AOC-Based Efficient Waiting Time Management in Hospital

Li Tao

Abstract

Long waiting list or waiting time in public health is an endemic and challenging problem faced by many countries in the world. To manage waiting time is a complex problem because it involves both impersonal factors (e.g., inefficient patient scheduling) and human factors (e.g., dynamically change patient behaviors). Traditional mathematical modeling (e.g., queuing theory) has been used to deal with various scheduling problems (e.g., care units scheduling optimization). However, these approaches, which are often processed in a centralized manner and often regard the health care system/hospitals as deterministic systems (e.g., constant patient arrival rate, stable care service capability), are insufficient to tackle distributed patient scheduling problems involving patient dynamic behaviors in the real world. On the other hand, system dynamics approach is efficient in qualitatively analyzing causing factors of waiting time but meet challenges to address the same problem of scheduling patient flow as mentioned above. In this paper, we mainly focus on a distributed dynamic patient scheduling (DDPS) problem which aims to alleviate the overall waiting time in a hospital. Based on a self-organized computing paradigm called autonomy-oriented computing (AOC), we provide a distributed strategy in which autonomous entities corresponding to organizations are deployed in a temporal constraint network (edge denotes temporal constraint between two nodes), and are capable of scheduling patients to shorten waiting time in total by individual behaviors such as competition and cooperation.

1 Introduction

Long waiting list or waiting time in public health is a notorious problem in most of the countries all over the world [23]. It is reported by [14] that in 1999, there were almost 2 million patients waiting for outpatient services and 1 million patients waiting for inpatient or special care. Averagely, 49% inpatients should wait at least 3 months and 26% waited more than 6 months. Similarly, the waiting time for public health supported patients varies from about 3 to 4 months for patients in Norway [4][14].

The reasons of excessive waiting time can be divided into two levels: (i) macro level: e.g, government policies, resource allocation planning, and (ii) micro level, like limited resources, inefficient doctor-patient interaction, fluctuation of patient number and patient type, central controlled organization management, non-cooperate independent machine-like organizations (departments/units) and etc. For all the reasons above, waiting time problem can not be easily tackled from normal mathematical approaches (e.g, queueing theory)[7][9] and traditional top-down systems approaches (e.g, system dynamics)[21][22].

1.1 Challenges

How organizations managing waiting time more efficiently is a hard task because it involves: (i) impersonal factors like scarce care resources, inefficient resource management and patient scheduling, and (ii) human factors such as redundant doctor-patient interaction, unpredictable patients behaviors as dropping a prearrange treatment, and so on. Figure 1 shows the main direct and indirect causing factors of waiting time and the importance of waiting time management in health care system.

In addition, real waiting time management problem is complex in nature because of:

- **Distributed health care resources**: Health care resources with attributes of quality/quantity/types are distributed geographically which causes various problems, e.g., convergence referral flow, fluctuation of treatment cost and waiting time, distinct treatment plan, and so on.
- **Dynamically changing demands**: Request for health care is dynamically changing because of unpredictable diseases, uncertainty patient decision making, patient status natural transfer (e.g, from sick to healthy or to dead), and etc.
- **Independent organization decision making**: Traditionally, organizations in health care system are regarded as a part of deterministic system. They almost make decisions (e.g., patient scheduling) based on own

