Towards Model-Based Policy Elaboration on City Scale Using Game Theory: Application to Ambulance Dispatching

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Abstract. The paper presents early results on the development of a generalized approach for modeling and analysis of the interaction of multiple stakeholders in city environment while providing services to citizens under the regulation of city authorities. The approach considers the interaction between main stakeholders (organizations of various kind, citizens, and city authorities) including information and finances exchange, activities taken and services or goods provided. The developed approach is based on a combination of game-theoretic modeling and simulation of service providers interaction. Such combination enables consideration of confronting stakeholders as well as determined (e.g., scheduled) and stochastic variation in characteristics of system's elements. The goal of this approach development is supporting of analysis and optimization of city-level regulation through legislative, financial, and informational interaction with organizations and environment of a city. An example of ambulance dispatching during providing emergent care for acute coronary syndrome (ACS) patients is considered. The example is analyzed in a simplified linear case and in practical application to dispatching ambulances providing service for ACS patients in Saint Petersburg.

Keywords: Game theory · Queueing theory · Discrete-event simulation
Policy making · Ambulance dispatching · Acute coronary syndrome

1 Introduction

Currently, complexity city structure is rapidly growing. An idea of a smart city [1] is developed as a way to increase a city performance and human life quality. Still, there are multiple situations where the roots of a problem come from confronting interests of citizens, organizations or global goals (like improving life quality). One of the ways to understand and manage such situation is the application of game theory (GT) to understand optimal behavioral patterns of multiple stakeholders. Nevertheless, the complexity of modern cities leads to the need of considering various temporal and spatial factors regarding citizens' life, existing city environment, and key stakeholders activities. Having this in mind, a mixture of GT-model with models of city environment and various

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services in it may be applied. An important goal of this direction of research and development is supporting of city regulation through centralized and decentralized decisions, rules, and policies. In this paper, we present early results in the development of a generalized approach which combine GT modeling with modeling and simulation of city services to manage complex a city and uncertainty in structures and processes in it.

One of the important cases which may be considered in this way is providing healthcare in large cities. The high uncertainty of medical processes [2] is enforced in complex city health care structure with the diverse population being processed in the irregular environment. Moreover, the activity of hospitals, ambulances, drug stores, health insurance companies while providing health care is under the influence of personal interests and limitations (organizational, legislative, financial, policy-based, resource-based, etc.). Although the main goal of health care system is improving life quality, activity in a complex environment with limited resources may lead to cooperation or in contrast concurrency or/and confront between main actors. Additionally, diversity in patients and hospitals, as well as the complexity of healthcare environment (as a part of city environment) lead to growing importance of value-based healthcare [3] as a tool for assessing the impact from healthcare service.

For example, one of the crucial problems is overcrowding and queueing in hospitals. In this case, GT approach may provide certain insights on strategies for improvement, e.g., through collaboration between patients [4], between hospitals [5], between patients and doctors or nurses [6], etc. In the same time, diversity, temporal and spatial variation, the uncertainty of processes make the system more complex and leads to the application of modeling and simulation to the proper estimation of possible scenarios (see, e.g., [7]). On the other hand, city and country government may influence this process significantly through the introduction of regulation through organizational, financial support or defining policies for stakeholders. Still, to assess the possible scenarios a solution should be developed which considers all important aspects of complex city and healthcare environment. In this paper, we discuss the development of model-based solution based on the proposed approach for assessing and elaboration of possible policies in acute coronary syndrome (ACS) patients delivered by ambulances in Saint-Petersburg.

2 Conceptual Basis

2.1 Key Players in City Environment

Complex city environment includes multiple stakeholders involved in providing services, delivering goods, and supporting various city-scale activities. In many cases these stakeholders follow own interests in addition to support achieving the main (usually global) goal. These interests lead to complex patterns of interaction aimed at fulfilling personal tasks. In many cases, the relationship between external and personal goals as well as weights of these goals varies. E.g., in health care, global goal (improvement of population life quality) is of very high importance. Nevertheless, considering activity in circumstances of limited resources personal goals cannot be eliminated. In this section, a brief systematization of main stakeholders is provided to distinguish the main roles of actors and interaction channels (see Fig. 1).

Key considered in the approach include the following roles:

- *Service providers* acting in a city environment and delivering specific services for citizens. A specific type of service providers is transportation service providers, related to mobility of citizens and goods. Service providers may interact within a particular scenario involving several roles and procedures of interaction.
- *Citizens* are the main target consumer of the provided services. Usually, the goal of service providing is considered in a tight relationship with citizens' quality of life support. In addition to services, citizens use personal transportation.
- *City authorities* or other centralized controlling actors are intended to support high-level regulation of activities where it is required to support the development of city, systematic improvement of citizens' life quality and following higher goals (political, economic, etc.).

