselves. The field experts join this conclusion. The KPIs therefore include a division in average performance and performance for the more difficult cases which are often neglected by the system.

The analyses of the KPIs are based on 10 replications per strategy to avoid biased judgment due to the stochastic nature of the model's parameters. The replications are joined together in order to construct 95% confidence intervals for each KPI in each allocation strategy. The difficulty identifier (mentioned in the data analyses section) is used to distinct the average performance from the performance on difficult cases. Difficulty has been separated in 5 groups sorted from minimal to maximal difficulty. The two groups of the highest difficulty represent the performance on difficult cases. By means of Pareto analysis we illustrate the trade-off between efficiency en fairness in the system as summarized in Figure 4 which shows the average performance and performance on difficult cases in one overview. The spheres represent the performance scores of an allocation strategy. The horizontal axis illustrates the performance on the service level related KPIs while the vertical axis illustrates waiting line related KPIs. A lower value (towards the lower-left corner) represents better performance. The line in-between the spheres illustrate the continuum on which combined performance will be found depending on the relative importance of the performance types.

The graph shows that the average performance and performance for difficult cases differs significantly among the strategies. None of the strategies score similar performance. It also shows that the choice between a focus on average performance or difficult case performance greatly impacts the order of performance between the strategies as indicated by the rather long lines (except for centralized pulling). It further illustrates a trade-off between waiting line and service level aspects. It appears that decentralized pushing is performing best on waiting line aspects, whether it is on average or difficult case performance. It however loses on the service level aspect from both centralized pushing and pulling. The graph therefore helps to understand the effect of preferring one type of KPI above the other. In this analyses however, the importance of the KPIs is considered equal.