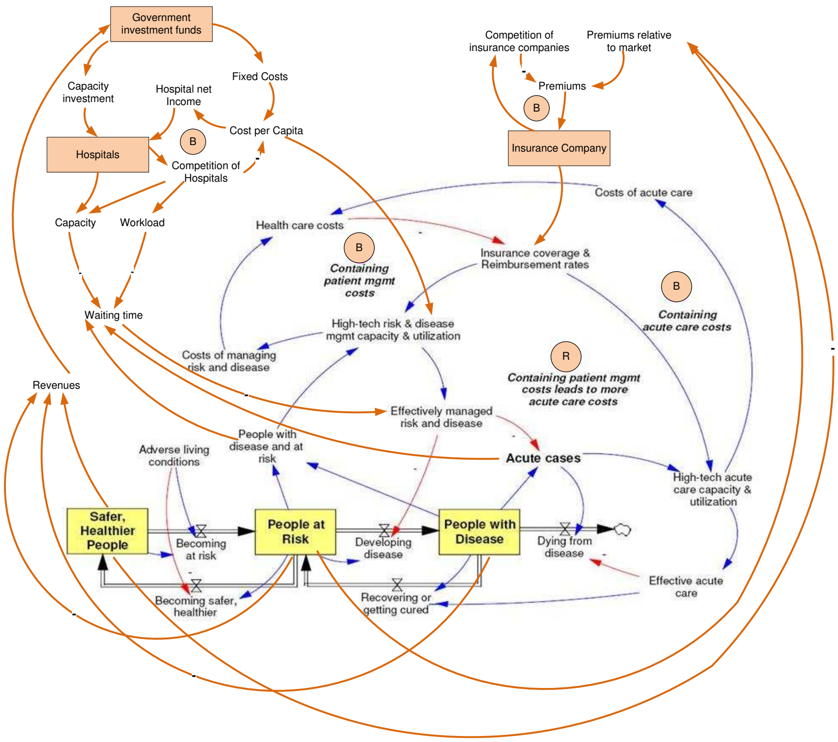

Figure 1: Causing factor of waiting time from system dynamics approach. This graph shows that hospital capability, workload efficiency and number of patients have direct impact on waiting time, and waiting time directly influences effectively managed risk and disease. (This graph is drawn based on the work of [12][13])

interests (e.g., first in first serve) rather than the global objectives (e.g., minimize total waiting time).

- **Non-linear and dynamic coupling between organizations**: The coupling relationships among organizations can not be easily expressed as linear function because they dynamic change case to case. E.g., there is weak coupling among organizations in routine, while strong coupling in emergency cases.

- **Incomplete non-centralized information**: Information (e.g., about patient treatment plans, patient decisions, organization circulation) is partially available for organizations as well as for patients due to the open, distributed, dynamic and large scale (thousands of patients, number of organizations) nature of health care system.

In the past, several approaches have been used to solve waiting time related problems, ranging from mathematical modeling to complex system theories. Queueing theory [9][7] has been adopted to schedule patients in the context of single organization with static and global patient information. However, these piecemeal works cannot easily extended to solve an open, dynamic and large scale (means not limited in a department or one kind of resource, but at a hospital level with hundreds of departments and resources) scheduling problem. Also, complex systems theories like system dynamics have been used to study waiting time and predict the efficiency of management polices from global level. This top-down approach has limitations to provide a practical solution representing the dynamics and to reveal the basic rules which resulted in such a complex problem.

1.2 Our Consideration

In order to efficient patient scheduling in an open, distributed, dynamic and large scale context, it is necessary for us to understand what are the forces causing waiting time and what are the mechanisms underline such a distributed dynamic patient scheduling (DDPS) problem. In this paper, we study DDPS problem aims to shorten waiting time in the hospital level from a new perspective called Autonomy Oriented Computing (AOC)[15][16][18]. AOC is a new paradigm which model phenomenons or problems from a bottom-up approach. The patterns or solutions for a complex problem will be emerged from a natural like self-organize process. Based on AOC framework, the organizations in hospital can be regarded as intelligent entities. They behave (e.g., compete, cooperate) according to intrinsic behavior rules towards their own goals. Ultimately, global objective (an efficient patient schedule) will be achieved through the process of entities self-organization.

In detail, there are some interesting and important questions we should try to answer:

- What are the organization connection structures at different levels of health care system? Intuitively, we suppose they are network-liked structure. So, what kind of network it belongs to?
- What are the characteristics of this kind of network and how to identify? For example, what are the key nodes (bottlenecks in treatment flow) and key edges? How about the coupling between nodes? These kinds of characteristics may have important physical meaning.
- What are the mechanisms with which organizations can achieve a global target by process of self-organization?
- What patterns or structures can emerge from these adaptation evolution process? E.g., whether the network structure will be evolved from self-organization process?