An essential part of the considered problem is limited resources (public or private) which are accessed by service providers or/and by citizens. The mentioned stakeholders may interact through the various channels or a combination of these channels:

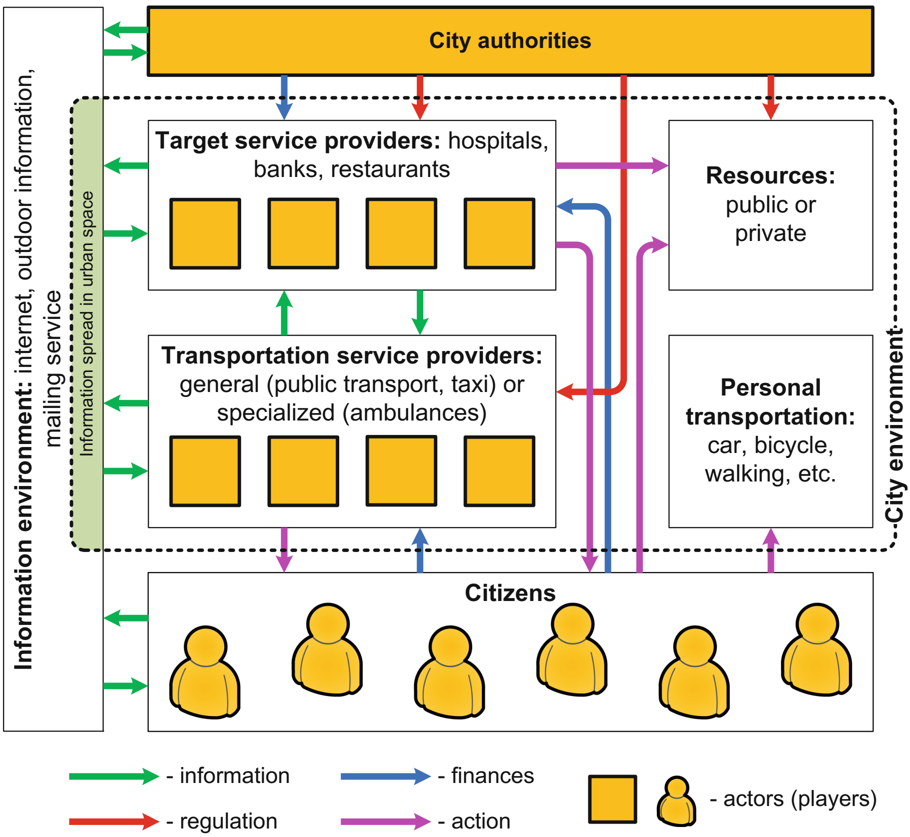

Fig. 1. The conceptual structure of multiple actors in a city environment.

- *Information* transfer may be performed in direct communication between actors or within the information environment. The information environment in general case includes various ways of delivering information through a media in public (broadcast) or private (directed) way.
- *Financial* interaction includes various payments between actors.
- *Regulation* is usually applied by city authorities to control service providers and available resources in a city environment.
- *Action* denote direct interaction between stakeholders: providing services, accessing resources, the mobility of citizens, etc.

The topology of stakeholders' interaction and mutual influence via various channels depending on a particular application. The only one element in this structure is usually presented in any application developed within the proposed approach. City authorities influence is considered as persistent centralized control, delivered by policies and laws, financial support (especially important for state organizations), and public information delivering.

One of the main goals of the developed approach in investigation and elaboration of possible ways of centralized regulation which may be applied in a multi-agent environment with personal interests of the stakeholders. For example, it could be applied to balance the automatically regulated behavior of the stakeholders towards global goals.

2.2 Patterns of Hybrid Modeling

Personalized, cooperative and collective decision making with multiple roles of stakeholders is considered in a framework of GT to identify self-adjustment of the system. In the same time, modeling and simulation of city environment enable deeper analysis of diverse temporal and spatial structures and processes, variation in behavior of the stakeholders, explicit and implicit relationship between them, etc. In this section, various patterns for a combination of GT approaches and city-scale models are considered. The patterns involve (a) GT models describing the interaction between stakeholders; (b) models of the city as a complex system (CS); (c) simulation models (SM) to assess selected scenarios application.

1. *CS-GT*. CS model may be used to assess topology of interaction between stakeholders, possible cooperation, available resources and typical behavior of stakeholders. GT provide additional structuring of the CS models with predicted strategies including cooperation, selected behavior. GT-based structuring becomes especially important in cases where CS model is difficult to identify directly, or in case of changing state and structure of a system (here GT-approaches may be applied within data assimilation algorithms).
2. *SM-GT*. SM enables complex estimation of game parameters, including stochastic parameters (e.g., with non-trivial distribution) of a system, assessment of utility function in various conditions, scenarios and system's structure, etc. GT provides rules identified according to strategies to describe the behavior of simulated entities.