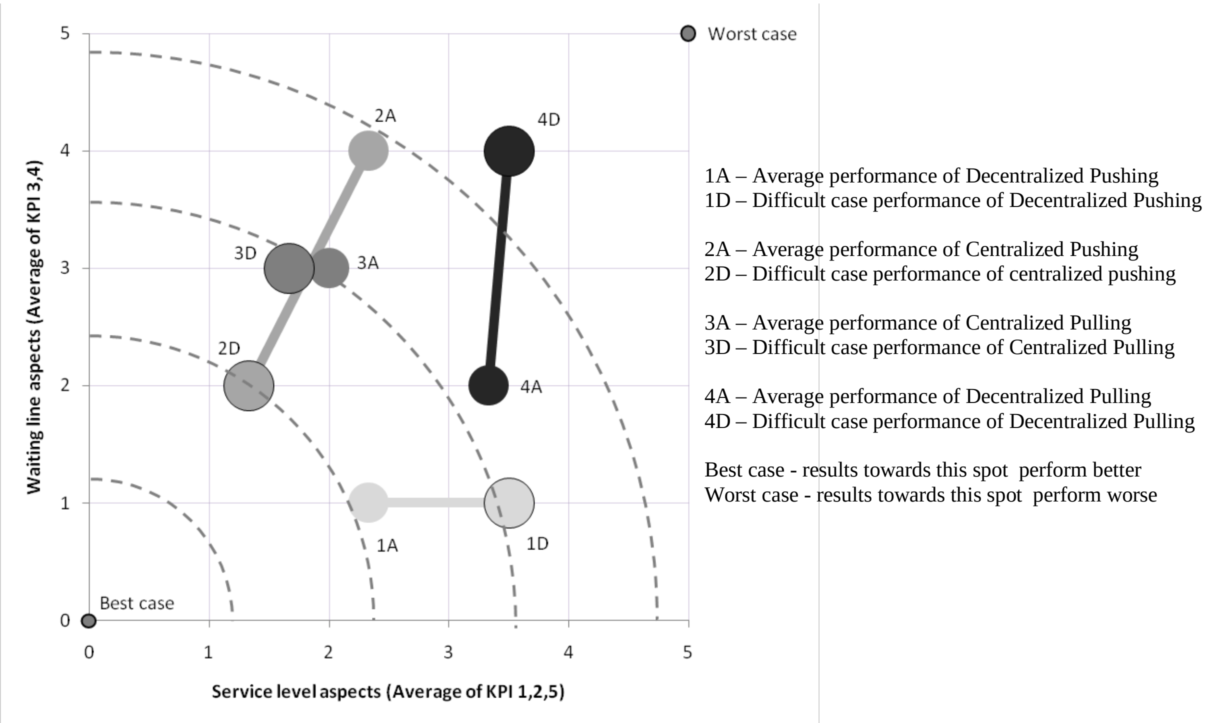

Figure 4 Trade-off between waiting line and service level aspects.

The relative importance of difficult case performance over average performance is difficult to quantify. There the following assumptions about its ratio explain the effect of a certain choice.

I. Average performance is important, difficult case performance not. This is the set of small spheres, which results in an order of strategies (best strategy first): 1,3,4,2

II. Average performance is equally important as difficult case performance. This is the spot in the middle of the lines. Order of strategies (ampersand means equal): 1,2&3,4.

III. Average performance is not important, difficult case performance is the important measure. This is the set of big spheres. Order of strategies: 2,3,1,4.

IV. Average performance should be respected, however difficult case performance is of a higher importance to avoid the neglecting of these difficult cases. This is the spot on the line which is found between the middle of the line and the bigger spheres. Order: 2,1&3,4.

These assumptions are not randomly chosen but rest on the way the system is judged by different people. Assumption I is related to the traditional way of judging the performance in the youth care system as it is still used currently. Assumption III, on the other hand, is related to the perception of field experts and researchers who claim that the difficult cases should be the primary focus of performance measurement since they are in the greatest need for care. Assumption II is the simplest method to share the importance of both these views and will likely be the result when discussions in the youth care sector don't bring forward a preference for one or the other. Assumption IV is our point of view since it emphasizes the importance of the difficult case performance while it still respects the average performance. It is considered that a slightly worsened average performance isn't bad as long as the difficult cases can profit significantly from it. The balance should be towards the point that these difficult cases cannot profit anymore without significantly decreasing the average performance. It is acknowledged that such an strategy would require a change in the financial system because the current system would underpay the care providers who are paid on an average case basis.

6 CONCLUSIONS AND FUTURE WORK

We have presented an approach for analyzing a number of resource allocation strategies in the youth health care sector while including an extensive set of constraints and behaviours from the real world system. The model successfully simulated many of the complex relations between the involved parties in the system. We demonstrated the ability of the model to incorporate different allocation strategies while maintaining an overall structure which deals with the common tasks outside the allocation procedure. We discussed the differences between the scenarios and their impact on system performance. The introduction of a case's urgency into performance measurement leads us to the advice of the push from a centralized queue strategy for future resource allocation in the youth health care sector. The postponement of the actual allocation in this strategy ensures a higher level of fairness in treatment provision by the care providers because they cannot avoid the difficult cases anymore.

Our approach shows the usefulness of agent-based modelling in complex environments like the youth health care sector where much of the problem is related to coordination and communication between different parties. The research therefore contributes to research in information systems and agent-based simulation by not only showing its usability in such a setting but also showing the ability to study alternative strategies which couldn't be studied otherwise with this level of complexity. We also contribute to research in information systems by advising a different allocation strategy. This strategy will increase social welfare by increasing the system's fairness for provision of treatment.

We intend to study further alternative strategies. Within the four strategies there is plenty of room to introduce alternative concepts such as auctioning and case exchange between care providers. We further intend to introduce an implementation of a human preference model into the decision making process as well as human computer interaction. The agent-based architecture of the simulation model is ideally suited to implement such alternatives since it only involves changes in the respective agents. Currently, our evaluation process for the simulation results are based on a balanced scorecard technique. We are planning to define a multi-attribute utility function as a comparison and extension to the current approach. Such a function would allow the floating transition of the trade-offs between different desired properties of patients' allocation.

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