Specifically, this paper will focus on how to model and design strategies to solve DDPS problem based on AOC framework. The main objective of this paper is not only to provide a distributed solution for dynamic scheduling problem, but to verify that whether a behavior based distributed strategies are more suit to solve DDPS like problems (e.g., supply chain management in e-market, task scheduling in web service, and so on).

The rest of this paper is organized as follows. In section 2, we briefly summarize some typical related work related to efficient waiting time. In section 3 we define and formulate DDPS problem in detail. Section 4 proposes our strategy based on AOC. Lastly, we summarize this paper in section 5.

2 Related work

To better waiting list/time, endeavors include (i) exploring solutions and strategies from theoretical study, and (ii) carrying out practices in real world.

Theoretically, extended from classic job shop scheduling problem (JSSP) [5], traditional mathematical modeling techniques like queueing theory [7] [9]have been commonly adopted to schedule patients. Paper [7] constructs a queueing model to assess the impact of service outages, to approximate patient flow times and to evaluate a number of practical applications. Paper [9] surveys a range of queuing theory results in the areas of waiting time and utilization analysis, system design, and appointment systems. It also considers results for systems at different scales, including individual departments (or units), health care facilities, and regional health care systems.

However, there strategies extended from JSSP are not suit to solve DDPS problem in real world because there are some apparent differences between them.

- JSSP has global information about tasks and executive time. It can provide an optimal solution by central planning without regard to polynomial calculation time. But DDPS faces dynamic changing tasks with local information.
- JSSP is a complicated problem while DDPS is a complex problem which needs the ability of reorganizing or self-organizing in real time.
- JSSP often focuses on a small scale. Here, small scale means how to schedule number of tasks onto a few pipelines which have simple linear connection structure. However, DDPS involves a much bigger and complex scale. The number of organizations (similar to pipeline) is big. And there are network liked temporal interconnected structures among organizations.
- JSSP has a static problem space and is a NP-complete problem. But the problem space of DDPS is dynamic changing and more complex.

DDPS also can be regarded as a kind of distributed Constraint Satisfy Problems. It has temporal constraints among some organizations and maximum treatment time limit. As the similar reasons we mentioned above (JSSP is one kind of CSP problem), we can not use the classic methods (e.g, Backtracking method) as well as multi-agent oriented constraint satisfaction approach proposed by [17] to solve DDPS problem.

Due to the limitation of mathematic modeling strategies to efficient manage waiting time, many other researches resort to complexity science to rethinking of health care managerial and this way is believed to be a promising attempt [8][19][20]. System Dynamics (SD)[6], which deal with internal feedback loops/causing flow (figure 1 is an example) that affect the behavior of an entire system through interrelated components, is commonly used to understand the roles and relationships of different components in health care system, and to analyze the efficiency of health care management strategies and policies. For example, paper [10] predicts policies (subcontracting, a program of extending the working day to the afternoon, and waiting list updating) to entail excessively long waiting list in Spain are useless in the long-term. paper [21] and [22] find out that waiting time cannot be shortened proportionally to substitutability among NHS hospitals. Although this traditional top-down complex system approach offers ways to think/understand health care systems that enable us to have new insights about the nature and functions of it, they cannot provide practical solutions and cannot address some key problems such as DDPS.

Practically, many governments (e.g., England [2], Canada [3]) carry out policies to improve waiting time by strategies of giving political pressure and central direction to organizations which mimicked a command economy, and placing a much heavier emphasis on choice, competition and plurality of provision. However, these efforts are not efficient in practical. The real practice conducted by NHS do not just to cut waiting times but 'to move the NHS away from a culture of waiting to a culture of booking' [11]. According to Civitas statistics (number of patients waiting and length of time spent waiting for an inpatient appointment is shown as an example in Figure 2), although the waiting time has been improved to some extent, there are still a lot of tough works to do. So, DDPS problem has practical significance in real world.

3 DDPS Problem Statement

The DDPS problem is not a simply static scheduling problem because of unpredictable human factors such as dynamically changing patient/doctors behaviors, fluctuation of patient numbers and so on. Therefore, there are some key problems we should consider when tackle the problem of efficient patient scheduling.