3. *The explorative analysis* includes cyclic interaction within patterns 1 or/and 2 to elaborate and analysis of various hypotheses (also, includes what-if analysis), understand detailed structure of the system.
4. *Optimization, policy and decision making* also include the cyclic application of patterns 1 or/and 2 but for strictly defined goal (e.g., elaboration of best policy for stakeholders' regulation).

Patterns #1 and #2 are more structural and general. To consider integration with SM and CS it is important to consider game type in relation to (a) problem, being analyzed, (b) data structures available for exchange in these mixtures. Patterns #3 and #4 are mainly aimed at application development. Here the most important issue is automatization of uncertainty control to provide most valid and credible modeling and simulation results to support gaining new knowledge (pattern #3) or elaboration of result solution (pattern #4).

3 Case Study: ACS Patients Delivering

This section presents early results on the analysis of a selected case study with application of the developing approach for mixing GT models with models of complex city environment for analysis and optimization of processes within the city environment.

3.1 Problem Definition

World Health Organization reports [8] cardiovascular diseases as a major cause of death the world. Many of them, such as acute coronary syndrome (ACS) or stroke, require urgent and specialized care to be applied within several hours, whereas delays lead to significant increase in risks of complications and even death of a patient [9]. Usually, patient in such condition is delivered with an ambulance to a hospital for coronary angiography with possible percutaneous coronary intervention (PCI, i.e., angioplasty, stent placement which are considered as a major and preferable therapy in these cases). As a result, the goal of the healthcare system is lowering of delays from the appearance of acute state to surgery. This delay is mainly related to dispatching and routing of ambulances to deliver the patient to the selected hospital. Most of the works in the area are focused on delivering process [10, 11]. Still, the important part is a selection of the best hospital which available for processing of such patient. The hospital may be not available due to the overcrowding and queues for limited surgery facilities (which may be occupied either by acute or by the planned patient). Modeling of hospital's surgery facilities may help to assess hospital readiness to accept patient [7]. On the other hand, hospitals are often stimulated by the government, city, or local authorities towards processing as many patients as it is possible. In such condition, it is possible to consider the acceptance of the patient by a hospital as a personal decision taken by a hospital (as a service provider) considering existing queue to available surgery facilities and risks for a particular patient (assessed remotely). This leads to possible consideration of such situation within a framework of the proposed approach. Here hospital and ambulances are service providers, regulated by global authorities with financial support and policies and aimed towards achieving the global goal at the same time keeping own interests.

In Saint Petersburg, the death rate from cardiovascular diseases is about 10% higher than Russia's national average. This is typical for large cities [12] mainly due to the higher average age of the population. In 2015 there were 7913 ambulance calls were related to ACS, 46.7% of patients with ACS were treated with PCI, and 8.6% of patients with ACS died (8.2% within 24 h). Also, the expert analysis shows that the treatment can be improved in 20.1% cases of early deaths among patients. One of the known ways for improvement is reducing transportation delays. The hospital network in Saint Petersburg includes 16 hospitals with ACS facilities (13 of them are working 24/7). Still, this set of hospitals is significantly heterogeneous. Hospitals have own schedule of facilities and doctors, specialization. Also, the spatial distribution of hospitals increases the diversity of patient flow density due to calls placement and availability of current traffic load.

In this research, a model of ACS patients delivering with a special focus on dispatching (selection of target hospital) is developed to analyze the decision made collectively by ambulance service and hospitals.

3.2 ACS Patients in Simplified Case

We started with a simplified case to elaborate detailed solution furtherly applied to an actual network of hospitals and flow of ACS calls in Saint Petersburg. A simplified case (Fig. 2a) include two hospitals H_1 and H_2. Hospitals are placed in opposite ends of a line. Patients P_i appear uniformly in between these hospitals within Poisson process with rate λ. The patient is delivered to the selected hospital in a time $T_{transp.} \sim |P_i - H_i|$, where $H_i \in \{H_1, H_2\}$.

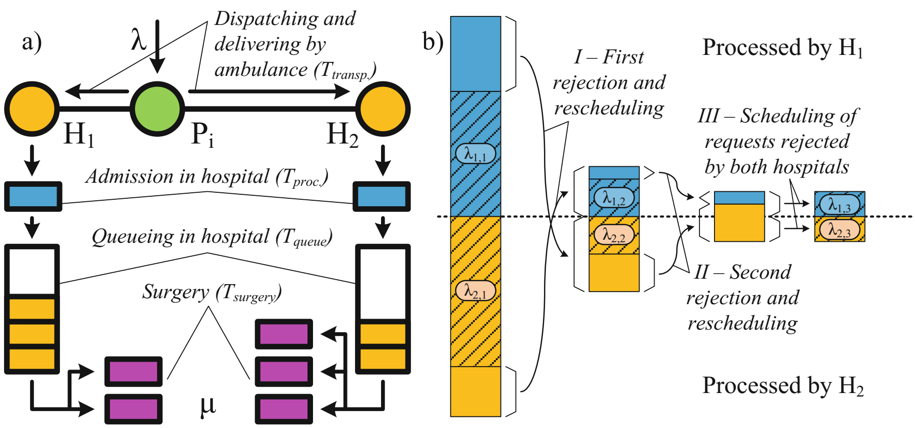

Fig. 2. Simplified case (a) dispatching and queueing; (b) three-stage rescheduling.

Each hospital has a queue to the surgery facilities that produce a delay of T_{queue}. Additionally, time $T_{proc.}$ is spent for various supplementary processes (interaction with admission department, registration of patient, etc.). Finally, patient goes to the surgery and it takes $T_{surgery}$ to complete it (with processing rate $\mu = 1/T_{surgery}$). As a result, total time is calculated as follows:

$$T = T_{transp.} + T_{proc.} + T_{queue} + T_{surgery}. \tag{1}$$

Considering the process with a queueing theory we can conclude that for each hospital, having request rate of λ_i, processing rate μ_i, and number of parallel surgery facilities n_i the probability of empty queue, the probability of k patients in a queue, the average length of a queue, and average processing time are respectively

$$p_i^{(0)} = \left(1 + \sum\nolimits_{j=1}^{n-1} \frac{\rho_i^j}{j!} + \frac{\rho_i^{n_i}}{(n_i - 1)!} \frac{1}{n_i - \rho_i}\right)^{-1}, \tag{2}$$

$$p_i^{(k)} = \frac{\rho_i^k}{k!} p_i^{(0)}, \tag{3}$$

$$L_i = \frac{\rho_i^{n_i+1}}{n_i!} \frac{n_i}{(n_i - \rho_i)^2} p_i^{(0)}, \tag{4}$$

$$\widetilde{t}_i = \frac{L_i}{\lambda_i} + \frac{1}{\mu_i}. \tag{5}$$

Here $\rho_i = \lambda_i/\mu_i$. Within the simplified example we suppose that $\widetilde{t}_i$ is estimation of a sum $T_{queue} + T_{surgery}$, $T_{proc.} = 0$. As calls are distributed uniformly over the range between hospitals $T_{transp.}$ is estimated as average time of delivering patients from source part of the range. E.g. for basic delivering to the nearest hospital the range is divided into equal parts and $T_{transp.} = 0.25 t_c$, where t_c is time of transportation along the whole range. As a result, $T_i = T_{transp.} + \widetilde{t}_i$.

In this simplified case we consider two main strategies for hospitals:

- Strategy A. Accept all incoming requests.
- Strategy R. Partly reject requests in case number of patients in queue exceed predefined N_{lim}.

In the later strategy R, the probability of rejecting is

$$p_{reject}(\lambda_i) = 1 - p_i^{(0)} - \sum\nolimits_{k=1}^{N_{lim}} p_i^{(k)}. \tag{6}$$

Normally, all the requests must be processed. In case of hospitals takes different strategies (AR or RA) rejected requests are processed by the hospital with strategy A. As a result, request flow is changed:

$$\lambda_1^* = \lambda_1\left(1 - p_{reject}\left(\lambda_1\right)\right), \lambda_2^* = \lambda_2 + \lambda_1 p_{reject}\left(\lambda_1\right). \tag{7}$$

Here is the case where the first and second hospital has R and A strategies respectively. The opposite situation (AR) leads to exchanging of indices in Eq. (7).

In case of both hospitals with strategy R, we consider the application of recursive processing of requests in three stages (Fig. 2b). Firstly, the request scheduled to hospitals are rejected with probability $p_{reject}\left(\lambda_i\right)$ and flow $\lambda_i^{R1} = \lambda_i p_{reject}\left(\lambda_i\right)$ is redirected to another hospital. In the second round of rejection, redirected patients are rejected with probability $p_{reject}\left(\lambda_i + \lambda_{1-i}^{R1}\right)$. Finally, flow $\lambda_i^{R2} = \lambda_{1-i}^{R1} p_{reject}\left(\lambda_i + \lambda_{1-i}^{R1}\right)$ is redirected for uniformly rescheduling between hospitals (without more rejections). Thus, result inflow of each hospital is composed of three parts:

$$\lambda_i^* = \sum\nolimits_{j=1}^{3} \lambda_{i,j}, \tag{8}$$

where

$$\begin{gathered}
\lambda_{i,1} = \lambda_i\left(1 - p_{reject}\left(\lambda_i\right)\right) = \lambda_i - \lambda_i^{R1}, \\
\lambda_{i,2} = \lambda_{i-1}^{R1}\left(1 - p_{reject}\left(\lambda_i + \lambda_{1-i}^{R1}\right)\right) = \lambda_{i-1}^{R1} - \lambda_i^{R2}, \\
\lambda_{i,3} = 0.5\left(\lambda_i^{R2} + \lambda_{i-1}^{R2}\right).
\end{gathered} \tag{9}$$

Considering rescheduling the transportation time is also changed according to the following rules:

$$T_{transp.}^{AA} = T_{transp.}^{RA} = 0.25 t_c, \tag{10}$$

$$T_{transp.}^{AR} = \frac{0.25 + 0.75 p_{reject}\left(\lambda_{\mathrm{R}}\right)}{1 + p_{reject}\left(\lambda_{\mathrm{R}}\right)} t_c = \left(1 - \frac{1}{2\left(1 + p_{reject}\left(\lambda_{\mathrm{R}}\right)\right)}\right) t_c, \tag{11}$$

$$T_{transp.}^{RR} = \frac{0.25\lambda_{i,1} + 0.75\lambda_{i,2} + 0.5\lambda_{i,3}}{\lambda_i^*} t_c. \tag{12}$$

To assess utility and global solution quality in GT-models we introduce score function $u_i = \lambda_i / T_i$ and global average time $g = \left(\lambda_1 T_1 + \lambda_2 T_2\right) / \left(\lambda_1 + \lambda_2\right)$. The utility function is constructed to maximize flow of processed patients and minimize processing time. Whereas g is constructed to minimize the processing time in the whole system. As a result, game matrix will be the following

$$M = \begin{bmatrix} \left(u_1^{AA}, u_2^{AA}\right) & \left(u_1^{AR}, u_2^{AR}\right) \\ \left(u_1^{RA}, u_2^{RA}\right) & \left(u_1^{RR}, u_2^{RR}\right) \end{bmatrix}, \tag{13}$$

while the global quality of the solution could be assessed through the searching of the minimum in the matrix

$$G = \begin{bmatrix} g^{AA} & g^{AR} \\ g^{RA} & g^{RR} \end{bmatrix}. \tag{14}$$

The described solution was evaluated for searching of Nash equilibrium (at this stage pure strategies were considered). The search was performed at various rates $\lambda \in [0.5;3]$ and $\mu \in [0.5;3]$ and configurations of available facilities $n_i \in \{1, 2, 3\}$. Results are presented in Figs. 3 and 4.