(1) **Patient arrival and flow:** What are the arrival patterns of patient according to time and season? What are the behaviors of patient like reneging from a queue because of the queue length? What conditions may trigger there unpredictable behaviors?

(2) **Manpower characteristics:** What are the patterns of doctors (or staffs) facing different conditions of waiting queue? That means, with the incensement of waiting queue, does doctors will speed up their treatment process as quickly as possible or may suddenly slow down their working efficiency because they realize their ability is insufficient in any case or their feel quite tied. What conditions may result in such unanticipated doctors' behaviors?

(3) **Structure of the health care system or hospital:** At present, organizations are almost independently especially for outpatient care service. However, these organizations may have some underline structures (e.g., organized by temporal constraints) which may shorten waiting queue. Thus, we need to ask: Is current health care system structure appropriate for patient efficiency? What structures will the system evolve to?

(4) **Adaptive and distributed patient scheduling:** How to design a distributed self-organization mechanism considering dynamic attributes of patients and doctors? How about the performance of this mechanism?

In this paper, we start from a simple scenario to study how to schedule patients automatically and dynamically by distributed cooperated organizations in a hospital. Then we will extend our strategy to more complex situations considering more dynamic behaviors of patients and doctors.

In the scenario, we assume there is a classic hospital where reside several loosely coupled but relatively independent organizations like reception, diagnosis, electrocardiogram and etc. The capability of each organization which is denoted as Υ_i for organization i is stable. Some organizations have temporal constraint relationship. For example, department for consultation is normally visited after register. But electrocardiogram examination and radiological examination do not have sequence requirement. We suppose the structure of organizations in hospital is a network (figure 3 is an example). Here, each node means an organization or a department in health care system and directed edge points the temporal order of two organizations. That means, some organizations should be visited in sequence (single directed arrow shown in figure 3) while others need not follow the temporal constraint (double directed arrow shown in figure 3).

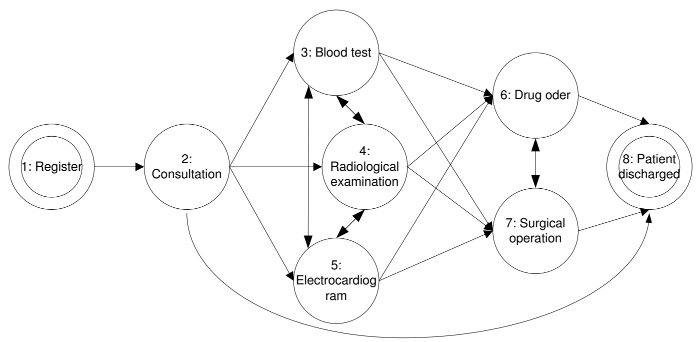

Figure 3: Illustration of organization network of hospital. In this graph, node means department in a hospital. Directed edge shows temporal constraints.

Definition 1: ***Hospital Organization Network***. Graph $G =< V, L >$ is a predefined hospital organization network. $V = \{v_1, v_2, ..., v_n\}$ is the set of nodes, which denotes the set of n organizations, and $L = < v_i, v_j > | 1 \leq i, j \leq n, i \neq j$ is the set of directed edges which shows the sequential constraints. For example, the directed link $< v_i, v_j >$ means that the work on v_i should be done earlier than on v_j.

The behaviors of patients dynamically change. Patients come into hospital randomly day to day. They may join in (e.g, referral from other hospitals) or quit (e.g, referral to other hospitals, decide not continue to this treatment, die, recovery and etc.) from waiting queue of each organization randomly. A simple example of patient states transition is