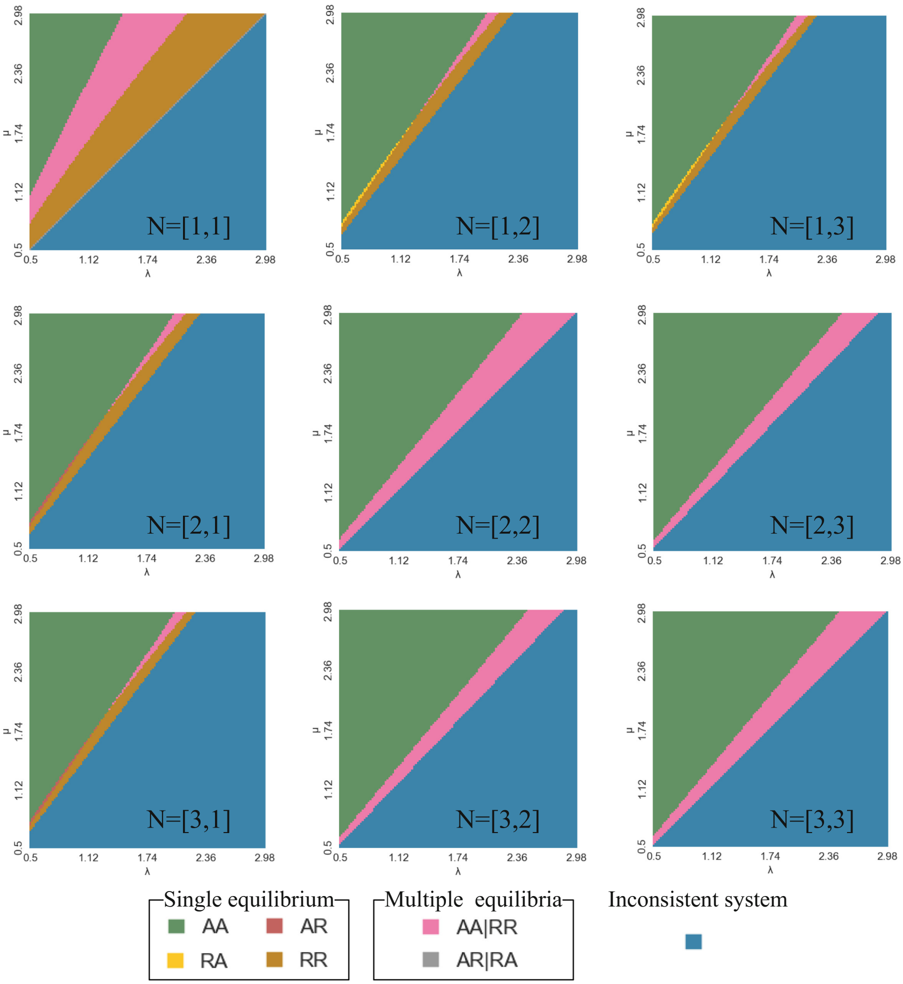

Fig. 3. Nash equilibria for various request rate (λ), processing rate (μ), and number of available parallel surgery facilities (N), colors depict combination(s) of strategies identified as equilibrium. (Color figure online)

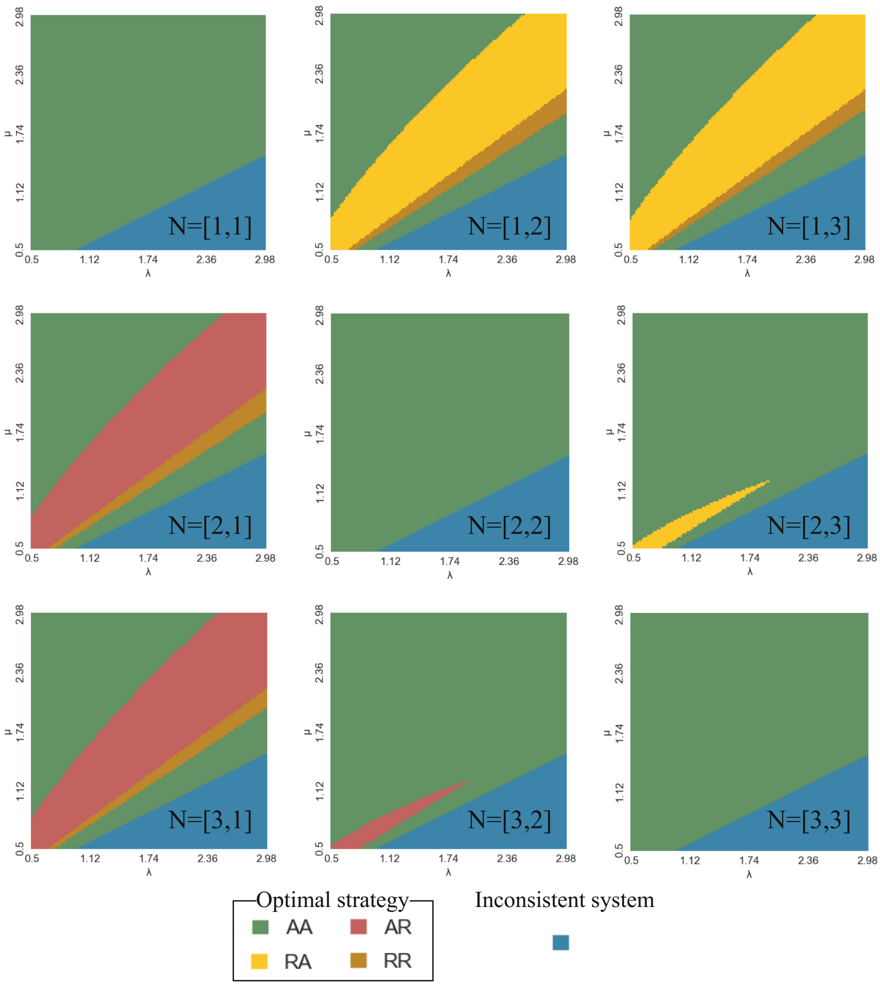

Fig. 4. Globally best solution for various request rate (λ), processing rate (μ), and number of available parallel surgery facilities (N), colors depict combination of strategies with lowest average time. (Color figure online)

Considering Nash equilibria with matrices (13) for various request and processing rates (Fig. 3), the simplest situation where λ and μ allows processing request with low probability of queuing is usually characterized by A strategy taken by both hospitals (AA, here and further a combination of two letters denote strategies taken by first and second hospital respectively). The opposite situation is when the configuration and strategies of two hospitals are insufficient for processing of given incoming request flow. This situation mainly comes to constantly growing queue ($\rho_i = \dfrac{\lambda_i}{\mu_i} > 1$) and is considered as inconsistent (during the automatic processing we interpret it as $u_i = -\infty$). We consider a whole system as inconsistent when a situation exists where one player cannot avoid inconsistency (both available strategies lead to $u_i = -\infty$). More interesting situations appear where queueing is possible, but the system can manage it. The situation may lead to either situation where RR strategies are considered as equilibrium or situation where there are two equilibria (AA and RR) depending on the ration of λ and μ. Moreover, on the border of the areas of such situation more complicated combinations of strategies appear: AR, RA or both equilibria at the same time.

Figure 4 shows globally best solutions according to the criteria (14) characterized by smallest average processing time for total request flow (Fig. 4). Here, the inconsistent situation leads to $g_i = +\infty$. A system considered as inconsistent when $\min(G) = +\infty$ (which is weaker criteria comparing to one described earlier for M matrix and therefore the area of inconsistency is smaller in Fig. 4 comparing to Fig. 3).

An important observation from a comparison of the results presented in Figs. 3 and 4 is various situations where the globally optimal solution (a combination of strategies for two hospitals) differs from the one selected with equilibrium state. Still, the deterministic inference available with queueing theory is not enough in the case where high uncertainty (like in case of healthcare) appears. To analyze the situation in more details a discrete-event simulation model was developed representing the same simplified case. Figure 5a shows simple run of this model with two hospitals in RA situation. The simulation may show situations where overcrowding events appear in hospitals with unlimited A strategy. This results in the multi-modal distribution of total time (Fig. 5b) in such hospitals. Using A strategy leads to higher mortality and complication risks, but also it comes with a higher throughput of the hospital.

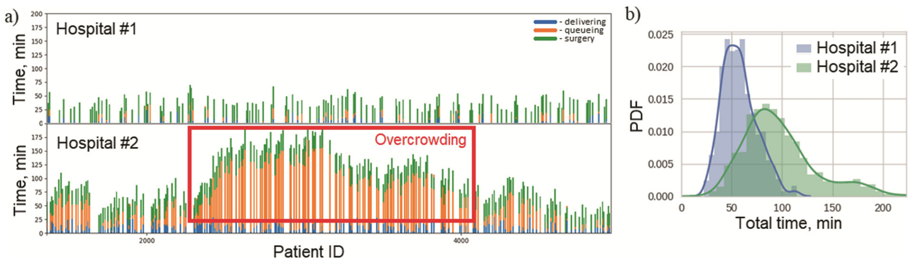

Fig. 5. Discrete-event simulation with queueing for a simplified case in RA situation (a) timelines for sequential patients; (b) total time distribution.

3.3 ACS Patients Delivering in Saint Petersburg

Multiple equilibria appearing depending on flow parameters even in the simplified case along with the high uncertainty of the processes leads to complex strategies which may vary over time (considering scheduling of real hospital facilities, temporal and spatial variation of patient flow, etc.). Figure 6 shows ACS calls in Saint Petersburg during 2015 (circles). The hospitals are denoted with stars of the same color as calls processed in it. Size of a star depicts a number of processed calls. It could be clearly seen that most of the calls are served by the nearest hospital and the city could be divided into several “areas of responsibility” of hospitals (green dividing lines are identified with SVN