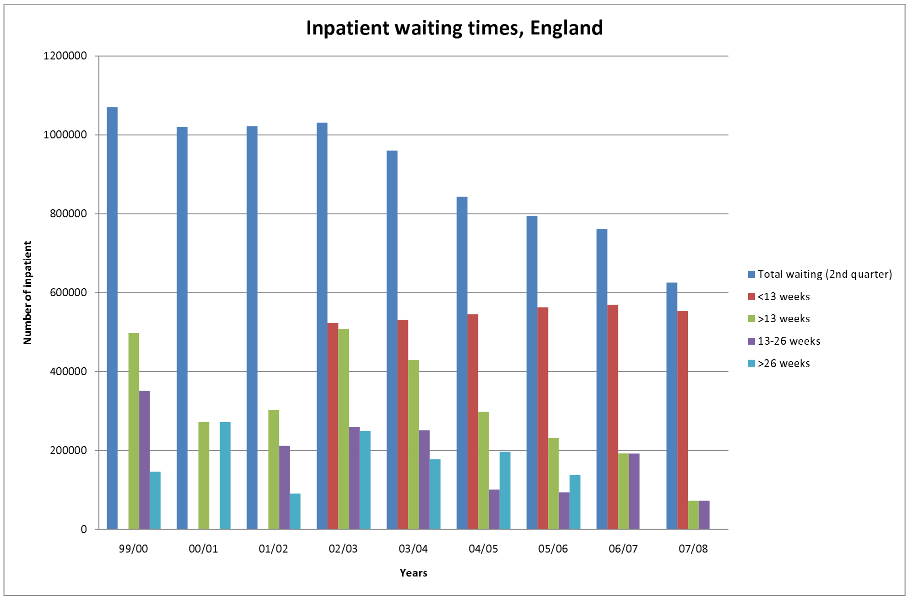

Figure 2: Number of patients waiting and length of time spent waiting for an inpatient appointment, England, 1999/2000-2007/2008 (data is not complete in year 1999/2000-2001/2002). The statistic shows that although the waiting time of inpatient has been controlled less than 26 weeks, the number of waiting inpatient is still large. (Data is adopted from [1][2])

shown in figure 4. Here, in this first simple case, we only consider the dynamics of patient arrival rate which denotes as λ per day.

Each day, there is a global patient treatment information collected by hospital. We formalize it as:

Definition 2: A ***Global Patient Treatment Information*** is a growing matrix $PatientTreat = \{pt_{kj} | 1 \leq k, 1 \leq j \leq n\}$. Where pt_{kj} is a triple which denoted as $< treat_{kj}, in_{kj}, out_{kj} >$. Here, $treat_{kj}$ is the estimated treatment time with organization j for patient k. in_{kj} is the actually treatment start time and out_{kj} is the actually treatment finished time.

The goal of our first task is to to minimize the total waiting time for a given fixed number of patients in a hospital. This will be calculated by personal waiting time per person and be evaluated waiting time efficiency rate:

Definition 3: ***Patient Personal Waiting Time***. Let $ST_i = in_{i1}$ denotes the start time (time to enter into the first department which normally be the registration department) and $ET_i = out_{in}$ denotes end time (time to leave the last node) of patient i in the hospital. Thus, a waiting time of patient i can be expressed as:

$$W_i = ET_i - ST_i - \sum_{j=1}^{n} treat_{ij}$$

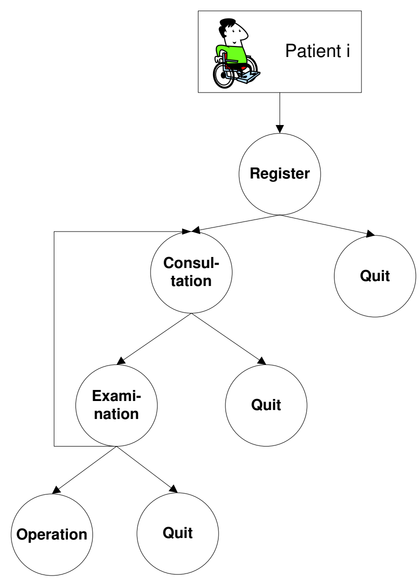

Figure 4: Illustration of patient treatment state transition. In each stage, patient may make a decision about whether come to next stage treatment or quit from current waiting queue. This also demonstrates one kind of patient dynamics.