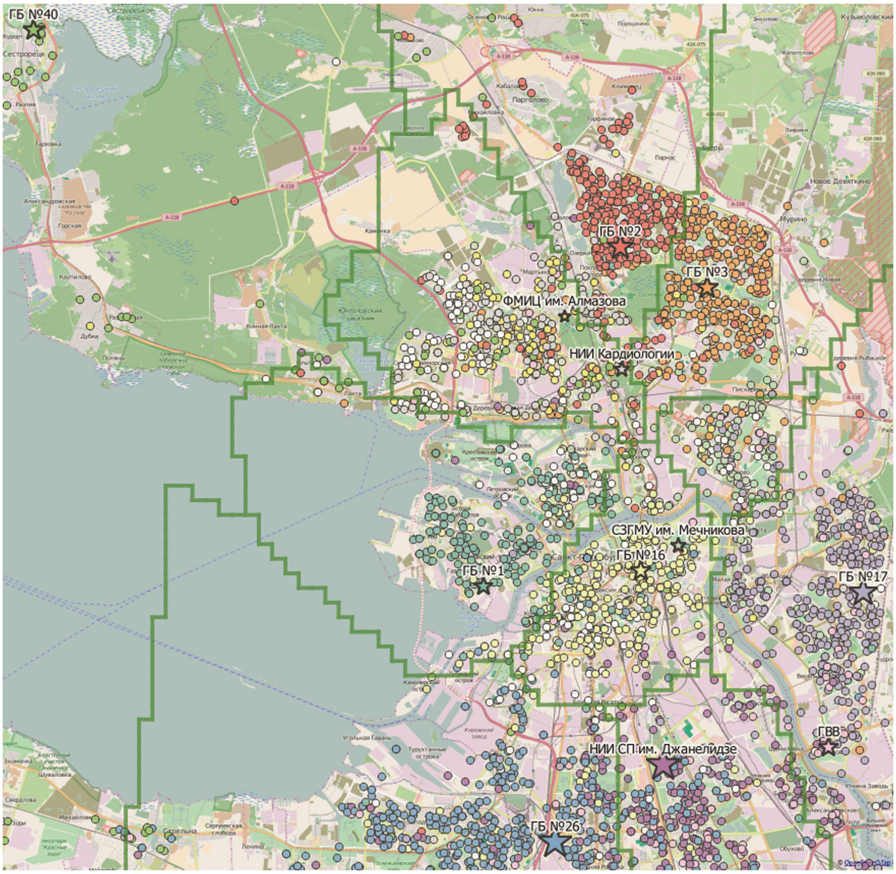

Fig. 6. ACS calls (circles) and target hospitals (stars of corresponding colors, size is proportional to number of processed calls) in Saint Petersburg. (Color figure online)

classifier which predicts target hospital for each point on the map). Still, several features bring complication into the task:

- For most hospitals, there are calls from the areas of neighbor hospitals (usually, near the border) which appears when the traffic or hospitals' load shift the dispatcher's decision towards the other hospital. These calls form blending areas between hospitals which are rather wide in many cases.
- There are cases where the patient is delivered to rather a far hospital. In some cases, it is caused by patient own request (which of cause is checked for not violating requirements of the ambulance service). Still, in many cases, this was an objective decision taken by the dispatcher in a situation of overcrowded nearest hospitals.
- Also, there are several areas with a high mixture of target hospitals (see, e.g., the area to the north from the map center).

- Finally, it worth to mention that the flow of patients varies significantly during 24 h in its level and in the spatial pattern of usual appearance (e.g., by switching working/ touristic areas with sleeping areas).

The mentioned observations lead to the conclusion that the decision of dispatcher often has significant uncertainty and depends on multiple factors. To work with the uncertainty and apply the developed solution to the real world case the SM-GT mixture of models will be extended (a) with enhanced delivering simulation delivered within the previous research of authors' [13]; (b) with additional analysis in GT model where the solution becomes multi-dimensional having many stakeholders (besides 16 hospitals, city authorities, and patient being delivered may be considered as stakeholders); (c) with optimization of policies for potential improvement of ambulance dispatching system.

4 Conclusion and Future Works

The developed approach is designed for investigation of multiple stakeholders' interaction during a service providing in the city environment. For example, the approach may be applied to the task of policy optimization or investigation of various scenarios in a city environment. To support this, a combination of GT and city environment model is hired. A working example is devoted to the analysis of ACS patients' delivery with ambulances and possible optimization of this process. Still, the presented research is still ongoing. Further directions of the research include the following.

The general approach will be developed in more details with the elaboration of typical patterns of modeling and simulation with an especial focus on GT application for support of modeling collective decision making and uncertainty management. E.g. consider a mixture of GT and SM a sensitivity and stochastic assessment could be used to analyze possible switching from one equilibrium to another.

The considered GT solution will be extended with more flexible approaches than Nash equilibrium searching in pure strategies. This includes: mixed strategies for probabilistically assessment of strategies, evolutionary strategies for adaptation of the model to the changed environment, quantal response equilibrium (QRE) for dealing with bounded rationality in decision making and working with multiple equilibria with switching between them, consideration of cooperative games for more complex stakeholders' interaction, etc.

Within the considered case study, the further development of the solution includes the detailed elaboration of the of the implemented GT and SM solution and its application to the actual structure of hospitals in Saint Petersburg. The goal is to access a design policy of patient delivery process regulation through introduced policy, financial support, and information exchange.

Finally, the developed solution is aimed to be enriched with the previous experience of authors. Namely, the solution may be used to extend the experimental solution for decision making in ambulance dispatching and routing, developed previously by the authors [7]; implementation of collaborative decision making support tool [14] as a way of cooperative decision making; including of data-driven predictive models of ACS cases [15] for enhanced prediction of episodes and more precise assessment of risks and length of stay for a patient.

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