Definition 4: ***Waiting Time Efficiency rate*** can be calculated by two ways. The first way is to see the average waiting time with a fixed patient number m.

$$\bar{WT} = \frac{\sum_{i=1}^{m} W_i}{m}$$

Another way is to see the median waiting time of m patients. This index is denoted as M_{e-wt}. To calculate this index, we first need sort the patient personal waiting time from small to large. Then we can use the equation below:

$$M_{e-wt} = \begin{cases} W_{\frac{m+1}{2}}, & \text{if } m \text{ is odd} \\ W_{\frac{m}{2}} + W_{\frac{m}{2+1}}, & \text{if } n \text{ is even} \end{cases}$$

Given definitions above, some specific problems related to our first task are shown below:

- Distributed scheduling mechanism: How to design a distributed scheduling mechanism from bottom-up systems approach?
- Performance: Can the local behavior-based strategy efficiently schedule patients? How long will it take to form a scheduling scheme? How about the performance and complexity compared with other scheduling strategies?
- Scalability: When the number of entities (means organizations) and the number of arrival patient increase can the distributed scheduling mechanism remain efficient?

4 AOC-Based Strategy Formalization

Following AOC framework given in [15][16], each organization is regarded as an autonomous entity which interact with each other as well as the environment and behave according to own behavior rules to reach their local objective. The global objective which is to minimize average waiting time will be achieved in the last.

Definition 5: Each node has an ***Entity*** e. It can be described by a state space $< id, patientOrder, utility, rules >$. Where id is the unique ID of organization where this entity resident. $patientOrder$ is the calling schedule arranged by entity based on $utility$ and $rules$. The $rules$ includes some local behavior like greedy-select, cooperative-select, competitive-select.

Definition 6: The ***Local Environment*** of entity e_i denotes as E_{l_i}. $E_{l\_i} =< neighourID, neighourID.patientOrder >$ In our strategy, an entity can only get the local information which send by parent nodes (which have a directed edge into this entity)and sibling nodes (which have bidirectional edge with this entity).

Definition 7: ***Global Environment*** $E_g = PatientTreat$ provides the prospective treatment time of each patient at all organizations.

An important issue in designing a distributed scheduling strategy is how to enable entities rapidly scheduling patients with direct/indirect interaction. we design three kinds of behaviors for entities to select and arrange their own patient treatment queue.

(1) **Greedy Selection Behavior** is a personal behavior strategy of entity that each entity will select patient with shorter treatment time prior than those with longer treatment time. Of course, the temporal constraints of overall treatment time period of one patient should be considered.

(2) **Cooperative Behavior** will happen among parent nodes and children nodes. If the order of patient i at organization j is later than the order in the schedule of its children $j.children$, then entity j and children entities $j.children$ will cooperate to adjust the patient order. The strategies of how to cooperate will be studied in later work. In this paper, we randomly chose one entity to keep his order. Therefore, other entities will adjust the patient order to keep up the changes and to satisfy the temporal constraints.

(3) **Competitive Behavior** will happen among sibling entities. If the orders of patient i among sibling entities are contradictory, then entities will compete with each other to win the handling priority. The strategies of how to compete will be designed in later work. As well, in this paper, we randomly chose one entity to keep his order. Other entities will adjust the patient order to keep up the changes and to satisfy the temporal constraints.

5 Summary and Future Work

Organizations (departments/units) in hospital can be regarded as living cells or autonomous entities. This paper assumes that a tough and complex problem—-distributed dynamic patient scheduling problem will be solved by local behaviors like cooperation and competition of individual entity. An initial model yields this idea has been proposed from Autonomy Oriented Computing (AOC) approach.

The purpose of our work is not only to provide an efficient distributed and natural like solution to ease waiting time, but also to reveal that shaping the perspective from bottom-up approach (e.g, organization's local behaviors to system's global pattern perspective in health care) is a different but useful tool when solving complex problems. Our work also provide a practical example for complex organization management problems in other areas besides health care in real world.

Future works include (i) to fine-tune our AOC-based model and strategies to better match the situations in real world, (ii) to justify the efficiency and analyze the characteristics of this approach. As well, due to the critical role of organization structure, we will (iii) study some important issues related organization structure in health care system (i.e, organization structure formation and evolution in health care) which have been mentioned in section 1 in the future.

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